Perceptual Based Visualizations for Time-Dependent Semantics

by

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Abstract

Time-dependent semantics are concepts that vary over a period of time. We interact with time-dependent semantics on a daily basis, such as reading weather forecast, inspecting market fluctuations, and studying personal financial trends. However, some of them are difficult to comprehend due to their inherent complexity. Visualizations using simple animations have commonly been used for depicting and communicating time-dependent concepts. Research on visualizing time-dependent information places a strong emphasis on the adequate representation of the information being visualized. In this thesis I develop novel representations for a class of time-dependent concepts used in the information sciences. Despite the advantages of using animation for time-dependent semantics, a recurring problem is the visual overload of moving objects as the density of information increases on the screen. The visual overload hinders attention and comprehension. This thesis also addresses the issue of adequately presenting information to enhance attention in animated scenes.

The first study (consisting of three stages) focuses on representing complex time-dependent concepts using simple visual representations, modeled on existing perceptual theories. In the first stage, a set of visual representations are created for a selected class of time-dependent concepts. In the second stage, the best representations for the time-dependent concepts are produced through a user evaluation. In the third stage, the visual representations are evaluated for their ability to enhance comprehension in an area of application, such as quantum algorithms. Results of the user evaluations show that there

is a significant increase in comprehension when animations based on perceptual theories are used for representing the selected class of time-dependent concepts.

The user evaluations also suggested that users quickly loose attention to important aspects of an animated scene, as the number of animations and time-dependent changes in the scene increase. Hence, the second phase of the thesis focuses on improving the presentation of animated scenes. The improvement is based on a focus+context technique known as Semantic Depth of Field (SDOF), which reduces the visibility of unimportant information in the scene. Results of a user evaluation show that the accuracy of tracking multiple targets improves when techniques such as SDOF are added to the presentation of animated displays.

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Declaration

The experiments described in Chapters 4 and 5 have been published in the proceedings of the 9th International Conference on Information Visualization [KIT05]. The experiment described in Chapter 6 has been accepted and presented as a poster in the IEEE Symposium on Information Visualization 2005 [KI05].

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1. Introduction

To a large extent, information used in the information sciences consists of abstract concepts. In areas such as software engineering or algorithm design, the meanings of the concepts or semantics have to be properly understood in order to construct robust and efficient systems. A significant amount of these semantics are presented visually, through node-link diagrams, such as UML (Unified Modeling Language) and symbols (mathematical, historical, directional, etc.), as shown in Figure 1. The visual representations are used in the development of systems to facilitate communication between end-users and developers. As a result, the proper development of systems depends on the effectiveness of the visual representations for conveying the semantics intuitively.

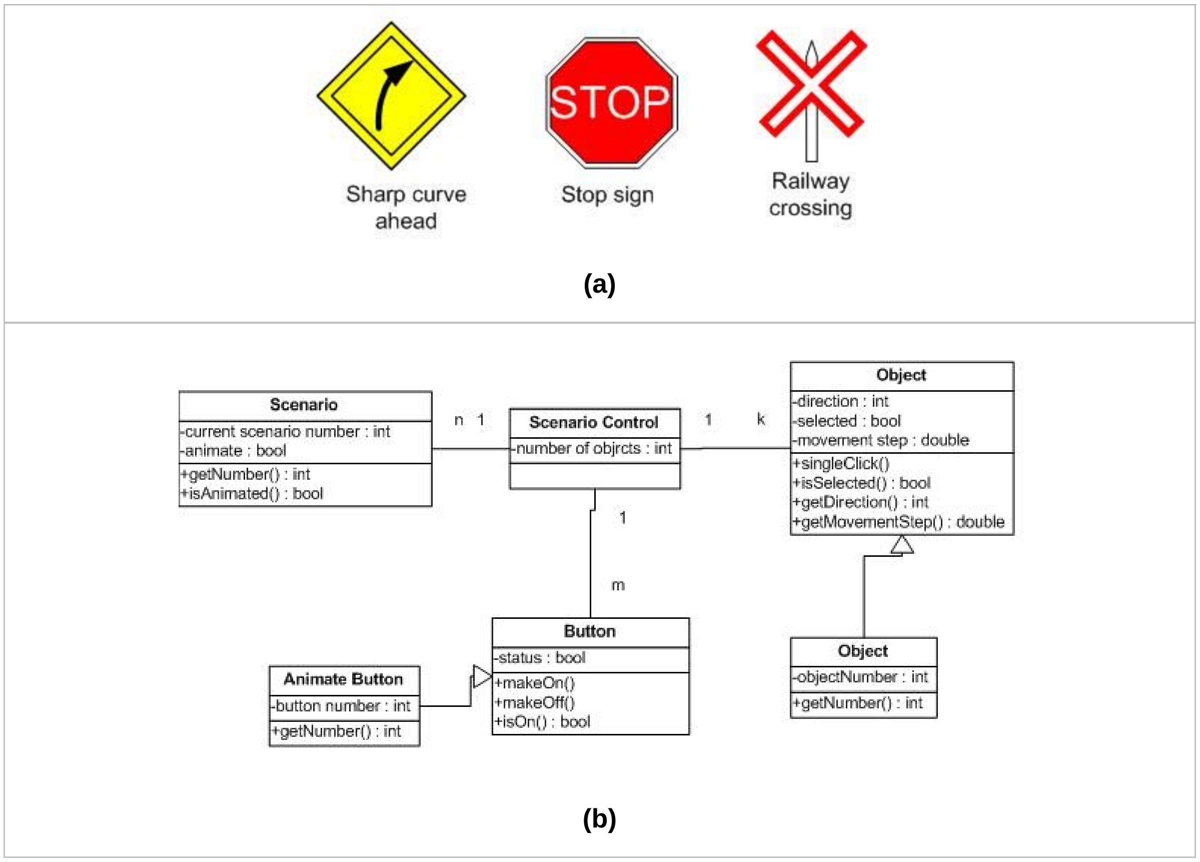


Figure 1: Symbols are simple conventions for communicating information. (a) Road signs communicate warnings, dangerous conditions, and information on road directions, and (b) UML diagrams communicate class information, relationships, dependencies, and instances of class objects.

On a strictly temporal dimension, a significant number of abstract concepts or semantics can be classified into two general categories. The first category consists of semantics that are independent of time or semantics that stay the same over a period of time, referred to as *time-independent semantics*. In software engineering the concepts of inheritance, dependency, and aggregation are examples of time-independent semantics. For example, in the case of inheritance the parent-child relationship is static and remains the same throughout the life-time of a system. Time-independent semantics are usually represented by drawings or static images. For example, in the information sciences, static diagrams have been used extensively to describe various components or functions of a computer such as its architecture, or the structure of logic circuits. Static images usually describe non-temporal data, or data that does not change over time.

The second category of semantics is used for describing abstract information over a period of time. In my thesis, I refer to these semantics as *time-dependent semantics*. The timeline of a project in software engineering, the constant entering and exiting of computers in a real-time network, the change in state of a human body over a period of time, or simply the changes occurring in the environment are all good examples of time-dependant semantics. In such cases, the information is contingent on some temporal property. Figure 2 below schematically depicts the relationship between time-dependent semantics and time.

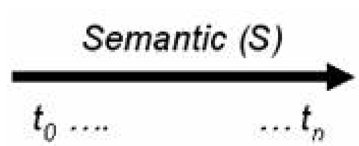


Figure 2: A time-dependent semantic is one whose complete description takes place over a period of time.

Dynamic visualizations are animations for representing time-dependent semantics [RCM93]. Studies have suggested that dynamic displays assist users in creating a mental model of the processes that change over time in a given system [BCS99, KST01]. Such models, improve the ability of the user to comprehend the dynamics of a system, with increased efficiency, and hence reduce the mental processing load on the user [KS02, CU93, HS93]. Dynamic visualizations are commonly seen in video games, radar based systems, weather forecasting software, and in pedagogy. A significant number of studies have investigated the use of dynamic visualizations. In some cases the representations have been effective and in other cases dynamic visualizations have impeded user understanding. However, in general these systems have focused on three major aspects: the representation, the presentation, and the interaction.

- **Representation:** Abstract information needs to be encoded visually such that the user can quickly and easily comprehend the information. Representation is the possible encoding of abstract information onto the visual display.
- **Presentation:** Along with representing complex information visually, it is also important that these visual representations be presented efficiently. Here, presentation cues can also be employed to enhance the representations and improve efficacy in communicating the abstract information.
- **Interaction:** Interaction consists of allowing the user to manipulate the visual presentation to accomplish their tasks or objectives. Using interactive techniques, users can create their own scenarios and attempt to solve them.

As with many visualizations dynamic systems in particular need to be built upon well-founded representations, and need to present the information in a manner that will allow users to attend to parts that are important. In my thesis I have focused on two main aspects of visualizing dynamic systems: the **representation** and the **presentation**. In the first part of my thesis, I have developed representations for a small set of time-dependent semantics based on theories of perception. The underlying assumption is that perceptual theories provide a general framework, with well founded guidelines of human capabilities, and can assist in the design of certain visual representations. In an effort to evaluate the set of representations that I have designed, I have evaluated them in a pedagogic setting in the field of quantum computing.

A critical component in dynamic visualizations is the presentation. When a scene is presented to a user with many moving parts it can be difficult for the user to attend to information relevant to the task. The problem can be stated as how to maintain the user's focus and attention on a subset of the display, without them losing context of the entire scenario. In the second phase of my thesis, I have analyzed various techniques for improving attention in dynamic scenarios, using focus+context techniques. The predictions in the second part of my thesis were that focus+context techniques can improve the presentation of dynamic systems. Hence, in my research, I have evaluated the effectiveness of these techniques in dynamic applications.

1.1. Goals and Objectives

The main goal of my thesis is to improve comprehension in complex dynamic scenarios. As mentioned earlier, there are three major aspects to improving comprehension; representation, presentation, and interaction.

In this thesis I focus on the factors of representation and presentation. I discuss related work and then evaluate different representation and presentation techniques that can be employed in dynamic scenarios. The factor of interaction, though briefly introduced, is not concentrated upon in this study. This is simply because it is beyond the scope of the thesis and the study of interaction techniques and their practical applications to dynamic systems is considered as future work for this research.

Hence, my overall goals for this research can be listed out as such:

- Analyze the effectiveness of employing visual representations to convey complex information and evaluate them through experimental methods.

- Analyze and evaluate different focus+context methods of presenting visual information with the aim of improving dynamic systems.

1.2. Methodology

I have listed below the methods I used to achieve my goals. I evaluated the efficacy of my representation techniques in three phases:

- **Phase 1:** In the first phase, I shortlisted some general dynamic concepts and created various visual representations for each of them. Each concept had a set of 3-4 representations, which I felt were suitable to denote the respective concept.

- **Phase 2:** In the second phase, I analyzed the representations that were created in Phase 1. The results of this experiment shortlisted one visual representation per concept, from the set of alternative representations.

- **Phase 3:** In the third phase, I evaluated the visual representations from Phase 2 using quantum algorithms. The focus of this experiment was to evaluate the efficacy of these representations in a practical pedagogical application.

In the second half of my study, I evaluated the efficacy of presentation techniques through an experiment. This experiment compared different methods of presenting visual information and produced the most efficient one of these representations.

Overall, my thesis is structured as follows. Chapter 2 describes various studies that support and discourage the use of animation to represent dynamic information. Chapter 3 describes various perceptual (static and dynamic) issues related to the research in this thesis. Chapter 4 is concerned with the adequate representation of time-dependent semantics. Chapter 5 describes the validation of the visual syntax described in chapter 4. Chapter 6 focuses on the study that was designed to evaluate the effectiveness of a focus+context technique to the presentation of dynamic data. Chapter 6 is followed by the conclusion, acknowledgement, references, and appendix.

2. Dynamic visualization for eliciting comprehension

To a large extent time-dependent semantics or temporal-based information are represented using dynamic visualizations or animations. Animations are highly successful for representing physical phenomenon that varies with time, such as weather forecasts or radar displays. However, for representing abstract information, the benefits of animation have to be accounted for on a case-by-case basis. Several studies have shown that animation can improve comprehension while other studies have not shown any positive effects of animation. Most results conclude that interaction is an important element in using animations. However, very little investigation has taken place to examine the effects of alternative representations or presentations of dynamic or time-dependent concepts using animation. In this chapter I present the set of studies that support the use of animation and those that do not. Finally, I present a concrete example of a time-dependent semantic that has been represented and presented in alternative forms.

2.1. Static or Dynamic?

The question of whether to show time-dependent information using static diagrams and visualizations or dynamic animations has been of long standing interest to researchers in information visualization and cognitive science [TMB02, Bae98]. The results are mixed and inconclusive on when to use dynamic representations. On one hand studies have shown that animations can enhance user comprehension and on another hand animations have deterred knowledge acquisition.

2.1.1. Studies reporting the benefits of animation

Intuitively, dynamic visualizations (or animations) seem to be the most natural way of conveying concepts that change over time. Animations have been used in several contexts, particularly as learning aids [BBG+99, Bae98], for showing causal relationships [WNB99, ET03a], for supporting visual queries in large diagrams [WB04], and for interacting with hierarchical visualizations [RMC91, SZ00]. While there are not many applications that use these visualizations for depicting temporal data, the ones that do, show positive results.

In the field of pedagogy, dynamic visualizations have been commonly used for describing the dynamic and behavioral aspects of software systems, algorithms, and networks. Some examples of dynamic visualizations include concepts for expressing sequence flows, state transitions, and causal events. These visualizations constitute a significant core in the design of algorithms and data structures. They also appear in disciplines such as: the social sciences for describing social interactions, in chemistry for explaining chemical reactions (transformation of compounds), and in physics for describing the effects of physical laws (such as gravity) or the motion of sound waves.

Dynamic visualizations have also been used extensively in various educational systems in an effort to visually simulate dynamic behavior and hence, augment the students' appreciation towards difficult concepts [Bae98]. In the field of computer science, extensive research has been performed in analyzing effective methods of improving comprehension of complex concepts such as in data structures [BB01], algorithms [BCS99], using animations.

Baecker [Bae98], utilized animation to describe the working details of various sorting algorithms. The main motivation behind using animation was to simplify the explanation of dynamic sequences to students using animations. Dynamic sequences were created that traced the sorting of a set of numbers using the different algorithms. The study focused on displaying the properties of nine unique sorting techniques. The sorting techniques were divided into three general categories; insertion sort, selection sort, and exchange sort techniques. The primary form of representation in this study was the use of animated images to depict the values being sorted. However, the type of representation and animation varied between the three general categories. In the insertion sort category of sorting algorithms, the individual items were represented as vertical bars, where the height of the bar was in proportion to the position of the number on the mathematical number scale (i.e. the larger the number, the larger the height of the corresponding bar). In the selection sort category, the individual items were represented as horizontal bars. In the exchange sort category, the items were represented in a tree structure (Figure 3). As the animation progressed and the numbers were sorted, the bars changed position smoothly to represent the change in the physical location of the number in the given set. Color schemes were used to distinguish between different states of the simulation and the speed was modified according to the complexity of the concept that was being described. The participants in this study were divided into two groups. One group received a textual description of the algorithm while the other group was shown the dynamic sequences. The results of Baecker's study suggested that although students were able to understand the dynamic phenomena, the improvement in understanding was significant when visual simulations were used to enhance the concepts.

Stasko [Sta97] conducted a study, on university students, that evaluated the efficacy of animations in teaching computer algorithms. The algorithms that were applied were sorting algorithms and the students were asked to create the animations themselves as it was hypothesized that self-preparation of the animations would improve comprehension. An interactive animation system, called the BALSA system, was constructed that accepted an input of ASCII commands. The main aim of this system was to help the students understand the fundamental workings of the algorithm, by building it from the basics. The main form of representation of information in this study was in the form of simple polygons and lines that were used to create the visual representations. The students had to choose their own representations such as bars, circles, lines and tree structures, depending upon the type of problem. During the simulation, they viewed the animation as a sequence of visual representations, and were also supplied with extra information on the algorithm in the form of "print" statements (previously specified by the students themselves). The students were also allowed to control the speed of the animation by either stepping through the animation or by pausing at any desired time. The BALSA system was evaluated in a student environment, by allowing students in an algorithm course to apply the concepts that they learnt in class, such as quicksort and minimum spanning tree algorithms, to build their animations. The results of this study were encouraging as the students commented that they understood the concepts better because they created the animations by themselves and were able to visually view the dynamics of the concept.

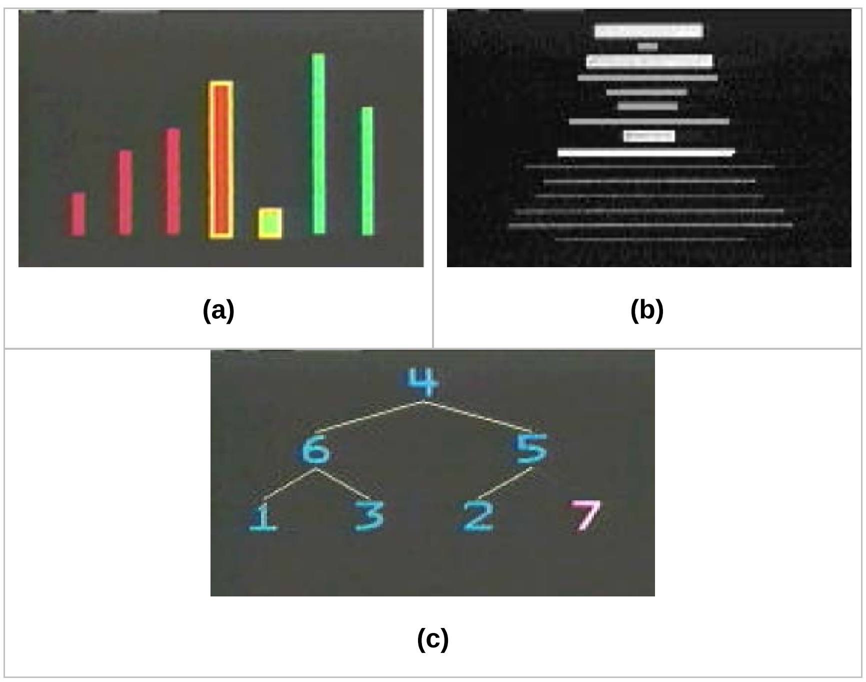


Figure 3: Sorting techniques were shown in the form of dynamic visualizations (a) insertion sort, (b) selection sort, and (c) exchange sort techniques [Bae98].

Another study was conducted by Sonnier and Hutton [SH04] to analyze the effect of dynamic visualizations in teaching various concepts in physics, mathematics and computer science. The concepts that were tested were all dynamic such as algebraic equations for mathematics, optic flow for physics, and sorting techniques for computer science. The visual representations grew more complex as the complexity of the process increased. For example, simple concepts such as acceleration, in physics, were represented in the study using the factors of speed and physical displacement. However, for more complex concepts, such as heat analysis, complex visual animation that included colors, texture, and shading were used (Figure 4). One of the experiments focused on elucidating the concepts of linear programming, using dynamic visualization. One group of participants viewed an animation of a linear program, while the other group was provided with textual study material of the same concepts. At the completion of the experiment, the participants of both the groups were quizzed on the concepts described to them. The results of this study showed that there was no significant improvement in comprehension in high aptitude participants (experts). However, in participants with lower aptitude (novices), significant difference was noticed, as the animations enabled these participants to get a clearer view of the dynamic concept. Hence, the study concluded that even though dynamic visualization may not be suited for all types of people, it certainly helps in providing introductory information about complex concepts.

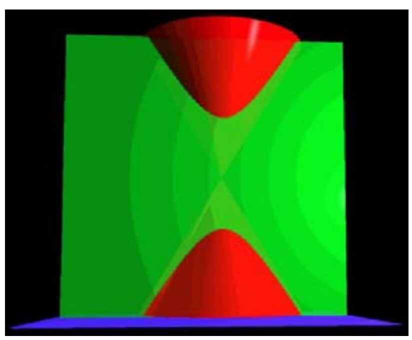


Figure 4: Screenshot of a plane moving through a conical section to create hyperbolic curves [SH04, Hut04].

2.1.2. Some applications of dynamic visualization

In addition to research being conducted in the field of visualization, there are many visual systems that have been created to improve comprehension and simplify complex concepts into dynamic simulations. None of these systems have evaluated the effectiveness of their representations but have described their benefits at a purely pragmatic level.

Stasko [Sta92] created a tool called XTANGO that allows users to construct animations for complex procedures. The system employs color coded, real-time, multi-dimensional techniques, and smooth animation to simplify user described concepts. The uncomplicated design of the system does not require any prior expertise in graphics. The primary forms of representation were simple polygons (circles, rectangles, squares etc.), and lines, which were provided in the form of C programming constructs and were animated by the XTANGO animation package. A functionality of this system is its dynamic execution of the program constructs, which allows for on-the-fly execution of given information. This feature is very useful as users can change the data sets and view new simulations without the need for recompilation. Stasko [Sta92] states that using the XTANGO system, it is interesting to see the various types of animations that are created by users and also the various concepts that are regarded as complex enough to be animated by this system.

Becker et al. [BB01] created a system that could be used by university students to study advanced data structures. The tool aims at simplifying the concepts by allowing the students to create their own animations. The primary form of representation was using rectangles and lines to represent and connect the values in a B-tree structure. The system also contains some basic examples that can be manipulated by the students to view different results. Using this tool, students can create their own data structures (e.g. B-trees), can add and delete nodes, and add and delete keys from the structure. During these addition and deletion operations, the students can view the B-tree restructuring itself according to the new commands presented to it and the effect that these restructurings have on the rest of the data structure. The researchers state that this system is useful to students and instructors alike as it is versatile and can be used for dynamic and interactive demonstrations. Instead of creating individual, time-consuming presentations, instructors save valuable time by simply demonstrating the dynamic reactions of the data structure to different sets of data input. From the students' point of view, this system enables the exploration of data structures concepts, the repetition of actions until the concept is clearly understood, at the students' leisure.

2.1.3. Studies reporting the negative effects of animations

While animation has enhanced comprehension in certain cases, there is evidence that static representations can be as good as animations. In cases such as the explanation of instructions for assembling objects, animations have not shown major benefits over simple arrows. Tversky et al. [TZL+00] have shown that static images can be used as effectively as animations to portray information and have consolidated several types of symbols that can be used to represent information. Some of these symbols are: lines that are curved or straight to show the shape of the path, combinations of lines forming objects such as squares to show the occurrence of some type of physical object, intersecting lines to show intersecting roads, or lines or bars to show gradients or quantitative values in graphs. Similarly, the authors state that static arrows are as effective as animations in showing temporal sequence and direction of motion. This is because static arrows can be easily understood and hence need not be animated unnecessarily. The consensus of this study is that there are many cases where static images can be used as effectively as animation and hence it is unnecessary to use animation in all situations.

In a study by Reiber et al. [RH88] animated images were shown to be incapable of conveying Newton's laws of motion with significant improvement over the static representations. These studies show that in some cases change over a period of time can be represented by static images. However, the changes in these studies were of a sequential nature, and hence did not hold the high level of complexity that is seen in concurrent or parallel structures.

Though dynamic visualization, in the form of videos, has been widely accepted and encouraged, a study by Pane et al. [PCJ96] refuted the assumption that dynamic visualizations can be used in all situations to improve user comprehension. In their study, experiments were conducted to compare the advantage of dynamic visualization (in the form of videos or computer simulated presentations) over text and carefully selected still images. The experimental environment, called Advanced Computing for Science Education (ACSE), explained the concepts of biological processes in the form of text, images, videos, and simulations. The learning effects of participants in this experiment were compared to a control condition, which was a mixture of text and static images. The experiment recorded factors such as the time taken to complete given tasks, performance in a review test, and student attitude. The results of the experiments showed that there was insignificant improvement in user comprehension between the dynamic presentations and static images, if the static images were chosen carefully such that they gave a clear description of the process. However, significant increase was noticed in user comprehension, with dynamic representations, in scenarios where the outcome was unpredictable due to the variable nature of input data. Hence, the study concluded that dynamic representations should not be used as stand-alone mediums of instruction, especially in situations where dynamic concepts can be adequately represented by carefully selected static images and textual material.

Another study by Morrison and Tversky [MT01] compared the enhancement in comprehension, of students, between the mediums of text, a mixture of text and static images, and animated graphics. The experiment was conducted on university students and factors such as concept explanations and time restrictions were manipulated between the different groups over three experiments. In the first experiment of this study, the participants were given clear explanations of the concepts with logical reasoning and were also allowed to re-read the material without any time restrictions. The results of this experiment showed that there was no difference between learning concepts using static or dynamic materials. In the second experiment, the concepts were explained to the student (without a time constraint), but the logical reasoning was omitted. In this scenario the results showed that, though participants who had less ability to create mental images performed better with graphics over text-only representations, there was no significant difference in comprehension between static and dynamic simulations for any of the participants. The final experiment was similar to the second experiment, with a time constraint. The results of this experiment suggested that the participants with low spatial ability did not perform as well as the other participants. However, the reason for this difference in performance was attributed to the time constraint and not to the method of concept representation. Also, as with the previous experiments, the participants performed better with images over text, but without any significant difference between static and dynamic visualization. The overall consensus of this study was that even though visualization provides an improvement over a text-only approach, dynamic visualization does not show any significant improvement over static visualization. However, in this study, there is no specific indication about the actual concepts that were tested on the students. Hence, it can be argued that the concepts that were displayed might not have been dynamic enough to warrant the need of dynamic visualization.

2.2. Summary of related research

One study that establishes a cursory summary of the benefits and drawbacks of animation was designed by Kehoe et al. [KST01]. The main aim of this study was to analyze the reasons for the vast difference in opinions of employing dynamic representations to display complex information. In this study, the authors described three possible explanations, inefficacy of the representations used in the animations, inadequacy of evaluation methods, and deficiency in experimental design. Kehoe et al. claimed that, in contrast to previous studies, where all the participants were asked to answer questions in an exam-like scenario, their study consolidated a home-work environment where participants were not subjected to a time constraint and were allowed to study and answer the questions at their leisure. Also, the participants were allowed to refer to any of the study material while answering the questions, hence creating a home-work scenario. The concept that was used in this study was the binomial heap and the participants were divided into two groups, animation and non-animation. Both the groups were allowed to read their respective study materials over a webpage. In addition, for the animation group, the animations were provided as links on the webpage. The students were not restricted to any time frame, though the amount of time they took for various tasks was recorded. The results of this study showed that there was a very slight difference when participants of both groups were asked questions that required theoretical knowledge such as definitions. However, a significant difference in comprehension was observed when students were practically asked to demonstrate the concepts they have learnt in a sample binomial heap. In addition, a significant reduction in interest was noticed among students in the non-animation group towards the end of the questionnaire session, as they were experiencing difficulty in practically implementing the concepts they had learnt. Overall, the results of the experiment were quite encouraging and Kehoe et al. stated that they were able to hypothesize three distinct factors that were prominent in improving comprehension; animations were more useful if they were interactive and did not impose any time-restriction on learning the concepts, animations help learning even if they do not completely describe the concept as they help in providing motivation by making the learning process less of a challenge, and algorithm animation is best suited for describing practical details of the workings of algorithms.

Summarizing the research conducted by the various authors, I have consolidated a table which describes some of the situations where animation has proven to be effective and situations where animation has either been ineffective or has impeded efficient comprehension.

Animation has proved useful	**Animation has not been useful / has impeded comprehension**
In simplifying complex dynamic information into simple visual	When used in scenarios where the concepts are very simple and/or the information can

representations such as in data structures, algorithms, physics, chemistry, etc.	be represented adequately using static images.
In expressing dynamic behavior such as sequence flows, causal events, social interactions, and state transitions.	When used in excess, causing an overload of information and impeding judgment rather than enabling it.
When used to improve user interest and improve comprehension of complex concepts.	When changes in the dynamic scenario are very far apart and hence can be amply represented using static images.
When used in interactive systems that allow the user to explore the concepts using animations, improving the users' interest.	When small changes in the system are inconsequent and the larger, more important changes can be represented by static images.
As an added supplement to other forms of information such as textual, quantitative, etc. to improve understanding of the concepts.	When they have replaced other information, such as quantitative values and textual information, abstracting valuable information.
As a method of reducing time-consuming information processing, by viewing visual representations that are easily assimilated by the eye and processed quickly.	When they have been used in situations where they are of use only to novices who have a low visualizing capability and hence are cumbersome to the experts.

In an effort to maximize the effectiveness of animation in conveying information, a study was conducted by Tversky et al. [TMB02] that examined the efficacy of dynamic over static images. The study compared research performed by various scientists, who claimed that in their respective studies, dynamic visualizations proved to be an improvement over static images. This study argued that many of the previous studies do not compare the two types of representations on a fair scale. Tversky and Betrancourt [TMB02] proposed two guidelines for constructing effective animations: *Congruence* and *Apprehension*. The principle of congruence suggests that the animation should correspond to the internal structure or to the content being represented. The principle of apprehension implies that the structure of the animation should be readily perceived and comprehended. Tversky et al. [TMB02] state that in many cases the higher performance of dynamic representations can be attributed to the fact that more information is displayed, when compared to the static images, and not to the superiority of the dynamic representations themselves.

With regards to my thesis, whenever possible, I have followed the above given guidelines of congruence and apprehension in the construction of my visual representations. However, I note here that there is one significant difference between the types of dynamic representations that have been evaluated in the studies described above and the ones that I have constructed. Most types of visualizations in the previous studies consisted of dynamically changing the spatial location of the objects, of highlighting parts in a temporal sequence or of adding and removing items from the display (these are all defined as animation as some aspect of the display is being dynamically updated). As will be described later in my thesis, the representations that I have constructed consist of smooth transitions that change one or two visual attributes of the object being animated (tweening), to denote a semantic. The spatial location and the direction of motion are not critical for representing the semantics that have been selected for my thesis. The main focus of my study is to determine whether the change of visual attribute(s) and the visual relationship between the objects will lead to an appreciation of the semantic being represented. The animation will only be used to depict the change of visual features over some arbitrary time frame; no meaning is attached to the physical movement of the objects.

2.3. Interaction as a medium of improving comprehension

The above discussed studies lead to a general consensus that pure dynamic visualizations (videos) do not always contribute to the improvement in user comprehension. They suggest that it is important to involve the user in the dynamic process as it increases his/her interest in the ongoing activity, i.e. it is essential to allow a user to *interact* with the visualization and to explore all the various possibilities that the dynamic process has to offer.

Several studies report on the benefits of allowing the user to control dynamic visualization by means of interactivity. This is necessary if a user is to understand properly the evolution of the semantic over time. A study by Byrne et al. [BCS99] evaluated the effect of animations on learning algorithms. They found that a high level of interactivity, which allowed the learners to control the animation, was more important than animation without interaction. They concluded that interactivity with animation constituted a necessary and integral part of the learning process. Another study by Saraiya et al. [SSM+04] evaluated a list of features that made the visualization of algorithms effective in pedagogic situations. They concluded that stepping through the visualization was more effective than running it without any interruptions.

Another study was conducted by Grissom et al. [GMN03] to analyze the effectiveness of dynamic information representation in computer science education. In this study, the authors focused on comparing three levels of an engagement taxonomy defined by [NRA+02]; no viewing (information is displayed text only), viewing only (information is visually represented, but interaction with the representations is not permitted), and responding (information is visually represented and interaction with the representations is permitted). The authors conducted a within subjects study, using a visualization tool called JHAV́E, that dynamically simulates sorting techniques. On comparing pretest and posttest scores, the results of the study showed that participants who interacted with the dynamic representations performed significantly better than the other two groups. The study suggested that as student interaction with a concept increases, the comprehension level also increases. Also, the subjects in the responding group were students of a lower level course when compared to the subjects in the other two groups, which further justifies the fact that interaction improves visual comprehension. However, as mentioned earlier, the factor of interaction is beyond the scope of this thesis and hence will not be developed or evaluated.

2.4. Presenting animation

A critical component in dynamic visualizations is to allow the user to focus on parts of the display effectively. It can be inferred that presenting information such that the user can better focus on moving parts is critical in improving comprehension. Jones et al. [JS00] investigated the effect of animated diagrams to show temporal relationships in the flow of blood through the heart. Their overall study consisted of two separate studies, each of which compared different aspects of viewing dynamic concepts through animation. Their first study aimed at comparing static and animated representations of blood flow through the heart. The static sequences were shown in a paper format while the animated sequences were shown on a CD-ROM. The study consisted of two types of tasks; an open task where the participants were required to investigate by themselves the working of the heart, and a structured task where the students were given a set of concepts to learn and understand. The participants were divided into four groups, each group being a unique combination of the type of task (open or structured) and type of display (static or dynamic). The result of this study suggested that though there was insignificant improvement over using animation instead of static representations, significant difference was seen when the task was structured compared to an open task. This was because the participants were given a set of guidelines, a limit of what they should learn, and which of the several concepts are most important at that time. Hence the overall consensus of this study was that comprehension is improved if the users' attention is directed towards important events of information rather then allowing them to discover the dynamic changes for themselves. This is because when numerous dynamic changes are occurring in a system, it is more efficient to direct the viewers' attention to important changes rather than allow them to get lost in a sea of dynamic changes.

In order to further evaluate the affect of animation, a second comparative study was made by Jones et al. [JS00] between dynamic and static approaches. The aim of this study was to evaluate the improvement in knowledge when using animated displays instead of static displays. The participants were again divided into two groups, similar to the previous study, with the only difference that participants who were in the dynamic visualization group did not receive any textual information along with the animation.

Again the results of this study showed that there was no difference between using static or animated displays. However, it was noticed that with repeated viewing of the animation, user comprehension seemed to improve as the participant knew what type of information to look out for. Also, the study suggested that in cases where the attention and focus of the participant was captured and directed to a particular dynamic concept or event, the participant was able to understand the concept better and retain it in a much better fashion. The overall consensus of this study states that animation is useful and provides more information when compared to static approaches, only when the animation is structured, provides a good set of guidelines, and directs the user's attention to important events. It is therefore critical not only to develop adequate representations but also to control the amount and type of animation that is employed so that the user is not overloaded with unnecessary information.

2.5. Causality: an example of time-dependent semantic

The studies described so far evaluate the effectiveness of animations for showing information that is dynamic in nature. The semantics are various: ordering of items in the case of sorting, direction of flow in the case of movement, order and direction in the case of assembling instructions. The semantics evaluated are not atomic and are intermeshed. One very common and unitary form of time-dependent semantic is *causality*. In general terms causality is defined as the occurrence of one event being the cause of another event [Sol04]. For example, pushing a table can cause the table to move, or the pumping action of the heart causes the blood to flow out of the heart, or the change in state variables in a computer system causes the system to behave in different ways. The semantics for which I have developed visualizations are analogous to the semantic of causality, i.e. they describe general and abstract concepts, they are atomic, and they are time-dependent. Hence, I discuss the representation of causality as an example of a time-dependent semantic.

2.5.1. Causality as a generic time-dependent semantic

Causality occurs in various types and forms. In philosophy David Hume (18th century) believed that there are relations of time and space that are necessary to cause causal effects. The definition of causality in philosophy lies in the actions of human beings, and of God. Human beings are the cause of actions, deeds, thoughts, etc, while God is said to be the cause of nature, natural disasters, life, birth, death etc. In law, causality takes an important stance. The investigation into events generally asks the question, “Why did such an event occur”. For example, “Why was the person caught stealing?”, or “Why was he/she stealing in the first place?” Most questions in the practice of law are the investigation of why certain events occurred and what conclusions can be drawn from the investigations. Hence, the cause of the event is crucial to finalizing the verdict. In science, causality has many roots. In mathematics, causality can be shown in many variables of mathematical equations. For example, a summation equation can have many different results based on the range of the input variables. Similarly, in physics, gravity can be the cause of an apple falling or the unbending property of light can be the cause of shadows. In the field of computer science, the value in variable **A** can be the cause of action on variable **B**. Hence, in almost every field of the information sciences, causality is encountered.

2.5.2. Alternative forms of representing causality

The semantic of causality has been represented in many different forms. The most common representation is through a causal graph. A causal graph is a directed graph, which contains nodes and relationships between the nodes. The nodes constitute the events and the edges of the graph denote the relationship between the events. The direction of the edge denotes the cause and effect of a certain event, i.e. the node at the start of the edge is considered the cause and the node at the end of edge (arrow-head side) is the effect. These causal relationships can be direct, for example, walking for a long time causes sore feet (Figure 5.a) or indirect, such as poor information creates poor tutorials which in turn result in poor efficiency, comprehension, and satisfaction (Figure 5.b).

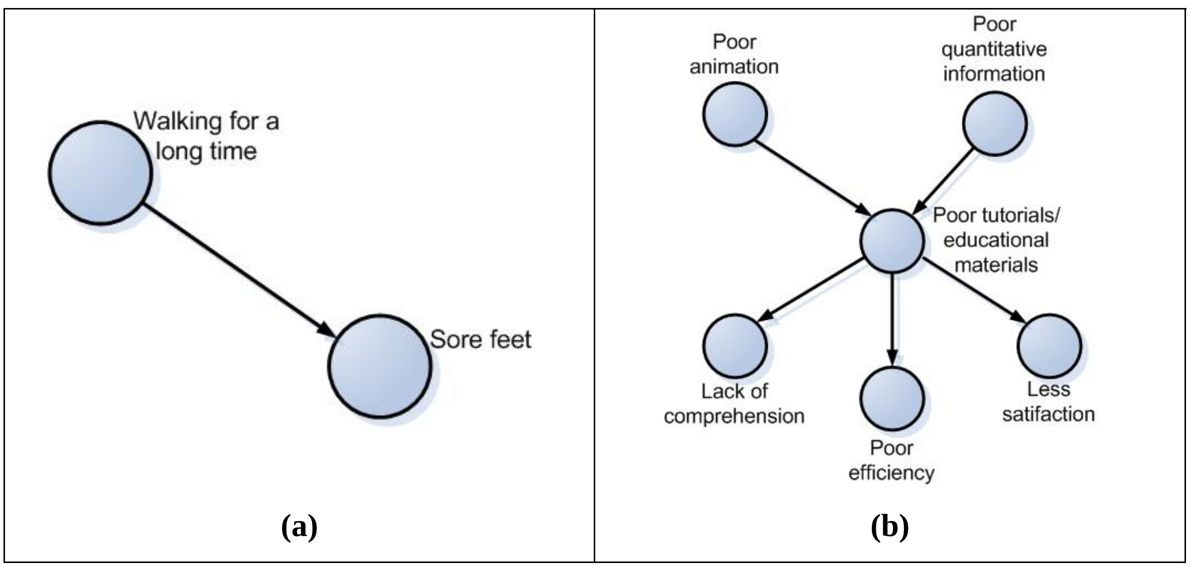


Figure 5: Causal Graphs. (a) Direct representation and (b) indirect representation of cause and effect.

An alternative form of representing causality is through animations. Ware et al. [WNB99] conducted three experiments to determine the type of causality that can be perceived by users. In their study [WNB99], they defined a causality vector called the *visual causality vector (VCV)* that represented the relation of causality between two objects. He tested the VCV using three metaphors of visual perception:

- ***The Pin-ball metaphor:*** In this metaphor, a stationary object **B** is hit, or pushed, by a moving object **A**. The resulting cause is a movement of **B** in a wave like fashion (Figure 6 (a)).
- ***The Prod metaphor:*** This metaphor is similar to the pin-ball metaphor, the only different being that object **B** is hit by a rod, instead of another moving object (Figure 6 (b)).
- ***The wave metaphor:*** This metaphor is based on the vertical oscillatory motion of wave forms. Here, a circular object is acted upon by a wave, and the object bobs up and down as the wave passes under it (Figure 6 (c)).

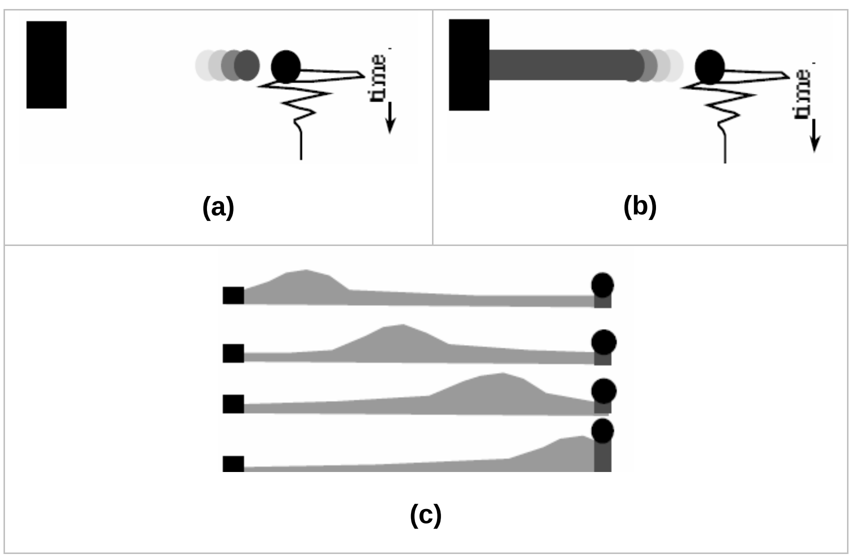


Figure 6: Causality was analyzed using three metaphors: (a) Pin-all metaphor, (b) Prod metaphor, and (c) Wave metaphor [WNB99].

Participants in this study were shown the visualizations and asked to decide if the representation shown to them depicted no relation, some relation or a strong causal relation between the objects. Preliminary results of this study showed that when object **B** started moving before it was hit by object **A**, no relationship was distinguished by the users, as **B** was perceived to be moving under its own influence and not due to any external force. When **B** started moving just as, or slightly after, **A** hit it, a causal relationship was determined by the participants. Some relationship was also perceived by the participants when **B** started moving a little while after **A** hit it. Ware et al. [WNB99] state that the concept of perceiving causal relations seemed to be dependent on the temporal relations between the cause and the effect. During the study, they also noticed that causal terms such as triggering and launching were highly complex and not easily comprehended by the participants. Hence, to evaluate if visual dynamics helped in understanding the causal relations, Ware et al. [WNB99] conducted an informal verbal follow-up study. In this study, they questioned the participants to get a good idea of how much of the concept they actually understood from the animation shown to them. Overall, it can be inferred from this study that complex concepts in causality are better understood if they can be represented by simple dynamic representations. This study is one of the earliest and very popular studies in the field of causality and has formed the basis for many other studies that research the efficiency of visually representing causality.

Using the wave metaphor of Ware et al. [WNB99], Solheim [Sol04] conducted a series of experiments to analyze the representation of node-link diagrams using causal animation. The experiments aimed at determining if the ideal timing for causal relations, as stated by Ware et al. [WNB99] was truly ideal to represent node-link diagrams. In this study, a simple two node diagram was acted upon by the wave and the participants' task was to adjust the time of wave travel between the nodes so that the causality is perceived between the nodes, i.e. the wave passes through the nodes in such a way that it seems like the first nodes released the wave that hit the second node. The results of these experiments showed that causal relation representations do fall in the ideal time as stated by Ware et al. [WNB99], which inferred that causal animation could be represented by node-link diagrams.

Elmqvist and Tsigas [ET03b] created an innovative method of visualizing causal relations, called the Growing squares technique. In this technique causal relations between processes executing in a system are visualized in the form of colored squares, as shown in Figure 7. The main focus of this study was to compare this technique to an already existing technique called time-space diagrams. According to the authors, there are many applications for visualizing causal relations in data mining, for example, determining software deadlocks, monitoring parallel programs, etc. Each process in a system is given a particular color. As a process interacts with another process, the color of the first process flows into the new process and the new process is filled in a checkered fashion. Each process contains the colors of all the processes that have affected it, no matter how indirectly. All the participants in this study had prior knowledge of the time-space representation of processes. Each participant was given various tasks of recognizing the process flow and relations in the visualization. The results of the evaluation suggested that there was significant increase in comprehension with the Growing Squares technique, and this is because by viewing the colors, participants found it very easy to distinguish the various processes that have affected the current processes.

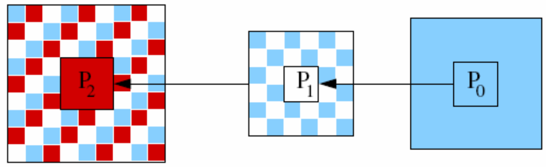


Figure 7: Process P0 sends a message to P1 which then sends a message to P2. The colors of processes P0 and P1 therefore spill into P2 [ET03b].

2.6. Chapter summary

In this chapter I have described related research that has been conducted to analyze the effectiveness of animation. The results of several studies that investigated the effectiveness of animation are not conclusive. However to a greater extent the representation and the presentation of the concepts play a significant role in assisting users to understand the underlying concepts. In this chapter I also discuss some guidelines that have been proposed by researchers for creating effective animations. The chapter concludes with an example of time-dependent semantic of causality.

The main hypothesis in this research is that adequate representations are necessary for depicting high level concepts or semantics. The representations that I have developed have been derived from research in perception. I will next discuss the related research in perception that has formed the basis of my thesis.

3. Related perceptual issues

One way to create effective representations is to base the design on guidelines from human perception. The human visual system is capable of recognizing visual properties very rapidly. As a result, theories of perception can leverage the design of visual constructs if they are applied adequately. In this thesis, theories of perception related to stationary object identification and motion are applied. Both are discussed below.

3.1. Static perception issues

Our visual system has evolved to facilitate object recognition in our environment. At a very high level, object recognition is achieved through a three stage process [War03] (Figure 8). At each stage the visual system extracts more information about the object so that the person can consolidate all possible information available about the object in order to recognize it accurately and efficiently. In the first stage primitive features such as line contours, edges and textures are identified. In the second stage patterns are formed and in the final stage objects are identified.

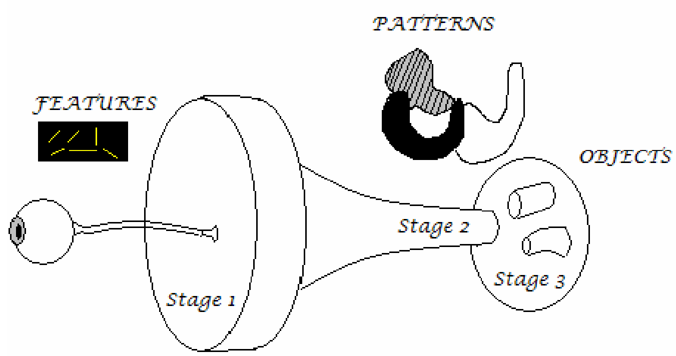


Figure 8: The human eye processes an image in three stages (a) features, (b) patterns, and (c) complex object shapes [War03].

3.1.1. Feature Processing

The first stage of the eye processes only the simple visual features of an object. These primitive features include components of a given object. These components include color, edges, and textures of the object. The color of the object is identified by color receptors in the eye, most of which are identified as combinations of the basic colors of red, blue, green, and yellow. The edges define the boundaries and distinguish between the different faces of the object. These edges can be vertical, horizontal, oblique, angled, curved, wavy, etc. Finally, the texture of the object is the outer appearance of the object and can be categorized in to groups such as smooth, shiny, grainy, coarse, fine, rough, bumpy, etc. In the chair example of Figure 9, some of these attributes that contribute to the first stage of visual processing can be seen.

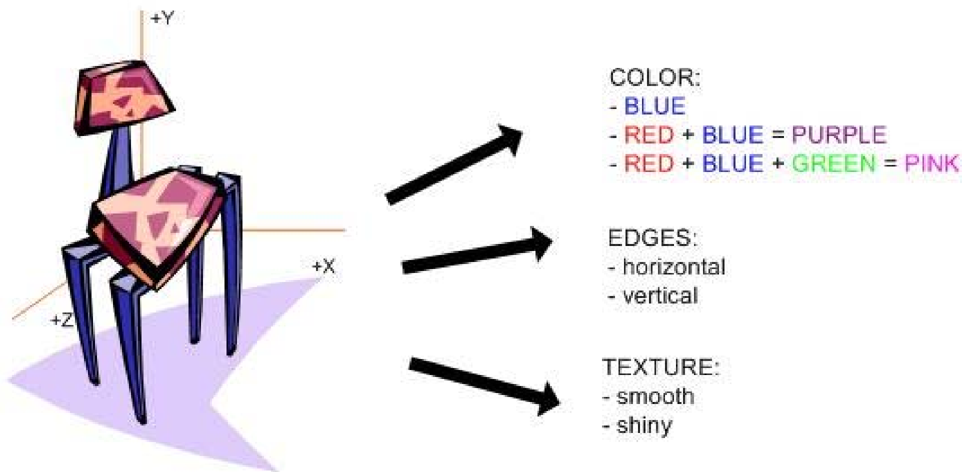


Figure 9: First stage processing distinguishes features such as color, edges, and texture

A general theory of human visual system known as preattentive processing is relevant in this stage of the object recognition process [War03]. This theory states that objects can contain certain properties that enable them to stand out conspicuously from the surroundings and hence, can cause the human eye to perceive them almost instantaneously and unconsciously. These properties can be color, shape, orientation, length/size, grouping, and curvature variance etc. of the objects. An example of preattentive processing is given in Figure 10. The target object 'pops-out' from the set of distracters. This phenomenon takes place in parallel and users perform equally well on dense as well as sparse scenes. The first stage of visual processing is mostly preattentive processing, as the most obvious features of the concerned objects strike the eye and are recognized almost immediately.

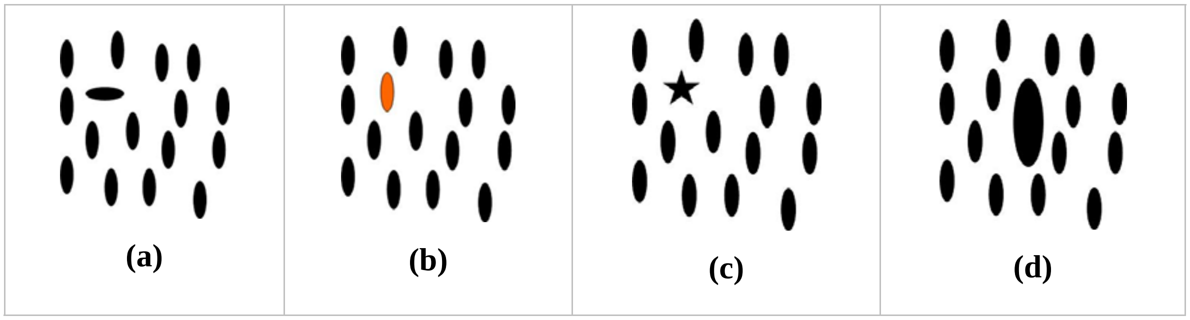


Figure 10: A object having a property that is distinguishable from the rest of the group is immediately perceived through preattentive processing, due to difference in (a) orientation, (b) color, (c) shape, and (d) size [War03].

3.1.2. Pattern matching

In the second stage of processing the visual system extracts and locates patterns in the scene. This stage is commonly referred to as pattern matching and can be explained by Gestalts Laws of pattern perception [26]. The Gestalt laws relevant to our discussion have been described below:

- The property of **proximity** states that objects that are physically close together can be grouped together as a single group. In the chair example in Figure 11 the legs, back, and seat of the chair can be classified as one group due to their proximity with each other.

- The property of **similarity** states that objects that are similar are generally grouped together. In the chair example, the legs of the chair are all similar and are hence grouped together as belonging to the same group.

- The property of **symmetry** states that objects that are symmetrical can be recognized faster than non-symmetrical objects. In the chair example in Figure 11, it is easy to recognize the chair as there is symmetry (if the chair is vertically cut in half, each half is a mirror image of the other). However, it would be more difficult to recognize the same chair if only one half of the object (half of the base, half of the back projection, or only two legs) was shown.

- The property of **common state** states that objects that move together can be grouped together as belonging to the same general group. In the chair example in Figure 11, as all the components of the chair are moving together around the y-axis, they are perceived as belonging to the same group.

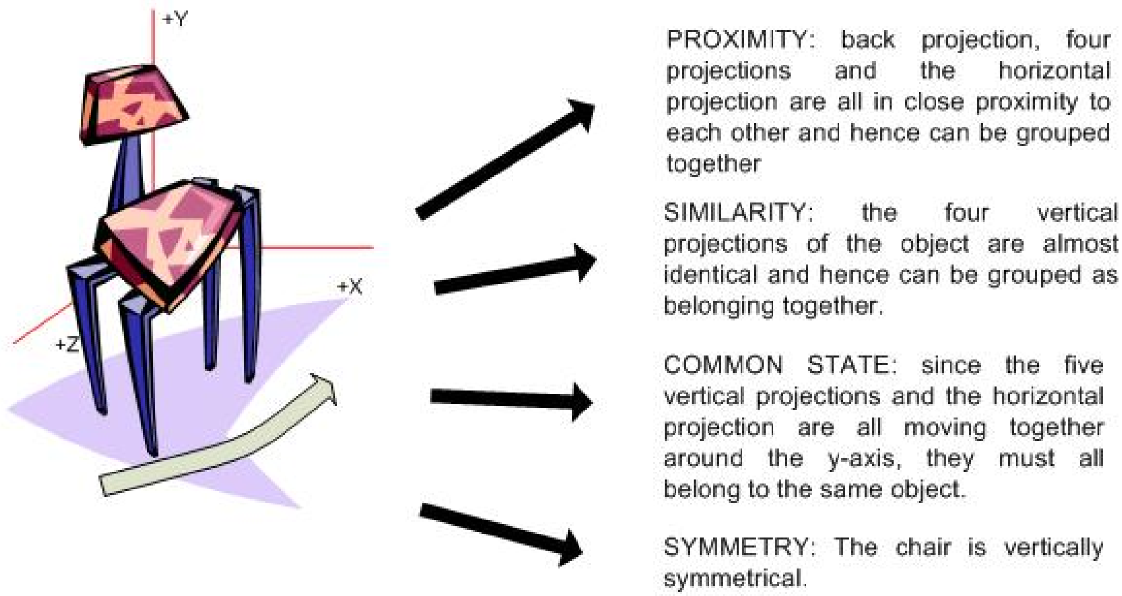


Figure 11: Second stage processing distinguishes features such as proximity, similarity, common state, and symmetry.

3.1.3. Object recognition

At the final stage the structure of the object is extracted for identification. At this stage entry level classification takes place such that the general class of objects to which the current object belongs to is identified. In Figure 11, by recognizing the general features of the object, the object can be easily classified into the broad category of four-legged objects. Hence this eliminates items which do not normally contain four legs (or protrusions), such as buildings, roads, hills, and boxes. The object can also be classified into the less broad category of four-legged items that contain a back projection, which further eliminates objects like lamps, and fans. Therefore, by recognizing the structure of the object in this stage, the number of possibilities of what the object represents, can be narrowed down, hence reducing the processing load on the person.

Also, in this stage, the three-dimensional features of the object are analyzed and applied to the object to aid recognition. One important contribution in this area has been made by Biederman [Bie87], who proposed simple three-dimensional object representations that have a vast scope in visual representation of complex constructs.

3.1.3.1. Geon theory

Beidermann [Bie87] defined a set of 36 primitives, or geons, that could be used to construct any physical object perceivable by the human eye. These concepts were defined based on curvature, symmetry, colinearity, parallelism, and cotermination of two-dimensional objects. On comparison of the above defined concepts, Beidermann states that:

- **Colinearity vs. curvature:** A straight line among curved lines can be easily distinguished as there is no degree of straightness that has to be analyzed, i.e. if a line is straight then it is absolutely straight (it cannot be termed as somewhat straight).
- **Symmetry vs. parallelism:** Symmetrical objects are those objects that retain their shape on reflection and rotation, while parallel objects retain their original shape only on reflection. Beidermann [Bie87] states that symmetrical objects can be easily distinguished when compared to parallel objects because a person is able to process symmetry much faster than parallelism.

- **Cotermination:** Cotermination is concerned with the vertices of an object that define its edges or boundaries. It is more difficult to distinguish an object if the vertices are deleted when compared to the midsection of an edge being deleted. The reason for this difficulty is attributed to the fact that with the deletion of vertices, continuity between the edges is compromised and made ambiguous.

In addition, Beidermann [Bie87] claimed that any three-dimensional object in space can be projected into a two-dimensional plane. Such a projection occurs in day-to-day life and is the basis for recognition of various objects. The two dimensional projection can then be broken down in a series of simple shapes such as cylinders, cones, wedges, and blocks. Various combinations of these geons can be used to distinguish various objects. While creating an object, along with the type of geon that is used, the order in which all the geons are placed relative to each other, is also imperative to recognition.

Beidermann [Bie87] conducted an experiment to analyze his guidelines for perception of complex concepts through simple representations. In this experiment subjects were appointed to different tasks that compared between the different perception rules. Simple line drawings of 36 objects were displayed to the participants, with varying properties such as the number of components making the objects, complexity of the objects, size of the objects etc. The main focus of this experiment was to analyze if geons that represented the most evident features of the object are satisfactory to aid the recognition of the object by the human eye. The time taken and the error rates were recorded and analyzed. The results of the experiment stated that:

- Viewing objects as photographs did not have any significant improvement over viewing the same object as a line drawing. The author states that features such as color, texture, patterns, and brightness, which are visible in color photographs, are not needed for first-order recognition of the object. The initial recognition takes place by looking at the basic components that make up the object. However, the study also states that in cases where it is difficult to view or predict the edges of an object, then factors such as color, texture or lighting can be useful.

- While viewing objects that are not complete or are degraded, it is important to make sure that the continuity in the object is not compromised. There are two types of object degradation that need to be considered. If the object has degraded in such a way that the vertices that have been deleted were a join of more than two edges, then there is ambiguity as to what type of join was actually present at the edge, before degradation. In such cases it is impossible to state with confidence what was actually the structure of the object at that edge and this type of degradation is called ***non-recoverable degradation***. If the vertices of the object have degraded in such a way that there is still no ambiguity in what the structure of the object at the edge might be, then the edge can be redrawn and this type of degradation is called ***recoverable degradation***. Biedermann [Bie87] states that if the degradation of an object is non-recoverable, then object recognition becomes very difficult and mostly impossible (Figure 12).

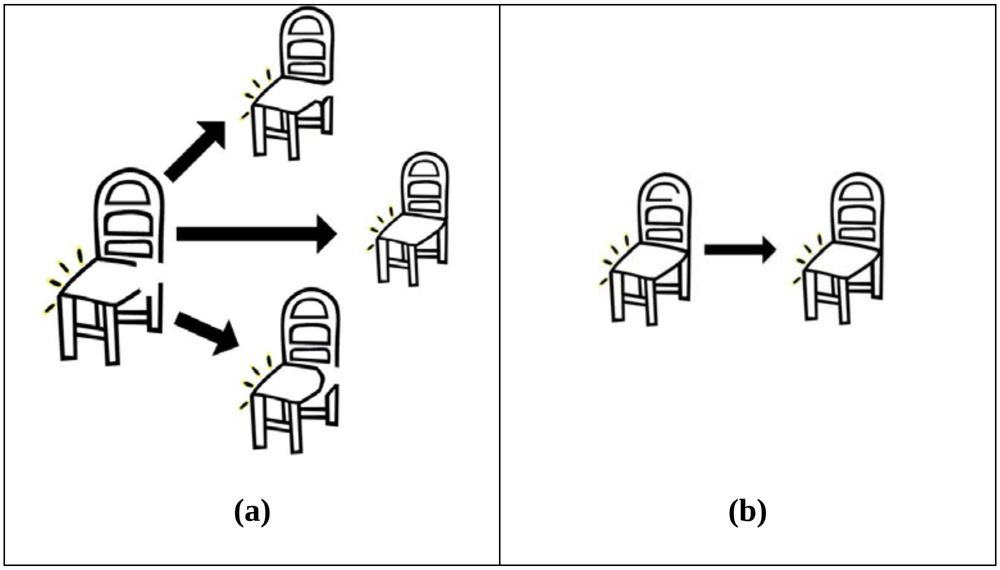


Figure 12: (a) Non-recoverable edge degradation causes ambiguity, (b) recoverable edge degradation does not cause ambiguity.

Another property that has been discussed by Beidermann [Bie87] is variability in viewing the object, i.e. different views of the same object. The reasons for ambiguity can be that the view, orientation or ordering does not relate to the image of the object in a real world space. For example, it would be difficult to recognize a table if only a view of the legs or the base of the table is shown.

Consolidating all the above guidelines, it can be noted that, according to the theories of structure-based perception, the human visual system recognizes objects in our environment by first decomposing them into primitives or blobs [Bie87]. After decomposition, a set of rules that describe the relationships between the primitives are used to perform entry level classification. These rules or relations primarily contribute to object recognition. The relationships between the primitives preserve their two-dimensional silhouette structure, are robust under viewpoint transformation, and are categorical [Bie87]. Some of these relational rules are described as follows:

- **SIM:** Similarity - Shape of primitives plays a primary role while color and texture are surface properties that play a secondary role in entry level classification. For instance, for entry level identification of a table, its color or texture does not play a significant role. The visual system first identifies the table's primitives such as the legs and the base, and recognition proceeds based on the relationship of these.

- **VER:** Verticality – A primitive "A" can be on-top-of, bottom-of or beside another primitive "B", and this contributes significantly to object identification. In the case of a table, the legs are to the bottom-of the base or conversely the base is on-top-of the legs.

- **MUL:** Multiples – An exact amount of counters is not necessary to identify multiples. For instance, if a table consisted of five legs instead of four, it would still be recognized as a table.

The three phase process can be summarized in the figure below.

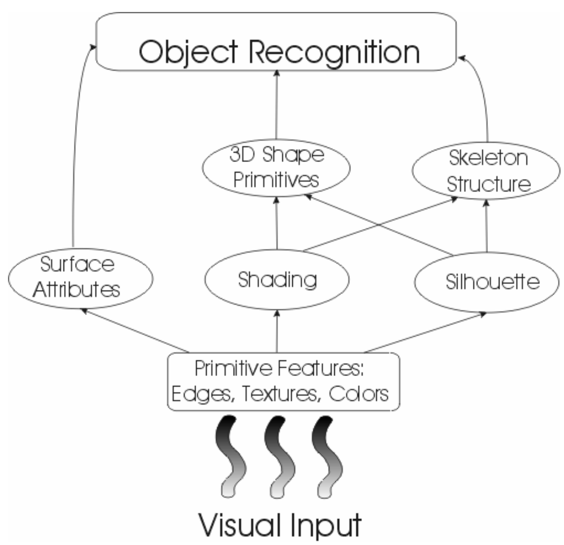


Figure 13: The three phase process to visual image processing are feature processing, pattern matching, and object recognition.

Working with the three stages of processing, Ware [War03] states that the color, shape, pattern, and surface texture can be varied in different ways to create simple objects. These objects can then be used to represent the properties of complex semantics.

3.2. Motion perception

Motion of an object is recognized if the object does not remain static over a period of time. Motion here can be recognized as a physical movement of an object along any one of the six directions of movement (+x, -x, +y, -y, +z, and -z axes) or along an inclination to these axes. Motion can also be visualized in the form of rotation of the object along any one of the six directions (x-clockwise, x-counterclockwise, y-clockwise, y-counterclockwise, z-clockwise, and z-counterclockwise). Another form of motion is distortion, which can be seen when the structure of an object is modified due to internal or external forces. In the case of the object in Figure 11, the motion of the object is shown to be a rotation in along the y-axis.

There are many ways to represent dynamic motion of objects. Factors such as color, texture, shade, lighting etc can be used to describe change in an object. However, one of the most popular methods of representing dynamic change in an object has been through depicting the motion visually. Some of the reasons for the increasing popularity of visual motion are that it is "perceptually efficient", information can be easily perceived, "technologically inexpensive", and "having high potential", as not much research has been done in this field and there are still a large number of untapped resources in this area of research [Bar98]. Motion also has many technical advantages; it is easy to code and create, it is dynamic and hence can represent dynamic concepts, and it can be built on top of existing representations, without having to replace them [Bar98].

Sekuler et al. [SWB88] conducted an extensive study into the perception of visual motion in dynamic scenarios. According to them, motion is distinguished in several stages; in the first stage motion is perceived by neurons in the occipital lobe. The main function of neurons in this area is to determine the direction of travel of the object in motion. Hence, the distinction of a person running from right to left is recognized as different from a person running from left to right by these neurons. After the initial processing by the first-level neurons, processing is transferred to neurons in the middle section of the temporal lobe. The main features of the dynamic object that are distinguished in this section are direction with higher precision (i.e. distinguishing between a 60° and an 80° angle), speed of object, color, texture, and luminance of the object. This information is then passed onto the next level of more specialized neurons that distinguish more finite features of visual motion.

In addition to describing the different stages of motion perception, Sekuler et al. [SWB88] also analyze several factors relating to motion perception such as motion detection, trajectory, direction, speed, coherence etc. Some of these factors have been described below:

- ***Detection of motion:*** General motion detection is generally performed in the first stages of information processing in the temporal lobe. According to the authors, “motion involves a continuous change in the spatial position of a single object over time” [SWB88]. For example, if a table moves from one end of the room to the other end over a period of time then motion is perceived, even if the eye did not see the actual movement of the table. However, there are many situations where motion is not easily perceived. One of these situations is if the motion is too fine to be distinguished, i.e. if the table moves very small distances at large intervals. In this case only the overall motion can be recognized after a certain period of time. Another situation where motion is sometimes not detected is when it is viewed in isolation. In most realistic situations, motion is perceived relatively, i.e. the movement of a table is perceived relative to the stationary nature of the floor on which it stands.

- ***Detection of direction:*** The authors state that distractors such as vertical or horizontal lines can adversely influence motion perception. This is because the perpendicular nature of these lines forces the perception of motion in a perpendicular direction. However, visual techniques such as dots moving in one direction, are quite popular in describing the direction of motion and hence, enhancing motion perception[SWB88, TZL+00].

- ***Detection of motion from optic flow:*** Detection of motion is perceived by the flow of information through the optic channels of the human system. According to the authors, the movement of an object can cause visual changes in time and space, which provides information such as speed, distance, and direction, and this movement is termed as optic flow. This optical information gives humans the capacity to judge the obstacles they might encounter in their path and also gives an idea of the movement of objects in synchrony or in asynchrony with them. For example, a baseball player uses optic flow to visualize the trajectory and speed at which the ball is heading towards him/her, so as to angle the bat and be prepared for the encounter. Sekuler et al. [SWB88] also state that, optic flow helps in distinguishing the shape, structure, and 3-dimensional nature of the object from motion, as motion can cause deformation that helps in viewing different dimensions of the object.

- ***Detection of transparency in dynamic objects:*** When many objects are moving around in the same spatial region, then there is the problem of being able to distinguish between the objects accurately. Sekuler et al. [SWB88] state that there are several factors such as speed, direction, depth, etc. that influence motion perception. The authors state that research in this area has shown that the human eye is capable of perceiving motion by the displacement of objects over time (relating to speed and direction). However, to clearly distinguish between the objects, the above factors should not be too close. The factor of depth influences motion perception when speed and direction are very close and not easily distinguishable.

- ***The aftereffects of motion:*** As Newton's third law of motion states, "Every action has an equal and opposite reaction"; the same principle can be applied to the perception of visual motion. Every action of motion has an equal and opposite reaction on the surrounding. For example, if a person sitting in a stationary train and is viewing an adjacent train that is pulling out of the station. After some period of time, the person feels that it is he/she who is in motion and the adjacent train is stationary. It is only by looking out the other side of the train, and observing that the train is still in its original spot, does the person realize that his visual perception played tricks on him. The main reason for this illusion is because initially when the visual motion is perceived by the eye, some neurons adapt to this direction of motion while some neurons adapt to the opposite direction of motion, to provide a balance. After some time, the forward-direction neurons get tired and the perception of information reduces in these neurons, but the backward-direction neurons are not affected. Hence, there is an imbalance and the motion is perceived in the opposite direction [SG63].

- ***Tracking multiple objects in motion:*** Although the motion of an object provides a person with a lot of information about the dynamic nature of the object, it also increases complexity of the scenario. This complexity tends to increase as the number of objects in the scene increases, hence reducing perception and comprehension. In such situations the presence of visual cues can help in improving the comprehension by reducing the amount of visual information in the scene.

Nowadays most systems are growing in size due to a large increase in the amount of information, the number of users, and the number of tasks; and the author hypothesizes that visual motion cues will reduce cognitive load on the user and improve comprehension of information [Bar98]. Bartram et al. [BWC01] analyzed the various advantages and disadvantages of motion cues in dynamic scenarios. In this study, the authors conducted a series of experiments to evaluate their hypotheses. In the first experiment, motion cues were compared against cues such as color and shape (as separate experiments), to determine the most effective among them. In these experiments, the participants were given a simple task to perform, which was replacing all the 0s by 1, in a table containing the numbers 0 to 9. While the participant was concentrating on the given task, the rest of the screen outside of the table, which contained many objects, either moved or changed color or shape at sometime. The participant was asked to inform the system immediately when they saw any of the symbols outside the table area move. The error rates and response times were analyzed. The results of the experiment suggest that color and shape cues are not as effective as motion cues in providing dynamic information. Also the experimental results suggested that as the distance of the dynamic object moves away from the center of the eye, perception through color and shape reduces.

As part of the same study, a second experiment was conducted by Bartram et al. [BWC01] to analyze the distractive and detective effects of motion in visualizing information. In this experiment, participants were tasked on three different tasks ranging from less attention demanding to high attention demanding; read a text-file (less demanding), playing solitaire, and playing Tetris (highly demanding). While performing these tasks, the subjects were distracted by different types of objects, moving in different patterns, on the screen. The participants were asked to inform the system anytime an object distracted them from concentrating on the primary task. Four types of distractors were used: a linear distractor that moved up and down, a pop-out distractor that increased and decreased in size, a blinking distractor, and a traveling distractor, which moved about the screen. Each of these distractors was presented in slow and fast speeds. The results of this study suggested that most motion cues (except blinking) are more distinguishable when they were slow rather than fast. Also, the efficiency of detecting the distractions is reduced when the task gets more complicated, as more attention is given to the primary task, rather than to the distractors. The result also suggested that of all the cues, the cues that contained motion, such as the linear and the traveling cues were the most easily detected.

3.3. Chapter summary

All the studies so far support the intuition that dynamic concepts should be represented dynamically in order to provide the maximum comprehension. It can also be stated that there are many factors to be taken into account while representing dynamic information, such as the type of representations to construct, the factor of time, the influence of visual motion to enhance dynamic scenarios, the problems of complexity of motion in dynamic scenarios, and the methods of improving focus and attention in dynamic scenarios. Consolidating the guidelines suggested by researchers in this field, the next chapter will explain the basis representations for the first phase of my research, along with an experimental evaluation of these representations.

4. Representation: Visualizing time-dependent information

Irani [Ira02] created a set of perceptual representations for visualizing structured time-independent concepts, such as those found in UML diagrams. These representations, based on the geon theory stated by Beidermann [Bie87], are general and can be used to represent concepts in many fields of study, including this study. Hence, the dynamic representations that I endeavor to create, are based on the representations of Irani et al. [ITW01, Ira02]. Some of the relevant representations have been described below, along with a description of my application of these representations to depict dynamic concepts.

4.1. Representation of Time-Independent Semantics

4.1.1. Representing the concept of generalization

An object is a generalized form of another if both show similar features. Such similar objects can then be said to belong to the same group. This relationship is described as a “is-a” relationship, which indicates that an object is-a part of some class or group of objects. For example, a chair is-a furniture, a laptop is-a computer etc, as furniture and computer are generalized instances of chair and laptop respectively. Irani et al. [ITW01, Ira02] manipulated several visual features of objects in order to determine the features that represent generalization of objects. In their experiments, several objects were shown to the participants, who were asked to point out those objects that they thought were of the same kind. The properties that were manipulated were color and shape. The results of this experiment show that shape was preferred over color as a method for representing the concept of generalization.

4.1.2. Depicting dependency between objects

An object is said to be dependent on another object if changes in the second object affect the first object. For example, living beings depend on their eyes to see, a light bulb depends on electricity to burn, etc. The dependency property is a relationship between two objects, where one of the objects is termed as the master (dependee), with the other as the slave (dependent). Irani et al. [ITW01, Ira02] created different visual representations to show the property of dependency. These representations were, broken lines between the dependent and dependee (Figure 14.a), a solid connecting line between the dependent and dependee (Figure 14.b), placing the dependee on top of the dependent (Figure 14.c), placing the dependent and dependee in close proximity to each other

(Figure 14.d), and placing the dependent on top of the dependee (Figure 14.e). Irani conducted an experiment and asked the participants to choose the most relevant representation for dependency. The results of the experiment stated that most participants choose the dependent being placed on the dependee (Figure 14.e) as the most relevant and obvious representation of dependency. The reason for this is because it seemed that the dependent object was being supported by the dependee object, hence exhibiting dependency.

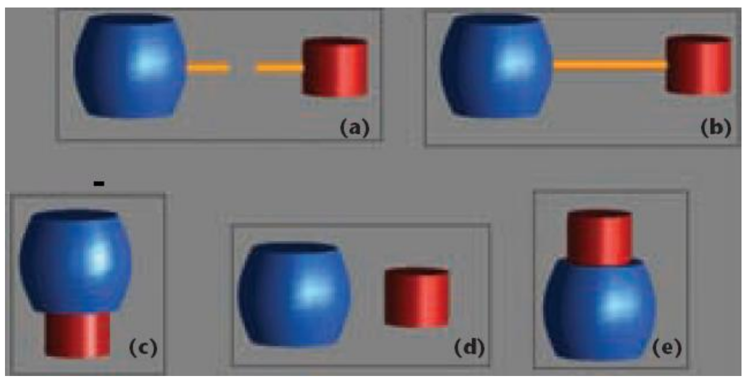


Figure 14: Representation of dependency using (a) broken lines, (b) solid connecting line, (c) placing dependee upon dependent, (d) proximity, and (e) placing dependent upon dependee [Ira02].

4.1.3. Depicting multiplicity between objects

Multiplicity between objects is depicted when an object is connected to multiple instances of another object. Several examples such as spawning of multiple processes by a parent process, public sign-boards showing the occurrence of multiple people in an area etc. are all examples of multiple instances. Irani et al. [ITW01, Ira02] created visual relationships that depicted multiplicity; multiple containments of an object within the relationship (Figure 15.a), close proximity between the objects (Figure 15.b), multiple connections between the objects (Figure 15.c), a solid connection between the objects (Figure 15.d), and a conical connection between the objects (Figure 15.e). They hypothesized that multiple connections between the objects (Figure 15.c) were the best method of representing multiplicity. Upon testing, this hypothesis was supported along with another hypothesis that the number of connections in the relationship need not represent the actual number of instances of the objects. That is, it is not necessary to show five connections if there are five instances of an object. The main idea behind this representation is to show that there is an occurrence of multiplicity in this relationship; the quantitative details are not imperative.

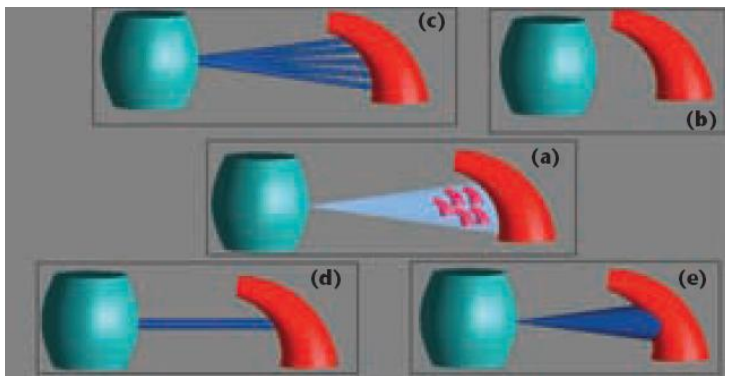


Figure 15: Representation of dependency using: (a) multiple containments, (b) proximity, (c) multiple connecting lines, (d) solid connecting line, and (e) conical connection [Ira02].

4.2. Creating perceptual semantics for time-dependent information

Based on the representation suggested by Irani et al. [ITW01, Ira02], my aim was to create similar generalization representations for time-dependent semantics. I carried out my investigation in a three-phase process. In the first phase, I constructed different visual representations for three time dependent-semantics. The semantics were chosen because they represented general behavior of objects when evaluated over a time frame. The semantics have been listed below:

- **State Transition** – An object changes its state from one to another over a period of time. This semantic implies that based on the property that changed, the object moves from one group to another.
- **Interdependence** – Mutual dependency is created between objects over a period of time. This semantic implies that a change in one of the inter-dependent objects affects the other one too.
- **Multiple States** – An object exists in different states at the same time. This semantic implies that a property of an object changes in such a way that it belongs to more than one group at the same time.

In each case I used a perceptual principle, based on the representations by Irani et al. [ITW01, Ira02], to construct at least one of the instances. The other members of the set were made up of what I thought were reasonable alternatives. In the second phase, I conducted a multipart evaluation study to determine if the subjects agreed with me on my choice of mappings. In the third phase, I validated the best mappings by combining them into diagrams that described quantum algorithms. Experiment 1 outlines the first and second phase of this study.

4.3. Experiment 1: Evaluating semantic representations

This experiment aims at evaluating the semantic representations created in the first phase of this study. The goal of the experiment is to conduct a user evaluation of the representations and to short-list a set of representations for previously recognized general semantics.

4.3.1. Participants

24 students (computer science majors), between 18 – 25 years of age, from a local university participated in this experiment. The participants were divided into two groups based on their individual expertise and experience with quantum computing. 12 of the participants were familiar with the quantum semantics through a graduate level course in quantum computing (experts). The other 12 students, though having heard of quantum computing, claimed to never have had any exposure to this field of science (novices).

In order to evaluate the simplicity of my representations, none of the participants, experts or novices, were given any training prior to the experiment. Also, the participants were individually tested.

4.3.2. Materials

The experiment consisted of displaying three concepts; state transition, interdependency, and multiple states. For each of these states, 3-4 perceptual representations were created. The representations for each concept were shown together on a screen. Each participant was allowed to animate the representations by clicking on its corresponding *"Animate"* button. The participant was also allowed to replay and stop the animation at any point in time. The concepts were represented as three-dimensional objects, wherein the shape or color of the object was insignificant to the concept being represented. The representations for each concept were displayed three times (three trials per concept), in a Latin-square fashion. During each trial, the shapes, colors and order of the objects were altered randomly, to avoid learning effects.

The experiment was conducted on a 17 inch Flat screen LG monitor, on a P4 processor. A 3-button Logitech mouse was used for interacting with the circuit. The keyboard was used to load new trials during the experiment.

The following sections describe the concepts being tested, the experimental procedure and the evaluation results and discussions. For clarity, I have separated each of the sub-experiments for each of the time-dependent semantics, together with the evaluations results, into individual sub-sections.

4.3.3. State Transitions

In general terms, I infer the semantic of a state transition when an object changes state over time. State transitions occur naturally in our environment, for example when water changes state from liquid to solid or to gas. State representation can be generally defined as the deformation or evolution of an object such that it does not belong to its current class and has to be placed elsewhere. Often, program objects have internal states, which change as an algorithm is executed. For example, in Dijkstra's shortest-path algorithm, a node can be in one of two states, corresponding to whether or not its distance from the source has been determined.

The semantic of state transition suggests that an object changes its belonging from one class to another over a period of time. This means that at time t_0 the object belongs to class A and at time t_n the same object belongs to class B. Same shape primitives can be most effectively used to classify objects into categories [Mar82, Bie87, ITW01]. From this I hypothesize that state transition can be depicted by a smooth change of object shape.

4.3.3.1. Representing State Transitions

To test this hypothesis, I created four representations for showing state transitions. Each representation changes one property of the object in a smoothly animated manner (also referred to as tweening). The changes are the following visual attributes of the object: Color change (Figure 16.a), Shape change (Figure 16.b), Orientation change (Figure 16.c), and Size change (Figure 16.d). As mentioned earlier, the actual colors, sizes, shapes and orientations of the object were not important and were randomly generated. Also, the arrows in the figure were not included in the experiment, and are just used here to show the flow of the animation.

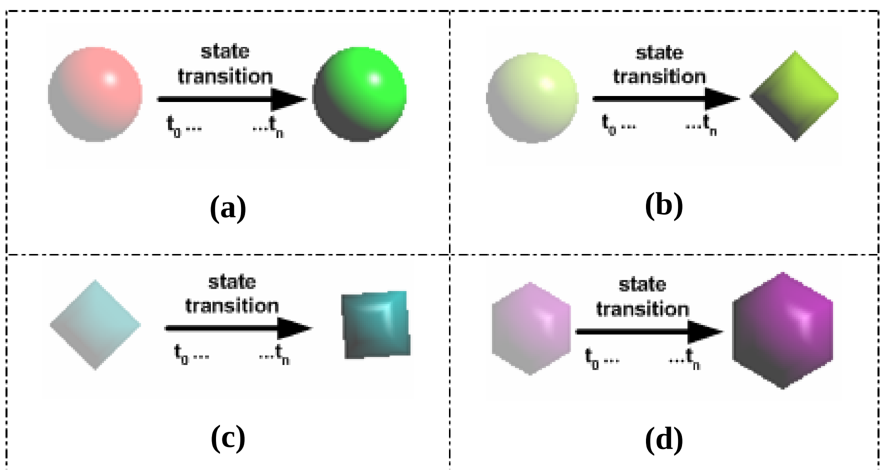


Figure 16: Depicting state transition by changing (a) color, (b) shape, (c) orientation, (d) size.

4.3.3.2. Rationale

In order to evaluate the efficacy of state transition, four representations were created. A description of these representations and the rationale behind these representations is as follows:

- **Change in color (Figure 16.a):** When an object changes color, it can be assumed that it has moved from one state to another. This is seen in many scenarios, for example, when vegetables cook on an electric stove or in an oven, color is added to a canvas, a metal is heated over a furnace. Change in color can be easily visualized by the eyes as it forms one of the fundamental features in entry-level object recognition [War03].

- **Change in shape (Figure 16.b):** This feature has been hypothesized as the most favorable representation for state transition. According to the studies conducted by Irani et al. [ITW01, Ira02], the principle of generalization is best represented by change in shape. Change in shape is seen as one of the most obvious methods of state transition in our environment. For example, water changes to ice, a slab of marble is carved into a beautiful statue, clay is molded into figurines, etc.

- **Change in orientation (Figure 16.c):** This method is not the most obvious representation for a state transition. However, orientation is a type of evolution and hence can technically be used to represent state transition. This forms our basis to use orientation as an alternative form of state transition. Examples of this type of state transition include changing the view angle of the eye, rotating a bowl 180° to obtain a hat, etc.

- **Change in size (Figure 16.d):** Change in size is a common method of comparing objects, as it symbolizes a positive evolution of an object. However, it is not hypothesized as the optimum method of representing a transition which could be an evolution or degradation. However, as I have not come across any study that applies this form of representation in similar situations, for evaluation purposes, I have included it as an alternative form of state transition.

4.3.3.3. Evaluating State Transitions

The first step of the experiment was to explain the concept of state transition to the participant. The description was general so that even a novice (a participant who is unfamiliar with these concepts) would understand the concepts. The four representations for state transitions were then displayed and the participant was asked to rank the representations according to their preference (4 was given to the most favored representation and a rank of 1 was given to the least favored one).

A χ^2 test on the results shows that there are no statistically significant differences in selecting the best representations between novices and experts (P-value of 0.098 for null hypothesis of agreement between novices and experts). Therefore the results were combined. The average rankings of all 24 subjects are shown in Chart 1. A top-down test of correlation on the average rankings shows a strong agreement between all 24 subjects for the best-ranked representations (P-value < 0.0001 for null hypothesis of no correlation between rankings chosen by 24 subjects). As seen in the chart above, state transition is best depicted using a “change of shape” representation (B). This representation is significantly better than the second best representation of a “change in color” (A) (with 95% confidence, the probability that any subject, novice or expert, would choose B over A is between 0.47 and 0.762).

The results of this part of the experiment support the hypothesis that a ***change in shape*** can be used to represent state transition.

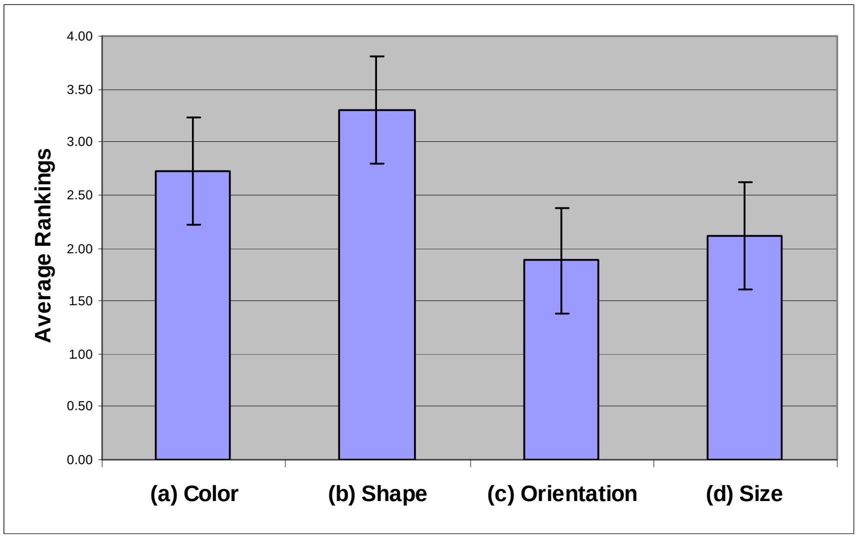


Chart 1: Average rankings of state transitions (4 equals most favorable, 1 equals least favorable)

4.3.4. Interdependence

Interdependence is a common semantic that manifests itself over a period of time. This relationship is common and exists, for example, between employers and employees or between variables in a system.

The semantic of interdependence suggests that two objects, over a period of time, become interdependent upon one another. Irani et al. [ITW01] suggest that dependency between two objects can be represented by placing them in proximity to one another, typically with the dependent on-top-of the dependee. Based on this, I hypothesize that spatial proximity with partial intermeshing can be used to represent interdependence between two objects.

4.3.4.1. Representing Interdependence

I constructed four representations for the semantic of interdependence, as Figure 17 illustrates. To show that two objects become interdependent, the representations consisted of change to a common color (Figure 17.a), smoothly inserting a connection between two objects (Figure 17.b), change to a common shape (Figure 17.c), and moving two objects closer to each other and partially meshing them to each other (Figure 17.d).

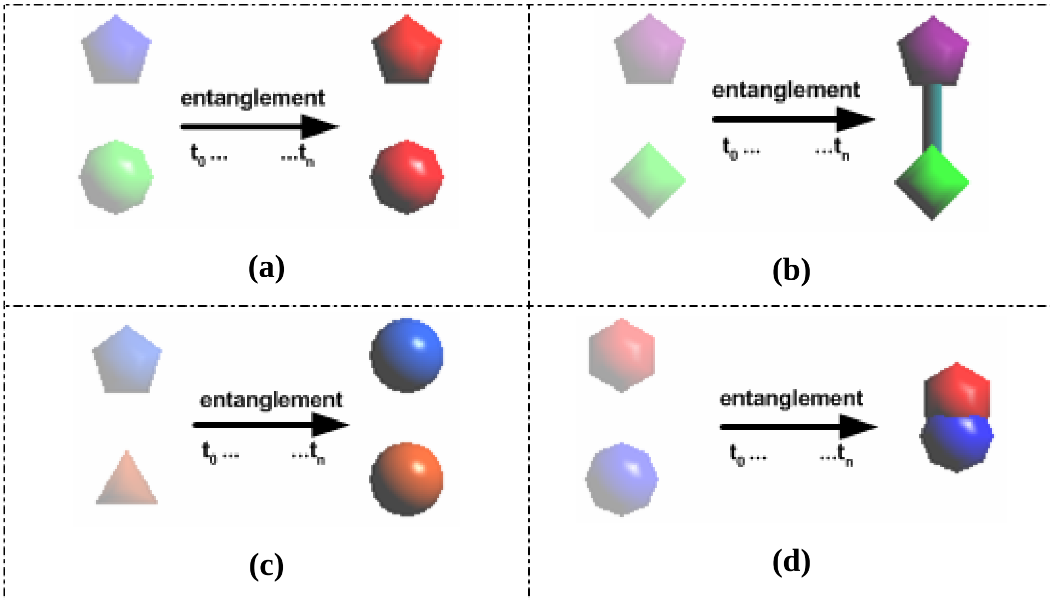


Figure 17: Representing interdependence by (a) change to common color, (b) creating a connection, (c) change to common shape, (d) proximity with partial inter-meshing.

4.3.4.2. Rationale

In order to evaluate the efficacy of interdependence, four representations were created. A description of these representations and the rationale behind these representations follows:

- **Change to common color (Figure 17.a):** Similar to the rationale used in the concept of state transition, an object that changes color could give an impression of change in state. Hence, it could also be assumed that if two objects changed their color to a common color, then the two objects can be said to belong to the same class. Hence, changing the color of objects to a common color shows the creation of a relationship between these objects. However, as this relation could be anything such as parent-child, similarity, duplication inheritance, etc. I believe that change to common color represents dependency ambiguously, and hence I have categorized it as an alternative representation.

- **Creating a connection (Figure 17.b):** Connections between objects tend to show a strong relationship or bond between the objects. For example, the umbilical cord that connects the mother to a new born baby, an object hanging by a thread, etc. While connections such as the thread that supports the object do show a type of dependency (cutting the thread will cause the object to fall), connections such as the umbilical cord do not show this dependency (even if the umbilical cord is cut, the mother and child can independently survive). Hence, this representation has been employed as an alternate representation for this concept.

- **Change to common shape (Figure 17.c):** Similar to change to common color, changing the shape of the objects to a common shape can emphasize a relationship between two objects. However, due to the ambiguity as to the exact nature of this relationship, I hypothesize that this may not be the best representation of interdependency, and hence have used it as an alternative representation.

- **Proximity with partial-intermeshing (Figure 17.d):** This method has been hypothesized as the most favorable representation for interdependency as it follows from the principle of dependency suggested by Irani et al. [Ira02]. However, dependency is a one-way relationship (A is dependent on B **OR** B is dependent on A), while interdependency is a mutual two-way relationship (A is dependent on B **AND** B is dependent on A) between the objects. Hence, it is not sufficient to display interdependency by placing one object on top of the other. Therefore, a partial meshing technique has been included in the representation, which shows an unbiased relationship between the interdependent objects.

4.3.4.3. Evaluating Interdependence

Similar to the evaluation of state transitions, the participants were allowed to execute the different animations and rank them from 4 (best) to 1 (worst). The representations for this semantic were also shown on three separate screens, with the location, color and shape of the objects randomized.

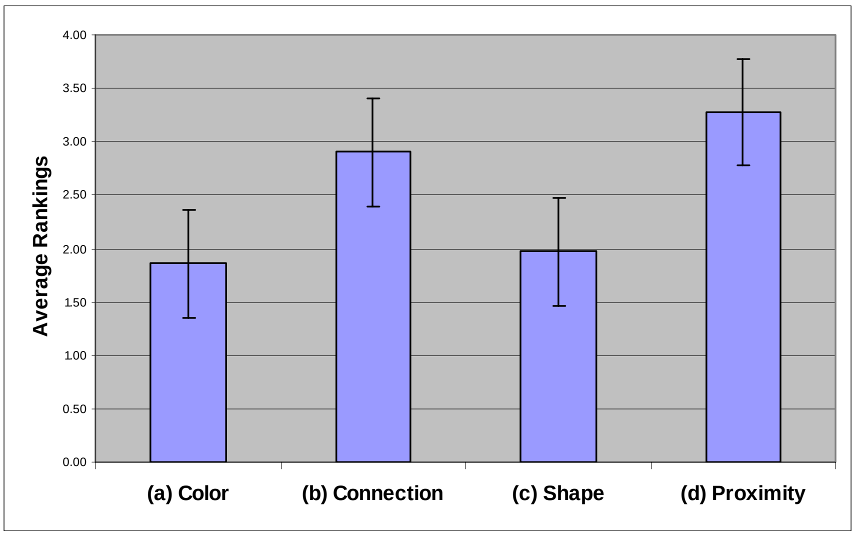


Chart 2: Average rankings for interdependence (4 equals most favorable, 1 equals least favorable).

A χ^2 test on the results shows that there were no statistically significant differences in selecting the best representations between novices and experts (P-value=0.4076). The results were therefore combined and the average rankings of all 24 subjects are shown in Chart 2. A top-down test of correlation on the average rankings shows a strong agreement between all 24 subjects for the best-ranked representations (P-value < 0.0001). As seen in the chart above, interdependence is best depicted using "proximity" (D). This representation is significantly better than the second best representation of a “connection” (B) (with 95% confidence, the probability that any subject, novice or expert, would choose D over B is between 0.46 and 0.76).

The results support the hypothesis in that ***proximity with partial inter-meshing*** of objects can be used for representing interdependence.

4.3.5. Multiple States or Superposition

The semantic of superposition occurs when an object exists in multiple states, simultaneously. In its essence, superposition represents the concept of multiplicity that develops over a period of time. This semantic occurs in several contexts. For example, a parent process can spawn multiple child processes. This happens dynamically and creates a one-to-many relationship between the parent and child processes of a multi-threaded program. Some objects can also assume multiple states. For example, water can be liquid, solid or gaseous.

One-to-many semantics can be depicted using multiple objects [Pai52, ITW01]. Since superposition is an extension of the concept of multiplicity, I hypothesize that multiple objects can be used for representing this semantic.

4.3.5.1. Representing Multiple States

Three representations were created to depict the relationship of multiple states. According to previously defined perceptual guidelines by Irani [Ira02], multiple instances of an object can be represented by multiple connections. Hence, to show that an object is in multiple states, the representations of multiple duplicates (Figure 18.a), multiple containments (Figure 18.b), and multiple merged shapes (Figure 18.c) were employed.

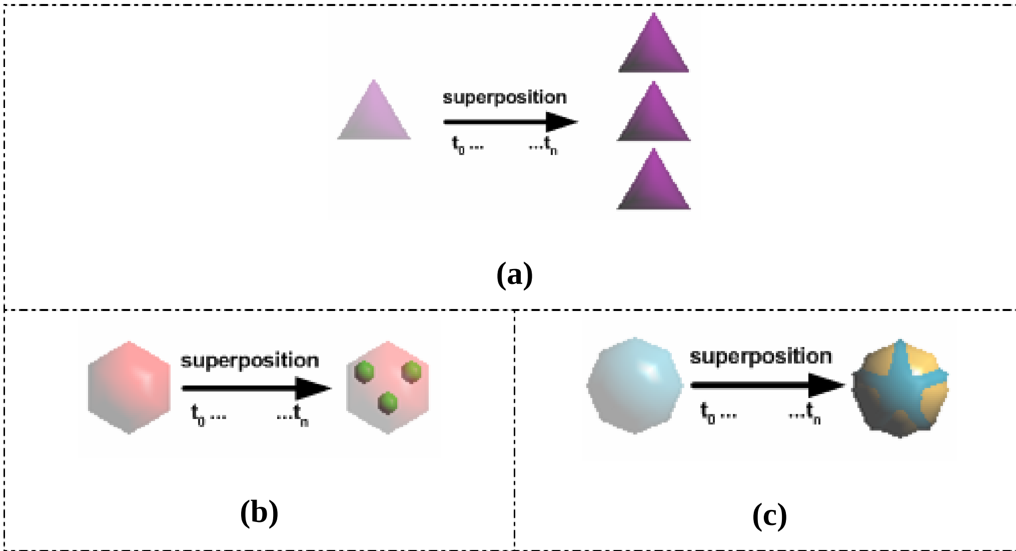


Figure 18: Representing multiple states by (a) multiple duplicates, (b) multiple containments, and (c) multiples merged.

4.3.5.2. Rationale

In order to evaluate the efficacy of depicting multiple states, three representations were created. A description of these representations and the rationale behind these representations follows:

- **Multiple duplicates (Figure 18.a):** This representation is hypothesized to be the most favorable representation for multiple states. According to Irani [Ira02], multiple connections between two objects can be represented by multiple connecting lines. An extension of this principle can be stated as, "multiple instances of an object can be represented by multiple duplicates of the object". This principle abstracts quantity for semantic, i.e. it focuses on emphasizing the occurrence of multiplicity and does not care about the exact number of multiples that have been created. This concept also follows from **MUL**[Bie87], which states that an exact number of multiples is not necessary to represent multiplicity.

- **Multiple containments (Figure 18.b):** This method is very similar to the multiple duplicates principle. This representation aggregates the multiples duplicates of an object inside the circumference of the object itself. The object itself is made transparent so that the multiple duplicates can be easily seen. Even though this representation conserves space when compared to the previous representation, it is hypothesized that this representation will not be favored as the best because it is complex and might not be comprehended easily.

- **Multiples merged (Figure 18.c):** This representation was inspired from the hypothesized representation for state transition. In state transition, an object that has changed its state is represented by a change in shape. Hence, if there exists multiple states, each of which has a unique shape, then objects belonging to these states will take on the shape of the respective states. In addition, if an object is in more than one of these states at the same time, then it will take on a shape that is a combination of the shapes of all the states that the object is present in. Hence, the shape of the resulting object is a merged combination of multiple shapes. This representation again is not believed to be the most favorable as it is complex and not easily comprehensible. Also if the colors of the objects that are combined are the same then the multiples shapes cannot be differentiated.

4.3.5.3. Evaluating Multiple States

The same steps as those used for evaluating state transitions and interdependence, were performed. Subjects were given the following description for multiple states: "If object X is in multiple states then it is said to exist in more than one state at the same instant in time."

A χ^2 test on the results shows that there were no statistically significant differences in selecting the best representations between novices and experts (P-value= 0.3458). Therefore the results were combined and the average rankings of all 24 subjects are shown in Chart 3. A top-down test of correlation on the average rankings shows a strong agreement between all 24 subjects for the best-ranked representations (P-value=0.026). As seen in the chart above, multiple states are best depicted using "Multiple Duplicates" (A). This representation is significantly better than the second best representation of a "Multiple Containments" (B) (with 95% confidence, the probability that any subject, novice or expert, would choose A over B is between 0.65 and 0.91).

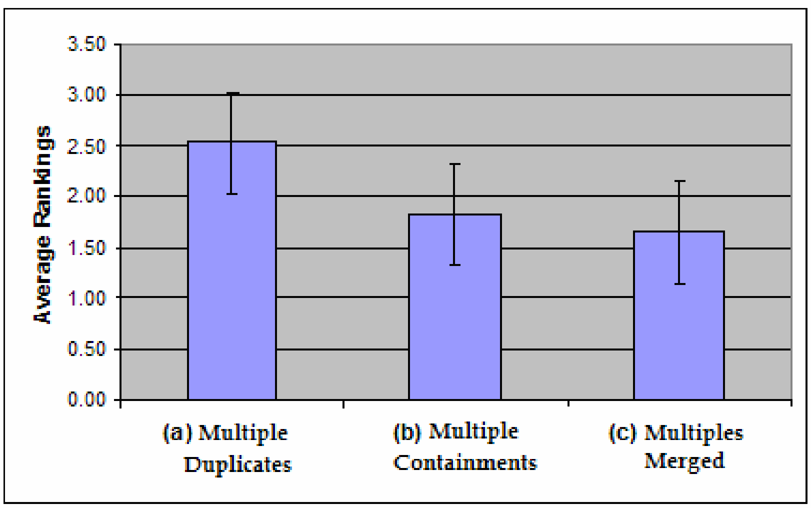


Chart 3: Average rankings for multiple states (3 equals most favorable, 1 equals least favorable)

These results confirm the hypothesis that ***multiple duplicates*** can be used to represent multiple states.

I have summarized the relationships between perceptual, time-dependent, and time-independent semantics in Figure 19. The visual vocabulary that was created for the time-dependent semantics is linked to a set of perceptual semantics via the representations used for depicting time-independent semantics. This was possible since the meanings for the time-independent semantics strongly resembled the concepts explicated using the time-dependent semantics.

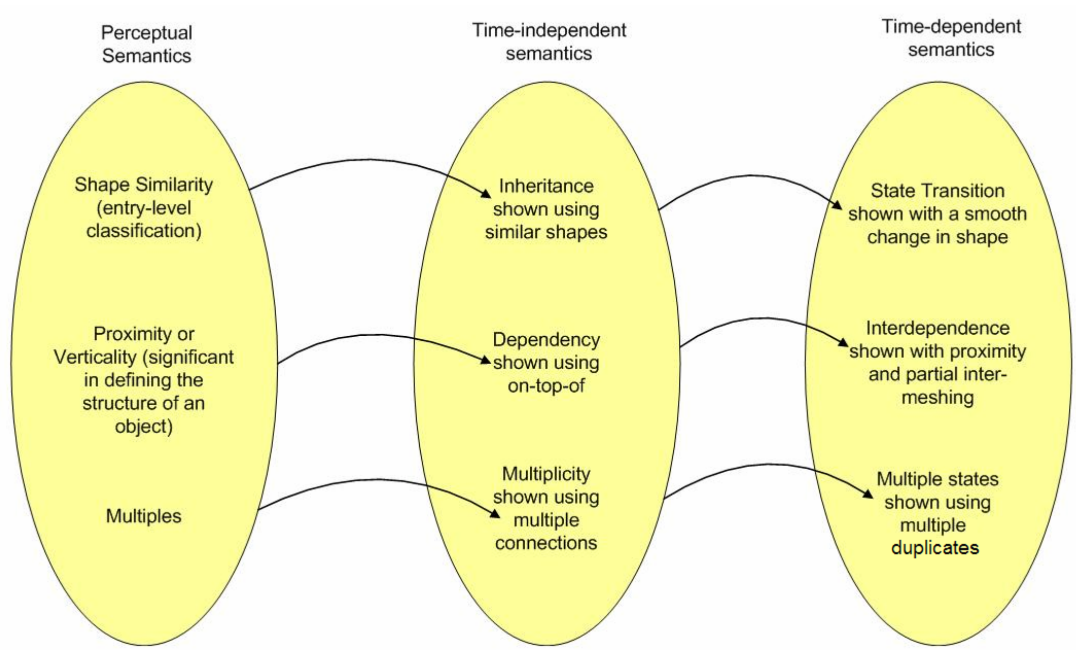


Figure 19: Relationship between perceptual, time-dependent, and time-independent semantics.

4.3.6. Discussion

This experiment was conducted to shortlist visual representations for the various time-dependent concepts. The results support the hypothesis with significant results. The best representations for state transitions, interdependence and multiple states were shown to be change in shape, proximity with partial intermeshing, and change to multiple duplicates respectively. Also, there was high significance between the best and second best representation, which showed that most participants interpreted the representations similarly and were consistent with their responses. Also, along with quantifiable results, useful user feedback was obtained during the experiment. All the participants expressed their approval to depicting complex concepts using simple representations. Also all the participants (experts and novices) were satisfied with the general explanations that were provided at the onset, and did not have problems understating the explanations. Many participants remarked that the representations were very clear and distinct, and hence they did not get confused or did not have to choose between equally favored representations. However, there were some exceptions. Two participants (one expert and one novice) expressed that a combination of the visual representations might be more effective than a change in only one property, for example, state transition might be more comprehensible by a combination of a shape and color change. However, this might not be practical as it increases the complexity of the visual display. Another participant was concerned with the amount of space and time that is being used to show the change. In this experiment, all the objects moved along a horizontal path from the left to the right end of the screen, to show change over a period of time. The space that was used for the animation was determined to suit this experiment, and hence is modifiable. However, one important point to note here is that the speed of the animation should also be adjusted according to the space that is available. Further study should be done to assess the speed to space ratio in dynamic scenes. Another valid comment from this participant was that as the space and the number of objects increase, there will certainly be an increase in the clutter and confusion on the screen, which needs to be considered. One approach to solving this problem is to provide additional visual techniques that reduce the visual congestion in cluttered scenes. This issue is of critical importance in highly dynamic scenes. Finally, one participant also remarked that the relation between the concepts and their respective visual representations can be elucidated when these are put into context, i.e. if they are displayed in a practical scenario.

In conclusion, two critical points were noted from the user opinions. The first one is that the visual representations should be tested and analyzed in a practical dynamic scenario, to determine their efficiency, which is the focus of the next phase in this thesis. Secondly, when the number of objects in a dynamic scene increase, object tracking becomes more difficult. Hence, additional visual techniques that improve comprehension in such scenarios need to be examined, which is the focus of the third phase of this thesis.

4.4. Chapter Summary

This chapter attempts to create visual representations for complex time-dependent concepts. The representations are based on perceptual theories and previous studies on time-independent semantics. Three concepts were short-listed for this purpose: state transition, interdependence, and multiple states; all of which are very general and can be seen or experienced in day-to-day life. For each of these concepts various sets of visual representations were created. An experiment was conducted to evaluate the most favorable of these representations. For state transition, shape change was favored; for interdependence, proximity with partial-intermeshing; and for multiple states, multiple duplicates were favored by the participants.

The next phase (phase 3) of this study aims at validating these representations in a dynamic field of information science. For this purpose, I have chosen to validate them in quantum computing simply because all the concepts that have been short listed here can be seen in fundamental quantum computing concepts. Hence, by applying them to this field, I will be able to test the intuitiveness of my representations in simple and complex dynamic scenarios. The next chapter focuses on validating these representations.

5. Validating the time-dependent representations: An application to quantum algorithms

Quantum computing is a field of computer science that uses the laws of quantum mechanics to perform computational tasks. Quantum computing is a multidisciplinary subject, whose concepts stretch across the fields of physics, mathematics and computer science. As a result, computer science students find it challenging to understand the complex concepts pertaining to quantum phenomena. Quantum calculations are also highly dynamic and unpredictable and therefore, professors are unable to satisfactorily explain quantum behavior, using static examples. In the field of quantum computing, there are several systems [IAD04, RHM+00] that break down complex quantum concepts into simple animations, in an effort to improve user comprehension.

5.1. Quantum Algorithms

Quantum computing has emerged as an important interdisciplinary field, merging theories in mathematics, physics and computer science. So far, a significant portion of research in quantum computing has focused on the design and display of quantum algorithms. These algorithms exploit quantum phenomena such as non-locality of quantum systems, superposition of states, quantum interference, and entangled quantum systems to perform information processing. Quantum phenomena are usually difficult to understand intuitively and often require complex mathematical descriptions. As a consequence, it is a challenge to properly assess the results (intermediate and overall) of the steps throughout the execution of quantum algorithms.

A commonly used representation for quantum algorithms is a circuit, similar to the one found for representing classical logic circuits (Figure 20). A quantum circuit identifies the sequences or step-by-step procedure in which the quantum operators are applied. In a circuit diagram, nodes represent operations and links connecting the nodes represent the state of the quantum register before and after the execution of a quantum operation. In quantum circuits, nodes are referred to as quantum gates. Qubits in the quantum register are identified using a quantum notation, called the *Dirac notation,* as |0> or |1>, when in a basis state, and as a|0> + b|1> when in a superposed state (a and b are real coefficients such that $|a|^2 + |b|^2 = 1$). The entire configuration and connections of quantum gates represents a given algorithm.

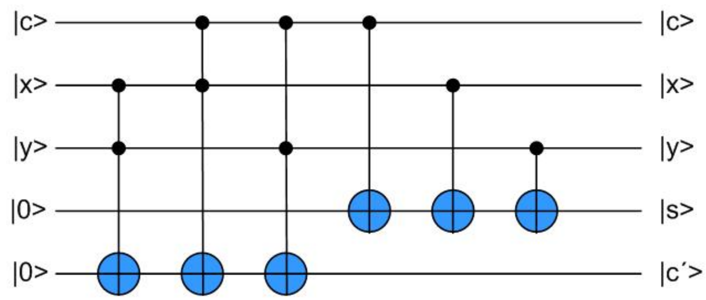


Figure 20: A quantum circuit for an algorithm that adds two input qubits (|x> and |y>) to give the sum (|s>) and carry (|c>).

5.2. Quantum visualization systems

A recent study by Imre et al. [IAD04] describes the Quantum Designer and Network Simulator (QDNS), which is useful for creating and simulating complex quantum circuits. The QDNS (Figure 21) features a graphical interface that is easily comprehensible and useable by novices and experts alike. Users can create quantum circuits by defining the input data and the gates. Users can also run the circuits and view the output data in three different modes; complex mode, absolute mode and graphical mode. In the complex mode, the whole state of the circuit is displayed. In the absolute mode, the probabilities of measuring the circuit are displayed in a textual manner and in graphical mode, the same probabilities, as in the absolute mode, are displayed using graphical charts. The QDNS is useful for students as the graphical interface enables easy visualization of the changes that are occurring in the system, due to the action of the gates on the qubits. However, the QDNS requires a certain level of expertise to understand the charts and the quantum representation that is outputted by the system. Hence, it is not desirable for novices.

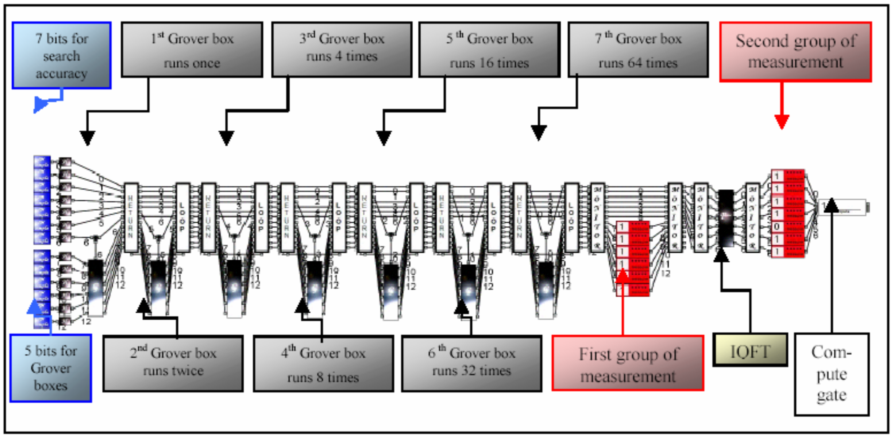


Figure 21: Quantum counting set up for 13 bits in QDNS [IAD04].

Quasi [EWM00], a commercial quantum system, created at the University of Karlsruhe, allows users to graphically create and simulate quantum circuits. The interface supports a maximum input size of 20 qubits. The user can add gates to the circuit, execute the circuit, and view the mathematical results. The system also includes few user defined circuits, like Shor's and Grover's algorithms, which can be loaded and executed, hence reducing a significant amount of the user's time that would be spent in creating the circuits. The system has four windows; the first window (Figure 22(a)) displays a graphical representation of the quantum circuit along with the gates and inputs. The second window (Figure 22(b)) displays the output in a textual form (complex numbers). The third window (Figure 22(c)) displays the length and direction of the outputs as a graphical chart and the fourth window (Figure 22(d)) displays the real and imaginary parts of the output, also as a graphical chart. Quasi has some useful features such as *step-forward* and *step-backward*, which allow the user to step through the circuit one gate at a time and hence view the intermediate results. As an extended feature for larger circuits, the system also allows the user to step forward or backward 5 gates at a time, so as to allow users to skip uninteresting steps. Another interesting feature of this system is that as the circuit is being executed, a vertical bar is displayed to indicate the point of execution. A simulation of the Deustch algorithm in Quasi has been shown in Figure 4. One of the major drawbacks of the Quasi system is the representation of the output. The system does not contain much explanation on the solutions it displays. Also the graphical charts are not easy to understand and require a high level of expertise to comprehend it. In addition, although the circuit is represented graphically in the first window, during the execution there is not much graphical indication as to the states of the qubits in the circuit. Hence, it is not user-friendly and understandable by novices.

The quantum systems described in this section represent current systems that are being used to create quantum circuits. However, even though these systems are graphical, they have high limitations to the amount of graphical information they can display. These graphical displays, though better than pure quantum notation, are still highly complex and cannot be understood by non-experts. To properly understand the inner workings of quantum algorithms, several key concepts or semantics need to be identified and understood. These semantics occur throughout the execution of quantum algorithms and describe the relationships between the various qubits in the system. A significant level of expertise is required to understand the outputs at each execution stage of an algorithm. Hence, there is a need to create a system that breaks down the complex concepts into perceptual notation that can be understood by experts and novices alike.

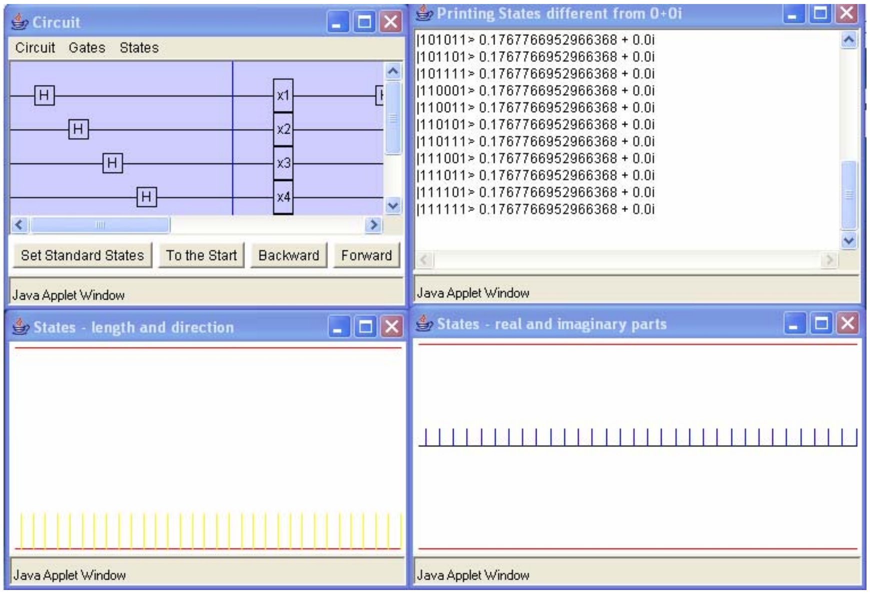


Figure 22: Simulation of the Deustch algorithm in Quasi. (a) Graphical circuit representation of the algorithm, (b) Output of the execution in textual form, (c) Length and direction of output and (d) Graphical chart mapping the real and imaginary values [EWM00].

5.3. Experiment 2: Representing complex Quantum concepts using perceptual notations

The first experiment focused on determining the set of representations that are simple, but effective enough to describe various time-dependent semantics. The results of the first experiment provided a list of “best” representations for the previously selected semantics. In order to evaluate the visual representations, a second experiment was conducted to evaluate the effectiveness of the mappings in a typical pedagogic scenario.

The semantics of state transition, multiple states and interdependence all occur within the framework of quantum algorithms. Hence, to validate the representations short-listed in the first experiment, I tested their capacity for eliciting information in quantum algorithms. In particular, I was interested in determining whether the visual notations facilitate intuitive identification of a concept. Hence, the below described experiment was conducted.

5.3.1. Participants

18 students from the University of Manitoba participated in this evaluation. The participants were in their 3rd year or higher of their computer science undergraduate engineering degree. The factors for this experiment were the display type (perceptual notation vs. quantum notation) and the error rate, which was measured by assessing the effectiveness of the notation in conveying the semantic. None of the subjects had any previous experience with the semantics used in this study.

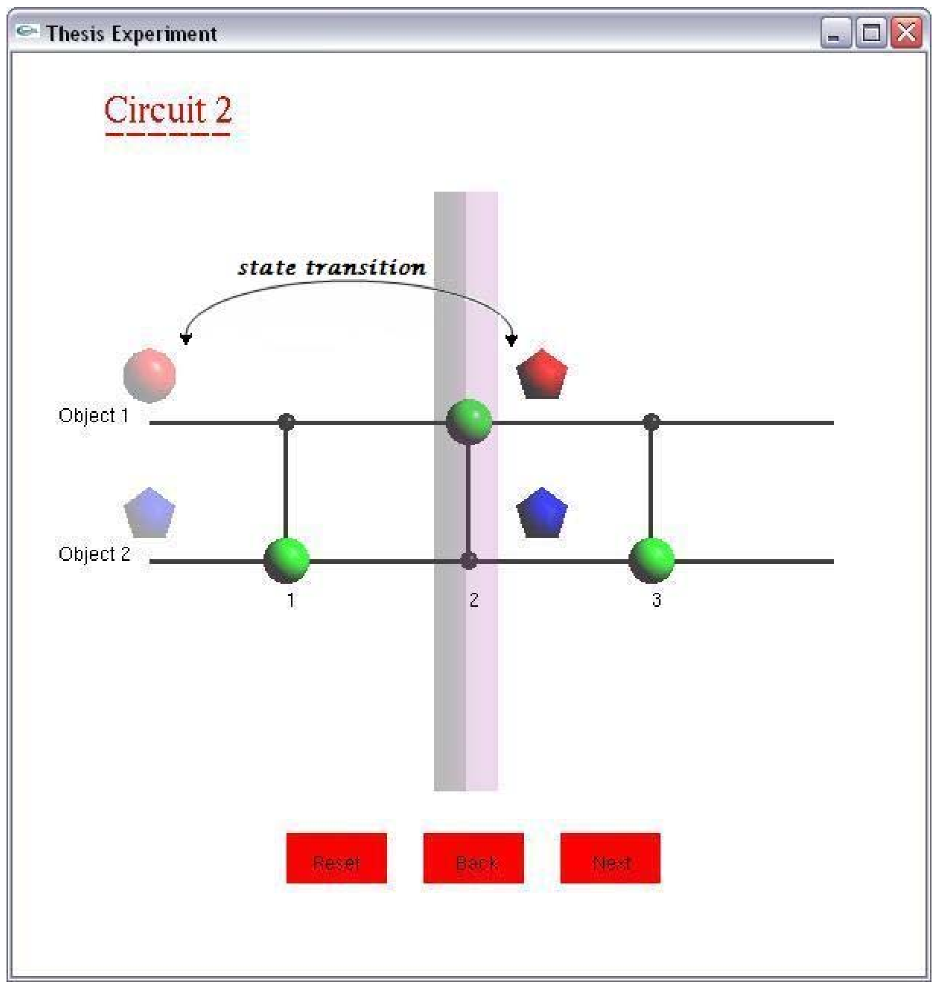
5.3.2. Materials

Four circuits (or four algorithms) were constructed for the experiment. The circuits differed in complexity, i.e. two of the circuits contained more algorithmic steps than the other two, and notation type, i.e. two of the circuits displayed the output in quantum notation and the other two displayed the output in perceptual notation. Each circuit consisted of several gates which acted upon the inputs to the circuit. The inputs to the circuits were called objects and were transformed by the nodes in the circuit during the course of the execution. The experiment used a 2x2 (2 notation types, text and graphics, and 2 levels of complexity, simple and complex) within-subject design. As the experiment was evaluated on novices, no quantum terms (such as qubits or gates) were used to describe the components of the circuits.

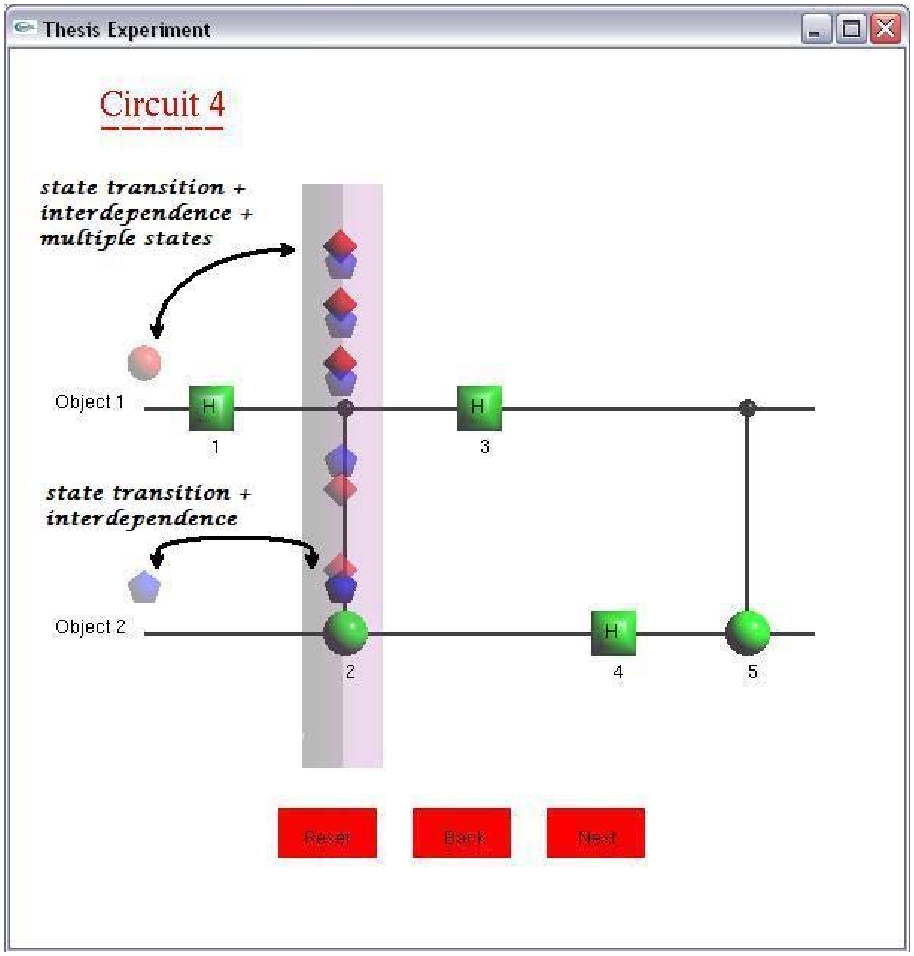
The participants were given access to two buttons, labeled 'Back' and 'Next', to allow manual execution of the algorithm in a stepwise fashion. The 'Next' button caused the movement of the execution to the next step in the circuit and displayed the intermediate results. The 'Back' button allowed the participant to replay the current step of the execution.

Finally, the display consisted of an execution bar that highlighted the current position of execution in the circuit. As the participant clicked the 'Next' or 'Back' buttons, the execution bar moved accordingly to show the current step of execution. A snapshot of the experiment has been shown in Figure 23 below.

The experiment was conducted on a 17 inch Flat screen LG monitor. A 3-button Logitech mouse was used for interacting with the circuit.



(a)



(b)

Figure 23: (a) Circuit that depicts the algorithm of swapping two objects, (b) Arbitrary complex algorithm (annotations were not included in the experimental setup).

5.3.3. Procedure

At the beginning of the experiment, the goals of the experiment were outlined to the participants. They were then given a brief overview of the setup of the experiment and were explained the functionality of the 'Back' and 'Next' buttons, and their use in executing the algorithms. The participants were also informed that they were required to answer one question, given on the questionnaire, at the completion of each intermediate step in the execution. They were not given any training of the concepts that they would be tested upon. The reason for this was to test the intuitiveness of the visual notation developed.

Each of the participants were shown the four circuits in a Latin square fashion and were asked to answer a series of multiple choice questions. The questions were all of the form, “What is the state of object 1 after it passes through gate 1” etc. There were three concepts that were shown to the students in different combinations; change in state, change to multiple states, and change to combined states. The answers to the questions were combinations of these states and the participant was instructed to choose only one choice per question, from the list of given choices. For the simple algorithms, the participant was asked to indicate their understanding of the overall goal of the circuit. This question was of the form, “Circuit 1 might perform the follow task. Ans: (a) combine the inputs, (b) swap the inputs, and (c) it is a random circuit”.

At the completion of the experiment, the participants were asked to fill out a subjective questionnaire, to serve as experimental feedback. The questions asked in this questionnaire were of the form, “Did you have any trouble understanding the concept of state change”. Participants were asked to give brief explanations on the parts of the experiment that they found ambiguous or particularly difficult to comprehend.

5.3.4. Results and Discussion

Each subject was given a score of 1 if they matched the correct representation to the semantic or a score of 0 otherwise. Results are summarized in Table 1, which reports error rates by algorithm size. The results are obtained by averaging each subject’s scores. A One-Sample T-Test (or Sign Test) statistically shows that overall subjects performed better with the perceptual notation ($p < 0.01$). Subjects performed slightly better with the quantum representation over the perceptual notation on small circuits. However, the difference is not statistically significant (p-value=0.403). For large circuits, subjects performed significantly better with the perceptual notation than the quantum representation ($p < 0.001$). From the qualitative question for the simple circuit, all the users were able to identify the purpose of this circuit, both with the quantum and perceptual notation.

	Quantum Notation	Perceptual Notation
Simple	11.46%	18.75%
Complex	61.31%	24.65%

Table 1: Error rate in matching the animation to the correct semantic.

The results suggest that the perceptual notation is particularly useful for more complex quantum algorithms. In complex algorithms qubits can undergo several forms of transformations (such as from a single to multiple state). Hence, my perceptual representations can be used to effectively describe these transformations.

Overall, the participants indicated that the animations assisted their comprehension of the stepwise operations in the quantum circuit. In the questionnaire, participants were given the options of commenting on the experiment and on the representations that were displayed to them. The questions targeted the simplicity of the individual representations and of the overall animation. For example “Did you have any difficulty in understanding what was meant by a change in state in the experiment”, targeted a single concept that was animated. These comments provided us with useful feedback on the concepts that are deemed complex by the participants and also on how they interpreted the visual representations. Most of the participants did not find any difficulty in viewing the animations, however many of them pointed out that since there were many animations occurring at the same time, they did not know which ones to focus on. Many of the participants pointed out that the visual representations were not really necessary in the simple circuits as they could understand the concept quite well with the quantum notation itself. The reason behind this insignificance is attributed to the simplicity of the concept itself, as it could be clearly elucidated using the quantum notation. However, all of them agreed that as the complexity of the circuit increased, the visual representations were more efficient in depicting the details of the dynamic concept. One participant also commented that the visual representations should not replace the quantum notation; instead it should supplement it for maximum effectiveness.

Due to limited training, all of the participants were initially quite confused about the representations and also about the tasks that has been set out for them. Within a couple of trials, most participants were able to understand the concepts and submit appropriate responses. However, there was a small group of participants who took a much longer time to comprehend and respond. Some of these participants claimed that they were extremely confused and did not understand any of the concepts that were visualized. Through observation and repeated questioning, I have reached the conclusion that this poor performance is mainly due to the low spatial ability of these participants, as they needed an in-depth explanation to visualize a concept, which was not provided. One participant completely misunderstood the tasks and answered based on the location of the representations, rather than the properties of the representations themselves (***Participant 13:*** "Wasn't sure what was meant but I thought it (*combined state)* was whenever there were objects, object 1 and object 2 on the same side of the circuit"). In the end, however, all the participants appreciated the usefulness of viewing concepts using visual representations.

One main issue that was observed during the experiment was that the participants were confused by the amount of information shown to them on the screen. Some of the participants complained that there was too much animation on the scene and hence they did not know which animation to focus upon. Some commented that they had to replay some of the animation as the missed the details because they were distracted by something else happening in the scene. One participant expressed that even though it is important to view all the changes happening in the scene, there seem to be many distractions. This issue is commonly seen in many dynamic scenes (radar control, animated games) where due to the overloading of information on the scene important events are missed. Hence, the analysis of the results of this study brought the next step into light; *it is not sufficient to **represent** complex concepts, it also important to **present** this visual information efficiently*. Hence, the next step in this thesis focused on improving the presentation of dynamic scenes.

5.4. Chapter Summary

This chapter describes the validation of perceptual representations as they have been applied to quantum computing. The visual representations constructed and described in the previous two chapters can be used to represent complex concepts or time-dependant semantics. An experiment was conducted to validate the perceptual representations, by comparing them to algorithms represented using the standard quantum notation. Results show a distinct improvement in comprehension as the complexity of the quantum algorithms increase. However, in order to make the representations more effective, interaction techniques need to be developed for controlling the visualizations.

In addition, as the complexity of the animations increase, the number of simultaneous events also increases. Hence, many small details in the animation can be missed out or unintentionally ignored as the human eye is not able to view all parts of the animation at all times. This is a very common and recurring problem not only in quantum algorithms, but also in many dynamic systems that display large amounts of visual animated information. In an effort to solve this attention loss problem many studies have tried to evaluate various focus and attention techniques in graphical displays. These studies are mentioned in the next chapter and form the main source of inspiration for my study towards improving presentation and comprehension. However, as many of these studies do not satisfy the requirements of dynamic multiple object scenarios, further work needs to be conducted to analyze techniques that can improve the focus and attention in complex dynamic scenarios, which is the focus of the second part of this thesis.

6. Presentation: Assisting comprehension in dynamic systems using Focus+Context techniques

Many areas of information science employ dynamic simulations to depict temporal concepts. In most dynamic simulations, constant interaction exists between objects on the scene. A person viewing the scene has to then keep track of multiple events that occur simultaneously or one after the other in quick sequence. A drawback of dynamic simulations is that the scene consists of many continuous simulations, all of which are important to the overall picture, but some of which might not be critical at a certain instant of time, i.e. at some instant in time in a dynamic scene, there could exist some events which might not be considered crucial by the viewer when compared to some other events. However, with pure visualization (absence of any visual cues), the viewer might be forced to view both wanted and unwanted simulations, thus overloading the viewers' memory and decreasing comprehension. Hence, it is very important to reduce the amount of information that is displayed to the user so that they can focus on what is critical. However, care should be taken that the overall picture is not disrupted and still be understood.

6.1. Multiple object tracking issues in information science

Two example areas that experience the problem of visual information overload are radar tracking and animated games. Radar tracking can be defined as the monitoring and coordination of airplanes in specified sections of airspace. This monitoring is performed by specialized and highly trained radar controllers who work from a controlling tower and coordinate with the pilots flying their individual airplanes. A radar controller tracks flight details such as direction of travel, altitude, and speed of each flight within his/her jurisdiction very closely and issues instructions to the pilots, in order to avoid any air collisions. When a flight exits its current airspace and enters another airspace, the controller of the new airspace is immediately notified and the responsibility of monitoring is transferred to the controller of the new airspace.

One of the main issues in radar control is the problem of focus. In a dense scene, the controller is not able to focus upon a subset of flights that he/she feels requires special attention over a particular period of time. Also, as the controller is able to view only his/her designated section of the airspace, he/she does not have the capacity of anticipating flights that might enter the airspace, unless specifically notified. Also, even if the controller is notified of an incoming flight prior to its entry, it is difficult for him to get immediate access to all the information of the incoming flight, such as direction of travel, speed, weight of flight, size of flight, and altitude.

Figure 24 shows a section of a radar screen as seen by radar controllers. Each circle on the screen indicates the presence of a flight in this particular area of the airspace. Along with circles, indicating the presence of the flight, information such as: flight name and number, altitude, speed, direction of travel, distance from an aerodrome, and status codes are also displayed. The screenshot showed above displays only a small section of the actual airspace that is controlled by one radar controller. The display also shows typical high density traffic. Hence it can be clearly seen that as the number of flights on the screen increase, the scene gets increasingly complex. Also the visible airspace does not have much information on flights that are about to enter or those that have just left.

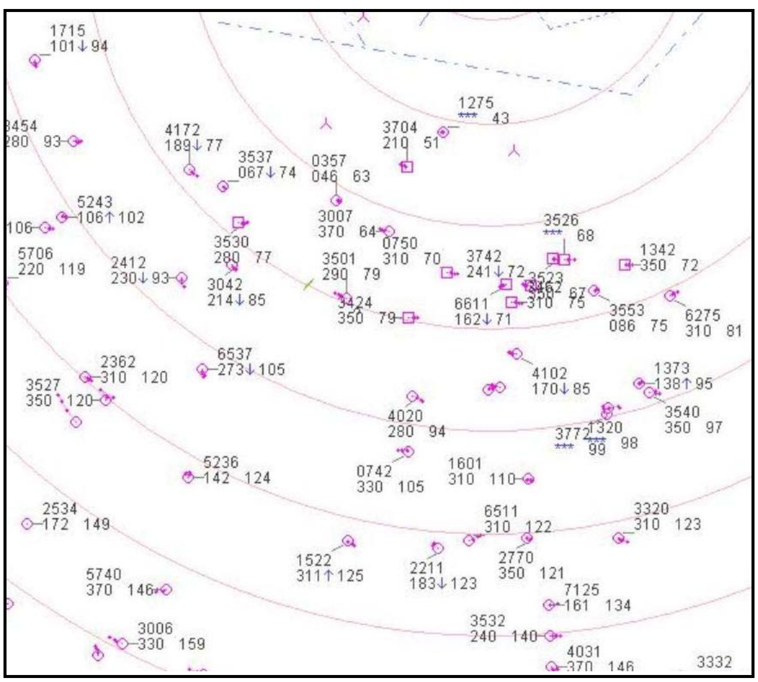


Figure 24: Screenshot of typical high density traffic in an air traffic controller's window (courtesy of NAV Canada).

Therefore, it would be extremely convenient if the flight information is presented in such a way that controllers are able to view the sections of the airspace, outside their jurisdiction, along with their designated airspace. However, the question here arises in determining how to show both the designated and outer airspace, while avoiding an increase in the complexity of the scenario. In other words, "How can the airspace be presented such that the controller knows what is happening outside his/her designated airspace, without any ambiguity about what planes lie in their jurisdiction?" I will address this issue later in this chapter.

Another popular application that contains highly complex scenarios is animated games. Nowadays, games are becoming highly sophisticated, graphic, user-interactive, and complicated. A typical action game consists of a hero (game player) who has to fight against one or more enemies in order to win the game. In such a scenario, the hero generally fights against many other characters at the same time or in close succession. In addition to the character that the hero fights with, there could be many other objects in the scene, which could effect the player's concentration, called distractors. A distractor is any object that currently exists in the scene but is not of the utmost importance to the hero at that instant in time. Distractors could be human, like other characters in the scene, objects, like buildings, trees, rocks, and river etc. or user-interactive facilities, like user controls, help menu, chat dialog etc. Even though such distractors are not important at that instant of time to the hero, they could be crucial to the scene itself and to the ambience of the game (Figure 25). For example, in such situations the question arises, "How can the presentation of complex games be improved, such that the players can concentrate on the enemies he/she are currently fighting against, but not loose track of what else is happening in the scene?"

Figure 25: Screenshot from "Age of Mythology", by Microsoft and Ensemble studios. Scene consists of hero (es) fighting against enemies, along with user information such as health, minimap, resources, messages etc.

There exist several studies that have analyzed techniques for improving feedback and attention in dynamic systems. Techniques such as Digistrips [Mer03] evaluated the importance of object tracking in air traffic control. Air traffic is monitored by controllers, who are designated with various sections of the air space. The responsibility of the controller is to monitor all flights entering, leaving, or traveling within his/her jurisdiction, avoiding any collisions. Digistrips uses visual cues such as animation, vibration, flickering, color, texture, and transparency to display information and to capture and direct users' attention to important events in the display.

However, such techniques mostly display auxiliary information and do not truly visualize dynamic motion. Hence, the above questions still stand and can be stated in general as, "How can focus and attention in complex dynamic scenarios be improved such that the overall context is not lost?” The rest of my research focuses mainly on this problem.

I have developed this part of this thesis from mainly two areas of research: multiple target tracking and semantic depth of field.

6.2. Multiple target tracking

One of the most natural methods of dynamic visual processing by the human eye is preattentive processing. Preattentive theory, as explained previously allows the human eye to recognize events or objects without any attentive effort. However, as with most other natural abilities, there is a limit to how much information can be preattentively processed. As amount of important information and auxiliary information increases, the cognitive load on the brain increases.

Recognizing this problem, many researchers have conducted experiments to test the effects of increasing complexity on human comprehension. A study by Allen et al. [AMP+04] showed that as the complexity of a scene increases, pre-attentive comprehension is drastically affected, even if the participant is a trained professional in multiple target tracking. This study compared the comprehension between radar controllers (trained experts) and undergraduate students (untrained novices) in complex high cognitive load scenarios. The experiment consisted of a screen containing a small solid box in the center and surrounded by many solid crosses. The participants were required to concentrate on the solid box throughout the experiment. Some of the crosses on the screen were selected as targets and flashed to the participant. During the course of the experiment one of the objects on the screen changed shape and the participant’s task was to state if the changed object was a target or not. Overall, the experts fared better than the novices in the experiment, since the experts were trained in object tracking. The results of the experiment showed that both experts and participants could keep track of up to six targets. Above that the error rate drastically increased. To further test the degradation in accuracy with increasing targets, Allen at al. [AMP+04] conducted a second experiment where participants were asked to perform an extra vocal task along with all tasks of the previous experiment. The results of this study showed that there was a significant decrease in accuracy rate as the number of tasks increased. In the second experiment, experts could track to a maximum of four targets while novices could track to a maximum of only two targets.

Pylyshyn and Storm [PS98] suggested a model called the FINST model that explained how participants were able to track many independent targets simultaneously. According to the FINST model, the eyes of a person generally focus on one area of the scene, called the locus of visual attention. However, without moving their eyes, the authors state that it is possible to shift the locus of visual attention such that the eye can distinguish regions which were not visible previously. This is called pre-attentive processing and this is used very commonly to track multiple moving targets simultaneously. According to authors, FINST can be described as references to certain features of objects such that they stand out and can be tracked by the eye preattentively, independent of the position of the objects in the scene. Pylysyn and Storm [PS98] conducted a study to evaluate the FINST model. In the first experiment, 10 objects were shown to the participant, out of which a random subset of objects, called the targets, was flashed to the participant. The objects then started moving in random paths around the scene and eventually a square would be flashed on one of the objects in the scene. The participants' task was to keep track of the objects that were flashed in the beginning and to determine if the square was flashed on a target during the course of the experiment. The participants were given a chin-rest that constrained the movements of the head, and were also restricted from moving their eyes. The results of the experiment stated that the participants were able to track up to a maximum of 5 targets and that the FINST model was used to keep track of the objects. Also, as with the previous studies, an increase was seen in the error rate and the response rate with an increase in the number of targets. The results of this experiment also suggested that the reason for this tracking efficiency could be that the participants were tracking multiple objects in parallel and hence could track more number of objects at the same time. To determine if this is the actual cause, a second experiment was conducted were the targets were placed far apart such that the eye could focus on only one target at a time, hence forcing serial processing of the object. The results of this experiment showed a considerable decrease in efficiency and object tracking capability. The overall study stated that the FINST model forms a good basis for tracking multiple objects in dynamic scenarios. The ability of the participant to track multiple objects can be attributed to (a) the process of tracking objects in parallel and (b) the existence of FINST references tagged to the objects, which makes them distinguishable from the other objects.

Yantis [Yan92] conducted a series of experiments to further analyze the different methods that viewers employ to remember multiple events. Yantis states that there are two main methods in which viewers remember multiple objects: (a) location of the object and (b) features of the object. The study focused on the latter and aimed at analyzing the perceptual groups that are formed and maintained by participants in order to distinguish targets (important events) from non-targets (unimportant events). The focus of the first series of experiments was to determine the type of perceptual groups that are formed in order to keep track of objects. Though agreeing to the theory of FINST suggested by Pylyshyn and Storm [PS98], Yantis suggested an alternative method by which participants could track multiple targets. According to Yantis's theory, the participant groups the objects into a virtual polygon and then keeps track of the polygon, which can change shape, location, size and orientation constantly. To analyze this theory, Yantis conducted experiments similar to those conducted by Pylyshyn and Storm [PS98], with the difference that the targets were placed according to the virtual polygon theory. In each trail of the experiment, a random number of targets were initially chosen and placed in a virtual polygon such as a triangle, pentagon etc. The type of movement of the targets during the execution was varied between the experiments (some experiment had random movement of the targets while some constrained the targets to the virtual polygon model). The overall consensus of this study was (a) participants performed better with the perceptual grouping model and could track up to a maximum of 5 objects, (b) the error rate increased as the number of targets increased, (c) participant initially performed better when they were informed about the grouping strategy beforehand when compared to groups which had to discover the grouping strategy by themselves. However, the performance decreased over time when all the groups had practiced the grouping strategy enough to be able to group the objects without much effort. Also, when the virtual polygon that the objects were placed in remained rigid and convex, then the performance was improved as relative positioning help participants to keep track and find targets that were not in the locus of visual attention. The study thus stated that participant naturally formed virtual polygons that helped them remember relative positions of objects. However, this tracking ability was most efficient when the polygon remained rigid. Any violation of a target from the boundaries of this virtual polygon caused the participant to automatically eliminate the object from the list of targets, hence reducing object tracking efficiency.

The above studies have analyzed and discovered various methods that viewers make virtual visual cues to assist their memories with multiple object tracking. However there is a limit to how many cues the viewer can make without overloading the memory and adding to the visual confusion instead of decreasing it. Hence, the best method to reduce this processing overload, is to provide the display with external visual cues that are not virtual and do not depend on the processing capability of the viewer. On this note, many studies [SSM+04] have listed out various factors needed to improve complex dynamic scenarios. One of these factors is the reduction of the number of distractors in the scene. Every distractor on the scene adds to the total cognitive load on the user. Studies claim that reducing the number of distractors allows the user to focus on the logical concepts and hence makes the animation more effective. Other studies such as [FS97] have analyzed the need for improving focus in animated scenarios. This study [FS97] has suggested a set of guidelines that would help improve focus and attention in dynamic educational applications. Some of the guidelines have been considered in determining the type of technique that might help in improving visual displays. The guidelines from [FS97] that have been considered have been listed below, along with my rationale for accepting them or rejecting them as techniques that enable improvement of dynamic information displays:

- **Motion:** This guideline states that an object that starts moving causes the eye to be attracted towards it. Hence, important information can be represented as moving entities. However, his guideline is useful in a static scenario or where the unimportant information is static, and not in an extremely dynamic scenario.

- **Revelation of information:** This guideline states that systems should exercise control over their animations such that only the important information is shown in an orderly fashion and not shown before it is needed. However, this again might not be effective if auxiliary information is needed at all times and cannot be removed from the scene just because it is not in focus at that time (e.g. In the game screenshot in Figure 25, all the user information is needed even though it is not being accessed at that point in time).

- **Symbols:** This guideline suggests that by using symbols such as arrows, users can be guided to important information or events. Though this seems to be a possible guideline in static or dynamic scenarios, there are two obvious drawbacks with this guideline: **(a)** If all the objects in the scene were of the same shape or if none of the objects existing in the scene were already in the shape of an arrow, then an arrow can be used to point out information, as it is a unique shape and will draw attention. However, if the objects are all of different shapes or if the arrow representation already occurs in the scene, then an arrow will not draw any attention to it and it will be ignored as just another part of the scene. Also, if there are many different shapes in the scene, the arrow might not stand out as unique, and hence might not be effective. **(b)** In a scene that is less crowded, an arrow might be noticed. However, it should be noted that an arrow is an object by itself and drawing arrows on the scene will increase the number of objects in the scene and thereby increase its density. Hence, in a highly cluttered scene, an arrow might cause unnecessary increase in complexity, might be occluded by other objects, or might itself mask important information on the scene. However, as this type of representation is possible in a practical situation, the arrow has been employed as an alternative highlight representation in the experimental evaluation of focus and attention techniques.

As the focus is to improve the comprehension of dynamic scenes by adding visual cues to enable focus and attention, the above given guidelines form a strong basis for the representations used in this thesis.

Faraday and Sutcliffe [FS97] conducted an experiment to analyze the effectiveness of their guidelines. The results of this study showed that techniques such as highlighting information do show an improvement in focus and attention and eventually in comprehension. A study by Healey et al. [HBE96] evaluated the use of hue and orientation of objects to promote preattentive processing. Results of this study favored both the use the hue and orientation and stated that the performance of the participants was considerably improved when visual cues were provided using these two techniques. Overall the study stated that it was the presence of a visual cue, and not the type of cue (hue or orientation) that improved performance. Another study by Franconeri et al. [FHS05] states that motion is not always efficient in capturing or drawing attention as there are other factors such as brightness of the scene or object, and looming which also play an important part. The results of the study state that by varying brightness around a scene, users' attention can be focused to required sections of the scene.

Inspired by previous research, in this study, I will try to attract attention by highlighting only those objects that are important, while ignoring the rest. The main focus here is to help improve users attend to important information. Many visual techniques, such as, size, color, animation, symbols, etc have been used to focus users' attention on important information. One of these techniques is called *Semantic Depth of Field* (SDOF) and will be explained in the next section.

6.3. Semantic Depth of Field (SDOF)

A method for providing feedback and drawing attention has been through the use of semantic depth of field (SDOF) techniques. SDOF techniques employ the use of the 3-dimensional properties of visual displays. In this technique, all objects are assumed to be located in a 3-dimensional space of clear and unclear objects. Objects that are considered distractors are shown less clearly to the eye, compared to the targets. This focuses the users' attention on objects that are clearer (targets) than on the objects that are unclear (distractors). This difference in clarity can be achieved in several different ways such as reducing the size of the unimportant objects, increasing the size of the important objects, blurring the unimportant objects, or dimming the unimportant objects.

Several studies [KMH01, KMH02, KMH$^+$02] have analyzed the effect of SDOF in static scenarios. SDOF is achieved by using blurring techniques to distinguish between important and unimportant objects. Kosara et al. [KMH01] state that the natural tendency of the human eye is to bring any item of interest to the center of vision and focus upon it. By blurring the edges of unimportant objects, the SDOF method forces the eye to focus on the sharper objects. The studies state that the SDOF method is a *cue* method of information visualization. In the cue method the visual cues are used to tag objects that are grouped based on similar features. These visual cues are then used to show the different groups of objects as and when required. Similarly, the blurring technique focuses on reducing the visibility of the edges of the object and hence is a type of visual cue.

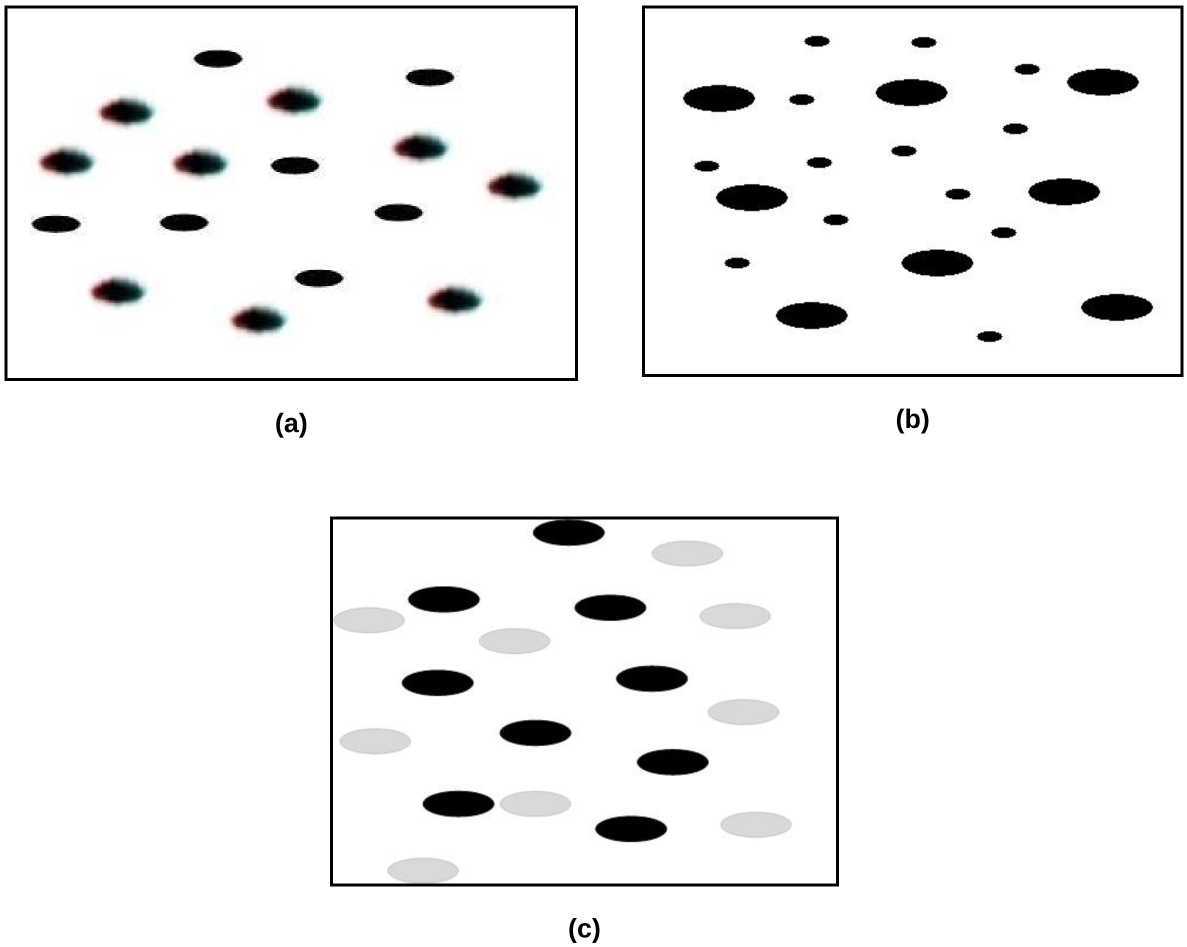


Figure 26: SDOF can be shown by using (a) blurring, (b) zooming, or (c) dimming techniques.

Some of the main properties of SDOF can be stated in the studies [KMH01, KMH02, KMH$^+$02] as follows:

- SDOF does not affect the physical properties of the object, except for it sharpness. Hence characteristics such as color, texture, shape, and size of the object are unaltered as no distortion of the object occurs. Hence object recognition is unaffected.

- SDOF technique is useful in pedagogical situations as important events and concepts can be pointed out without losing the overall context of the tutorial.
- The SDOF technique focuses on reducing the sharpness of objects that are unimportant and ignores the important objects. Hence, the important objects are unaltered.
- SDOF is can be used to give an overview of information or can be used to draw attention to specific sections of the information. For example, in a large data sample, SDOF can be used to show different trends in the data by highlighting only those data points that are included in the trend line and blurring out the rest.
- SDOF can be used by color-blind users, and also in black and white display systems, as the technique is not dependent on color.
- SDOF technique is intuitive because it does not require special expertise and does not need any extensive explanations.

The spatial effect in SDOF is achieved through the use of blurring techniques, i.e. the targets retain their normal clarity, while the distractors are blurred out. Studies [KMH01, KMH02] have shown that participants were able to intuitively detect targets among distractors and did perform better with SDOF than without them. In one study, Kosara et al. [KMH+02] evaluated the ability of participants to preattentively locate important objects in a complex scenario. The first experiment of this study evaluated the efficiency of distinguishing between sharp and blur objects. The results of this experiment stated that, with proper control over the level of blur, the participant was able to locate sharp objects efficiently with SDOF. The second experiment tested the efficiency of SDOF when intermixed with other features such as color and orientation. The results of this experiment stated that the SDOF technique is efficient even when mixed with color or orientation.

In the above studies blurring of objects has been used to highlight objects of importance. In order to blur an object, the colors at the edges of the object are spread out around the object, to display a hazy image [KMH01, KMH02, KMH+02]. Though studies have shown the efficiency of this technique, two very obvious disadvantages of this technique of SDOF can be seen:

- A blurred object occupies more space than a sharp object, as the hazy coloring of the edges requires more space. This is an inefficient display method in a complex scenario where efficient space usage is essential.
- In cases of overlap, blurring becomes inefficient as blurring can obscure objects that might have been visible without SDOF.

In dynamic scenarios, due to the active nature of the objects, overlapping is a common and accepted result. Hence, given the disadvantage of using blur as mentioned above, a new method of SDOF has been devised. In this method, the opacity of the object is manipulated. Important objects, as per SDOF principles, are unaltered. However, the objects that are not of top priority are made translucent. This technique helps to improve focus and attention in the following ways:

- By making the unimportant objects translucent, the attention of the human eye is drawn to the objects that are opaque and hence brighter.

- The translucency of the object does not occupy any more space than the opaque object and hence can also be used in congested scenarios.

- As unimportant objects are translucent, they do not occlude any important objects behind them and hence are well suited for overlapping situations.

Due to the above listed advantages, in this study, I will be evaluating the efficiency of using translucency as an SDOF method of improving focus and attention in dynamic scenarios. The design of the experiment has been inspired from a study by Mould and Gutwin [MG04], which consists of a dynamic scenario, containing many 2-dimensional squares, one of which is deemed the target. The participants' tasks include tracking a target among several distractors. Though the aim of the experiment is not the same as this study, the setup of the experiment seems to be a feasible setup for the following reasons:

- All the objects are of the same shape and color to eliminate any recognition effect due to shape or color.

- The dynamic nature of the scene in their study is ideal as this study also focuses on improving attention in dynamic scenarios. Also the locations and paths of the objects are random, which eliminates learning effects.

The experimental process and results are discussed in the next section.

6.4. Experiment 3: Evaluating SDOF techniques to focus and attention in dynamic displays

The human visual system has a very limited capacity of keeping track of multiple objects that are displayed dynamically. Studies [AMP+04, Yan92] have shown that even with training and expertise, human capability of tracking multiple objects is quite minimal. These studies state that on average, participants could track up to a maximum of 5-6 objects simultaneously. These studies also suggest that an increase in the number of objects and/or distractors reduces the object tracking capability considerably [AMP+04, Yan92]. However, several other studies [MG04] have shown that object tracking can be considerably improved by providing visual cues such as feedback that draws users' attention to crucial events in a scene. Hence, the purpose of this experiment is to analyze two visual techniques, namely highlighting and SDOF, and to evaluate which of the techniques provides greater improvement in comprehension.

6.4.1. Participants

20 students from a local university participated in this experiment. Though no prior expertise was required in any field of information science, only participants with a computer science background were tested to avoid any learning bias. The age range of the participants was between 20 – 25 years. Prior to the start of the experiment, the participants were given a description of the system along with a demonstration and practice trials of the concepts being tested. All participants had normal or corrected-to-normal vision.

6.4.2. Materials

The experiment consisted of tracking objects displayed on the screen. Two groups of objects were shown; large number of objects (Number (N) = 30) and small number of objects (N = 15). All the objects were of the same shape (Edges (E) =4) and color, while the size was varied randomly between the objects. In addition, the initial spatial positions of the objects were randomly generated with no overlapping or occlusion.

The system was created on an OpenGL platform using C programming language. The experiment was conducted on a 17 inch Flat screen LG monitor. A 3-button Logitech mouse was used for interacting with system.

6.4.3. Experimental conditions

The experiment was conducted by manipulating three independent variables (target space, type of semantic, number of objects) and the results were evaluated based on two dependent variables (number of errors, time taken to provide an answer).

6.4.3.1. Independent variables

Three variables were manipulated to conduct the experiment:

- **Number of objects (N):** The number of objects in the experiment were divided into two groups: small and large. The small group consisted of 15 objects and the large group consisted of 30 objects. These groups were randomly chosen at the beginning of the trial and the number of trials was distributed evenly among these groups, with 27 trials per group (per participant).

- **Target space (TSp):** The number of targets in the experiment was manipulated between different trials. The targets referred to the group of objects in the experiment that were considered to be of critical interest during that period of time. This group was randomly generated at the beginning of each trial. The target space varied randomly between: small (MIN = 1 and MAX = 3), medium (MIN = 4 and MAX = 6), and large (MIN = 7 and MAX = 9). The target space was randomly distributed throughout the experiment with 18 trials per group (9 trials with small number of objects and 9 trials with large number of objects). At the beginning of each experimental trial, a random number of objects within the target space were chosen as the ***targets.*** These essentially were the objects that belonged to the target space **AND** underwent transition during the experiment trial. As before, the number of targets was randomly generated before each trial.

- **Type of semantic (TSem):** Two types of visual semantics were evaluated and compared with a standard visual technique. The standard technique was simply pure animation without any visual cues. The two techniques that were compared were the SDOF technique (using dimming) and the Highlight technique (using arrows for symbols). The type of technique was randomly chosen before each trial and was distributed evenly throughout the experiment. Each technique was tested 18 times per participant (9 trials for small number of objects and 9 trials for large number of objects). Each of the 9 trials was further subdivided into groups of 3 trials based on the size of the target space (3 trials for each of small, medium, and large target spaces).

6.4.3.2. Dependent variables

- **Number of errors (E):** At the finish of each trial, the participant was asked to choose the targets that changed during the experiment. The number of errors was then calculated as the number of targets that were selected ***less*** the number of wrong answers that were provided.

- **Time taken to provide an answer (T):** The total time taken to complete a trial was calculated to evaluate the efficiency and simplicity of the semantic representation.

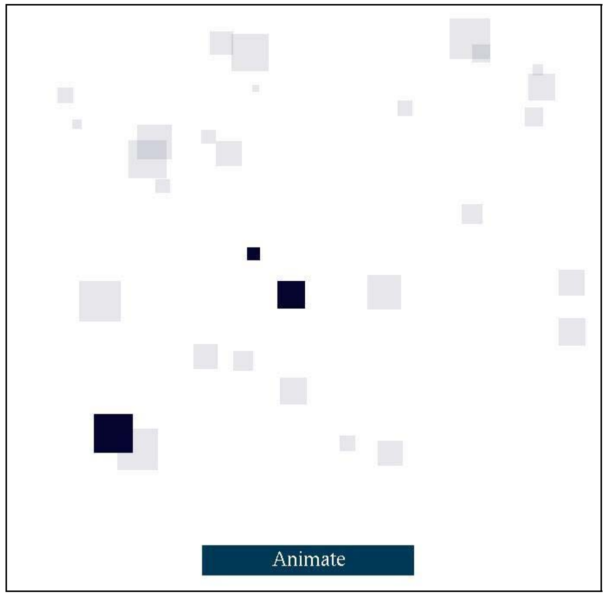
The total time included the time from the beginning of the animation to the time when the animation was stopped (either manually or automatically). This time did not include the time taken to flash the target space at the beginning of the experimental trial.

6.4.4. Procedure

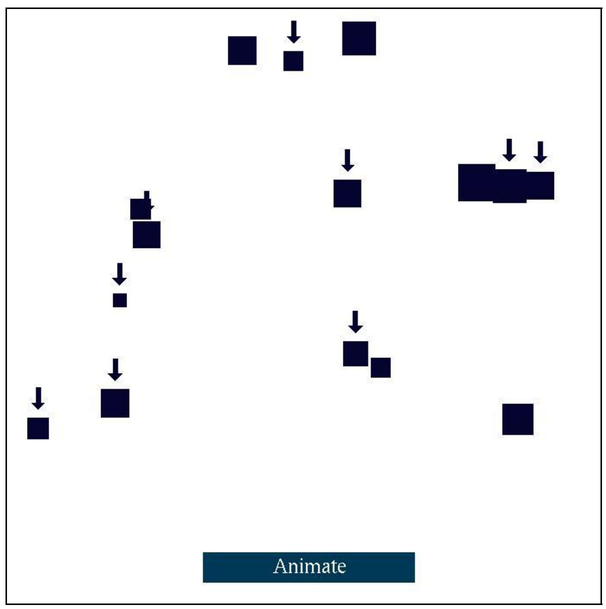
The experimental simulation was as follows; initially a *target space* (chosen randomly) was flashed to the participants for 3 seconds. After 3 seconds, the objects commenced moving around the screen in random paths, with constant speed. After about 10 seconds, a randomly chosen subset of the target space *(targets)* changed size. The main task of the participants was to view the target space that was flashed to them at the beginning of the simulation, keep track of the target space objects as they moved about the screen, and determine which of the target space objects changed size during the simulation. The participants were asked to hit a key (space bar) to notify as soon as they have an answer ready. In the event that the participant was not able to reach a conclusion even after 15 seconds, the simulation was automatically terminated. Whether was manually or automatically terminated, the animation was suspended and the target space objects were highlighted in a different color. The participants were then required to manually click on the targets (within the highlighted target space) that they saw changing during the experiment. In addition, the participants were warned beforehand that there could be some objects, not belonging to the target space, that might change size *(distractors)*, and that these objects should be ignored as best possible. Providing an answer for each trial was not mandatory and the participants were allowed to skip to the next trial if they did not see any change or were not sure of the answer.

Three display methods were compared in order to determine if SDOF can facilitate multiple target tracking: No Indication (NI), Semantic Depth of Field (SDOF), and a Highlight method to show the objects that were changing. In all three methods the target space was initially flashed. In the NI method there was no indication during the course of the animation of the occurrence of change. In the SDOF method, all the distractors were dimmed out while the target space objects were untouched. In the Highlight method, all the target space objects were highlighted by pointed arrows, while the distractors were unchanged (Figure 27).

The experiment was counterbalanced using a Latin square design and was manipulated based on three independent factors; number of objects (small/large), size of target space (small/medium/large), and type of semantic (NI/SDOF/Highlight). All possible conditions of these three factors were tested (54 trials/participant). The scoring scheme along with a discussion of the results has been described below.



(a)



(b)

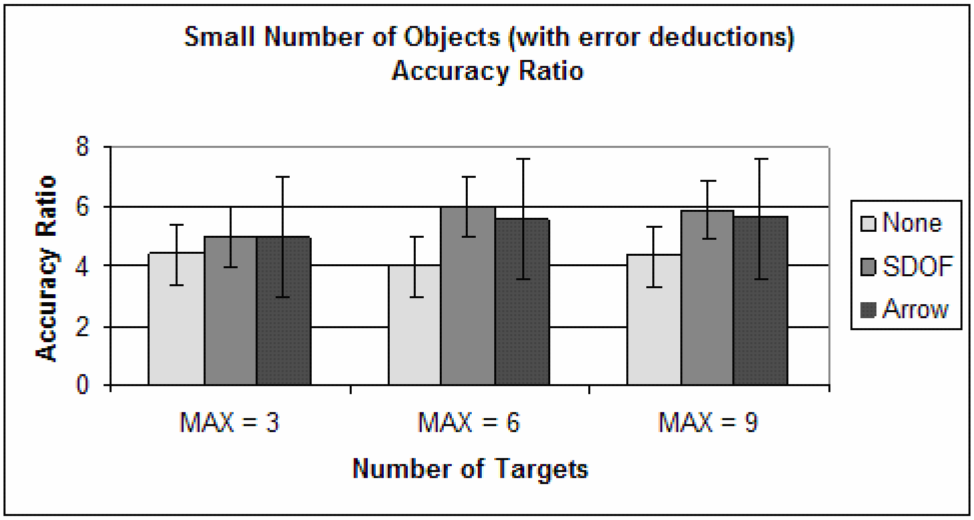
Figure 27: Experimental screenshots. (a) SDOF technique for N=30 and TSp = (MIN=1, MAX=3), (b) Highlight technique for N=15 and TSp = (MIN=7, MAX=9).

6.4.5. Results and Discussion

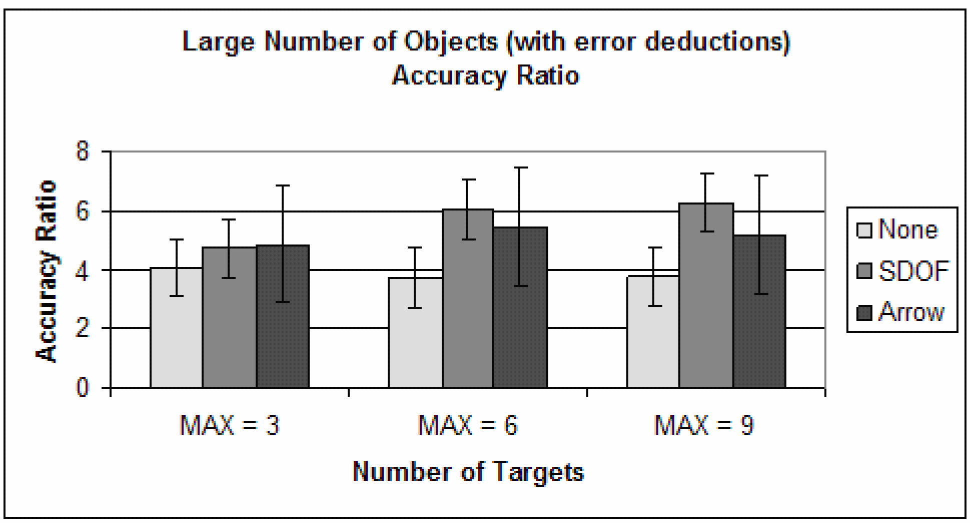
The participant was evaluated based on the number of correct answers (number of objects that they chose in the target space that actually changed during the animation) and time taken (amount of time elapsed before they stopped the simulation to submit their answers). Two different types of errors occurred in the responses, error-1 and error-2. Error-1 is defined by: (number of targets that were not selected)/(size of target space). Error-2 is defined by: (number of non-targets that were selected)/(size of the target space).

For each trial, the participant received one point for each correct answer and for each error (error-1 or error-2) the final score of the participant was reduced by one point. The score for each trial was calculated individually and averaged across all 54 trials. Some of the scores appeared in the negative range as in some cases, participants had more errors than correct answers. Hence the final scores were normalized to bring all the scores to the positive range (>=0). The normalized values were calculated by adding $|x|$ where x was the smallest negative value in the range of scores. The final values used for the analysis was the number of correct responses or accuracy rate. Figure 28 shows the averages values for all the normalized correct responses.

The results were analyzed using repeated measures ANOVA tests. All the scores followed a normal distribution and the analysis was performed on the average values. The results show a significant difference between the different visual techniques NI, SDOF, and Highlight conditions ($p < 0.001$). The mean accuracy rate for SDOF is 5.64 objects which is highly significant when compared to NI (mean (μ)= 4.03 objects) and Highlight (μ = 5.27 objects). There is also a highly significant difference between NI and Highlight conditions ($p < 0.001$). This analysis states that overall, it is better to have some visual technique than having no technique at all (both SDOF and Highlight are significantly better than NI) and also that between SDOF and Highlight, the SDOF technique is significantly better and has higher accuracy rates (p = 0.032).



(a)



(b)

Figure 28: Average accuracy rate of choosing targets in scene with (a) 15 objects and (b) 30 objects.

A separate analysis on the density reveals that increasing the number of objects does not have a significant decrease in performance, as I had predicted (p = 0.082). In these results searching for the target space in a larger density does change the accuracy performance for each of the three techniques as indicated above ($p < 0.001$). Participants are more accurate with SDOF than with NI or Highlight.

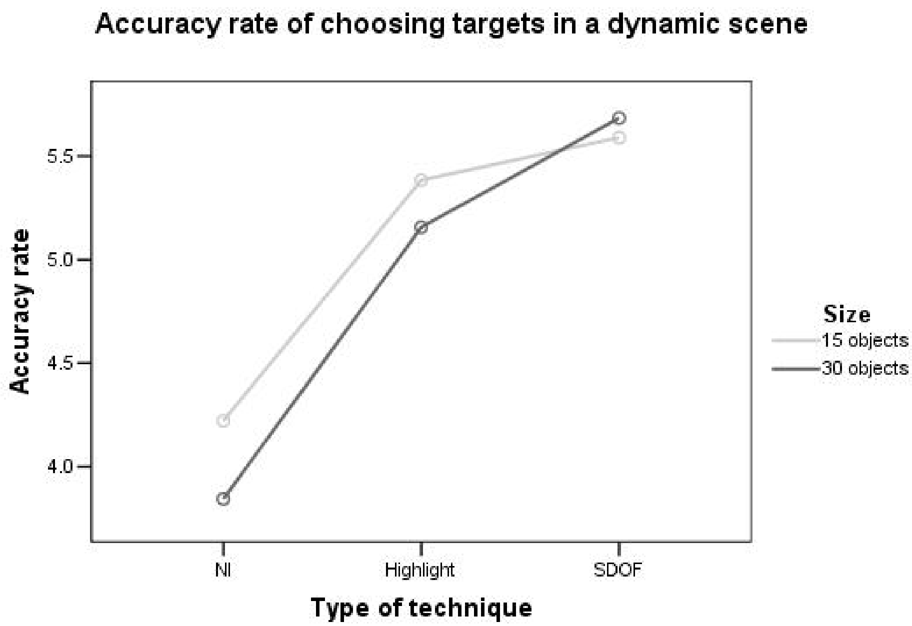


Figure 29: Accuracy rate of choosing targets in a dynamic scene (technique vs. number of objects in the scene).

Figure 29 displays the accuracy rate of the different techniques between the two densities of objects on the screen. Statistically, there is no significance between the accuracies for small (15 objects) or large (30 objects) densities of the objects in the scene. However, in the graph a small difference is seen between the two accuracies for each condition. For NI, the accuracy is higher with small density and reduces with larger density ($\mu_{15} = 4.2$ vs. $\mu_{30} = 3.8$). This is because there are more distractions in the scene and hence, the user has to sort through higher densities of traffic and hence can loose track of the objects easily. Similarly, the Highlight technique also shows a decrease in the accuracy as the number of objects in the scene increase ($\mu_{15} = 5.4$ vs. $\mu_{30} = 5.2$). This is mainly because as the Highlight technique itself increases the number of objects on the screen (each arrow occupies space on the screen and is counted as an object). Hence, in a scene with high density the Highlight is inefficient in reducing the clutter. This is apparent when the results for SDOF are viewed. As SDOF temporarily dims the unimportant objects form the scene, it reduces clutter and hence is more useful as the density of the scene increases ($\mu_{15} = 5.6$ vs. $\mu_{30} = 5.7$).

An analysis on the effect of target space on performance shows that there is a main significant effect of target space on accuracy judgment ($p = 0.002$). Pairwise comparisons show that there is a significant effect between the 3-object target space and the 6- and 9-object target spaces ($p=0.002$ and $p<0.001$, respectively). However, there is not a difference between the 6-object and 9-object target spaces. ($p=0.776$).

Figure 30 displays the mean accuracy rates between the different sizes of target space. It can be seen here that there is a very small variation between the accuracy ratios of the 6 and 9 objects group, for all three conditions. This is because the participant has reached the maximum number of objects that they can track [PS98]. Even with the SDOF technique, though there is a slight improvement in accuracy between the 6 and 9 groups, it is very insignificant. This insignificance can be attributed to the complexity of the experiment. In the experiment, the participants were asked to keep track of a target space, which was a subset of the total objects in the scene. An additional complexity was that only a subset of the target space changed during the trial, and not the entire target space. This meant that even after a technique was applied, there was still a certain amount of tracking that needed to be done. Hence, it cannot be really said from these results if the application of these techniques has an effect on the number of objects that can be tracked in the scene. Nonetheless, the results state that the SDOF and Highlight techniques do increase the efficiency and accuracy of tracking multiple objects.

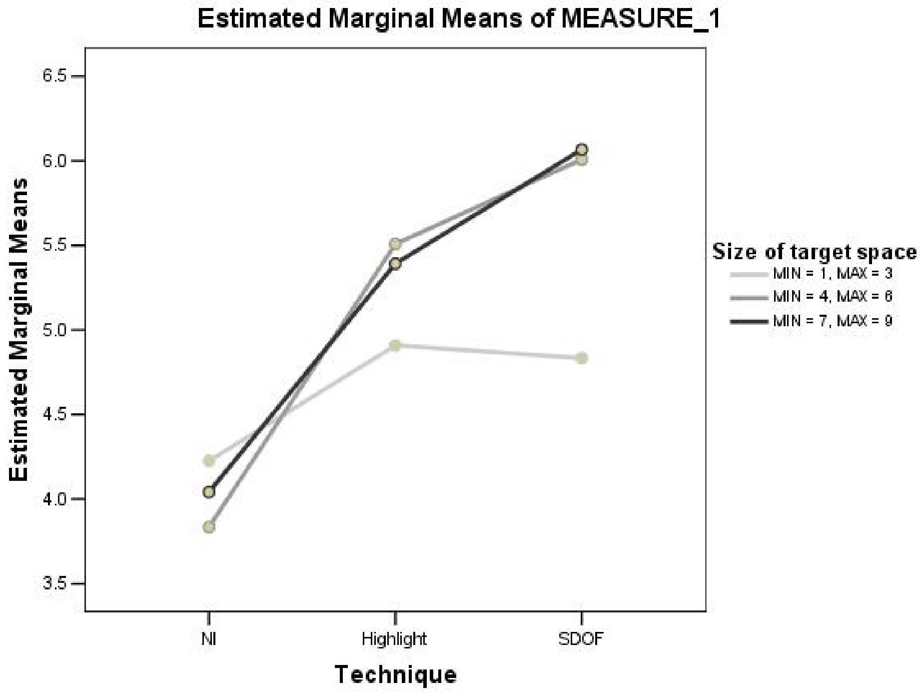


Figure 30: Accuracy rate of choosing targets in a dynamic scene (technique vs. size of target space).

An analysis on performance times shows that there is a significant difference in performance between the techniques ($p = 0.004$, $\mu_{NI} = 10.04$ seconds, $\mu_{Highlight} = 9.47$ seconds, $\mu_{SDOF} = 8.43$ seconds). Pairwise comparisons shows a significant difference between SDOF and NI ($p = 0.003$). However there are no significant differences between SDOF and Highlight ($p = 0.084$) and between Highlight and NI ($p = 0.465$). The figure below shows the average performance times for each of the three techniques.

Figure 31 displays the average times taken to respond using the three conditions. Though statistically insignificant, the difference between the three conditions can be clearly seen. From the graph, it can be confidently stated that using a visual technique certainly improves response time, when compared to no technique. However, between the techniques the difference is not statistically significant. This can be attributed to two reasons. The first one is that the densities of the scene were not too different. For example, if the experiment had been conducted with one scene of 15 objects and another of 200 objects or more, then the difference might have been more apparent. This is mainly because the Highlight technique is not efficient in high density scenarios, as the arrows add to the clutter. Another reason for this insignificance is due to the complexity of the experiment, i.e. participants had to track a subset within a subset of objects, as explained previously. However, the results of the time analysis do give an indication that the SDOF technique becomes significantly better as the density of the scene increases.

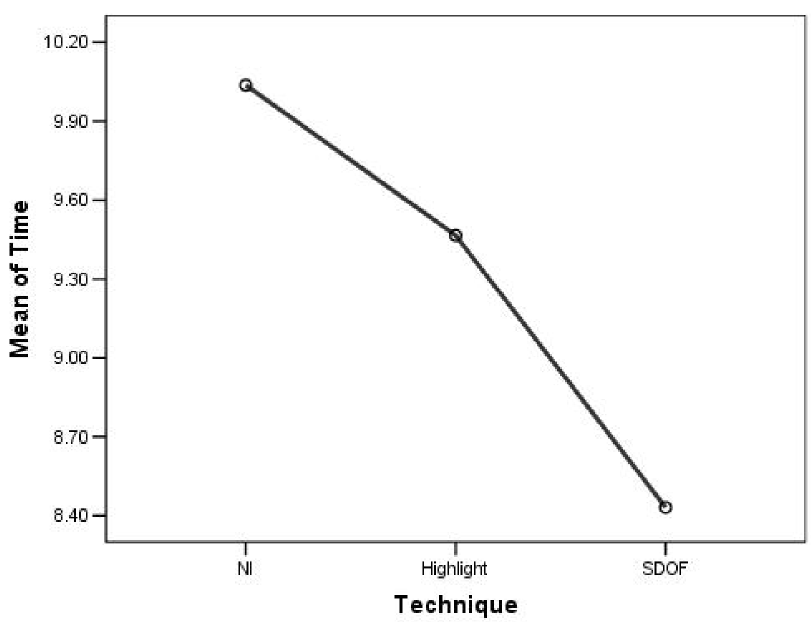


Figure 31: Average time taken to respond using each of the three techniques.

The questionnaire for this experiment also consisted of a user feedback section, which provided valuable opinions from the participants. This feedback has been summarized in Table 2.

Summary of user feedback			
Question	**NI**	**SDOF**	**Highlight**
Overall preferred technique	0%	80%	20%
Technique would be preferred for daily tasks	0%	80%	20%
Technique preferred in small density scenes	0%	70%	30%
Technique preferred in high density scenes	0%	80%	20%

Table 2: Summary of user feedback. Values depict the percentage of participants that preferred a certain technique in a given scenario.

All of the participants agreed that a visual technique did improve presentation in dynamic scenarios. Most of the participants preferred SDOF to the Highlight technique. These participants commented that with the SDOF technique, they could see the changes in the scene more clearly, as they were not distracted by the unimportant objects. This preference was more evident in high density scenes as the participants mentioned that the Highlight technique caused more confusion as the number of objects in the scene increased. Some of the participants preferred the arrow technique and commented that they were liked the fact that there was something physically pointing to the important objects. This is mainly because these participants were not used to the SDOF technique and hence liked the technique they were most familiar with and have used on occasions. With small densities scenes, some participants preferred the Highlight technique over SDOF, again because the Highlight technique was something that was familiar and seen occasionally, and also because it did not matter much if the arrows increased the density of the scene, as the scene was sparse. The preference shifted to SDOF in high density scenes, as the participants realized the amount of space that was unnecessarily occupied by the Highlight technique. However, there were still some participants who preferred the

Highlight technique, again mainly because of its familiarity. Overall the feedback was extremely encouraging and the participants were very interested in practical applications of the SDOF technique.

7. Conclusion

Many areas of information science deal with the simplification of complex concepts using visual techniques. One class of information that is commonly seen is information that is dependent on time, called time-dependent information, or simply dynamic information. Dynamic information is any information that changes over a period of time, for example change in facial features of a child as it grows into an adult.

Dynamic information is difficult to comprehend as it is changing constantly and does not retain its properties long enough to be understood. Also many dynamic systems contain series of state changes, and even though the initial and end states of the system can be viewed, comprehension is difficult as the inner workings of the system are not explicit. Hence it is very important to design techniques that elucidate the comprehension of dynamic concepts.

One method of simplifying dynamic concepts is by depicting them through animations. Animations are visual representations which, due to their dynamic nature, are apt for representing dynamic concepts. Animations abstract the complex information and depict them in the form of simple visual displays. However, a drawback in using animations is that too much animation can hamper comprehension. When animation is used excessively, the display becomes cluttered and the users' mind is overloaded with unnecessary information. Hence, to avoid such problems, it is also imperative to design techniques that improve the presentation of animated displays.

Therefore, in an effort to design techniques to elucidate complex information, this thesis focuses on the aspects of providing adequate representations and improving the presentation of dynamic concepts.

7.1. Representation

Representation consists of encoding abstract information into simple visual illustrations for elucidating complex concepts. In this thesis, I have created some general representations and evaluated them in a practical scenario. I divided this part of my research into three phases.

In the first phase I shortlisted three concepts (state transition, interdependence, and multiple states) which are dynamic and complex, and created visual representations for each of them. The representations were modeled based on visual perceptual theories [War03] and studies by Irani et al. [ITW01, Ira02].

- **State transition:** The concept of state transition states that an object can change from one state to another over a period of time. I created four representations for this concept: change in shape, change in size, change in color, and change in orientation.
- **Interdependence:** Interdependence is stated as the existence of an invisible connection between two objects such that changes in one object also affect the other object. I created four representations for this concept: change to a common color, change to a common shape, creating a physical connection between the objects, and increasing the proximity with partial intermeshing.
- **Multiple states:** The concepts of multiple objects states that an object can exist in more than one state simultaneously. I created three representations for this concept: change to multiple duplicates, change to a multiple contained shape, and change to a multiple merged shape.

In the second phase I evaluated my representations to determine the most favored representation for each concept shortlisted in the previous phase. The hypothesis was that state transition would be best represented by a change in shape, interdependence by proximity with partial intermeshing, and multiple states by multiple duplicates. In this experiment, the participants were shown all the representations and were asked to grade the representations based on their preference. A top down correlation of the results for the three concepts stated that there was significant agreement among the subjects that "change of shape" was the best representation for state transition, "proximity with partial intermeshing" was the best representation for interdependence, and "change to multiple duplicates" was the best representation for multiple states. The results also stated that the best representation for state transitions was favored 1.2 times more than the second best representations, the best representation for interdependence was favored 1.5 times more than the second best representation, and the best representation for multiple states was favored 1.4 times more than the second best representation. Overall, the results of the experiment were in keeping with the hypothesis and showed significant favor towards the representations that were hypothesized as the winning candidates.

In the third phase I validated my representations in a complex dynamic scenario. The field of research that was chosen for this phase was quantum computing simply because this field contained all the dynamic concepts that had been created and shortlisted in the previous two phases. This validation was also performed through an experiment on local university students. In this experiment different quantum algorithms were shown to the subjects. Half of these algorithms were represented using the traditional quantum notation while the other half were represented using the visual representations from the previous phase. In addition, half of the algorithms were simple algorithms while the other half were slightly more complex. The focus of this experiment was to validate if there was an improvement in comprehension of the individual concept and the overall algorithm when the concepts were represented using visual representations in a practical scenario. The results of this experiment state that for simple circuits, the quantum notation was 1.1 times better than the visual representations. This improvement was insignificant and its reason was that the small circuit was too simple and hence did not need any visual simplification. However, for larger circuits, the results were more significant and stated that the visual representations were 2 times better than the quantum notation in depicting the dynamic concepts. Most of the participants were also able to understand the overall picture and answered the general questions correctly.

Summarizing the representation phase of the thesis, my main contributions were the shortlisting of few general dynamic concepts, the creation of visual representations for these concepts, the validation of these visual representations, and the evaluation of these representations in a dynamic scenario. Most of the participants agreed that the visual representations helped them understand the concepts better and also increased their interest towards learning more about the concept. However, one reoccurring issue noticed during the experiments was that as the complexity of the scene increased, participants found it more and more difficult to focus on the important events or objects in the scenario. This was mainly because as the number of animations on the scene increased, the users was overloaded with excess information, which eventually resulted in loss of focus and attention in the scene. Hence, the next phase of the thesis was designed to analyze methods of improving the presentation of dynamic displays, so as to enhance user comprehension.

7.2. Presentation

Presentation consists of improving visual displays such that important information is easily visible and can be focused on quickly. In dynamic displays, due to a large amount of variable information on the scene, users have to assimilate a lot of information (some of it unnecessary or unimportant), thereby causing an overload on the mind. Hence in such situations it is not surprising if the users miss out on critical events occurring in the scene, as they might have been too distracted by multiple other events. Presentation of information is therefore highly essential in visual representations as it helps to control the amount of information that is displayed and the method it is displayed so as to enable maximum comprehension.

F+C techniques are one of the most popular techniques that help focus the user's attention on critical events and important concepts. In this thesis, I have evaluated one F+C technique, called SDOF. The SDOF technique uses depth of field to bring important events in and out of the user's focus. This technique reduces the visibility of all objects or events that are not considered high-priority at that particular instant of time. SDOF uses visual methods such as blurring or dimming to achieve this effect. The SDOF method used in this research is the dimming method, wherein all the objects that are considered unimportant are dimmed and made less visible to the users. Hence the users focus on the objects that are more visible and are not distracted by the unimportant events.

I have validated my SDOF technique through an experiment on local university students. The experiment compared the SDOF technique to a no-indication technique (NI), where no visual presentation method was included to enhance the display, and to a Highlight technique, where arrows were used to highlight the critical objects in the scene. The experiment was varied based on three parameters; number of objects in the scene (15 or 30), type of presentation method (NI, SDOF or Highlight), and number of targets (important events) (1-3, 4-6 or 7-9) in the scene. The experiment was designed in a Latin square fashion with 54 trials/participant. The main focus of the experiment was to analyze the number of errors and the time taken by the participant in distinguishing between the targets and non-targets in each of the trials. The hypothesis for this experiment was that as the complexity of the scene increases, i.e. as the number of objects and/or targets on the scene increase, the SDOF method will prove more efficient than the NI or the Highlight methods in displaying important events in the display.

The results of the experiment were in keeping with the hypothesis that the SDOF method will be the most efficient in improving the presentation of visual information. The results also stated that with small number of objects (N = 15), the SDOF technique was 1.3 times better than the NI condition and was 1.01 times better than the Highlight condition. The reason for the lack of significance between the accuracy rates of the SDOF and Highlight conditions was due to the lower number of objects on the scene, the scene was not cluttered and hence, both highlighting techniques worked equally well. However, the significance between these two techniques and the NI condition is clearly seen, which states that providing techniques to improve the presentation is essential to improving the comprehension of the animation. For large number of objects (N = 30) in the scene, the SDOF technique was 1.5 times better than the NI condition and was 1.2 times better than the Highlight technique. These results show that as the number of objects in the scene increase, the SDOF technique becomes more efficient in displaying important objects or events. This is mainly because the highlighting technique itself increases the number of objects on the scene, which in turn increases the density of the scene instead of reducing it. In addition, the results stated that, with SDOF, users took 1.2 times less than NI and 1.1 times less than the Highlighting method, to provide answers.

7.3. Contributions

The main contributions of this research have been listed below:

- The first contribution was the shortlisting of a set of dynamic concepts that are general and complex and need to be visually simplified to enable comprehension. Though this list did not encompass all the general dynamic concepts, it can be seen as a start and as a stepping stone to identifying concepts that require visual enhancement for better understanding.

- The second contribution was the creation of visual representations for the complex dynamic concepts. For each concept, at least 3-4 visual representations were designed. Even though only one of each set of representations was considered the most efficient for the corresponding concept, the analysis and the rationale behind the alternative representations is also an important contribution of this research.

- The third contribution was the evaluation of the visual representations in a practical dynamic scenario. Though dynamic animations have been used in fields such as data structures and algorithms, quantum computing is a relatively new field, which is truly dynamic, and in which not much research has been done towards simplifying the complex concepts. Hence, by evaluating the representations in this field, this study has partially contributed to both the research and pedagogy in quantum computing.

- The fourth contribution of this study is the design of various visual presentation techniques to enhance focus and attention in dynamic scenarios. This study designed two innovative ways of presenting visual information. Even though the SDOF method has been tested before [KMH+02], the SDOF method with dimming is the innovation of this study. Similarly, even though the method of using highlighting objects using symbols, such as arrows, has been discussed, no study has tested this technique practically. Hence, this study presents an innovative contribution to visual presentation by evaluating both these techniques.

- The fifth contribution to this study is the evaluation of the F+C techniques in a dynamic scenario. Even though studies have tested the SDOF method or have analyzed how many targets can be tracked simultaneously by a user, no study has combined these two factors and tested multiple target tracking using SDOF. Also no study has compared different methods of highlighting in dynamic scenarios.

The overall contribution of this study is the creation of a good foundation in both representation and presentation of complex dynamic information, which can be used to further the research in the area of information visualization.

7.4. Future Work

In this thesis I have laid the groundwork for research into improving the efficiency of dynamic information comprehension. This research details the initial studies that have been conducted using innovative representation and presentation methods. However, more analysis needs to be done to determine the different types of visual techniques that can be employed to enhance dynamic information. In this section I have outlined future work that can be done in each of the factors of representation, presentation, and interaction.

7.4.1. Representation

Some of the future work in the representation section has been outlined below:

- **Shortlisting more concepts:** Only three general dynamic concepts have been shortlisted for the purpose of this study. However, it would be interesting to research more general concepts and eventually consolidate a list of concepts that can be seen over a wide range of scenarios. Visual representations can also be created for them and shortlisted using similar experimental methods.

- **Evaluating the representations:** The representations in this study have been evaluated using quantum algorithms, since all the shortlisted complex concepts were encountered in quantum computing. However, after generating more general visual representations, it would be interesting to analyze the representations in other fields of information science, such as data structures, causality etc.

7.4.2. Presentation

I have listed some of the future work in the presentation section below:

- **Comparing different SDOF techniques:** This study focuses on SDOF with dimming to highlight important objects in the scene. However, some studies [KMH01, KMH+02] have used SDOF with blurring to achieve the same goal. Hence it will be interesting to compare the two techniques to determine if one of the techniques is better than the other or if there is no significant difference in replacing one for the other.

- **Comparing to other highlighting methods:** Along with comparing the two SDOF techniques, it will also be interesting to compare the SDOF technique used in this research to other highlighting methods such as drawing an outline or highlighting the edges of the important objects.

7.4.3. Interaction

This thesis has only focused on the factors of representation and presentation in dynamic scenarios. However, there is a third factor of interaction that is very important to capture and retain the user's interest towards a complex concept or dynamic event. Hence there is considerable future work that can be done in this area. Some of the future work in this area has been listed below:

- **Applying different methods of interaction:** Different methods of improving user interest through interaction can be evaluated. Some of these methods involve allowing the user to create their own animations, to control the speed of the animation, to start and stop the animation whenever need, and to rerun an animation as many times as required.
- **Evaluating the interaction methods in a practical scenario:** In order to determine the efficiency of the interaction methods, it is necessary to evaluate them in a practical scenario, such as an educational system.

7.4.4. Combining Representation, Presentation, and Interaction: A Prototype

One future work is to create a visual system that displays the concepts using the representations that have been given in this thesis and allows users to interact with the system. The system should also incorporate the SDOF (with dimming) method to improve critical sections of the display, and interaction methods to improve user's interest. A prototype of such a system has been started based on quantum computing. In this prototype, users can create quantum algorithms and execute them. The process of creating the algorithms is interactive and does not need any prior knowledge of computers or quantum computing. User can choose the type of inputs, the type of gates and can drag and drop it onto the quantum circuit. After the entire circuit has been created to the user's satisfaction, it can be executed. The circuit execution will be shown in the form of a smooth animation, where the dynamic changes in the circuit will be represented using the representations created in the first part of this thesis. The user can choose important events in the circuit that they would like to be informed about and when these events occur, the system will highlight them using the SDOF method described in the second part of the thesis. The user can also interactively stop, resume, and rerun the animation multiple times if necessary. Hence, this prototype incorporates the three factors of representation, presentation, and interaction to improve users' comprehension, attention, and interest towards the dynamic concepts.

Appendix A: Questionnaire for Using Animation to Represent Time-Dependent Semantics *(Experiment 1)*

A study carried out by Dr. Pourang Irani and Nivedita R. Kadaba as part of a Master's thesis.

Thank you for participating in this experiment. This experiment tries to evaluate different graphical representations for depicting semantic information. The results of this evaluation will influence the choice of representations in the final tool and will be used as part of the master's thesis. All the steps of the experiments are self-explanatory and there are no foreseen risks associated with this experiment. If you wish to participate in this experiment, please fill out the information below.

Name: ____________________________________

Email: _____________________________________

Have you had previous exposure to graphical tools that use animations to teach concepts (any type of concept, but should be based on animations). **Yes/No**

Have you taken a course in quantum computing, or have any idea about basic quantum computing or quantum mechanics concepts, prior to this experiment. **Yes/No**

Informed Consent

I understand that my participation in this experiment is voluntary and that my evaluation will be used as part of a master's thesis. I understand that any personal information given by me will be kept confidential and will only be used by the experimenter for direct correspondence, if necessary. I also agree that I may withdraw from the study at any point of time.

I have read this statement and agree to its terms.

Signature: ______________________________**Date:** ____________________

Comments:

Subjective Questionnaire

State Transitions

Definition: An object **X** is transformed from state **1** to state **2** over a certain period of time.

*Rank from 1-4 (1=worst, 4=best) the representation that object **X** is changing states.*

	A		B		C		D	
Screen 1								
Screen 2								
Screen 3								

Entanglement

Definition: If objects **X** and **Y** are entangled, then over a period of time, an action on any one of the objects will cause both the objects to react in the same way.

*Rank from 1-4 (1=worst and 4=best) the representations that **X** and **Y** are entangled.*

	A		B		C		D	
Screen 1								
Screen 2								
Screen 3								

Superposition

Definition: If object **X** is in superposition, then it is said to exist in more than one state at the same instant in time.

*Rank from 1-3 (1=worst and 3=best) the representation that **A** is in superposition.*

	A		B		C	
Screen 1						
Screen 2						
Screen 3						

Thank you.

Appendix B: Questionnaire for Using Animation to Represent Time-Dependent Semantics (Experiment 2)

A study carried out by Nivedita R. Kadaba and Dr. Pourang Irani as part of a Master's thesis.

Thank you for participating in this experiment. This experiment is phase two of a three part experiment.

In phase 2 of this experiment, we have evaluated some semantics that we felt can be used as representations of complex concepts. The goal of the experiment is to evaluate the effectiveness of our concept in representing information.

We request you to answer all questions asked in the evaluation sheet. Please feel free to add any comments at the end of the evaluation. Any information given will be kept confidential.

Thank you for your co-operation.

Nivedita R Kadaba

Pourang P. Irani

<u>Declaration by participant:</u>

I declare that I have read the information about the experiment and give my full consent to using my results in the evaluation of the experiment. I am also fully aware that any personal information supplied by me will be kept highly confidential.

Signature:

Name:

Email address:

<u>Circuit 1</u>

1. What are states of the two objects after passing through **GATE 1?**

A:

Object 1

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

Object 2

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

2. What are states of the two objects after passing through **GATE 2?**

A:

Object 1

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

Object 2

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

3. What are states of the two objects after passing through **GATE 3?**

A:

Object 1

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

Object 2

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

4. Circuit 1 could perform one of the following processes:

a. Combine two input objects
b. Swap two input objects
c. It is a random circuit, with no specific goal

Circuit 2

1. What are states of the two objects after passing through **GATE 1?**

A:

Object 1

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

Object 2

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

2. What are states of the two objects after passing through **GATE 2?**

A:

Object 1

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

Object 2

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

3. What are states of the two objects after passing through **GATE 3?**

A:

Object 1

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

Object 2

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

4. Circuit 2 could perform one of the following processes:

a. Combine two input objects
b. Swap two input objects
c. It is a random circuit, with no specific goal

Circuit 3

1. What are states of the two objects after passing through **GATE 1?**

A:

Object 1

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

Object 2

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

2. What are states of the two objects after passing through **GATE 2?**

A:

Object 1

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

Object 2

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

3. What are states of the two objects after passing through **GATE 3?**

A:

Object 1

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

Object 2

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

4. What are states of the two objects after passing through **GATE 4?**

A:

Object 1

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

Object 2

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

5. What are states of the two objects after passing through **GATE 5?**

A:

Object 1

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

Object 2

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

Circuit 4

1. What are states of the two objects after passing through **GATE 1?**

A:

Object 1

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

Object 2

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

2. What are states of the two objects after passing through **GATE 2?**

A:

Object 1

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

Object 2

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

3. What are states of the two objects after passing through **GATE 3?**

A:

Object 1

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

Object 2

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

4. What are states of the two objects after passing through **GATE 4?**

A:

Object 1

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

Object 2

a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

5. What are states of the two objects after passing through **GATE 5?**
A:

Object 1
a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

Object 2
a. Is in multiple states
b. Is in a combined state
c. Changed its state
d. Changed state and is in multiple states.
e. Changed state and is combined
f. Changed state, is in multiple states, and is combined
g. No change

---

1. Do you find any difficulty in viewing the animations?
A:
a. Yes.
b. No.
c. Maybe *(Please explain) :* ______

2. Did you have any difficulty in understanding what we meant by a change in state in the experiment?
A:
a. Yes.
b. No.
c. Maybe *(Please explain) :* ______

3. Did you have any difficulty in understanding what we meant by multiple states in the experiment?
A:
a. Yes.
b. No.
c. Maybe *(Please explain) :* ______

4. Did you have any difficulty in understanding what we meant by a combined state in the experiment?
A:
a. Yes.

   b. No.
   c. Maybe *(Please explain) :* ______________________________

5. Did you think that the graphical method was more understandable that the text only method?
   A:
   a. Yes.
   b. No.
   c. Maybe *(Please explain) :* ______________________________

6. Do you have prior expertise in quantum computing? Yes No

7. Please mention any comments or suggestion you might have.

Thank you for you co-operation.

Appendix C: Questionnaire for Evaluating Perceptive techniques to capture users' attention during dynamic movement *(Experiment 3)*

A study carried out by Nivedita R. Kadaba and Dr. Pourang Irani as part of a Master's thesis.

Thank you for participating in this experiment. This experiment is *Phase 3* of a three-part experiment.

In this phase of the experiment, our focus is on evaluating various visual techniques that can be used to direct users' attention to an area of interest, during the course of a dynamic simulation.

You will be shown a scenario consisting of multiple objects, of the same shape and color, but varying in size. The objects are divided into two groups: target space and non-target space. Objects in the target space will initially flash for a few seconds. All the objects on the screen will then start moving about. All the objects will move in random paths, with constant speed, and change paths every few seconds. After a stipulated length of time, some objects will start changing their size.

The goal of the experiment is to keep an eye on all the objects that belong in the target-space and to remember which of these objects changed during the course of the simulation. The total simulation will last about 25-30 seconds/screen. After the completion of each simulation, the objects in the target-space will be highlighted and your task is to choose the objects that you know changed during the simulation (from among the target space). Also, to analyze the speed in which our representations divert focus, we have the added option of stopping the simulation before it ends, if you have the answer ready. If during the course of the simulation, you feel that you know which of the target-space objects are changing, you are can hit the **space-bar** key and the simulation will end. You will then be taken to the screen where you can choose the objects that you saw changing.
Thank you for your co-operation.

Nivedita R Kadaba
Pourang P. Irani

<u>Informed Consent</u>

I understand that my participation in this experiment is voluntary and that my evaluation will be used as part of a master's thesis. I understand that any personal information given by me will be kept confidential and will only be used by the experimenter for direct correspondence, if necessary. I also agree that I may withdraw from the study at any point of time.

I have read this statement and agree to its terms.

Signature: ______________________________ Date: ____________________

Do you experience any discomfort while viewing animations or dynamic simulations **Yes / No**

Small Number of Objects

	None			**Dim**			**Arrow**		
	Trials			**Trials**			**Trials**		
3	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
	Trials			**Trials**			**Trials**		
6	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
	Trials			**Trials**			**Trials**		
9	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**

Large Number of Objects

	None			**Dim**			**Arrow**		
	Trials			**Trials**			**Trials**		
3	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
	Trials			**Trials**			**Trials**		
6	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
	Trials			**Trials**			**Trials**		
9	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**

Please answer the following questions:

1. Among the three techniques shown to you, which technique did you prefer over the others?

   a) No **b) Dimming** **c) Arrow**

2. Given a chance, would you use the above chosen technique in daily activities like in educational tutorials, games etc.?

   a) Yes **b) No**

3. Were you more comfortable in the scenario with less number of objects or more number of objects?

   a) Less **b) More**

4. In the scenario that contained **less** number of objects, which technique did you prefer over the others?

   a) No **b) Dimming** **c) Arrow**

5. In the scenario that contained **more** number of objects, which technique did you prefer over the others?

   a) No **b) Dimming** **c) Arrow**

6. What was your opinion on the speed of the experiment?

   a) Too Fast **b) Reasonable** **c) Too Slow**

7. Would you like a course credit for this participation or the compensation amount?

   a) Course Credit **b) Compensation**

8. Please mention any other comments you might have.

____

____

Thank you.

Nivedita R. Kadaba.

Appendix D: SPSS Analysis results comparing accuracy of the three target tracking conditions (NI, SDOF, and Highlight) in Experiment 3.

Test #1 – SDOF vs. Highlight vs. NI

Descriptives

Accuracy

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
NI	120	4.0333	.90790	.08288	3.8692	4.1974	2.00	8.00
SDOF	120	5.6361	1.28991	.11775	5.4030	5.8693	3.67	10.67
Highlight	120	5.2694	1.14845	.10484	5.0619	5.4770	2.33	9.33
Total	360	4.9796	1.31659	.06939	4.8432	5.1161	2.00	10.67

ANOVA

Accuracy

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	169.252	2	84.626	66.686	.000
Within Groups	453.043	357	1.269		
Total	622.295	359			

Post Hoc Tests

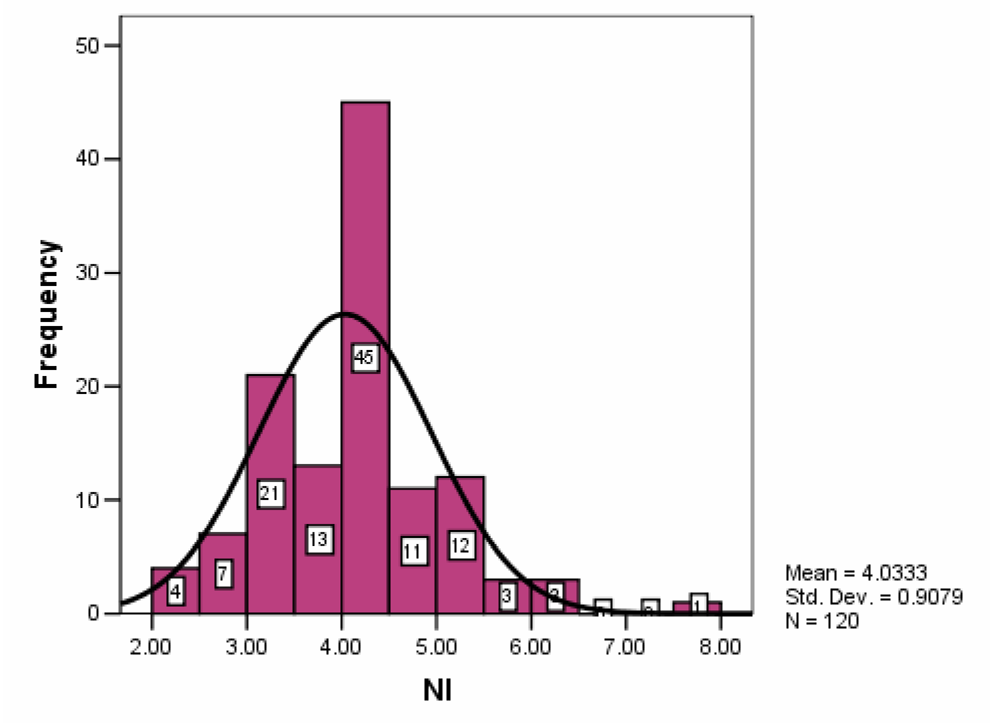
Multiple Comparisons

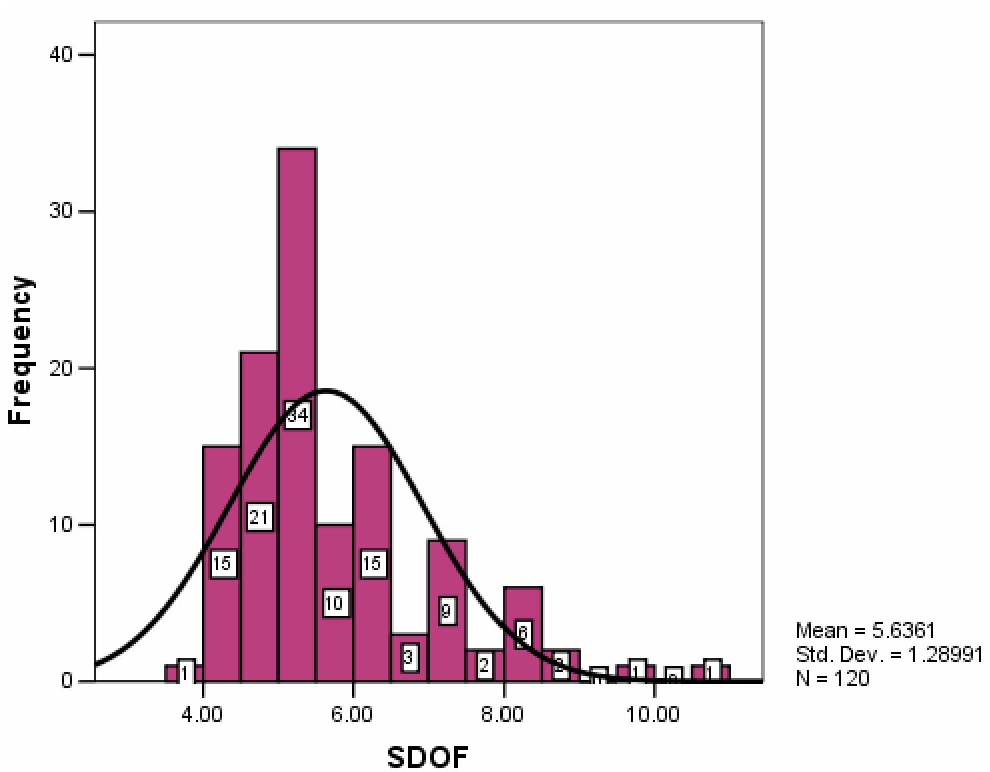
Dependent Variable: Accuracy
Tukey HSD

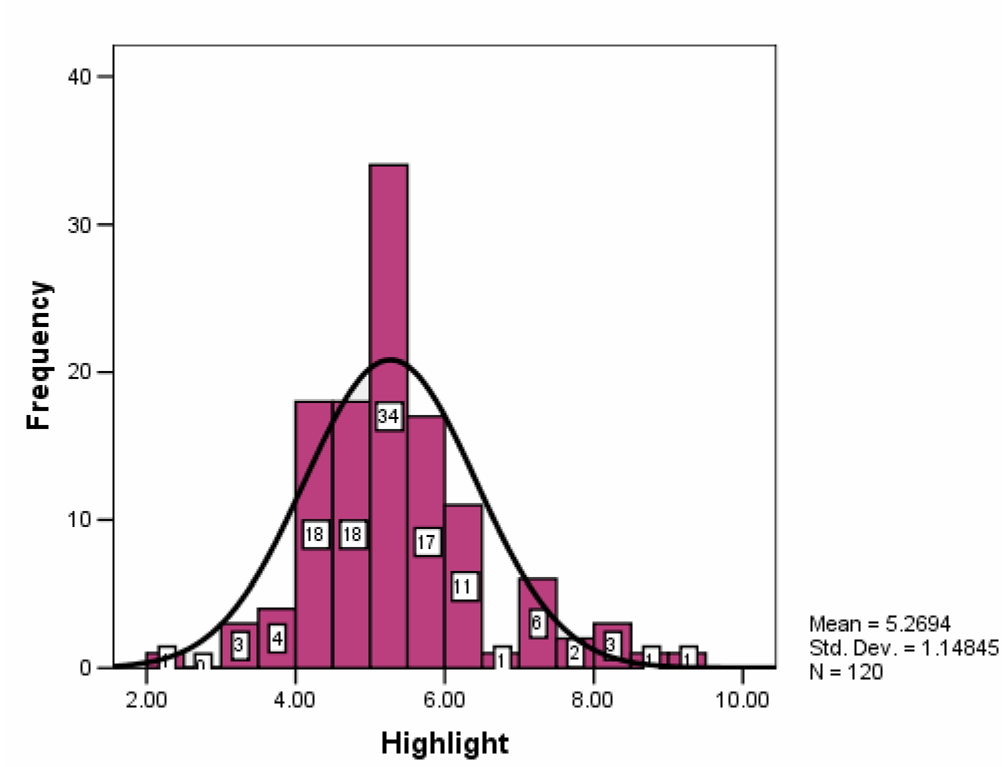
(I) TType	(J) TType	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
NI	SDOF	-1.60278(*)	.14543	.000	-1.9451	-1.2605
	Highlight	-1.23611(*)	.14543	.000	-1.5784	-.8938
SDOF	NI	1.60278(*)	.14543	.000	1.2605	1.9451
	Highlight	.36667(*)	.14543	.032	.0244	.7089
Highlight	NI	1.23611(*)	.14543	.000	.8938	1.5784
	SDOF	-.36667(*)	.14543	.032	-.7089	-.0244

* The mean difference is significant at the .05 level.

Histograms


Frequency
50
40
30
20
10
0
2.00
3.00
4.00
5.00
6.00
7.00
8.00
NI
45
21
13
11
12
7
4
3
Mean = 4.0333
Std. Dev. = 0.9079
N = 120


Frequency
40
30
20
10
0
4.00
6.00
8.00
10.00
SDOF
34
21
15
15
10
9
6
3
2
1
Mean = 5.6361
Std. Dev. = 1.28991
N = 120



Test #2 – Effects of Density on Accuracy

Within-Subjects Factors

Measure: MEASURE_1

tech	size	Dependent Variable
1	1	NI_15
	2	NI_30
2	1	SDOF_15
	2	SDOF_30
3	1	Highlight_15
	2	Highlight_30

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
tech	Sphericity Assumed	169.252	2	84.626	64.192	.000
	Greenhouse-Geisser	169.252	1.800	94.028	64.192	.000
	Huynh-Feldt	169.252	1.853	91.331	64.192	.000
	Lower-bound	169.252	1.000	169.252	64.192	.000
Error(tech)	Sphericity Assumed	155.562	118	1.318		
	Greenhouse-Geisser	155.562	106.202	1.465		

	Huynh-Feldt	155.562	109.338	1.423		
	Lower-bound	155.562	59.000	2.637		
size	Sphericity Assumed	2.612	1	2.612	3.125	.082
	Greenhouse-Geisser	2.612	1.000	2.612	3.125	.082
	Huynh-Feldt	2.612	1.000	2.612	3.125	.082
	Lower-bound	2.612	1.000	2.612	3.125	.082
Error(size)	Sphericity Assumed	49.314	59	.836		
	Greenhouse-Geisser	49.314	59.000	.836		
	Huynh-Feldt	49.314	59.000	.836		
	Lower-bound	49.314	59.000	.836		
tech * size	Sphericity Assumed	3.493	2	1.747	2.572	.081
	Greenhouse-Geisser	3.493	1.984	1.761	2.572	.081
	Huynh-Feldt	3.493	2.000	1.747	2.572	.081
	Lower-bound	3.493	1.000	3.493	2.572	.114
Error(tech*size)	Sphericity Assumed	80.136	118	.679		
	Greenhouse-Geisser	80.136	117.038	.685		
	Huynh-Feldt	80.136	118.000	.679		
	Lower-bound	80.136	59.000	1.358		

Pairwise Comparisons

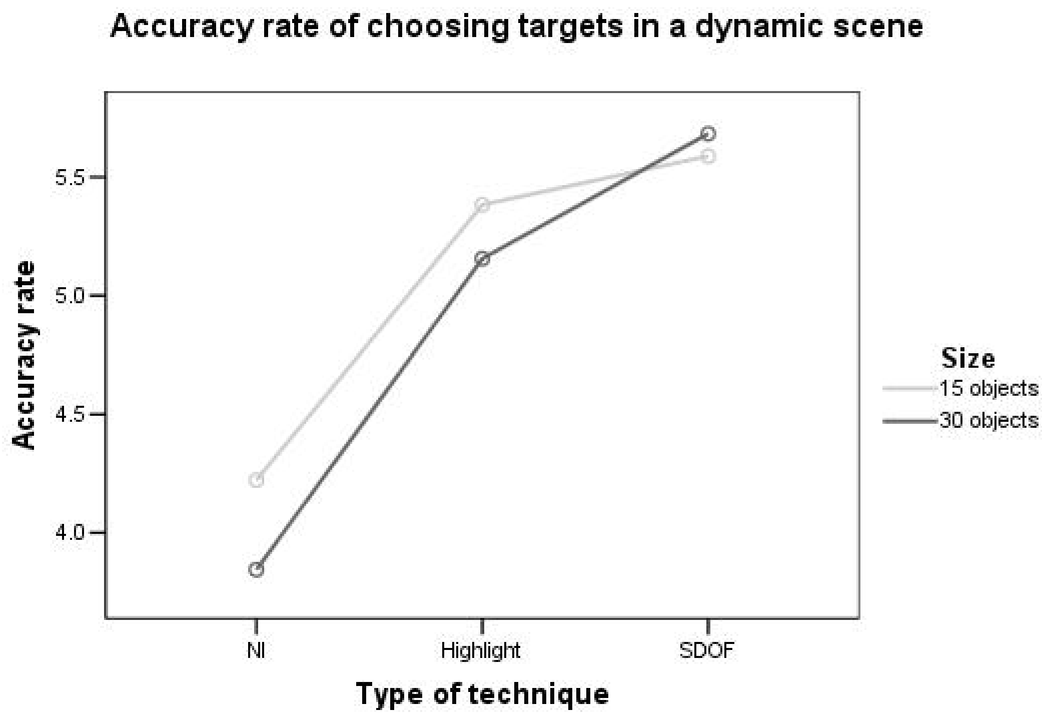
Measure: MEASURE_1

(I) tech	(J) tech	Mean Difference (I-J)	Std. Error	Sig.(a)	95% Confidence Interval for Difference(a)	
					Lower Bound	Upper Bound
1	2	-1.603(*)	.171	.000	-1.945	-1.261
	3	-1.236(*)	.133	.000	-1.502	-.970
2	1	1.603(*)	.171	.000	1.261	1.945
	3	.367(*)	.138	.010	.091	.642
3	1	1.236(*)	.133	.000	.970	1.502
	2	-.367(*)	.138	.010	-.642	-.091

Based on estimated marginal means

* The mean difference is significant at the .05 level.

a Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).



Test #3 – Space and Technique Interaction

Within-Subjects Factors

Measure: MEASURE_1

tech	space	Dependent Variable
1	1	NI_3
	2	NI_6
	3	NI_9
2	1	SDOF_3
	2	SDOF_6
	3	SDOF_9
3	1	Highlight_3
	2	Highlight_6
	3	Highlight_9

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
tech	Sphericity Assumed	169.252	2	84.626	85.077	.000
	Greenhouse-Geisser	169.252	1.957	86.494	85.077	.000
	Huynh-Feldt	169.252	2.000	84.626	85.077	.000
	Lower-bound	169.252	1.000	169.252	85.077	.000

Error(tech)	Sphericity Assumed	77.587	78	.995		
	Greenhouse-Geisser	77.587	76.316	1.017		
	Huynh-Feldt	77.587	78.000	.995		
	Lower-bound	77.587	39.000	1.989		
space	Sphericity Assumed	19.054	2	9.527	7.074	.002
	Greenhouse-Geisser	19.054	1.697	11.228	7.074	.003
	Huynh-Feldt	19.054	1.766	10.788	7.074	.002
	Lower-bound	19.054	1.000	19.054	7.074	.011
Error(space)	Sphericity Assumed	105.044	78	1.347		
	Greenhouse-Geisser	105.044	66.187	1.587		
	Huynh-Feldt	105.044	68.881	1.525		
	Lower-bound	105.044	39.000	2.693		
tech * space	Sphericity Assumed	30.849	4	7.712	9.201	.000
	Greenhouse-Geisser	30.849	3.613	8.538	9.201	.000
	Huynh-Feldt	30.849	4.000	7.712	9.201	.000
	Lower-bound	30.849	1.000	30.849	9.201	.004
Error(tech*space)	Sphericity Assumed	130.756	156	.838		
	Greenhouse-Geisser	130.756	140.913	.928		
	Huynh-Feldt	130.756	156.000	.838		
	Lower-bound	130.756	39.000	3.353		

Pairwise Comparisons

Measure: MEASURE_1

(I) tech	(J) tech	Mean Difference (I-J)	Std. Error	Sig.(a)	95% Confidence Interval for Difference(a)	
					Lower Bound	Upper Bound
1	2	-1.603(*)	.138	.000	-1.882	-1.324
	3	-1.236(*)	.124	.000	-1.486	-.986
2	1	1.603(*)	.138	.000	1.324	1.882
	3	.367(*)	.124	.005	.115	.618
3	1	1.236(*)	.124	.000	.986	1.486
	2	-.367(*)	.124	.005	-.618	-.115

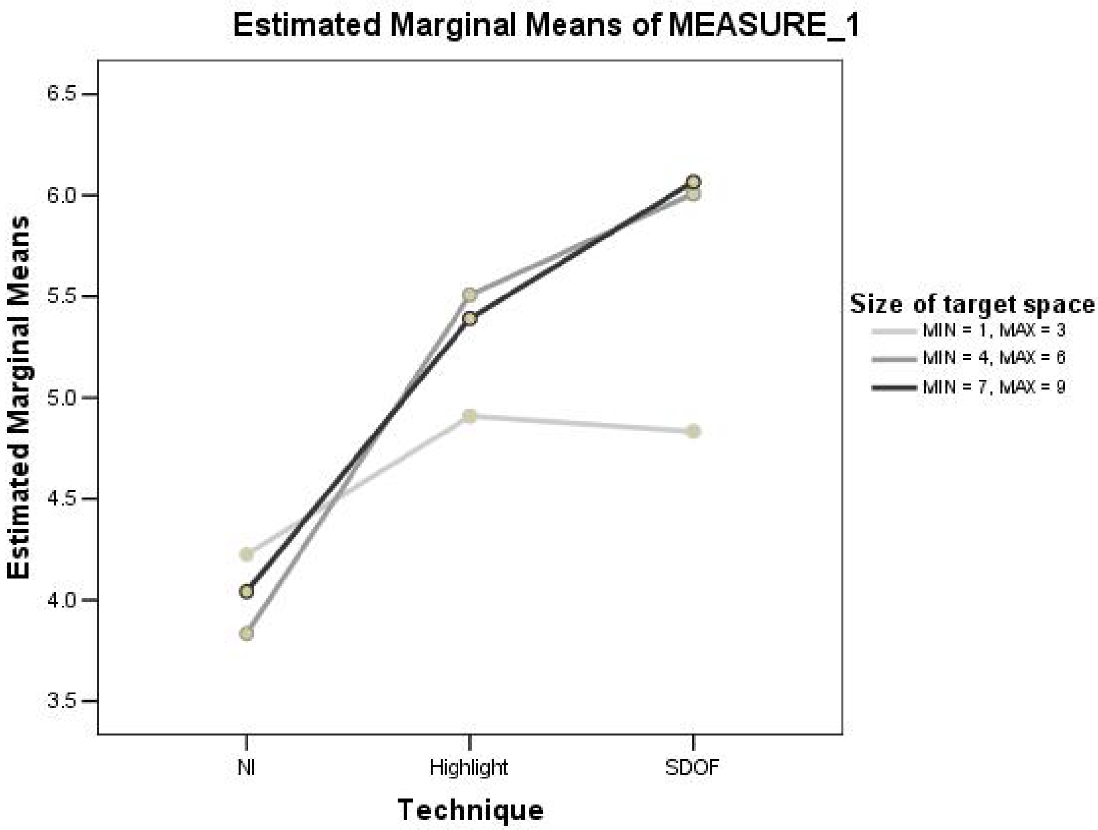
Based on estimated marginal means
* The mean difference is significant at the .05 level.
a Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Pairwise Comparisons

Measure: MEASURE_1

(I) space	(J) space	Mean Difference (I-J)	Std. Error	Sig.(a)	95% Confidence Interval for Difference(a)	
					Lower Bound	Upper Bound
1	2	-.461(*)	.118	.000	-.700	-.222
	3	-.511(*)	.152	.002	-.818	-.204
2	1	.461(*)	.118	.000	.222	.700
	3	-.050	.174	.776	-.402	.302
3	1	.511(*)	.152	.002	.204	.818
	2	.050	.174	.776	-.302	.402

Based on estimated marginal means
* The mean difference is significant at the .05 level.
a Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).



Test #4 – Time Analysis

Descriptives

Time

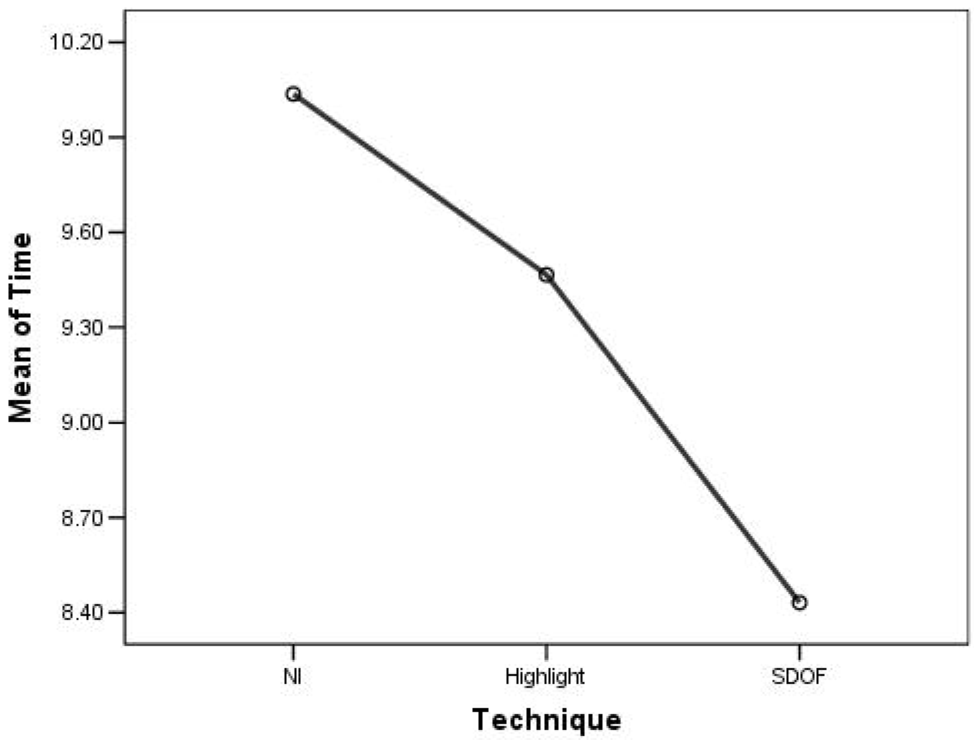
	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
NI	120	10.0371	4.31842	.39422	9.2565	10.8176	3.30	16.70
SDOF	120	8.4313	3.22342	.29426	7.8487	9.0140	3.07	16.69
Highlight	120	9.4656	3.61842	.33031	8.8116	10.1197	3.19	16.70
Total	360	9.3113	3.79588	.20006	8.9179	9.7048	3.07	16.70

Multiple Comparisons

Dependent Variable: Time
Tukey HSD

(I) TType	(J) TType	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
NI	SDOF	1.60574(*)	.48381	.003	.4671	2.7444
	Highlight	.57142	.48381	.465	-.5672	1.7101
SDOF	NI	-1.60574(*)	.48381	.003	-2.7444	-.4671
	Highlight	-1.03432	.48381	.084	-2.1730	.1043
Highlight	NI	-.57142	.48381	.465	-1.7101	.5672
	SDOF	1.03432	.48381	.084	-.1043	2.1730

* The mean difference is significant at the .05 level.



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