Visualizing Causal Semantics using Animations

Nivedita R. Kadaba, *Student Member, IEEE*, Pourang P. Irani, *Member, IEEE*, and Jason Leboe

Abstract— Michotte's theory of ampliation suggests that causal relationships are perceived by objects animated under appropriate spatiotemporal conditions. We extend the theory of ampliation and propose that the immediate perception of complex causal relations is also dependent on a set of structural and temporal rules. We designed animated representations, based on Michotte's rules, for showing complex causal relationships or causal semantics. In this paper we describe a set of animations for showing semantics such as causal amplification, causal strength, causal dampening, and causal multiplicity. In a two part study we compared the effectiveness of both the static and animated representations. The first study (N=44) asked participants to recall passages that were previously displayed using both types of representations. Participants were 8% more accurate in recalling causal semantics when they were presented using animations instead of static graphs. In the second study (N=112) we evaluated the intuitiveness of the representations. Our results showed that while users were as accurate with the static graphs as with the animations, they were 9% faster in matching the correct causal statements in the animated condition. Overall our results show that animated diagrams that are designed based on perceptual rules such as those proposed by Michotte have the potential to facilitate comprehension of complex causal relations.

Index Terms—Causality, visualization, semantics, animated graphs, perception, visualizing cause and effect, graph semantics.

1 Introduction

Causal relations are deeply rooted in human reasoning and appear in many contexts. Cause-and-effect relationships are used for explaining natural phenomena (the iron will become red under the influence of fire) and for specifying and resolving research questions (do horror movies lead to aggressive behaviour?). In most cases such relationships are intermeshed in the collection of information and data available to the user. To better comprehend cause-and-effect relationships, many visual representations, typically in the form of diagrams, have been developed and are being used extensively.

Causal graphs constitute the most common representation of cause-and-effect relationships. These are directed acyclic graphs, in which vertices denote variable features of a phenomenon and edges denote a direct causal claim between these features (Fig. **1**). These graphs have appeared in many forms: Feynman diagrams in physics [18], Lombardi diagrams to explain secret deals and suspect relations [6], and influence diagrams to represent the essential elements of a decision problem such as decisions, uncertainties, and objectives, and how they influence each other [16]. In all these variations, the causal graphs replace long verbose descriptions or complex mathematical formulations that describe events with their causes and effects.

Although, node-link causal graphs provide information about cause-and-effect, in certain cases it can be very difficult to make credible causal inferences from linking lines and arrows [21]. They may produce many implicit and powerful assumptions, but they cannot convey the entire structure of the information to find out what is actually going on. In some instances, it is essential that the *meaning* or the *semantic* of the causal relationship be clearly revealed. For example, car manufacturers could understand better the quality of the tires being produced if a causal graph indicated that glass has a *stronger* influence than thorns in causing a flat tire; or that a flat tire has a *larger* impact on steering problems than it does on noise (Fig. **1**).

What seems to be lacking in the traditional forms of graphs is the capacity to convey different types of complex causal relations or semantics. Very little knowledge exists for properly visualizing complex causal relationships. The central question we address is how to make causal graphs more informative or carry precise meanings? In an effort to respond to this question we first defined a subset of the various types of causal semantics that may exist. We produced animated and static designs for depicting rich causal semantics. Our static design is an enhancement to the basic causal graph. The animated designs are based on perceptual theories explaining how we infer causal relations. In a first study, we carry out a passage recall task to compare our static diagrams to the animated representations. Our results show that participants are able to recall passages better when they are complemented with animated instead of static diagrams. In a second experiment we test whether causal representations can be intuitively and immediately captured upon viewing animated causal graphs. The results show that participants were able to comprehend causal semantics quicker when the relations were displayed with animations that were created based on results from theories of perception.

2 Related Work

The work described in this paper is largely inspired by work comparing animated and static diagrams, prior visualization techniques for causal relations, and from perceptual theories of causal inferences.

2.1 Animated or Static?

There has been a long standing debate on whether designers should display information using static or animated displays. To this end, numerous studies have investigated the effect of animated diagrams on comprehension. Results of one study by Tversky et al. [15] show that static representations can be as effective as their animated counterparts. Tversky et al. [15] suggest that if the symbols used in the static representations are intuitive and clearly depict the information being represented, then static diagrams can replace animated diagrams, even in datasets containing temporal relationships.

Pane et al. [10] conducted a study to show that static and animated visualizations, when used properly, can be equally effective. In their study, experiments were conducted to compare the advantage of animated diagrams (in the form of videos or computer simulated presentations) over text and carefully selected still images. The results of the experiment showed that there was no significant difference in comprehension between static and animated representations, if both the representations were chosen carefully and represented the same information.

Another study by Morrison and Tversky [8] compared the enhancement in comprehension, of students, with plain text, text along with static images, and text along with animated diagrams. In a

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series of three experiments Morrison and Tversky conclude that text recall is enhanced with the complementary presentation of graphical information. However, in neither of their experiments do animations outperform static representations.

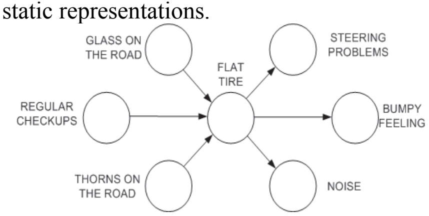

Fig. 1. Causal graph depicting the effect of glass or thorns on a tire, and the effect of a flat tire on driving conditions.

While the above discussed studies do not show that animation present any benefits, several other studies suggest that animations can be effective in various educational systems to simulate the behaviour of concepts that are contingent upon temporal properties and thereby augment the learner's ability to comprehend difficult concepts [21].

While many studies have been designed to compare and evaluate the effectiveness of animated designs, none of these provide any conclusive evidence on the beneficial properties of animation. However, we believe that if the animations are created with certain spatiotemporal rules, then they can effectively convey the information being represented.

2.2 Visualizing Causal Relations

A number of visual representations have been designed for showing causal relations. Hasse diagrams constitute one of the earliest systems for showing causal concepts. They have been used for representing distributed systems [11], parallel processes [17], or any other type of information structures that consists of causal events. Hasse diagrams can be difficult to comprehend as the layout of the graph creates a large number of intersecting lines. Furthermore, to view the causal chain the user has to backtrace along the various edges. As with causal graphs, Hasse diagrams are not equipped to show causal semantics. Additionally, enhancing Hasse diagrams would result in more clutter and make it difficult to visualize complex causal relationships.

Elmqvist and Tsigas [5] designed a Growing-squares technique to depict causal dependencies between processes in a system. With Growing-squares, each process is given a unique colour. When processes influence one another, their colours intermix in a checkered fashion over a time frame. Growing-squares takes advantage of animation to show gradual increases and decreases of influences in a system. A user evaluation showed that users were significantly faster (~25%) in answering questions related to causal events using Growing-squares in comparison to Hasse diagrams [5]. A significant redesign of the Growing-squares visualization would be necessary if it included additional causal semantics to the system.

Growing-polygons are an enhancement to the growing-squares technique [4]. In this approach, each causal factor is represented by an n-sided polygon and a colour. Each polygon is further divided into sectors for each of the factors in the system. As one factor influences another, over a timeframe, the colour of the first flows into its respective sector of the second, representing the effect. A user evaluation by Elmqvist and Tsigas [4] showed that users were 58% faster and 21% more accurate in answering causal questions with growing-polygons than with Hasse diagrams. Additionally, Growing-polygons is capable of showing certain types of semantics such as depicting two factors that have a simultaneous effect on one another and the semantic of transitive causality, i.e. if A influences B and B influences C, then A influences C. However, significant modifications to the visualization is necessary in order to include semantics such as strong or weak causal factors and large or small causal outcomes.

Ware et al. [19] designed a number of visual representations for showing causal information in node-link diagrams. They defined a visual causal vector (VCV) that represented a causal relation between two entities. The VCV was tested using several metaphors that were designed with a number of spatiotemporal rules that are necessary for perceptually inferring causal effects [19]. Results from their study showed that the nature of the metaphor is less critical than the spatiotemporal rules that were used for showing the causal relations. Their results inspired some of the work presented in this paper. In particular, we extended their results for depicting semantics that can provide rich descriptions of naturally occurring causal relationships.

While the representations described above have facilitated viewing causal relationships in a passive way, a number of systems have relied on some form of interactivity for showing causality. The influence explorer [16] allows users to interactively inspect the influence of factors on different outcomes. The interaction is provided by means of slider bars that control the amount or range of influence of one factor on the effect. Neufeld and Krisstorn [9] used a variation of the influence explorer in which dynamically varying the values of causing factors shows the amount of influence on the final outcome. Such systems can be successfully used in situations that necessitate causal reasoning for making decisions. However, neither method is equipped with the ability to depict various forms of causal semantics.

2.3 Perceiving Causality

Michotte's *theory of ampliation* suggests that we perceive or infer causality when a moving object strikes another and sets the latter into motion [7]. The causal inference is immediate upon presentation to our visual system.

The experiments developed by Michotte initially concentrated on mechanical causality. In the basic experiment, referred to as *launching*, subjects see two immobile rectangles (L and T) of different colours on a uniform white background. The experiment begins when the launcher (L) moves at a constant speed toward the target (T). When L reaches T, it stands still and the latter starts moving (Fig. 2). Subjects, even though unaware of the purpose of the experiment, responded with descriptions that were endowed with causal meaning. Some descriptions included phrases such as "L pushes T", "L launches T", or "L projects T".

Michotte carefully controlled various factors to determine the conditions under which causal inferences would still be produced. Temporal conditions were one of the most contributing elements for appropriately perceiving "launching". Specifically, the *time between impact and movement of the target* needs to be maintained to a maximum of 100 msecs. For delays beyond 150 msecs, the object L and T appear to move independently [7].

The *size and shape* of objects can vary significantly without depreciating causal inferences, as long as the objects are perceived as independent upon the point of impact. Thinés [14] used triangular arrays of lights spots and found that subject responses were not affected by a change in shape. Also when L and T are perceived to be created from different types of material (i.e. L is a light spot and T is a solid object) launching responses were still obtained [7].

Absolute speed restrictions on the launcher and target are necessary for observing proper launching effects. Velocities beyond 110 cm/sec are perceived as the launcher passing through the target (tunnel effect). On the lower limit, velocities of either launcher or target below 3 cm/sec weakens the launching effect.

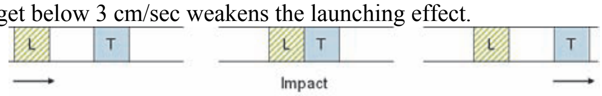

Fig. 2. Simple launching experiment. The launcher (L) upon impact stops and sets the target (T) into motion.

The *relative ratio of velocities* between L and T is considered important in maintaining causal inferences. The character of the causal structure is considered best when the movement of the target is slower than that of the launcher [7]. When the reverse is applied, very different responses are provided, in particular that of the target being autonomous in its movement.

In addition to temporal conditions, spatial information such as the *length of the paths* travelled by L and T should be carefully manipulated. In essence the causal responses start to degrade once the path of the target extends beyond its radius of action, i.e. naively related to the velocity of both objects [2, 20]. After a certain length of path, which can be empirically determined, the target appears to be autonomous. The *direction* taken by the launcher-target couple is also critical in inferring the relations. Best results are achieved when the target's path follows the line of action created by the launcher.

Several studies have extended Michotte's results to analyze the effects of context environments on the perception of causality. These studies state that existence of a causal event in the surrounding environment improves the perception of causality in a non-causal event by ~80% [12]. Another interesting study is one which examines the ability of perceptual grouping to influence causality [3]. In this study, the authors show that connectivity between a causal and non-causal event improves the perception of causality in the non-causal event, which has some bearing on the connected lines that are employed in visualizing our causal graphs.

3 Semantics of Causal Relations

The work of Michotte and others suggests that certain spatiotemporal conditions favour the perception of causal phenomena. We reasoned that if we could map the semantics of causal systems onto a set of perceptual semantics we could create diagrams that are more informative and that give rich descriptions.

We define a set of causal semantics as:

Causal amplification – In abstract terms, we talk about causal amplification when a factor is causing an increase in the final effect. For example, studying for an exam improves performance (Fig. 3).

Causal dampening – Causal dampening means that a causal agent is having an overall negative or opposite effect on an outcome. For example, taking medication "reduces or dampens" the symptoms of a flu (Fig. 4).

Causal multiplicity – When two or more agents are contributing to the causal effect we refer to this as causal multiplicity. In this definition it is implicit that the effect is only present when all the causing agents are simultaneously contributing to the overall effect. In more concrete terms, causal multiplicity appears in many contexts such as active and passive learning having a combined influence on scholastic success (Fig. 5).

Causal strength – In abstract terms, we can talk about causal strength when a given agent is contributing more or less significantly to an effect than any other causal agent. For instance, active learning has a stronger impact than passive learning for scholastic success (Fig. 5).

4 Visual Designs

We produced several alternative designs for representing the causal semantics described above. We have two large categories, static representations and animated representations. We first define several keywords that are used to describe the causal relations:

Factor: A factor is the cause in a causal relationship, and is represented as a labelled circle. For example, cold weather, stress, and immunity are all factors.

Target: A target is the variable acted upon by a factor or a combination of factors. For example, flu is the target which is acted upon by the factors mentioned above.

Relation: A relation signifies a causal action occurring between a factor(s) and the target and is represented as a line emerging from the factors to the target, which is directed from factor to target in the static and undirected in the animated representation.

Influence: A factor can have a weak, moderate or a strong influence on the target. For example, cold weather can have a weak, moderate or strong influence on flu.

Effect: A target can have several different effects based on the combinations of factors and the strengths of their influences. The effect can be positive (increases the target) or can be negative (decreases the target).

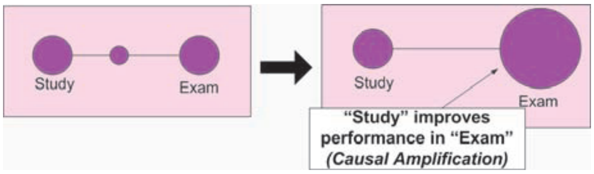

Fig. 3. Factor (Study) causing increase in outcome (Exam) – Causal Amplification

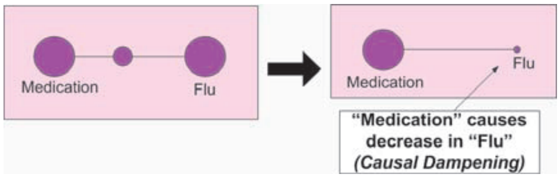

Fig. 4. Factor (Medication) causing decrease in outcome (Flu) – Causal Dampening

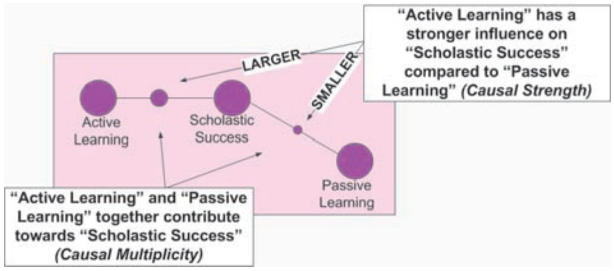

Fig. 5. Factors (Active Learning, Passive Learning) have combined effect on outcome (Scholastic Success) – Causal Multiplicity; One factor (Active Learning) has more influence than the other (Passive Learning) – Causal Strength

The above terms define the structure of the causal relations that were tested in the experiment. For the purposes of the experiment, we define two types of causal relations that were presented to the participants:

Positive causal relations: where the factor(s) had positive influences on the target, and the effect was positive.

Negative causal relations: where the factor(s) had negative influences on the target, and the effect was negative.

The various causal semantics defined above can be illustrated through the following scenario. For instance, "Cold Weather" and "Low Immunity" (causal multiplicity) together can cause an increase in "Flu" (causal amplification). On the other hand "Medication" can relieve "Flu" (causal dampening). Together "Medication" and "Taking Rest" (causal multiplicity) can also relieve "Flu" (causal dampening). In the latter case, "Medication" has a stronger effect than "Rest" in relieving "Flu" (causal strength). It is possible to capture these semantics using a variety of visual representations, described below.

4.1 Static Design

We designed a number of static representations to express the causal semantics. The final design was the outcome of several brainstorming sessions during which alternative drawings were sketched and examined for their intuitiveness and ability to reflect accurate information.

4.1.1 Representing Causal Relations with node-link arrows and glyphs

This representation enhances traditional causal graphs with additional visual encodings. Factors are connected to a target using directional arrows; the direction of the arrow determines the cause and the effect in the relation. A positive or negative influence is denoted by a plus sign (+) or by a minus sign (—) attached to a factor (Fig. 3). The size of the glyph depicts the strength of the influence on the target. Causal multiplicity is depicted by using glyphs of the same colour to represent factors that act on a target simultaneously. Near the target, a series of bars are placed to show the magnitude of the effect. Bars along the positive y-axis describe an amplified effect while bars along the negative y-axis describe a dampened effect. The order of the bars depicts the order in which each causal action takes place.

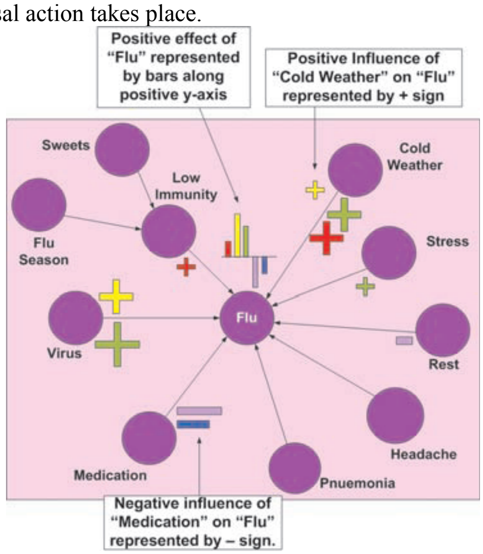

Fig. 6. Representation of the flu graph using nodes, links, +, —, bars, and colors

4.2 Animated Design

We designed several methods of animating the causal relations to depict the causal semantics. We utilized the same process as that described above for designing the animated diagrams. Our diagrams were based on Michotte's rules for perceiving causal information [7].

4.2.1 Representing causal relations by animating the target

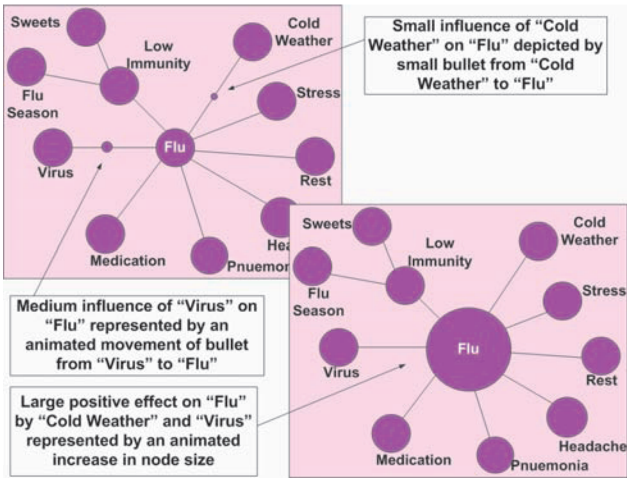

Fig. 7. Representation of a causal relation using simple animation. (a) "Virus" and "Cold Weather" have a combined effect on "Flu", and (b) the effect is a large causal amplification (the "Flu" node expands to a large size).

This representation uses simple animations and Michotte's theory of ampliation [7] to generate the sensation of a causal interaction between the factors and the target. The causal relation is displayed by the factors and the target as a simple graph with undirected lines to connect the factors to the target. A factor's influence on the target is displayed in the form of a smooth animation comprising of a bullet moving from the factor to the target, at a speed of 12cm/sec, along their connecting line. Causal multiplicity is described by simultaneous ejections of bullets from the factors, in the relation. Causal strength is determined by the size of the bullets. As the bullet(s) hits the target, the size of the target is modified based on the type of influence. One difference between our visualizations and those of Michotte is that the target changes shape instead of being launched. This is mainly due to the design of the causal graphs which do not allow for movement of the nodes themselves. Nonetheless, the speed at which the target changes is controlled at 10 cm/sec, which again is in keeping with Michotte's absolute speed guidelines. Also, the time between the impact and modification of the target is kept to a maximum of 50 msec. Causal amplification is depicted by an increase in the size of the target, while causal dampening is depicted by a reduction in the size of the target. The magnitude of the effect is described by the degree of expansion or shrinkage of the target when it is hit by the bullet(s). For example, in Fig. 7, "Virus" and "Cold Weather" have a combined effect on "Flu" (causal multiplicity); "Cold Weather" has only a small influence compared to the medium influence of "Virus" (causal strength). "Virus" and "Cold Weather" increase the chances of getting "Flu", as the "Flu" node expands when the bullets hit it (causal amplification), and the magnitude of this effect is large.

5 Experiment 1: Comparing Passage, Passage+Static and Passage+Animated Representations

The goal of this experiment was to evaluate the two different visualizations that depict causal semantics. Our hypotheses were as follows:

Hypothesis 1: Participants will perform the recall tasks better when the causal relations are enhanced with visualizations.

Hypothesis 2: Participants will perform more accurately and with faster response times when the causal relations are enhanced with animated (vs. static) visualizations.

5.1 Method

5.1.1 Subjects

Forty-four undergraduate psychology students of a local university participated in this experiment. The ages of the students varied from 23 to 30 years. None of the students had any formal training with computers, perceptual visualizations or causal relations. The participants also confirmed that they had good English language skills, normal to corrected vision, and did not suffer from a history of colour blindness, which was required to distinguish between the various colours displayed during the experiment.

5.1.2 Materials

The experiment comprised of three methods for representing simple causal relations. These relations were displayed as passages, static diagrams, and animations. The passage representation was provided in the form of an English passage, printed on an 8½″ x 11″ paper. The static graphs were created using Microsoft Visio and projected onto a 60″ x 60″ screen. The animations were created using Macromedia Flash™ and were also projected on the same screen.

The static diagrams and the animations were run on a Windows XP computer. The visualizations were projected with a 1024 x 768 pixel screen resolution.

5.1.3 Design

We used a 3×2 within subject design. The two independent variables were: Representation Type and Statement Type.

Representation type

Three types of representations were shown to the participants; Passage, Static, and Animated.

Passage: In this representation type, the participants were provided with passages to read for a limited amount of time. The passage consisted of 10 relations in total; 5 positive and 5 negative. The relations were separated from each other as separate paragraphs with distinct titles. Each sentence in a paragraph described one causal relation.

Static: In this representation type, the participants were shown a static graph projected onto a screen. The graphs described causal relations using + and − signs, bars, and connecting lines. Colours were used to connect the influences with the effects. Upright or inverted bars of varying sizes depicted the type and magnitude of effect and varying sizes of + and − signs were used to describe the strengths of the influences.

Animation: In this representation type, the participants were shown an animation projected onto a screen. Each causal relation was clearly defined by a 2 second gap. The influences were depicted using animated bullets. The expanding and shrinking of the target was used to depict the type of effect, and varying sizes of bullets and the target were used to depict the strength of the influences and the effects.

Statement Type

At the completion of each trial, the participants were given a set of causal relations and were asked to identify whether they had seen these relations previously in the experiment. The statements that the participants were asked to match were of two types:

Correct: A correct statement is one where all the components of the given relation match a relation provided during the experiment. For this statement the participant would need to enter a "True" response to get a correct score.

Incorrect: An incorrect statement could either be one that was not presented to the participant or one that was presented, but in which parts of the causal relation were inaccurate. The participant would need to select "False" to get a correct score.

5.1.4 Tasks

The experiment consisted of three phases; passage-only, passage + static and passage + animation. The participants were given two tasks to perform. The first task was the *memorization* task where the participants were asked to read and/or view the causal relations, and memorize as many as they could within a time period. Depending on the condition, the memorization task of the participant varied slightly. In the passage-only condition, the participants' task was to read the given passage for 4 minutes. The participant was then asked to fill the next four minutes by performing simple filler tasks such as connecting a sequence of dots. In the passage + static condition, the participants first read the given passage for 4 minutes to memorize the causal relations. They then viewed the static graph for the next 4 minutes to support what was read previously. Similarly, in the passage + animated condition, the participants first read the given passage for 4 minutes and then viewed the animation for the next 4 minutes. As the length of the animation was only 60 seconds, the animation repeated itself four times to fill the 4 minute slot.

The second task was the *recall* task where we asked participants to respond to whether a selected relation we presented was either Correct or Incorrect (as described above) within a 5 minute timeframe.

The representation types were fully counterbalanced using a Latin square design. Each participant viewed three of six passages, with one passage per condition. Each questionnaire consisted of 14 questions, with 7 questions of each statement type. The statement types were randomly distributed within the questionnaire. Overall, with 44 participants, 2 independent variables, and 7 questions per statement type, a total of 1848 responses were collected for analysis.

5.1.5 Procedure

The experiment was conducted in three phases. In the first phase, we ran a colour blindness test [1] to ensure that the participants could distinguish the colours in the static graphs. We then conducted a 20 minute training session, where we described the representation and statement types to the participants in detail. We showed examples of the passage, static, and animated representations and quizzed the participants to ensure that they had understood the representations. We then showed a sample questionnaire, and the participants were told how to record their responses. We conducted the experiment after the training session. Conditions were randomly assigned and time constraints were strictly enforced. At the completion of each condition, the participants were asked to answer the questionnaire corresponding to the condition, within a time limit of 5 minutes. At the end of 5 minutes, the participants were asked to stop answering and move to the next condition. On completing all three conditions, the participants were asked to record their individual opinions of the representations and the experimental procedure, in an informal questionnaire. We captured the number of correct responses that the participant gave in each of the conditions. The participant was given a maximum score of 1 for each correct answer they provided. If the participant answered only parts of the answer correctly, we awarded only a corresponding fraction of the maximum score.

5.2 Results and Discussion

Following the procedure described in the Method section, we first computed the proportion of accurate responses made by each participant for each of the experimental conditions. These data were then submitted to a 3×2 repeated-measures Analysis of Variance (ANOVA), treating memorization condition (passage-only vs. passage + static vs. passage + animated) and statement type (correct vs. incorrect) as within-participant factors. This analysis revealed a main effect of memorization condition, $F(2, 86) = 6.76$, $MSe = .035$, $p < .005$. The basis for this main effect was that participants were more accurate in making judgments about causal relationships in the passage + animated condition than in both of the other two memorization conditions. Specifically, participants made about 8% more accurate responses in the passage + animated condition than in the passage-only condition (.64 vs. .56), $F(1, 43) = 7.79$, $MSe = .031$, $p < .01$, and they made about 10% more accurate responses in the passage + animated condition than in the passage + static condition (.64 vs. .54), $F(1, 43) = 11.01$, $MSe = .040$, $p < .005$.

There was no reliable difference in response accuracy between the passage-only and passage + static conditions, $F < 1$. Moreover, the main effect of statement type was not reliable, $F(1, 43) = 2.86$, $MSe = .062$, $p > .05$, although participants were about 5% more accurate in responding to correct statements than incorrect statements (.60 vs. .55). Finally, the effect of presenting an animated diagram on response accuracy did not depend on whether the test statement was correct or incorrect (memorization condition × statement type interaction, $F < 1$).

The results of this experiment partially concur with both our hypotheses. The results show that visualizations do help in improving recall of causal passages (*Hypothesis 1)*. However this improvement was shown only by the animations. We think the reason the static representations did not prove very effective was because it is quite difficult to adequately distinguish between the different colours displayed. On-screen clutter was another problem adversely affecting this representation. Finally, even though the effects (bars next to the target) described the timeline of the causal relations, on-screen clutter reduced any semblance of order in the influences (+ and − signs) which made the task extremely tedious. Fig. 8 shows a decrease (albeit insignificant) in the accuracy rate when the causal relations were enhanced using static images.

The results also show that our animations performed better than the static images (*Hypothesis 2)*. We think this is because the animations did not depend on colours, showed only one relation at a time, and also described a smooth and continuous timeline. We also think that designing our representations based on Michotte's guidelines contributed to a better performance with the animations. The results also showed that the participants were able to distinguish correct and incorrect relations more accurately in this condition. Two drawbacks of this representation were noticed during the evaluation. One drawback was that the sequential nature of the animation did not allow skipping to a required relation, which can be overcome by allowing interactions with the animations. A second drawback was that the absolute sizes of the influences (bullet size) or the effects (degree of expansion or shrinking of the target) were not easily distinguishable due to the absence of a legend. Only relative judgements were possible.

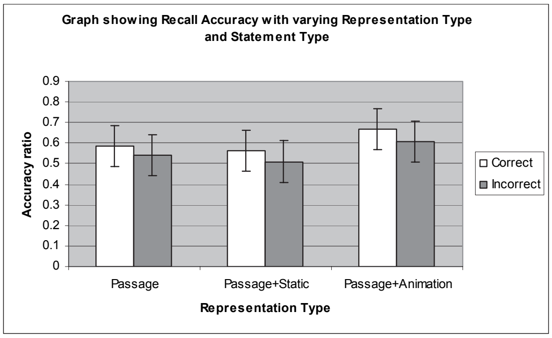

Fig. 8. Accuracy rate of recognizing correct and incorrect causal relations across the three conditions.

An analysis of the informal questionnaires also showed interesting results. More participants (*p=67.4%)* agreed that visual enhancements do improve memory and help in recall tasks. However, a considerable number (*p=32.6%)* of participants did not agree and were quite content with reading the passages only; this can be attributed to their superior memorizing abilities. When asked to compare between the static and animated images, the participants were noncommittal as to which technique was better. Based on the task, they claimed either the static images or the animations to be more accurate and interesting. More participants (*p=60.3%)* agreed that the animations enhanced the memory better than the static images. However, they claimed (*p= 58.7%)* that it was easier to view the strengths of the influences with the static images. Finally, a major observation during the experiment was that pure animation seemed to be quite boring as it constrained the participants to a fixed order and timeline and did not give any room for intellectual exploration.

The results of the first experiment showed that participants were able to comprehend causal relations better when the textual passages were complemented with static and animated representations. However, we are not able to conclude from the experiment whether the static and animated representations we have designed can naturally and intuitively elicit causal relations. Furthermore, we cannot infer from our results whether one type of representation is better than the other for showing the selected set of semantics. As a result we designed a second experiment to compare the effectiveness of static and animated representations in describing causal relations.

6 EXPERIMENT 2: STATIC VS. ANIMATED REPRESENTATIONS

The goal of this experiment was to compare the effectiveness of our static and animated representations in describing causal relations. We were interested in identifying whether representations for complex semantics based on Michotte's rule of perceiving causality would elicit accurate and rapid responses. Our hypotheses for this experiment were as follows:

Hypothesis 1: Participants will perform the recall tasks better when the causal relations are enhanced with animations.

Hypothesis 2: Participants will be able to respond faster when the causal relations are enhanced with animations.

6.1 Method

6.1.1 Subjects

One hundred and twelve (112) undergraduate psychology students of a local university participated in this experiment. None of the participants had performed the previous experiment and were not familiar with the objectives of our study. The participants satisfied the same selection criteria as in Experiment 1 (age, no colour blindness, normal to corrected vision, no prior experience with causal graphs).

6.1.2 Materials

The experiment consisted of two major conditions for representing the relations; static images and animations. The experiment was generated as a .NET program with the embedded static and animated Macromedia 8 flash files. Individual copies of the program were executed on a Windows XP computer and displayed on a 17" Dell monitor with a 1024x768 pixel screen resolution.

6.1.3 Design

We used a 2×4 within subject design. The two independent variables were: Representation Type and Statement Type.

Representation type

Two types of representations were shown to the participants: Static and Animated.

Static: In this representation type, the participants were shown a static graph that contained about 1 – 2 causal relations. We kept the graphs simple as we wanted to identify whether subjects were able to intuitively capture the concepts presented in the atomic relationships. In the initial design of the static graphs, which we used in experiment 1, we found that the + and – glyphs were redundant cues because the upright and inverted bars already described the type of the outcome to be either positive or negative. As a result we replaced these by square (■) glyphs to avoid displaying redundant information. The size of the glyph represented the strength of the influence. Colour was used to distinguish the different sets of causal relations.

Animation: In this representation type, the participants were shown an animation which contained about 1 – 2 causal relations. The features of the animation were similar to the previous experiment. We maintained, to the best of our ability, the animated syntax equivalent to the static syntax with the exception of applying Michotte's rule in the animated case, and replacing those with descriptive glyphs and symbols in the static case. We felt that these mappings were as close as we could get for providing a fair basis for both representations.

Statement Type

At the completion of each trial, the participants were shown a statement based on the relation(s) they viewed. In order to isolate and test the effectiveness of various components of our representations, we asked participants to correctly match four types of statements that were created from our initial set of semantics:

Type of outcome (S1): This type of statement tested the ability of the participant to distinguish between positive and negative outcomes in the causal relation. In the experiment, the outcome of the causal relation was represented by upright/inverted bars in the static and by expansion/shrinking of the target in the animations.

Strength of influence (S2): This type of statement tested the ability of the participant to comprehend the amount of influence a factor had on the target. In the experiment, the strength of influence was depicted as varying sizes of square (■) glyphs in the static graphs and different size bullets in the animations.

Magnitude of the outcome (S3): This type of statement tested the ability of the participant to comprehend the magnitude of the outcome when a factor influences a target. The magnitude of the outcome was displayed as varying sizes of upright or inverted bars in the static condition and in the animated representations the targets would expand or shrink.

Combination of components (S4): This statement type tested the ability of the participant to identify all the constituent elements of a causal relation, such as the type and magnitude of outcome and strength of the influence. We believe this type of statement was the most complex and evaluated the overall effectiveness of the static and animated representations in displaying causal relations.

6.1.4 Tasks

The experiment consisted of showing multiple random trials of static and animated graphs. As in the previous experiment, the experiment consisted of two tasks; *memorization* and *recall*. In the *memorization* task the participant was shown the causal relations for a pre-determined length of time (9 seconds per causal relation). Within this period the subject was asked to carefully view all the possible relationships that existed. In the *recall* task, the participant was shown a statement, based on the relations that were just viewed. For example, they would be presented with a statement that was not based on real facts (i.e. they could not answer correctly without seeing the graphs) such as "Female mosquitoes have a positive effect on malaria". After reading the statement, the participant was asked to hit one of two keys (B = 'Yes' or N = 'No', B was taped with a "Y" on top of it) depending on whether they agreed with the statement or not based on the previously viewed graph. We asked the participants to provide as accurate an answer as possible and to respond quickly. Upon providing an answer, the trial automatically ended and the setup presented the next trial.

6.1.5 Procedure

The experiment was conducted in two phases. The first phase was the training phase, where the participants were asked to self-train themselves by running a pilot tool that displayed static and animated causal relations. They were presented with statements that were similar to what would be displayed during the experiment. The participant was given the opportunity to run the pilot as frequently as needed, but was not able to obtain explanations from the experimenter regarding the meanings of the relations or the visual representations. After completing the self-training phase, the participant was asked to run the experimental program.

The second phase was the experiment phase. The trials in the experiment were divided into 6 sessions. At the end of each session, the timers were paused and the participant was allowed to take a break if required.

6.1.6 Results

The main variables of interest in this experiment were the completion times in responding the question and the accuracy of the users' responses. Each accurate response of the participant was awarded one point. The analysis for response times only considered accurate responses. The results are summarized in **Fig. 9** and Fig. 10.

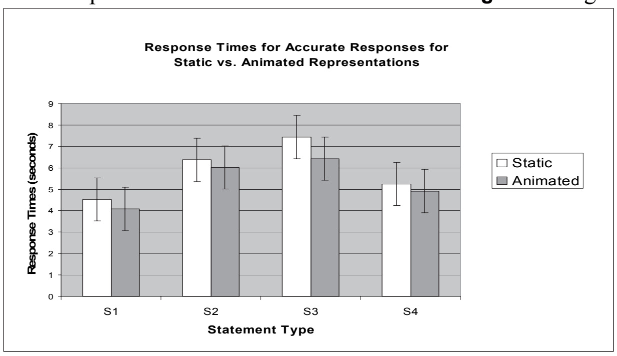

Fig. 9. Response rate for correctly identifying the type of causal relation across all four types of statements.

The data was analysed using a 2×4 repeated-measures Analysis of Variance (ANOVA), treating representation type (static vs. animated) and statement type (S1-S4) as within-participant factors. This analysis revealed a main effect of representation condition, $F(1, 111) = 126.418$, $p < .001$. The basis for this main effect was that participants were 9% quicker in making judgments about causal semantics in the animated condition than in the static condition. (5.36 secs vs. 5.90 secs). This analysis also revealed a main effect of statement type, $F(1, 3) = 263.176$, $p < .001$. The basis for this main effect was that performance with statements S2 (6.19 secs) and S3 (6.93 secs) was significantly lower with statements S1 (4.31 secs) and S4 (5.1 secs) (all p-values between pairs of conditions were < 0.001). Finally, the effect of presenting an animated diagram on response rate did not depend on the type of statement, (representation type × statement type interaction, p=.428).

Analysis of the accuracy rates did not reveal any significant differences between representation types F(1,111)=2.089, p=.151, 82.1% for static and 83.2% for animated. This high accuracy rate, along with no difference between the major conditions is particularly noteworthy as it suggests that both representations captured or represented the semantics in an equivalent manner. Accuracy rates were lower on statements of type S3 (80.3%) and S4 (79%) in comparison to S1 (87.2%) and S2 (84.2%).

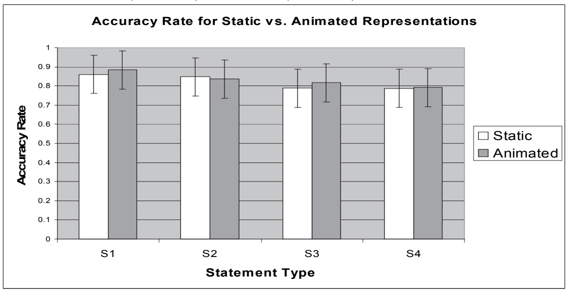

Fig. 10. Accuracy in matching the visual representations to the causal relations across all four types of statements.

7 Discussion

The results of both experiments suggest overall that animated diagrams can facilitate comprehension of complex causal relations. We discuss the ability of our representations for allowing users to 'immediately' see complex relations and suggest some guidelines for designers who are interested in depicting causality.

7.1 'Immediate' perception of causal relations

The second experiment was designed to test whether our representations would elicit an 'immediate' inference of the information embedded by the graphs. The results of experiment 2 support our hypotheses that animations can describe causal relations better than static diagrams. The accuracy rates of both the static and animated representations were similar and this can be attributed to the simplicity of the causal semantics being depicted. However, significant differences can be seen with the response times, where participants were able to provide accurate answers in less time when the causal relations were displayed using animations. When comparing the results based on statement type, we see that participants performed best (~88% accuracy rate) in comprehending statements of type S1 (i.e. identifying whether there was a positive or negative outcome). This may suggest that we have a potentially strong representation for showing semantics of causal amplification and causal dampening. We found that participants took the longest amount of time for responding to statements of type S3 (i.e. identifying the magnitude of the outcome) in comparison to the others. This is highly attributed to the difficulty in distinguishing and recalling the different absolute sizes of the influences being displayed. An alternative would be to present labels for showing numbers or specific values. As per our predictions, statements of type S4 (combination of all types of causal relations) were the most difficult to comprehend with an accuracy rate of 79%). This may suggest that with larger or more complex diagrams, other forms of representations or interactions may be necessary [13].

7.2 Applicability of our visualizations in practice

One concern with any new visualization design is its applicability in practice and its usability in different areas of information science. We have addressed these issues, some of which will form part of the future work for our research.

One of the major issues is the concern of scalability. Our causal designs are simple, and can be easily created. Even though, we have used small graphs in our experiments, we infer from our studies that the visualizations will perform similarly with larger graphs. However, we do acknowledge that as the graphs increase in size, additional interaction techniques would be necessary for improving the comprehensibility of the semantics. Interaction techniques will be useful as the users will be able to isolate and animate only those parts of the large graph that are of interest at any time. Finally, with the use of interaction users can create different what-if scenarios and view the effects in the causal graphs.

Several application areas will also benefit from our visualizations. In the medical and pharmaceutical fields, the animations can be used in radio therapy, surgery, and in drug research to visualize the effects of medication on diseases. In the educational field, the animations can be used in the form of educational games in children's hospitals to educate the children on how to control symptoms of their diseases. In computer science, the visualizations can be used to show program structures, timelines, workload division, and system by-products. In general, causal semantics are applicable to numerous daily activities. Our visualizations are simple but powerful enough to capture some of the more complex semantics that are encountered on a regular basis.

7.3 Recommendations to designers

Based on our findings we provide several recommendations:

Animated representations based on Michotte's rules for perceiving causality can assist in showing complex causal relationships. In particular accurate spatio-temporal rules should be utilized in the construction of animated causal graphs.

In the absence or impracticality of displaying animated representations, static graphs that can accurately contain and depict an equivalent amount of information as the animated graphs, can be constructed.

Semantics of causal amplification and dampening can be accurately captured by increasing or shrinking the nodes representing the causal outcomes.

Causal multiplicity and causal strength need to be carefully designed to avoid possible ambiguities.

8 Conclusion

This paper reports on the construction and evaluation of visual semantics that enhance information content in causal diagrams. Our representations are based on perceptual rules for recognizing causal occurrences, as suggested by Michotte and Thinés [7]. In this study we have short-listed some commonly encountered causal events, and have created static and animated visual semantics to represent them.

In two experiments we study and compare the effects of our novel designs. In the first experiment we study the causal relationships for their influence and efficiency in memory recall situations. In our experiment we created several arbitrary causal situations and tested the ability of participants to recall the semantics with and without visual aids. The results of our study show that accuracy rates did not improve significantly when the causal passages were complemented with static diagrams; the reasons mainly attributed to limitations of colour and on-screen clutter. However, the results showed that the accuracy rates increased by 8% over the passage-only condition and by 10% over the passage + static condition, when the passages were supplemented with animations. We believe that the spatiotemporal properties of animation can enhance information content and improve comprehension of complex causal relations.

In a second study we evaluate the 'immediacy' of perceiving causal relationships. We compare users' ability to understand and match, without training, the visual representations to the correct causal statements. Our results show that participants are 9% faster with the animated representations than with the static graphs. Our results also show that participants were equally accurate with both types of representations, suggesting that both designs are informationally equivalent.

The study reported in this paper constitutes the first step in identifying whether animations based on perceptual theories of causality are effective for showing complex causal relationships. In future work we will explore the scalability of our representations to larger datasets, will identify and create semantics for more causal events such as causal transitivity and threshold causality, and evaluate our representations with real-world data.

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