Analyzing animated representations of complex causal semantics

Nivedita R. Kadaba*
University of Manitoba

Pourang P. Irani†
University of Manitoba

Jason Leboe‡
University of Manitoba

Abstract

Causal relationships are inherent in the world around us and are intrinsic to our decision making process. Michotte's *Theory of Ampliation* suggests that the perception of causality can be enhanced under appropriate spatiotemporal conditions. We extended this theory and proposed that simple static and animated designs, based on structural and temporal rules, enable the perception of complex causal semantics, such as additive, mediated, and bidirectional causalities. Results of our experiment showed that participants were $\sim$5% more accurate and $\sim$8% faster with the animations, than with the static representations. Overall our results show that animations that are designed based on perceptual rules assist the comprehension of complex causal relations.

CR Categories: H.1.2 [Information Systems]: Models and Principles—User-Machine Systems H.5.2 [Information Systems]: Information Interfaces and Presentation—User Interfaces;

Keywords: Causality, visualization, semantics, animated graphs, perception, cause-effect, static, animation

1 Introduction

Causal relations are intrinsic to human reasoning and are used habitually as a critical component of our decision making process. A causal relation describes a cause–effect phenomenon wherein an event *causes* another event to occur. Causal relations can represent physical phenomena such as "the fire will cause the iron rod to turn red hot", or psychological phenomena such as "the minister's speech inspired me to vote for him". Such relations are essential to decision making in several areas of information science and are fundamental to determining natural occurrences (do dark clouds mean rain?) or in resolving research questions (do video games increase obesity rate in children?).

To better comprehend cause-and-effect relationships, several visual representations typically in the form of diagrams have been developed. Causal graphs represent the most common representation of cause-and-effect relationships. These are directed acyclic graphs, comprised of vertices that denote the *factors* and *targets* and a directed line that depicts a direct causal claim between them (Figure 1). These graphs have appeared in many forms: Fishbone diagrams to describe causes and effects in quality management processes [Ishikawa 1991] and influence diagrams to represent the es-

Figure 1: *A simple causal graph showing (a) factor: pollen, (b) target: allergic reaction, and (c) relation: directed line.*

sential elements of a decision problem such as decisions and uncertainties, and how they influence each other [Tweedie et al. 1995]. In all these variations, visualization of the causal information replaced verbose descriptions of the same.

A critical drawback of causal visualizations and traditional causal graphs is the difficulty in distinguishing between different types of causal semantics and the challenge of conveying additional important information regarding these semantics, which form an intrinsic part of causal judgements. For example, from Figure 1, a doctor will be able to provide better treatment if, in addition to knowledge about the allergens in the environment, he/she knew the quantity of the factor and/or how much is required to cause serious concern. We have addressed this problem in our study and have designed simple, descriptive, and informative visualizations for six complex causal semantics that are encountered in daily life. Results of our study comparing static and animated causal visualizations show that simple animations based on spatiotemporal rules enhance the perception of causal information.

2 Related Work

Our research has been inspired by several related studies in the areas of causal perception and causal visualization.

2.1 Causal Perception

The concept of causal perception has been of research interest for many decades. Michotte and Thinés's [1963] initial experiments comprised of two solid objects L (the *factor*) and T (the *target*); L moved towards T, hit it, and caused T to move. Based on their observations, they suggested that causal perception can be best achieved by adhering to a set of spatiotemporal rules [Michotte and Thinés 1963]:

- ***Absolute speed*** of the factor and target must be less than 110 cm/sec in order to perceive a causal event. Objects moving at larger speeds presented a *tunnel effect*, wherein the factor was perceived to have *passed through* the target.
- ***Time delay between impact and movement*** should be kept below 100 msecs, with an upper limit of 150 msecs, over which the factor and target are perceived to be unrelated.
- ***Relative ratio of velocities*** is critical to create a causal connection between the factor and target. Michotte and Thinés [1963] suggested that targets should move slower than their factors in order to communicate the transmission of causal influence.
- ***Size and shape*** of the factors and targets are not critical to give a causal impression. Michotte and Thinés [1963] suggested that participant performance was not adversely affected when

*e-mail: nrkadaba@cs.umanitoba.ca
†e-mail: irani@cs.umanitoba.ca
‡e-mail: leboej@cc.umanitoba.ca

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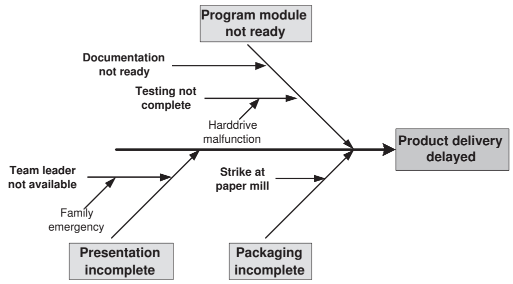

Figure 2: *A Ishikawa fishbone representation of the causes of delay in product delivery.*

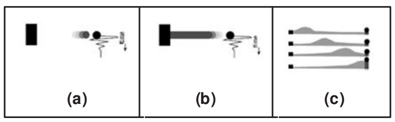

Figure 3: *Representing causal relations using VCV metaphors (a) Pin-ball metaphor, (b) Prod metaphor, and (c) Wave metaphor.*

physical objects were replaced with triangular patterns of light.

The innateness of causality can be seen through recent research, which has suggested that causality can be perceived in children as young as 9 months [Schlottmann and Surian 1999]. The study showed that infants who were shown a causal event were more effective in reorienting themselves to a reversed animation of the same, than infants who were shown a non-causal event. Several other studies have shown that causality can also be perceived in a contextual environment. These studies state that the existence of a causal event in the surrounding environment improves the perception of causality in a non-causal event by $\sim 80\%$ [Scholl and Nakayama 2001].

2.2 Visualizing causal relations

Some of the oldest forms of causal representations are Hasse diagrams, which use parallel lines to depict processes and connecting lines to depict interactions along a timeframe. Hasse diagrams have been widely used to represent information configurations that comprise of causal events, such as distributed systems [Rehn 2004]. A drawback of Hasse diagrams is that it does not distinguish between different types of causal semantics such as multiple factors, mediated or bidirectional causalities. Another issue is that of clutter, which increases significantly as the number of causal relations in the scenario increase.

The Ishikawa or fish-bone diagrams [Ishikawa 1991] employ a static method of representing causal semantics and have been used for cause-effect analysis in project management scenarios. In Ishikawa diagrams the effect is written at the right end of the “main bone” of the diagram and causes are written as side bones off the main bone (Figure 2). This diagram allows for categorization of the factors and for describing indirect influences on the final target, but it is spatially limited in the number of events it can represent. It also does not incorporate multiple targets or shared factors (factors directly or indirectly connected to more than one bone in the diagram).

Several recent studies have employed animations to visualize causal semantics. Ware et al. [1999] defined a *visual causal vector* (VCV) to describe a causal association between two objects. They tested the VCV using pin-ball, prod, and wave metaphors (Figure 3). In each of these metaphors, physical features of the factor (object, rod or wave) provided additional information about it; for example, speed of the factor described intensity of the influence or direction of travel (wave metaphor only) showed positive or negative influences. Results of this study showed that spatiotemporal rules were critical to causal perception.

Elmqvist and Tsigas designed two techniques, Growing Squares [Elmqvist and Tsigas 2004] and Growing Polygons [Elmqvist and Tsigas 2003] to visualize casual processes in a system. Growing Squares used dynamic color flows and checkered patterns to depict process interactions. On the other hand, Growing Polygons utilized n-sided and n-sectioned polygons (n = number of processes in the system) with color flows to show causal events in the system. Both methods used concentric growth to depict timelines. Although, on comparison, both techniques performed better than Hasse representations of the same information, some of their drawbacks include dependency on color, space wastage issues, and inability to visualize additional information such as amount/type of influence or effect.

Several studies have also included interaction techniques to enable fast and selective processing of the causal information. Spence and Tweedie [1998] designed the Attribute Explorer, which allowed users to adjust attribute values of the objects in a scenario and incorporated *responsive interaction* to quickly provide the results of user-queries (within 0.1 seconds). Similarly, Neufeld et al. [2005] designed a system that dynamically varied the values of factors to show the amount of influence on the 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 Visual representations: Static or Animation?

There has been a long standing debate among designers concerning the use of static and animated visualizations to represent information. Static images such as icons, lines, and bars have been used to represent geographical and scientific information [Tversky et al. 2000]. Animations on the other hand have become a popular mode of representing dynamic information. Tversky et al. [2002] defined two principles for effective visual representations. The *Congruence* principle states that a visualization should directly relate to the information being displayed and the *Apprehension* principle states that the visualization should be simple and easy to comprehend. Tversky et al. [2002] attributed the poor performance of animations to their complexity and thereby, inability in conforming to both rules.

Bogacz and Trafton [2005] conducted a study to determine, which of three representation types, a static image, a sequence of static images or an animation, was preferred by meteorologists when making weather predictions. Results of the study showed that the participants preferred looking at a sequence of images rather than the corresponding animation. However, results also showed that the forecasters used their expertise to convert these images into animations in their mind for the purpose of extracting dynamic information. This study concluded that animations are only useful if they provide more information than what is contained in the static images. However, this study was tested using experts and cannot be generalized to users with low spatial ability.

Although there is no conclusive evidence on which of static or animated representations are better, we believe that if animations are simple and designed based on certain structural and temporal rules then they can effectively convey the information being represented. However, in order to be fair to the arguments posed by previous research in this area, we have also designed equivalent static representations for each of our causal semantics and have compared them to our animations.

3 Causal semantics

Michotte's research suggests that visualizations based on spatiotemporal rules are effective in describing causal events. These spatiotemporal rules have formed the basis for creating the animated representations in our study. We reasoned that if we designed our animations using these perceptual rules, we would create visualizations that are descriptive, informative, and intuitive.

The focus of our research is two-fold; *define* and *visualize*. The *definition* process involves segregating the different types of causal semantics inherent in human reasoning. In order to simplify our tasks, we defined two groups of semantics: simple and complex. In the *visualization* process we developed static and animated representations to illustrate the causal information and conducted user-studies to test our designs.

3.1 Simple causal semantics

Simple causal semantics comprise of the building blocks for causal relations. In addition to describing the basic components of a causal relation such as *factors*, *targets*, and *connecting line*, this category also includes basic causal information:

Causal amplification occurs when a factor influences a target and brings about an increase in the outcome. For example, low immunity *increases* the chances of falling ill.

Causal dampening occurs when a factor causes a decrease in a target's effect. For example, medicine *reduces* infection in the body.

Causal multiplicity is described when two or more factors combine to produce the final effect. For example, stress and a virus *together* cause fever.

Causal strength compares the influences of two or more factors and determines which is stronger/weaker than the other. This decision has implications on the final outcome. For example, a virus has more influence (is *stronger*) than stress in causing a fever.

Kadaba et al. [2007] tested static and animated representations of the simple causal semantics. Results of a *Memory Recall* experiment showed that participant's performance improved when textual descriptions of the causal relations were enhanced using visualizations. A second study evaluating the *Intuitiveness* of the representations showed that participants were $\sim 9\%$ quicker when the causal information was visualized using animations. In this work, we have extended the vocabulary of causal relationships by including a novel set of more complex causal relations. Our purpose is to assess which form of representation (static or animated) invokes in the viewer, the complex relations defined below.

3.2 Complex causal semantics

Our complex causal semantics are intrinsic to the human decision making process. These semantics are either (a) extensions or (b) combinations of the simple semantics. In this study, we compare static and animated representations of these semantics in order to determine their intuitiveness in representing the causal information.

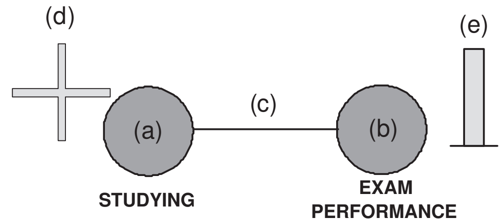

Figure 4: *Simple causal relation showing (a) factor, (b) target, (c) relation, (d) influence, and (e) effect.*

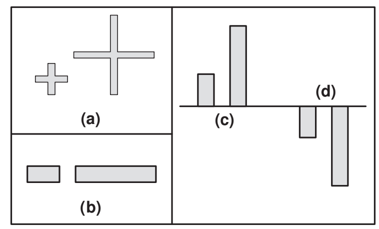

Figure 5: *Static glyphs depicting (a) small and large positive influence, (b) small and large negative influence, (c) small and large increase in effect, and (d) small and large decrease in effect.*

We first define several keywords that will be used to describe the components of a causal relation:

Factor A factor is the initiator of a causal event. It is represented as a labeled node in the causal graph. In Figure 4(a) the factor is "Studying".

Target The target is the outcome of the event. It is also represented as a labeled node in the causal graph. In Figure 4(b) the target is "Exam Performance".

Relation The relation signifies a causal action occurring between the factor and the target and is represented by a connecting line. In Figure 4(c) the connecting line informs us of a causal relationship between Studying and Exam Performance.

Influence A factor that causes a change in a target is said to have an *influence* on the target. A factor can have a weak or strong and positive or negative influence on the final outcome. In Figure 4(d), Studying has a *large positive* influence on Exam Performance.

Effect of a target is dependent upon the factors that influence it. Effect can be weak or strong and can increase or decrease. In Figure 4(e), Studying causes a *large increase* in Exam Performance.

3.2.1 Visual representations

We built two types of representations to describe our causal semantics:

Static representation

The static design is an extension of a traditional causal graph. Factors and targets are represented as nodes, and the relationship between them is represented by the connecting line. Influences are described using glyphs; positive influences are drawn as **+** glyphs and negative influences are drawn as **-** glyphs next to their respective factors. The effect is displayed as bars next to the target; upright bars depict an increase in the outcome and inverted bars depict

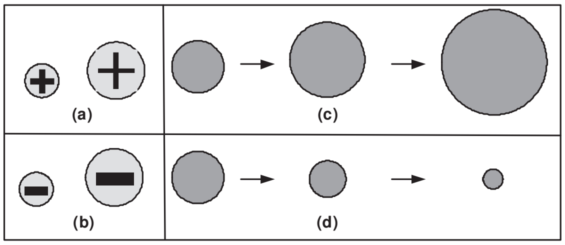

Figure 6: *Animated glyphs depicting (a) small and large positive influence, (b) small and large negative influence, (c) small and large increase in effect, and (d) small and large decrease in effect.*

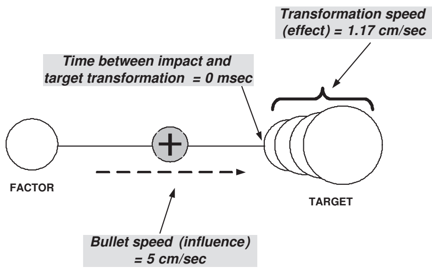

Figure 7: *Description of the spatiotemporal guidelines that were employed to build our animated representation.*

a decrease in the outcome. In addition to the type, the quantity of an influence or effect is also represented by varying the size of the glyphs and bars (Figure 5).

Animated representation

Our animated design is also a variation of a traditional causal graph where the factors and targets are represented as nodes and the relation is described by the connecting line. Influences are depicted by animated bullets that move from the factor to the target. Type of influence is denoted by a positive or negative sign within the bullet while amount of influence is depicted by its size. Effect on a target is illustrated by a change in target size; expansion denotes an increase in effect and shrinking denotes a decrease in effect. Finally, quantity of effect is described by the amount to which the target expands or shrinks (Figure 6).

We applied Michotte's structural and temporal rules to build our animations [Michotte and Thinés 1963]. Michotte and Thinés's guidelines suggest that *absolute speed of the factor* should be less than 110 cm/sec. In our designs, influences from the factor move at an absolute speed of ∼5 cm/sec, which allows the eye to travel smoothly from the origin to the destination. We also followed the guideline that suggested that *time between impact and movement* should be less than 100 msec. As we wanted to retain a strong causal context in our visualizations, we did not incorporate any delay (0 msec) between bullets hitting the target and the target transforming. However, in contrast to Michotte and Thinés's studies [1963], our targets do not move; instead they transform. Nonetheless, as deformation is also a type of change in the target, we applied Michotte and Thinés's [1963] guidelines for *relative ratio of velocities* and designed our target transformations at a speed of ∼1.17 cm/sec, which is less than the factor's speed (Figure 7).

3.2.2 Defining complex causal semantics

We now define the set of complex causal semantics as:

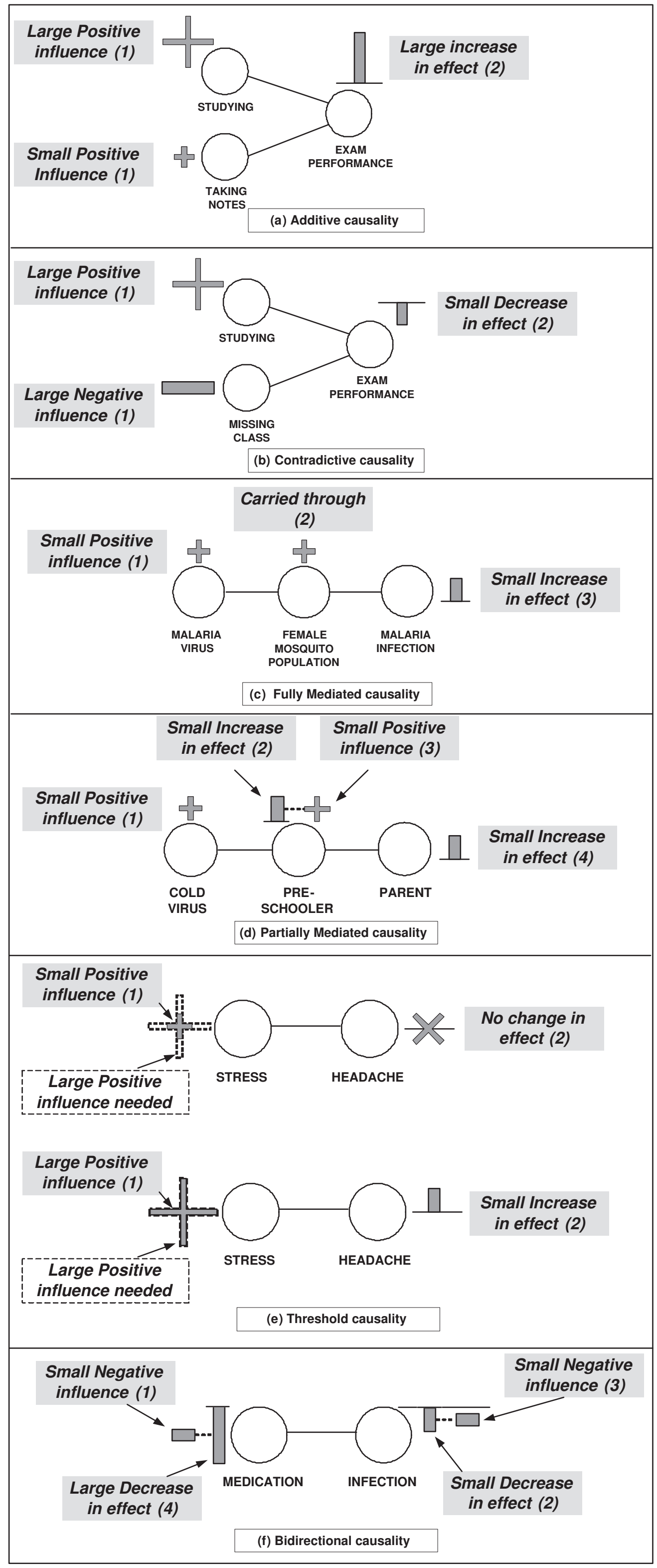

Figure 8: *Static representations using causal graphs, nodes, connecting lines, and glyphs. Numbers denote the order of occurrence of the causal event. Arrows were not displayed during the experiment.*

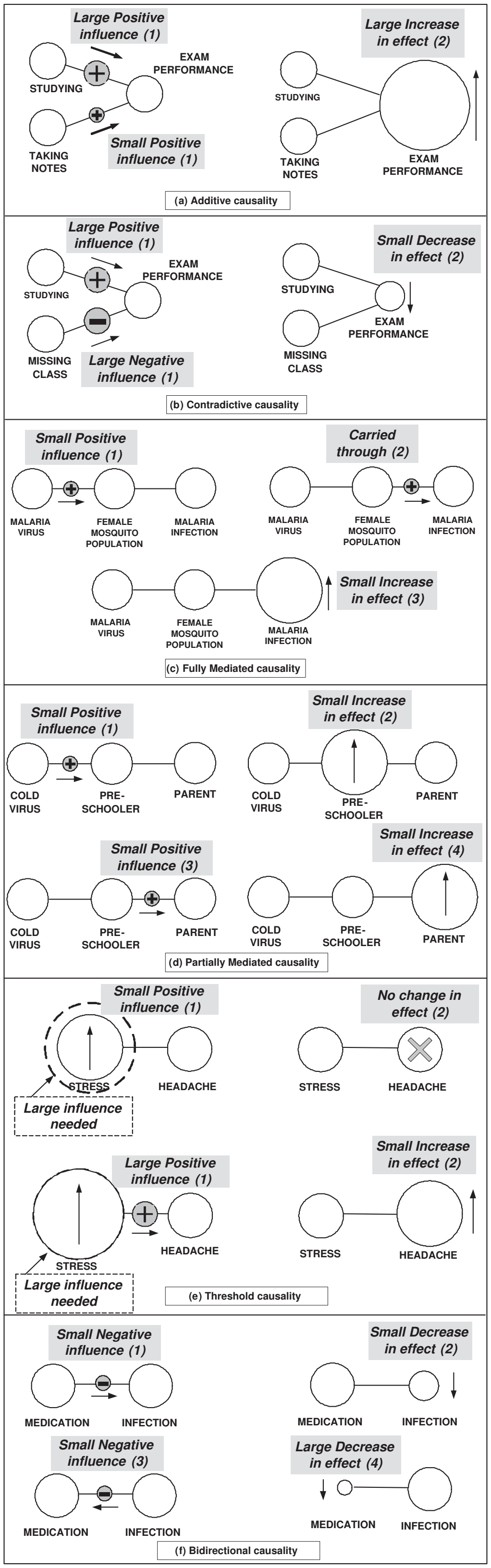

Figure 9: *Animated designs using causal graphs, nodes, connecting lines, animated bullets, and target transformations. Numbers denote the order of occurrence of the causal event. Arrows were not displayed during the experiment.*

Additive causality In additive causality all influences are of the same type and "add up" to produce the final effect. For example, in Figure 8(a) and Figure 9(a), Studying and Taking Notes both have a positive influence on Exam Performance.

Contradictive causality In contradictive causality causal influences can contradict each other and the final outcome will depend upon the strongest influence. In Figure 8(b) and Figure 9(b), Missing Class has a negative influence and contradicts the positive influence of Studying on Exam Performance.

Fully mediated causality Meditated causality introduces the concept of mediators which carry influences from the factors to the targets. In fully mediated causality, the mediator acts only as a carrier and is itself not affected by this causal transfer. In Figure 8(c) and Figure 9(c)), the Malaria virus is carried by the mediator (Female Mosquito Population) to cause Malaria Infection in human beings.

Partially mediated causality In partially mediated causality the mediator becomes an intermediate target as it passes the influence from the factor to the target. In Figure 8(d) and Figure 9(d), Cold Virus affects a Preschooler as he/she transfers the influence to his/her Parent.

Threshold causality Threshold causality allows users to define a minimum value or *threshold* for the factor to have an influence on the target. In Figure 8(e) and Figure 9(e), at least a large amount of Stress is required to cause a Headache.

Bidirectional causality Bidirectional causality describes a dual-state relationship between the factor and target, where the factor and target exchange roles after the first pass. In Figure 8(f) and Figure 9(f), Medication reduces Infection and in turn as Infection decreases Medication intake is also reduced.

4 Experiment: Comparing static and animated representations of complex causal semantics

Our causal designs were based on Michotte's spatiotemporal rules that have been effective in perceiving causality. Also, in an effort to conform to Tversky's [2002] *Congruence* and *Apprehension* principles for good visual design, our static and animated representations are simple and show only critical causal information, with minimal redundancy.

The goal of this experiment was to compare the intuitiveness of our static and animated representations in describing complex causal relations. In this study, we endeavor to assess the accuracy and speed at which participants can perceptually extract causal information using our visualizations. The hypotheses for this experiment are as follows:

- **Hypothesis 1:** Participants will perform more accurately when the causal relations are described using animations.
- **Hypothesis 2:** Participants will be able to respond faster when the causal relations are depicted as animations.

4.0.3 Subjects

49 undergraduate psychology students of a local university, between the ages of 20 – 30 years, participated in this experiment. None of the students had any formal training with 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 color blindness.

4.0.4 Materials

The experiment was executed as a .NET program with embedded static and animated Macromedia Flash™ files. Individual copies of the program were executed on a Windows XP computer and displayed on a 17″ Dell monitor with a 1024×768 pixel screen resolution.

4.0.5 Design

The experiment comprised of a 2×6 within subject design. The two independent variables were: Representation Type and Semantic Type.

Representation type

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

- **Static:** In this representation type, the participants were shown a static visualization of the causal semantics with 1 – 2 causal relations. In the case where 2 causal relations were shown, both the relations were shown simultaneously and colors were used to differentiate between the relations. A scenario with 1 causal relation was displayed for 27 seconds, while a scenario with 2 causal relations was displayed for 54 seconds, in order to equalize the viewing times of the two visualizations.
- **Animation:** In this representation type, the participants were shown an animation which also contained 1 – 2 causal relations. Each relation was isolated and shown separately. In addition, the animations were repeated three times to enable comprehension and memorization. Scenarios with 1 causal relation were viewed for 27 seconds (9 seconds/relation $\times$ 3 repetitions) and scenarios with 2 causal relations were viewed for 54 seconds (18 seconds/relation $\times$ 3 repetitions).

Semantic type

At the completion of each trial, the participants were presented with a statement describing one of the six semantics and were asked to determine if this description matched the relation that was visualized.

Through this design, each of the six semantics were labeled and tested in isolation: Additive causality (S1), Contradictive causality (S2), Fully mediated causality (S3), Partially mediated causality (S4), Threshold causality (S5), and Bidirectional causality (S6).

4.0.6 Tasks

Participants were given two tasks per trial:

- **Memorize:** In this task the participants were asked to view a static graph or animated graph for 9 – 18 seconds and memorize the causal relation(s) being depicted.
- **Respond:** In this task the participants were provided with a semantic description, in the form of a statement, and were asked to match it to the relation in the memorization task. For example, after displaying a video on “Book Sales”, we would present the statement, “A LARGE POSITIVE amount of Audience Feedback causes a LARGE INCREASE in Book Sales”. The participant will now have to determine if the influence and effects (quantity and type) matched the information displayed in the visualization (factor and target names were not altered when the statement was presented). Two types of statements were displayed; Correct, where all the components of the statement exactly matched the relation, and Incorrect, where only some of the components of the given statement matched the relation viewed in the memorization task. Participants were required to respond “Yes” (‘B’ key on the keyboard) for a Correct statement or “No” (‘N’ key on the keyboard) for an Incorrect statement, in order to score a point.

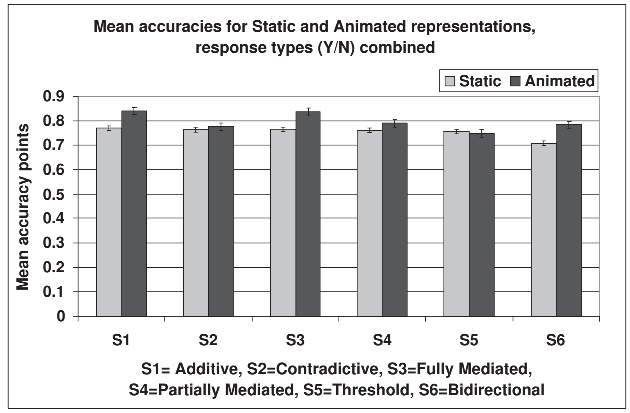

Figure 10: *Mean accuracies for static and animated representations, separated by semantic type.*

4.0.7 Procedure

The experiment was divided into two phases. In the training phase, the participants were asked to run a pilot version of the program until they were comfortable with the experimental tasks. In the experiment phase, the trials in the experiment were divided into 6 sessions. Each session comprised of 24 trials, with 12 trials displaying static graphs and 12 trials displaying animations. At the end of each session, the timers were paused and the participants was allowed to take a break if required.

4.0.8 Results

Accuracy points

Two values were recorded for each answer provided by the participant; accuracy points and response time. These data were then submitted to a $2 \times 6 \times 2$ repeated-measures Analysis of Variance (ANOVA) treating representation type (static vs. animation), semantic type (additive vs. contradictive vs. fully mediated vs. partially mediated vs. threshold vs. bidirectional), and response type (yes vs. no) as within-subject factors. The analysis showed a main effect of representation type $F(1, 48) = 20.339$, $MSe = .025$, $p < 0.001$. A comparison of the means showed that participants were $\sim$5% more accurate when causal relations were represented using animations. The results suggested that participants were able to understand the animations better and were able to make better comparisons with the given statements. The analysis also showed a main effect of semantic type $F(5, 240) = 4.267$, $MSe = .028$, $p < 0.005$ and a comparison of the means showed that participants were least accurate in recognizing bidirectional causality statements (mean accuracy = 0.745). Compared to bidirectional causality, participants were $\sim$1% more accurate in recognizing threshold causality (mean accuracy = 0.752), $\sim$4% more accurate in recognizing contradictive causality (mean accuracy = 0.770) and partially mediated causality (mean accuracy = 0.775), and $\sim$7% more accurate in recognizing additive (mean accuracy = 0.804) and fully mediated causality (mean accuracy = 0.801) statements. In addition, the analysis showed interaction effects between semantic type and response type $F(5, 240) = 2.656$, $MSe = 0.032$, $p < 0.05$, which sug-

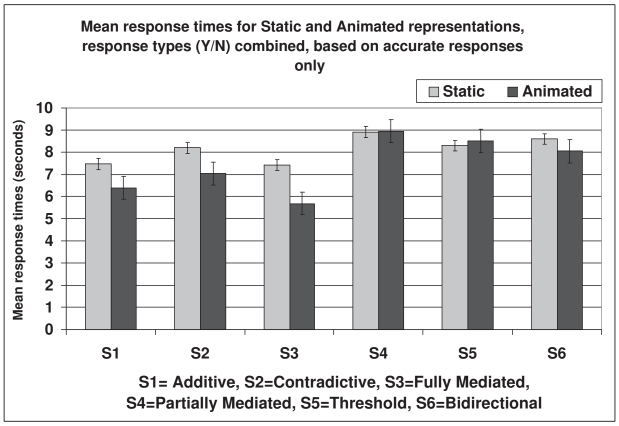

Figure 11: *Mean response times for static and animated representations, separated by semantic type.*

gests that participant performance with a particular semantic was dependent upon whether a correct or an incorrect statement was presented to them.

Response times

An analysis of the response times showed a main effect of representation type $F(1, 43) = 12.118$, $MSe = 9.906$, $p < 0.005$. The basis for this main effect was that participants responded faster when the causal relations were visualized using animations than static representations. Specifically, participants were $\sim$8% faster with animations than static graphs (7.441 seconds vs. 8.115 seconds) as the animations were more intuitive and could be understood faster. The analysis also showed a main effect of semantic type $F(5, 215) = 15.266$, $MSe = 7.705$, $p < 0.001$. The basis for the main effect suggests that participant performance was dependent upon the type of semantic that was displayed. Specifically, participants took the longest to respond to partially mediated causality statements (mean = 8.847 seconds) while, on an average, they were 0.59 seconds ($\sim$6%) faster in responding to threshold causality statements, 0.63 seconds ($\sim$7%) faster in responding to bidirectional causality statements, 1.22 seconds ($\sim$14%) faster in responding to contradictive causality statements, 1.8 seconds ($\sim$20%) faster in responding to additive causality statements, and 2.2 seconds ($\sim$25%) faster in responding to fully mediated causality statements. The analysis also showed a main effect of response type $F(1, 43) = 10.564$, $MSe = 10.500$, $p < 0.005$. Interestingly, a comparison of the means showed that participants were $\sim$8% faster in recognizing a mismatch between the displayed relation and the given statement than in recognizing a match. This suggests that participants were able to comprehend the causal information presented to them and were quickly able to recognize differences between the visualization and given statement. In cases where the relation and statement matched, the participant might have taken longer to double-check and ensure that they were providing a correct response.

The analysis also showed significant interaction between representation type and semantic type $F(5, 215) = 5.495$, $MSe = 4.850$, $p < 0.001$. The results suggest that participants took less time to recognize a match when the semantics were represented using animations, except in the case of partially mediated causality where participants were $\sim$9% faster with the static than the animated representations (9.43 seconds (static) vs. 10.38 seconds (animation)) and with threshold causality statements where participants took the same amount of time with both static and animated representations. The reason animations did not perform better than static when representing partially mediated causality could be attributed to the complexity of the relation, which necessitated replaying before a response could be provided. With threshold causality statements, both representations were equally descriptive and obvious and that is why we deduce that the participants performed equally fast with both representations. With respect to recognizing a mismatch, participants performed with generally better response times when the relations were represented using animations than static graphs, except with threshold and bidirectional causality statements, where they responded slightly faster with static representations. The larger response times for these two semantics could again be related to the time taken to replay the relation in the mind before providing a response. The main analysis also showed significant interaction between semantic type and response type $F(5, 215) = 9.182$, $MSe = 5.159$, $p < 0.001$ which suggests that the time taken to recognize a match between the given statement and displayed relations was dependent upon the semantic being tested. Finally the analysis showed significant interaction between all three variable groups; representation type, semantic type, and response type $F(5, 215) = 2.469$, $MSe = 4.363$, $p < 0.05$, which suggests that participant response times were significantly influenced by the condition (representation type vs. semantic type vs. response type) that was presented.

5 Discussion

The results of our study show that participants were $\sim$5% more accurate and $\sim$8% faster when the causal relations were represented using animations. Also, participants were $\sim$8% faster in recognizing a mismatch between a relation and a statement as they took longer to verify that they were providing the correct answer when they recognized a match. Finally, participant performance depended upon the combination of representation type, semantic type, and response type that was presented during each trial of the experiment. The analysis of our results concurs with both our *Hypothesis 1* and *Hypothesis 2* that animations are more efficient than static-graphs in visualizing complex causal relations. The analysis also shows that as the complexity of the semantics increases, animations are more effective in elucidating the complex causal concepts.

5.1 Comparison to existing techniques

A main advantage of our visual representations is the additional features they provide when compared to existing techniques. Some of these features are listed below:

- Our animated visualizations use animations to effectively depict dynamic information, in contrast to Hasse and Ishikawa diagrams which only show static relationships and do not display changes to the causal connections.
- Our representations have the ability to provide additional information such as type (positive or negative) and amount of influence or effect. VCV's wave metaphor displays some of this information such as amount and type of effect and amount of influence, but it does not show type of influence.
- Our research has defined the various types of causal semantics that are encountered in the universe and categorized them based on the number of agents in the relation and their collective behaviors. Ishikawa, VCV, growing polygons, and growing squares provide some features such as mediated causality and additive causality. However, these features are not explicitly defined and have to be inferred from the visualizations.

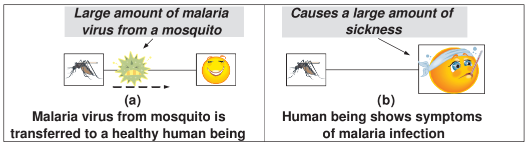

Figure 12: *Our causal graphs can be redrawn using simple glyphs to aid education in students and young children.*

5.2 Applications of our visualizations

A main concern with any research is it applicability in practice and in the area of information science. We have identified and addressed these issues as part of the future work. A major concern in our research is scalability. Our study only focussed on defining the causal semantics and designing simple visualizations using small graphs. However, we recognize the potential issues with our designs as the number of nodes and/or causal relations increase. Therefore, future work will focus on interaction techniques that allow users to isolate and view only parts of the graph at a time. These techniques will also allow users to create what-if scenarios and execute them to discover new results.

Several application areas such as medicine, business, and education will benefit form the usage of our designs. Our designs can be used to visualize patient and environmental data in hospitals that will be useful to doctors in determining medications and to patients for self-monitoring purposes. In small and large businesses our causal graphs can be used for project management, workload division, and timelines. In education, our visualizations can be used in class rooms and will encourage student-teacher interaction. One idea could be to augment our representations with simple glyphs to provide realistic descriptions of causal events, as shown in Figure 12.

In general, causal semantics are applicable to numerous daily activities. Our visualizations are simple but powerful enough to capture some of the complex causal semantics that are encountered in daily life.

6 Conclusion

Our study has focused on the problem of visualizing complex causal information that are observable in the world around us and are fundamental to the decisions we make everyday. Several forms of causal representations have been designed [Ishikawa 1991], and while they describe the occurrence of a causal claim between two objects, they are inadequate in providing additional information about the event, which is crucial when making judgements. Recent causal visualizations have also incorporated the dynamic nature of a causal event through smooth animations [Ware et al. 1999; Elmqvist and Tsigas 2004], however they also do not enable identification of the various forms of causal semantics that are available in the environment. Our study therefore aimed at defining these causal semantics and designing simple visualizations that can be used to identify them.

As part of this study, we defined six complex causal semantics that we encounter in daily life; additive causality, contradictive causality, fully mediated causality, partially mediated causality, threshold causality, and bidirectional causality. We also designed simple static and animated representations to depict these semantics. Our animations were built using perceptual guidelines and spatiotemporal rules [Michotte and Thinés 1963]. We conducted a user-study in order to compare the intuitiveness of our representations and to determine the better type of design. Results of our study favored animations as participant accuracy and response times improved when the causal information was visualized using our animations. The purpose of this study was only to define various form of causal semantics and to determine if perceptual rules can be applied to depict them. In future work we will explore interactive techniques that enable manipulation and discovery of causal relations, and will test the visualizations in applications that have day-to-day relevance.

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