Evaluating Graphical Perception of Visual Motion for Quantitative Data Encoding

Shaghayegh Esmaeili, Samia Kabir, Anthony M. Colas, Rhema P. Linder, and Eric D. Ragan

Abstract—Information visualization uses various types of representations to encode data into graphical formats. Prior work on visualization techniques has evaluated the accuracy of perceived numerical data values from visual data encodings such as graphical position, length, orientation, size, and color. Our work aims to extend the research of graphical perception to the use of motion as data encodings for quantitative values. We present two experiments implementing multiple fundamental aspects of motion such as type, speed, and synchronicity that can be used for numerical value encoding as well as comparing motion to static visual encodings in terms of user perception and accuracy. We studied how well users can assess the differences between several types of motion and static visual encodings and present an updated ranking of accuracy for quantitative judgments. Our results indicate that non-synchronized motion can be interpreted more quickly and more accurately than synchronized motion. Moreover, our ranking of static and motion visual representations shows that motion, especially expansion and translational types, has great potential as a data encoding technique for quantitative value. Finally, we discuss the implications for the use of animation and motion for numerical representations in data visualization.

Index Terms—Information visualization, animation and motion-related techniques, empirical study, graphical perception, evaluation.

1 Introduction

Mapping data values to appropriate corresponding visual representations is a fundamental necessity in making information visualization effective and understandable. For example, when looking at a bar graph, the *length* of the bars is used to represent different values. Other examples of visual encodings include: use of *position* in scatter plots; *color* in heat maps; and use of *angle* and *area* in pie charts. An appropriate choice for visual encoding is important to help users more accurately interpret values, perform comparative tasks more efficiently, or improve success in various other data inspection tasks. Different types of visual representations are perceived and interpreted differently by viewers. Knowledge of *graphical perception* of visual encodings' properties refers to the visual decoding of information encoded on graphs [1] and is essential in allowing visualization designers to effectively communicate data. Prior research has studied the effectiveness and rankings of perceptual accuracy of such encodings through empirical studies [1], [2], [3], [4]. For example, the use of *position* and *length* encodings are known to be highly effective for quantitative values while supporting high accuracy in human interpretation, whereas some forms of visual representations (e.g., *color*, *texture*, *volume*) have limitations for enabling accurate human judgement of numerical values.

Our research seeks to advance the foundational knowledge of graphical perception of visual representations through research of the use of motion for data encodings. While motion and animation are commonly employed in digital visualizations for transitions in information visualization (e.g., [5], [6], [7], [8], [9]), representing movement in maps and scientific visualization (e.g., [10], [11], [12]), and to show temporal change (e.g., [13], [14], [15]), empirical research of motion representing numerical values is limited in visualization literature. Yet several qualities of motion perception could prove advantageous for data encoding and potentially broaden the design space for visualization. For instance, human vision is adept in quickly detecting movement and can also distinguish different types, patterns, and states of motion [16]. Perceptually, motion can also quickly grab viewers' attention [17]. People have a stronger ability to perceive motion in their lateral view than any other graphical elements [16], which could lead to benefits in large control-panel visualizations or peripheral displays. While prior research has explored the utility of different motions to represent categories or groups [17], [18], the addition of novel research of human judgment of motion encodings for numerical data can enable new design options for a wide range of visualization applications.

In this work, we investigate the graphical perception of quantitative data encoding using motion. The primary goal of this paper is to answer the following research questions:

- How do different types and attributes of motion encoding for quantitative data affect accuracy of human graphical perception?
- How do different types of motion visualization compare to conventional static encodings in terms of graphical perception accuracy?

To address our research questions, we conducted two controlled experiments to measure user graphical perception accuracy of different motion encodings of numerical data. The first experiment tested the perception accuracy of different variations of motion encoding in terms of type, speed, and synchronicity. We then used the findings from

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experiment 1 to refine our different motion encodings techniques for further study in a second experiment. In experiment 2, we compare a refined set of motion encodings to static encoding methods. We present the results with ranking of accuracy for the graphical perception of quantitative values to account for both static and motion encodings.

The results are promising for the use of motion for numerical visualization, and the contributed empirical knowledge from our studies can translate to important implications for visualization design. Prior work has only focused on investigating visual motion for animated transitions, categorical value encoding, and representing movements. However, our work contributes to the foundational knowledge of graphical perception of visual representations by providing a thorough empirical study investigating the role of dynamic visual channels for quantitative data encoding compared to traditional static visual channels.

2 Related Work

Our research of motion for data encoding is related to existing research in graphical perception and the use of animations in visualization.

2.1 Graphical Perception of Data Encodings

The study of perceptual judgments of different visual representations of data values is foundational to information visualization. Numerous studies have directly evaluated the accuracy of judgments (sometimes called *graphical perception*) of quantitative encodings. Perhaps the best known of such studies, Cleveland and McGill [1], compared primary graphical encodings such as position, length, direction, angle, and color to provide a ranking in terms of perceptual accuracy for distinguishing differences. Their findings show that graphical perception of numerical values encoded by position and lengths are highly accurate, whereas the values that texture or shading represent are less accurate in terms of graphical perception. More recently, Heer and Bostock [4] recreated McGill and Cleveland's work by incorporating crowdsourcing into their perception test methodology. They included new graphical components in their study but ultimately arrived at a similar ranking as Cleveland and McGill [1]. In a related study, Saket et al. [19] also evaluated perceptual tasks with visual encodings of numerical values, but they focused on interactive visualizations allowing manual adjustment of visual representations. In their study, instead of asking participants to detect the difference between encoded values, they asked their users to change different graphical components to match a target value. Taking a different approach, Chung et al. [20] assessed Bertin's retinal variables in terms of perceptual orderability, i.e., how well different visual encodings can support the interpretation of numerical order. Similar to Heer and Bostock's work [4], Chung et al. incorporated crowdsourcing into their studies and provided findings on which variables are orderable and how they affect the performance of min and max judgments.

Our work also evaluates perceptual judgments but focuses on motion as a visual encoding for data. Ultimately, it would be valuable to consider how motion compares to other encodings for numerical judgments. However, many different variations of motion are possible for data representation. Thus, our work provides foundational studies about different types of motion encodings for quantitative values.

2.2 Motion in Visualization

Prior research has incorporated motion into visualizations for a variety of different purposes. Motion and animation are commonly employed in digital visualizations for transitions in information visualization (e.g., [5], [6], [7], [8], [9], [21]), representing movement in maps and scientific visualization (e.g., [10], [11], [12]), and to show temporal change (e.g., [13], [14], [15]). In a broad sense, animation covers a variety of ways for showing visual change over time, and different visualizations have incorporated different types of animations and motions. Motion is becoming more popular in mainstream online publications, charts, maps, and applications [22]. The New York Times, for example, published an interactive motion graph that depicts income mobility [23]. In another instance, Bartram and Ware investigated the salient features of motion that can be used meaningfully in animation and video creation [24]. They explored different motion features and identified features that can express particular emotions.

Focusing on perceptual capabilities and attention to motion, Bartram et al. [18] incorporated motion in graphs for grouping and filtering in visual searches. They explored several pre-attentive features of motion to discover how it might be used for visual search. They incorporated perceptual tests of motion encodings. In particular, they tested angular differences and direction.

Huber and Healey also used motion to encode categorical data in visualizations [17]. Their work explored three perceptual dimensions of motion: flicker, direction, and velocity. They suggest minimum values that are required to distinguish between different values of motion properties. We draw our design of motion encoding development from their guidelines. Their work showed that, like color and texture, motion could be used to encode categorical data representation. They recommended these features could replace color and size for categorical data representation. Also, similar to our work, their study considered whether flickering animations were synchronized coherently such that cycles started together, and they found synchronized flicker to be more quickly and easily distinguishable than asynchronous animation.

Bartram and Ware [18] discuss the advantages of using motion for encoding categorical data and clusters of related data. They showed even small coherent motions could highlight and establish a perceptual grouping between otherwise dissimilar visual objects. Therefore, they suggest that motion properties can be used for pre-attentive search and filtering groups of data, specifically focusing on motion as a perceptually efficient display dimension and its grouping effect. Similar to our presented study, this work has studied different types of motion, such as translational motion and size changes. However, previous studies focus on categorical data rather than quantitative data encodings.

In the pre-attentive process of acquiring an overview from visualizations, we take advantage of detectable features of graphical components (such as grouping and color coding) [25]. Thus, when using motion for any pre-attentive processing, prior research has focused on investigating parameters and types of motion which can be distinguished with little conscious effort [26].

Animation can also be used in graphs or visualization to make it more purposeful or attractive. For instance, Archambault et al. [27] developed animation in dynamic graphs to help create mind maps more successfully. In a recent work, Romat et al. [28] studied different types of animation in the edges of node-link diagrams to show relationships between nodes. This work considered different patterns, frequencies, and speeds in animated edge textures used in the connecting lines in network graphs to show distinct categories of links.

Motion has been incorporated into different visualizations to aid search and processing. Nakayama and Silverman [29] used motion for the experimentation of serial and parallel conjunctive search (i.e., when looking for an object with two or more relevant features which may not be distinct [30]) in visual displays. In their visual search experiments, they have used multiple color television monitors to see how the human visual system can search via serial or parallel processing on conjunctive dimensions. They used motion as a stimulus dimension of display systems along with other dimensions such as color. Their findings showed how serial processing is better for the conjunctive search since, compared to a simple search, participants were unable to perform a parallel search for the anomalous motion over a given color, and their reaction time was also significantly higher. Motion has also been used to facilitate search techniques in visual queries [31]. They showed that spatial grouping among stimuli in a visual search dramatically affects search time performance. They show that motion may not be a unitary dimension and also provided evidence for separate processing of speed and the direction in stimuli.

Taking a different approach, Kerlic [32] used independent moving objects to depict large multidimensional data. His "boids" implemented animated geometric objects of different shapes and interactive views for further investigation. Instead of encoding every dimension of data points, he showed that we can save rendering time and simplify the visualization by visualizing only essential features. Van [33] used motion to visualize multiple features, such as speed and direction of flow patterns in fluid dynamics. Fluid dynamics have a more direct metaphor for representing animation. Our research looks at how abstract scalar values can be encoded via motion.

Etemadpour and Forbes investigated different types of motion to identify clusters in multidimensional data [34]. They investigated the minimum difference in terms of speed that is perceivable by participants. They found that more similar movements were more difficult for participants to distinguish. In another example, Chen et al. [35] demonstrated flickering animation to represent point overdraw in scatter plots in multi-class matrix views. In their work, more flickering in a region of a scatter plot could be perceived as point density, but their work did not explore the encoding of quantitative values.

As another interesting use of motion in visual interfaces, Velloso et al. [36] studied interaction techniques that allow users to simulate motion for target selection in an interactive way. While not directly related to numerical data encoding, this work relates to the human ability to categorically distinguish and produce distinct types of motions.

Overall, previous research has successfully demonstrated the use of motion to signify different properties in visual systems. The ability to use motion to represent categorical information is fairly well established, although specific empirical studies and guidelines on effectively using motion encodings are still limited. To our knowledge, markedly little work has directly evaluated the use of motion for quantitative scalar values. Our research examines motion encoding for quantitative data using different variations of motion attributes, such as type, speed, synchronicity, and how accurate these encodings are regarding graphical perception. Our work provides empirical data to ground future research of using motion for numerical encoding in information visualization.

3 Experiment 1: Different Types of Motion

This paper presents two controlled experiments to study graphical perception of motion encodings for quantitative data. First, experiment 1 evaluates the feasibility of different types of motions for data encoding through an experiment studying variations of motion encodings in terms of the type of motion, speed, and synchronicity. The primary purpose of this experiment is to investigate considerations for the use of motion encodings for scalar values regarding different motion properties. The results of this experiment provide preliminary insights about encoding quantitative data with motion, and establish a basis for refining speed and synchronization of different motion encodings to compare with static ones in experiment 2.

3.1 Goals

Previous research has established the encoding of quantitative data values into graph using different static elements (e.g., length of bars in bar charts, position of points in scatter plots, and area or angle in pie charts.) In this experiment, we aim to explore the encoding of numerical values using different motion parameters and investigate how successful people are in precisely perceiving the numerical differences. Therefore, as the first step, we aim to study various data encoding visualization designs comparing different motion properties. The results of this experiment would give us a better understanding on which of the motion parameters and values are more suitable for encoding quantitative values.

3.2 Motion Variations

To answer our first research question, it is important to test different motion parameters in a controlled experiment to better understand what forms of motion might work best to represent quantitative values. We decided to explore data encoding using three major features of motion: motion type, speed, and synchronization. In the following paragraphs, we discuss each one of these features in more detail.

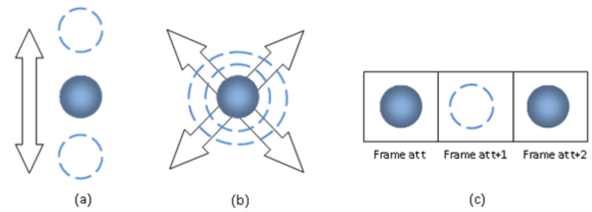


Fig. 1. Motion types: (a) vertical motion (b) expansion motion (c) flickering motion. Arrows show the movement direction.

3.2.1 Motion Type

For the purposes of our experiment, we use the term *motion type* to describe how visual objects change position, shape, or appearances over time. We decided to study three basic types of motions to cover a range of glyph animations: *vertical linear* motion, *flickering* motion, and *expansion* motion, where objects expand and contract. These motion types are of high importance as established in prior works to be useful for data encoding [17], [37]. These motion types are illustrated in Figure 1.

In the *vertical* linear motion, a glyph (in a shape of a circle) oscillates up and down vertically along a straight line with a speed associated with the encoded value. We chose this motion type to represent animations involving translational movement of visual objects in the screen space. For *flickering* motions, the object flicker (i.e., disappear and reappear) at regular intervals based on the given speed. This type of motion was chosen to represent animations where visual objects remain at the same location and do not change in size. In *expansion* motion, the visual object animates to change size with a particular speed. Objects continuously expand to a larger size and then compress back to a smaller size in subsequent intervals. This type of motion was chosen to represent animations where location is constant; however, they change in size. We included these three motion types in the first experiment to examine their influence on the perceived accuracy of numerical values.

3.2.2 Motion Speed

The speed of a moving object can be measured in different ways [38]. Examples of different methods for measuring motion include: frequency (i.e., cycles per second), cycle time (i.e., time for a single cycle), or movement rate (i.e., distance per second.) For our purposes of comparing different types of motion, we use cycles per second (f in Hertz) and cycle time (T in seconds) to quantify animation speed. Cycle time T is inversely proportional to the cycles per second ($f = \frac{1}{T}$), i.e., as frequency increases, cycle time shortens.

We designed the study to test a range of motion speeds. Based on perceptual research suggesting it can take between $f = 0.2$ and 0.3 Hertz at the minimum to detect velocity changes [39], [40], we decided on $f = 0.2$ Hz as the minimum bound for speed in our study. The maximum speed of $f = 3$ Hz was chosen based on our informal testing to avoid extreme speeds that may not be reasonable to distinguish, but also cover a sufficient range of speed that might be used in different applications (we note that, for digital presentations, perceptual thresholds may depend on a display's update capabilities, and formalizing the bounds of motion detection is outside the scope of our presented research).

TABLE 1
Ratio values in experiment 1. The first column, *Ratio*, is the scalar value encoded by the ratio of the third and second column.

Ratio	Circle 1 Speed (Cycles per Second)	Circle 2 Speed (Cycle per Second)
1.125	1.6	1.8
1.786	1.4	2.5
1.8	0.2	0.36
3 (pair 1)	0.2	0.6
3 (pair 2)	1.0	3.0
5	0.4	2.0
7	0.4	2.8
10	0.3	3.0
12.5	0.2	2.5
15	0.2	3.0

We decided to use two moving circles with different speed values in our experiment with the goal of measuring human perception of the numerical speed difference of the second circle compared to the first one. This decision was inspired by the prior studies in the graphical perception of static data encodings, such as Cleveland and McGill's [1], but translated it for investigating dynamic data encodings with motion. Participants were asked to quantify the ratio of the speed difference between the two moving circles. For the task in our study design, we used relative comparisons of motions, where each value of ratio can be encoded with two objects moving with different speed values. Larger ratios would display one circle moving faster than another one. On the other hand, if the numerical value of the ratio is small, circles would move with speed values close to each other.

To explore the effect of different ratios on the perceived accuracy, we decided to test a large range for ratio values considering the minimum and maximum speed bound. To test the possible ratios with different motion encodings, we first started at 0.2 Hz and 3 Hz for the speed of circle 1 and 2, respectively, to have the highest ratio (i.e., 15), and continued decreasing that for the rest of the ratios. Due to the practical limitations regarding the study duration, it was not feasible to test for all possible values of ratios between 1 and 15 (including both whole number and decimal point values). Therefore, we decided to pick ten different ratio values considering that they: (a) cover the entire chosen range, (b) consist of both whole number and decimal point values for ratio, and (c) cover the values of speed in the minimum and maximum speed bound (i.e., between 0.2 and 3 Hz). Table 1 shows the ratios used in experiment 1. The encoded ratio with value of 3 has two pairs. In this case, we included both a fast-speed value pair and a slow-speed value pair.

3.2.3 Synchronization

For a given motion type, synchronization can also be modified and affect the graphical perception of encoded values. In our study, synchronization refers to whether the movement of two or more things happens at the same *time* or *rate* whilst each moving object would have a different speed value. In the context of our experiment, we defined the absence of synchronicity when one of the moving objects is continuously moving without any interruption and dependence to the other object. It is important to investigate how users would respond to the presence and absence of any synchronization between the movements of two objects.

Two moving objects can be synchronized both in terms of time or number of cycles. For the time-based synchronization, given the same time period, all objects will complete different numbers of cycles depending on how fast or slow they are. In the later version of synchronization (i.e., number of cycles), all objects complete a given number of cycles in different periods depending on their speeds. We conducted a pilot study to test both synchronization methods. All pilot study participants found the time-based synchronization very confusing as the circles can stop suddenly in the middle of completing a cycle. One way to reduce this issue is to use only whole numbers for data encoding. However, it would cause a constraint on the overall criteria of quantitative encoding. Therefore, we decided to implement synchronization based on a given number of cycles. On the other hand, for non-synchronized motion, the objects will move continuously without any interruptions. We hypothesized that aligned cycles would support easier comparison since the time it takes for the two circles to align could be an indicator of quantifying the speed difference.

3.3 Experimental Design

Experiment 1 followed a within-subjects design, and each participant completed all conditions using our web-based application. Our goal was to investigate which motion encoding scheme could prompt participants to provide the most accurate estimate of the underlying scalar value. We had three independent variables:

- Motion type with 3 levels (flicker, vertical, and expansion).
- Synchronization with 2 levels (synchronized, not-synchronized).
- Ratio (ratio between values of encoded pairs) with 10 levels: 1.125, 1.786, 1.8, 3 (pair: 0.2 and 0.6), 3 (pair: 1 and 3), 5, 7, 10, 12.5, 15.

In total, each participant completed 60 trials (3 types of motion $\times$ 10 ratios $\times$ 2 sessions for the presence or absence of synchronization). We counterbalanced the order of synchronization sessions across all participants, and the ordering of the trials within these sessions was randomized for each participant.

3.4 Study Task and Measures

The study had participants complete a series of perceptual judgments testing various configurations of motion encodings. In each trial, participants would look at a specific type of motion visualization, including two circles with different speeds. Their task was to estimate the difference between the speed of paired motion encoded numbers by answering a question in the form of: “How many times faster is circle 2 compared to circle 1?”.

We decided to use a slider control in our study application for selecting the response value since providing dynamic feedback on the slider handle, especially in the tasks that require precision, would reduce over or underestimation bias [41]. Additionally, the slider length was decided to be almost three times longer than needed to prevent any bias or steering toward specific values during the selection period.

This task provided us a baseline to investigate the perceptual error given different configurations of motion encodings. We logged participant’s answers (their perception of the scalar difference between circles) and the response time (from the time they see a new trial to the time they hit the submit button) to further evaluate the precision of users’ perception.

3.5 Procedure

The study was approved by our associated Institutional Review Board (IRB). Participation was voluntary, and extra credit was offered as compensation for approved courses. We conducted the study as a laboratory study, with all participants completing the study using the same computer labs. All participants completed the study on computers with 23-inch monitors and 1440×900 resolution. After completing the consent process, participants were randomly assigned to a group dictating the order of synchronized or non-synchronized trials. Afterward, participants were instructed by the experimenter about the study structure, their tasks, and the application environment. Then, they performed three sessions with optional breaks of 3-5 minutes between each.

The first session was a practice session for participants to get familiar with the application and graphs; no data was analyzed from the practice session. We collected data for the second and third sessions, where participants only viewed non-synchronized motion trials in one session; in the other session, all trials were synchronized. The participant could proceed to the next trial only after finishing the current trial. After completing all trials, participants were asked to fill out a brief online questionnaire including demographic and interview questions about their opinion and experience during the study. Each participant took approximately 30 minutes to complete the study.

3.6 Participants

Experiment 1 was completed by 92 participants. All were university students aged between 19 and 54 years (median: 21 years), with 68 who identified as male and 24 as female. In terms of experience with visualization, 80 reported having frequent or regular experience with data graphs, charts, and information visualization. The other 12 participants reported a minimal level of experience with information visualization.

4 Experiment 1 Results

This section describes the analysis and results from experiment 1. We measured both: 1. the error rate (as a percentage) of perceived accuracy, and 2. response time for each trial. We calculated the error rate as:

$$\text{Error rate } = \frac{|\text{judged ratio } - \text{true ratio}|}{\text{true ratio}} \times 100 \quad (1)$$

The participant’s answer (i.e., judged ratio) would indicate their judgment of the difference ratio between speed of two circles in each trial. Response time was the logged time in seconds, i.e., from the time the participant was shown each trial to the time they submitted their answer. In total, we started our data analysis with 5520 data points (92 participants × 60 trials) for both dependent variables: error rate and response time.

4.1 Data Analysis: Error Rate and Response Time

To address our research questions, we needed to test how different parameters of motion affected the response time and accuracy of the perceived difference between graphs.

To analyze the differences between the various motion encodings, we used a data analysis approach similar to previous studies of graphical perception [1], [4] to establish a foundation on how accurately people perceive encoded quantitative data in regards to different parameters of motion. Similar to as done by Cleveland & McGill [1], we apply a log transformation (log_2) to account for inflated measures for judgements of larger value differences.

Before hypothesis testing, we performed outlier handling based on the 1.5×IQR rule, where a data point is considered an outlier if it was more than 1.5 times the interquartile range beyond the first or third quartiles. We applied outlier removal on our log-transformed data for each combination of independent variables separately, i.e., based on each motion type and whether they are synchronized or not. Overall, we excluded 0.44% of collected data for error rate and 5.60% for response times. We further investigated outliers for any possible issues related to specific participants or conditions, but we did not find any patterns in the distribution of outliers. We completed the rest of the data analysis steps with log-transformed data, excluding the outliers.

We analyzed error and response times using two-way repeated-measures factorial ANOVAs to test for effects of the different motion types and synchronicity variations. When checking assumptions for parametric testing of both log error rate and response time,the normality assumption was met, but we found sphericity assumption was an issue for some metrics; in such cases, we report the test results with Greenhouse-Geisser (GG) correction. ANOVA test effect sizes are provided by generalized eta-squared (η^2_G). Reported tests use a significance level of $\alpha = 0.05$.

4.2 Results: Error Rate and Response Time

In this section, we present the results of the statistical tests on error rate and response time.

4.2.1 Error Rate

Figure 2 shows the error rate results across all conditions. The ANOVA test found a significant main effect of type with $F(1.78, 80.99) = 18.41, p < 0.001$ with GG estimate of $\epsilon < 0.89$ and $\eta^2_G = 0.03$. A Bonferroni-corrected posthoc analysis found the *vertical* motion type to have significantly lower error than *flicker* ($p < 0.001$) as well as *expansion* ($p < 0.01$). It also showed a significant difference between *expansion* and *flicker* ($p < 0.01$). Overall, *vertical* had the highest accuracy (i.e, least error), and *flicker* had the least accuracy.

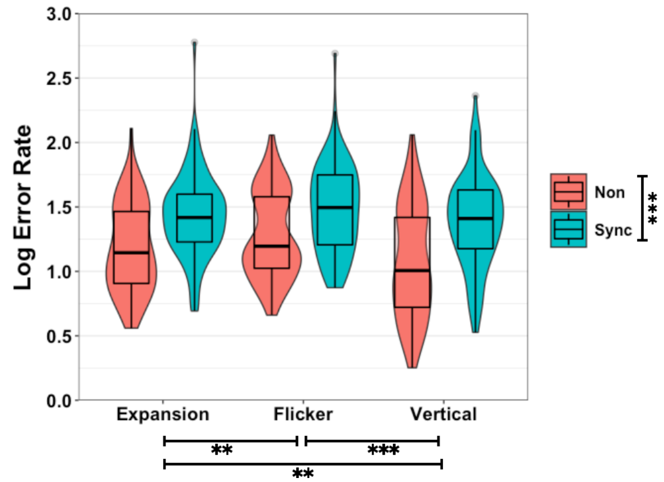


Fig. 2. Average log error rate for different variations of the motion encodings from Experiment 1. Statistical significance at $p < 0.01$ and $p < 0.001$ are denoted by (**) and (***), respectively.

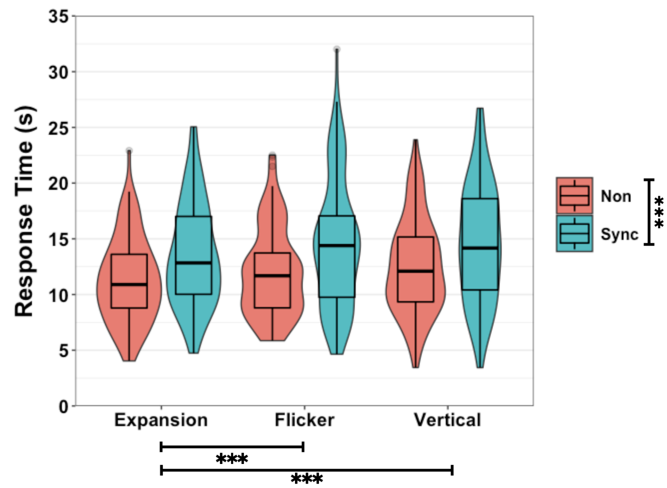


Fig. 3. Average response time for different variations of the motion encodings from Experiment 1. Statistical significance at $p < 0.001$ is denoted by (***).

Additionally, the ANOVA test found a significant main effect of synchronization on log error rate with $F(1, 91) = 81, 36, p < 0.001$. Error was significantly lower for non-synchronized motion compared to synchronized motions.

We also detected a significant interaction effect between synchronization and motion type with $F(2, 182) = 3.12, p < 0.001$. Figure 4 shows the interaction plot of motion type and synchronicity. This interaction effect indicates that the *differences* among the types of motion are greater for the nonsynchronous motion design than for the synchronous version.

4.2.2 Response Time

Figure 3 shows the response time results across all conditions. The ANOVA test found a significant main effect of motion type on response time with $F(2, 182) = 12.99, p < 0.001$. A Bonferroni-corrected posthoc analysis found the *Expansion* motion type to have significantly lower response

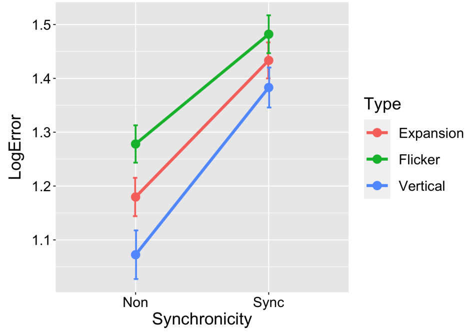


Fig. 4. Interaction plot displaying fitted values of the dependent variable (error rate) on the y-axis while the x-axis shows the values of the first independent variable (motion type). The lines represent values of the second independent variable (synchronicity) with a significant interaction effect seen by the different line slopes. Error bars represent standard error.

time than both *Vertical* motion ($p < 0.001$) and *flicker* ($p < 0.001$).

The ANOVA test also found a significant main effect of synchronization with $F(1, 91) = 26.47$ and $p < 0.001$. Response time was significantly lower for non-synchronized motion compared to synchronized motions.

No interaction effect was detected between synchronization and motion type on response time.

5 Experiment 2: Comparison of Static and Motion Graphical Encodings

Continuing the work from experiment 1, we conducted a within-subjects user study comparing motion encodings with static data encodings. We designed our second study of motion encodings based on the results of experiment 1. This section presents the goals, experimental design, and detailed explanation of experiment 2.

5.1 Goals

In this experiment, we aim to compare different types of motion encoding to static encodings, and investigate how motion encodings would rank similar to the Cleveland & McGill's ranking of graphical perception accuracy of static data encodings [1].

To address our second research question, we evaluated different visualizations encodings by conducting a controlled experiment including quantitative evaluation methods. For our experimental study, we created a web-based application (similar to experiment 1) to test user perception of different visualizations. Our goal was to investigate which visualization encoding could prompt participants to provide the most accurate estimate of the underlying scalar value and rank motion encodings compared to the other conventional visualization methods. In this experiment, the participant's task was to estimate the difference between two quantitative encoded values shown with various types of encodings. This task provided us with a baseline to investigate the perceptual accuracy given different configurations of motion encoding compared to conventional static visualizations.

5.2 Experimental Design

Our controlled study followed a within-subject design, and each participant completed all the trials for different visualization using our web-based application. The application consists of a series of perceptual judgments testing various configurations of encoding.

We had two independent variables:

- Visualization Type with 9 levels: length, position, color, angle, area, vertical (motion), expansion (motion), flicker (motion), and vibration (motion)
- Ratio (ratio between values of encoded pairs) with 6 levels: 1.5, 2, 2.5, 3, 3.5, 4

We decided on the different static visualizations types similar to the encodings in Cleveland and McGill's study [1]. We restricted ourselves to the static encodings of *length*, *position*, *angle*, *area*, and *color* due to the study duration limitation. However, we made sure to cover the complete ranking of static encodings. We chose *length* and *position* since they are the highest-ranked by Cleveland & McGill and *color* since it was one of the lowest-ranked. *Area* and *angle* serve as two midpoints. *Expansion* can also be seen as an extension of the *area* encoding, i.e., a natural augmentation of area changing at different speeds over time; hence, examining the static area encoding would prove to be useful. For the motion encodings, we used similar motion encodings as experiment 1: *vertical motion*, *flicker*, and *expansion*. We also added *vibration* as a proxy for sinusoidal motion as mentioned in Ware et al.'s work [42].

To decide on the ratios between the encoded values of two graphs, we used ratio values similar to those from the study performed by Saket et al. [19]. In their study, the target value was either 25%, 50%, 75%, 125%, 150%, 175%, 200% of the original value. However, in our study, we always made the second visualization (on the right-hand side) larger than the left. Therefore, we changed our ratios to 1.5, 2, 2.5, 3, 3.5, 4, while still matching those ratios used in Saket et al.'s study [19]. Figure 5 shows our visualization design for different types of encodings.

In total, each participant completed 108 trials: 9 visualizations $\times$ 6 ratios $\times$ 2 repeats. The ordering of these trials were randomized for each participant to avoid an order bias in the data analysis.

5.3 Study Task and Measures

In each trial, a participant would look at a specific type of visualization with two graphs that have encoded two pairs of values with a particular ratio. The participant's task was to answer a question in the form of: "How many times [farther/larger/faster/darker] is the [position/area/speed/color] of [circle/bar/angle] 2 compared to [circle/bar/angle] 1?". The exact wording of the question in our application depended on the specific condition and visual encoding.

For each trial, we logged participant answers for the scalar difference between graphs and the response time to use as measures for our data analysis.

5.4 Procedure

The study was approved by our associated Institutional Review Board (IRB). Participation was voluntary, and extra

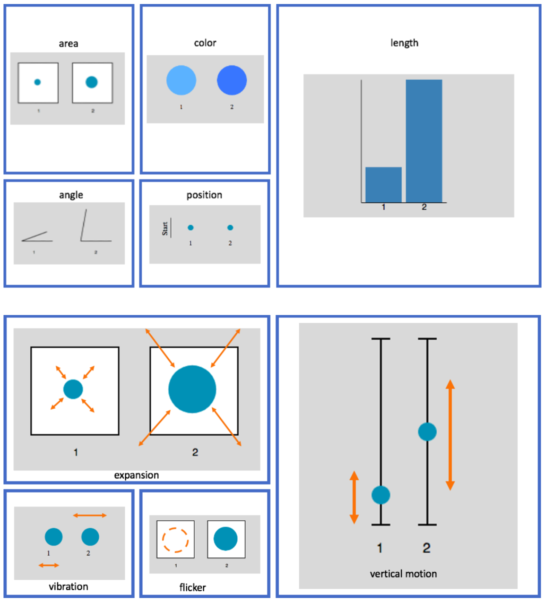


Fig. 5. Encoding types: static (up) and motion (bottom). The arrows show the direction of movement, and the length of the arrows indicate the speed of movement, i.e., longer arrows show faster motion. See supplementary materials for more clear visualizations design, especially for motion-related ones.

credit was offered as compensation for approved courses. Initially, we had plans to conduct the study as a laboratory study with participants completing the procedure using one lab computer. However, due to the COVID-19 pandemic, we had to adjust our procedure to an online format. The study was administered as a "live" monitored online study with a custom web application. We developed the study application with HTML, CSS, JavaScript, and the D3.js library [43]. All studies were conducted through synchronous Zoom sessions where participants received the user study link and shared their screen with the experimenter for observation purposes. After obtaining the informed consent, participants were instructed by the experimenter about the study structure, their tasks, and the application environment. Afterward, the participant performed the study in three parts with optional breaks of 1 to 2 minutes.

The first part was a practice round for participants to get familiar with the web-based application, and the task; no data was logged during the practice session. During the practice, each participant completed one random static trial and one random motion trial. The purpose of the practice round was to help explain the task and make sure the participant understood the types of comparison. In the second part, each participant performed 108 randomly assigned trials of perceptual tasks. The participant could proceed to the subsequent trial only after finishing the current trial. In the third part, participants would fill out a brief online questionnaire including background (such as demographic, education, data visualization expertise) and free-response questions about their opinions and experience during the study. Each participant took approximately 30 minutes to complete the study.

5.5 Participants

In Experiment 2, we had 41 participants of different occupations, such as graduate and undergrad students, software, and mechanical engineer. Sixteen participants self-reported as female, and 25 reported as males. Ages ranged from 20 to 40 years, with a median age of 27 years. When asked to rate their experience with information visualization, 68.30% of the participants rated themselves 3 and 4 (*Average* and *Advanced*, respectively) on a 1–5 scale. There was no report of colorblindness.

6 Experiment 2 Results

In this section, we first describe the methods used to analyze the collected data from experiment 2. We then provide an overview of our results. More detailed quantitative results have been listed in Figure 6.

We collected data from 41 participants where each participant had 108 trials (6 ratios $\times$ 9 encoding types $\times$ 2 trials each.) We measured both: 1. the error rate (as a percentage) of perceived accuracy, and 2. response time for each trial. We calculated the error rate similar to experiment 1 (see equation 1). In total, we started our data analysis with 4428 data points (41 participants $\times$ 108 trials) for both dependent variables: error rate and response time.

6.1 Data Analysis: Error Rate and Response Time

We tested how different types of encodings affected response time and accuracy of the perceived difference between graphs and where motion-related encodings stand compared to other static encodings. Therefore, we used the same data analysis approach as Experiment 1 (see section 4.1), but to compare motion to conventional static methods. We removed outliers based on the 1.5$\times$IQR rule for each encoding type separately. Overall, we excluded 1.13% of collected data for error rate and 3.86% for response times. By further investigating the outliers, we did not find any patterns or issues in the distribution of outliers.

To investigate whether there are any statistically significant differences between the nine independent encoding types regarding error rate and response time, we conducted a one-way repeated-measures ANOVA. Before testing, we checked that both log error rate and response time data met the assumptions of the one-way ANOVA test. The normality assumption was met for parametric testing, but Mauchly's Test of Sphericity indicated that the assumption of sphericity had been violated for both log error rate and response time. To address this issue, we report test results with corrected degrees of freedom using Greenhouse-Geisser (GG) estimates ($\epsilon < 0.73$ for error rate and $\epsilon < 0.68$ for response time). ANOVA test effect sizes are provided by generalized eta-squared (η^2_G), and reported tests use a significance level of $\alpha = 0.05$.

6.2 Results: Error Rate and Response Time

In this section, we present the results of the statistical tests on error rate and response time. We found a significant main effect of encoding type for both error rate and response time. We followed with Bonferroni-corrected posthoc comparisons to identify specific encoding types with significant differences. Figure 6 shows the detailed results of our statistical tests for both error rate and response time.

6.2.1 Error Rate or Accuracy

Figure 6a shows average error rate by different encoding types. Our results indicate that *length* has the lowest and *vibration* has the highest error rate across all encoding types. In motion-related encoding types, *expansion* has the lowest, and *vibration* has the highest error rate. For static encoding types, *length* has the highest accuracy, and *color* has the least. Accuracy of *position* and *length* is significantly better than all other encoding types, which is consistent with the results from Cleveland & McGill [1]. Pairwise comparison did not detect any significant differences between *expansion*, *angle*, *flicker*, and *vertical motion*, which can be interpreted as a group of encoding types with similar accuracy. We also detected no significant differences between *area* and *color*. The last encoding type in our accuracy ranking is *vibration* which is significantly less accurate than all other encodings. *Vibration* being error-prone could be caused by the intrinsic higher frequency (compared to a vertical motion), since participants reported eye strain which made it more difficult for them to judge the difference of speed.

6.2.2 Response Time

Figure 6c shows average response time by different encoding types. Our results indicate that *color* has the fastest and *expansion* has the slowest response time across all encoding types. For static encodings, *color* has the fastest response time, and *area* has the least. Additionally, we compared our response time results to similar static encoding types in Saket et al. study [19]. Our response time results for *length*, *position*, and *area* are consistent with their study in regards to their rankings (fast to slow); however, our results show faster response times for *color* and *angle*. This inconsistency might be due to the difference in study design approaches since interactivity was an essential factor in their encodings design. On the other hand, the fast response time of *color* encoding is consistent with similar empirical studies of graphical perception done by Nowell et al. [44] and Cleveland and McGill's [1]. In motion-related encoding types, *vibration* has the fastest, and *expansion* has the slowest response time. These results indicate that participants spent less time on *vibration* encodings, but they have the least accuracy in regarding visual perception. On the other hand, participants have spent the longest time on *expansion*, which has the highest accuracy among motion encodings.

Based on our statistical test results, we ranked encoding types based on both accuracy and response time. Table 2 shows our ranking as well as Cleveland and McGill's ranking of accuracy. Our ranking of static encodings in regards to accuracy is highly consistent with Cleveland and McGill's. Considering both static and motion encodings, *position*, *length*, and *expansion* are among the best, and *area*, *color*, and *vibration* are the worst in terms of accuracy. However, our ranking in regards to response time is different from accuracy. Overall, static encoding has a faster response time compared to motion encodings. To some extent, we expected this outcome for response time since participants would probably spend more time observing cycles of motion encodings to decide on the perceived difference. However, it is still valuable to empirically have a relative comparison of response time between different encoding types. In summary, our results of accuracy show that human perception of motion encoding is relatively accurate, especially for *expansion*, *flicker*, and *vertical motion*.

TABLE 2
Ranking of the encoding types based on accuracy and response time with better performing encodings higher in the list. Rows indicate significant differences between encodings. Motion encodings are shown in bold blue text.

Our Study (Experiment 2)		Celevland & McGill [1]
Time	Accuracy	Accuracy
Color	Position, Length	Position
Angle, Length, **Vibration**	**Expansion**	Length
Position, Area, **Flicker**	Angle, **Flicker**, **Vertical motion**	Angle
Vertical motion, **Expansion**	Area, Color	Area
	Vibration	Color

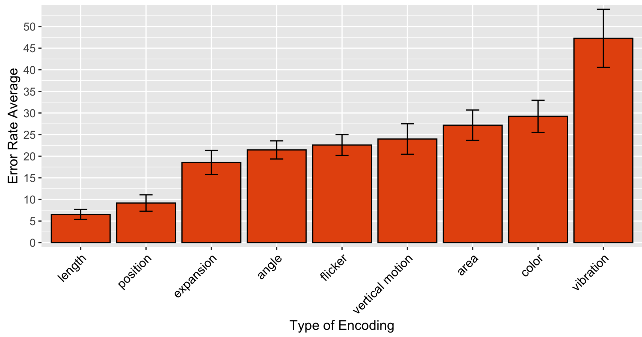
6.3 Bias Analysis: Accuracy of Estimations

In addition to considering absolute accuracy, we analyzed the observed error rates with consideration for participants' tendencies to over or underestimate encoded values across different representations. This can be considered a type of perceptual *bias* for data interpretations, and similar analyses are commonly performed in studies of graphical perception (e.g., [1], [19], [45], [46]).

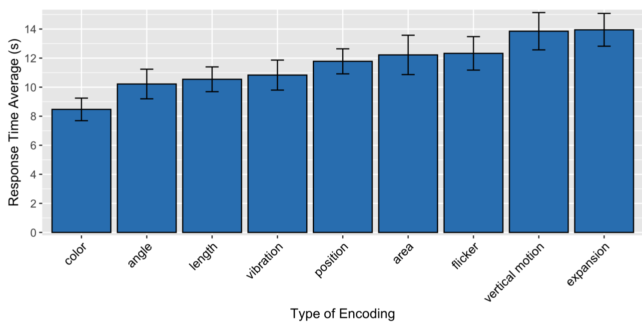
To assess bias, we use the directional error between judged ratio responses and true ratio responses (Δ = estimated ratio $-$ actual ratio), where a positive Δ indicates overestimation and negative Δ indicates underestimation. To test for evidence of bias, we analyzed the total of directional errors per encoding with a one-sample t-test to compare with an expected baseline of 0, i.e., when the mean of Δ across all estimations is 0, it shows that there is no bias in estimations. We checked the normality condition for the data of each encoding type before testing. The assumption was met for all encoding types. We summarize the results of the one-sample t test in Table 3. The results show that the mean of the total bias is significantly different from 0 for some encoding types with a $p < 0.05$. In other words, there is a significant bias of underestimation for *angle*, *length*, *expansion*, *flicker*, and *color* encoding types.

TABLE 3
Results of bias analysis for all encoding types. The bold red stars show a significant presence of bias. The significance level is $\alpha = 0.05$.

Encoding	Bias	Estimation	Significance	
angle	-0.570	underestimate	$p < 0.05$	*
area	0.026	overestimate	no	
position	-0.091	underestimate	no	
length	-0.104	underestimate	$p < 0.05$	*
expansion	-0.283	underestimate	$p < 0.05$	*
flicker	-0.230	underestimate	$p < 0.05$	*
vertical motion	0.144	overestimate	no	
vibration	-0.257	underestimate	no	
color	-0.740	underestimate	$p < 0.05$	*



Test of Within-Subjects Effects for Error Rate	
Type of Encoding ($F_{(5.84,233.60)} = 68.49, p < 0.001, \eta^2_G = 0.73$)	
Significant Post-hoc Comparisons of Types of Encoding	
(Ranked from most accurate to least)	
length **vs.** expansion, angle, flicker, vertical motion, area, color, vibration	$p < 0.001$
position **vs.** expansion, angle, flicker, vertical motion, area, color, vibration	$p < 0.001$
expansion **vs.** area, color, vibration	$p < 0.01$
angle **vs.** color, vibration	$p < 0.05$
flicker **vs.** color, vibration	$p < 0.05$
vertical motion **vs.** color, vibration	$p < 0.001$
color **vs.** vibration	$p < 0.001$



Test of Within-Subjects Effects for Response Time	
Type of Encoding ($F_{(5.44,217.60)} = 32.56, p < 0.001, \eta^2_G = 0.68$)	
Significant Post-hoc Comparisons of Types of Encoding	
(Ranked from fastest response time to slowest)	
color **vs.** angle, length, vibration, position, area, flicker, vertical motion, expansion	$p < 0.001$
angle **vs.** position, area, flicker, vertical motion, expansion	$p < 0.01$
length **vs.** position, area, flicker, vertical motion, expansion	$p < 0.05$
vibration **vs.** flicker, vertical motion, expansion	$p < 0.05$
position **vs.** vertical motion, expansion	$p < 0.05$
flicker **vs.** vertical motion, expansion	$p < 0.05$

Fig. 6. Results of error rate (top) and response time (bottom) for different encodings along with statistical test results. Bar charts represent mean of error rate (top) and mean of response time (top) for each data encoding. Error bars represent lower and upper Gaussian confidence limits based on the t-distribution.

7 Discussion

In this work, we investigate considerations for the use of motion encodings for scalar values. To support future research of methods for embedding motion encodings into data visualizations, the presented studies provides foundational knowledge about how different types of visual motion can best be used to represent human-interpretable numerical values and how accurate their graphical perception are compared to static encodings.

7.1 Promising Motion Encodings

While previous research has shown motion encodings can be effective for categorical data (e.g., [47]), our experiments empirically demonstrate how differences in motion type do significantly influence perceptual accuracy for scalar values. Our experiments tested which specific motion features were easier for participants to perceive accurately. Results of our first study showed that among the three tested motion types, the translational *Vertical* motion was the most accurate overall, *Expansion* motion would be at the middle, and *Flicker* motion had the least accuracy. In addition, the time results indicated that *Expansion* had significantly shorter response times compared to *Vertical* motion, though Figure 3 indicates a very small effect size. Our second experiment provides context for graphical perception of motion encodings with respect to static encodings. Perhaps the most notable finding is the that the *expansion* motion encoding is ranked relatively high in the list—just after *position* and *length* regarding accuracy—which suggests high potential in use for quantitative information visualization. Considering the results of both experiments, *expansion* and *vertical* motions had higher accuracy rates among the motion types, while *flicker* and *vibration* had less accuracy. Therefore, we suggest further research needs to be done on how and in what contexts to use *expansion* and *translational* motion as a display dimension. *Flickering* and especially *vibration* motion did not demonstrate convincing levels of accuracy and performance to make them compelling candidates for quantitative mapping. Many participants also subjectively reported not preferring the vibration encoding type, and some also reported that *flicker* and *vibration* cause them to have eye strain which made it more difficult to judge the difference of speed.

Another important and interesting finding from our study was that non-synchronized motions were significantly easier to be compared than synchronized motions in terms of both speed and accuracy. This was counter to our original hypothesis that aligned cycles would support easier comparison, and a prior study by Huber and Healey [17] found strong significant advantages of synchronized flickering animations. The major difference between our studies was the focus on quantitative estimation of values rather than merely detecting differences, as is needed for distinguishing categorical representations. For accurate comparisons of rates, synchronizing animations seems to add difficulty by introducing periods where one item is waiting for the other to finish its cycle, which means there is less time available for participants to directly observe and compare the motion differences. This difference has important design implications for the use of motion for different purposes in visualization, where categorical encodings may do better with synchronization while scalar encodings may do better without synchronization. Further research may be warranted into encodings with discrete numerical values or other variations of motion that could allow influence strategies used for motion comparison.

7.2 Motion in Practical Visualizations

The presented experiments evaluated performance measures through a comparison of motion data encodings in a controlled and isolated setting. This allowed for high experimental control and provided empirical findings and suggestions for encoding numerical data with motion. However, practical applications of motion in visualizations will likely involve combinations with multiple visual cues (e.g., position, color, size, shape). Further, it would be uncommon only to show two animated items together, as visualizations generally aim to display numerous data values at once to aid comparisons and identifications of trends. Thus, while the simplistic and controlled study design is standard for visualization evaluations of graphical perception (e.g., [1], [4], [19]), it is also necessary to consider more complex scenarios or with multidimensional data.

Our results are particularly of value for expanding the design space of information visualization in encoding numerical values. Designers can incorporate motion qualities individually or as an additional data coding dimension along with other visual cues. In particular, animated maps have been shown to be highly important in enhancing analysts' ability to express data in scientific visualizations [10], [11]. For example, the dynamic variables can be used to indicate the location of a phenomenon, its attributes, or display changes in its spatial, temporal, and attribute dimensions. In such cases, motion-related data encoding would be a candidate to encode the numerical attributes of data in animated maps to better communicate the quantitative values and their comparison. It is especially important to study motion due to its ability to distract or attract attention in peripheral vision. Thus, it is essential to also consider cases of interpreting numerical values from motions among a field of several moving objects (such as study methods similar to those used by [17], [18], [47]). It would also be interesting to explore perceptual tests in environments where there are many distractions or multi-tasking scenarios. One of the properties of motion as an encoding is that it can grab attention quickly, and further research in this direction could prove beneficial for broadening potential application contexts. In particular, when users are working with different high-density information displays or dashboards, it would be a potential benefit of motion encoding not only to guide users' attention but also simultaneously provide numerical perception and convey information through quantitative data encoding. Overall, the contributed knowledge of visual motion opens numerous paths for exploring motion encodings for different purposes.

7.3 Future Work

We found significant underestimation bias for both motion encodings (i.e., *expansion* and *flicker*), and static encodings (i.e., *length*, *angle*, and *color*). While previous research has explored possible underlying causes of bias in the graphical perception of static visualizations [19], [45], [46], [48], [49], it would be interesting to study the potential sources of bias in motion encodings to mitigate them in future data visualization techniques with motion.

We conducted our first experiment in controlled lab space using the same device for all participants, but we were not able to conduct our second experiment in person due to the COVID-19 pandemic. Since our study was online, we did not have control over users' physical devices, their screen size, and resolution. We acknowledge that these differences might have effects on users' graphical perception; however, we did ask participants to set their resolutions during the study session for partial reduction of display differences. We suggest that future work in an online setting takes the system-based differences into account and logs them for further testing of their effects on the graphical perception.

Many visual applications may find benefits to using motion and animation to encode quantitative data values. In multidimensional data visualizations, motion may be valuable as an additional type of encoding available. Visual search of particular movements may be easier than static encoding such as color [47]. Since motion is discernible through peripheral vision, motion may also be beneficial as part of peripheral displays may allow users to monitor quantitative information without incorporating such values as part of the focal region of a display.

Print media may be waning in popularity [50] as mainstream media outlets incorporate multimedia and animated formats [23], [51], [52], [53], [54] into public discourse. Future research can further investigate how motion can be incorporated into more chart types and geographical plots.

8 Conclusion

We investigated user graphical perception of quantitative data encoding using different types of motion. We conducted two controlled experiments to measure users' perception of numerical differences of motion-encoded techniques, and compare them with the graphical perception accuracy of conventional static data encodings, such as length, area, angle, and color. The first experiment tested different properties of motion including three motion types, i.e., *vertical motion*, *flicker*, and *expansion*, and presence or absence of synchronicity. The second experiment focused on comparing data encoding of quantitative data between motion encodings and static encodings in terms of graphical perception accuracy and response time. The results show that different types of motion encodings can significantly affect numerical judgments, which indicates the importance of further research of the fundamental approaches for using motion and animation for quantitative data representation. We also found out that expansion and vertical motion encodings have a high accuracy compared to some static encodings. This finding indicates the promising potential of motion as a display dimension for quantitative data. The presented research can serve as a foundational basis for future research on quantitative motion encodings in more advanced visualization scenarios.

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