# The Impact of Interactivity on Comprehending 2D and 3D Visualizations of Movement Data

Fereshteh Amini, Sébastien Rufiange, Zahid Hossain, Quentin Ventura, Pourang Irani, and Michael J. McGuffin

**Abstract**—GPS, RFID, and other technologies have made it increasingly common to track the positions of people and objects over time as they move through two-dimensional spaces. Visualizing such spatio-temporal movement data is challenging because each person or object involves three variables (two spatial variables as a function of the time variable), and simply plotting the data on a 2D geographic map can result in overplotting and occlusion that hides details. This also makes it difficult to understand correlations between space and time. Software such as GeoTime can display such data with a three-dimensional visualization, where the 3rd dimension is used for time. This allows for the disambiguation of spatially overlapping trajectories, and in theory, should make the data clearer. However, previous experimental comparisons of 2D and 3D visualizations have so far found little advantage in 3D visualizations, possibly due to the increased complexity of navigating and understanding a 3D view. We present a new controlled experimental comparison of 2D and 3D visualizations, involving commonly performed tasks that have not been tested before, and find advantages in 3D visualizations for more complex tasks. In particular, we tease out the effects of various basic interactions and find that the 2D view relies significantly on "scrubbing" the timeline, whereas the 3D view relies mainly on 3D camera navigation. Our work helps to improve understanding of 2D and 3D visualizations of spatio-temporal data, particularly with respect to interactivity.

**Index Terms**—Information visualization, spatio-temporal data, movement data, interactive visualization, evaluation

## 1 Introduction

GPS receivers and RFID technology have made it easier and more common to track the location of automobiles, boats, airplanes, smartphones, equipment, merchandise, and people. Standard productivity tools such as Excel are incorporating add-ons to tackle the common task of analysing large data sets of this type. There is a growing need for visualizations tools to help understand and analyze such data, commonly referred to as spatio-temporal data.

Examples of large data sets include Microsoft's GeoLife data [1] which contains movements of almost 200 people over four years. However, even teasing apart the movements of one person over one week can be challenging to understand. The 2D visualization in Fig. 1, which was generated by Google Latitude, makes it clear *where* a person has been, but not *when* they were at different places, in *what order* the places were visited, and *how many times* each place was visited. This is partly because 2D suffers from overplotting and occlusion. If multiple people's movements were shown on a 2D map, it would also be difficult to tell if they visited the same places at the same time or at different times.


- *F. Amini, Z. Hossain, and P. Irani are with the Department of Computer Science, University of Manitoba, Winnipeg, MB R3T 2N2, Canada. E-mail: {amini, zahid, irani}@cs.umanitoba.ca.*
- *S. Rufiange, Q. Ventura, and M.J. McGuffin are with École de technologie supérieure, Montreal, QC H3C 1K3, Canada. E-mail: sebastien@rufiange.com, ventura.quentin@gmail.com, michael.mcguffin@etsmtl.ca.*


*Manuscript received 5 July 2013; revised 28 Feb. 2014; accepted 25 May 2014. Date of publication 4 June 2014; date of current version 26 Nov. 2014. Recommended for acceptance by J.-D. Fekete. For information on obtaining reprints of this article, please send e-mail to: reprints@ieee.org, and reference the Digital Object Identifier below. Digital Object Identifier no. 10.1109/TVCG.2014.2329308*

An alternative visualization of such movement data uses a 3rd dimension as a time axis. Movements thus become trajectories in a 3D space, with latitude, longitude, and time providing the coordinates of the trajectory.

Such a visualization is sometimes called a "space time cube" [2] (which we abbreviate as STC), and is perhaps best known in the software product GeoTime[1] [3] which has been available commercially since 2005. Theoretically, a 3D (or STC) visualization may allow a user to understand the timing, ordering, and repetitions of events in space-time, and gain an overall understanding of an entire data set.

To better understand the advantages or tradeoffs between 2D and 3D visualizations of movement data, quantitative, experimental evaluations are needed. With other types of data, past studies comparing 2D and 3D visualizations have found mixed results [4], [5], [6], sometimes finding that 3D was worse in certain cases, possibly because of the complexity of navigating in 3D and understanding 3D relationships. Very few previous studies have been performed to compare 2D and 3D visualizations of movement data, the most recent of which [2] may have limited external validity due to the design choices made in their study, as we will discuss. Our current work aims to compare more realistic implementations of 2D and 3D visualizations, in part inspired by GeoTime [3], a mature commercial product.

The current work presents three contributions. First, we propose a novel taxonomy of the types of questions that can be asked of spatio-temporal data. This taxonomy is extensible to additional dimensions, and classifies both basic questions as well as questions about behaviors of groups of people (such as group meetings). Second, we

1. GeoTime is a registered trademark of Oculus Info Inc.

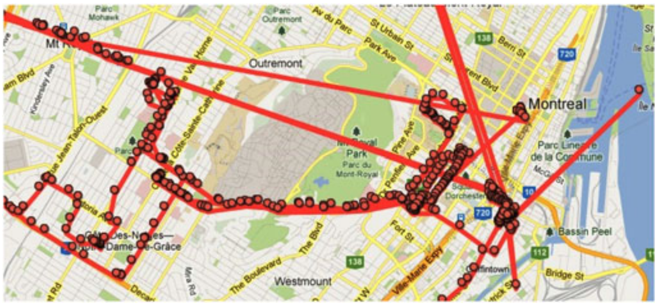


Fig. 1. Movements of a smartphone over seven days, as captured by the Backitude application for Android, sampling at 15 second intervals, and subsequenttly visualized with Google Latitude. Gaps and discontinous jumps in the data are caused by traveling through tunnels and by occasional spurious errors.

present a new experimental comparison of 2D and 3D visualizations of movement data, with realistic implementations of interactive camera controls and the use of a time slider in both visualization techniques. Third, we present a way to analyze the experimental data to uncover details about the role of different interaction techniques in contributing to overall performance time.

## 2 Related Work

Spatio-temporal data visualization can be dated back to at least Minard's famous 1869 map [7], [8]; however, it has only gained attention in recent years, as analysis of such data has become a necessity in many data rich domains and applications. Furthermore, tools such as Google Latitude are incorporating methods for visualizing spatio-temporal data sets, albeit for less complex data sets than those used by domain experts. Researchers working on different domains (e.g., computer science, Geographic Information Systems (GIS), and urban simulation) realize the need for better sense making tools and solutions when it comes to spatio-temporal data sets. The challenge, however, remains the same and that is to depict temporal and spatial information simultaneously. We survey two major areas of relevant work: visualization of movement data (i.e., trajectory data) and performance evaluation of 2D versus 3D spatio-temporal data visualization. Visualization of movement data can be further divided into 2D map-based, abstract space, and 3D space-time representations.

### 2.1 Visualization of Movement Data

Analysis of information in space and time has gained special importance not only by the professional analysts but also by today's modern society citizens [9]. Solutions for visualization of spatio-temporal data in the existing literature differ based on the characterizing aspects of this type of data set and have been reviewed by researchers [9], [10], [11]. The space dimension in this type of data can either be "fixed and stationary" or "dynamic and changing" over time (i.e., movement data) for the target object of interest. Depending on the context, there could also be extra attribute information attached to the temporal and spatial properties of the data [12], [13]. In a recent comprehensive review, N Andrienko and G Andrienko [14] describe and categorize the techniques for visualization of movement data from the analysis point of view. They separate these categories based on whether or not the analyst is interested to 1) looking at the trajectories of moving objects as a whole, 2) looking inside trajectories to detect particular movement characteristics and patterns, 3) having a bird's-eye view on movement and analyze the distribution of multiple movements in space and time, and 4) investigate movement in context with focus on relationships and interactions between spatio-temporal objects.

Focusing on movement trace data, another major categorizing factor is the number of dimensions used to display or render visualizations. This refers to whether only two dimensions are used to represent the movement data (we refer to this category of solutions as 2D) or a third dimension is also used to encode *time*, forming the 3D (or STC) category of solutions. It is important to note that spatial information can also be three dimensional if latitude, longitude, *and altitude* are all inputs to the visualization system, but in this research project, 3D refers to techniques that use time as the third dimension.

### 2.2 2D Map-Based Representation

2D map representations have been the primary method of visualization for movement traces and researchers have studied the problem of finding an effective representation of time that can be nicely integrated with the 2D space information [15]. As described by Turdukulov and Kraak [16], there are four main types of representations in 2D: Single 2D map, multiple 2D maps and linked views, map animation, and 2D display of abstract spatial information.

In the single 2D map design, time labels, arrows, and lines are usually the visual cues added to the representation to incorporate time as well as other subtle properties of movement data such as direction [17], [18]. In [19], authors present three different approaches to visualize multivariate (e.g., time, position, identification, draught, destination, etc.) trajectories of vessel movement. All of these approaches are presented using a 2D map to represent space and the trajectories are drawn on top using lines. Different visual cues are used to visualize extra attributes. For example, color is chosen to show trajectory density. Although in the more advanced approach of this visualization, it is possible to distinguish various moments over time, queries for trajectories with specific timestamps are not possible.

In order to better represent time changes for movement trace data, a series of static 2D maps (a.k.a. small multiple maps) can be used to show trajectories for different timestamps [20]. A limited number of 2D maps with trace data can be presented to the user at a time. Ivanov et al. [21] describe a visualization system with a separate timeline view for temporal information, which is linked to the 2D floor plan with embedded trace representation. Similarly, in [22], [23], [24] linked views are used to visualize temporal data and spatial information in terms of a 2D map with trajectory overlays.

The above mentioned 2D solutions and designs are limited to small amounts of data and few time intervals and use textual representation of time as opposed to the alternative graphical representation. Hence, clutter is a big issue due to plotting of temporal data over spatial data. In addition, the small multiples and linked views require high cognitive load and have been found to be hard to compare [25].

Furthermore, the use of animation has been exploited for better understanding of relationships between different properties of a data set and various visual pieces in a representation. Animated maps are a result of employing animation to show changes of attribute data over time and on a map [26], [27]. Griffin et al. [25] have researched the effectiveness of animated maps and compared it to static small-multiple maps. The results of their controlled experiment shows that map readers can identify more moving clusters more quickly using animated maps. The type and speed of animation can also play an important part in whether or not animation is effective or not. In [28], authors compare various types of animations for showing the relationships between different structures. Smooth transitions were shown to help users maintain the visual relationships between the different views. Also animation speeds that complete a viewpoint change in one second are sufficient for maintaining perceptual constancy. Effects of smooth transitions and have further been investigated in [29] finding dramatic benefits on user performance and guidelines on how to avoid some of the costs associated with animated transitions.

An alternative to animated playback is to provide the user with an interactive time slider (e.g., [22], [23]). Theoretically, this could allow the user to more quickly navigate through the data and find valuable information, by sliding more quickly through time spans of lower interest, and slowing down when there is more temporal detail. Previous evaluations of time-varying visualizations have sometimes only allowed animated playback, foregoing the evaluation of a time slider [30]. In our study, users had access to both animated playback and a time slider, making the evaluation more realistic and giving users more flexibility.

### 2.3 Abstract Space Representation

The 2D approaches mentioned above all keep the original spatial structure intact hence incorporation of extra attributes and time in the visualization makes them cluttered. There are, however, another group of 2D visualization methods proposed in the literature, which exploits abstract space representations. For instance, authors in [31] use the line graph metaphor to represent time on an abstract space. The result is a proximity-based visualization of movement trace data in which the spatial relationships (e.g., distance among objects) are preserved.

### 2.4 3D Space-Time Representation

Adding the third axis to represent time takes us to the alternative 3D group of visualizations that combine space and time in a single display. Originally proposed by Hägerstraand [32] and known as space-time cube, in this form of representation, space and time are thought of as being inseparable and movement is depicted as trajectories in 3D with time being one of the coordinates. This idea has been expanded by other researchers in the field [33], [34]. A potential problem with the STC approach is occlusion in case many trajectories are involved. To facilitate manipulation and perception of information, STC has been extended with interactive techniques [35]. A more advanced version of STC enhanced with timeline as the main interaction device, time zooming or focusing, and linking of maps with corresponding symbols is presented in [36]. The enhanced version of STC that supports many of these features has been turned into a commercial software application called GeoTime [3], [37].

Recent work by Tominski et al. [38] presents a solution based on the STC with the focus on trajectory attribute data, i.e., movement data which includes other attributes. By stacking 3D color-coded bands on a 2D map and ordering the bands based on the temporal information, the trajectories and their attributes are visualized while temporal information is directly perceivable. Extra visual cues are also added to the bands to depict direction and other properties.

Another drawback of the STC approach, besides occlusion, is distortion of both space and time due to projection which makes it hard to perceive depth. Even though 3D representation of movement data has been introduced, much research is being devoted to finding suitable forms of representing this complex data set.

### 2.5 Evaluation of 2D versus 3D Visualization of Movement Data

We next survey evaluations of 2D and 3D visualizations of movement data. The most closely related work to our study is by Kristensson et al. [2]. The authors compared 2D and 3D visualizations of movement data, asking users to answer four types of questions:

- Category1: simple "when" & simple "what+where"
- Category2: simple "when" & general "what+where"
- Category3: general "when" & simple "what+where"
- Category4: general "when" & general "what+where"

The 2D visualization was found to be significantly less error prone for category 2 questions, and 3D was found to be significantly faster with category 4 questions. One explanation for these results is the design choices made for both 2D and 3D visualizations.

In their [2] experiment, the 2D view allowed for interactive pan and zoom, but did not have any time slider or animation. Instead, text labels showing the times of "critical time points" could be displayed or hidden by hitting a keyboard key. The 3D view allowed for pan, zoom, and rotation, and a "measurement plane" could be moved up or down the time axis, with the current time of the plane displayed. We intentionally made different choices in the design of our own experiment, to test a more consistent implementation in both 2D and 3D visualizations. In particular, we note that Kristensson et al. [2] argue against using time sliders and animations "because users cannot get an overview of the data set at a glance with such representations". This is true, but in their 2D condition, users had to read text labels to understand timing and sequencing, which we suspect is slower than using a time slider or animation. Furthermore, the ability to move a "measurement plane" in their 3D condition is very similar to having a time slider, whereas an analogous feature was not available in their 2D condition. Temporal zooming or focusing in the form of a timeline has been shown to be a necessity with large data sets [36]. Finally, the text labels in their 2D condition were not available in the 3D condition.

With permission from Occulus Info Inc., we imitated some of the design choices made in GeoTime [39] which supports many similar design elements and interactivity features in previous implementations of the STC [33], [35] and has benefited from iterative design improvements and experience with real users. GeoTime supports both a time slider (which moves a horizontal plane) and animations. We made text labels, a time slider, and animations available in both our 2D and 3D conditions.

In [2]'s experiment, it is unclear how camera operations such as rotate were performed. If the user must click on small widgets or icons to perform camera operations, this impedes performance, due to the cost of pointing at the widgets or icons, sometimes repeatedly. This cost can be modeled with Fitts' law [40]. We instead designed 2D and 3D camera operations so they could be performed anywhere in the viewport, without first acquiring any widgets. This requires that the user first learn the appropriate mouse buttons to invoke each operation, but is reasonable for users who are at least mildly expert.

Examining other previous evaluations, [41] is a thesis that evaluates STC, comparing it to other visualizations of movement data including single and multiple static maps, and animation with the aim of finding the best visualization for movement patterns (e.g., speed change, return to the same location, stops, etc.). Animation was found to perform better than the other evaluated techniques for all patterns except stops, and returns to the same path both of which performed better in STC. Although complexity was considered to be an independent variable in the experiment, it was geared towards trajectory size and not complexity of the questions themselves which is shown to have a big impact when designing spatio-temporal visualization methods [42]. Animation was one of the main visualization methods compared in this study and as we argue that it is a requirement when dealing with large data sets in any of the 2D and 3D visual representations and not a representation to compare against. Therefore, we have made animation always available throughout our experiment setup.

In [43], authors present the results of user centered study and a focus group interview with the domain experts in geovisualization. Both 2D and STC visual representations were available to the users with no specific questions. Users saw new opportunities with STC since it gave them a new perspective on how to look at their data. Information on the effectiveness of different visual variable are also presented to be used by future designers following the STC paradigm.

Kjellin et al. [44] conducted experiments to predict the meeting place of moving objects based on the past history. After the initial round of tests, improvements needed to be made to the STC design only to find little performance advantages for STC. Other studies with similar goal of evaluation of 2D and 3D STC visualizations have also been conducted [45], [46], [47], [48] and mixed results have been reported leaving the need for further investigation. More specifically, an experiment with controlled selection of tasks and features is required to better understand the tradeoffs between the two visualization methods.

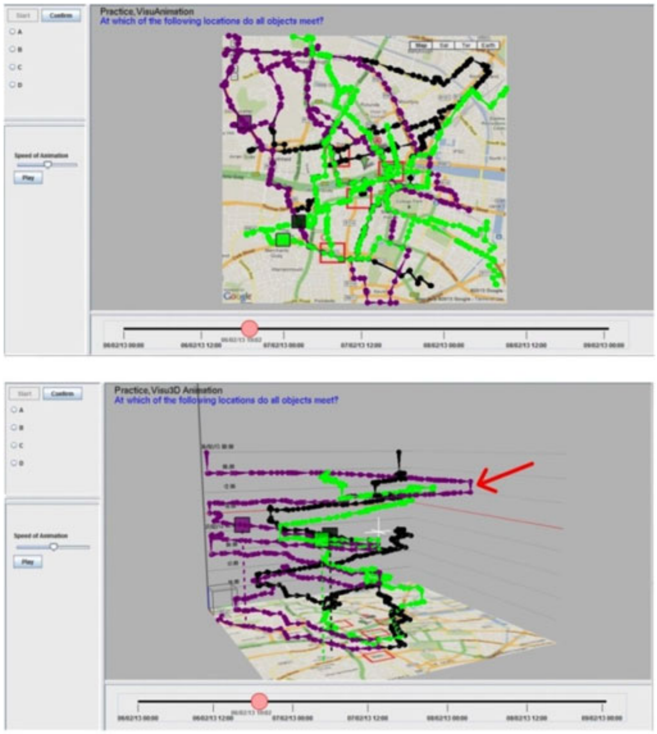


Fig. 2. (**Top**) The 2D visualization of movement data in our STV application. Movements of three objects are shown in green, purple, and black. Colored dots show individual locations, and are connected by tapered line segments similar to an arrow head pointing in the direction of the object's motion. The location of each object at the time selected in the time slider along the bottom is shown by squares. Red squares on the map mark specific locations; these may be referred to in the question, or may also appear as choices in the answers at the top left. In the panel on the left, a Play button toggles animated playback. When the user drags the time slider, or activates animation, the positions of the green, purple, and black squares update to show movements. (**Bottom**) The 3D visualization in STV. Each of the green, purple, and black squares now have dotted lines projected below them to help see their current geographic location. In addition, the red line segments along the "back walls" of the 3D space indicate the current time to the user. The red arrow indicates an example of a stationary object.

## 3 Space-Time Visualizer (STV)

We implemented an experimental testbed application called STV that supports 2D and 3D visualization of movement data (Fig. 2).

In both the 2D and 3D views, the left mouse button can be clicked and dragged anywhere in the main viewport to pan (i.e., translate the camera up, down, left, right), and the mouse scroll wheel can be rolled to zoom in or out. In the 3D view, the right mouse button can be clicked and dragged anywhere in the main viewport to tilt and rotate the scene.

In addition, whenever the user hovers the mouse cursor over any of the dots in the main view marking a location, a "datatip" (or tooltip) appears indicating the date and time of that dot. The user may also left-click on a dot to select it, causing the datatip for that dot to remain on the screen persistently. Thus, the user may select one dot, and hover over a second dot, to make the datatips for both visible, which can be useful for figuring out the time interval between two dots.

Finally, hitting the enter key on the keyboard toggles the appearance of labels on *all* dots. However, during our

TABLE 1
Interaction and Visual Mappings for 2D and 3D Designs in STV

| | | 2D Map | 3D Space-Time |
|---|---|---|---|
| Interaction | **Pan** | Mouse left button | Mouse left button |
| | **Zoom** | Mouse Wheel | Mouse Wheel |
| | **Orbit** | N/A | Mouse Right button |
| | **Time Slider** | Mouse left button | Mouse left button |
| | **Toggle Time Label** | Enter key | Enter key |
| Visualization | **Time** | Labels | Labels + Time Axis |
| | **Space** | 2D Map | 2D Map |
| | **Object** | Colored Dots | Colored Spheres |
| | **Position (Time)** | Time Slider | Time Slider + Highlighting Time Axis |
| | **Position (Space)** | Squares on Map | Squares with Dotted Line Projection |
| | **Direction** | Triangles | Triangles |

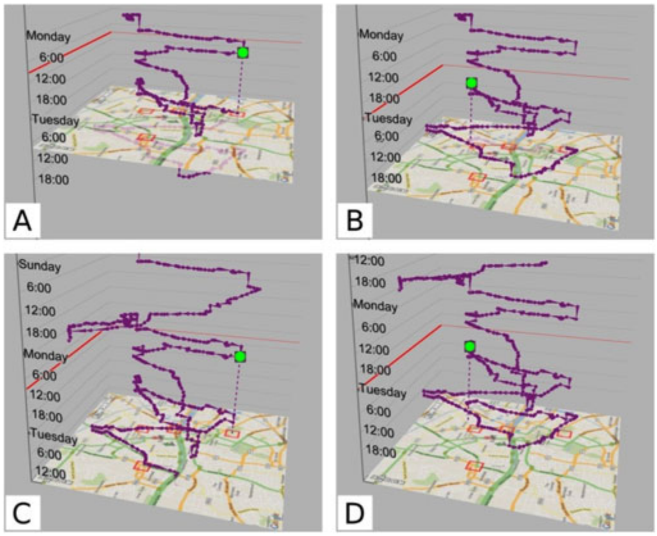

Fig. 3. Screenshots of our STV testbed application (edited by hand to increase legibility), showing two design options. A and B show a “moving plane”: the ground plane, red reference line, and vertical position of the green icon all move downward as time advances. C and D show a “moving trajectory”: the ground plane, red reference line, and vertical position of the green icon are all fixed, but the trajectory moves upward as time advances. A and C show Monday morning at 10:00, B and D show Monday evening at 23:25.

experiment, this last feature was not used by the participants. Table 1 includes a list of all the visual and interaction mappings for the 2D and 3D designs in STV.

## 3.1 Design Choices for 3D Visualization of Movements

In the course of developing our STV testbed application, we identified some design dimensions that should be considered when designing a 3D “space-time cube” visualization of movement data.

### *3.1.1 Direction of Time*

In our first version of STV, in the 3D view, we had time increasing upward. This seemed the natural and obvious way to do things; however, alternative approaches are possible, such as displaying time increasing downward, as done in GeoTime. Using the software, the reason became clear: when the user wishes to see an animated playback of events in 3D, or see the history of movements leading up to a specific event, having time increase downward means that (1) the present location of the actors or entities can be close to a ground plane displaying the geographic map, making it easier to see their present positions on the map, and (2) the recent history of their movements remains visible above this ground plane, rather than disappearing below it. We thus adopted the same convention in STV. Fig. 3 shows screenshots, all with time increasing downward.

### *3.1.2 Relative Motion of Visual Elements*

We implemented three additional options in STV to control how elements move with respect to each other. In all cases, a red horizontal line shows the selected time on the time axis, and an icon along each trajectory shows the selected location of the actor or entity (the green icon in Fig. 3). First, we can have the ground plane and trajectories fixed (with respect to the camera’s current position), and move the red line and the icons as time progresses. This means that the distance between icons and the map on the ground plane will vary with time. When icons are very far from the map, it is more difficult to understand the locations of actors.

Second, we can have the red line and icons displayed at a fixed distance from the ground plane, and move the ground plane, red line, and icons with respect to the trajectories as time progresses. This prevents the icons from ever getting very far from the map. There are two variants on this possibility, depending on which elements are moving with respect to the camera: we can have a “moving plane”, where the plane (and red line and icons) move with respect to the camera, or “moving trajectories”, where the trajectories move with respect to the camera.

The “Moving plane” approach also implemented by [2] and [35] is shown in Figs. 3A and 3B. We found that this has the disadvantage that the plane changes angle with respect to the camera, requiring the user to adjust the camera at different times to keep the map legible. “Moving trajectories” is shown in Figs. 3C and 3D. This design choice seemed the best, and was used in STV during our experimental evaluation. It is also the approach used in [3].

### *3.1.3 Offset between Present and the Ground Plane*

In both the “moving plane” and “moving trajectories” approaches, an additional design parameter is the vertical distance between the present (indicated by the red line and vertical position of icons) and the ground plane. Both STV and GeoTime allow this to be varied. Setting this distance to zero places icons directly on the map, whereas a non-zero value allows the user to see an interval of the future movements of the icons. There is a tradeoff between increasing this distance to make more of the future visible, and decreasing the distance to make it easier to perceive the locations of icons on the map. With a non-zero distance, dashed vertical lines show the projections of icons on the map to ease judgments of locations (Fig. 3).

# 4 Questions About the Data

This section presents a taxonomy of questions that can be asked about movement data. This taxonomy is the result of many design/pilot iterations using several different types of questions and is built on the conceptual models and typologies presented by prior research, some of which we mention here.

The notion of "question type" first introduced by Bertin [49] refers to variables in the data where each type can have three different "reading levels" depending on whether the variables map to a single element (i.e., elementary), a set of elements (i.e., intermediate), or the whole phenomenon (i.e., overall). Andrienko et al. [50] take a more general approach when building their conceptual model and focus on "search levels" to add the exploration dimension. By considering spatio-temporal data the authors still distinguish the components in the data similar to Peuquet's [51] approach. While we like Bertin's idea of differentiating between different reading levels, we find little or no difference between the intermediate and overall levels and similar to [10], our taxonomy is based on two levels for each variable. In what follows, we elaborate on previous concepts in classifications of questions about the data while focusing on movement data variables and patterns [52].

Data sets of the movements of multiple objects over time can be thought of as multidimensional multivariate data ("mdmv" data [53]), where *object* and *time* are the two dimensions (independent variables) and *spatial position* is the dependent variable. In other words, spatial position $x = f(o, t)$ is a function of object o and time t, where x is a vector encoding the latitude and longitude. We will use location or space as synonyms for spatial position.

Over the course of our research, we have considered several examples of questions that might be asked about such data sets, and different ways to classify such questions. We observe that, in the questions we have considered, each of the variables involved in the question (object, time, spatial position, or derived variables such as speed) may have one particular value that is being referred to by the question (e.g., one object, one time, one location), or multiple values (e.g., multiple objects, multiple events). We distinguish these two cases with the terms *singular* (s.) and *plural* (pl.). Furthermore, the value(s) in question may be known (k), or unknown (u). While this is similar to [10], our definition of known versus unknown resulted from pilot run observations, is focusing on whether the value is explicitly given in the question or user has to perform some discovery action on the particular value. We also classify the overall question complexity (i.e., level) and not the components within it. This classification is possible by looking at the combinations of the variable types in the question. For each variable, there are thus four possibilities: {known, unknown} x {singular, plural} = {k.s., u.s., k.pl., u.pl.} (Fig. 4). We now illustrate with some examples.

In the simplest questions, all variables have singular values. These questions might ask what the (unknown) value of one variable is, given the values of two other variables:

- Where is the red object at 14:00? **[o:k.s.; t:k.s.; x:u.s.]**
  In slightly more difficult questions, we can again have singular values, but two or three unknowns. The below example involve one value that is extremal (a maximum or minimum). Because such extremal values are not explicitly given in the question, we classify them as unknown:
- When (or where) is the eastern-most position reached by any of the objects? **[o:u.s.; t:u.s.; x:u.s.]**
  The question above can be rephrased as: Of *all* the objects, there is *one* that reaches a more easternly position than any other object, and we want to know when (or where) this occurs. So, even though the question requires the user to consider all objects as candidates, there is one particular object that is being referred to, hence the value of the object variable is singular (just as many moments in time and many spatial positions may be candidates to consider, but there is one particular moment and location that is being referred to by the question, and so these variables also have singular values).
  Other questions can be constructed in terms of derived variables, such as speed:
- Which object has traveled more distance between 10:00 and 12:00? **[o:u.s.; t:k.s.; speed:u.s.]**
  The question above involves an interval of time, however we still classify its time value as singular, because we consider the interval of time to be relatively small. This is analogous to classifying a location like "museum" as a singular value, even though it is an extended region of space. However, if a question was referring to *multiple* events within a relatively large interval of time (or a large region of space), we would classify the temporal (and spatial) values as plural.
  Next, we consider questions that refer to multiple events at different times (i.e., multiple values for time, and possibly multiple values for spatial position):
- Which object is on the campus area for the longest time? **[o:u.s.; t:u.pl.; x:k.s.]**
  The question above involves a *duration*, which is equal to the temporal difference between two events: arriving on the campus, and leaving the campus. Since it involves two events, the values of time are plural, but because only one location is involved, the value of x is singular. We could also say that *duration* is a derived variable, and its value here is extremal.
  Finally, questions may refer to multiple objects:
- Are any two persons at the same place at 9:00? **[o:u.pl.; t:k.s.; x:u.s.]**
  Questions of this type are classified using the dimensions of object, time, and space. However, as shown with the example involving speed, it is possible to extend the taxonomy by adding arbitrary additional dimensions. For example, further dimensions might include "pattern" or derived variables.

# 5 Experimental Evaluation

## 5.1 Goal

The purpose of the user study was to determine whether the 2D or 3D condition was better in answering each of the six questions listed in the previous section.

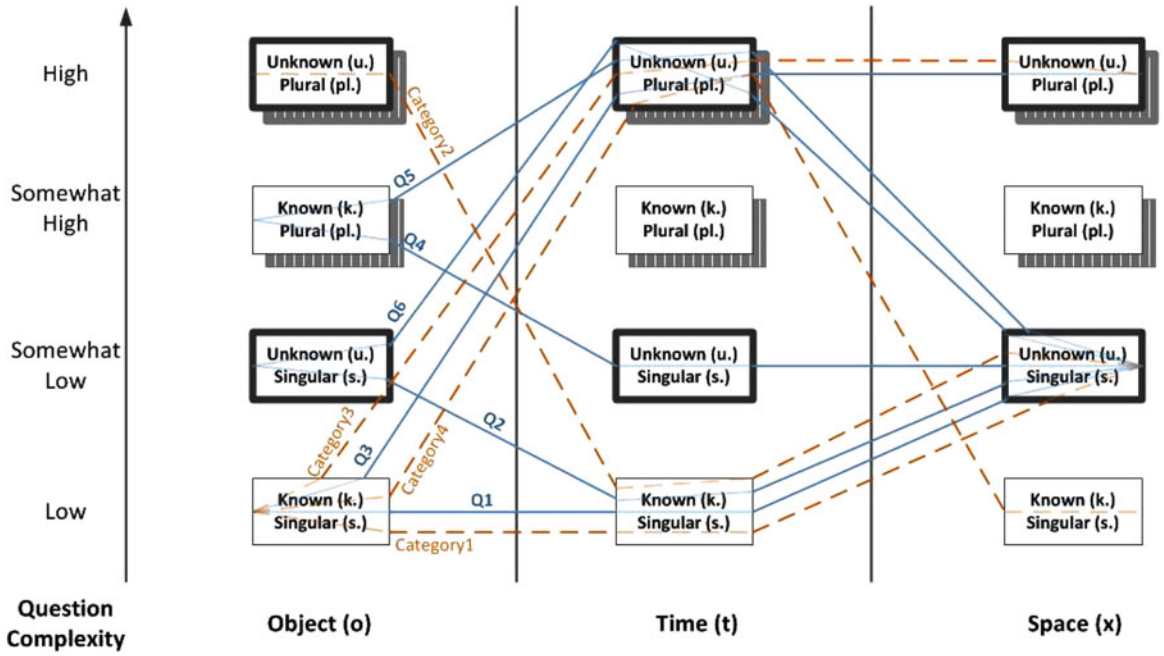


Fig. 4. Taxonomy of questions for movement data. The blue solid lines show the type of questions in our study, and the orange dashed lines show the type of questions in the study conducted by Kristensson et al. [2].

### 5.2 Apparatus

The experiment testbed application was run on a Dell OptiPlex 9010 PC, with an Intel Core i7-3770 3.4 GHz CPU, 16 GB RAM, an AMD Radeon HD 7,570 graphics card, running Microsoft Windows 7 Professional 64 bit, connected to a Dell U2312HM 23 inch monitor.

The software testbed application was run in full-screen mode, at a $1{,}920 \times 1{,}080$ resolution. Users operated the testbed with a mouse, and could also hit the Enter key on the keyboard to toggle (i.e., show or hide) labels.

### 5.3 Participants

Twelve undergraduate students (two females) majoring in computer science aged 21 to 30 years participated in the experiment. We also conducted post hoc power analysis with sample size of 12 and the effect sizes between Cohen's d $= 0.4$ to d $= 0.8$ (i.e., between medium to large effect size) and alpha level $p < 0.05$. The post hoc analyses revealed the statistical power for this study was calculated to be in the range of 0.88 to 0.99, which is more than adequate (i.e., power $>0.80$) for detecting the specified effect size level.

### 5.4 Data Sets

For this study, we decided on simulating movement data sets to better control the characteristics of the data. These characteristics support the kind of questions we are interested in evaluating in our experiment, which open source real trajectories that are currently available did not provide. To generate the synthetic data sets, we used the maps of English speaking cities and avoided modern cities with only horizontal and vertical streets knowing our algorithm can easily be applied to those simpler maps. We then wrote a Java program to create a node-link graph by putting nodes on each intersection as well as on any sudden street direction changes. Edges were drawn between any adjacent nodes. This gave us a realistic node-link graph that had more than 2,500 nodes and 3,400 edges.

Trajectories were generated based on the node-link graphs described above and by applying several different constraints for each data set. The following is the list of these constraints for each trajectory which are based on the patterns and characteristics of sample real trajectories: number of meeting points, the home node (staying during night), the breakdown of movement times during morning, noon afternoon, evening, and night. To generate a trajectory, source and destination nodes were selected randomly and Dijkstra's SP algorithm was used to find the path between nodes.

Nine data sets were prepared:[2] one data set d0 to be used for a discovery phase (both in 2D and 3D), two data sets d1 and d2 to be used for warm-up trials (one in 2D, the other in 3D), and six data sets d3,. . . , d8 to be used for actual trials (three in 2D, three in 3D). The data set d0 had trajectories over the (familiar) home city of the participants, whereas data sets d1 , . . . , d8 each had different trajectories in a 2nd city unfamiliar to the participants, and each containing three moving objects over three days. Although the trajectories were generated algorithmically, they followed the streets of real-world cities, and covered a distance of approximately 10 square kilometers, which gave us a relatively dense set of trajectories.

### 5.5 Questions

To prepare our experimental study, we first performed a pilot study involving a variety of the question types discussed in Section 4. The pilot study involved users answering the questions with the 2D and 3D visualization techniques. We expected 3D to be superior for answering several of the questions, because we thought users would

2. http://hci.cs.umanitoba.ca/projects-and-research/details/stv.

be able to directly "see" answers in 3D without spending time using the time slider to scroll through time. Somewhat to our surprise, 2D was found to be no worse than, and sometimes superior to, 3D for all the questions (significantly better for some questions, and not significantly worse for the others). Our subjective impression of using 3D is that it is often difficult to perceive the geographic position of a trajectory for a given time without first using the time slider to position the ground plane at that time and see the relevant intersections between the ground plane map and the trajectories. There is a general difficulty in judging depth and distance in 3D, partly due to a lack of depth cues (such as stereopsis and head coupled display). Even after rotating the 3D scene to look at the trajectories and map from above, the perspective projection can make it difficult to see where objects are located at a given time.

We nevertheless suspected that 3D could be good for getting an overview of the data set, and for perceiving relationships between multiple objects, especially when objects repeated the same movements multiple times, causing overplotting and occlusion in a 2D view. For example, in Fig. 1, the movements cover certain routes multiple times, making it impossible to tell how many times these routes were covered without using a time slider to replay the movements. It is possible that 3D would be better for this task, by allowing the user to more directly count the number of sub-trajectories of a given shape.

For our full experiment, we generated new data sets as described in Section 5.4 containing meetings of multiple objects and repeated movements, and chose a new set of six questions. Considering the overall taxonomy of possible questions, Fig. 4 illustrates the questions used in our study (blue lines) and the questions used in [2]. In the following we list and label the questions and give an example:

- Q1 (**basic**). Where was the green object on 06/02/13 at 14:30? **[o:k.s.; t:k.s.; x:u.s.]**
- Q2 (**speed**). Which object is moving the fastest on 08/02/13 between 19:30 and 20:30? **[o:u.s.; t:k.s.; speed:u.s.]**
- Q3 (**complex**). How many times the green object has been stationary for 3 hours? **[o:k.s.; t:u.pl.; x:u.pl.]**
- Q4 (**cluster-space**). At which of the following locations all objects meet? **[o:k.pl.; t:u.s.; x:u.s.]**
- Q5 (**cluster-object**). How many meetings have taken place in which all objects are involved? **[o:k.pl.; t:u.pl.; x:u.s.]**
- Q6 (**cluster-time**): Which object is usually late to the meetings? **[o:u.s.; t:u.pl.; x:u.s.]**

The choices above were made to see how users examine sequences of events and ultimately identify a pattern. The first three questions above involve individual objects. Question 2 was chosen to test the possibility that 3D might be good for judging the slope (speed) of trajectories. This had already been somewhat tested in the pilot, but the full experiment gave us a chance to test it more fully. We also suspected that 3D would be useful for noticing when an object is stationary (see red arrow in Fig. 2 for an example), which motivated the choice of Question 3 above. Questions 4-6 involve meetings of multiple objects (we will refer to these as cluster-based questions).

Eight variants of each of the six questions (Q1 through Q6) were prepared, with one variant for each of the data sets d1, ..., d8, yielding a total of 48 questions. All questions were multiple-choice questions with three or four possible answers for each question.

## 5.6 Design

For each of the visualization techniques (2D and 3D), users were first presented with the user interface showing the d0 data set, and allowed to interact with the testbed application during a discovery phase. They were shown all features of the testbed application, in an attempt to get them comfortable with the software. After a few minutes, they were then shown the warm-up data set d1 or d2, and asked to answer the six questions for that data set. During the warm-up and after the experimenter covered the list of all the features in the tool, users were closely observed and encouraged to ask questions to make sure they understood all the features presented as well as all the interactions available to find the answers. In cases where the participants seemed confused about a particular feature previously explained to them or when they asked questions, they were reminded of the features and shown strategies that could help them answer questions more quickly by taking advantage of all the features, for example: scrubbing the timeline efficiently in 2D, or rotating the 3D view to look at the scene from different camera angles to better identify certain features in the data (e.g., to find meetings, trajectory slopes, locations, etc.). Next, the user was presented with three subsequent data sets (either d3, d4, d5; or d6, d7, d8) and asked to answer the six questions for each data set.

At the start of each trial, the question was displayed at the top of the window (see blue text in Fig. 2) with no visualization. After the user had read and understood the question, they clicked on the "Start" button in the upper left corner, at which point the visualization appeared and the timer was started. The user could then interact with the visualization (panning, zooming, rotating, dragging the time slider, hitting the "Play" button and adjusting the animation speed, hitting Enter to toggle labels, and hovering over, or clicking, points in the visualization). When the user had determined the answer to the question, they selected the answer from the radio buttons in the upper left corner, and clicked the "Confirm" button, at which point the timer was stopped if there was no error. However, if the user's first answer was incorrect, the user had to try again, with a maximum of three attempts before going on to the next trial. This discourages the participant from being less careful in an attempt to finish the experiment faster, and instead encourages them to put in a reasonable effort at getting the correct answer on the first attempt.

The order of presentation of visualization techniques, and the assignment of data sets and visualization techniques, were both fully counterbalanced. Each quarter of participants performed one of the following:

(d1, d2, d3, d4) in 2D followed by (d5, d6, d7, d8) in 3D,
(d1, d2, d3, d4) in 3D followed by (d5, d6, d7, d8) in 2D,
(d5, d6, d7, d8) in 2D followed by (d1, d2, d3, d4) in 3D,
(d5, d6, d7, d8) in 3D followed by (d1, d2, d3, d4) in 2D.

The questions for each data set were randomly shuffled for each user. In total, not counting warm-up trials, there

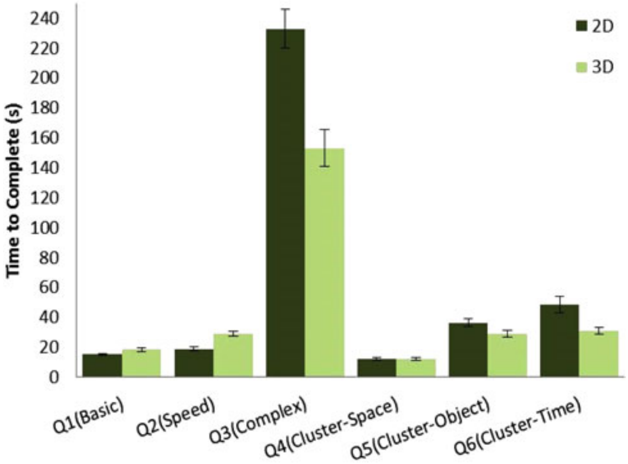


Fig. 5. Average time to complete for each task presented separately for 2D versus 3D visualization styles.

were 2 visualization techniques (2D and 3D) $\times$ 3 data sets per technique (d3, d4, d5; or d6, d7, d8) $\times$ 6 questions per data set (Q1 through Q6) $\times$ 12 users = 432 trials.

## 6 Results

We used an Analysis of Variance (ANOVA) test at the significant level of $\alpha = 0.05$ with a Bonferroni adjustment to carry out all the statistical analysis for this paper. As the completion times were positively skewed, we performed a logarithmic transformation (which resulted in distributions being close to normal) before analyzing the data.

The within-subject variables were visualization technique (i.e., 2D versus 3D), and question type (i.e., Q1 to Q6). The two dependent measures for which we performed the tests were the total time taken to answer a given question and the number of attempts it took until the right answer was picked by the participants. The latter was measured in terms of the error rate. We also measured separate times spent by the participants on various interaction features available in the tool: use of the time slider and different camera control features including zoom in/out in the space dimension as well as panning and rotating of the space dimension. All the interaction features were available in both 2D and 3D techniques except the rotating functionality which was only available in the 3D technique.

In this study, we focus on the specific questions that can be performed using interaction features available in the 2D and 3D techniques for visualization of movement data. Therefore, to examine the data more closely, we consider participants' performance on a question by question basis.

### 6.1 Time to Complete

The average time to complete for 2D and 3D visualizations is plotted for each question in Fig. 5. Error bars correspond to standard error. There is an overall main effect of question type for the time to complete ($F_{5,55} = 126.811,\ p < 0.001$). We can observe Q3 taking the longest, and therefore analyze all questions separately.

The results further reveal main effect of visualization style ($F_{1,11} = 11.37$, $p = 0.006$) in favor of 3D. There is also a significant statistical difference for question type $\times$ visualization style interaction ($F5, 55 = 13.425, p < 0.001$).

#### 6.1.1 Effect of Visualization Style on Each Question

As expected the mean response time for the question in the complex category (i.e., Q3) is significantly higher than response times for all other questions ($F5{,}55 = 497.001$, $p < 0.001$). The question in this category was unique in the sense that it required going through the whole data set and counting specific patterns in time and space. Focusing on this question, we found main effect of visualization style on the time to complete: it took significantly lower amount of time to answer this question in 3D using all the visualization and interaction features ($F_{1,11} = 159.817,\ p < 0.001$). We also observed differences in time to complete for questions in the cluster-based category which involved finding patterns in time and space for a cluster of objects. The results support our hypothesis that the 3D visualization is efficient when answering cluster-based questions. In particular it was significantly faster for the participants to answer Q6 using the 3D visualization ($F_{1,11} = 9.211$, $p = 0.003$). Fig. 6 plots the average completion time for Q3 and Q6 for the 2D and 3D visualizations.

Taking a closer look at the rest of the questions and applying post-hoc analysis, we did not detect a main effect of visualization style on Q1 in the simple question category ($F_{1,11} = 0.313,\ p = 0.577$). This category of questions has been studied in the literature and similar results have been reported [2]. Our initial experiment design also included more questions from this category, however, after two rounds of pilot experiments without significant differences, we decided to shift our focus to more complex questions especially cluster-based questions (i.e., Questions 3-6).

To our surprise, there were not any main effects of visualization style shown for Q2 in the speed category ($F_{1,11} = 2.663,\ p = 0.104$). We had hypothesized that this category of questions would be easier and faster to answer in 3D since there are additional visual cues to observe slopes in the space time cube setup.

#### 6.1.2 "Time to Complete" or "Interaction Time"?

In most of the commercial and study setups for 3D space time cube [37], different interaction features are provided to build a complete system that is capable of answering different questions such as the ones targeted in our study. As mentioned in the previous sections, we too have included several of such interaction features in our system. Prior similar studies for 2D versus 3D performance analysis and comparison have mostly focused on the overall time to complete for questions but it is important to examine interaction process separately to get a better understanding of the potential causes of main performance effects in such visualization systems. Therefore, we have also measured the time spent using each interaction feature separately. In this paper, we call the time during which, the participants did not use any of the interaction features, the "static exploration" time. However, it is worth noting that this does not mean that discovery does not occur during interaction since there is definitely some exploration time intertwined in the interaction times. It is very hard to separate the two since the

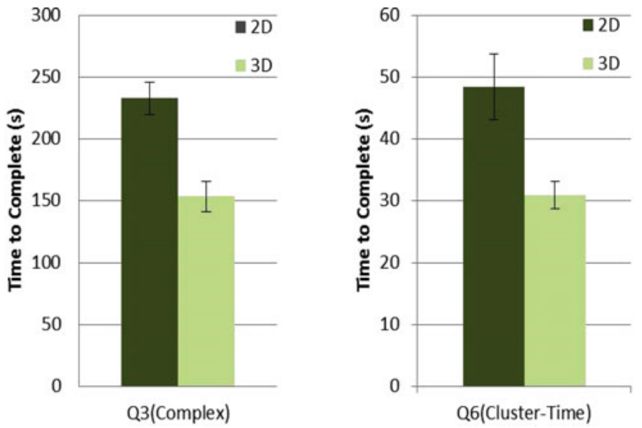


Fig. 6. Average time to complete for Q3 and Q6 presented separately for 2D versus 3D visualization styles.

participants use interaction tools while exploring the data visually at the same time.

We can see from the stacked and clustered percentage charts in Fig. 7 that interaction time is largely contributing to the overall time to complete in both the 2D and 3D visualizations. This is especially true under the 3D condition where the static exploration time is lower in comparison to the times spent on interaction. This is partly because of the additional interaction feature for rotating the space dimension. In retrospect, one reason the users may have spent much time rotating the camera view is to benefit from structure from motion [54], i.e., the depth cue that results from a changing point of view. It is plausible that this would be less necessary, and user performance would improve, if they had a stereoscopic display of the 3D scene. In addition, zooming and panning are used far more in the 3D than in 2D. On the other hand the time slider interactivity was used far more in 2D than in 3D because of the fact that using the 3D technique, we can take advantage of the time axis for temporal queries.

By breaking down the overall time to complete into the interaction time and static exploration time, we can now see more pronounced differences as the main effect of question type × visualization style interaction on the static exploration time. In addition to previous statistical significances for Questions 3 and 6 (Fig. 6), we also found main effect for Q5 which shows significant lower completion time using the 3D technique ($F_{1,11} = 10.848$, $p = 0.001$).

An interesting observation to be made here is with regards to the complex category (i.e., Q3). Although we can still observe a significant difference as the main effect of visualization style ($F_{1,11} = 239.956$, $p < 0.001$), the effect is reversed and the static exploration phase took significantly shorter amount of time using the 2D technique. This can again be correlated to the interaction time since participants spent a significant amount of time using the time slider to answer this question in 2D compared to 3D ($F_{1,11} = 1288.932$, $p < 0.001$). This once again confirms the direct relationship of interaction time with the overall response time.

Furthermore, we illustrate the sequence of interactions and static exploration using Gantt charts. Fig. 8 shows an example of this sequence and the duration of each interaction in the 2D and 3D visualizations respectively. There was much more switching between different interaction features as well as static exploration with no interaction using the 3D visualization technique.

### 6.2 Error Rate

Fig. 9 shows error rate averages for each question. Overall, low error rates of lower than 5 percent were measured for most question types except Q3 (i.e., over 30 percent). As expected, error rates are higher for complex and cluster-based categories of questions.

We observed main effect of question type on error rate ($F_{5,55} = 25.737$, $p < 0.001$) and once again Q3 is greatly contributing to this effect. Further post-hoc analysis showed no statistical significances in error rates when it comes to visualization style ($F5{,}55 = 0.266$, $p = 0.616$). Referring to Fig. 9, we can see that error rates are higher in 3D for Q5 and Q6, however, we did not detect an overall main effect of question type × visualization style interaction for error rate ($F5{,}55 = 0.932$, $p = 0.467$).

### 6.3 Subjective Evaluation

In addition to tracking performance measures, we also collected subjects' opinions regarding each visualization technique at the end of the experiment. Participants replied to eight statements on a Likert-scale with responses ranging

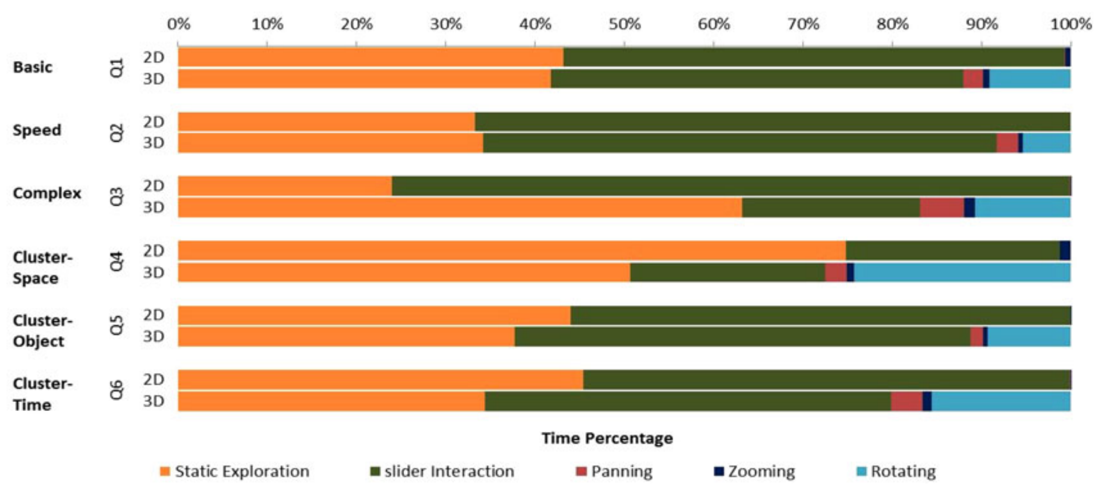


Fig. 7. Percentage of time spent on interaction features and static exploration for each question and separately for 2D versus 3D visualization styles.

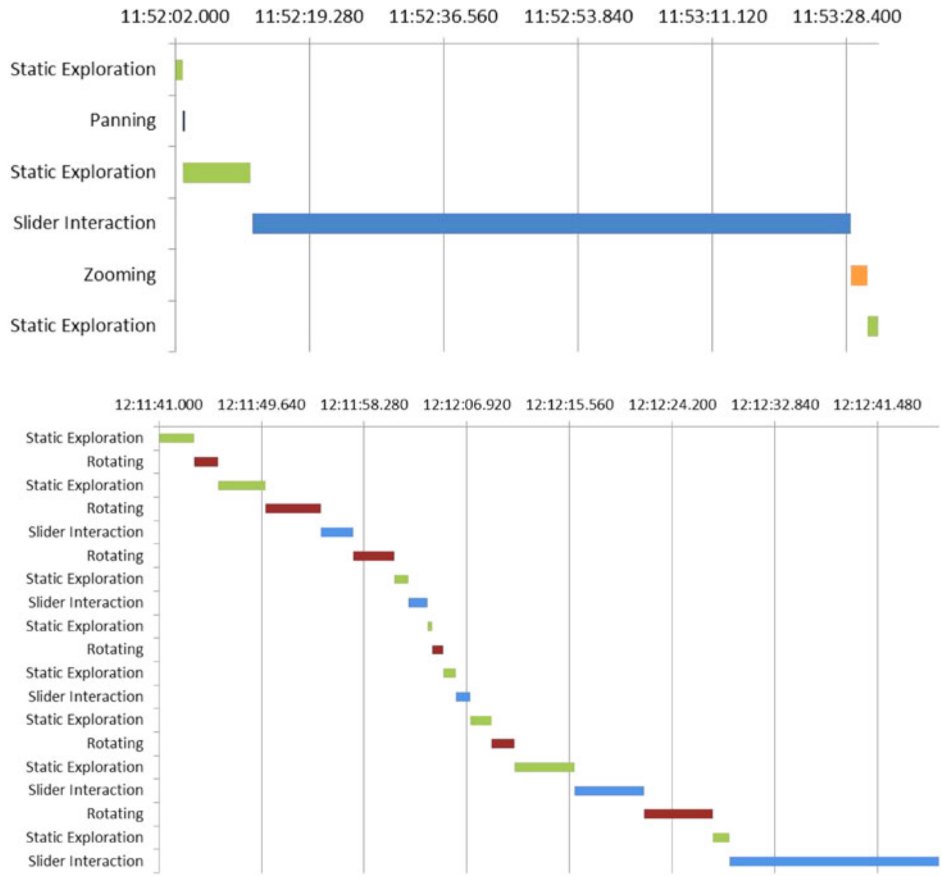


Fig. 8. Interaction sequence and duration for Question 5 using the 2D visualization (top), and the 3D visualization (bottom).

from 1 (Not preferred/Very difficult) to 5 (Preferred/Very easy). The median scores are summarized in Table 2. The statements were based on the questions that were answered about movement data earlier in the experiment. Using the Wilcoxon Signed Ranks test at the significant level of $\alpha = 0.05$ overall, there was a significant difference in participants' preference choosing the 3D visualization technique over 2D ($p < 0.001$) but no significant difference in overall difficulty level when using either one of the visualizations. When asked to rank the visualization styles for each question in terms of preference, participants significantly favored 3D over 2D for Questions 3, 4 and 6. Amongst all, it is interesting to see Q3 from the complex category is significantly favored in 3D over the 2D technique in terms of preference ($p < 0.001$).

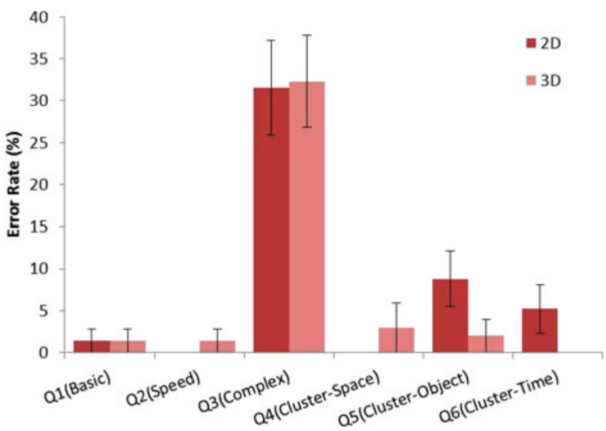


Fig. 9. Error rate for each question separated for 2D versus 3D visualization styles.

### 6.4 Open Comments

We also asked each participant to provide us with open comments and suggestions for possible improvements they would like to see for any of the visualization systems. Keeping in mind that the participants had experienced both of the representations; they were able to compare the visualization styles.

Several participants felt that it was "easier" to answer the questions using the 3D technique. The 3D technique was perceived as "very cool" and "much better" for getting all the required information for the questions. One of the participants, who had started the experiment with the 3D style, mentioned that he missed 3D when switching to 2D because

TABLE 2
Ranking (1-5) Median for Each Statement in the Subjective Evaluation Form

| | 2D | 3D |
|---|---|---|
| Overall preference | 3.00 | **5.00** |
| Tool preference in Q1 (Basic) | 5.00 | 5.00 |
| Tool preference in Q2 (Speed and Slope) | 4.00 | 4.50 |
| Tool preference in Q3 (Complex) | 1.00 | **5.00** |
| Tool preference in Q4 (Cluster-Space) | 3.00 | **5.00** |
| Tool preference in Q5 (Cluster-Object) | 4.00 | 5.00 |
| Tool preference in Q6 (Cluster-Time) | 3.50 | **5.00** |
| Overall difficulty | 4.00 | 4.00 |

of the fact that in 3D "the time info is embedded into the visualization".

There were some particular comments about the interaction features included in both of the visualization techniques. One participant stated that although questions were easier to do using the 3D technique, they required more panning and rotating compared to the 2D style. Two of the participants found the time slider hard to use.

Some perceived the 3D style as "busy" and "messy" at first but mentioned that they were "more comfortable" with it and were able to "find their way around" after using it for a while during the practice rounds. Considering the fact that the participants were not domain experts nor did they have extensive experience using 3D visualizations (except from some gaming experience), it is interesting to see that most preferred the 3D technique.

The suggestions to improve the system included having the filtering feature to be able to filter objects, a more precise date and time query tool, and in the 3D style having a better display of the information on the time axis.

## 7 Discussion and Limitations

During the process of designing the experiment for our study, our choice of questions was based on the result of series of pilot studies and motivated by identifying the ways in which the 3D view would be superior and this did not necessarily include the wide range of possible questions that can be asked about a data set with moving object traces. The use of such approach could, therefore, explain why it appears that the 2D Map visualization was not superior in any of the tasks which contradict some of the findings by Kristensson et al. [2].

The complexity of questions with movement data varies from very low level of complexity where there exists only one unknown component to very high complexity where multiple compound or plural components are unknown and of interest to the analyst. When evaluating any visualization method designed for this data set, it is important to carefully select and include questions which cover the complexity spectrum as much as possible.

The results of our study show that the 3D space-time cube style of visualization is beneficial (i.e., quicker to answer) specially when users have to examine sequences of events to identify a complex behavior (e.g., identifying meetings and stationary moments in time) within object movement data sets.

Furthermore, we captured the analysis process of movement data and made interesting observations about how a visualization system is used with such data sets. In a realistic scenario, users utilize various interaction features during analysis. We found that in relation to the overall time to complete, the time spent on interaction takes up a significant chunk of total performance time as opposed to the time spent exploring the visualizations statically, i.e., without interactions. Additionally, drawing the sequence and duration of the interactions revealed distinct differences between the 2D and 3D designs: use of the time slider was extensive in 2D whereas in 3D many switches between different interactions and static exploration were observed.

The complexity of moving objects varies from one object along a simple trajectory to as many moving objects along geometry of trajectories. Therefore the level of complexity influences the effectiveness of the visualization. Although, the accessibility of open source data sets is on the rise, there are still several privacy and confidentiality issues associated with the access to the more complex data sets. Therefore, many researchers still choose to simulate their data sets in order to better control the different aspects and characteristics of the data. We too, decided on simulating the data sets used in our study to make sure it is complex enough for the types of questions involved, which also makes the data sets sensitive to variations of complexity.

## 8 Conclusion and Future Work

Through our experimental comparison of 2D and 3D visualizations of movement data, we have analyzed in more detail the fraction of time spent by the user performing different interactions. As discussed, in some questions, interactivity dominates performance efficiency and including this element is key to understanding how and when users employ different interactive widgets.

Future work might include combining the advantages of 2D and 3D visualizations, as also alluded to by Kristensson et al. [2]. One approach would be to provide the user with a quick way of smoothly transitioning between a 3D perspective view and a 2D orthographic view, allowing the user gain a bird's-eye view of trajectories when desired [55]. Future designs based on the 3D space-time cube visualization should also consider minimizing the need to switch between various interaction features by carefully selecting features to provide a system that is capable of seamless transitions between interactive elements. For example, different widgets included in the system (e.g., slider widget in STV and rotation widgets in GeoTime) may be replaced by an alternative method of interaction depending on the target user and commonly performed queries.

Another interesting direction for future work can be user studies to investigate other variables in the data set as well as other visualization techniques. Amongst all, we can name studies to investigate 2D versus 3D, versus stereoscopic 3D, path complexity and tortuosity, time constrained gisting, and investigation of long-term benefits of the 3D visualization through a longitudinal study.

## Acknowledgments

The authors wish to thank the participants for their time. This research was funded by an NSERC Strategic Grant awarded to Pourang Irani and Michael McGuffin.

## References

[1] Y. Zheng. (2007). Geolife: Building social networks using human location history [Online]. Available: http://research.microsoft.com/en-us/projects/geolife/

[2] P. O. Kristensson, N. Dahlback, D. Anundi, M. Bjornstad, H. Gillberg, J. Haraldsson, I. Martensson, M. Nordvall, and J. Stahl, "An evaluation of space time cube representation of spatiotemporal patterns," *IEEE Trans. Vis. Comput. Graph.*, vol. 15, no. 4, pp. 696–702, Jul./Aug. 2009.

[3] T. Kapler and W. Wright, "Geotime information visualization," in *Proc. IEEE Symp. Inf. Vis.*, Oct. 2004, pp. 25–32.

[4] A. Cockburn and B. McKenzie, "Evaluating the effectiveness of spatial memory in 2d and 3d physical and virtual environments," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, 2002, pp. 203–210.

[5] M. Tory, A. E. Kirkpatrick, M. S. Atkins, and T. Moller, "Visualization task performance with 2d, 3d, and combination displays," *IEEE Trans. Vis. Comput. Graph.*, vol. 12, no. 1, pp. 2–13, Jan. 2006.

[6] G. Wang, M. J. McGuffin, F. Bérard, and J. R. Cooperstock, "Pop-up depth views for improving 3d target acquisition," in *Proc. Graph. Interface*, 2011, pp. 41–48.

[7] A. H. Robinson, "The thematic maps of Charles Joseph minard," *Imago Mundi*, vol. 21, pp. 95–108, 1967.

[8] E. R. Tufte, *The Visual Display Quantitative Information*. Sussex, WI, USA: Graphics Press, 1983.

[9] G. Andrienko, N. Andrienko, U. Demsar, D. Dransch, J. Dykes, S. I. Fabrikant, M. Jern, M.-J. Kraak, H. Schumann, and C. Tominski, "Space, time and visual analytics," *Int. J. Geographical Inf. Sci.*, vol. 24, no. 10, pp. 1577–1600, 2010.

[10] N. Andrienko, G. Andrienko, and P. Gatalsky, "Exploratory spatio-temporal visualization: An analytical review," *J. Vis. Lang. Comput.*, vol. 14, no. 6, pp. 503–541, 2003.

[11] C. Zhong, T. Wang, W. Zeng, and S. M. Arisona, "Spatiotemporal visualisation: A survey and outlook," in *Digital Urban Modeling Simulation*. New York, NY, USA: Springer, 2012, pp. 299–317.

[12] C. Ware, R. Arsenault, M. Plumlee, and D. Wiley, "Visualizing the underwater behavior of humpback whales," *IEEE Comput. Graph. Appl.*, vol. 26, no. 4, pp. 14–18, Jul. 2006.

[13] A. Slingsby, J. Wood, and J. Dykes, "Treemap cartography for showing spatial and temporal traffic patterns," *J. Maps*, vol. 6, no. 1, pp. 135–146, 2010.

[14] N. Andrienko and G. Andrienko, "Visual analytics of movement: An overview of methods, tools and procedures," *Inf. Vis.*, vol. 12, no. 1, pp. 3–24, 2013.

[15] D. J. Peuquet, "Making space for time: Issues in space-time data representation," *GeoInformatica*, vol. 5, no. 1, pp. 11–32, 2001.

[16] U. Turdukulov and M.-J. Kraak, "Visualization of events in time-series of remote sensing data," in *Proc. 22nd Int. Cartographic Conf., Mapping Approaches Changing World*, 2005, pp. 9–16.

[17] I. R. Vasiliev, "Mapping time," *Cartographica: Int. J. Geographic Inf. Geovis.*, vol. 34, no. 2, pp. 1–51, 1997.

[18] D. Phan, L. Xiao, R. Yeh, and P. Hanrahan, "Flow map layout," in *Proc. IEEE Symp. Inf. Vis.*, 2005, pp. 219–224.

[19] N. Willems, R. Scheepens, H. van de Wetering, and J. J. van Wijk, "Visualization of vessel traffic," in *Situation Awareness With Systems of Systems*. New York, NY, USA: Springer, 2013, pp. 73–87.

[20] E. R. Tufte and E. Weise Moeller, *Visual Explanations: Images Quantities, Evidence Narrative*. Sussex, WI, USA: Graphics Press, 1997.

[21] Y. A. Ivanov, C. R. Wren, A. Sorokin, and I. Kaur, "Visualizing the history of living spaces," *IEEE Trans. Vis. Comput. Graph.*, vol. 13, no. 6, pp. 1153–1160, Nov. 2007.

[22] G. Andrienko, N. Andrienko, and S. Wrobel, "Visual analytics tools for analysis of movement data," *ACM SIGKDD Explorations Newslett.*, vol. 9, no. 2, pp. 38–46, 2007.

[23] M. G. de Oliveira and C. de Souza Baptista, "Geostat—A system for visualization, analysis and clustering of distributed spatiotemporal data," in *Proc. 13th Annu. Brazilian Symp. Geoinformat.*, 2012, pp. 108–119.

[24] A. Thudt, B. Dominikus, and S. Carpendale, "Visits: A spatiotemporal visualization of location hitories," in *Proc. Eurographics Conf. Vis.*, 2013, pp. 79–83.

[25] A. L. Griffin, A. M. MacEachren, F. Hardisty, E. Steiner, and B. Li, "A comparison of animated maps with static small-multiple maps for visually identifying space-time clusters," *Ann. Assoc. Amer. Geographers*, vol. 96, no. 4, pp. 740–753, 2006.

[26] M. Harrower, "A look at the history and future of animated maps," *Cartographica: Int. J. Geographic Inf. Geovis.*, vol. 39, no. 3, pp. 33–42, 2004.

[27] A. M. MacEachren, *How Maps Work: Representation, Visualization, Design*. New York, NY, USA: Guilford Press, 2004.

[28] G. Robertson, K. Cameron, M. Czerwinski, and D. Robbins, "Polyarchy visualization: Visualizing multiple intersecting hierarchies," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.: Changing World, Changing Ourselves*, 2002, pp. 423–430.

[29] M. Shanmugasundaram, P. Irani, and C. Gutwin, "Can smooth view transitions facilitate perceptual constancy in node-link diagrams?" in *Proc. Graph. Interface*, 2007, pp. 71–78.

[30] L. Zaman, A. Kalra, and W. Stuerzlinger, "The effect of animation, dual view, difference layers, and relative re-layout in hierarchical diagram differencing," in *Proc. Graph. Interface*, 2011, pp. 183–190.

[31] T. Crnovrsanin, C. Muelder, C. Correa, and K.-L. Ma, "Proximity-based visualization of movement trace data,'' in *Proc. IEEE Vis. Anal. Sci. Technol.*, 2009, pp. 11–18.

[32] T. Hägerstraand, "What about people in regional science?" *Papers Regional Sci.*, vol. 24, no. 1, pp. 7–24, 1970.

[33] M.-J. Kraak, "The space-time cube revisited from a geovisualization perspective," in *Proc. 21st Int. Cartographic Conf.*, 2003, pp. 1988–1996.

[34] U. Demšar and K. Virrantaus, "Space–time density of trajectories: Exploring spatio-temporal patterns in movement data," *Int. J., Geographical Inf. Sci.*, vol. 24, no. 10, pp. 1527–1542, 2010.

[35] P. Gatalsky, N. Andrienko, and G. Andrienko, "Interactive analysis of event data using space-time cube," in *Proc. 8th Int. Conf. Inf. Vis.*, 2004, pp. 145–152.

[36] M.-J. Kraak, "Timelines, temporal resolution, temporal zoom and time geography," in *Proc. 22nd Int. Cartographic Conf.*, 2005.

[37] R. Eccles, T. Kapler, R. Harper, and W. Wright, "Stories in geotime," *Inf. Vis.*, vol. 7, no. 1, pp. 3–17, 2008.

[38] C. Tominski, H. Schumann, G. Andrienko, and N. Andrienko, "Stacking-based visualization of trajectory attribute data," *IEEE Trans. Vis. Comput. Graph.*, vol. 18, no. 12, pp. 2565–2574, Dec. 2012.

[39] T. Kapler and W. Wright. System and method for visualizing connected temporal and spatial information as an integrated visual representation on a user interface. (2007, 02 Feb. 20). *Patent US 7180516* [Online]. Available: http://www.patentlens.net/patentlens/patent/US_7180516/

[40] I. S. MacKenzie, "Fitts' law as a research and design tool in human-computer interaction," *Human-Comput. Interact.*, vol. 7, pp. 91–139, 1992.

[41] B. Demissie, "Moving objects in static maps, animation, and the space-time cube," Master's thesis, Int. Inst. Geo-Inf. Sci. Earth Observation, Faculty of Geo-Information Science and Earth Observation, University of Twente, Enschede, The Netherlands, 2008.

[42] J. Dykes, A. MacEachren, and M. Kraak, "Impact of data and task characteristics on design of spatio-temporal data visualization tools," in *Exploring Geovisualization*. Amsterdam, The Netherlands: Elsevier, 2005, pp. 201–222.

[43] I. Kveladze and M.-J. Kraak, "What do we know about the space-time cube from cartographic and usability perspective?" in *Proc. AutoCarto Int. Symp. Autom. Cartography*, Columbus, OH, USA, 2012, pp. 16–18.

[44] A. Kjellin, L. W. Pettersson, S. Seipel, and M. Lind, "Evaluating 2d and 3d visualizations of spatiotemporal information," *ACM Trans. Appl. Perception*, vol. 7, no. 3, p. 19, 2010.

[45] N. Willems, H. van de Wetering, and J. J. van Wijk, "Evaluation of the visibility of vessel movement features in trajectory visualizations," *Comput. Graph. Forum*, vol. 30, no. 3, pp. 801–810, 2011.

[46] J. D. Morgan, "A visual time-geographic approach to crime mapping," Ph.D. dissertation, Dept. Geography, Florida State Univ., Tallahassee, FL, USA, 2010.

[47] A. Kjellin, L. W. Pettersson, S. Seipel, and M. Lind, "Different levels of 3d: An evaluation of visualized discrete spatiotemporal data in space-time cubes," *Inf. Vis.*, vol. 9, no. 2, pp. 152–164, 2010.

[48] K. Vrotsou, C. Forsell, and M. Cooper, "2D and 3D representations for feature recognition in time geographical diary data," *Inf. Vis.*, vol. 9, no. 4, pp. 263–276, 2010.

[49] J. Bertin, *Semiology of Graphics: Diagrams, Networks, Maps (wj berg, trans.).* Madison, WI, USA: University. of Wisconsin Press, Ltd, 1983.

[50] G. Andrienko, N. Andrienko, P. Bak, D. Keim, S. Kisilevich, and S. Wrobel, "A conceptual framework and taxonomy of techniques for analyzing movement," *J. Vis. Lang. Comput.*, vol. 22, no. 3, pp. 213–232, 2011.

[51] D. J. Peuquet, "It's about time: A conceptual framework for the representation of temporal dynamics in geographic information systems," *Ann. Assoc. Amer. Geographers*, vol. 84, no. 3, pp. 441–461, 1994.

[52] S. Dodge, R. Weibel, and A.-K. Lautenschütz, "Towards a taxonomy of movement patterns," *Inf. Vis.*, vol. 7, nos. 3/4, pp. 240–252, 2008.

[53] P. C. Wong and R. D. Bergeron, "30 years of multidimensional multivariate visualization," in *Proc. Sci. Vis.: Overviews, Methodol. Techn.*, 1997, pp. 3–33.

[54] J. T. Todd, "The visual perception of 3d shape," *Trends Cogn. Sci.*, vol. 8, no. 3, pp. 115–121, 2004.
[55] C. Collins and S. Carpendale, "Vislink: Revealing relationships amongst visualizations," *IEEE Trans. Vis. Comput. Graph.*, vol. 13, no. 6, pp. 1192–1199, Nov./Dec. 2007.

**Fereshteh Amini** received the master's degree in computer science and is currently working toward the PhD degree at the University of Manitoba, Canada. Currently, she is working as a research assistant at the University of Manitoba's HCI Lab doing research with the focus on visualization of spatiotemporal data.

**Sébastien Rufiange** received the BEng degree in software engineering in 2008, and the PhD degree from ÉTS, Montréal, Canada, in 2013. He has taught courses on software engineering and design. His research interests include the visualization of information and networks, evolution, and software visualization. He is currently a postdoctoral researcher at INRIA Bordeaux Sud-Ouest (Bordeaux, France), working on network visualizations.

**Zahid Hossain** received the bachelor's degree in computer science and engineering from the Bangladesh University of Engineering and Technology, and is currently working toward the master's degree at the University of Manitoba in Canada where he does research in information visualization and human computer interaction.

**Quentin Ventura** is currently working toward the BEng degree in software engineering from Université de Technologie de Compiègne and the MEng degree in information technologies from École de Technologie Supérieure. His research interests include information visualization and spatiotemporal data.

**Pourang Irani** received the BSc and the PhD degree from the University of New Brunswick, Canada. He is an associate professor in human-computer interaction at the University of Manitoba. His work focuses on the design, implementation and evaluation of novel software and hardware interfaces for advanced interactions and visualizations.

**Michael J. McGuffin** is an associate professor at ETS, a French-language engineering school in Montreal, Canada, where his students and he do research in information visualization and human-computer interaction. He has published three papers cited more than 100 times each, and in 2009, his paper at the IEEE Information Visualization Conference (InfoVis 2009) received an Honorable Mention. Papers and youtube videos of his research are at http://profs.etsmtl.ca/mmcguffin/.