Temporally Transformed Map Animation for Visual Data Analysis

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***Abstract*— Animated maps are widely used in visualizing the temporal aspect of geographical data, even though their effectiveness depends on multiple factors and is far from obvious. This paper presents one method to complement map animations with a transformation that manipulates the temporal dimension. This temporal transformation, in which events were located equally into a time period, applies the idea of spatial transformation, which is familiar from cartography. We performed a user test with a transformed animation of two different datasets to demonstrate how the transformation presents different spatio-temporal relationships. The test indicates that the transformed animation can reveal spatio-temporal patterns which cannot be detected from a traditional animation, such as the order of very dense events. The users found the transformed animations insightful and useful. For complex visual analysis the combination of the transformed animation and timeline visualization seems to be the most effective.**

Keywords- map animation; temporal transformation; user testing.

I. INTRODUCTION

A map animation is a common method for visualizing spatio-temporal information. The reason for this is simple: an animated map allows spatial information to be presented on a map and, at the same time, it naturally uses the temporal dimension for presenting changes over time. However, an animated map does not automatically result in effective comprehension. The comparison between animations and static visualization methods has been considered in many studies, both in graphics [1] [2] and in cartography [3] [4] [5], and the results from these studies show variation in the superiority of the methods, depending on the types of tasks and datasets.

Fabrikant et al. [6] point out that well-designed map animations are inherently different from well-designed static maps and comparison between these two methods is not even meaningful. They argue that instead the attention should be focused on studying when and why these methods do work. Lobben [7] showed that animations are better suited when users' tasks deal with time, and also found some evidence that static maps could work better with location-based tasks. Simultaneous changes at many discrete locations are difficult to perceive from an animation but as a presentation of general spatio-temporal patterns and the behaviour as a whole an animation can be most valuable [8].

It is evident that user control affects the usability of an animation and the effectiveness of its comprehension. In many cases, it improves users' performance [9], but at the same time, user control may distort the continuity of the animation so much that the advantages of the animation are lost [8]. Especially if an animation contains long still periods and/or dense temporal clusters, the ability to control the speed of the animation becomes essential. However, it is clear that the user control tools always increase the users' cognitive load and produce a split attention problem [10].

These inefficiencies suggest that in order to support the interpretation of map animations, we should search for methods that overcome the limitations of animations. These kinds of methods would be especially required in exploratory tasks when making sense of spatio-temporal behaviour. With static maps, cartographic transformations such as density transformation are used to present a phenomenon from different perspectives and to reveal patterns that would otherwise stay hidden. This inspired us to study the possibility of benefiting from similar transformations of the temporal dimension in animated maps. We performed a concept testing with interviews with the test users to test the effectiveness of temporal transformation in detecting spatio-temporal patterns.

The theoretical background and practical details of the transformation are explained in the next two sections. After that, the test animations, test setting, and interviews, as well as the results, are presented. Finally, discussion of the results takes place and conclusions are drawn.

II. MOTIVATION

The spatial and temporal dimensions of geographic data share commonalities, such as scale and its relation to the level of detail of the phenomena that are represented [11]. When we present a real-world space on a map, we shrink the presentation into a smaller scale and, in most cases, explicitly inform the users about the scale. In a map animation, real-world time is usually correspondingly scaled into a shorter display time. Despite the fact that the temporal scale, just like the spatial scale, has a strong influence on the observation and understanding of the phenomena, the temporal scale is not commonly calculated and expressed numerically. Instead, the passing of time is presented as a relative location of a pointer on a time slider.

There are also similarities between the temporal and spatial relationships of objects. The temporal topological relationships presented by Allen [12] show many similarities to spatial data: moments in time can be ordered, and temporal objects can be equal to, meet, overlap with, or

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include each other. However, because of the one-dimensional nature of time, the temporal order is unambiguous and each point object can have only two neighbours in time: the one which is the closest before and the one after. The only temporal metric relationship is the length of time (the duration of an event or an interval between two events), corresponding to distance in space.

The duration, order, and rate of change of the dynamic visual variables [13] make it possible to present different spatio-temporal datasets meaningfully in an animation. Typically, the duration of the scenes is kept constant throughout the whole animation, and in animations which present change in time, the order of the scenes is chronological. The rate of change depends on the sampling rate of the real-world phenomenon in the dataset. The duration and rate of change together produce the perceived speed of the animation. If we want the change in the animation to look smooth, the rate of change must be small enough and successive scenes must follow each other fast enough. If the sampling rate is too low, extra data frames should be interpolated between them to give the impression of smooth animation.

The idea of many of the geographic transformations, such as generalization and equal density transformation, makes sense when they are adapted to the time dimension, while some other transformations cannot strictly be applied to the time axis because of the one-dimensional nature of time. Monmonier [14] gives examples of how to apply spatial generalization operators such as displacement, smoothing, and exaggeration to the temporal dimension of dynamic statistical maps, but his motivation is to avoid incoherent flicker and twinkling dots and instead allow the perception of salient patterns in dynamic thematic maps. Kraak [15] has also experimented with the transformation that he calls “from time to geography”, with static presentation. It stretches the famous Minard’s Map according to the temporal dimension in such a way that the time periods with slow or no movement stretch the spatial representation of the trajectory. This example differs from so-called travel time cartograms since it does not consider any location as a reference point to which the travelling times are calculated. Andrienko et al. [16] present a time transformation called a “trajectory wall”, where the time axis of a space-time cube is modified to present the relative order of the events. Therefore, trajectories that follow the same route do not overlap with each other, but form a wall in which the order of the trajectories on the time axis is determined by their starting times.

In this study, we propose the temporal transformation of animation in order to present the data from a different perspective and with a different temporal emphasis in order to support the analysis of spatio-temporal phenomena. Our research question was whether this transformation can be comprehensible and useful to users. For the study, we created transformed map animations of two different datasets with different temporal structures. As a result of the transformation, the events in a dataset were evenly located in time over the whole time period, keeping their order. The basis of this transformation is somehow similar to a trajectory wall, since it preserves the order of the events, but it is implemented with a dynamic display. We call this transformation “equal density transformation” because it equalizes the time intervals between consecutive events.

III. EQUAL DENSITY TRANSFORMATION

Spatially, in equalized density transformation the areas of high density of the phenomenon are made bigger and the areas of low density become smaller, so that the spatial density of the phenomenon becomes constant [17]. This transformation is presented in an example in Figure 1. The distances between points are equalized and the reference grid stretches and shrinks correspondingly. In the temporal version of equalized density transformation, the time intervals between each two consecutive events are equalized in length over the whole time period. Equal density transformation is performed by dividing the events evenly into the time period of an animation. If the dataset contains events that feature duration, their start and end times are simply handled as separate objects on the timeline. In this transformation, the accurate timestamps of events are lost, but the temporal topological relationships remain constant. Should there be any events with exactly the same timestamp, their mutual order must be determined by some other attribute.

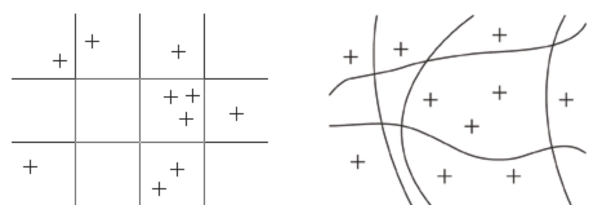

Figure 1. Spatial equalized density transformation illustrated with a small example dataset.

Two example sets of events in their original form and after the equal density transformation are shown in Figures 2a and 2b. From them it can be seen that the density of the events reflects the degree of the transformation. When the events are condensed, their time period is stretched to last longer. Consequently, time periods with sparse events are “fast-forwarded”. This reduces the user’s temptation to fast-forward those periods when some potentially important information may remain unobserved.

IV. USER TEST AND INTERVIEWS

In this section, we first describe the animated dataset, the making of the test animations, and the implementation of the test and user interviews. The results from the test and interviews are presented in the next section.

A. Test Data and Animations

The aims of the user test were to find out whether the test users prefer the transformed animation or the original, whether they find the transformation useful, and whether they really understand the effect of the transformation. Therefore we prepared a set of questions that the test users were to answer while viewing the animations. The number of times they viewed each animation and the additional comments they made during the test were recorded.

The dataset used in this test contained Twitter messages, so-called tweets, from the area of Port-au-Prince, Haiti, from a four-month period after the earthquake in January 2010. Twitter was used to search for help and food or water supplies and also to find missing persons. A Twitter user can allow the exact coordinates of the tweets to be saved and shown by the service provider, and all these tweets were included in the test dataset.

For this test, two different datasets were prepared. The first dataset covered the four-month period after the earthquake, but to keep the size of the dataset reasonable, every tenth tweet was selected. In this dataset, most of the tweets were strongly compressed into the first days and weeks of the time period, and after that the density of the tweets decreased remarkably. This dataset is henceforth referred to as the “Every 10th” dataset and is shown on a timeline in Figure 2a. The other dataset contained the very first tweets right after the earthquake. To achieve the same number of objects (193 tweets), the dataset was cut to cover about an 84-hour period. Because of the problems in electricity production in Haiti, only those tweets that were sent between 6 am and 6 pm were successfully published. This caused strong periodicity in the data. This dataset is henceforth referred to as the “First days” dataset and is shown in Figure 2b. Both datasets were equal density transformed by using Microsoft Excel. In the transformed datasets, the time interval between two consecutive events is the whole time period divided by the number of events. Figure 2c shows the effect of the equal density transformation; these two datasets become similar. The timestamps are not visible in this timeline, because they were artificially modified and did not correspond to the real-world time.

Four map animations were made with ArcGIS10; two presented the original “Every 10th” and “First days” datasets and two presented the equal density transformed datasets. All animations were of equal length, 60 seconds, and they each contained 193 events. The events were presented on a background map with red dots that appeared brightly and faded to a less saturated red after that. A screenshot from one animation is shown in Figure 3. In addition to the animations, the timeline visualizations were presented in the test view immediately below the test animations to help the test users to comprehend the temporal patterns of the data.

B. *Test Setting*

At the beginning of the test, the main concepts of the test, such as pattern and spatio-temporal information, were introduced to the user and the user was able to familiarize himself/herself with an example of the animations, layout, and arrangements of the user interface.

The test contained two parts. One part presented the original and transformed animations of the “First days” dataset and the other part the corresponding animations of the “Every 10th” dataset. Each test user performed both parts, but the order of these parts varied between the users in order to avoid the influence of the learning effect. These two parts were identical in terms of their layout and arrangements.

In the first phase, the user first had the opportunity to view only the original animation as many times as he/she wanted, and after that was asked to answer Questions 1.1 and 1.2 (Table 1). The questions dealt with the overall impression of the dataset. Then the user viewed the temporally transformed animation and answered the same questions. The order of the animations was fixed to this, because we wanted to simulate the explorative analysis task where the user first gets an overview of the data and then uses more complex tools, focusing on more detailed analysis.

In the second phase, the user could use both of these two animations to answer three more detailed questions (Questions 2.1-2.3 in Table I) about the behavioural patterns of the data. Because of the differences in the datasets, the questions varied slightly between the two datasets.

After finishing both parts of the test, the user was interviewed. The interview was semi-structured and covered the following topics:

- Was the temporal transformation as a method easy to understand?
- What could have made the transformation easier to understand?
- Did you use the animation, timeline, or still picture of the animation to answer the questions?
- Was the transformed animation useful when answering the questions? Why?
- In what tasks was the transformation especially useful?
- Could this kind of tool be useful in your job?

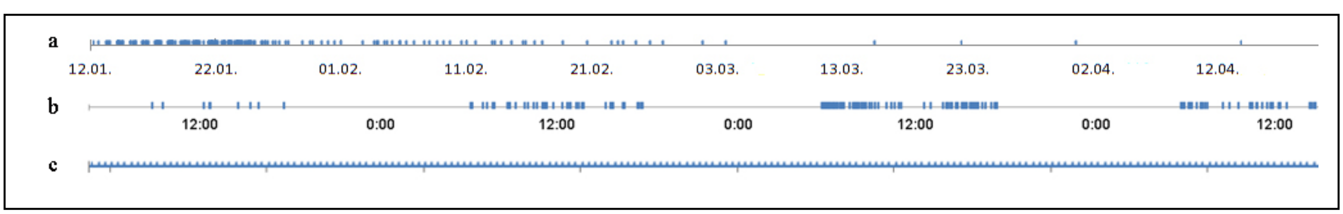

Figure 2. The top row (a) shows the “Every 10th” dataset visualized on a timeline. The middle row (b) shows the “First days” dataset visualized on a timeline. The scales of the timelines are different. The bottom row (c) shows both datasets after the equal density transformation.

Some users had already discussed these topics during the test, and in these cases not all the questions were explicitly gone through during the interview.

TABLE I. QUESTIONS IN THE USER TEST.

Q	"First days" dataset	"Every 10th" dataset
1.1	What kind of patterns do you find from the data?	
1.2	Are there any events which seem not to fit the data or draw your attention in some other way?	
2.1	Where are the first and last events of the dataset located?	In what area are the first ten events of the dataset located?
2.2	Is there a location on the map where there are multiple sequential events? Where is it?	Are there time periods when the events are clustered into a certain area?
2.3	Is there an area on the map where the events are clustered both spatially and temporally?	Does the centroid of the events move during the animation?

The test was completed by nine users. They were professional cartographers or geographers with experience of temporal datasets. Four of them were female and five male. Their ages varied between 28 and 55 years.

The users did the test on a laptop computer that was connected to a data projector. The evaluator observed the user's performance via the data projector, calculating the viewing times for each animation. The users could answer the test questions either by typing their answers into a textbox on the display or verbally to the evaluator, who wrote those answers down. The answers in the interviews were also written down by the evaluator.

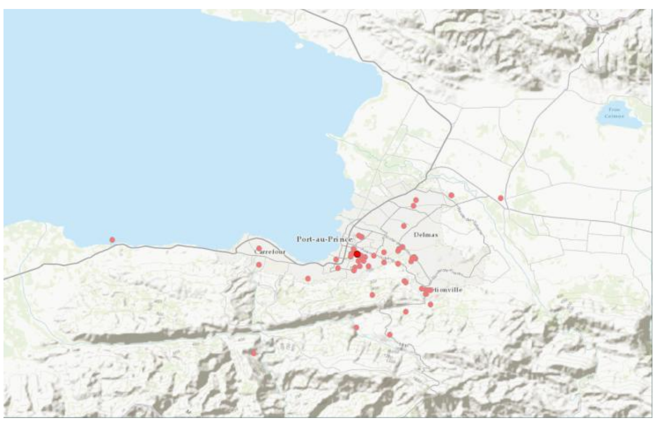

Figure 3. A screenshot from the transformed animation of the "First Days" dataset. The latest event is seen as a bright red dot in the middle of the map. Basemap: Esri 2013.

C. Analysis of the Material

From the user test, the following indicators were analyzed:

1. the number of times the user viewed each animation in each task, and whether he/she viewed the whole animation or the viewing was discontinued;
2. the kinds of behaviour patterns the user found from the animations and whether these findings were appropriate;
3. whether the user's impression of the phenomenon represented in the dataset differed between the original and transformed animations.

From the users' comments during the test and their answers in the interview, the following factors were calculated:

1. positive and negative comments the users made about each animations;
2. faulty and inaccurate interpretations that the users made from the animations;
3. cases where the user made different interpretations from the same dataset on the basis of the two animations.

Because of the small number of test users, no statistical significance parameters were calculated from these results.

V. RESULTS

In the test, the users chose to view the transformed animation slightly more often than the original animation. This trend was particularly clear with Questions 2.1 and 2.2, which dealt with so-called elementary lookup tasks [18]. With more complex analysis tasks, the users tended to interrupt the flow of the original animations by pausing or fast-forwarding, while the transformed animations were more often viewed in their entirety. This pattern can be seen in Table II. The first, **bold** number in each box marks the times when the animation was viewed completely, and the second number (in parentheses) marks the times when the animation was viewed partially, which means that the user paused, fast-forwarded, or interrupted it in some other way during the viewing. Every row in the table corresponds to one task in the test.

The differences between the results for the two datasets in Question 2.3 are caused by the difference in the questions. With the "First Days" dataset, the question concerned the whole time period, and therefore the users had no choice but to view the animation completely. On the contrary, with the "Every 10th" dataset the task was to find a spatio-temporal cluster, and the users could stop viewing the animation after finding the first one.

TABLE II. THE VIEWING TIMES OF EACH ANIMATION

	Every 10th dataset		First Days dataset	
	original	*temporally transf.*	*original*	*temporally transf.*
Q 1.1 and 1.2	**16**(2)		**16**(2)	
Q 1.1 and 1.2		**15**(2)		**17**(0)
Q 2.1	**2**(10)	**3**(14)	**5**(6)	**3**(12)
Q 2.2	**4**(5)	**9**(2)	**6**(1)	**11**(0)
Q 2.3	**6**(10)	**9**(4)	**9**(1)	**8**(0)

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When viewing the transformed animation of the “First days” dataset, in the first phase of the test six out of the nine users mentioned that they perceived a location at which several events appeared sequentially. This location can be seen as the latest and brightest dot in Figure 3. Later, when explicitly asked (Q2.2), the remaining three users also perceived it. From the original animation, none of the users perceived this kind of behaviour at first, and after the question Q2.2, only one user mentioned that he also saw that phenomenon in the original animation, “but much more weakly than in the transformed animation”. This location with sequent events proved to be a police station in the centre of Port-au-Prince. Our assumption is that the inhabitants of the city went to the police station to seek their missing relatives after the earthquake, and the police used Twitter to support the search and rescue efforts.

The users learned to favour the transformed animation with some tasks even during this kind of very short test. For the questions Q2.1 and Q2.2 the transformed animation was used approximately 40% more often than the original, and was viewed more often without interruption. With the question Q2.3 the preference between the animations varied, depending on the dataset, but the transformed animation was viewed in its entirety more often.

In the interviews most of the users had a positive attitude towards the transformed animations. They were apparently pleased and said that the transformation was “charming” or “nicer”. They also mentioned that the transformed animation was “better” and “easier to watch”. Two users said that the transformed animation was “exhausting” and its “continuous info flow was tiring”. However, these two users also commented that the transformation was useful in some cases. A summary of elements calculated from the interviews is shown in Table III.

TABLE III. SUMMARY FROM THE INTERVIEWS

	Original animation	**Temporally transformed animation**
More useful (pos.)	2	14
Unpleasant to view (neg.)	1	2
Misinterpretations		2
Different interpretations	8	

The users had varying opinions about the applicability of the transformation. For some tasks performed in the test, some of the users said that the transformed version was “essential”, while others said that it did not suit those tasks. When asked about the use cases for this kind of transformation, the users mentioned several possible application areas in addition to elementary lookup tasks dealing with time. For example, traffic planning, crowd movement analysis, environmental analysis, and oil destruction activities were proposed. The users also pointed out the possibility of combining the analysis of the temporal dimension on the timeline with behavioural analysis of the transformed animation.

From the interviews it became clear that a proper temporal legend could have improved the performance; five of the nine test users mentioned this when asked about development ideas. More specifically, the idea of colouring the events according to their timestamp was mentioned by several users. Another suggestion was to improve the linking between the timeline and the animation; a moving pointer should show the flow of time of the transformed animation on the timeline of the original data.

The test results indicate that it is essential to ensure that the user understands how the transformation influences the animation. In several cases (eight out of the 27 behaviour descriptions recorded) the users’ impression about the phenomenon varied between the original and transformed animations, even though they knew that the animations presented the same dataset. Some clear misinterpretations appeared; in one case the user grouped the last events of one day and the first events of the next day into the same spatio-temporal cluster despite the fact that there was a 12-hour gap. The same user also made a false statement about the location of the last event of the dataset.

VI. DISCUSSION AND FURTHER RESEARCH

The user test shows that the equal density transformation of the animation revealed the position of sequential events that were not detected from the original animation. We believe that this pattern would have remained unnoticed without the transformation. Additionally, this pattern was found spontaneously; in the majority of cases it arrested the attention of the users without any specific search task. This is an important feature of the visual analysis tool when it is used for data exploration and data mining.

As the interviews with the users proved, the power of the equal density transformation lies in the fact that it can reduce the user’s need to interrupt the animation, and therefore offers a smooth overall evocation of the phenomenon. At the same time it eases the cognitive load on the user by offering a continuous, temporally predictable change with no congested periods. It emphasizes the order of the events and equalizes them in relation to time, thus attributing equal significance to all the events.

The findings indicate that the disadvantage of the transformation is that misinterpretations of the transformation are possible or even probable. These misinterpretations could be minimized with a temporal legend in which the user can always perceive the phase of the animation. Furthermore, properly designed colours for the events could indicate the degree of the transformation, and these colours could be used for linking the timeline and the animations.

The idea of colouring the events according to their timestamp also arose repeatedly in the interviews. The users suggested, for example, that the colour of the point-type events might change smoothly day by day. This would help the user to detect spatio-temporal clusters from the map and also communicate about the temporal discontinuities in the data.

However, a disadvantage of the use of colour as a temporal legend is that one cannot visualize any attribute data by means of colours at the same time. When the events are point-type and visualized with small, round objects, other ways to present attribute information are limited. Therefore, consideration should be given to whether the combination of these two variables with the use of colour is possible. Brewer [19] proposed a set of colour scheme types to be used with bivariate data, but this set does not contain the combination of qualitative attribute information and a bipolar subordinate variable. The temporal transformation can affect the time either by stretching or shrinking it, and therefore its visualization should also be bipolar. If the degree of temporal transformation is simplified to binary data (= slower or faster than the original), then Brewer's "qualitative/binary" combination can be used. In this schema, the qualitative data is visualized with different hues and the binary data is visualized with the lightness of the colour. It must be noted that Brewer's model is designed for choropleth maps, and its applicability to point-type data is not obvious. Therefore it is clear that more research is needed to test whether discrimination between these two variables is possible in a use case similar to the case in this study.

Another possible way to provide the information about the speed of the animation is sound. [20] suggests sonic input to represent the passing of time. This could also be a useful technique with an animation with changing speed, since human hearing is relatively sensitive to changes in rhythm and pitch. A user test with a sonic legend and a larger number of test users is our future research plan.

The lack of attribute information is a limitation of this study. In this study, we tested the concept of equal density transformation and therefore wanted to keep the test arrangement as simple as possible. It would be possible, for example, to classify the tweet messages according to their thematic content, and visualize this classification by the use of colour.

Because of the simplification of the test procedure, the user control over the animations was also limited. The users did not have a chance to adjust the speed of the animation or to filter its content. However, we offered the most common user control tools; playing, pausing, and the opportunity to jump to any moment in the animation. A wider selection of control tools would have increased the cognitive load on the user and drawn the user's attention away from the task being tested.

VII. CONCLUSIONS

The human ability to adopt information from temporal animation is limited. If the animation runs too fast, is too long, or presents too many events simultaneously, a user can easily miss some information, and therefore is not able to form a full image of the phenomenon being presented. The traditional control tools of an animation, such as pausing, jumping to a specified scene, or looping, have a limited capability to improve this understanding.

This paper presented a novel method for transforming the temporal dimension of map animations by equalizing the interval between two consecutive events. The user test proved that the transformation can reveal patterns that would have been left unnoticed with traditional animation. It seems to be understandable for the users and useful for spatio-temporal analysis in parallel to an original, non-transformed animation.

In exploratory analysis a rich variety of tools that complement each other is a necessity. The results from this user test and interviews indicate that equal density transformation might be an appropriate technique to complement a set of such analysis tools.

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