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Assisting the Detection of Spatio-Temporal Patterns in Temporally Transformed Map Animation

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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. Especially when the temporal structure of a dataset is irregular, new methods for exploratory analysis are required. This paper presents a novel method to manipulate map animations by transforming the temporal dimension so that events are located in equal intervals into a time period. This temporal transformation applies the idea of spatial equal density transformation, which is familiar from cartography, in order to ease the cognitive load on a user caused by the temporal congestion of the dataset. A user test with a transformed animation of two different datasets indicated that the transformed animation is useful in revealing spatio-temporal patterns, which could not be detected from an original, untransformed animation. The transformed animations were found insightful and useful by the test users. These findings indicate that a temporally transformed animation would be a useful addition to a toolbox for exploratory analysis of spatio-temporal data.**

Keywords-map animation; cognitive load; temporal transformation; equal density; user testing.

I. INTRODUCTION

This paper is extending the previous study of temporal transformation [1] with more thorough review of cognitive load and a task definition of exploratory analysis.

A map animation is a common method for visualizing spatio-temporal information. The reason for this is simple: an animated map follows the congruence principle [2], which achieves the natural correspondence between the subject and its representation, by allowing spatial information to be presented on a map and, at the same time, using 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 computer graphics [2] [3] and in cartography [4] [5] [6]. The results from these studies show variation in the superiority of the methods, depending on the types of tasks and datasets.

Fabrikant et al. [7] pointed 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 argued that instead the attention should be focused on studying when and why these methods do work. Lobben [8] 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 [9].

Harrower and Fabrikant [9] argued that passive viewing of an animation, without any control tools, is more valuable in an early phase of an analysis, offering an overall picture of the phenomenon. It is evident that in later phases user control may increase the usability of an animation and the effectiveness of its comprehension. In many cases, user control improves users' performance [10], but at the same time, it may distort the continuity of the animation so much that the advantages of the animation are lost [9]. The use of control tools always produces a split attention problem and increases the users' cognitive load [11].

These inefficiencies of traditional animations suggest that in order to support the interpretation of map animations we should search for methods to overcome these issues. These kinds of methods would especially be required in the exploratory analysis of spatio-temporal datasets with an irregular temporal structure containing long still periods and/or dense temporal clusters.

Especially with temporally irregular datasets, the ability to control the animation becomes essential. Without any control, such an animation would be inefficient and dull, and sudden changes could easily be missed [9]. Dykes and Mountain [12] argue that animations that present time linearly and continuously are not suitable for all kinds of exploratory analysis tasks, and call for more advanced visualization methods.

The rest of the paper is organized as follows: Section II motivates the study and Section III discusses the cognitive load of animated maps. Section IV presents the equal density transformation and Section V covers the user test and interviews. The results are presented in Section VI, after which these results are discussed in detail in Section VII. Finally, conclusions are drawn in Section VIII.

II. MOTIVATION

The dynamic visual variables duration, order, and rate of change [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, although Harrower and Fabrikant [9] provide a reminder about the possibility of modifying the duration of the scenes dynamically during the animation. In animations that present changes over time, the order of the scenes must be 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.

Monmonier [14] gave 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 was to avoid incoherent flicker and twinkling dots and instead allow the perception of salient patterns in dynamic thematic maps. Kraak [15] experimented with the transformation that he calls "from time to geography", for static presentations. 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, and, correspondingly, fast movement is shrunken into shorter. 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] presented 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.

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 a similar transformation of the temporal dimension in animated maps.

In this study, our aim was to ease the interpretation of temporally irregular datasets by presenting the data from a different perspective and with a different temporal emphasis. For the study, we created transformed map animations of two different datasets with different temporal structures. As a result of the transformation, the events recorded 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 [16], since it preserves the order of the events, but it is implemented in a dynamic display. We call this transformation as "temporal equal density transformation" because it equalizes the time intervals between consecutive events. Our hypothesis was that this kind of transformation could support the analysis of spatio-temporal phenomena. We performed concept testing and interviews with users to study the potential of temporal equal density transformation in detecting spatio-temporal patterns.

III. COGNITIVE LOAD OF MAP ANIMATIONS

In this section, we look at those parts of cognitive loads that are relevant for this research. This is to demonstrate the effect of human cognitive processes when studying irregular spatio-temporal datasets.

The human brain collects information from the environment through several information channels and processes this data in working memory. The number of objects that the working memory can handle at one time is limited; estimate of this differ from 7±2 [17] to only three or four [18]. From working memory, we move processed information to long-term memory, which has practically unlimited capacity. The research on this moving process has developed cognitive load theories [19].

Theories of cognitive load are widely accepted and used, but in the context of this study it is meaningful to specify which part of the data visualization causes an increase in the cognitive load. Paas et al. [19] divide the cognitive load into three parts: the intrinsic, extraneous, and germane cognitive loads. The intrinsic cognitive load is caused by the data itself, the extraneous cognitive load means the unnecessary information caused by the visualization or user interface, and the germane cognitive load deals with the presentation of the task and even the motivation of the user to fulfil the task. If the data contains thousands of separate objects, we must, in one way or another, enable all these objects to be handled in the working memory. In cartography, this intrinsic cognitive load is usually handled by means of generalization or classification of the data. For decades, cartographic visualization has aimed to reduce the extraneous load of unnecessary information by selecting, filtering, and emphasizing the relevant parts of the information. Clarifying the task of the user and presenting the information in a feasible way are essential in order to reduce the germane cognitive load.

Alternatively, we can discuss the "load on the working memory" or simply "mental load". Mayer and Moreno [20] use the term mental load when presenting a scenario in which both information channels, verbal and visual, are overloaded. As a solution for this kind of overload Mayer and Moreno suggest segmenting the information into parts. The principle is that enough time must be given for the user to process one part of the information before the next part is presented. This processing time can be pre-defined or the user can give a signal (for example, by clicking "continue") that he/she is ready to move on.

With animated map visualizations this segmenting means that the duration of the scenes [13] must be selected to be such that the user can perceive all the important elements on the map. The more elements that are visible, the more time we need to perceive them all. However, as mentioned earlier, the temporal structure of the dataset can have such a nature that simply slowing down the animation is not reasonable. Therefore, we must search for other ways to offer the time needed for processing.

IV. EQUAL DENSITY TRANSFORMATION

The spatial and temporal dimensions of geographic data share commonalities, such as scale and its relation to the level of details of the phenomena that are represented [21]. 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 either by number or a line. In a map animation, real-world time is usually correspondingly scaled down 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 in an animation. Instead, the passing of time is presented as a relative location of a pointer on a time slider. This time slider often works both as a temporal legend and a control tool.

In addition, the spatial and temporal dimensions have some similar topological and metric relationships. The temporal topological relationships presented by Allen [22] show many similarities to spatial data: moments in time can be ordered, and temporal objects can be equal to, meet, overlap with, or 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 that 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 idea of many of the geographic transformations, such as equal density transformation [23] and fish-eye zooming [24], are adaptable to the time dimension, while some other transformations cannot strictly be applied to the time axis because of the one-dimensional nature of time.

Spatially, in equal 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 [23]. This transformation is presented in an example in Figure 1. The distances between points are equalized and the reference grid stretches and shrinks correspondingly.

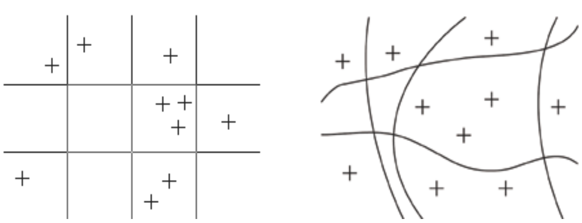

Figure 1. A small spatial example dataset (left) and the effect of spatial equalized density transformation to it (right).

In the temporal version of equal density transformation that we study, the time intervals between each two consecutive events are equalized in length over the whole time period. Equal density transformation is performed by counting the number (N) of events (E) in the dataset in the time period (P), which is the time between the time stamps of the first (t_0) and last (t_n) event of the dataset, and then calculating the new time stamps t' for each E. Each event E gets its own portion equal length of the time period and is placed in the middle of its portion.

$$t'(E_i) = t_0 + (i - 1/2) * (P/N)$$

If the dataset contains events that feature duration, their start and end times are simply handled as separate events 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 or one must diverge from the principle of equality and present those events at the same time.

An example of a set of temporal events in its original form and after the equal density transformation is shown in Figure 2. Events are presented in changing colour, emphasizing their order. In Figure 2, it can be seen that the degree of transformation reflects the density of the events. When the events are condensed, time around them is stretched to last longer. Consequently, time periods with sparse events are speeded up. This reduces the user's temptation to fast-forward those periods that might cause some potentially important information remaining unobserved.

The temporal equal density transformation follows the segmenting solution suggested by Mayer and Moreno [20]. It gives enough time to perceive every single event and, simultaneously, eliminates the unnecessary empty periods, which would grow even longer if the animation were slowed down traditionally. Therefore, it avoids composition of artificial groups, which can happen when segmenting the time into equal periods. Segmenting the time dimension into periods of equal duration and presenting all the events in one period at the same time is a method used when animating maps. The aim is to reduce the required computer capacity and the cognitive load on the user. However, this segmenting causes a common problem: if the dataset is artificially divided into even time periods, it is possible that temporal clusters in the dataset get unintentionally chopped. On the other hand, events that end up in the same period are automatically grouped together even though they can actually be temporally rather far from each other.

It must be underlined that like spatial equal density transformation, this temporal transformation can serve different purposes. Spatial equalization can be used to show the relative importance or weight of areas with different densities of objects, or for the closer examination of dense clusters. Similarly, temporal transformation can make all the events visible and reveals the temporal order of the data. At the same time it reduces the worthless empty periods. This feature is more important than in static spatial visualizations, where the user can simply ignore the areas with no events. If temporal equalization were used to show the importance of different periods, the visualization of the timeline, as in Figure 2, would play a critical role.

V. USER TEST AND INTERVIEWS

In this section, we first describe the datasets and the test animations, the test setting and interviews, and finally the analysis of the results.

The aim of the user test was to find out whether the transformation would support the recognition of spatio-temporal patterns in the analysis process. Therefore, we prepared a set of test animations and 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.

A. Test Data and Animations

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 the tweets with these coordinates 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, only 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. The densest period was around January 22nd. This dataset is referred to as the “Every 10th” dataset and is shown on a timeline (a) in Figure 3. 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 referred to as the “First days” dataset and is shown in timeline (b) in Figure 3. Spatially, the events of the “First days” dataset are clustered more into the centre of Port-au-Prince, while the events of the “Every 10th” dataset are spread more evenly over the area of the city (Figure 4). It must be emphasized that the users never saw these datasets side by side as in Figure 4, because they examined only one dataset at the time.

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. Timeline (c) in Figure 3 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. In addition to the animations, the timeline visualization was presented in the test view immediately below the test animation (Figure 4) to help the test users to comprehend the temporal patterns of the data.

The effect of the transformation to the animation of the dataset “Every 10th” can be seen in Figure 5. In the upper figure, both animations are paused after 15 seconds. In an original animation (left), majority of the events are already appeared while the events in the transformed animation (right) run slower. In the lower figure, where the animations are paused after 45 seconds, this difference is almost tied.

In the “Every 10th” dataset, the events are congested into the first days and weeks after the earthquake, the most dense period being around January 22nd. The “First days” dataset shows that there were no events between 6:00 pm and 6:00 am, and that there were relatively few events on the very first day after the earthquake.

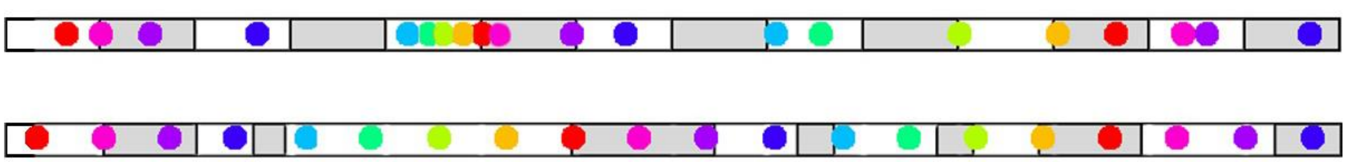

Figure 2. An example showing temporal events on a timeline (above) and the same dataset after the temporal equal density transformation (below). Grey and white areas behind the event points indicate the time units; in the upper timeline they are all of equal length, but after the transformation those time units with many events stretch and those with fewer or no events shrink.

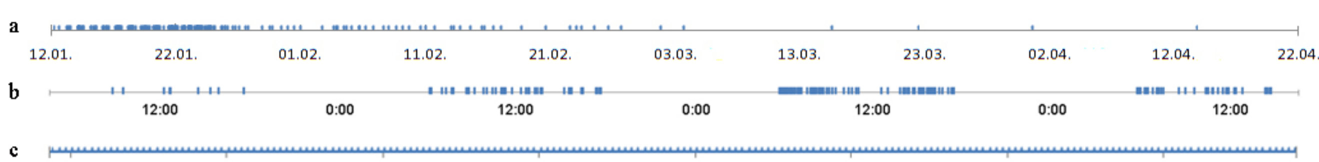

Figure 3. The top row (a) shows the “Every 10th” dataset visualized on a timeline. The middle row (b) shows the “First days” dataset visualized on a timeline. Note that the scales of the timelines are different. The bottom row (c) shows both datasets after the equal density transformation.

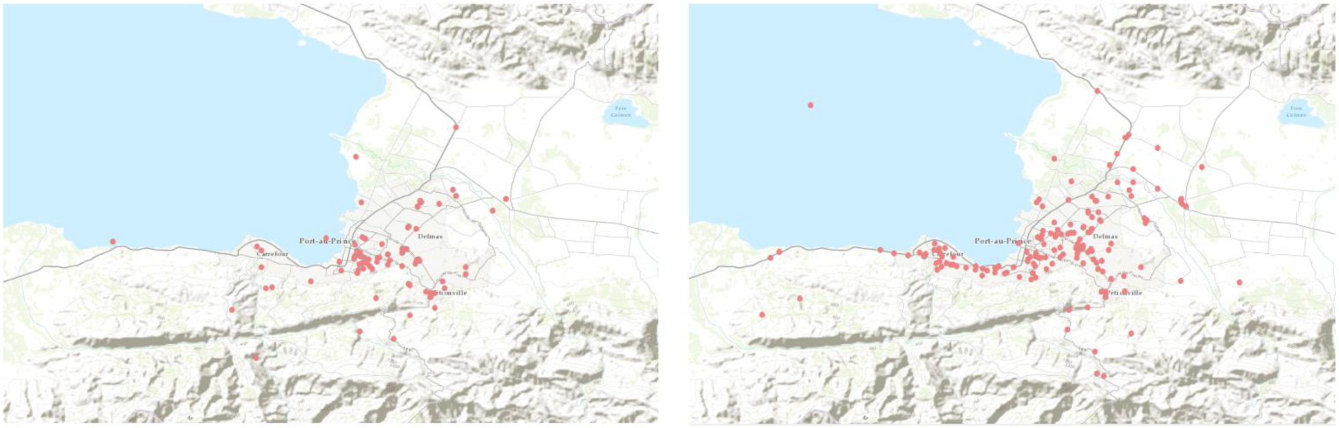

Figure 4. Spatial distribution of the events of both datasets used in the user test, “First Days” (left) and “Every 10th” (right). During the first days, there were very few events from outside the urban area of Port-Au-Prince.

B. Test Setting

Main concepts and terminology of the test, such as *pattern* and *spatio-temporal information*, were introduced to the user in the beginning of the test. Then the user was able to familiarize himself/herself with an example animation (a 10-second clip showing a zoomed part of one 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 I). 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?

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.

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.

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?

C. Analysis of the Material

From the user test, the following indicators were analysed:

1. the number of times the user viewed each animation in each task, and whether he/she viewed the whole animation or was the viewing 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.

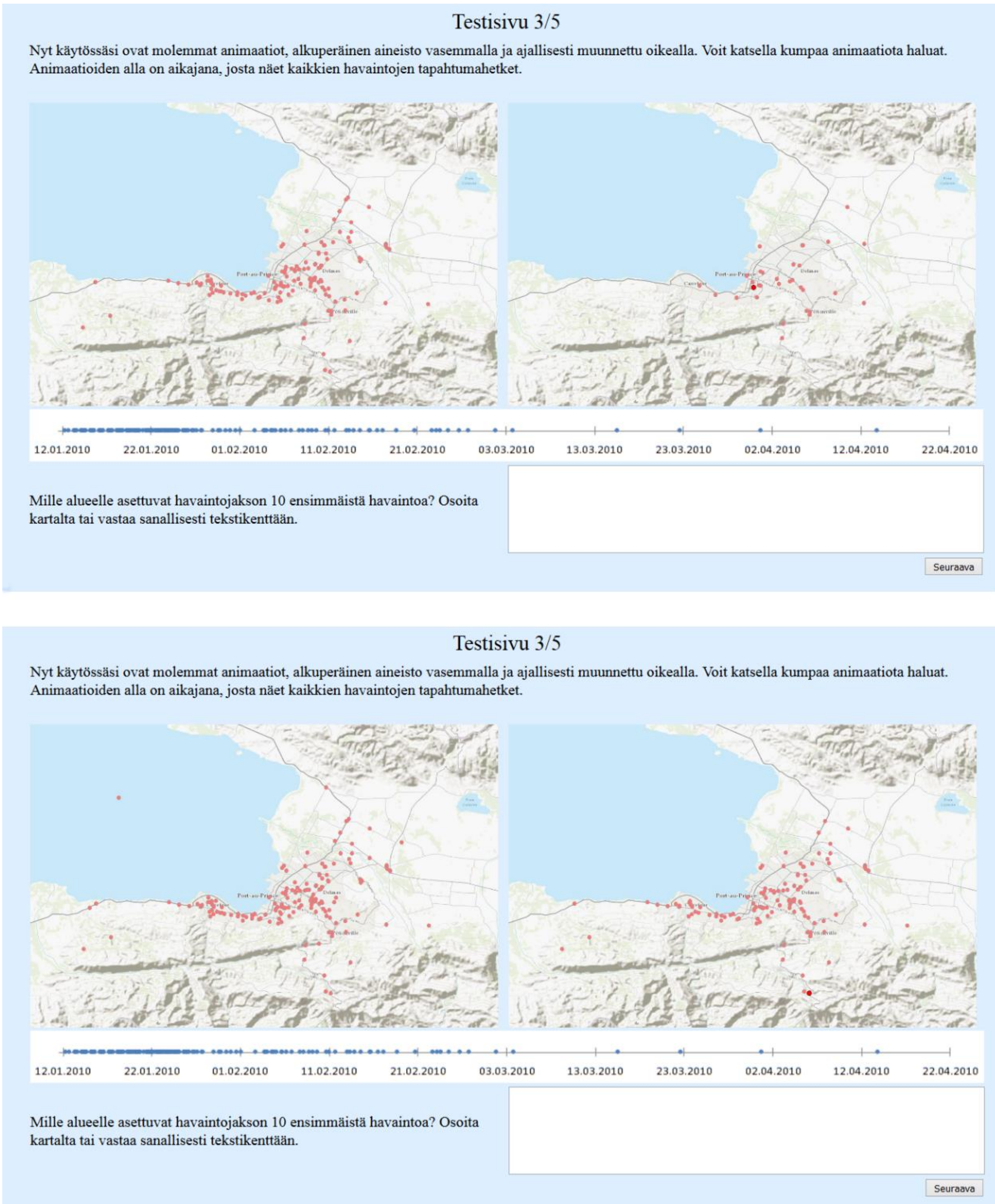

Figure 5. The test setting and the effect of the transformation. The original animation of "Every 10th" dataset is on left and the transformed animation of the same dataset is on right. Above the animations is a short instruction text. Under the animations is the timeline of the dataset showing its temporal structure. On bottom left is the task question, and on bottom right is the text box in which the user can write the answer. On upper figure, both animations are paused after 15 seconds. On lower figure, the animations are paused after 45 seconds.

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.

VI. 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 [25]. 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 IN THE USER TEST

	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)

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 the upper-right map of Figure 5. 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	Not applicable	2
Different interpretations	8	

The users had varying opinions about the applicability of the transformation. For example, when the task was to find spatio-temporal clusters (Q 2.3), 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.

VII. DISCUSSION AND FURTHER RESEARCH

The results presented above are discussed from two different perspectives: usefulness and limitations of the temporal equal density transformation that was tested. These considerations are followed by the evaluation of the study.

A. *Usefulness of the Tested Transformation*

The user test shows that temporal equal density transformation of the animation revealed the location of sequential events that were not detected from the original animation. These sequential events were temporally so close to each other that, without the transformed animation, this pattern would have remained unnoticed by most users. Additionally, this pattern was found spontaneously; in the majority of cases it arrested the attention of the users without any specific search task. This kind of capacity is an important feature of the visual analysis tool when it is used for data exploration.

As the test results and interviews with the users suggest, the power of the temporal equal density transformation lies in the fact that it seems to 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.

B. *Limitations of the Tested Transformation*

The findings indicate that the disadvantage of the transformation is that misinterpretations of the effect of the transformation are possible, even probable. These misinterpretations could be reduced with a temporal legend in which the user can always perceive the phase of the animation. For a more sophisticated approach, we suggest two possible solutions for this problem; segmenting and colour.

The equal density transformation itself is simultaneously in line and contradiction of the principle number 2 of Mayer and Moreno [20]: "Provide pauses". It gives the user time to recognize each event separately, but lacks the longer pauses needed for processing the information in order to move it into long-term memory. This was also found from the user feedback on the test: one user stated that the animation was "exhausting". Our suggestion is to add longer pauses to mark natural time periods in the data. These pauses would work for two purposes: they give time for the user to process the information more deeply, and separate the natural time periods from each other. These time periods could be, for example, days, but the phenomenon can also have such a nature that using midnight to divide the periods can cause the splitting of temporal clusters. This solution would be suitable for bigger datasets, if the events of one period were being processed as one mental chunk with no intention to understand more than the overall behaviour of the phenomenon.

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 events might change smoothly day by day. This solution would help the user to detect spatio-temporal clusters from the map and it also communicates 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 [26] 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 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. Kraak et al. [10] suggest 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.

C. Evaluation of the Study

In this study, we tested the concept of temporal equal density transformation and therefore wanted to keep the test arrangement as simple as possible. The influence of attribute information was not evaluated in this study; therefore, we suggest that the method studied here is better suited to pre-processed data where the selection of relevant events is performed beforehand and the interest of the analyst is in the spatio-temporal behaviour of the data. However, this method does not rule out the possibility of classifying the events according to their thematic content and visualizing this classification by colour, if colour is not used to present the flow of time (as suggested earlier).

Because of the simplicity of the test procedure, the user control over the animations was limited. The users did not have a chance to adjust the speed of the animation nor 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 might have increased the cognitive load on the user and drawn the user's attention away from the task being tested.

Finally, we want to emphasize that temporal equal density transformation, in the form that was tested here, is suitable only for relatively small datasets because it shows every event individually. Theoretical maximum number of events can be calculated by multiplying the minimum time of each eye saccade and attentional blink caused by the perception time of one event (together they take approximately 300 ms) with the maximum length of working memory without any revision (20 seconds). With this calculation we suggest that no more than 60-70 events should be presented consequently without pausing. Additionally, the method was only tested with two datasets with different temporal structures: one with decreasing intensity of events and the other with clear variation of empty and dense periods. More tests are needed to study the usefulness of the method with different spatio-temporal datasets.

VIII. CONCLUSIONS

The human ability to adopt information from an animated map 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 equal density transformation of the temporal dimension of map animations by equalizing the time intervals between each two consecutive events. The user test showed that the transformation can reveal patterns that would have been left unnoticed with traditional animation. Transformed animation in parallel to an original, untransformed animation seems to be understandable for the users and useful for spatio-temporal analysis.

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 temporal equal density transformation might be an appropriate technique to complement a set of such analysis tools. Our suggestion is that temporal equal density transformation should be used for those datasets that a) have an irregular temporal structure and b) are small enough to be able to be examined individually. The transformed animation could, if reasonable, be segmented so that the natural periods in the dataset are separated from each other with a longer pause. As a result of these kinds of improvements the transformed animation, complemented with an original, untransformed animation to offer an overall image of the phenomenon, would complete the toolbox of spatio-temporal exploratory analysis.

REFERENCES

[1] S. Multimäki and P. Ahonen-Rainio, "Temporally Transformed Map Animation for Visual Data Analysis," The Seventh International Conference on Advanced Geographic Information Systems, Applications, and Services (GEOProcessing 2015), C.-P. Rückemann and Y. Doytsher (eds.) IARIA Feb.2015, pp. 25-31, ISSN: 2308-393X, ISBN: 978-1-61208-383-4.

[2] B. Tversky, J. B. Morrison, and M. Betrancourt, "Animation: can it facilitate?" International Journal of Human-Computer Studies, vol 57, 2002, pp. 247-262, doi:http://dx.doi.org/10.1006/ijhc.2002.1017.

[3] D. Archambault, H. C. Purchase, and B. Pinaud, "Animation, small multiples, and the effect of mental map preservation in dynamic graphs," IEEE Transactions on Visualization and Computer Graphics, vol. 17(4), pp. 539-552, 2011, doi:http://dx.doi.org/10.1109/TVCG.2010.78.

[4] A. Koussoulakou and M.-J. Kraak, "Spatio-temporal maps and cartographic communication," The Cartographic Journal, vol. 29(2), pp. 101-108, 1992, doi: http://dx.doi.org/10.1179/caj.1992.29.2.101.

[5] T. S. Slocum, R. S. Sluter, F. C. Kessler, and S. C. Yoder, "A qualitative evaluation of MapTime, a program for exploring spatiotemporal point data," Cartographica, vol. 39(3), pp. 43-68, 2004, doi:http://dx.doi.org/10.3138/92T3-T928-8105-88X7.

[6] A. Griffin, A. MacEachren, F. Hardisty, E. Steiner, and B. Li, "A comparison of animated maps with static small-multiple maps for visually identifying space-time clusters," Annals of the American Cartographers, vol. 96(4), pp. 740-753, 2006, doi:http://dx.doi.org/10.1111/j.1467-8306.2006.00514.x.

[7] S. I. Fabrikant, S. Rebich-Hespanha, N. Andrienko, G. Andrienko, and D. R. Montello, "Novel method to measure inference affordance in static small multiple displays representing dynamic processes," The Cartographic Journal, vol. 45(3), pp. 201-215, 2008, doi:http://dx.doi.org/10.1179/000870408X311396.

[8] A. Lobben, "Influence of data properties on animated maps," Annals of the Association of American Geographers, vol. 98(3), pp. 583-603, 2008, doi:http://dx.doi.org/10.1080/00045600802046577.

[9] M. Harrower and S. Fabrikant, “The role of map animation for geographic visualization,” In: M. Dodge, M. McDerby, and M. Turner (Eds.), Geographic Visualization. John Wiley & Sons, 2008, doi:http://dx.doi.org/10.1002/9780470987643.ch4.

[10] M.-J. Kraak, R. Edsall, and A. MacEachren, “Cartographic Animation and Legends for Temporal Maps: Exploration and or Interaction,” In: Proceedings of the 18th International Cartographic Conference, Stockholm, Sweden, 1997, pp. 253-260.

[11] M. Harrower, “The cognitive limits of animated maps,” Cartographica, vol. 42(4), pp. 349-357, 2007, doi:http://dx.doi.org/10.3138/carto.42.4.349.

[12] J.A. Dykes and D.M. Mountain, "Seeking structure in records of spatio-temporal behaviour: visualization issues, efforts and applications," Computational Statistics & Data Analysis, vol. 43.4, pp. 581-603, 2003, doi:http://dx.doi.org/10.1016/S0167-9473(02)00294-3.

[13] D. DiBiase, A. M. McEachren, J. Krygier, and C. Reeves, “Animation and the role of map design in scientific visualization,” Cartography and Geographic Information Systems, vol. 19(4), pp. 201-214, 265-266, 1992.

[14] M. Monmonier, “Temporal generalization for dynamic maps,” Cartography and Geographic Information Science, vol. 23 (2), pp. 96-98, 1996, doi:http://dx.doi.org/10.1559/152304096782562118.

[15] M.-J. Kraak, “Mapping Time: Illustrated by Minard's Map of Napoleon's Russian Campaign of 1812.” ESRI Press, California, 2014.

[16] G. Andrienko, N. Andrienko, H. Schumann, and C. Tominski, “Visualization of trajectory attributes in space-time cube and trajectory wall,” in Cartography from Pole to Pole, Lecture Notes in Geoinformation and Cartography, M. Buchroitner, N. Prechtel, and D. Burghardt, Eds. Springer-Verlag Berlin Heidelberg, pp. 157-163, 2014, doi:http://dx.doi.org/10.1007/978-3-642-32618-9_11.

[17] G.A. Miller, “The magical number seven, plus or minus two: some limits on our capacity for processing information,” Psychological review, vol. 63(2), pp. 81-97, 1956, doi:http://dx.doi.org/10.1037/h0043158.

[18] R.A. Rensink, “Internal vs. External Information in Visual Perception,” Proceedings of the 2nd international symposium on Smart graphics, Jun. 2002, pp. 63-70, doi:http://dx.doi.org/10.1145/569005.569015.

[19] F. Paas, A. Renkl, and J. Sweller, "Cognitive load theory and instructional design: recent developments," Educational psychologist, vol. 38.1, pp. 1-4, 2003, doi:http://dx.doi.org/10.1207/S15326985EP3801_1.

[20] R.E. Mayer and R. Moreno, "Nine ways to reduce cognitive load in multimedia learning," Educational psychologist vol. 38.1, pp. 43-52, 2003, doi:http://dx.doi.org/10.1207/S15326985EP3801_6.

[21] G. Andrienko et al., “Space, time, and visual analytics,” International Journal of Geographical Information Science, vol. 24 (10), pp. 1577-1600, 2010, doi:http://dx.doi.org/10.1080/13658816.2010.508043.

[22] J. Allen, “Maintaining knowledge about temporal intervals,” Communications of the ACM, vol. 26(11), pp. 832-843, 1983, doi:http://dx.doi.org/10.1145/182.358434.

[23] B. FitzGerald, “Science in Geography 1: Developments in Geographical Method”. Oxford University Press, 1974.

[24] M. Sarkar and M.H. Brown, “Graphical Fisheye Views of Graphs,” Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 1992, pp. 83-91, doi:http://dx.doi.org/10.1145/142750.142763.

[25] N. Andrienko and G. Andrienko, “Exploratory Analysis of Spatial and Temporal Data – A Systematic Approach.” Springer, Berlin, Germany, 2006.

[26] C. A. Brewer, “Guidelines for Use of the Perceptual Dimensions of Color for Mapping and Visualization,” International Symposium on Electronic Imaging: Science and Technology. International Society for Optics and Photonics, 1994, pp. 54-63.