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Comparison of Temporally Classified and Unclassified Map Animations

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While animation is a natural and, under certain circumstances, effective way to present spatio-temporal information, it has its limitations. Studying animations of large point datasets can be cognitively very demanding. Aiming to help users to comprehend such data, this study presents a new concept of temporal classification. A phenomenon is classified into periods of increasing, decreasing, and steady intensity, and each is assigned different colours in an animation. This concept was tested with a group of experts in the field of the phenomenon. The results suggest that this kind of classified animation, together with a traditional animation presenting the same dataset, supports users in their analysis process and adds to the impression they get of the phenomenon. It also seems that the viewing order of the animations matters: the full potential of the tested method is reached by viewing the traditional version first and temporally classified version after that.

KEYWORDS: spatio-temporal pattern; temporal classification; map animation; visualization; concept testing

INTRODUCTION

While collecting big spatio-temporal datasets has become easier, effective tools and techniques are increasingly needed for understanding the phenomena represented by these data. Animation, as a time-bound method, is one of the conventional techniques for visualizing such data. However, animation has its limitations (Kriglstein, Pohl, and Smuc 2014; Aigner et al. 2011; Lobben 2008; Tversky, Morrison, and Betrancourt 2002). The capacity of an animation to support an analyst depends on several factors, including the task, the type of phenomenon, and the structure of the data in question. When there is continuity in the movement of the phenomenon being visualized, an animation is at its best (Harrower and Fabrikant 2008; Andrienko, Andrienko, and Gatalsky 2005). But a dataset containing a large number of point-type events makes for a demanding presentation, especially if it does not provide such clear continuity. Human perception is particularly sensitive to appearance and movement, but at the same time it is easily overloaded (Kluender et al. 2006). When the perception of the user is constantly loaded with newly-appearing points, subtle patterns in the animation can easily be missed.

In analytical and exploratory use, when the user's task is not strictly defined beforehand, a single view of the data seldom reveals all the relevant aspects of a phenomenon. Therefore, multiple views, each displaying the data in a different way are valuable. Shneiderman (1996) suggests several data visualizers: *overview first, zoom and filter, then details-on-demand*. Animation can work especially well for getting an overview of a phenomenon (Harrower & Fabrikant 2008). Then, when a more detailed examination is needed after the overview, different ways to handle the massive information load of an animation can follow: the user can, for example, zoom in on a smaller area or a shorter time period for detailed examination or filter a subset of data based on some attribute information.

While task-definition is an essential part of designing analysis software, it is not always possible in analytical and exploratory use, when the user is seeking "something,"—for example, behavioural patterns of any kind. Visual data analysis can effectively bring human knowledge and capabilities to the exploratory process (Compieta et al. 2007). While some noise reduction is usually performed as pre-processing of the data, it is important that nothing potentially important is left out of the dataset before the interesting pattern is found. This conflict between the need to reduce the information load on the user, and the necessity to see everything, inspired us to seek a method where the behaviour of the phenomenon is visualized in such a way that a certain viewpoint is emphasized but no data reduction is conducted. In this paper we present a novel data classification method for map animations and study whether and how this method adds capacity to the exploration of spatio-temporal data.

To study the usefulness of this kind of temporally classified animation in comparison to an unclassified animation, we carried out a user test to find out how a temporally classified animation affects the user's impression of the phenomenon compared to an unclassified animation, and whether the viewing order of the animations matters if the temporally classified animation is used together with the unclassified animation.

In the user test, the subjects studied a phenomenon using both a temporally classified animation (henceforth called classified animation) and an unclassified animation (henceforth called traditional animation). The subjects were experts in the field of the visualized phenomenon. In the test, we examined the extent and contents of the users' descriptions of the phenomenon, based on the animations, and their opinions and feedback of the animations. In the following sections, we first explain the concept of temporal classification in detail. Next, we introduce the data and animations used in the test and explain the test setting. After that we present and discuss the results of the user test, and finally, draw conclusions.

CONCEPT OF TEMPORAL CLASSIFICATION

In cartography, maps with a large number of objects are known to burden users' cognitive processes (Bunch & Lloyd 2006). Classification of the data, based on attribute values, is performed to reduce the number of mental chunks that the user must handle at one time, and therefore increase the amount of information that can be effectively perceived. Classification can be made for static as well as animated maps (Slocum et al. 2009). Colour is a powerful attribute that can guide our attention (Wolfe and Horowitz 2004), therefore it is reasonable to use it to help the user cope with the information flow caused by constantly appearing events.

In this study, we propose a novel method to group data based on changes in its intensity into three classes: periods of increasing, decreasing, and stable occurrence of events. Furthermore, the data are divided into on meaningful spatial regions and the classification is done separately for each region. Thus, the method takes both the spatial and temporal characteristics of the data into consideration, and we can visualize homogeneous groups of events. The area can be divided, for example, by parallel zones, by a grid, or by some central point with circular zones inside each other. The division method plays a great role in how the movement or dispersion of the phenomenon is seen, and it is related to the modifiable areal unit problem (MAUP) of spatial analysis (Openshaw 1984).

The temporal classification method is comparable to the method of imposing a structure on the animation by segmenting, suggested by Harrower (2007). Patterson et al. (2014) agree that mental chunks can exist either in space or in time. The segments formed by temporal classification, presented in an animation one after another, can be seen as the mental chunks of an animation, a concept required by Harrower and Fabrikant (2008). In addition to this chunking of the data flow, temporal classification also guides the user's attention to potentially important patterns in the behaviour of the phenomenon by visually increasing their perceptual salience (Fabrikant & Goldsberry 2005).

TEST DATA AND ANIMATIONS

The dataset was downloaded from the Global Biodiversity Information Facility (**gbif.org**). It included all observations that voluntary bird observers made of grey and black geese (genera *Anser* and *Branta*) inside Finland in the year 2011. The total number of observations in the dataset was 18,175 and temporal resolution was one day. Some characteristics of this dataset required special attention. First, the number of observations does not equal the number of geese. This is because observation means one birder has seen either a single goose or a flock of geese. Second, the dataset does not include all occurrences of geese in the area, only the intersection of the birders and geese. Third, it is probable that the large difference in human population density between southern and northern Finland causes a bias in the dataset, as more observations occur in the south. Fourth, the spring migration shows much more strongly in the dataset than autumn migration, probably partly because the birders are more active in springtime.

Two test animations were made based on this dataset: classified and traditional animations. The animations presented the same observations, and each was 60 seconds in length. Presenting a 365-day period with a 1-day time interval gave a change rate of 0.164 seconds. Events which appeared on the map stayed visible for a time window of 7 days (1.15 seconds).

CLASSIFIED ANIMATION

To make a meaningful classification it is important to know your data; in our case this translates into knowing the behaviour of geese. Geese do not winter in Finland (except some individuals which stay on the southern shore), but great flocks migrate from southern Europe to nest in the north in the springtime. To reveal this south-north movement across Finland, the area was spatially divided into five latitudinal zones of 2° (Figure 1). The events from each zone were separately grouped into three classes according to changes in their intensity: increasing, decreasing, or steady. In this study, the classification was done manually from histograms of each zone's observations; changes shorter than two weeks were not taken into account. Figure 2 shows the histograms of the data of the two southernmost zones. The number of periods was not defined beforehand, but it proved to be seven in most of the zones: a steady period at the beginning of the year, strong increasing and decreasing periods caused by the spring migration, a steady summer period, weaker increasing and decreasing periods caused by the autumn migration, and again a steady winter period. In Figure 2, it can be seen how the peak of the spring migration happens a little earlier in the southernmost Zone 1 than in Zone 2. The difference in the total number of observations is also visible; the peak is twice as high in Zone 1 as in Zone 2.

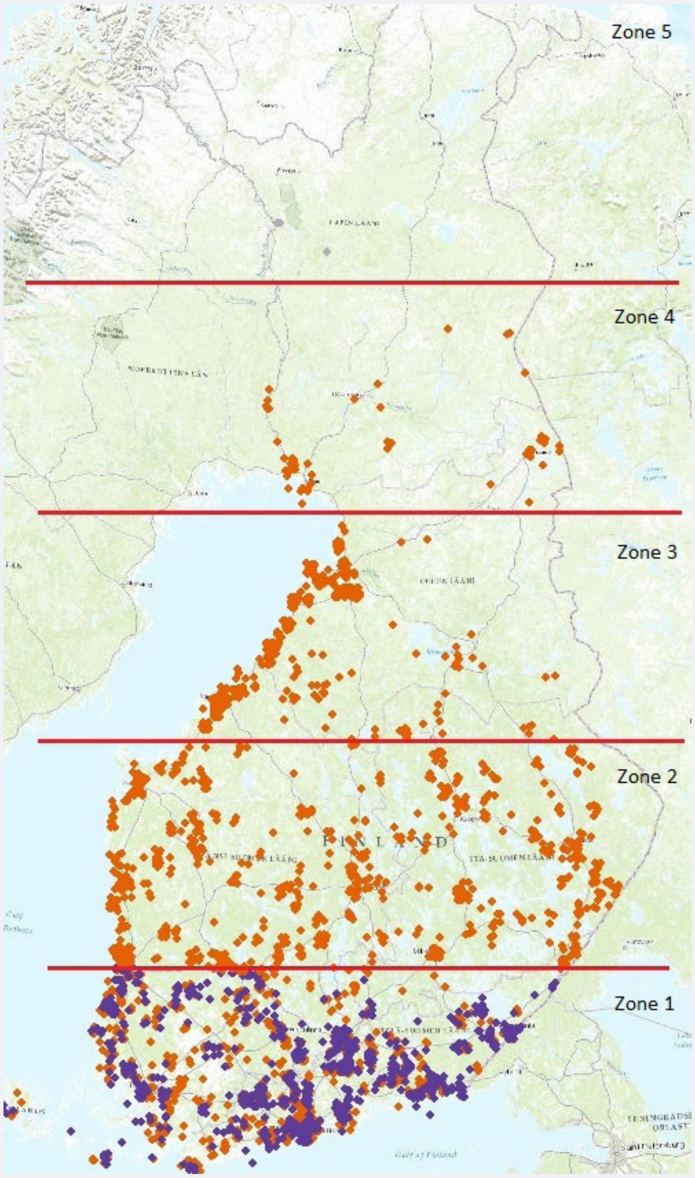

Figure 1. The area is divided into five zones with equal width in a south-north direction. Basemap: Esri 2014.

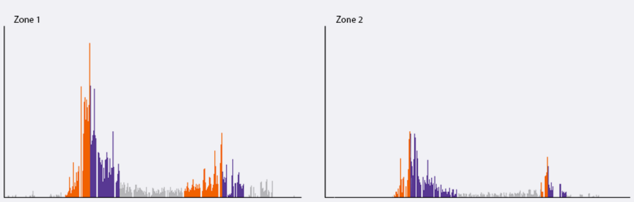

Figure 2. Histograms showing observations of the two southernmost zones for a one-year period.

In the classified animation, the points were coloured with a diverging colour scheme, where neutral grey represented the steady periods, and the increasing and decreasing periods were coloured with the complementary colours orange and purple, respectively. These colours are argued to be colour-blind-friendly (**colorbrewer.org**).

TRADITIONAL ANIMATION FOR COMPARISON

In the traditional animation, the colour of the events changed over time smoothly from yellow (January) via orange, red, and purple to blue (December). Figure 3 compares the classified animation to the traditional animation. The upper row shows three screen captures from the classified animation and the lower row screen captures of the corresponding moments in time from the traditional animation. In March, the phenomenon is steady (very few observations). In April, the growth of the phenomenon has spread to the north (except the northernmost parts), but at the same time it is already decreasing in the southern part of the country. In May, the phenomenon is decreasing throughout the whole country. In the traditional animation, the flow of time can be seen in the change of the colour of the dots. The change in the amount of events, however, can be seen only by the number of dots, and it is not very distinguishable.

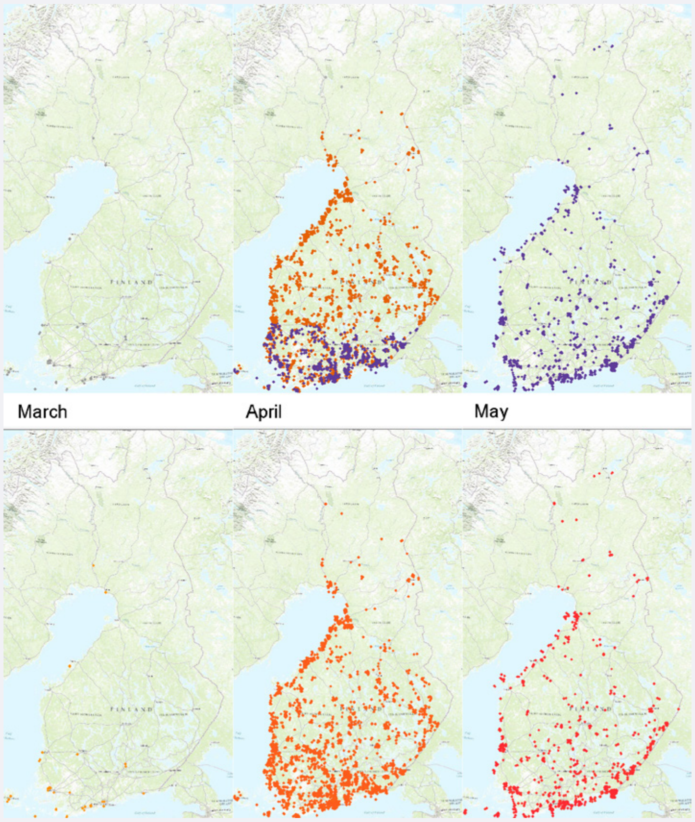

__Figure 3.__ Three screen captures from each animation. The figures in the upper row are from the classified animation, and the lower row shows the corresponding frame in the traditional animation. All captures are from the middle of the month. Basemap: Esri 2014.

In the classified animation, in April, the orange and purple dots are mixing in the southern part of the country. This is because of the partial accumulation of the events in the test animation; the behaviour of the phenomenon has just changed to decreasing in this zone, and the last events of the previous increasing period are still visible.

USER TEST FOR COMPARING TEMPORALLY CLASSIFIED AND TRADITIONAL ANIMATION

The user test was carried out over the Internet. The test users were reached through the mailing list of BirdLife Finland, a society of bird observers, and they were all experienced birders. The 45 participants were randomly divided into two groups: Group 1 saw the classified animation first and the traditional animation second, Group 2 saw the animations in the reverse order. Otherwise, their test settings were identical.

The test consisted of two parts. At the beginning of the first part, the principles of the first animation were introduced briefly. Then the users were told to view the animation once or twice, after which, they were asked to describe the behaviour of the geese in their own words. Next, some claims about the behaviour of the geese were presented, and the users were asked to mark whether those claims were true or false. However, the results from the true-false claims were not used in this study because of an unforeseen bias: the "correct" answers were based on interpretations by the researchers using the same data and visualizations, and therefore could not been verified as being truth. The same process was repeated with the second animation: users were introduced to the upcoming animation, viewed it once or twice, described the behaviour, and answered true-false claims about the behaviour.

In the second part of the test, users were presented with a list of claims concerning the usability and pleasantness of the animations, and they were asked to mark their preferences between the animations. Finally, they had a chance to give their opinion of both animations in their own words, and were asked whether the animations gave them new information and what kind of phenomenon animations might suit best.

ANALYSIS AND RESULTS

Three analyses were conducted on the collected answers. First, the descriptions of the phenomenon were analysed with a verbal protocol method (McGuinness & Ross 2003). Next, the users' preferences between the animations were compared. Then, the free feedback on the animations was analysed by dividing all comments into four categories: positive feedback, negative feedback, mentions of new information, and mentions of potential use cases. Finally, the results of two user groups were compared against each other, as well as the results produced by the two animations.

To ensure comparability between the animations, some user responses were left out of the analyses. This was done if: 1) the subject did not fulfil the task of describing the phenomena at all, 2) the subject used only a few words, or 3) the subject wrote a description only for one of the animations. Answers from 11 users from each group were included in the analyses. In each group there were three females and eight males. The most common age group was 60–69 in Group 1 and 50–59 in Group 2. One of the users in Group 1 was colour-blind, but the answers of this user did not stand out from the others in the group and were therefore included in the analysis.

VERBAL DESCRIPTIONS OF THE PHENOMENON

Differences in the extent of the descriptions of the phenomenon between the two animations were apparent in the answers. A verbal protocol analysis was carried out to define these differences quantitatively. Verbal protocol analysis is a method in which all the verbal or textual feedback collected from the users is analysed in such a way that common patterns (ideas, tasks, descriptions, etc.) are recognized and calculated from the data (McGuinness & Ross 2003). Typically, these protocols cannot be defined beforehand, but they are recognized while going through the material. The encoding of the protocols was first performed separately by two researchers, after which those encodings were merged.

The statistical significance of the results from the verbal descriptions was tested with a T-test for unequal variances (independent when comparing animations or groups, and dependent when comparing the numbers inside the group).

From the data collected in the user test, different protocols were recognized from the texts: 1) appearance or disappearance, 2) number, increase, or decrease, 3) location, 4) direction, 5) route, 6) duration or speed of the movement, 7) relative time, 8) absolute time, and 9) animation time. Then these protocols were organized into three different categories: existence, movement, and time. The protocols and their categories are shown in Table 1, which also shows a few example words or expressions from each protocol, translated from Finnish.

	Protocol	Example Words or Expressions
Existence	appearance / disappearance	"migration starts" "first birds appear"
	number	"a few birds" "the number of birds is increasing"
	location	"in Northern Finland" "in the Southwest shore"
Movement	direction	"to north" "to inland"
	route	"following the shoreline" "along the main waterways"
	duration / speed	"rapidly moving flocks" "within a short time"
Time	relative	"first…then" "later" "at the beginning"
	absolute	"on March" "during the summer" "spring migration"
	animation	"around 17 seconds" "during seconds 12–35"

Table 1. *The protocols used in the verbal protocol analysis.*

The total number of words in these descriptions, excluding those sentences which only commented on the usability or visualisation of the animations, was also calculated. The calculated numbers of each protocol and word counts are shown in Table 2. All the results that are discussed more detailed below are statistically significant ($p < 0.05$).

The results of the protocol analysis reveal that the contents of the descriptions of the phenomenon varied between the user groups, and also between the animations, in the "existence" and "time" categories. The third category, "movement," gained the smallest number of mentions from both groups, and no statistically differences were not found. The cause for this might be that there was no actual movement in the animations, but rather the spreading behaviour of static events.

In the "existence" category, mentions of the "number" protocol more than doubled from 34 to 73 between the animations in Group 2 while the change between the animations in this protocol was not significant in Group 1. In the "location" protocol, Group 2, who saw the traditional animation first, made more than twice as many (144 vs. 64) mentions.

In the "time" category, the number of mentions of the "relative time" protocol was greater after the classified animation (65) than after the traditional animation (20) in both groups. Group 1 mentioned the relative time more often after the first animation than after the second, while in Group 2 the number of mentions of this protocol increased between the animations. On the other hand, the number of mentions of the "real-world time" protocol grew between the first and the second animation in both groups, but the total number of mentions in this protocol was bigger in Group 2 (104) than in Group 1 (74).

The word count reveals that Group 2 used more words after both animations, classified and traditional, when describing the phenomenon. The number of words after the first animation the users saw (classified animation with Group 1, traditional animation with Group 2) was almost the same between the groups (431/426), but after the second animation, the number of words decreased into 291 in Group 1 but increased into 612 in Group 2.

USERS' PREFERENCES

The users were asked which animation (traditional or classified) they thought corresponded better to certain claims or descriptions. These results are presented separately for both user groups in Figure 4.

The results show that the classified animation was more often considered informative, insightful, and easy to understand than the traditional animation by both user groups. This preference is even stronger in Group 2, who saw the classified animation after the traditional one. The classified animation was experienced as being more confusing by Group 1, who saw it before the traditional animation. At the same time, however, the majority of the

Category	Existence			Movement			Time			Word Count
Protocol	appearance / disappearance	number	location	direction	route	duration / speed	relative	absolute	animation	
Group 1 Traditional	8	28	31	4	1	4	9	42	0	291
Group 1 Classified	10	37	33	7	2	2	31	32	4	431
Group 2 Traditional	8	34	64	3	5	3	11	45	0	426
Group 2 Classified	7	73	80	8	2	7	34	59	3	612
Traditional Animation Total	16	62	95	7	6	7	20	87	0	717
Classified Animation Total	17	110	113	15	4	9	65	91	7	1043
Group 1 Total	18	65	64	11	3	6	40	74	4	722
Group 2 Total	15	107	144	11	7	10	45	104	3	1038

Table 2. *The results of the protocols found in the verbal protocol analysis, for each group and animation.*

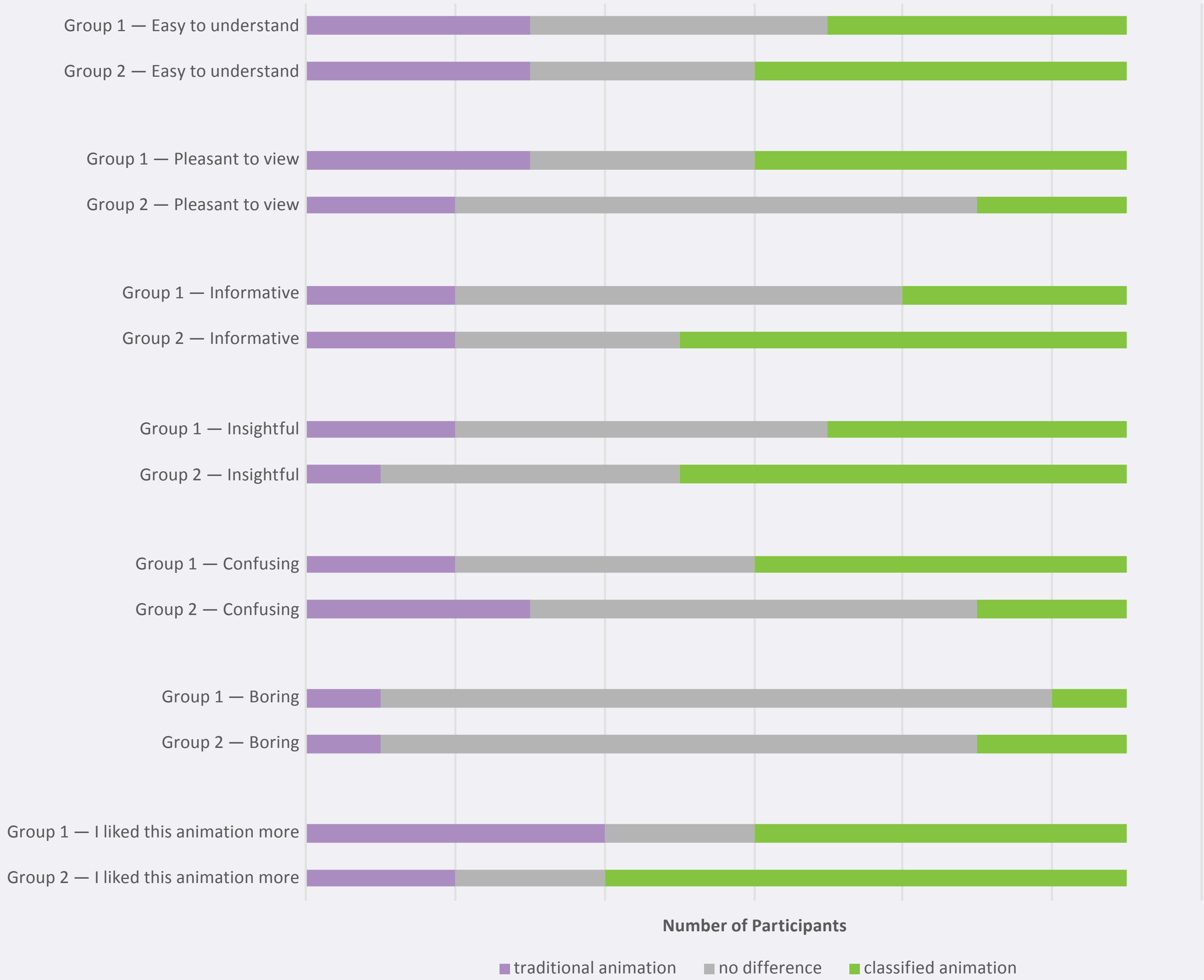

Figure 4. *The users' preferences between the animations. Group 1 viewed the classified animation first and traditional animation after that. Group 2 viewed the animations in reverse order.*

users in Group 1 stated that the classified animation was more pleasant to view.

FREE FEEDBACK

The free text feedback was sorted into the following groups: positive feedback, negative feedback, descriptions of potential use, and mentions of new information gained. These results are shown in Table 3. The classified animation received more positive comments. In both user groups, the animation that was viewed first received more mentions about the potential use cases, but Group 2 made remarkably more mentions of new information than Group 1.

DISCUSSION

The results from the protocol analysis suggest that the way users saw the data affected the way they interpreted it. One might assume that the animation that was seen first would have gained the more extensive description, and as the data in the second animation were the same, users might have a lower motivation to describe the same phenomenon again. However, the test users in Group 2—who saw the traditional animation first and the classified

	Positive	Negative	Potential Use	New Information
Group 2, traditional (first)	0	1	6	5
Group 1, traditional (second)	3	1	3	1
Traditional animation total	3	2	9	6
Group 2, classified (second)	6	1	3	6
Group 1, classified (first)	5	2	7	1
Classified animation total	11	3	10	7

Table 3. *Free text feedback from both user groups.*

animation after that—extended their verbal descriptions after the second animation. Their descriptions of the migration and behaviour of the geese were longer and more detailed. At the same time, Group 1 met our assumption: they saw the classified animation first, and it seems that they did not gain any new information when viewing the traditional animation.

Interestingly, while Group 2 produced more mentions of real-world time and location of the phenomenon, there was not much difference between the groups for the "appearance / disappearance" protocol. Even though the classified animation clearly shows those moments when the number of geese starts to grow, this feature did not encourage the users to mention, for example, the start of the migration. However, the classified animation led the users in both groups to mention relative time definitions more often. It seems that in some way it draws the users' attention to the order of the events rather than to the exact moment.

When the users were asked about their preferences between the animations, the classified animation received positive descriptions more often than the traditional one. The users even found the classified animation easier to understand, despite the fact that the method behind it was much more complex than in the traditional animation. This may have been caused by the continuous change in the colours in the traditional animation, which some users commented on as being confusing.

If the classified animation alone offered enough information for the users, Group 1 should have provided more detailed descriptions of the phenomenon based on the first animation than Group 2, but this was not the case. The word count after the first viewed animation was almost the same for both groups, and it increased after the second animation in Group 2 (traditional, then classified) but decreased in Group 1 (classified, then traditional). This, together with the fact that Group 2 gave more extensive descriptions and gained new insight, suggests that it is meaningful to start with a visualisation that provides an overview of the phenomenon and move to specific aspects of data after that, rather than vice versa. This is in line with the mantra of Shneiderman (1996), who urges data visualizers to offer an overview of the data first before any further examination.

One particularly interesting finding was that in several cases the users said that the autumn migration was located further east than the spring migration, which moves along the western shoreline. This is in line with common knowledge about the migration of geese in the area of Finland. However, with the classified animation, 9 users out of 22 stated that the autumn migration actually had a starting point on the west coast. This behaviour was not seen, or at least it was not mentioned, in descriptions based on the traditional animation. This suggests that the classified animation gave the users a novel stimulus, increasing users' understanding of the phenomenon. The traditional animation did not emphasize the beginning of the migration enough and therefore it only confirmed the previous knowledge that the users had.

The free-word feedback collected from the users supports the findings reported above. The classified animation got more positive mentions, but also one more negative mention. In several comments mentioned how the classified animation opened up new insights and was interesting. This is encouraging, because the test users were familiar with migration phenomenon, rather than being professionals in visual analysis of spatio-temporal information. The classified animation and the new information it brought to the animation were received positively overall, especially in the group that viewed it after they had seen the traditional animation first. They seemed to form a better overall image of the phenomenon, and they benefited from the classified animation more than the other group.

APPLICABILITY OF THE RESULTS

This study presents the temporal classification concept implemented with one dataset. The classification was tailored for the dataset manually with layperson's knowledge of the phenomenon. A systematic approach to the classification concept must be developed, defining specific limits for the increase and decrease, before it can be applied automatically to other datasets. However, any limits may be case-dependent and setting them may require expert knowledge.

This classification method works best with datasets in which the intensity of events changes gradually. If the dataset consists of long steady periods with very sudden stepped changes or short peaks, it is possible that these changes will become invisible in the classified visualization. The length of time that events stay visible will affect the degree to which events of different periods will mix during the animation. This may have a critical role in the readability and interpretability of the animation. Also, many factors concerning the classification process, such as the number of classes and the temporal resolution, affect the outcome of temporal classification. Depending on the choices made during the pre-processing, this method can emphasize very different things from the same dataset.

The steady periods in our dataset were all of the same type, containing relatively low numbers of events. The idea was that the use of grey as a neutral visualisation of steady periods can be associated with the non-interesting, quiet phase of the phenomenon, regardless of the intensity. It must be noted that while steady periods were of low interest in this particular dataset, they might be the most important thing in some other, and in that case the colours should, of course, be selected to highlight those periods.

The test users in the study were familiar with the phenomenon presented in the test animations, rather than with visual analysis tools. Their ages were also biased towards older people, because bird observation is a more common hobby among elderly people. It must be noted that in this age group the experience of computer use varies greatly. Therefore it cannot be supposed that these results will apply in a straightforward manner to all users, although Harrower (2007) questions the existence of differences between novices and experienced map users.

CONCLUSIONS

This study examined a classification method for symbolising animated events on the basis of their intensity and tested the usefulness of the symbolization for visual analysis. The area of the dataset was divided into spatial zones based on the assumed spatial behaviour of the phenomenon. After that, the events in each zone were classified into periods of increasing, decreasing, and steady intensity, and coloured according to those classes. An animation of the temporally classified dataset was tested together with another animation, in which the same dataset was coloured continuously across the time period. The test users described the phenomenon the animations presented and marked their preferences between the two animations.

The study indicates that temporally classified animation can be informative, insightful, and add a new perspective to animated data in analysis. In the user test, the classified animation led to richer analysis, especially with the group who saw the traditional representation before it. The users made positive comments on both animations, but especially the classified animation. However, the suitability of the temporal classification for datasets with different spatio-temporal structures has to be studied further before it can be promoted as a systematic approach. Formal definition of the classification, as well as the influence of areal division, is an ongoing project in our research group.

The study also suggests that the full potential of these animations can be reached by offering users both a traditional animation to get an overview of the phenomenon and a temporally classified animation for further analysis. This is in line with previous knowledge (e.g., Shneiderman 1996) that discusses the importance of first offering an overview of the phenomenon to the user. The user uses previous knowledge when building new knowledge and this is done better when the user first has an opportunity to familiarize themselves with the phenomenon without any additional information. On the grounds of these theories and the results of the study presented here, it is recommended that the traditional animation is viewed first and a more complex temporally classified animation after that.

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