Visual Mining of Multimedia Data for Social and Behavioral Studies

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ABSTRACT

With advances in computing techniques, a large amount of high-resolution high-quality multimedia data (video and audio, etc.) has been collected in research laboratories in various scientific disciplines, particularly in social and behavioral studies. How to automatically and effectively discover new knowledge from rich multimedia data poses a compelling challenge since state-of-the-art data mining techniques can most often only search and extract pre-defined patterns or knowledge from complex heterogeneous data. In light of this, our approach is to take advantages of both the power of human perception system and the power of computational algorithms. More specifically, we propose an approach that allows scientists to use data mining as a first pass, and then forms a closed loop of visual analysis of current results followed by more data mining work inspired by visualization, the results of which can be in turn visualized and lead to the next round of visual exploration and analysis. In this way, new insights and hypotheses gleaned from the raw data and the current level of analysis can contribute to further analysis. As a first step toward this goal, we implement a visualization system with three critical components: (1) A smooth interface between visualization and data mining. The new analysis results can be automatically loaded into our visualization tool. (2) A flexible tool to explore and query temporal data derived from raw multimedia data. We represent temporal data into two forms - continuous variables and event variables. We have developed various ways to visualize both temporal correlations and statistics of multiple variables with the same type, and conditional and high-order statistics between continuous and event variables. (3) A seamless interface between raw multimedia data and derived data. Our visualization tool allows users to explore, compare, and analyze multi-stream derived variables and simultaneously switch to access raw multimedia data. We demonstrate various functions in our visualization program using a set of multimedia data including video, audio and motion tracking data.

KEYWORDS: visual data mining, multimedia data.

INDEX TERMS: H.1.2 [Information Systems]: Models and principles - user/machine systems; H.5.1 [Information Interface and Presentation]: Multimedia Information Systems; H.5.2 [Information Interface and Presentation]: User Interfaces — Graphical user interfaces (GUI); H.3.3 [Information Storage and Retrieval]: Information Search and Retrieval; H.2.8 [Database Management]: Database Applications —Data mining

1 INTRODUCTION

With advances in computing and sensing techniques, multimedia data are ubiquitous. In particular, a large amount of high-resolution high-quality multimedia data (video, audio, EEG, and fMRI, etc.) has been collected in research laboratories in various scientific disciplines, especially in social, behavioral and cognitive studies. For instance, video-typing is a standard method to document participants' behaviors and responses in laboratory environments and everyday contexts which will be analyzed later by researchers to infer empirical results and new knowledge.

How to automatically and effectively discover new knowledge from rich multimedia data poses a compelling challenge. Multimedia data mining in general consists of two stages. In the first step, researchers extract some derived data from raw multimedia data. This step can be implemented by human coding or by using image/speech processing programs. For example, one may extract a time series of the location of a participant in a video clip to form one temporal continuous variable. Multimedia data contains a huge amount of information with various kinds. In video data, each frame may contain several objects and people in a scene. One can extract different properties from each entity (an object or a person) in an image frame, such as the location of the entity, the size of the entity, the speed of the entity, or the color change of the entity. Assume that there are M objects and N people appearing in a video clip, and K properties can be extract from each, we will have (M+N)K temporal continuous variables. With the increase of M, N and K, extracting all the information from a video clip seems not to be efficient and may not be possible. For another example, speech data seem to be relatively simple since we can code them (automatically or manually) as speech transcription. However, in addition to linguistic content, raw speech data also contains other information that may also be valuable, such as a speaker's gender and age, the speaker's emotional state encoded in speech prosody, and so on. Thus, how to identify and extract useful derived data is a challenge for researchers, which turns out to be a chicken-and-egg problem. To discover new knowledge in scientific studies, researchers may not know in advance what information is most critical and interesting, and should be extracted first. But meanwhile, without extracting some data first and computing some results based on those data, researchers may not know where to start.

In the second step of multimedia data analysis, researchers work on derived data (time series, etc.) with the goal to find interesting patterns. Recent advances in machine learning and data mining have provided effective data analysis tools to discover underlying patterns from time series[1]. However, data mining algorithms can effectively search and discover only pre-determined patterns and those patterns need to be statistically reliable. This limitation significantly constrains what can be achieved using standard data mining algorithms because the exploratory nature of discovering new knowledge requires the ability to detect uncommon (but interesting) patterns. This observation points to a similar chicken-and-egg problem like the one in the first step of data processing – without knowing what patterns to look for, data mining algorithms most often cannot work effectively in purely unsupervised mode. But meanwhile, a huge amount of information must be reduced and summarized in order to find meaningful results. Without the results from some forms of data reduction, researchers may not have concrete ideas on what to look for.

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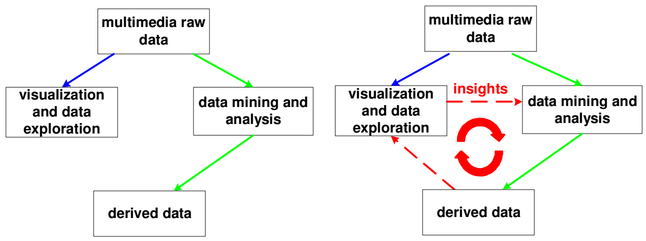

Figure 1. **Left**: Information visualization and data mining are traditionally treated as two topics. **Right:** Our approach builds the links between these two and by doing so forms a closed loop between visualization and data mining.

The key to solve the above problem is to develop a mechanism that allows data researchers to explore the data and gain some insights on how to analyze it[2]. In light of this, we propose to use visualization techniques that present the data in various informative ways and by doing so make it easier for researchers to employ their own visual perception system to detect new patterns that previously overlooked, to gain new insights, and to generate new hypotheses which will lead to new discoveries. Thus, our solution is to take advantages of both the power of human perception system and the power of computational algorithms. More specifically, researchers can use data mining as a first pass, and then form a closed loop of visual analysis of current results followed by more data mining work inspired by visualization, the results of which can, in turn, be visualized and lead to the next round of visual exploration and analysis. In this way, new insights and hypotheses gleaned from the raw data and the current level of analysis can contribute to further analysis.

As shown in Figure 1 (left), previous work either concentrates only on information visualization (the blue arrow line) or only on data mining (green arrow lines). A huge amount of information must be cut and summarized to be useful. But statistics and measures extracted from raw data may exclude interesting patterns embedded or even be misleading. We need a mechanism to represent the overall statistics and meanwhile make fine-grained data accessible. Information visualization provides a unique opportunity to accomplish this task. Often, potential users of information visualization are not aware of the benefits of visualization techniques on data mining; Or they use those techniques only as a *first* phase in the data analysis process. As shown in Figure 1 (right), we propose a more interactive mode between data mining and information visualization. In our system, researchers can not only visualize raw data at the beginning but also visualize processed data and results. In this way, data mining and visualization can bootstrap each other – the more informative visualization based on new results will lead to the discovery of more complicated patterns which in turn can be visualized again to lead to more findings.

In this paper, we will first briefly review related work. After that, we will introduce the multimedia dataset we used in this study. Next, we will present our visualization tool while focusing on several novel analytical functions we designed and implemented to visualize multimedia multi-stream data. We will explain how those visualization techniques allow users to actively explore the data, highlight certain properties and patterns in multi-stream data, and facilitate further data mining. We will also describe both the interface between visualization and data mining and the interface between raw multimedia data and derived data.

2 RELATED WORK

There are several visualization approaches for multivariate data over time in the literature (see an overview in [3]). TimeSeracher[4] is a time series exploratory and visualization tool that allows users to query time series by use of TimeBoxes, which are rectangular query regions drawn directly on a two-dimensional display of temporal data. ThemeRiver[5] is used to visualize thematic changes in large document collections. VizTree[6] is designed to visually mine and monitor massive time series data. It uses symbols to represent time series data first, and then codes those symbols in a modified suffix tree in which the frequency and other properties of patterns are mapped onto colors and other visual properties. Spiral [7] is mainly used to compare and analyze periodic structures in time series data, where the time axis is represented by a spiral, and data values are characterized by attributes such as color and line thickness. Van Wijk et al[8] designed a cluster and calendar-based approach for the visualization of calendar-based data. Those methods deal with linear time or highly periodic time, they aren't designed to handle event-based data which is typical in multimedia applications. And generally, those methods focus on visualization, navigation, or query only. Our approach provides an interactive tool to integrate visualization with data mining.

The present paper is also related to data mining. Various algorithms have been proposed to discover sequential patterns[1, 9, 10]. Those algorithms can only extract temporal patterns that frequently occur in the data. Depending on research topics, researchers may also be interested in searching for unexpected patterns. Most algorithms cannot easily accomplish this task.

3 MULTIMEDIA DATASET

The example dataset used to illustrate our work was collected from a laboratory environment wherein a pair of participants interacted with and talked to each other. The raw data were collected from three sensing systems:

- **Video**: there were three video streams recorded simultaneously with the frequency of 10 frames per second, and the resolution of each frame is 320x240.
- **Audio**: The speech of the participants was recorded at a frequency of 44.1kHz.
- **Motion tracking**: there were two sensors, one on each participant's head. Each sensor provided 6 dimensional (x,y,z, head, pitch, and roll) data points at a frequency of 120Hz.

The whole dataset was collected from five pairs of participants with a 10- minute interaction for each pair. In total, the dataset consists of about 90,000 image frames, 864,000 position data points, and 50 minutes of speech.

4 VISUALIZATION OF MULTIMEDIA DATA

4.1 An Overview

As shown Figure 2, there are two major display components in the application: a multimedia playback window and a visualization window. The multimedia playback window is a digital media player that allows users to access video and audio data and play them back in various ways. The visualization window is the main tool that allows users to visually explore the derived data streams and discover new patterns and findings. More importantly, when users visually explore the dataset, these two display windows are coordinated to allow users to switch between synchronized raw data and derived data, which we will discuss more later. We will first introduce the analytical functions in our visualization system.

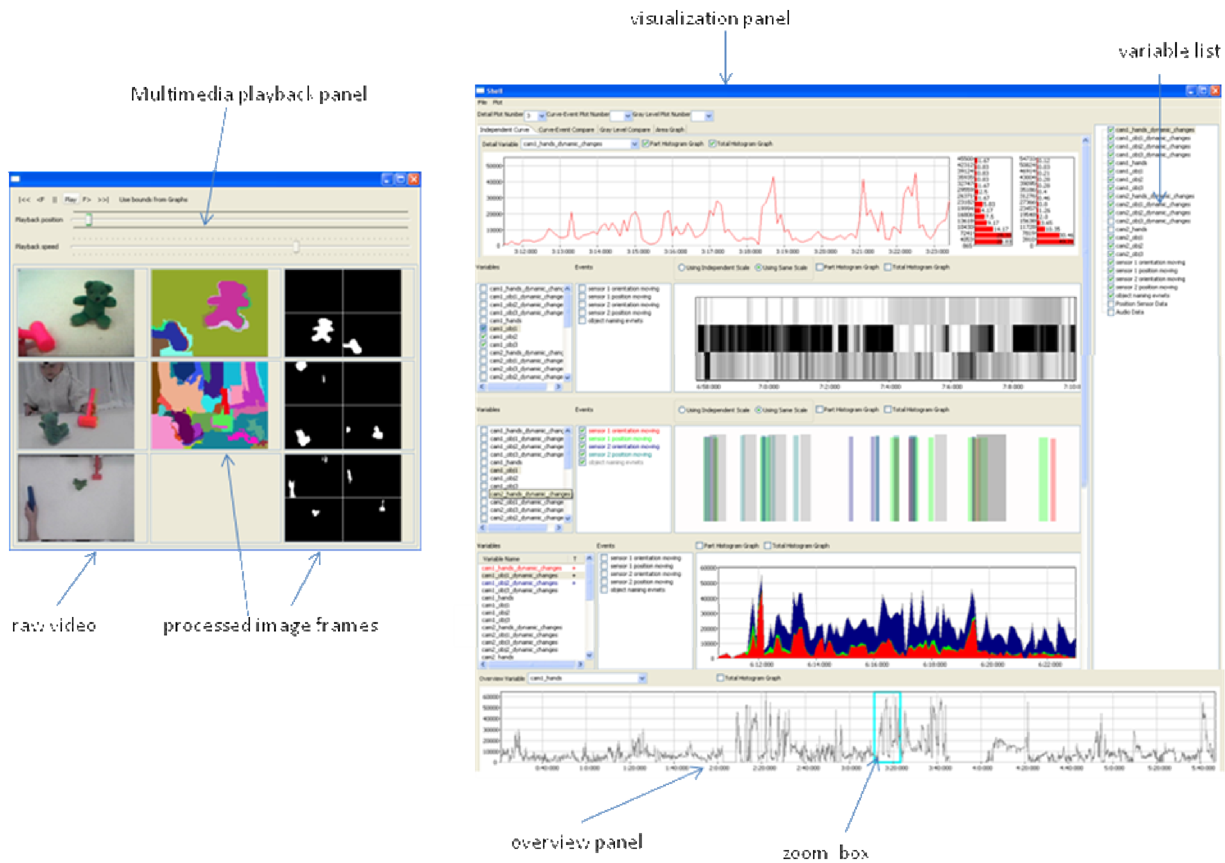

Figure 2. There are two major display components in the application: a multimedia playback window and a visualization window. The multimedia playback window is a digital media player that allows users to access video and audio data and play them back in various ways. The visualization window is the main tool that allows users to visually explore the derived data streams and discover new patterns and findings.

The main window in our visualization tool is designed based on TimeSearcher[4]. There are three display areas. After users load a multimedia data set, variables in the data set are displayed in a window in the upper right corner of the application. Each variable is labeled by its name. Users can select which ones they will load into individual display panels. These individual display panels and an overview display panel occupy the central area of the display window. The overview display panel at the bottom of the application is the place that users can select any of the loaded variables as a reference to present global trends in the data. Within the overview display, users can drag and resize a "zoom box" to define the area of interest in the time axis. This zoom box allows users to control the level of detail in the main display area wherein users can select and examine multiple variables simultaneously by zooming in the areas of interest defined by the zoom box in the overview panel and comparing multiple data streams side by side. We have developed various functions to visualize derived data streams individually or together to highlight different aspects of multimedia multivariable data

4.2 Data Representation and Visualization

From a multimedia data processing perspective, we propose that these temporal data can be categorized into two kinds: (1) continuous variables: related to time points (a series of single measurement at particular moments in time) and (2) event variables: related to time intervals (e.g. the onset and offset of an event). For example, the location of an object in a video is a continuous temporal variable that may vary over time. The time intervals when a participant is speaking can be captured as an event variable. In the following sections, we will first present how our visualization tool deals with continuous data and event data, and then we will introduce how we visualize these two kinds together and how users can perform event-based visual exploration.

4.2.1 Continuous Time Series Data

After loading the dataset, a list of continuous variables is displayed next to individual display panels, from which users can select one or multiple variables to display. Our visualization tool supports three ways to visually explore continuous time series data: (1) as individual data streams, (2) as a set of multiple data streams, and (3) as an arithmetic combination of multiple data streams. We will present each mode one by one.

Using curves to visualize individual data streams

The purpose is to allow users to explore individual data streams and examine both the overall statistics of a data stream and the statistics within a local window. As shown Figure 3, users can examine multiple streams at the same time, one for each display panel. Meanwhile, users can move the zoom box in the overview panel to zoom in and take a closer look within a certain duration

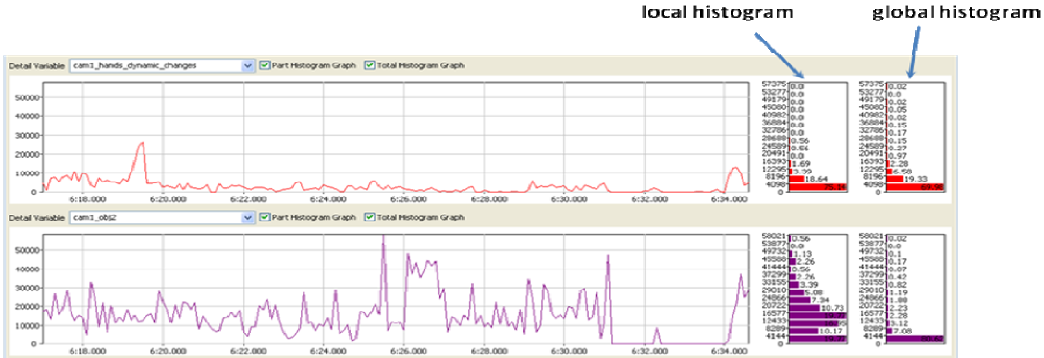

Figure 3. Using curves to visualize individual continuous data streams with local and global histograms. We can easily notice that the local histogram and the global histogram are similar for the first variable, while they are different for the second variable.

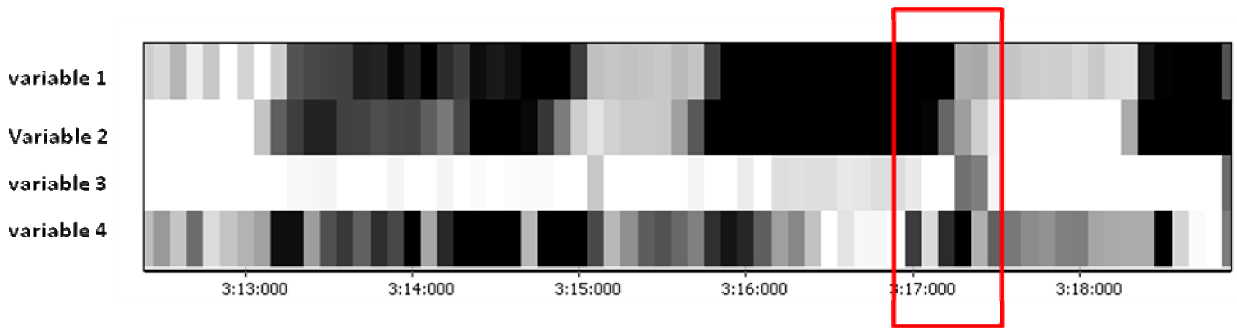

Figure 4. Using gray-level to examine a set of continuous variables. First, we can see that variable 1 and variable 2 are correlated while variable 3 and variable 4 are not. Second, the red box highlights a moment that all the variables are changing indicating a potentially interesting pattern in the data streams.

in time. A novel feature we added here is histogram display. There are two histogram plots -- one corresponding the overall histogram of the time series and the other corresponding to the local histogram of the current window. The local histogram is updated as users move the zoom box while the global histogram is constant. Compared with summary statistics and metrics (means and variances, etc.) extracted from the data, a visual plot of histogram reveals more fine-grained features such as whether distributions are uniform, normal, skewed, bimodal, or distorted by outliers, and as well as the range of the time series and the proportion of each bin. By doing so, our visualization tool transparently allows users to examine the overall distribution of the data and discover potential interesting features which can be then quantified and confirmed by calculating those features in data analysis. Moreover, by putting two histograms side by side, users can easily compare these two and detect whether the local statistics are the same with the global statistics from various perspectives. The top plot in Figure X shows an example that these two are different while the bottom one shows that they are quite similar. In this way, users can easily identify and extract those local durations that can be then used to interpret the underlying implications of those data patterns. Also, the time-query box designed by [4] can be added here as an advanced feature to explore individual time series.

Using gray-level representation to visualize a set of multiple data streams

The main purpose here is to visually display and explore two kinds of information: (1) the possible correlation between multiple data streams and (2) interesting joint patterns across multiple data streams. First, users are allowed to select multiple variables and display them as parallel gray-level data streams to explore the potential synchrony and correlation between multiple variables. For example, by viewing two time series together, users can easily detect whether two streams are correlated or not. As shown in Figure 4, human observers can immediately detect that the top two variables are closely correlated. Thus, even though the two streams are not perfectly aligned, our visual observation can tolerate and compensate for a certain degree of time shifting between two temporal streams. Moreover, even though the absolute values in the two streams are not perfectly matched, our visual system is still sensitive to the overall similarity between the two. Meanwhile, users can easily notice that the bottom two variables are not correlated indicated by asynchronized changes between two streams. The advantage here compared with data mining algorithms is that users can dynamically adjust their judgment of the similarity (time shifting or value differences) based on their visual observation. Users can make and test hypotheses in seconds, with no need to take the time to encode a data mining algorithm as an external tool. Moreover, our visual judgment is more flexible than parameterized data analysis algorithms. Users can easily extend this pairwise comparison to more general cases by selecting more than two temporal variables and examining the possible temporal correlations across all of them. To make this visualization more flexible, our visualization tool also allows users to select how to convert data values into gray levels, which can be either based on an individual data stream itself or normalized across all data streams displayed together.

Second, by simultaneously displaying multiple temporal streams, users can also spot interesting patterns between those data streams. Those interesting patterns usually cannot be easily calculated using data mining algorithms because there may be

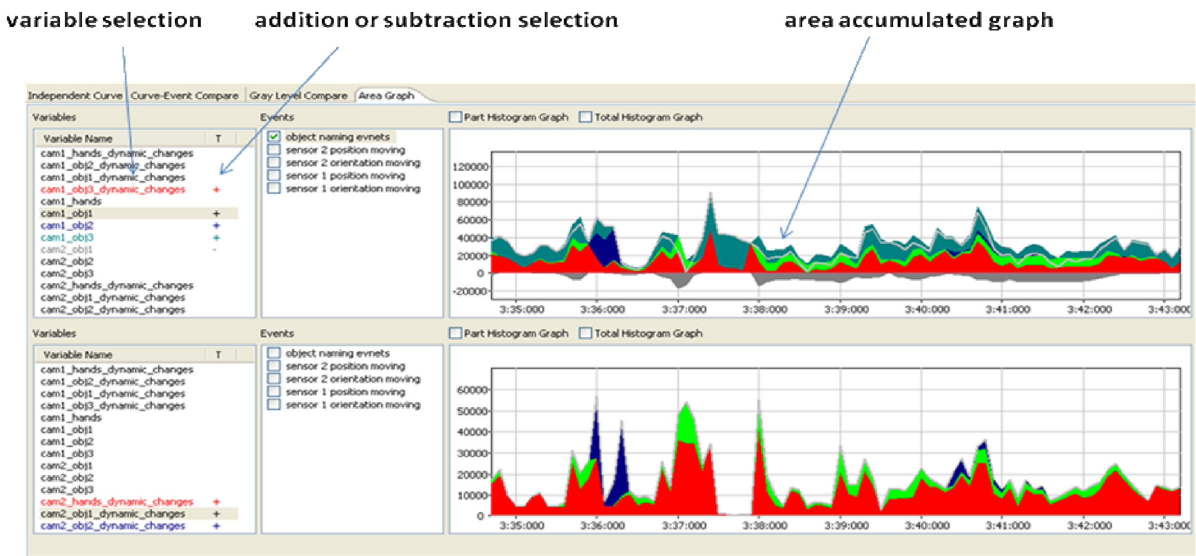

Figure 5. Using area graphs to visualize both an arithmetic combination of multiple data streams and the proportion of each component.

only a few instances of each pattern that are embedded in the sea of irrelevant data. Therefore, the algorithms are less likely to find interesting patterns because they do not occur often enough. Thus, without any insights what to look for, researchers cannot take advantage of the power of data mining techniques which are most often purely based on statistics and therefore can only either find pre-defined patterns or frequent patterns. Nonetheless, those patterns may be particularly interesting for scientific purposes which may lead to new knowledge discovery. Here lies in the advantage of our visualization. With data visualization, users can first visually spot those patterns (see an example in Figure 4 highlighted by a red box) and then use data mining techniques to quantify their observation and obtain more rational and objective results.

Using area graphs to visualize an arithmetic combination of multiple data streams.

Our visualization tool also allows users to examine the joint effects of continuous temporal variables by using area graphs. More specifically, users can select multiple continuous variables from the continuous variable list and decide the "sign" of each variable. We use area graphs to present those variables. A "+" sign (addition) will put a data stream above the time axis and a "-" sign (subtraction) will indicate that the variable should be put below the time axis. In this way, users can combine multiple temporal variables together (by addition and subtraction) in various ways and then visually explore the combined distribution. Figure 5 shows two examples in which users can explore not only the overall distribution of the combined variables, but also the proportion made up by each component (an individual variable, etc.) moment by moment.

4.2.2 Event Data

Events are presented as bars of color, with their size on screen corresponding to their duration. To select event variables for display, they are shown in a list next to the continuous variable list. Event data can be displayed alone or with continuous data. In both cases, each event is presented by a unique color. In this way, users can see not only an event itself, but also the conjunction of events because the overlapping of multiple colors will generate a new color. For example, if two events A and B are labelled as "red" and "green", then users can see four color categories: red-- "A^¬B", green – "¬A^B", yellow -- "A^B" and white – "¬A^¬B". In a more general case with more events, our color-based event visualization scheme is still able to represent all possible logic conjunctions of those events.

Now that users can visually explore several sequential patterns from a single event: (1) the frequency of the event; (2) its duration; and (3) its periodicity. Moreover, by displaying multiple event variables, our visualization tool allows users to explore sequential statistics across events, such as joint probability or transition probability. Joint probabilities are visually represented

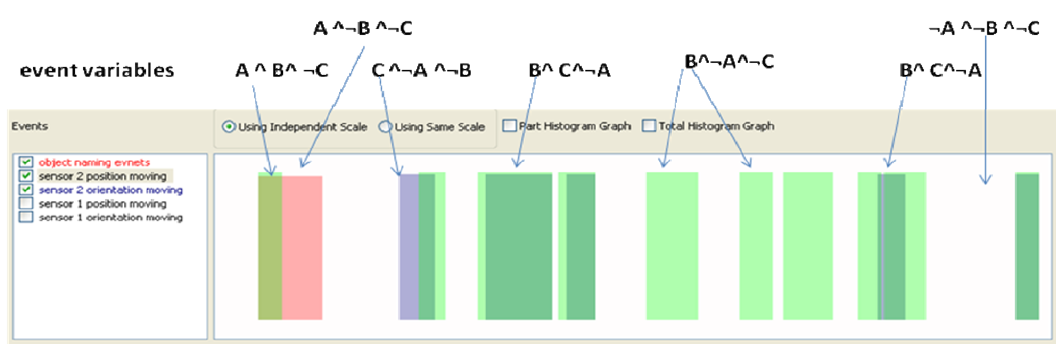

Figure 6. Our visualization of multiple event variables allows users to see not only individual events but also joint events.

by the overlapping (new color) of multiple events – how frequently the new combined event (A^B) occurs. There are two kinds of transition probabilities P(A|B) and P(A^B|B):

P(A|B): users can visually examine whether and if so how frequently event A occurs after event B (red and green bars are paired while red ones are always followed by green ones).

P(A^B|B): users can explore whether and if so how frequently the joint event A and B always occurs after event B.

Moreover, high-order transitional probabilities, such as P(A^B|C^D), can also be visually detected and examined. Although one can argue that those probabilities or frequencies can be calculated easily in data analysis, the practical problem in data exploration and knowledge discovery is that given multiple variables and many possible combinations of them with various logic operations (and, or, not) and in different orders, this combinatorial problem can be formidable. Now researchers can use our visualization tool to significantly reduce their search space by quickly going over the whole stream while rejecting uninteresting and unreliable patterns, and concentrating on interesting ones.

The above visualization is implemented by assigning different colors to different event variables that users select to display. To handle potential more complex patterns involving more variables and logic operations that may be hard for users to visually examine just based on color coding, we also allow users to define a new event variable by combining existing events with three universal logic operators (AND, OR, NOT). As shown in Figure 7, users can create a new event and assign a meaningful variable name for the new event. After that, the new event variable will be automatically added in the event list to allow users to select and visualize this new variable.

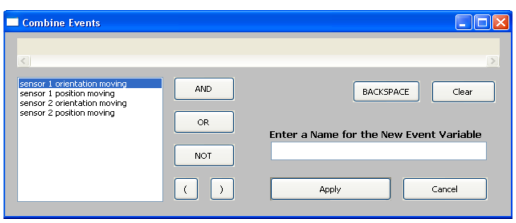

Figure 7. A new event variable can be defined based on a logic combination of existing events.

4.2.3 Concurrent visualization of continuous and event variables

The visualization functions described so far concentrate on visualizing either event variables or continuous variables. Here we present an approach to visually exploring the combination of these two. We are interested in exploring the potential complex patterns hidden in continuous variables **conditioned** on event variables – what trends and patterns exist in the continuous variables when certain events happen. Our approach is to use colors to visualize various events while using gray levels to visualize continuous values, and overlap these two. As shown in Figure 8, users can select multiple continuous variables displayed in parallel as before to visually spot potential patterns across those data streams. Meanwhile, users can also select multiple events (with different colors) overlapped on the top of gray-level continuous variables to visually examine the underlying patterns of continuous variables at those moments when a certain event happens. We allow users to select one or multiple events and also assign a transparency value for each event to highlight certain events over others. The other purpose of re-assigning transparency values is to allow users to trade-off between the visibility of events and the visibility of the underlying continuous data. Since the overall visualization effects are based on the combination of continuous and event variables, both of which change over time, we cannot use pre-defined transparency values that work perfectly across the whole data streams with different variables. Instead, users can dynamically adjust transparency values to find the best visualization effect in the current local window to visually examine both events themselves and as well as the underlying continuous values.

4.3 Event-based Interactive Visual Exploration

We observe that many multimedia data are essentially event-driven. Researchers can quantify their observations in terms of individual events, such as the event of a person entering a room, the event of a certain object appearing in a certain location, or the event of two people shaking hands. Therefore, we provide advanced functions to allow researchers to examine individual events thoroughly. As shown in Figure 9, after users select both an event and one or multiple continuous variables, all the instances in this event are listed. Now users can explore those moments one at a time and the corresponding continuous values are displayed and updated as well. In this way, users can examine in a fine-grained way the patterns of the underlying continuous variables within a certain event. While doing that, users also are allowed to change the time axis to zoom in or out to examine what happen before and after each instance of the selected event while the display panel is centered on the current instance. By visually exploring the data instance by instance, users can directly compare those moments to detect the similarities between these.

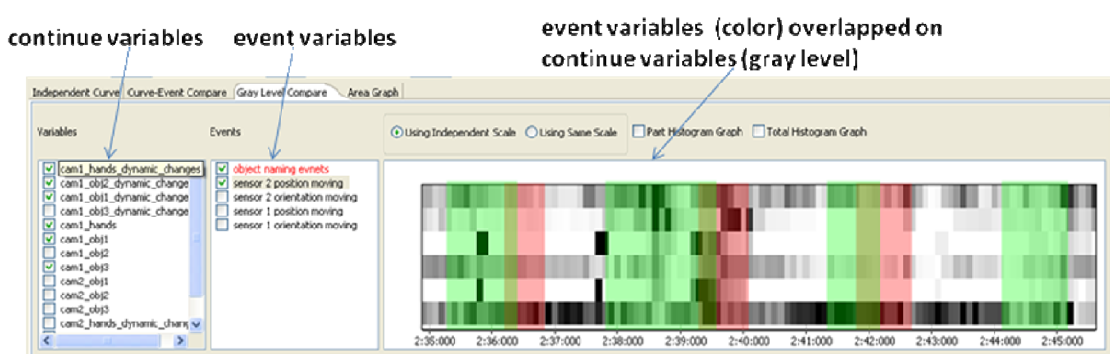

Figure 8. Users can select multiple continuous variables and multiple event variables. The display panel will highlight those continuous values at the moments when the selected events happen.

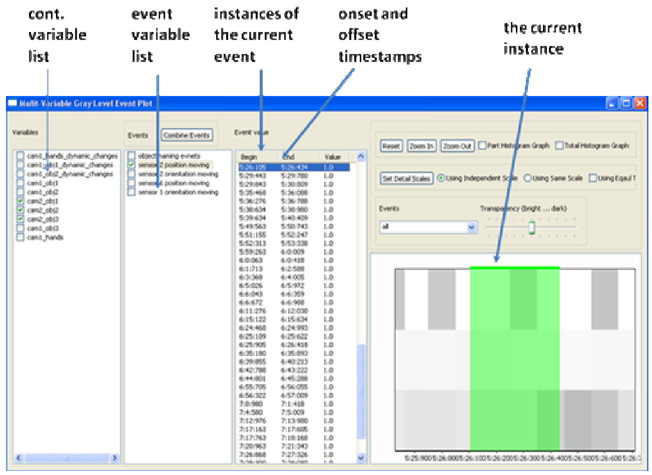

Figure 9. Users can visually explore individual instances of the same event one by one.

In this way, this event-based visual exploration allows users to gain insights about complex patterns between continuous and event variables which cannot be easily achieved by standard statistical data mining techniques. This is because data analysis algorithms may overlook interesting patterns in the data when they extract statistical patterns from the data. At the meanwhile, without a better understanding the data itself, researchers cannot simply keep track of all the details over time when a certain event happens. Visual exploration allows researchers to directly obtain the insights on complex patterns.

Our visualization tool also allows researchers to organize the data so that they can examine and comprehend the data better. Users can visually examine each instance of an event, and categorize the instances into groups. Then, the instances can be viewed side-by-side in their groups. As shown in Figure 10 (right) where each column shows the instances within the same group. Users can visually analyze and compare all the instances on the same display and regroup them as needed, a display technique called "small multiples" which works well for users [11]. This complete picture of all the instances allows users to examine both similarities within each group and dissimilarities across groups, and by doing so facilitate users to improve the overall grouping and thus more accurately discover various patterns from the underlying data. When users finalize their grouping, they can save the results of this visual analysis which can be directly used as a guide for further data analysis.

5 VISUALIZATION AND DATA PROCESSING

In addition to various analytical functions provided in our visualization tool to facilitate users to effectively examine the data visually, we also provide flexible interfaces between visualization and data mining that allows researchers to smoothly switch between these two. This section introduces two interfaces: (1) between raw data and derived data, and (2) between visualization and data analysis.

5.1 Synchronization of Multimedia Data and Visual data exploration

We have so far described various ways for researchers to visually examine and analyze continuous and event variables derived from multimedia data. We notice that derived data are extracted from raw multimedia data and can only include small subsets of the information available in the raw multimedia data. Therefore, it is important that users can refer to the raw multimedia data while exploring derived data. Our media playback panel allows users to play back video and audio data at various speeds, from fast forward/backward to frame-by-frame playback. Users can also control the onset of the playback and stop/restart the video at any moment. On the top of these standard video playback functions, we design and implement one critical component to connect multimedia playback with visual data mining. This feature is the ability to control the interval of video that is played back using the visual data mining tools. A key technical issue in implementing this feature is to synchronize in time video playback with users' ongoing visual exploration. We notice that there are two places that users can change the current

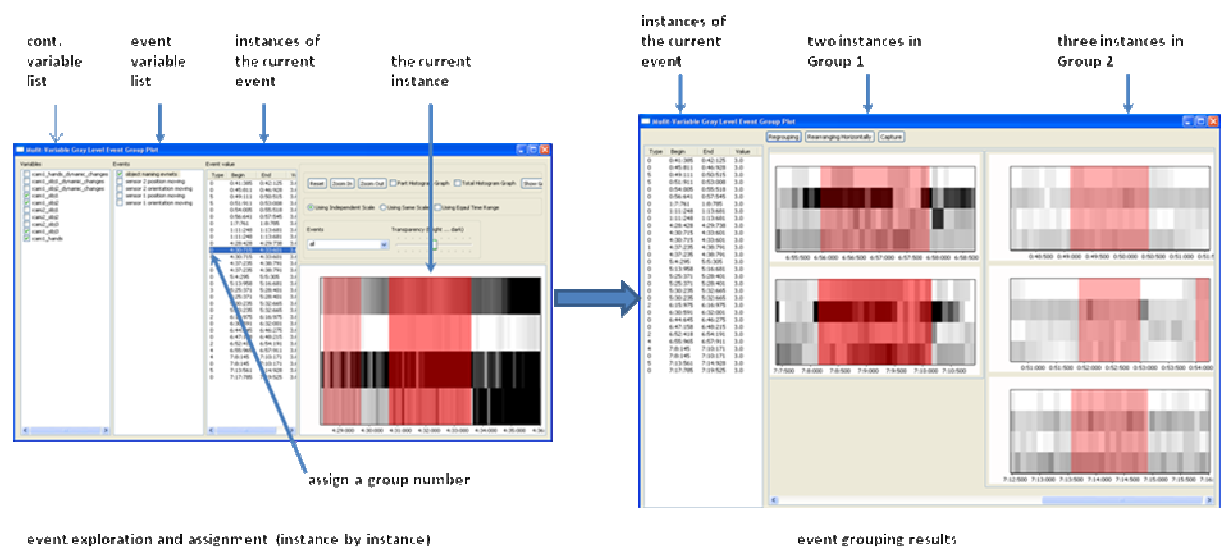

Figure 10. Event grouping. All the instances of the same event can be grouped based on the patterns of underlying continuous variables. The overall grouping results can then be visualized in one single panel where each column includes the instances belonging to the same group.

time in visual exploration and we have developed corresponding mechanisms to synchronize multimedia playback with visual exploration at those two places. First, users may drag or resize the zoom box in the overview panel to look in detail at particular parts of the dataset. When users do this, our playback program also updates the play head of playback so that if users switch to the media play panel and start to play the multimedia data, they will see raw multimedia data starting exactly with the moment that is being examined in the graphs. Second, when users explore the instances of a certain event page by page, we also synchronize the media playback with event exploration. In this way, users can watch multiple video and audio segments one by one, each of which corresponds to one instance of the event. The boundaries of a multimedia segment are defined by the onset and the offset of an event.

Access to raw multimedia data is critical in this kind of data mining since multimedia data contains more information and is more transparent to the human perceptual system than derived data. By visually exploring the current derived data and meanwhile examining the corresponding raw data, users can gain insights about what additional variables are missing and should be extracted from raw data. In this way, users can start with a small set of derived data, either continuous or event variables, and gradually augment the data exploration scale inspired by the observations based on the current results.

5.2 Visual Exploration and Data Mining

Our visualization tool supports various procedures that allow users to examine both raw and derived data, and gain insights and hypotheses about interesting patterns embedded in the data. All this is accomplished by human observer's visual system. In order to quantify and extend these observations, researchers need to develop and use data mining algorithms and statistics to extract and measure the patterns detected in visual exploration. We notice that different researchers may have different preferences of programming languages and may prefer to use certain software packages. To increase the flexibility to be compatible with data mining, our system allows users to use any programming language to obtain new results. Thus, data researchers can implement new data mining algorithms using their own analysis tools (from Matlab, to R and to C/C++) as far as users write the results into text files with pre-defined formats (one for continuous variables and one for event variables). New results will be loaded into our visualization program automatically since our visualization tool monitors the status of the workspace in real time. In this way, we propose a tight loop between visual exploration and data mining. The insights gleaned from visualization can be used to guide further data mining. Meanwhile, the results from the next round of data mining can be visualized which allows users to obtain new insights and develop more hypotheses with the data.

6 Conclusion

This paper proposes a new framework of visual mining of multimedia data. The key idea is to integrate data visualization and data mining. Based on this idea, we have developed a prototype system with several critical features to facilitate knowledge discovery. First, we decompose and represent multimedia data as a set of continuous variables and event variables. Second, we developed various ways to visualize these two kinds of variables separately and together. Third, we visualize not only raw multimedia data, but also all intermediate and final results of data mining, which allows researchers to access the "ground truth" of an experiment along with the results. Fourth, we provide a flexible interface between our visualization tool and data mining tools users may use. Overall, our visualization tool allows users to not only easily examine and synthesize information into new ideas and hypotheses, but also quickly quantify and test the insights gained from visualization. Our very next step is to conduct a systematical evaluation of our prototype system. We plan to use the experimental paradigm developed by[12] to test what kinds of new findings researchers (both experts and novices) can obtain by using this tool. By doing so, we will have a better idea of what are advantages and limitations of the current system and what will need to be improved in future work.

Acknowledgements

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