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Visual Data Mining Framework for Video Data

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Abstract **-With advances in computing techniques, a large amount of highresolutionhigh-quality multimedia data (video and audio, etc.) hasbeen collected in research laboratories in various scientificdisciplines, particularly in social and behavioral studies. How toautomatically and effectively discover new knowledge from richmultimedia data poses a compelling challenge since state-of-theartdata mining techniques can most often only search and extractpre-defined patterns or knowledge from complex heterogeneousdata. In light of this, our approach is to take advantages of boththe power of human perception system and the power ofcomputational algorithms. More specifically, we propose anapproach that allows scientists to use data mining as a first pass,and then forms a closed loop of visual analysis of current resultsfollowed by more data mining work inspired by visualization, theresults of which can be in turn visualized and lead to the nextround of visual exploration and analysis. In this way, newinsights and hypotheses gleaned from the raw data and the currentlevel of analysis can contribute to further analysis. As a first steptoward this goal, we implement a visualization system with threecritical components. We demonstrate various functions in ourvisualization program using a set of multimedia data includingvideo, audio and motion tracking data.**

Keyword **–**Datamining, Video Data, Multimedia, Frame-work

1. INTRODUCTION

With advances in computing and sensing techniques, multimediadata are ubiquitous. In particular, a large amount of higher solutionhigh-quality multimedia data (video, audio, EEG, andfMRI, etc.) has been collectedin research laboratories in variousscientific disciplines, especially in social, behavioral andcognitive studies.Multimedia data mining in generalconsists of two stages. In thefirst step, researchers extract some derived data from rawmultimedia data. This step can be implemented by human codingor by using image/speech processing programs.

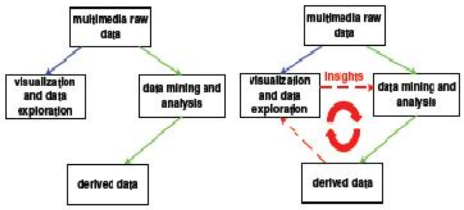


Figure 1: Multimedia Data Mining

To discover new knowledge in scientific studies, researchers may notknow in advance what information is most critical and interesting,and should be extracted first. But meanwhile, without extractingsome data first[1] and computing some results based on those data,researchers may not know where to start.In the second step of multimedia data analysis, researcherswork on derived data (time series, etc.) with the goal to findinteresting patterns requires theability to detect uncommon (but interesting).

2. RELATED WORK

There are several visualization approaches for multivariate dataover time Ituses symbols to represent time series data first, and then codesthose symbols in a modified suffix tree in which the frequencyand other properties of patterns are mapped onto colors and othervisual properties[2]. Spiral is mainly used to compare andanalyze periodic structures in time series data, where the time axisis represented by a spiral, and data values are characterized byattributes such as color and line thickness. Those methods deal withlinear time or highly periodic time, they aren't designed to handleevent-based data which is typical in multimedia applications. Andgenerally, those methods focus on visualization, navigation, orquery only. Our approach provides an interactive tool to integratevisualization with data mining.

3. MULTIMEDIA DATASET

The raw data were collected fromthreesensingsystems

Video: There were three video streams recordedsimultaneously with the frequency of 10 frames per second, and the resolution of each frame is 320x240.

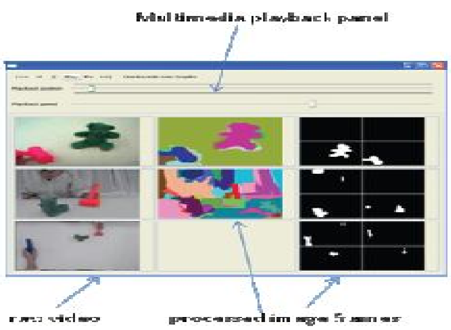
Audio: The speech of the participants was recorded at afrequency of 44.1kHz.

Motion tracking:There were two sensors, one on eachparticipant's head. Each sensor provided 6 dimensional(x,y,z, head, pitch, and roll) data points at a frequency of120Hz.The whole dataset was collected from five pairs of participantswith a 10- minute interaction for each pair.

4. VISUALIZATION OF MULTIMEDIA DATA

A. An Overview

As shown Figure 2, there are two major display components in theapplication: a multimedia playback window and a visualizationwindow. The multimedia playback window is a digital mediaplayer that allows users to access video and audio data and playthem back in various ways. The visualization window[3] is the maintool that allows users to visually explore the derived data streamsand discover new patterns and findings. More importantly, whenusers 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.



Figue 2. Multimedia Visualization Window

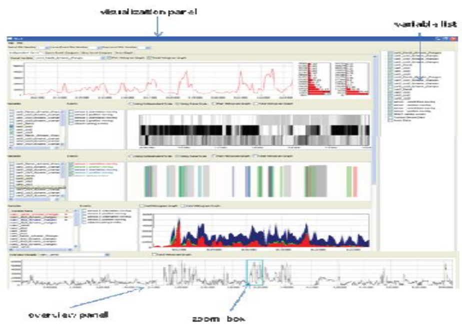


Figure3 : Multimedia Play Back Window

The main window in our visualization tool is designed based onTimeSearcher[4]. There are three display areas. After users load amultimedia data set, variables in the data set are displayed in awindow in the upper right corner of the application. Each variableis labeled by its name. Users can select which ones they will loadinto individual display panels. These individual display panels andan overview display panel occupy the central area of the displaywindow. The overview display panel at the bottom of theapplication is the place that users can select any of the loadedvariables as a reference to present global trends in the data. comparing multiple data streams side by side[5].we have developed various functions to visualize derived datastreams individually or together to highlight different aspects ofmultimedia multivariable data

B. Data Representation and Visualization

From a multimedia data processing perspective, we propose thatthese temporal data can be categorizedinto two kinds: (1) continuous variables: related to time points (a series of singlemeasurement at particular moments in time) and (2) eventvariables: related to time intervals (e.g. the onset and offset of anevent). For example, the location of an object in a video is acontinuous temporal variable that may vary over time.

C. Continuous Time Series Data

After loading the dataset, a list of continuous variables isdisplayed next to individual display panels, from which users canselect one or multiple variables to display.[6] Our visualization tools supports three ways to visually explore continuous time seriesdata: (1) as individual data streams, (2) as a set of multiple datastreams, and (3) as an arithmetic combination of multiple datastreams. We will present each mode one by one.

The advantage here compared with datamining algorithms is that users can dynamically adjust theirjudgment of the similarity (time shifting or value differences)based on their visual observation. Users can make and testhypotheses in seconds, with no need to take the time to encode adata mining algorithm as an external tool. Moreover, our visualjudgment is more flexible than parameterized data analysisalgorithms. Users can easily extend this pairwise comparison tomore general cases[7] by selecting more thantwo temporal variablesand examining the possible temporal correlations across all ofthem. To make this visualization more flexible. With data visualization, users canfirst visually spot those patterns and then use data mining techniques toquantify their observation and obtain more rational and objectiveresults.

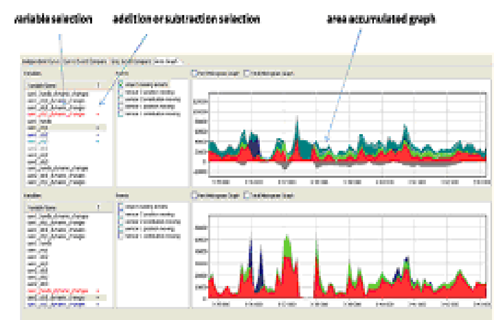


Figure 4: Using area graphs to visualize an arithmetic combination of multiple data streams

Our visualization tool also allows users to examine the jointeffects of continuous temporal variables by using area graphs. Morespecifically; users can select multiple continuous variablesfrom the continuous variable list and decide the “sign” of eachvariable. 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 putbelow the time axis. In this way, users can combine multipletemporal variables together [8].

The visualization functions described so far concentrate onvisualizing either event variables or continuous variables. Here wepresent an approach to visually exploring the combination of thesetwo. We are interested in exploring the potential complex patternshidden in continuous variables conditioned on event. Our approach is to use colors to visualizevarious events while using gray levels to visualize.

5. VISUALIZATION AND DATA PROCESSING

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

A. Synchronization of Multimedia Data and Visualdata exploration

It is important that users can refer to the raw multimedia data while exploring derived data. Our mediaplayback panel allows users to play back video and audio data atvarious speeds, from fast forward/backward to frame-by-frame playback.[9] Users can also control the onset of the playback andstop/restart the video at any moment. On the top of these standardvideo playback functions, we design and implement one criticalcomponent to connect multimedia playback with visual datamining. This feature is the ability to control the interval of videothat is played back using the visual data mining tools. A keytechnical issue in implementing this feature is to synchronize intime video playback with users' ongoing visual exploration. The boundaries ofa multimedia segment are defined by the onset and the offset of anevent.

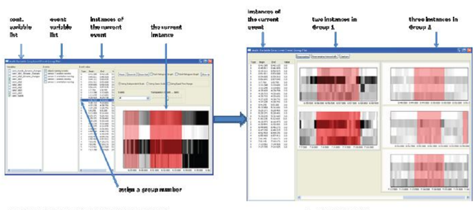


Figure 10. Event grouping. All the instances of the same event can be grouped based on the patterns of underlying continuous variables. The overall grouping results can then be visualized in one single panel where each column includes the instances belonging to the same group.

Figure5. Synchronization of Mulitimedia data

B. Visual Exploration and Data Mining:

Our visualization tool supports various procedures that allowusers to examine both raw and derived data, and gain insights andhypotheses about interesting patterns embedded in the data. Allthis is accomplished by human observer's visual system

6. CONCLUSION

This paper proposes a new framework of visual mining ofmultimedia data. The key idea is to integrate data visualizationand data mining. Based on this idea, we have developed aprototype system with several critical features to facilitateknowledge discovery. First, we decompose and representmultimedia data as a set of continuous variables and eventvariables. Second, we developed various ways to visualize thesetwo kinds of variables separately and together. Third, we visualizenot only raw multimedia data, but also all intermediate and finalresults of data mining, which allows researchers to access the"ground truth" of an experiment along with the results. Fourth, weprovide a flexible interface between our visualization tool and

Data mining tools users may use. Overall, our visualization toolallows users to not only easily examine and synthesizeinformation into new ideas and hypotheses, but also quicklyquantify and test the insights gained from visualization. Our verynext step is to conduct a systematical evaluation of our prototypesystem.

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