International Journal of Computer Communication and Information System (IJCCIS)
– Vol2. No1. ISSN: 0976–1349 July – Dec 2010

Visual Data Mining Framework for Video Data

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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- theart 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. We demonstrate various functions in our visualization 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, multimedia data are ubiquitous. In particular, a large amount of higher solution 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. 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.

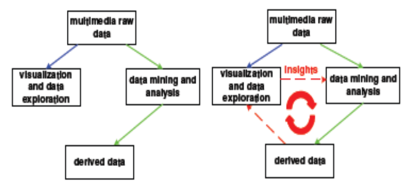

Fig 1: Multimedia Data Mining

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[1] 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 requires the ability to detect uncommon (but interesting).

2. RELATED WORK

There are several visualization approaches for multivariate data over time 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[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 integrate visualization with data mining.

.3. MULTIMEDIA DATASET

The raw data were collected from three sensing systems

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

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 mediaplayer that allows users to access video and audio data and playthem back in various ways. The visualization window[3] is the main tool 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.

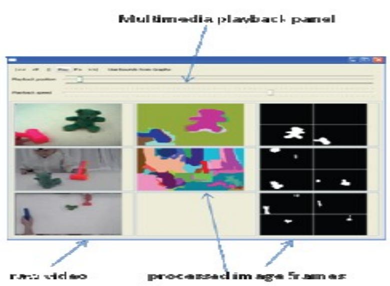

Fig 2. Multimedia Visualization Window

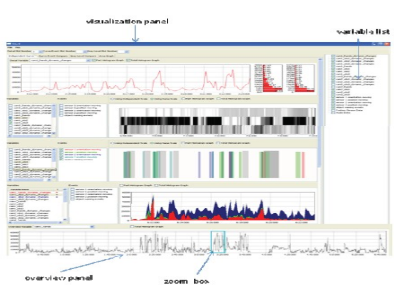

Fig 3 : Multimedia Play Back Window

The main window in our visualization tool is designed based on Time Searcher [4]. There are three display areas. After users load amultimedia data set, variables in the data set are displayed in a window 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 and an 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

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 singlemeasurement at particular moments in time) and (2) eventvariables: related to time intervals (e.g. the onset and offset of an event). For example, the location of an object in a video is acontinuous temporal variable that may vary over time.

4.3 Continuous Time Series Data

After loading the dataset, a list of continuous variables is displayed 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 data streams, 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 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 adata mining algorithm as an external tool. Moreover, our visualjudgment is more flexible than parameterized data analysis algorithms. Users can easily extend this pairwise comparison tomore general cases[7] by selecting more than two temporal variables and 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.

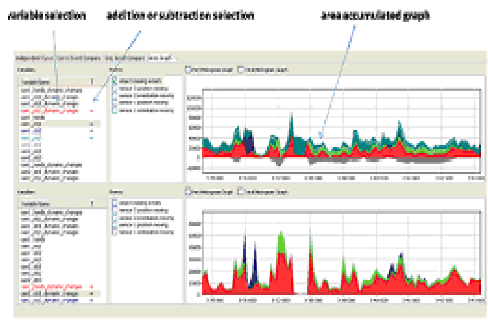

Fig 4: Using area graphs to visualize an arithmetic combination of multiple data streams

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 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 multiple temporal variables together[8] .

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 patternshidden in continuous variables conditioned on event. Our approach is to use colors to visualize various 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.

5.1 Synchronization of Multimedia Data and Visual data 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 at various speeds, from fast forward/backward to frame-by-frame playback.[9] 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 datamining. This feature is the ability to control the interval of videothat is played back using the visual data mining tools. A key technical issue in implementing this feature is to synchronize intime video playback with users' ongoing visual exploration. The boundaries of a multimedia segment are defined by the onset and the offset of an event.

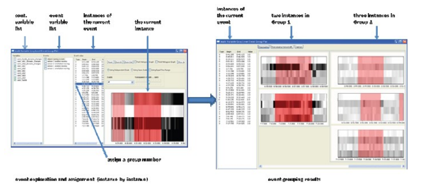

Figure 10. Event grouping. All the instances of the same event can be grouped based on the patterns of underlying continuous variables. The overall grouping results can then be visualized in one single panel where each column includes the instances belonging to the same group.

Fig 5. Synchronization of Mulitimedia data

5.2 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. All this 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 these two 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 tool allows users to not only easily examine and synthesizeinformation into new ideas and hypotheses, but also quicklyquantify and test the insights gained from visualization. Our very next step is to conduct a systematical evaluation of our prototype system.

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