Towards the Stress Analytics Framework: Managing, Mining and Visualizing Multi-Modal Data for Stress Awareness

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Abstract

Stress is experienced by many people on daily basis. Often it remains to be unrecognized and unnoticed. We propose a framework for stress analytics and describe technologies facilitating management and exploration of multi-modal affective data captured in physiological signals, such as galvanic skin response and heart rate, as well as in facial expression, in speech and in written text. We envision that stress analytics can become a useful tool as for individual personal use for stress-awareness as for researchers aiming to study the phenomenon of stress.

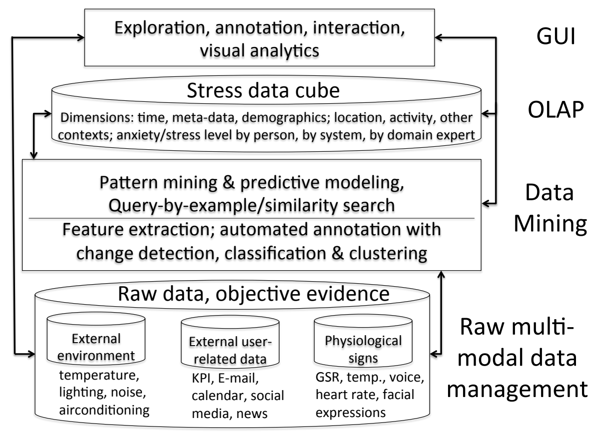

Figure 1. A high-level overview of the stress analytics framework.

1 Introduction

Chronic stress has become a serious problem affecting different life situations and carrying a wide range of health-related diseases, including cardiovascular disease, cerebrovascular disease, diabetes, and immune deficiencies [4]. In well-being research the problem of stress-management has been receiving an increasing attention [1–3, 5, 8].

In this paper we propose a general framework for stress analytics (Fig. 1). The framework contains the following parts: raw multi-modal data management, data mining support for feature extraction and automated annotation of raw data and pattern mining and predictive modeling over annotated data, Online Analytical Processing (OLAP) support slice and dice, zoom-in and -out functionality, interfaces supporting interactions between different components and a user, including e.g. annotation-to-evidence navigation.

We demonstrate how modern data management technologies can be used to implement the basic stress analytics system enabling management, analysis and automated stress classification of multi-modal affective data captured from text, speech, facial expression and physiological signals such as Galvanic Skin Response (GSR) and heart rate.

One of the principal goals is to empower users (or domain experts) to retrieve and interactively explore the raw data along with annotations, to discover and explore stress patterns, and to go back and forth from patterns and summaries to raw data containing concrete evidence of stress in one or more modalities so that stress can be understood and managed in a better way.

2 Stress analytics framework overview

Managing multi-modal data. The data originates from different heterogeneous sources; (i) sensors capturing physiological signals including GSR, skin temperature, heart rate, audio with voiced sound from speech, video with facial expressions, (ii) external user-related data including personal correspondence as text, calendar events and agenda and (iii) environmental context including temperature, humidity, lighting and noise levels.

Collected raw physiological signals often have to be preprocessed and aligned with each other. Alignment of raw data is done at the moment simply by using a global clock system synchronization. The preprocessing includes noise reduction, discretization, and dedicated feature extraction depending on the data source, e.g. extracting voiced sound from speech. We refer to [9] for a detailed explanation of preprocessing and automatic annotation of textual data, including sentiment analysis and to [6] for feature extraction from GSR and speech data.

Metadata and annotations to the collected data contains additional descriptive information e.g. where the data was collected (campus, home or street), what activity the subject performed (sitting, standing, walking or running), and when the data was taken. Annotation can be provided by a person or in an automated way. Automated annotation includes collected meta-data or event data and derived annotations, e.g. detected periods of stress, that can come as an output of different techniques including change detection, event detection classification and clustering.

Besides providing standard SQL-base querying of data we enabled finding the most similar time-series pattern (e.g. GSR or skin temperature) from the database for a given example. This shape-based Query-by-Example (QBE) functionality allows the domain expert to retrieve, classify and study particular stress pattern(s) across different subjects, time and other dimensions.

Exploring multi-modal data. Different **data mining** problem formulations can be used for stress analytics support. Change detection and classification are two general types of approaches allowing to indicate whether person was stressed over a particular time period. Clustering subjecting, who have the similar stress level during some time period(s) and/or with respect to the same gender, age, activity (i.e. potential stressor), helps to revile interesting patterns.

Pattern mining approaches can be used for finding a sequence of tasks, activities, and external factors which are related to the induced high stress level on the subject. Such patterns can be used for predicting the general subject's stress level in the future based on their past data.

The output of the data mining block, together with raw data, is used to populate **the stress data cube** supporting efficient interactive visualization of stress along predefined dimensions of interest. Based on this cube and raw data, a simple interactive user interface is provided to allow the user to navigate and explore the cube.

The stress cube metadata structure was implemented as a star schema. The fact table contains numerical measures for indicating a stress level. Dimensions include date, activity, stressor (task), location and email.

We used Mondrian (`mondrian.pentaho.com`), as an (open-source) OLAP server and Olap4j (`www.olap4j.org`) Java API to access the data.

For **shape-based QBE** functionality we utilized the existing UCR-Suite [7], the current state-of-the-art for searching time series subsequences using DTW and Euclidean distances. The original UCR-suite algorithm implementation in C language was rewritten in Java for compatibility.

Users can have control over their data and profiling information, i.e. they can add, delete and edit as raw data as annotations.

3 Concluding remarks

We discussed a blueprint of a stress analytics system with support for storing, management and exploration of multi-modal data. We have instantiated the proposed components of the stress analytics framework and conducted a feasibility study with real data collected during controlled experiments. The results of the study suggest that the proposed framework is rather generic and that developing extensions to capture data about sleep, nutrition and other daily living would be rather straightforward. The developed approaches provide useful functionality for stress awareness. The performed tests suggest that even with the commodity hardware it is possible to perform efficient retrieval, OLAP, query-by-example and visualization of annotated multi-modal stress-related data.

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