A review of "Detecting work stress in offices by combining unobtrusive sensors"

Raihan and Shafkat

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This paper discusses about issues regrading stress detection in the previous work. According to the author, previous works were conducted in a lab settings and not in a real office environment.

In previous work for psychological stress measurement, different machines, devices and sensors were used to collect data like brain imaging, heart rate, facial EMG, pupil diameter, skin conductance and so on. Recent non-restricted, non-aware, non-invasive heart monitoring system led the authors to deduce that psychological stress reaction is feasible for office setting.

In earlier research for facial expressions, emotion inducing videos were shown to the volunteer and then face videos, audio signals, eye gaze data, physiological signals were collected. Later research showed that, realistic setting can be implemented to find relation between facial expression and mental states.

Previously, several children was asked to solve a puzzle and their postures and it is concluded that they can give valuable information about mental states. With the help of Kinect the task has become much easier.

Keystroke, linguistic feature, mood rating are some of the ways to detect cognitive stress, arousal, valence, which was done in earlier period and they suggest that they can aid on retrieving information like workload and attention and mental state.

This project is termed as SWELL where user behavior is recorded as data and data is interpreted as user state and then based on that feedback is generated which then used as a guideline to adjust user behavior. Data collection methodology involves inducing stressor to daily task load. Using different unobtrusive sensors different data have been collected:

- Interactions using a computer logging tool
- Facial expressions using webcam
- Postures using Kinect
- ECG and skin conductance using body sensors

Various normalization methodologies are applied on the dataset and a window of certain time-frame is created to collect data from the user. Entire data consist of 149 columns and 2688 rows. To set ground truth of subjective experience validated questionnaires was used on:

- Task load
- Mental effort
- Emotion
- Perceived stress

After that following assumption were made on the following dataset:

- Facial expression, postures and physiology were reliably inferred from the raw sensor data
- Aggregated data over 1 minute yields valuable information
- Subjective ratings provide a good ground truth
- The subjective rating given to the entire condition can be used as ground truth for each separate minute

This paper has dealt with two challenges; one is methodological and another is applied machine learning. The earlier one is concerned with detecting stress using unobtrusive sensor and the later is with taking into account the individual differences.

In work stress detection, the algorithm that produced best result was SVM, reaching the accuracy of a little over 90%. ANN, random forest, decision tree, IBk all produced good result whuile Bayes, Bayes net and KStar performed poorly. While testing different modalities to distinguish stressor from non-stressor condition posture yielded the best performance and using other modalities cause it to reach the accuracy of 90%.

In mental effort detection, multiple regression models were tested on single and multiple modalities. It is deduced that, facial expression has strong correlation with mental effort and model tree approach yielded the best result having the correlation value of 0.8221 and RMSE of 0.5739.

Later, the authors tried to add participant id as part of the features to see it's effect in stress detection. It does not help the accuracy as it drops a bit. However, in metal state detection, participant's information contributes like a valuable feature. But, in both cases when this model is tested on unseen user the accuracy dropped dramatically and it varied from user to user.

Lastly, the authors tried to address individual differences properly. A clustering is performed to find different groups and this yielded computer activity groups, facial action unit groups and body movement groups. The mentioned models performed better on the subgroups than the general one. Using different features for different subgroups also worked well.