CNN based Mood Mining through IoT-based Physiological Sensors Observation

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Abstract
Mood can be defined as an emotional state, which is majorly described as having negative or positive valence and arousal. However, unlike emotional state, mood is less likely triggered with stimuli and less likely changed frequently. Facial expression based study can classify users emotion but cannot measure the valence and arousal level for extracting internal affective state. This paper proposed a mood mining approach from IoT-based physiological sensors observation. According to the Russell’s circumplex of mood (Figure 1), we considered six basic affective moods i.e. Happy, Excited, Angry, Distressed, Sad and Calm. We applied deep convolutional neural network (CNN) for mood mining from large volume of psychological sensor observations. The experimental results shows higher performance of mood mining in terms of classification accuracy.

1. Introduction
IoT based healthcare services opens the door of persuasive healthcare through combining intelligent technology, ubiquitous platform, and smart communication interface among users, service providers, and caregivers. The IoT [1] enabled smart health monitoring devices unlocks the vast opportunity of personalized healthcare services [2]. The physical and mental health are two essential cogs of quality life and well-being, however mental health is still remains in Fitch’s paradox. The mood mining is an approach to explore the human behavioral paradox through the modern deep learning framework. In this research, IoT-based smart biosensors are placed in human subject to collect physiological observations. While placing the biosensors for collecting physiological data, the video stimuli of happiness, excitement, anger or disgust, distress, sadness and calm or coolness are used to stimulate internal affection of the studied subject. Moreover, the subject rated the valence, arousal and dominance level of the played video just after watching it. In this research, we tried to realize the changes in physiological observations over the selected video stimuli of different affective moods. The research challenge is mapping the user provided valence and arousal score with the collected physiological signal component. In this study, the IoT-based [4] physiological sensor of Electro Dermal Activity (EDA), Electroencephalogram (ECG), and Photoplethysmogram (PPG) [5] are used to extract the arousal, and valence levels in the induced physiological data because of the video stimuli.

2. Literature Review
Affective mood is generally assess through psychological questionnaire e.g. Korean Mood Disorder Questionnaire (K-MDQ). Conversely, the state-of-the art research uses the facial expression based affective mood detection [6], cognitive analysis based mood recognition and psychological observation based affective mood classification [7]. However, most of the affective computing research generalized the emotion as the affective mood. Nevertheless, the facial expression based affective computing strategy can only classify user’s external emotion but cannot measure the valence and arousal level for extracting internal affective state, which are the key features of psychological mood [8]. We analyzed valence and arousal level in physiological signals to classify induced affective mood.

3. CNN architecture for Mood Mining
The system model of CNN based emotion recognition is presented in Figure 2. The psychophysiological observations are collected through body area networks of EDA, ECG, and PPG sensors. The signals are preprocessed in signal processing unit. The smoothing is performed for removing baseline wanders. A median filter is applied for noise removal. The features are stored in Hadoop distributed file systems (HDFS) in HBase.
training is performed through convolutional neural network (CNN) of deep learning. The kernels are applied in convolution layer for deep feature extraction, which creates several feature maps. The rectified linearization method is applied for increasing non-linear properties of decision function of whole network. The feature maps are down-sampling through pooling layer. The convolution, rectified linearization and pooling operations are performed in several cycles for convergence of the training. The connection to all activations is performed in fully connected layer therefore the activations are computed through matrix multiplication and bias offset. The trained convolution is used for testing purpose. The optimum convolution is determined from all individuals trained convolution and stored for the real-time mood recognition of individual’s emotional state. For real-time mood determination, the preprocessed psychophysiological observations feed into trained CNN and therefore the valence and arousal states of individual’s are determined. Afterwards the Russell’s Circumplex of Mood is applied to classify individual’s mood from the determined valence and arousal. However, to feed the huge data-flow of used sensors signals to the CNN, we have to modify the existing CNN architecture. To support additional parallelism, we have presented a CNN distributed CNN architecture as shown in Figure 3. We divide total dataset in several batches. Each batch is trained locally in a dedicated virtual machine (VM) unit. For learning convergence both the local and global error threshold should be validated.

4. Experimental Results

We did the test-bed experimental study to evaluate the performance of our proposed mood mining strategy. The video stimuli is used to expose moods of 30 subjects. Each of the subjects watched 24 movie clips of 2 minutes. At the end of each movie clip the subjects are asked to rate the arousal and valence levels of the watched movie clip. We used those ratings as the ground truths of different exposed moods of the subject. At the
beginning of starting the experiment, we placed Electro
dermal Activity (EDA), Electroencephalogram (EEG), and
Photoplethysmogram (PPG) sensors (as shown in Figure. 4) to
collect signals as the physiological observations of the subjects
while watching movies of different stimuli of mood expos.

![Fig. 4. Data-collection through ECG, EDA and PPG sensors
while watching the video stimuli](image)

Afterwards, we feed the signal observations with the ratings
to the proposed CNN architecture and trained the system. After
completion of training, we feed the network with testing dataset
without providing the ratings of the subject. The trained CNN
estimate the ratings as the output. Finally, we compare the output
eratings with the ground truth ratings from the subject and
determine the accuracy of mood classification as presented in
Table 1.

### Table 1: Experimental Results of Mood Classification as Confusion Matrix

<table>
<thead>
<tr>
<th></th>
<th>Happy</th>
<th>Excited</th>
<th>Angry</th>
<th>Distressed</th>
<th>Sad</th>
<th>Calm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Happy</td>
<td>93</td>
<td>17</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Excited</td>
<td>19</td>
<td>96</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Angry</td>
<td>2</td>
<td>2</td>
<td>87</td>
<td>14</td>
<td>12</td>
<td>3</td>
</tr>
<tr>
<td>Distressed</td>
<td>0</td>
<td>3</td>
<td>7</td>
<td>91</td>
<td>17</td>
<td>2</td>
</tr>
<tr>
<td>Sad</td>
<td>1</td>
<td>3</td>
<td>7</td>
<td>28</td>
<td>79</td>
<td>2</td>
</tr>
<tr>
<td>Calm</td>
<td>8</td>
<td>9</td>
<td>1</td>
<td>3</td>
<td>4</td>
<td>95</td>
</tr>
</tbody>
</table>

Average=[(93+96+87+91+79+95)/720]=0.751389

5. Conclusion

Analyzing human psychology is always challenging,
however state-of-the-art intelligent technology is approaching
towards unfolding the enigmatic world of affective computing.
Many research already shows the relation between the
psychological affect and psychological changes. The EDA sensor
technology is the pioneer one, which can measure human’s
sympathetic arousal. However, the EDA induced higher arousal
for both positive and negative psychological affect. Therefore, we
used ECG and PPG sensors observation to detect the exposed
valence of the used video stimuli. We applied deep learning
framework to extract the deep features in psychological
observations of different affective moods. The experimental
results shows average 75.14% accuracy in six different affective
moods. As IoT-based physiological sensors observation are
sequential, therefore recurrence neural network (RNN) can be
applied to increase the classification accuracy.

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