Affect Recognition in Learning Scenarios: Matching Facial- and BCI-Based Values

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Abstract—The ability of a learning system to infer a student’s affects has become highly relevant to be able to adjust its pedagogical strategies. Several methods have been used to infer affects. One of the most recognized for its reliability is face-based affect recognition. Another emerging one involves the use of brain-computer interfaces. In this paper we compare those strategies and explore if, to a great extent, it is possible to infer the values of one source from the other source.

Keywords—brain computer interfaces; affect recognition; random forest

I. INTRODUCTION

Several approaches have been used for affect recognition and researchers have explored how these approaches complement or supplement each other in learning scenarios [1]. Affect recognition using facial expression as input has been regarded as the most accurate measurement [2]. However, brain-computer interfaces (BCI) have not yet been incorporated. In this paper we describe our results correlating face-based and BCI-based values toward the verification of the interchangeability of these approaches in learning contexts. We have explored if, to a great extent, it is possible to infer the values of one source from the other source.

II. BACKGROUND

The face-based approach uses as input sequences of head and facial images. It performs best when the user stays within the camera’s viewing angle and avoids abrupt movements (e.g., reading on the screen or selecting with the mouse). In cases where the user is not quietly sitting (e.g., playing an active video game or participating in an active environment), the loss of data becomes problematic. Our research uses MindReader, face-based affect recognition software [3], which provides measurements for agreement, disagreement, concentrating, interest, thinking, and unsuresness.

The BCI-based approach uses non-invasive electrodes to capture brain-wave signals and uses pattern detection analysis of these signals to infer affective states [4]. The BCI allows the user to move freely and is able to provide accurate inferences; however, it is susceptible to electromagnetic interference and its setup encounters some difficulties (e.g., moisturizing the electrodes and maintaining their contact) that can cause missing or noisy data. Our research uses the Emotiv® EPOC headset [5], which reports measurements for excitement, engagement, meditation, and frustration.

III. CASE STUDIES

To explore the relationships between face-based and BCI-based approaches, we used data collected from participants engaged in two studies designed to stimulate distinct affects. The stimuli, protocol, and participant details for these studies are presented below.

Study one. The Guitar Hero® video game [7] was used for this study to generate both deep engagement and, at times, frustration [6]. The goal of the game is to press one or more colored buttons at the same time as moving target lights of the same color cross a line on the screen. The study consisted of a one-hour session, with the first 15 minutes allocated to practice, followed by a 45-minute session in which participants played four songs of their choice, one of each level: easy, medium, hard, and expert. Data was collected from six participants.

Study two. Text from an educational psychology textbook was used for this study. This text was presented in two ways: one with off-task images and captions (non-essential content) and the other containing only essential content. Having these two presentations allowed the evaluation of how the presence or absence of off-task images could impact the engagement of the reader and therefore the understanding of the reading. The study consisted of a one-hour session in which participants were presented with 10 pages and asked to read for understanding. Each participant was asked to complete a pre- and post-test. Data was collected from 27 participants.

IV. MATCHING VALUES AND DISCUSSION

The values collected from both approaches are in the range of 0 to 1 and represent the level of each affect. The sampling rate from the face-based approach is 10Hz while the sampling rate from the BCI-based approach is 8Hz; hence, the data needed to be synchronized. The data synchronization was done using a state-machine technique, in which it is assumed that an input value is “alive” until a new one arrives. The resulting dataset was composed of 10 rows per second (the higher sampling rate) and each row has the attributes of both approaches (ten values).

Random Forest (RF) [8] was used to model the relations between both approaches. RF uses a random selection of features and provides a ranking of the feature’s importance as a predictor. This makes RF a good choice for our multidimensional exploratory factor analysis. We built two RF models, the first one to predict each face-based inferred
affect using the BCI-based inferred affect and the second one to do the opposite, predicting each BCI-based inferred affect using the face-based inferred affect. The performance measure considered in our study is the correlation of the predicted values with the actual values. The obtained correlation values are as given in Table 1.

<table>
<thead>
<tr>
<th>BCI-based values</th>
<th>Correlation with predicted values using face-based values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excitement</td>
<td>0.284</td>
</tr>
<tr>
<td>Engagement</td>
<td>0.282</td>
</tr>
<tr>
<td>Meditation</td>
<td>0.188</td>
</tr>
<tr>
<td>Frustration</td>
<td>0.275</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Face-based values</th>
<th>Correlation with predicted values using BCI-based values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agreement</td>
<td>0.760</td>
</tr>
<tr>
<td>Concentrating</td>
<td>0.765</td>
</tr>
<tr>
<td>Dissagreement</td>
<td>0.794</td>
</tr>
<tr>
<td>Interested</td>
<td>0.774</td>
</tr>
<tr>
<td>Thinking</td>
<td>0.780</td>
</tr>
<tr>
<td>Unsure</td>
<td>0.828</td>
</tr>
</tbody>
</table>

The correlation values are not good for the models in which BCI-based inferred affects are predicted by the face-based inferred affects. But the reverse task, predicting face-based inferred affect by BCI-based inferred affect, provides reasonable correlational values. We expect this lack of symmetry because face-based detections are dependent outcomes of a person in some mental state, while the reverse is not true. We do not expect facial expressions to significantly drive the internal mental state of the person being studied; therefore, low correlations do not surprise us. A low correlation implies a poor model; analysis over that model is not valuable and may mislead. Consequently, we realize an analysis in terms of interpretability only for the models built for prediction of face-based inferred affects using BCI values as follows:

1) *Agreement* is inferred with excitement as the variable with most importance (factor>0.90) followed by engagement, frustration, and meditation (factor>0.75). Medium or high values of excitement increase the assumption of agreement, and meditation levels appear to proportionally affect the agreement level.

2) *Concentrating* is inferred with excitement and meditation as the variables with most importance (factor>0.90) followed by engagement and frustration (factor>0.80). High values of engagement and low excitement are related to concentration. Frustration and meditation do not show consistent dependence.

3) *Dissagreement* is inferred with excitement as the variable with most importance (factor>0.90) followed by meditation, engagement, and frustration (factor>0.80). Low values of excitement and frustration but high engagement and meditation are related to disagreement.

4) *Interested* is inferred with excitement as the variable with most importance (factor>0.90) followed by engagement, meditation, and frustration (factor>0.60). High values of frustration increase the assumption of interest; however, a detailed interpretation of the other variables is part of the ongoing work.

5) *Thinking* is inferred with excitement and meditation as the variables with most importance (factor>0.90) followed by engagement and frustration (factor>0.75). Higher values of engagement and low values of frustration and excitement increase the assumption of thinking.

6) *Unsure* is inferred with engagement and excitement as the variable with most importance (factor>0.90) followed by meditation and frustration (factor>0.75). High values of engagement and meditation and low excitement and frustration are related to uns veneres.

V. **Conclusions**

According to our results, it is fairly reliable to infer affect measurements obtained from a face-based affect recognition system using a BCI. In the inverse case, inferring the BCI values using the values from the face-based affect recognition system generates models with low correlation; therefore, they are not reliable.

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**References**


