Statistical Selection of CNN-Based Audiovisual Features for Instantaneous Estimation of Human Emotional States

Ramesh Basnet*, Mohammad Tariqul Islam*, Tamanna Howlader†, S. M. Mahbubur Rahman‡, and Dimitrios Hatzinakos §

*Department of EEE, Bangladesh University of Engineering and Technology, Dhaka 1205, Bangladesh
†Institute of Statistical Research and Training, University of Dhaka, Dhaka 1000, Bangladesh
‡Department of EEE, University of Liberal Arts Bangladesh, Dhaka 1209, Bangladesh
§Department of ECE, University of Toronto, Toronto, ON, Canada, M5S 2E4

Email: rbasnet198@gmail.com, tariqul@eee.buet.ac.bd, tamanna@isrt.ac.bd
mahbubur.rahman@ulab.edu.bd, dimitris@comm.utoronto.ca

Abstract—Automatic prediction of continuous-level emotional state requires selection of suitable affective features to develop a regression system based on supervised machine learning. This paper investigates the performance of features statistically learned using convolutional neural networks for instantaneously predicting the continuous dimensions of emotional states. Features with minimum redundancy and maximum relevancy are chosen by using the mutual information-based selection process. The performance of frame-by-frame prediction of emotional state using the moderate length features as proposed in this paper is evaluated on spontaneous and naturalistic human-human conversation of RECOLA database. Experimental results show that the proposed model can be used for instantaneous prediction of emotional state with an accuracy higher than traditional audio or video features that are used for affective computation.

1. Introduction

Automatic prediction of instantaneous affective state is becoming increasingly important in the recent years. Analysis of affective content is an interdisciplinary field involving research areas that includes computer vision, speech analysis, and psychology. To relate between measurable low-level features with corresponding affective state, certain models of emotion are required. Psychologists have used two major approaches, viz., categorical and dimensional to quantify the emotional states [1]. According to the categorical approach, the model of emotion was defined by Ekman, who grouped emotional states into six basic categories including the happiness, sadness, anger, disgust, fear, and surprise (see [2]). However, categorical approach fall short in situation where a small number of discrete categories may not reflect the complexity of human emotional states. In this context, continuous emotional model reflect more subtle and context specific emotions avoiding boundaries. As a result, research in area of affective computing is shifting from categorical approach to dimensional approach. In dimensional approach, Wundt [3] introduced 3D continuous space - valence, arousal, and dominance to represent emotional states of humans. Valence represents the degree of pleasure ranging from pleasant to unpleasant feelings. Arousal illustrates the activation level ranging from global feeling of dynamism to lethargy of an individual. Dominance characterizes the range of emotion from controlling sentiment to the controlled or submissive feelings. It is reported in [4] that the effect of the dominance dimension becomes visible only at points with distinctly high absolute valence values. In general, the valence and arousal account for most of the independent variance in emotional responses (see for example, [5]). Fig. [1] shows a few examples of facial appearances in the valance-arousal plane. It is seen from this figure that different emotional states such as stressed, excited, bored or relaxed feelings can be recognized independent of the subjects by the ratings of the dimensions valance and arousal. In general, the affective states of humans are estimated by

![Figure 1. Typical emotional states and human faces in the valence-arousal plane.](image-url)
extracting affective features from suitable sensors, and then relating between the low-level descriptors and high-level semantic meanings. Initial researches on affective content analysis confined in recognition of exaggerated expressions of prototypical emotions that are recorded in constrained environments [9]. Spontaneous expressions are also recognized using the differentially expressive components of the facial images represented by orthogonal 2D Gaussian-Hermite moments [7]. Nevertheless, challenges appear to solve for the problem of recognizing continuous level naturalistic emotions instantaneously those are displayed in our day-to-day life.

Prediction of continuous-level emotional states can be performed by extracting features from audio, visual or physiological signals. However, in practice, the former two-types of signals are preferred to the last-type of signal for feature extraction, because they are easily accessible and widely available. Finally, the instantaneous prediction of emotion requires that the nature of the features be dynamic instead of static. For example, in [8], the Gabor energy texture descriptors of neighboring frames are used as features of emotion. To remove redundant and irrelevant information in the regression process, suitable selection techniques such as those employ the correlation coefficients [9] and mutual information [10] are applied to certain features. Sudipta et al. [11] employed selected set of audiovisual features from the mel frequency cepstral coefficients (MFCC) and local binary patterns on three orthogonal planes (LBP-TOP) in minimum redundancy and maximum relevance (mRMR) pipeline to estimate continuous level emotional state in a multimodal framework. Recently, machine learning algorithms such as the hidden Markov model [12], the long short-term memory (LSTM) network [13], and the convolutional neural network (CNN) with LSTM [14] have been applied to predict the continuous-level emotional state.

Traditional methods of continuous-level affective computation use a large number of hand-crafted features. In the literature, the use of deep learning algorithms in affective computation is relatively new. The most successful type of deep learning method is the CNN [15], which usually predict emotional states by using a large set of affective features learned from the training data. To the best of our knowledge, the outcome of statistical selection of affective features learned by the CNN has not yet been investigated. Thus, there remains a scope of developing new deep learning algorithm using CNN such that the frame-by-frame emotional state can be estimated in real-time by the use of sufficiently low number of affective features chosen by a suitable statistical selection process. In this paper, we predict the continuous-level human emotional states instantaneously using a suitable selection of audiovisual features learned by the CNN. Specifically, the frame-by-frame instantaneous prediction of emotional states is performed by adopting mutual information-based selection process of the audiovisual features extracted from a suitable structure of CNN. We show that improvement of prediction result is obtained when only relevant features are taken care of and redundant features are eliminated.

This paper is organized as follows. Features extracted from audio and visual signals using a two-stream deep CNN are presented in Section 2. The feature selection and regression processes are detailed in Sections 3 and 4, respectively. Section 5 provides the experimental setup and comparison of the results to evaluate the proposed method. Finally, concluding remarks are given in Section 6.

2. Feature Extraction

In order to extract relevant information from audio and video signals for emotion prediction, we train an end-to-end CNN which provides affective features. The proposed CNN architecture is a 3-stage filtering scheme that employs the convolutional or fully connected layers as shown in the stick diagram of Figure 2. In this network, each of the convolution layers in the stages are followed by a ReLU and a max-pool layer. In the stick diagram of Figure 2, the layers convolution, ReLU, max-pool and LRN are shown using a triangle, a solid line, a converging trapezoid and a striped rectangle, respectively. The first stage of the proposed CNN model uses the convolutional filtering with ReLU activation and max-pool downsampling along with local response normalization (LRN). The overall output for the input frame $X_0$ in the first stage is represented as

$$X_1 = LRN(MP(\max(0, X_0 \ast W_1 + b_1)))$$

(1)

where $\ast$ is the convolution operation, $\max(0, \cdot)$ is the ReLU operation, $MP(\cdot)$ is the max-pool operation and $LRN(\cdot)$ is the local response normalization operation. Second stage uses the convolutional filtering with ReLU activation and max-pool downsampling, which is given by

$$X_2 = MP(\max(0, X_1 \ast W_2 + b_2))$$

(2)

The final stage of the network is a fully connected layer given by

$$X_3 = W_3^T X_2 + b_3$$

(3)

Overall in three stages, the parameters $W_1$, $W_2$ are convolution filter sets with bias terms $b_1$ and $b_2$, respectively, and $W_3$ is the weight matrix of the fully connected layer with corresponding bias $b_3$. We consider the output of the third stage as the features learned by the network. The final part of the CNN outputs the prediction of the emotional state, a fully connected layer that results in only scalars given by

$$y = W_r^T X_3 + b_r$$

(4)

where $W_r$ is the weight matrix, $b_r$ is the corresponding bias term of the regressor, and $y$ is the predicted value of emotional dimension.

In order to learn the end-to-end mapping function for predicting emotional state, the network parameters, i.e., the weights and bias terms are required to be estimated. The mean squared error (MSE) is easily differentiable and thus employed as the loss function for mini-batch optimization. The gradient-based momentum update algorithm [16] is employed to optimize the weights and bias terms. Moreover,
the dropout mechanism \cite{17} is employed after third stage of each of the networks for training purpose.

We trained the proposed architecture of CNN for both the video and audio streams. We add a superscripts \((v)\) for CNN trained on video stream and \((a)\) for CNN trained on the audio stream. The feature sets obtained from the video and audio streams using the CNNs are denoted as \(X_3(v)\) and \(X_3(a)\), respectively. These two sets are concatenated to obtain the complete audiovisual feature set \(\mathcal{F}\) of length \(L\) with elements as \(\{f_i\} (i \in 1, 2, \cdots, L)\).

3. Feature Selection

In order to select the relevant features and to eliminate the redundant features, the mRMR feature selection technique is used \cite{18}. The feature selection process also reduces the length of feature vectors and thus lowers the effective computational complexity. To calculate mRMR ranking of a dynamic feature \(f_i(t)\) \((i \in 1, 2, \cdots, L)\), we employ the difference between the maximum relevance and minimum redundancy criteria expressed in terms of their dynamic random variables \(F_i(t)\) \((i \in 1, 2, \cdots, L)\) given by \cite{18}

\[
\Psi_{R,F}(t) = \max_{F_i \in \mathcal{F}} \left[ \frac{1}{|\mathcal{F}|} \sum_{F_i \in \mathcal{F}} M(R(t), F_i(t)) - \frac{1}{|\mathcal{F}|^2} \sum_{F_i, F_j \in \mathcal{F}} M(F_i(t), F_j(t)) \right]
\]

where \(R(t)\) is the dynamic random variable of the ground truth of instantaneous emotional rating \(r(t)\), \(M(\cdot)\) is the mutual information of two random variables \(F_i\) and \(F_j\) given by

\[
M(F_i, F_j) = \int \int p(F_i, F_j) \log \frac{p(F_i, F_j)}{p(F_i)p(F_j)} dF_i dF_j
\]

where \(p(F_i), p(F_j)\) and \(p(F_i, F_j)\) are the probability density functions. Finally, the feature vector \(F_s\) consisting only the features \(\{f_{si}\} (i \in 1, 2, \cdots, L_s)\) with high values of mRMR ranking are constructed to predict the emotional states.

4. Prediction of Emotional Rating

In the proposed method, a regression technique is required to map the features to continuous-level emotional dimension. We employ the support vector regression (SVR) \cite{19} technique to predict the emotional states from the proposed audiovisual features by acknowledging that it is a well-established statistical learning theory applied successfully in many prediction tasks in computer vision. The kernel SVR implicitly maps the dynamic features into a higher dimensional feature space to find a linear hyperplane, wherein the emotional state can be predicted with a predefined soft error margin.

Given a training set of known emotional rating \(\Theta(t)\) \(\in \{F_s(t), r(t)\}\), where \(F_s(t)\) \(\in \mathbb{R}^{L_s}\) and \(-1 \leq r(t) \leq 1\), the emotional state is predicted using the test feature \(\hat{F}_s(t)\) as a regression function given by

\[
\hat{r}(t) = \sum_{i=1}^{L_s} \beta_i \Phi(f_{si}(t), \hat{f}_{si}(t)) + b
\]

where \(\beta_i\) are the Lagrange multipliers of a dual optimization problem, \(\Phi(\cdot)\) is a kernel function, \(f_{si}\) are the support vectors, and \(b\) is the weight of bias. In order to map the audiovisual features into the higher dimensional feature space for prediction, the most frequently used kernel functions such as the linear, polynomial, and radial basis function (RBF) can be used. With a view to select the parameters of the SVR, a grid-search on the hyper-parameters is used by adopting a cross-validation scheme. The parameter settings that produce the best cross-validation accuracy are used for
TABLE 1. COMPARISON OF PREDICTION PERFORMANCE OF EMOTIONAL DIMENSION VALANCE IN TERMS OF RMSE, CC AND CCC USING DIFFERENT FEATURES

| Features          | RMSE | CC    | CCC  |
|-------------------|------|-------|------|
| Audio (MFCC)      | 0.0696 | 0.5582 | 0.0069 |
| Visual (LBP-TOP)  | 0.0472 | 0.8032 | 0.1137 |
| Visual [8] (Gabor Energy) + LBP-TOP | 0.0481 | 0.8440 | 0.0431 |
| Audiospatial [11] (MFCC with δ and δδ + LBP-TOP) | 0.0469 | 0.7998 | 0.2592 |
| Proposed Audiovisual (CNN) | 0.0364 | 0.8924 | 0.3668 |

predicting the emotional state from the proposed CNN-based features.

5. Experimental Results

Experiments are carried out to evaluate the performance of the prediction method using features selected from the extracted features of the proposed CNNs on a multimodal corpus of spontaneous interactions in French, called the REMOTE COLLABorative and Affective interactions (RECOLA), introduced in [20]. The RECOLA database includes 9.5 hours of multimodal recordings such as the audio, video, electrocardiogram and electrodendritic activities that were continuously and synchronously recorded from 46 participants. Time- and value-continuous ratings of emotion were performed by six French-speaking assistants (three male, three female) for the first five minutes of all recorded sequences. Finally, the annotations of 10 male and 13 female participants were made publicly available. In the experiments, we used only the audio and video modalities from the database for predicting the continuous-level emotional scores. Among the subjects, videos of first 10 subjects have been chosen for training the CNN model and the videos of the remaining subjects have been chosen for testing purposes.

The input of the CNN for video stream is considered to be 128 × 128 pixels greyscale video frames. The number of filters in the weight vectors \( W_1^{(v)} \), \( W_2^{(v)} \), \( W_3^{(v)} \) and \( W_r^{(v)} \) with corresponding bias terms \( b_1^{(v)} \), \( b_2^{(v)} \), \( b_3^{(v)} \) and \( b_r^{(v)} \) are set to 128, 256, 512 and 1, respectively. The kernel size of both of the convolutional weights \( W_1^{(v)} \) and \( W_2^{(v)} \) is set to 5 × 5. The CNN for audio stream has been set up in a similar fashion. The input audio stream of each frame is taken to be of 60 ms in length, with a 20 ms overlap with audio stream of previous frame, sampled at 44.1 KHz. Thus, the number of filters in the weight vectors \( W_1^{(a)} \), \( W_2^{(a)} \), \( W_3^{(a)} \) and \( W_r^{(a)} \) with corresponding bias terms \( b_1^{(a)} \), \( b_2^{(a)} \), \( b_3^{(a)} \) and \( b_r^{(a)} \) are set to 32, 64, 512 and 1, respectively. The kernel size of both of convolutional weights \( W_1^{(a)} \) and \( W_2^{(a)} \) is chosen to be 20 with stride 2.

The feature vector \( F \) with length 1024 is constructed by concatenating learned affective features \( X_3^{(v)} \) and \( X_3^{(a)} \), each with 512 dimensions. The effective features are selected from this feature vector using the mRMR pipeline as explained in Section 3. Approximately 25% frames of video clips are considered for selection of effective features and the rest of the frames for predicting the emotional dimensions. We have discretized the range of ratings in 10-levels uniformly. The sets of 50-neighboring frames that have variation less than 20% for each of the levels are chosen for the purpose of selection process. The parameters such as the length of RBF kernel, weights, and bias of the SVR are optimized in terms of the mean absolute error (MAE) with five fold cross validation. The optimized SVR is employed first to select effective length of features those are ranked by the criterion mRMR, and finally for prediction of emotional dimension on the testing frames of the video.

The overall performance of prediction is compared with proposed learned audiovisual features from CNN, as well as audio features MFCC, visual features including LBP-TOP, the Gabor energy [8], and Paul’s ensemble of MFCC with δ and δδ and LBP-TOP [11]. Table 1 shows the overall prediction performance of the testing clips in terms of root mean squared error (RMSE), Pearson’s correlation coefficient (CC), and Lin’s concordance correlation coefficient (CCC). It is seen from the table that the proposed method of using audiovisual features learned by CNNs shows a 28.8% improvement of RMSE from the nearest method that employs hand-crafted features. Moreover, proposed method shows a 5.4% improvement of CC and 29.3% improvement of CCC from the method showing closest performance.

Figure 3 shows instantaneous prediction of the emotional dimension valence for subject 16 (male) and subject 23 (female) of RECOLA database. The regions chosen for feature selection process are marked in the figures. It can be observed from the figures that the proposed method can closely follow the affective ratings of ground truth. Moreover, it can be observed that Paul’s method as well as the Gabor energy curves shows sudden changes in estimation, which is in the complete opposite direction of the trend of the ground truth. Such, a misleading trajectory is absent for the case of proposed CNN-based features, which ensures that the learned features of CNN are robust. Also, if there is a sudden change of a dimension, then the proposed prediction can follow the trend within few seconds as per the frame-rate. Thus, the proposed instantaneous emotion prediction technique can be effective in developing real-time sensitive artificial listener (SAL) agents.

6. Conclusion

Automatic prediction of emotional states is crucial for developing SAL that has many potential applications requiring interaction between machines and humans. The generalized approach of prediction of emotional state follows the steps of extraction of affective features, selection of features, and mapping of selected features using a regressor. This paper has investigated the performance of instantaneous prediction of commonly-referred emotional dimensions, such as valence, using the extracted audiovisual features learned.
Figure 3. Prediction of valence dimension using the proposed method for subject number (a) 16 and (b) 23 of RECOLA database.

by CNNs. Extracted features are then selected by using the mutual information-based mRMR ranking. These low-level features are mapped on the emotional dimensions using the SVR technique. Performance of the proposed audiovisual features is compared with existing audio and visual features for prediction of instantaneous rating of emotional dimensions. The RMSE, CC and CCC calculated using different types of features show that the prediction performance improves significantly, when top ranked features are considered for the regression. Experiments on instantaneous prediction reveal that a moderate length audiovisual features learned by the proposed CNN-based method presented in this paper can provide a few seconds of settling time even when an emotional dimension changes sharply.

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