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An Artificial Intelligence for Detection of User's Emotion from the Micro Expression of Facial Images Using Co-activated Recurrent Neural Network

Vikas Singh**, *Siddharth Choubey
Shri Shankaracharya Technical Campus, Bhilai, India

Abstract
Human-computer intelligent interaction is a technically emerging field in computer science, which aims at improving the natural ways of interaction between computer and humans. The emphasis of our work relies on bridging the emotional gap between humans and computer i.e., to enable the computers to determine the emotional status of the users involved with through the facial micro-expressions. This work exploits existing methods of facial feature extraction using ABLATA and uses the proposed principal cluster classifier (PCC) based on newly modeled architecture of co-activated recurrent neural networks to automate the sequencization and feature determination of emotional states.

Keywords: *emotion detection, face feature extraction, recurrent neural networks, micro expression, artificial intelligence*

****Author for Correspondence*** E-mail: calmvikas@gmail.com

INTRODUCTION

There has been a growing interest in improving of human computer interaction in recent decades. Also, this budding field has been a principal research interest for different scholastic tracks i.e., computer science, engineering, psychology, and neuroscience. An example of effective work already achieved in this field is the “Smart-Kiosk” project at Compaq research laboratories [1]. Many researches also try integrating the computational models showing emotional skills as a part of what is called its “intelligence” [2, 3]. Other studies have carried the use of such similar these results to build an automatic methods to recognize human emotions from facial expressions derived from multimedia images and videos [4–8]. Since, there are several ways that humans used to exhibit their emotionsost notable and natural way is using facial micro-expressions. Such research was pioneered by Ekman and Friesen who started their work from the psychology perspective [6].Work on recognition of emotions from voice and video has been recently suggested and shown to work by Chen [9], Chen *et al.* [10], and DeSilva *et al.* [11–17]. The method employs many of the temporal information displayed in the video analysis. The emphasis behind using all of the temporal information is that any emotion being displayed has a unique temporal pattern. Many of the facial expression research works classified each frame of the video to a facial expression based on some set of features computed for that time frame. This excludes the work of Otsuka and Ohya [5], which used simple hidden Markov models (HMM) to recognize sequences of emotion.

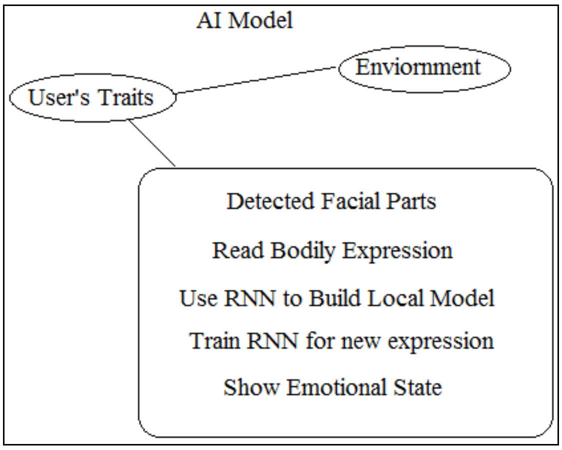

Fig. 1: *Generic Model of Emotion Detection.*

In this study we propose the development of a prototype of a model of an Intelligent Artificial Intelligence (AI) for assessing human interactive facial images with the computer system for the evaluation of the user's emotional state based on the classification of the facial micro expressions (Figure 1). Human-computer intelligent interaction is an emerging field of computer science aimed to build natural ways for to use computers as aids. In general, it is argued that for the interaction between human-computer it needs to fulfill the criteria of understanding of the rules of communication skills of humans. Among those skills is the ability to understand the emotional state of the person and the most expressive way humans display emotions is through facial micro-expressions. This AI enabled expert system forms a social interface that can begin to detect and label aspects of human emotional expression, and that respond to users experiencing frustration and other negative emotions with emotionally supportive interactions.

METHODOLOGY: PRINCIPAL CLUSTER CLASSIFIER (PCC) FOR DEEP LEARNING ALGORITHM USING RNN

The proposed method of model building of emotions from facial features using PCC builds on the works of recurrent neural networks. Generally, a multi-agent based RNN is a multi agent system gives referrals to one another but in order to do so it requires training or an effective representation of presupposition patterns to match and simultaneously mimic the reasoning capabilities on each end of the agent. Thus, this lead each agent to get acquired an acquaintances with its neighboring module. Forming a chain of module, which is susceptive enough to accommodate pervasive operations? However, it is still far from being remodel such anomalistic situation where dependency of the several parameters cannot be modeled for the expert system to form an adaptive network to perform intelligent operations. Thus, the two essential properties of an expert system or artificial intelligence lies within two components i.e., expertise and sociability. This is where our proposed algorithm Principal Cluster Classifier comes in to remodel the RNN for increasing its effectiveness against multivariable dependencies and self-modeling in the scenario of emotion detection from facial images. As shown in Table 1 the features extracted from our previous studies and latter modeled to give an estimate of the numeric equivalent of the positioning of the facial states with that of the averaging results in the basic emotional states.

The modeled RNN for PCC is formalized as follows: Given a sequence of input vectors (X_1, X_2, $X_{3,\ldots\ldots}$ X_n), the RNN computes a sequence of hidden states (H_1, H_2, $H_{3\ldots\ldots}$ H_n), and a sequence of outputs (O_1, O_2, $O_{3,\ldots\ldots}$ $O_{n,}$), by iterating the following equations

For 1: b_{jq}

for t = 1 to X:

$$H_n = \tanh(w_{HX}X_N + w_{HH}H_{N-1} + B_N) \quad (1)$$

$$k_i = w_{HH}.X_N + B_N + \sum_{i+1}^{N} \tanh(\delta_H.(1-y_{N-1}) \quad (2)$$

while j<X

$$k_j = w_{HO}.X_N + \sum_{i+1}^{N} \tanh(\delta_O.y_{N-1}) \quad (3)$$

$$O_N = w_{OH}H_N + B_O \quad (4)$$

end loop

$$\Delta w_{XX} = \eta.\delta_O.k_i.O_N \quad (5)$$

end while loop

$$PCC = \prod_{i=1}^{N} \Delta w_{XX}\, t_{f_t}(R_i, L_i) \quad (6)$$

end loop

In these equations, w_{HX} is the input-to-hidden weight matrix, w_{HH} is the hidden-to-hidden (or recurrent) weight matrix, w_{OH} is the hidden-to-output weight matrix, and the vectors B_N and B_O are the biases. The expression replaces the inputs received form feedback loops with a special initial bias vector checked for nonlinearity while ensuring that the training is done coordinate wise. η is the learning rate and k_i is the local induced field of activation potential for the i^{th} neuron, k_j is the co-activation neuron field for the next sequence of activation units,δ_H&δ_O are the pointer variable for the field and sub-field trace of an emotion, respectively. Where the integrated co-emotional involvement with principal and subsequent emotional states derived from PCC is depicted in Table 2.

Table 1: *Classifier Data for the Facial Expression.*

Objects	Overall	Anger	Sadness	Happiness	Neutral
Eyebrows	0.7300	0.8200	0.6600	1.0000	0.4600
Upper Lip	0.6800	0.5500	0.6700	1.0000	0.4900
Lower Lip	0.8100	0.8200	0.7800	1.0000	0.6500
Left Chick	0.8500	0.8700	0.7600	1.0000	0.7900
Right Chick	0.8000	0.8400	0.6700	1.0000	0.6700
Combined Data Points	0.8500	0.7900	0.8100	1.0000	0.8100

Table 2: *Confusion Matrix of the Combined Facial Expression Classifier.*

Emotions→↓	Anger	Sadness	Happiness	Neutral
Anger	0.7941	0.1834	0.0000	0.0300
Sadness	0.0623	0.8162	0.0000	0.1300
Happiness	0.0675	0.0039	1.0000	0.0000
Neutral	0.0001	0.0433	0.1500	0.8199

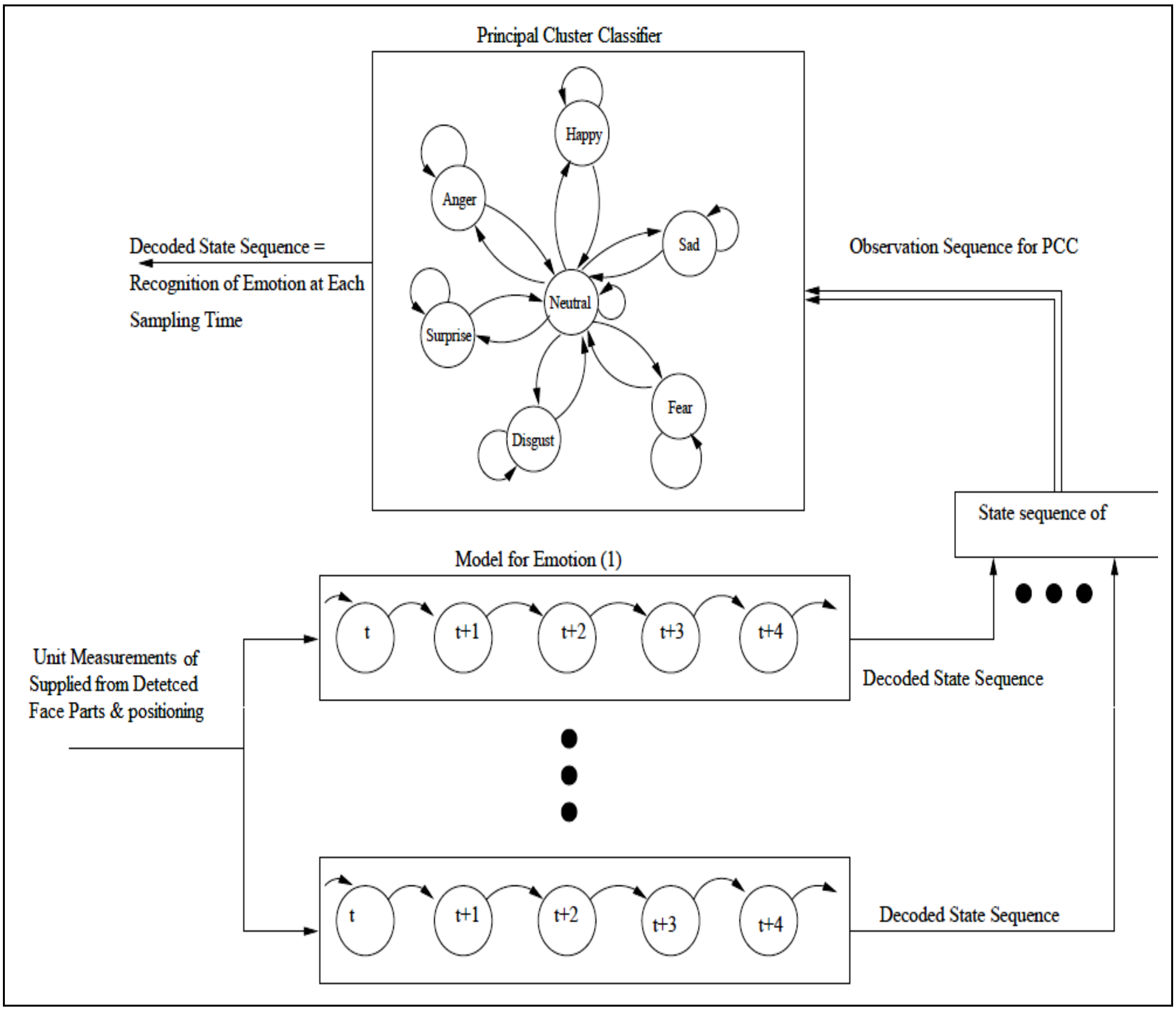

Fig. 2: *PCC Model for Emotion Detection.*

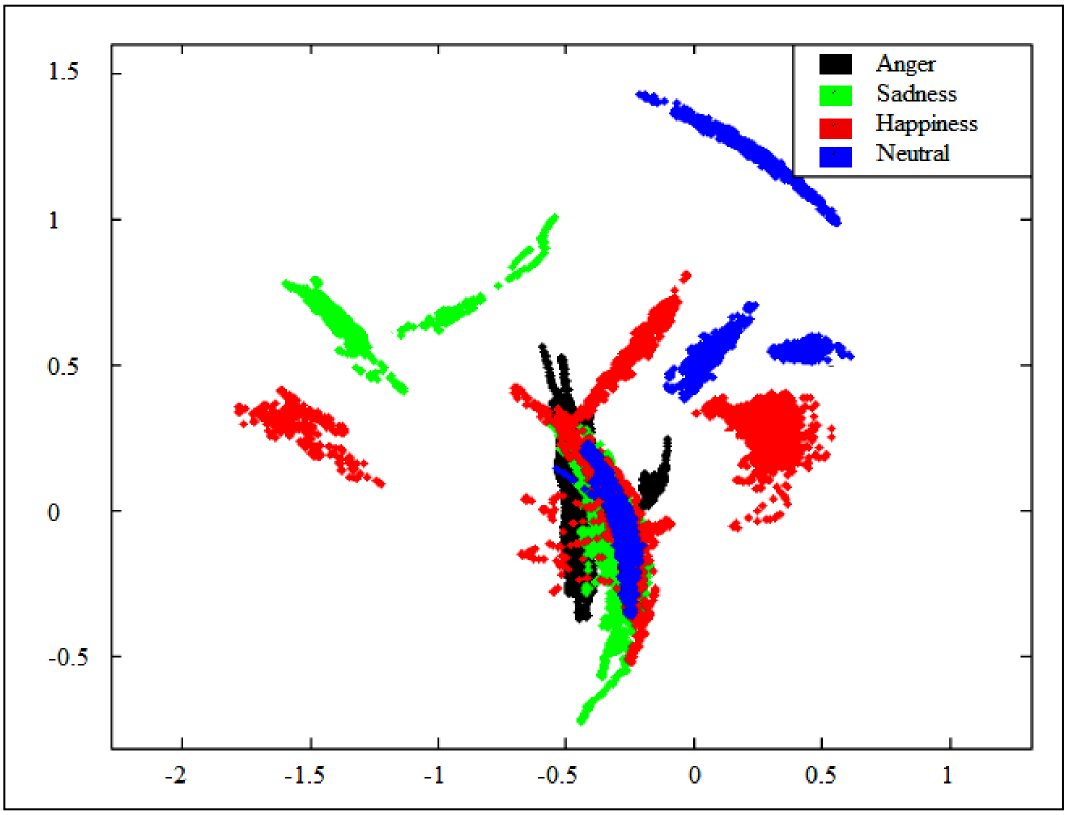

Fig. 3: *Multi-Dimensional Data for Clustering of Data Points for the Measures of Emotional State.*

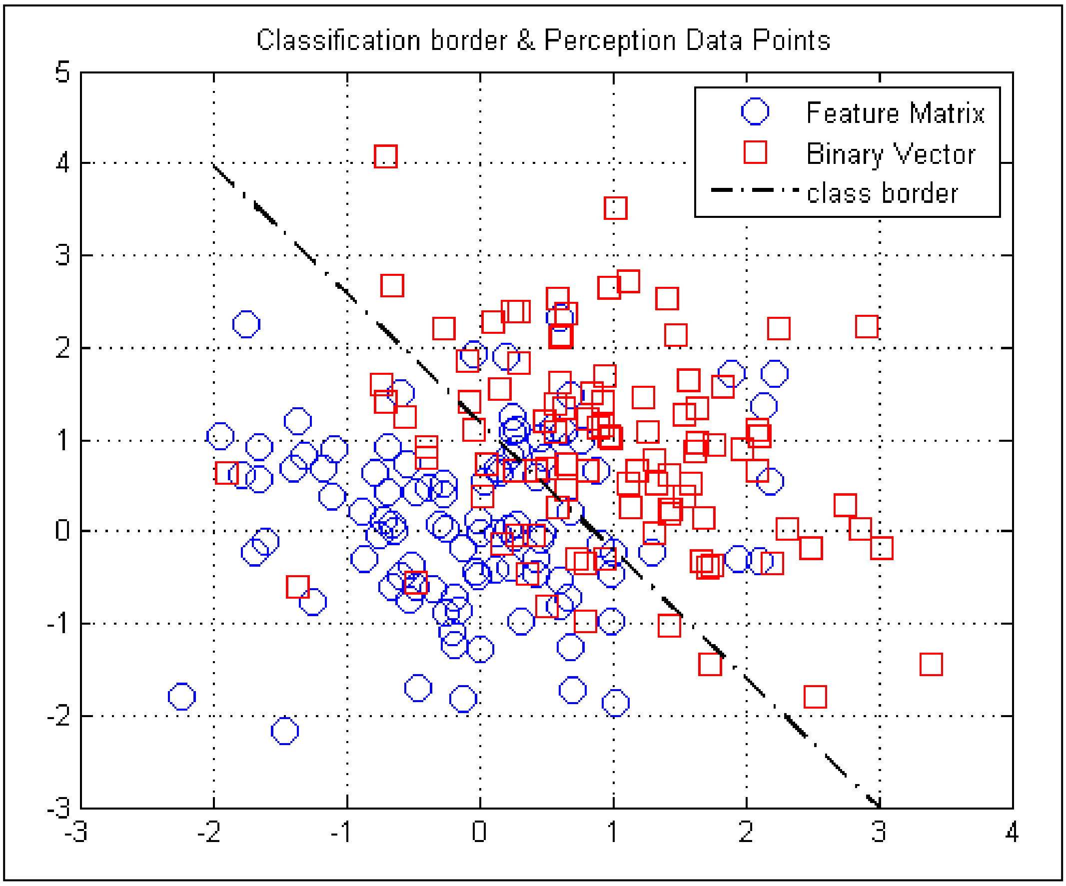

Fig. 4: *Cluster Classifier for Computational Segmentation of Data Points with Class Border for a Defining Emotional State.*

CONCLUSION

As shown in Figure 2 and Figure 3 the emotions involving with other co-emotional state is represented in multi-dimensional data plot while the categorization of the clusters is done by the proposed PCC to finely determine the true emotional states from the coherent database of the emotional data points. Also, in Figure 4 the results show the class borders determined through PCC for the miscible data points of two emotional states which were earlier difficult to categorize. This work gives a novel method for emotion determination through facial micro-expressions Emotion-specific PCC based RNN is reliable for automatic segmentation and recognition from a continuous signals (Figure 5). The experiments on the database involving with six people were studied and results were verified to show that the recognition rates for the tests are very high. However, the high performance derived from the proposed technique is steadily maintained over the influential categories like that of ethnic background and gender. This implies towards the effective use of the multidimensional classes to give the robust classification of cluster sets of differential categories involving with mixed emotions like disgust involving anger + hatred; neutral-sadness + engrossed, etc. The benchmark results favor its real-time application for autonomous lie detection. For the emotional state of a person individuals also use context as an indicator. This work is just another step on the way toward achieving the goal of building more effective computers that can serve us better.

Fig. 5: *Sample Sets for Emotion Detection by Proposed Method.*

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