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Discovering Big-Five Traits Based on Real-Time Facial Expression of Emotion

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Abstract— **Physiognomy is an emerging method in Image processing technology. Face is the reveal important aspects of human psychological traits, so the understanding of how facial expression relate to personal constructs is a major issue in social media. This study deals with operations and interaction between automatically extracted Real-Time facial expression of emotion and impressions of Big-Five personality traits. We use e-Motion system to instantaneously recognizing and displaying user emotion in real time Webcam video. The e-Motion system is purely based on "Analytical Geometry" distance analysis method and the results of this system first used in correlation analysis to discover relevance of each facial expression of emotion with respect to Big-Five traits from the observers of social video sites. Using dataset of crowd-observers of social video sites, the study decides facial expressions have significant correlation with Big-Five traits, here that personality traits are predicted and displayed as results. This methodology was used in many applications like Personal interview, User ID login, Video surveillance system, POS estimation, Detection of driver drowsiness and etc.**

Keywords— **traits, HMMs, Vlog, LDN**

I. INTRODUCTION

Facial expressions are fundamental component in social interaction. Humans use facial expressions to communicate their emotions, and to smooth or emphasize their points of view. Facial expressions are also commonly used to regulate communication. The human face has been widely documented in the social psychology literature as an important source of information in interpersonal impression. By impression, we mean the judgments that others make about a given person, in contrast to self judgments.

Emotions are experienced with the following scenario: First, there is a perception of an event, object, or an action. Then, there will be an evaluation of events, objects, or actions according to personal wishes or norms. Finally, the perception and evaluation result in a specific emotion. Considering this scenario for an emotional experience in response to multimedia content, emotions arise first through sympathy with the presented emotions in the content.

During the appraisal process for an emotional experience in response to multimedia content, a viewer examines events, situations, and objects with respect to their novelty, pleasantness, goal, attainability, capability, and compatibility with his/her norms. Then, the viewer's perception induces specific emotions which change the viewer's physiological responses. Of course person to person the emotions will change based on the situation but here we are doing the work fully based on the dataset, which is mainly focused on an identical reaction of maximum personality and the new dataset creation is a vast work, also the enough data was already given in it.

In this paper we examine personality impressions under the big five model, that posits that human personality can be represented with five dimensions, namely Extraversion (E), Conscientiousness(C), Openness to experience(O), Agreeableness(A) and Emotional stability(ES). The preliminary study was presented with the e-Motion tool.

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Personality Identification using facial features finds its applications in various areas. Some of them are military selection, fraud detection, criminal judging system, selection of actors, recruiting process. The facial features used as biometrics for authentication, can be used for other applications too.

The rest of this manuscript organized as follows. In section 2, we survey the related literature. In section 3 proposed system of this project including used dataset, system architecture and the experimental design. Finally we draw conclusion in section 4.

II. RELATED LITRATURE

A. Expression Recognition using Emotion Specific HMMs

Since the display of a certain facial expression in video is represented by a temporal sequence of facial motions it is natural to model each expression using an HMM trained for that particular type of expression. There will be six such HMMs, one for each expression: *happy(1), angry(2), surprise(3), disgust(4), fear(5), sad(6)*. There are several choices of model structure that can be used. The two main models are the left-to-right model and the ergodic model. In the left-to-right model, the probability of going back to the previous state is set to zero, and therefore the model will always start from a certain state and end up in an 'exiting' state. In the ergodic model every state can be reached from any other state in a finite number of time steps. By using left-to-right models with three states to model each type of facial expression.

B. Person-Independent Tests

In the previous section it was seen that a good recognition rate was achieved when the training sequences were taken from the same subject as the test sequences. The main challenge is to see if this can be generalized to a person independent recognition. For this test all of the sequences of one subject are used as the test sequences, and the sequences of the remaining four subjects are used as training sequences. This test is repeated five times, each time leaving a different person out (leave one out cross validation). The results indicate that in this case, the multilevel HMM gave better results than the one layered HMM, and both gave results much higher than pure chance. In general the recognition rate is much lower than the person dependent case (58% at best, compared to 88%). The first reason for this drop is the fact that the subjects are very different from each other (three females, two males, and different ethnic backgrounds); hence, they display their emotion differently. In fact, the recognition rate of subject 3, an asian woman, was the lowest in this case (36% for multilevel HMM).

C. Local Directional Number Pattern

The proposed Local Directional Number Pattern (LDN) is a six bit binary code assigned to each pixel of an input image that represents the structure of the texture and its intensity transitions. As existing system showed, edge magnitudes are largely insensitive to lighting changes. Consequently, we create our pattern by computing the edge response of the neighborhood using a compass mask, and by taking the top directional numbers, that is, the most positive and negative directions of those edge responses. The positive and negative responses provide valuable information of the structure of the neighborhood, as they reveal the gradient direction of bright and dark areas in the neighborhood.

III. PROPOSED SYSTEM

In this section we describe the overall structure of the project process. First the real-time video sequence can be fed into the e-Motion recognition system that recognized all the user emotion under the situation. The system works based on the features recognition, capturing the emotion and resulting as emotion percentage. Next we are thoroughly analyzing the system and took maximum level of emotion at one situation and correlate this with big-five personality traits. Traits are used to distinguishing the Quality or characteristics like charming smile, brilliant and etc….. In human face. Finally consolidated all the results and validating based on the application we are using the system for example personal interview, surveillance system, secure identification. The following Fig. 1 shows the structure of the process.

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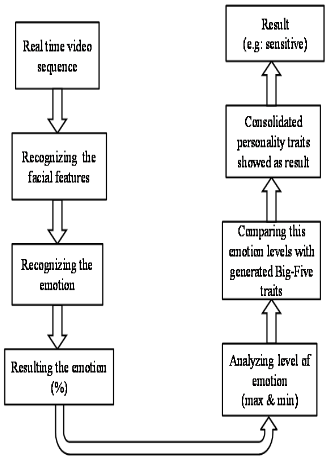

Fig.1. Overview of our approach for the study of the influence of facial expressions of emotion in personality impressions.

A. Facial Expression Recognition

Our real time facial expression recognition system is composed of a face tracking algorithm which outputs a vector of motion features of certain regions of the face. The following Fig. 2 Examine real-time facial expression recognition system.

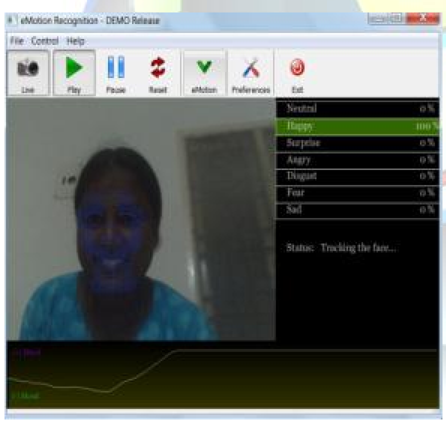

Fig. 2. A snap shot of our real-time facial expression recognition system.

B. Our Real-Time System

A snap shot of our real-time system with the face tracking and the recognition result is shown in Fig.2. The face tracking us use is based on a system developed by Tao and Huang [14] called the Piecewise Bezier Volume Deformation (PBVD) tracker. This face tracker uses a model-based approach where an explicit 3D wireframe model of the face is constructed. In the first frame of the image sequence, landmark facial features such as the eye corners and mouth corners are selected interactively. A generic face model is then warped to fit the selected facial features. The face model consists of 16 surface patches embedded in Bezier volumes. The surface patches defined this way are guaranteed to be continuous and smooth. The shape of the mesh can be changed by changing the locations of the control points in the Bezier volume.

The recovered motions are represented in terms of magnitudes of some predefined motion of various facial features. Each feature motion corresponds to a simple deformation on the face, defined in terms of the Bezier volume control parameters. We refer to these motions vectors as Motion-Units (MU's).

C. Dataset

The Vlog dataset is composed of 442 videos from the same number of YouTube vloggers, and a collection of vlogger personality impressions, and was previously used in [8]. The videos feature a monologue scenario in which vloggers talk in front of the camera during one minute, mainly showing head and shoulders, and display spontaneous behavior. The videos have different frame rates from 6 to 30 fps. All the videos were clipped to one minute duration. The dataset is balanced in gender, with 208 males (47 percent) and 234 females (53 percent). Though the vlog dataset has 442 videos only the 281 videos with better registration performance are used in our experiments.

D. Classifiers

Several classifiers from the machine learning literature were considered in our system and are listed below. We give a brief description for each of the classifiers and ask the reader to get more details from the original references. We also investigated the use of voting algorithms to improve the classification results.

The following algorithms describe the classifiers and its usage procedure.

Voting algorithms

Methods for voting classification, such as Bagging and Boosting (AdaBoost) have been shown to be very successful in improving the accuracy of certain

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classifiers for artificial and real-world datasets [28]. A voting algorithm takes an inducer and a training set as input and runs the inducer multiple times by changing the distribution of training set instances. The generated classifiers are then combined to create a final classifier that is used to classify the test set.

Bagging Algorithm

The bagging algorithm (**B**ootstrap **agg**regat**ing**) by Breiman [29] votes classifiers generated by different bootstrap samples (replicates). A bootstrap sample is generated by uniformly sampling m instances from the training set with replacement. T bootstrap samples B1,B2, . . . , BT are generated and a classifier C*i* is built from each bootstrap sample Bi. A final classifier C_ is built from C1, C2, . . . ,CT whose output is the class predicted most often by its sub-classifiers, with ties broken arbitrarily. Bagging works best on unstable inducers (e.g., decision trees), that is, inducers that suffer from high variance because of small perturbations in the data. However, bagging may slightly degrade performance of stable algorithms (e.g. kNN) because effectively smaller training sets are used for training each classifier.The following Fig.3 shows the learning curves of different classifiers.

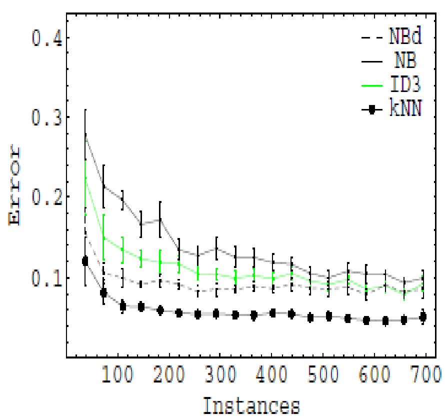

Fig.3. Learning curve for different classifiers. The vertical bars represent the 95% confidence intervals.

The term *learning curve* is used in two main ways: where the same task is repeated in a series of trials, or where a body of knowledge is learned over time.

When performing the error estimation we used n-fold cross-validation (n=10 in our experiments) in which the dataset was randomly split into n mutually exclusive subsets (the folds) of approximately equal size. The inducer is trained and tested n times; each time tested on a fold and trained on the dataset minus the fold. The cross-validation estimate of error is the average of the estimated errors from the n folds. To show the statistical significance of our results we also present the 95% confidence intervals for the classification errors.

IV. CONCLUSION

In this work we presented our efforts in discovering big-five traits based on facial expression of emotion. The used database is fully based on spontaneous emotions. We created a video kiosk with a hidden or real time Web camera which displayed segments of movies and was filming several subjects that showed spontaneous emotions. One of our main contributions in this work was to create a database in which the facial expressions correspond to the true emotional state of the subjects.

The result is hopeful enough to discover real-life applications of facial expression recognition with personality prediction in fields like surveillance and user mood evaluation. Adaptation of the present approach is being studied to sense mixed-emotions (for example, happiness and surprise, fear and disgust) that may arise in the human face.

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