Natural Facial Expression Recognition Using HMM and KNN

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Abstract: Face recognition has the most relevance in real life issues of security, criminal investigation, and verification intention. Thus it has a broad range of applications. Three issues in the field of face recognition are: illumination variation, pose variation and more importantly expression variation which is the main focus of this paper. Human-Computer Interaction is an emerging field of Computer Science where, Computer Vision, especially facial expression recognition occupies an essential role. There are so many approaches to resolve this problem; among them HMM is a considerable one. In this paper, we study Hidden Markov Model (HMM) and K nearest Neighbor (KNN) classifiers, and put forward a combined approach for facial expression recognition. There are eight different facial expression classified here: angry, annoyed, disgusted, grumpy, happy, natural, sad and surprise. The basic idea of this approach is to employ the KNN and HMM classifiers in a sequential way. Experiment on UT-DALLAS face database show that the proposed method has encouraging recognition performance

Keywords - Hidden Markov model; KNN; Active Appearance model

I. Introduction

In present day scenario computers have become more ubiquitous and indispensable part of our lives. For this same reason Human Computer Interaction (HCI) has become an emerging area of research and it is a prior necessity for imparting intelligence to computers to understand and act according to human behavior. Interpersonal communication is broadly classified into verbal communication and nonverbal communication. Verbal communication consists of only raw voice data input and nonverbal communication accounts for the tone and intensity of voice merged with facial expressions and gestures. The verbal part of the message contributes only 7% of the effect of the message as a whole, and the vocal part 38%, while facial expression contributes 55% of the effect of the speaker's message [4]. Therefore, automated and real-time facial expression recognition would be useful in many applications, e.g., human-computer interfaces, virtual reality, video-conferencing, customer satisfaction studies, etc. in order to achieve the desired result. Although humans detect and interpret faces and facial expressions in a scene with little or no effort, accurate facial expression recognition. In general, facial expressions are divided by psychologists into six basic categories: anger, disgust, fear, happiness, sadness, and surprise.

Face recognition systems architecture broadly consists of the three following tasks:

- Acquisition (Detection, Tracking of face-like images)
- Feature extraction (Segmentation, alignment & normalization of the face image)
- Recognition

One of the main problems in trying to recognize emotions is the fact that there is no uniform agreement about the definition of emotions. In general, it is agreed that emotions are a short-term way of expressing inner feeling, whereas moods are long term, and temperaments or personalities are very long term. Emotions can be expressed in various different ways, through voice, facial expressions, and other physiological means. Although there are arguments on how to interpret these physiological measurements, it is quite clear that there is a strong correlation between measurable physiological signals and the emotion of a person.

In the past 20 years there has been much research on recognizing emotion through facial expressions. This research was pioneered by Ekman and Friesen [1] who started their work from the psychology perspective. In the early 1990s the engineering community started to use these results to construct automatic methods of recognizing emotions from facial expressions in images or video [2][3][4][5][6].

II. Related Work

Although many studies on facial expression and emotions have been carried out for a long time, first of all, Paul Ekman and his colleagues' significant work about the facial expression in the 1970s became the foundation of the existing automatic facial expression recognition system [8]. Furthermore, Ekman and Friesen

postulated six basic emotions (anger, disgust, fear, happiness, sadness, and surprise) and produced Facial Action Coding System (FACS) to categorize facial expressions by describing changes in the facial muscles with Action Units (AUs) [1]. For the classification of facial expressions, classifiers are divided into two groups such as spatial and spatio-temporal approaches [9]. For frame-by-frame expression detection, many classifiers following spatial approaches have been extensively employed. These approaches use a still image or only a single frame in video sequences without temporal information. Neural Network (NN), Bayesian Network (BN), rule-based classifiers, Support Vector Machine (SVM) led to a good success for facial expression recognition. On the other hand, spatio-temporal approaches are not simple, but make better performance in video sequences than spatial approaches without temporal information. Hidden Markov Models (HMM) [10] has also been applied to facial expression recognition as one of the most popular classifiers among spatio-temporal approaches.

In 2011 Xufen Jiang did research in HMM based facial expression recognition, in which he proposed a new method [11]. Pu Xiaorong, Zhou Zhihu, Tan Heng and Lu Tai published a paper in that they proposed an HMM for partially occluded face recognition [12]. Another notable contribution is the work of Lahbiri, M. ; Fnaiech, A. ; Bouchouicha, M. ; Sayadi, M. ; Gorce, P. in 2013 which explores a novel HMM for facial expression recognition[13]. In this paper, we make a pre-classification with KNN, select the classes with high matching ratio as the basic classes of reclassification of HMM, which will reduce the workload of recognition calculation.

III. K-Nearest Neighbor (KNN)

In pattern recognition, the k-Nearest Neighbors algorithm (or k-NN) is a non-parametric method used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space. The output depends on whether k-NN is used for classification or regression. In k-NN classification, the output is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbor.

In K-NN regression, the output is the property value for the object. This value is the average of the values of its k nearest neighbors. K-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. The K-NN algorithm is among the simplest of all machine learning algorithms. Both for classification and regression, it can be useful to weight the contributions of the neighbours, so that the nearer neighbours contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbour a weight of 1/d, where d is the distance to the neighbour. The neighbours are taken from a set of objects for which the class (for K-NN classification) or the object property value (for K-NN regression) is known. This can be thought of as the training set for the algorithm, though no explicit training step is required

IV. Hidden Markov Model

HMM, as a dynamic time series statistical model of signals, has precise data structure and reliable capability of calculating. Moreover, it can extract reliable model through less samples, find out the model which is the most similar with test samples according to the theory of model matching. Therefore, HMM has become the main technology in speech and expression recognition and biologic series contrast. Because real condition is much more complex than what Markov chain can describe, HMM is developed on the base of Markov chain, now it becomes a widely-used statistical model in speech recognition. What HMM observes is not corresponding one to one, but percepts the existence and character of state. Because the state cannot be seen directly, it is called Hidden Markov Model which can implement statistical learning and probability reasoning. HMM is a double random process. One is Markov chain and the other is describing the statistical corresponding relation between every state and observation value. Because HMM describes the observation value series in statistical model, it has precise mathematic result and more integrally reflects the performance trait of whole observation value series.

HMM can be marked by $\lambda \square \square N$, M, π , A, $B \square \square$, N is number of states in Markov chain, M is number of possible corresponding observation value of every state, $\square \pi$ original possibility distribution vector, Apossibility matrix of state transfer, B possibility matrix of observation value, for continuous HMM, B is a group of possibility function of observed value. There are three algorithms in HMM. The first one is forwardbackward algorithm (given the model λ , compute the probability of the observation sequence O). The second is Viterbi algorithm (given the model λ and the observation sequence O, choose an optimal state sequence). The third is Baum-Welch algorithm (adjust the model parameters to maximize the probability of the observation sequence given the model λ)

V. Proposed Method

The block diagram of the automatic facial expression recognition system is shown in Fig. 1. HMMs, commonly used tool for automatic speech recognition, are utilized in this work as classification approach. The methods we propose automatically recognize the different facial expressions, using a multi-level HMM structure.

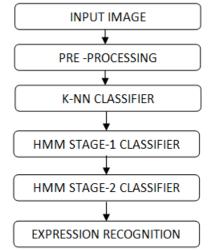


Fig 1 Automatic facial expression recognition

5.1. Reprocessing

1) Feature Extraction: Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which overfits the training sample and generalizes poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. Facial feature extraction method is proposed to solve two things: First, AAM is used to detect some feature points of the face automatically, then the center of eyes, mouth are calculated, finally the local texture information, global information and shape information are combined together to form the feature vector.

2) Dimension Reduction: Dimension reduction is a process of reducing the number of variables under observation. Principal Component Analysis (PCA) is guaranteed to discover the dimensionality of the manifold and produces a compact representation. By moving the points we can adjust the Model on the face image. That is, by adjust the width, size and lengh of AAM model points we can fix points on image. There are 68 AAM points are considered and place on image. After marking this points, it is like a mesh network. This points are set by using steepest descent method.

5.2. KNN Classification

In this paper, we propose to use the k-NN algorithm because it is simple and can conveniently output a very limited set of discrete values for each sequence of units. These outputs form the observed sequence to be input to the paired HMM in the second stage. The first stage uses N k-NN classifiers differing in their k value. This allows the system to take into consideration different degrees of variability in expressive cues (features) between levels of an affective dimension.

5.3. HMM Stage1 Classification

Each classifier of the first stage is paired with an HMM in this second stage. For each HMM, the observed sequence is based on the decision values output by its paired first stage classifier. HMM classification is processed. After that its result is stored in workspace. It will be used in next stage classification.

5.4. HMM Stage 2 Classification

In this decision fusion stage, the Markov property of temporal relationships in the sequences is further taken into account through the use of another HMM that fuses the outputs from the preceding stage. At the final stage of HMM classification, result was obtained. Here both data are collected from first stage and Second stage classification.

VI. Results

We have tested our result with the UT-DALLAS facial expression database. This database contains 208 females and 76 males' images of eight facial expressions (angry, annoyed, disgusted, grumpy, happy, natural, sad and surprise). From the database we have tested 15 images for expression angry, annoyed, happy, natural, sad and surprise and 7 images from disgusted and grumpy expression. Fig.2-9 shows the different facial expression recognized correctly.



Fig. 2. Output of Angry expression



Fig. 3. Output of Annoyed expression



Fig. 4. Output of Disgusted expression



Fig. 5. Output of Sad expression



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Fig. 7. Output of Natural expression



Fig. 8. Output of Happyl expression

Wemale20shock.IPG	
	m. iters: PMS_err 0 0 6 0 -1 -1 -1 -1
	Classification XNN classifier
	HMMA-steps 1 HMMA-steps 2
SURPRISE SURPRISE	Gabor Filter

Fig. 9. Output of Surprise expression

VII. Conclusion

In this paper, we have presented an automatic facial expression recognition system utilizing Matlab 2014a, which adopts the AAM to extract facial feature and KNN+HMM classify the facial expression emotion. A three stage classification approach, the output of a first-stage classification is used as observation sequences for a second stage classification, modeled as a HMM based framework. The k-NN will be used for the first stage classification. A third classification stage, a decision fusion tool, is then used to boost overall performance.

References

- [1]. P. Ekman and W.V. Friesen, *Facial Action Coding System: Investigator's Guide*, Palo Alto, CA: Consulting Psychologist Press, 1978.
- [2]. K. Mase, "Recognition of facial expression from optical flow," *IEICE Transactions*, vol. E74, pp. 3474-3483, October 1991.
- [3]. T. Otsuka and J. Ohya, "Recognizing multiple persons facial expressions using HMM based on automatic extraction of significant frames from image sequences," in *Proc. Int. Conf. on Image Processing (ICIP-97)*, (Santa Barbara, CA, USA), pp. 546-549, Oct. 26-29, 1997.
- [4]. Y. Yacoob and L. Davis, "Recognizing human facial expressions from long image sequences using optical flow," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 18, pp. 636-642, June 1996.
- [5]. M. Rosenblum, Y. Yacoob, and L. Davis, "Human expression recognition from motion using a radial basis function network architecture," *IEEE Transactions on Neural Network*, vol.7, pp.1121-1138, September 1996.
- [6]. L.S. Chen, "Joint processing of audio-visual information for the recognition of emotional expressions in humancomputer interaction," PhD dissertation, University of Illinois at Urbana-Champaign, Dept. of Electrical Engineering, 2000.
- [7]. Mehrabian, A." Communication without words", Psychology Today vol.2,no.4, pp.53–56,1968.
- [8]. P. Ekman. Strong evidence for universals in facial expressions: a reply to Russell's mistaken critique. Psychology Bulletin, 115(2):268–287, 1994.
- [9]. B. Fasel and J. Luettin. Automatic facial expression analysis: a survey. Pattern Recognition, 36(1):259 275, 2003.
- [10]. J. J.-J. Lien, T. Kanade, J. F. Cohn, and C.-C. Li. Detection, tracking, and classification of action units in facial expression. Robotics and Autonomous Systems, 31(3):131–146, 2000.

- [11]. Xuefeng Jiang "A facial expression recognition model based on HMM" IEEE 2011
- [12]. Pu Xiaorong ; Zhou Zhihu ; Tan Heng ; Lu Tai Partially occluded face recognition using subface hidden Markov models IEEE 2012
- Lahbiri, M.; Fnaiech, A.; Bouchouicha, M.; Sayadi, M.; Gorce, P. "Facial emotion recognition with the hidden [13]. Markov model" IEEE 2014