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DYNAMIC APPROACH FOR FACIAL RECOGNITION BASED ON EXPRESSION USING SVM AND LOCAL TERNARY PATTERN

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Abstract: **We present a new approach to facial expression recognition, which uses LTP (Local ternary pattern) consider local scale texture information to represent face images. The LTP histograms are extracted and concatenated into enhanced vector representing the face image in recognition. Then After data dimensionality reduction, the next step is data learning and classifying using SVM. The proposed new algorithm is apply to a facial expression recognition on Japanese Female Facial Expression (JAFFE) database, compare to other methods, this approach provides a better performance for gain.**
Keywords: **LTP, SVM, histogram, LBP.**

I. INTRODUCTION

To make the interactions between man and computer as natural as interpersonal interaction, it is necessary to make machines understand human facial expressions. Facial expression recognition (FER) by computer systems deals with the classification of facial expressions into various expression categories based on face images. It has been of interest to a growing number of researchers in the computer vision and pattern recognition communities during the last two decades because of its potential applications in a variety of areas such as human computer nature interaction, fatigue detection for drivers, deceit detection, e-education and e-business, Intelligent personalized house appliances, robotics as well as virtual reality.

One of the many difficulties on the study of FER is the high dimension of the input data. For example, an image with 32 × 32 pixels can be thought of as a point in a 1,024 dimensional observation space. High dimensional data will bring about the so-called "dimensionality curse" problem, so, automatic dimensionality reduction has been an important preprocessing step for FER. There are many ways to map the objects, described by high dimensional vector or by pairwise dissimilarities, into a low-dimension space. Among them, one of the most representative algorithms might be the principle component analysis (PCA) algorithm, the aim of which is to find a linear projection that transforms variables retain the maximum variance. Though PCA is a simple and powerful dimensionality reduction method, however it confined to be a linear mapping. Like PCA, multidimensional scaling is also a linear dimensionality method, which preserves dissimilarities between items, as measured either by Euclidean distance. However, nonlinear dimensionality reduction, which searches for intrinsically low-dimensional structures nonlinearly embedded in high-dimensional observation, has long been a goal of machine learning [1]. These techniques preserve dissimilarities as measured by some nonlinear squashing of distances, or shortest geodesic distances as with ISOMAP. Other methods attempt to preserve local geometry (e.g. LLE]) or associate high-dimensional points with a fixed grid of points in the low dimensional space (e.g. self-organizing maps or their probabilistic extension GTM). All of these methods, however, require each high dimensional object to be associated with only a single location in the low-dimensional space. This makes it difficult to unfold "many-to-one" mappings in which a single

In this paper, we use LTP as the dimensionality reduction toolkit on the study of FER, and then SVM as classifier to rate the data. Experiments were implemented on the Japanese female facial expression database (JAFFE). The highest FER rates attain 65 percent, better than traditional FER algorithms, such as PCA and LDA, which further proved the effectiveness of the proposed algorithm

II. LOCAL BINARY PATTERN

In recent years, some very discriminative and computationally efficient local tex-ture descriptors have been introduced. The performance gains offered by these newdescriptors have led to significant progress in applying texture methods to a large variety of computer vision problems. Arguably, one of the best of these new local texture descriptors is the local binary pattern (LBP) operator. First proposed by Ojalaet al, LBP has become one of the most widely used descriptors because of its resistance to lighting changes, low computational complexity, and ability to code fine details. Formally,
The LBP operator takes the form;

$$LBP(x_c, y_c) = \sum_{n=0}^{7} 2^n s(i_n - i_c) \quad \text{--(1)}$$

LBP is a simple yet very efficient operator that labels the pixels of an image by considering the properties of the neighborhood surrounding each pixel.The LBP operator can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis.

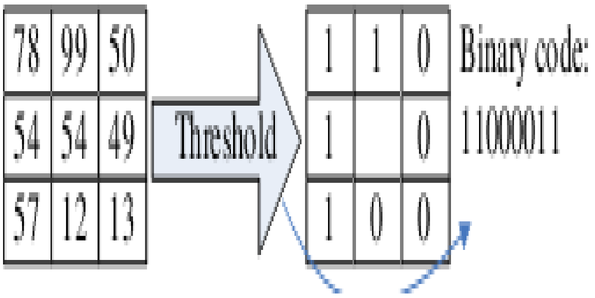


Fig 1: ilIustration of the basic LBP operator

III. LOCAL TERNARY PATTERNS (LTP)

The neighbor information of pixels that lie within the threshold is encoded implicitly by this splitting. Local binary pattern is a 2-valued (binary) code that is used in many applications .The LBP operator idea is based on just two bit values either 1 or 0. The LBP operator have weakness in below points.

- The LBP operator cannot distinguish between two pixel values if the first one is near the central pixel but a less average that pixel and the second undistinguishable one is far below the center pixel value
- In flat image areas, such as in face images, whereall pixels nearly have the same gray value, if a slight amount of noise were added to these areas the LBP operator will give some bits the value 0and others the value 1. So the LBP feature will be fluid and thus the LBP operator will not besuitable for analyzing these areas.

Local Ternary Patterns are derived from Local Binary Patterns. modied the original method to improve its robustness with regard to varying lighting conditions. In LTP, the sign function is changed from a binary function to a ternary function.

$$s(x) = \begin{cases} 1, & \text{if } x \geq T_h \\ 0, & \text{if } |x| < T_h \\ -1, & \text{if } x \leq -T_h. \end{cases} \quad \text{--(2)}$$

The ternary decision leads to two separate histograms, represent the distribution of the patterns resulting in 1, the other representing the distribution of the patterns resulting in a fig1.Two different histograms are calculated.

$$H_{I,lower}(i) = \sum_{x,y} (LBP_{r,p}(x,y) = -i) \qquad i = 0, \cdots, 2^P - 1$$

$$H_{I,upper}(i) = \sum_{x,y} (LBP_{r,p}(x,y) = i) \qquad i = 0, \cdots, 2^P - 1.$$

IV. SUPPORT VECTOR MACHINE (SVM)

The aim of Support Vector classification is to devise a computationally efficient way of learning 'good' separating hyperplanes in a high dimensional feature space, where by 'good' hyperplanes we will understand ones optimising the generalisation bounds , and by 'computationally efficient' we will mean algorithms able to deal with sample sizes of the order of 100 000 instances. The generalisation theory gives clear guidance about how to control capacity and hence prevent overfitting by controlling the hyperplane margin measures, while optimisation theory provides the mathematical techniques necessary to find hyperplanes optimising these measures. Different generalisation bounds exist, motivating different algorithms: one can for example optimise the maximal margin, the margin distribution, the number of support vectors, etc. the most common and well-established approaches which reduce the problem to minimising the norm of the weight vector.

V. MULTI-CLASS SVM

Dealing with the multi-classes classification issue, one-against-all SVM is a popular strategy. Supposed, there are k classes' data samples, the OAA-SVM classifier uses one SVM binary model to separate each of the classes from the rest. Formally, given a training set (x1,y1)..(xn,yn) with labels y i in [1…k] , the i-th SVM is defined as:

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum_i \xi_i$$
$$s.t. \quad \begin{cases} y_i(w \cdot x_i - b) \geq 1 - \xi_i \\ \xi_i \geq 0 \end{cases} \qquad for\,all\ i$$

where w is the normal vector perpendicular to the hyperplane that separates class y from the others, C is a regularization constant that trades of margin size and training error, I,ξ are the slack variables that measure the degree of misclassification of the datum I x and b is an offset scalar. This i-th classifier classifies each instance as belonging to the class i , or to the rest. The final classification of each instance is obtained by applying the following rule:

$$y_i = \arg \max_{i\in(1,\cdots,k)} \left(w_i^T y_i(x_i)+b_i\right) \quad \text{--(5)}$$

In the training phase, the i-th SVM is trained with all of the examples in the i-th class with positive marks, and all other examples with negative labels. In the classification step, the i-th SVM classifier classifies new instance, and its k values are the likelihoods that the instance belongs to each class. The last classification is get by selecting the class with the highest likelihood.

VI. EXPERIMENTS AND ITS RESULTS

The experiments of the proposed algorithm on facial expression recognition are implemented in the Japanese Female Facial Expression database. The database was taken at the Psychology Department in Kyushu University. It contains 183 images;

Fig2: sample database images

Which posed by 10 Japanese female models, which posed 3 or 4 samples of each of the six basic facial expressions and a neutral face. Some images in JAFFE were showed in figure. For simplicity, we select 3 instance images of per model at each expression (110 images in all) for our experiments.

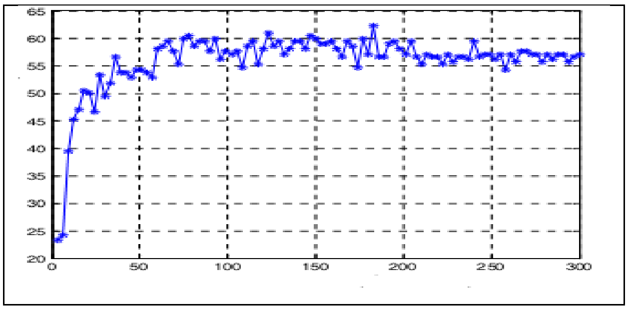
Fig3 : The sample iamges of the JAFFE database that have been excluded the non-face area

VII. RESULT ANALYSIS

We uses LIB-SVM model with RBF kernel function in our expression recognition experimentsAt first, we optimize the parameters on LIB-SVM model,which ensures SVM classifier works on its best condition in the designed facial expression recognition experiment.

$$k(x_i,x_j)=\exp\left(-\frac{\|x_i-x_j\|^2}{2\sigma^2}\right) \quad \text{--(6)}$$

This step includes optimization of the regulation constant C and kernel argumentThe regularization constant C is a cost parameter that trades of margin size and training error in SVM. At first, the performance of facial expression recognition was improved along with the increasing value of parameter C , and recorded its peak recognition rate 65.7% at 420 = C , but afterwards, the FER recognition rates tend to fluctuate widely when C continues to increase.



Dimensionality of dataset

Fig4: the FER rates changing with the data dimensions

Finally, we made a comparison between some conventional algorithms and our proposed algorithm on FER as shown in table I. The front four methods adopt LIB-SVM as the classifier. Table I shows the FER recognition rates of those methods. In
this contrast experiment, we can see the performance of algorithm LTP on FER, as LTP being an effective approach on facial expression feature extraction, is much more superior to PCA, KPCA, LDA and This has further proved our proposed algorithm is effective on FER

Method	SNE	PCA	LDA	KPCA	proposed
Recognition rate	45.7	53.8	53.6	55.7	62.4

Table 1: the performance comparison

VIII. CONCLUSIONS

A Novel approach for facial expression recognition based on Local ternary pattern plus SVM was proposed. Tested on JAFFE database, the proposed algorithm obtained a satisfactory result. The performance of the proposed algorithm is better than the traditional algorithms such as PCA, KPCA and LDA etc., and also superior to some newly introduced algorithm, such as FEA based on Gabor Histogram Feature.

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