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AGING FACE RECOGNITION UDING PRINCIPLE COMPONENT ANALYSIS AND ZERNIKE MOMENT

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ABSTRACT

Aging face recognition implies that making sure the same person's image within different ages. Recognition of a person from a group of images produced before or after test image was a difficult problem to be analyzed. This kind of problems came practically on child missing cases and also in criminal cases. There is a need to make sure that it's the same person, here 3 level learning is adopted, that is pre processing, feature extraction and also classification. In the case of feature extraction PCA (principle component analysis) and also Zernike moment are considered. In this method celebrity database is taken, which is a public domain database and thus gives a significant increase in accuracy.

I. INTRODUCTION

With the help of feature representation methods and feature classification models face recognition achieved great progress so far. Face recognition has got many practical applications that is like finding missing children, recognizing the criminals after years using their previous photographs, etc.

One of the main challenges in face recognition is that of changes in same person's images after many years. This happens due to aging process, there will being variation many facial structures like length of nose, change of face shape and also presence of wrinkles too.

In this paper, I propose a 3 step learning model, in the first step pre processing of images are done, and then feature extraction is done and in third classification of faces are also done. The aim of pre processing is an improvement of image data that suppresses unwanted distortions or enhances some image features important for further processing. Illumination normalization technique is used in pre processing.

Principal Component Analysis is a technique of dimension reduction. Here usually are surrounded by data with a large number of variables, some of which might be correlated. In the image there will be redundancy in the information that can be gathered by the data set. Thus in order to reduce the computational and cost complexities, PCA is used to transform the original variables to the linear combination of these variables which are independent.

The Zernike polynomials are a sequence of polynomials that are orthogonal. Zernike moments can represent properties of an image with no redundancy or overlap of information between the moments, their magnitudes are independent of the rotation angle of the object.

Euclidean distance or Euclidean metric is the "ordinary" distance between two points in Euclidean space. With this distance, Euclidean space becomes a metric space. The associated norm is called the Euclidean norm. Older literature refers to the metric as Pythagorean metric. A generalized term for the Euclidean norm is the L2 norm or L2 distance.

II. PROPOSED METHOD

Here new method is employed face recognition for aging purpose. That is by using illumination normalization, pre processing of images are done, using pca and Zernike moment feature extraction is done and the classification of images to its more similar ones are done using eucleidian distance techniques by checking on its similarities

1) First of all pre processing is done with the help of illumination normalization .
2) Then feature extraction is done , combining PCA and Zernike moment
3) Application of Euclidean distance is then done for comparison to find out the other images of same person.

In illumination normalization technique, illumination component is removed by subtracting the mean estimation from the original image. In order to standardize the overall gray level of different facial images, a ratio matrix of the quotient image an thus its modulus mean value is obtained. The exponent result of the ratio is approximate to a relative reflection component. Since the gray value of facial organs are less than the facial skin, post processing is applied to the images to highlight facial texture for face recognition. The first contribution of the developed approach is that the performance is more edible in processing illumination variation for face recognition.

PCA is feature extraction process can also be defined as the procedure of extracting the relevant information from a face image. This information must be valuable to the later step of identifying the subject with an acceptable error rate. The feature extraction process must be very efficient in terms of computing time and also memory usage. The output should also be optimized for the classification step. One of the most used and cited statistical method is the PCA. In general terms, PCA uses a vector space transform to reduce the dimensionality of large data sets. Using mathematical projection, the original data set, this may have involved many variables, can often be interpreted in just a few variables (the principal components).

It is the nature of the transformation that the eigenvectors arise from, this vector (and all multiples of it, because it wouldn't matter how long the vector was), would be an eigenvector of that transformation matrix. Eigenvectors can only be found for square matrices. And, not every square matrix has eigenvectors. And, given a matrix that does have eigenvectors, there are of them. Another property of eigenvectors is that even if the scale of the vector by some amount before multiplying. This is because if scale a vector by some amount, all you are doing is making it longer not changing it's direction. Lastly, all the eigenvectors of a matrix are perpendicular, ie. at right angles to each other, no matter how many dimensions you have. By the way, another word for perpendicular, in maths talk, is orthogonal. This is important because it means that express the data in terms of these perpendicular eigenvectors, instead of expressing them

It is a mathematical procedure that would performs a dimens ionality reduction by process extracting the principal components of the multi-dimensional data. The first principal component is found out by linear combination of the original dimensions that has the highest variability. The n-th principal component is then given by linear combination with the maximum variability, being orthogonal to the n-1 first principal components.

Ability of invariance and rotation is being analyzed and implemented with the help of Zernike moment. Zernike polynomials are one of infinite set of polynomials that are orthogonal over the unit. Geometric moment mpq of image f(x; y), where p; q are non-negative integers and (p + q) is called the order of the moment, is defined as

$$m_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^p y^q f(x,y) \mathrm{d}x \mathrm{d}y$$

Algorithms	Recognition accuracy
Face VACS	78.90%
Parc et al	79.80%
Duet.al	79.24%
Li et al	83.90%
Otto et al	79.08%
Zhen at al	81.27%
Gong.et.al	86.12%
Zhing et al	91.14%
LPS	92.11%
PCA and Zenike	92.75%

Table 1 : Comparison of accuracy with other methods

Euclidean distance is studied for classification. Similarities between test image and other images are being checked out using following formula.

$$d(\mathbf{p},\mathbf{q}) = d(\mathbf{q},\mathbf{p}) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \cdots + (q_n - p_n)^2}$$

$$= \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2}.$$

The one having least differences will be given as the result to face recognition across ages.

I. EXPERIMENTAL CRITERIA

As mentioned in the steps earlier in the proposed system image pre processing is done and after that feature extraction is done. Image classification is then continued using Eucleidian formulas.

The effectiveness of the PCA and Zernike moment feature descriptor against the popular feature descriptors in face recognition community. Specifically, the extracted raw features (before refinement) are used directly for face recognition. The comparative results are reported in Table 5.1. The LBP feature descriptor is the original LBP descriptor. The MLBP feature descriptor is an extension of LBP, by computing the LBP descriptor at four different sampling radii {1, 3, 5, 7}. Note that for fairness, here its used same sampling patterns with MLBP for the method. The HOG features are extracted with the suggested settings where face images are processed at three different scales. The SIFT feature descriptor quantizes both the spatial location and orientation of image gradient within an image patch, and computes a histogram in which each bin corresponds to a combination of specific spatial location and gradient orientation.

How many images are being corrected is analyses along with pervious methods. The result of proposed method look substantially high comparing to any other previous methods. 92.75% corrected images are being obtained with help of this method. Its being described in table 1.

Now present the benchmark result on the celebrity dataset, and compare it against the state-of-the-art approaches for aging face recognition. To ensure a fair comparison, all the methods listed in Table 1 are tuned to the best settings according to their original papers, and all the methods are using the same training and testing protocol: 10,000 pairs of faces (with the largest age gap) used for training and the other 10,000 pairs of faces (with the largest age gap) are reserved for testing.

II. RESULTS AND DISCUSSIONS

Experiments are conducted in MATLAB 2009b as simulation software. Test images used will compared with other images and a fruitfull result will be obtainesd that is always better than other methods, this brings more compatiblity and also reduces redundancy.

Figure 1 Training set

Figure 2 Normalized set

Test images as shown in figure 1 are normalized to figure 2 by illumination normalization. Then mean of these images are taken, after that test image(figure 3) will be given and result will be obtained (figure 4).

Figure 3 Test image

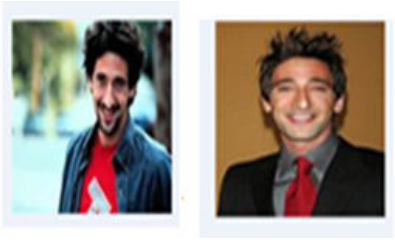

Figure 4 Output images

I. REFERENCES

1. Zhifeng Li, Dihong Gong, Xuelong Li, Dacheng Tao, MAY 2016,Aging Face Recognition: A Hierarchical Learning Model Based on Local Patterns Selection, IEEEE trasactions on image processing
2. Y. H. Kwon and N. da Vitoria Lobo, Jun. 1994, "Age classification from facial images," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 1994, 762–767.
3. X. Wang and X. Tang, "Random sampling LDA for face recognition," in Proc. CVPR, 2004, pp. 259–265.
4. Lanitis, C. Draganova, and C. Christodoulou, "Comparing different classifiers for automatic age estimation," IEEE Trans. Syst., Man, Cybern. B, Cybern., vol. 34, no. 1, pp.621628, Feb. 2004.
5. Ramanathan and R. Chellappa, "Face verification across age pro-gression," IEEE Trans. Image Process., vol. 15, no. 11, pp. 3349–3361, Nov. 2006.
6. Y. Fu and T. S. Huang, "Human age estimation with regression on discriminative aging manifold," IEEE Trans. Multimedia, vol. 10, no. 4,578–584, Jun.
7. G. Mu, G. Guo, Y. Fu, and T. S. Huang, "Human age estimation using bio-inspired features," in Proc. CVPR, 2009, pp. 112–115
8. C.Geng and X Jiand,"Face Recognition Using SIFT- PCA Feature Extraction and SVM "IEEE Trans. Multimedia, vol. 10, no. 4,578–584, Jun.2014 .
9. K. Zhu, D. Gong, Z. Li, and X. Tang, "Orthogonal Gaussian process for automatic age estimation," in Proc. 22nd ACM MM, 2014, pp. 857–860.
10. Z. Li, U. Park, and A. K. Jain, "A discriminative model for age invariantface recognition," IEEE Trans. Inf. Forensics Security, vol. 6, no. 2,pp. 1028–1037, Sep. 2011