Face Recognition Using Combination of Moments

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Abstract : The field of face recognition has been explored a lot and the work is still going on. In the proposed work, facial recognition will be done using feature extraction method. Three moments named Hu moments, Zernike moments and Legendre moments will be used for face recognition. For feature extraction, moments of different orders will be calculated which will form the feature vectors. The feature vectors obtained will be stored in the database and will be compared using three different classifiers named Minimum Distance classifier, Support Vector Machine (SVM) and K means.

***IndexTerms* - Face Recognition, moments, Classification.**

I. INTRODUCTION

A face recognition system can be defined as a computer application for automatically identifying or verifying a person from a digital image or a video frame from a video source. The most convenient way to do this is by comparing selected facial features from the image and a facial database. In today's world, as more and more interactions take place electronically, it becomes important to have an electronic verification of a person's identity.

Until recently, electronic verification took one of the two forms:
1- It was based on something the person had in their possession, like a magnetic swipe card or
2- something they knew, like a password.
The problem is, these forms of electronic identification aren't very secure, because they can be given away, taken away, or lost and motivated people have found ways to forge or circumvent these credentials. So, the ultimate form of electronic verification of a person's identity is biometrics; using a physical attribute of the person to make a positive identification.

Different approaches have been tried by several groups, working world wide, to solve this problem. Many commercial products have also found their way into the market using one or the other technique. But so far no system / technique exists which has shown satisfactory results in all circumstances. To cater this need face recognition as a field emerged. Face recognition or machine learning and pattern recognition in general, investigates aspects of data analysis in theory, experiments and applications.

The research is about developing, evaluating and applying support vector machines, non-linear dimensionality reduction techniques and evolutionary algorithms. The main paradigms include classification, clustering, outlier detection, regression and optimization.

These methods open a range of possibilities for interdisciplinary applications in fields such as architecture, finance, health, image processing, politics, neuroscience, robotics, and other domains of signal processing and pattern analysis.

In the proposed work, facial recognition will be done using feature extraction method. Three moments named Hu moments, Zernike moments and Legendre moments will be used for face recognition. Hu moments include a set of seven moments which are derived from the conventional geometric moments. These moments are invariant against rotation, scaling and translation. Legendre and Zernike moments have an orthogonal basis set and can be used to represent an image with minimum amount of information redundancy. These are based on the theory of orthogonal polynomials and can be used to recover an image from moment invariants. For feature extraction, moments of different orders will be calculated which will form the feature vectors. The feature vectors obtained will be stored in the database and will be compared using three different classifiers named Minimum Distance classifier, Support Vector Machine (SVM) and K means.

II. LITERATURE SURVEY

Many advances have been made in face recognition technology. Face recognition outside of a controlled environment is no simple task. Most facial recognition algorithms excel in matching one image of an isolated face with another; say a driver's license or a passport. In those situations, three important parameters—pose, illumination, and expression—are tightly controlled. Pose is how the subject is positioned relative to the camera—ideally straight-on. Illumination is the lighting conditions, which should be bright enough for the camera to capture the entire individual's features but not so bright that they are overexposed. Finally, the subject should be holding a neutral expression. Controlling these parameters helps minimize variation between any two images. As long these three factors are controlled, we have very efficient face recognition systems available in the market. Under ideal conditions, they can be up to 99% accurate.

But once those conditions start to deviate from the ideal—the lighting dims or a subject isn't looking straight into the camera, for example—accuracy drops significantly. Skewed images, where poses are anything but straight on, is one of the biggest challenges. Accurate face recognition requires reference points so the computer can correct for differences in distance and perspective between images. If one image is tilted relative to another, the computer celiminate that variation by lining up the reference points.

Hence the focus of research these days is to recognize face in an uncontrolled environment.

A lot of work has been done in the field of face recognition using Linear Discriminant Analysis. In [1], the author has proposed a novel Bayesian logistic discriminant (BLD) model which addresses normality and heteroscedasticity (problem in which the LDA algorithm assumes the sample vectors of each class which are generated from underlying multivariate normal distributions of common covariance matrix with different means). Chao-Kuei Hsieh, Shang-Hong Lai and YungChang Chen [2], proposed face recognition using an optical flow based approach. A single 2-D face image with facial expression is used. Information from the computed intrapersonal optical flow and the synthesized face image are combined in a probabilistic framework for face recognition. However, the proposed integrated system is more computationally costly. Color Space Normalization to enhance the Discriminating Power of Color Spaces for Face Recognition was used in [3]. Here the authors explain the concept of color space normalization (CSN) and two CSN techniques for enhancing the discriminating power of color spaces for face recognition. In [4], the author has combined Gabor features within the scope of diffusion-distance calculation. This strategy starts from the Gabor filtering that consists of three scales and six orientations. It is followed by the calculation of diffusion distance based on a Bayesian model. The recognition rate of the proposed algorithm reduces while handling the occlusions due to dramatical pose changes. Zhen Lei, Shengcai Liao, Matti Pietikäinen and Stan Z. Li [5], proposed a face representation and recognition approach by exploring information jointly in image space, scale and orientation domains.

In [6], Zhiming Liu and Chengjun Liu present a novel face recognition method by means of fusing color, local spatial and global frequency information. Specifically, the proposed method fuses the multiple features derived from a hybrid color space, the Gabor image representation, the local binary patterns (LBP) and the discrete cosine transform (DCT) of the input image. Weiwen Zou and Pong C. Yuen [7], proposed multi-image face recognition, instead of using a single still-image-based approach in order to handle complex face image variations in face recognition.

III. Feature Extraction

In image processing, feature extraction is a special form of dimensionality reduction. It involves simplifying the amount of resources required to describe a large set of data accurately. In the presented work, features are extracted from images using four methods: Hu moments, Zernike moments, Legendre moments and cumulants.

Hu moments

Hu moments have been derived from the geometric moments. Geometric moments are also known as regular or raw moments. These are nonnegative integers. Zernike in 1934 introduced a set of complex polynomials called the Zernike polynomials. These polynomials form a complete orthogonal basis set defined on the interior of the unit disc, i.e., x 2 + y 2 = 1. Complex Zernike moments are constructed using the set of Zernike polynomials. Zernike moments are the projection of the image density function on these orthogonal basis functions. The two dimensional Zernike moment for a continuous image function f (x, y) that disappears outside the unit circle. To calculate the Zernike moments of a particular image, we first take the centre of image as the origin and map the region of interest to the range of unit disc. Those image pixels which do not fall inside the unit disc are not used for computation. Thereafter, the image coordinates are described in terms of the length of the vector from the origin, the angle from the axis to the vector etc.

Legendre Moments Legendre moments were derived from Legendre polynomials as kernel function. Legendre polynomials were first proposed by Teague. These are orthogonal moments which can represent an image with minimum information redundancy. Thus the moments represent the independent characteristics of an image. Legendre moments are orthogonal moments and can be used to represent an image with minimum redundancy.

IV. Classification

Image classification involves analyzing the numerical properties of various image features and organizing the data into categories. In this paper, we have used three classifiers for classifying the data: minimum distance classifier, support vector machine and k nearest neighbor. In all the three methods, out of the ten orientations of each subject, eight were used for training the classifier and two were used as test cases.

Minimum distance classifier

The closeness of an incoming pattern to patterns of the possible pattern classes provides a measure in determining the pattern class of the pattern under consideration. As the classification is based on the minimum distance calculation, this method is called minimum distance classification procedure. Minimum distance procedure performs efficiently if pattern classes can be represented by a single prototype or by several prototypes around which the patterns form clusters.

In other words, the minimum distance classifier is used to classify unknown image data to classes which minimize the distance between the image data and the class in multi-feature space. The distance is defined as an index of similarity so that the minimum distance is identical to the maximum similarity.

Support Vector Machine

Machine Learning is considered as a subfield of Artificial Intelligence and it is concerned with the development of techniques and methods which enable the computer to learn. In simple terms development of algorithms which enable the machine to learn and perform tasks and activities. Machine learning overlaps with statistics in many ways. Over the period of time many techniques and methodologies were developed for machine learning tasks.

Family of machine-learning algorithms that are used for mathematical and engineering problems including for example handwriting digit recognition, object recognition, speaker identification, face detections in images and target detection.

SVM performs classification by constructing an N-dimensional hyperplane that optimally separates the data into two categories.

K Nearest Neighbor

In pattern recognition, the *k*-nearest neighbors algorithm (*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, a useful technique can be used to assign weight to the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbor a weight of $1/d$, where d is the distance to the neighbor.[2]

The neighbors 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.

A peculiarity of the *k*-NN algorithm is that it is sensitive to the local structure of the data.

V. METHODOLOGY

The method used for the proposed study is feature extraction. The value three moments, Hu, Zernike and Legendre will be calculated in various orders for each face (for different orientations). The orders which have least variations for different orientations of a single person will be selected for making the feature vector. Hence, instead of making the feature vector using different orders of one single moment, it will be made by assembling the selected values of moments. Different trials will be made using different combinations and different lengths of the feature vectors. The feature vector which gives the best results will be selected.

The feature vectors obtained will be stored in the database and will be compared using three different classifiers named Minimum Distance classifier, Support Vector Machine (SVM) and K means.

REFERENCES

[1] Ksantini, R. Boufama, B. Djemelziou, and Bernardcolin, 2010. A Novel Bayesian Logistic Discriminant Model: An Application to Face Recognition, Pattern Recognition, 43(4):1421–1430.

[2] Hsieh, C.K. Lai, S.H. and Chen, Y.C. 2010. An Optical Flow-Based Approach to Robust Face Recognition Under Expression Variations. IEEE Transactions on Image Processing, 19(1):233- 240.

[3] Yang, J. Liu, C. and Zhang, L. 2010. Color Space Normalization, Enhancing the Discriminating Power of Color Spaces for Face Recognition, Pattern Recognition, 43(4):1454–1466.

[4] Zhou, H and Sadka, A.H. 2011. Combining Perceptual Features with Diffusion Distance for Face Recognition. IEEE Transactions on Systems, Man, and Cybernetics Part C: Applications And Reviews, 41(5):577- 588.

[5] Lei, Z. Pietikäinen, M. Li, S.Z. and Liao, S. Face Recognition by Exploring Information Jointly in Space, Scale and Orientation. IEEE Transactions on Image Processing, 20(1):247- 256.

[6] Liu, Z. Yang, J. Liu, C. 2010. Extracting Multiple Features in the Cid Color Space for Face Recognition. IEEE Transactions on Image Processing, 19(9):2502- 2509.

[7] Zou, W Yuen, P.C. 2010. Discriminability and Reliability Indexes: Two New Measures to Enhance Multi-Image Face Recognition, Pattern Recognition, 43(10):3483–3493.