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# Person Identification by Lips using SGLDM and Support Vector Machine.

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## ABSTRACT

Biometric authentication techniques are more consistent and efficient than conventional authentication techniques and can be used in monitoring, transaction authentication, information retrieval, access control, forensics, etc. In many cases human identification biometric systems are motivated by real-life criminal and forensic applications. One of the most interesting emerging method of human identification, which originates from the criminal and forensic practice, is human lips recognition. In this paper we consider lips texture and color features in order to determine human identity. In our project, we are using Spatial Gray Level Dependence Method (SGLDM). For classification purpose, Support Vector Machine (SVM) will be used and for dimensional reduction Principal component Analysis (PCA) will be used. This quantative comparison is implemented through MATLAB. A standard XMV2TS database consisting sample images of seven persons is created. An analysis will be performed on all collected images and parameters will be compared to establish a working principle for person identification using lip recognition. The system will use threshold technique as identification tool.

**Keywords :** Biometric Authentication, SGLDM , SVM , PCA , Lip Recognition

## I. INTRODUCTION

Numerous measurements and signals have been proposed and investigated for use in biometric recognition systems .A biometric can be based on a person's either physical or behavioral characteristics the most popular measurements are fingerprint, face and voice [1]. Each of these biometric traits has their own pros and cons with respect to accuracy and deployment. Among these features, face recognition is able to work at a greater distance between the prospective users and the camera than other types of features yet; one critical issue of the face recognition system is that the system cannot work well if the target face is partially covered. Thus, considering a smaller part of a face for further recognition can be an effective way to solve this problem. Lip is the tactile sensory organ constituting the visible portion of the mouth. Since the lip data can be captured at a distance, it represents a passive biometric, as it requires no active user participation [2]. The challenge of using the lip as a biometric lies in the area of uniqueness and circumvention. The use of the lip region as a means of human identification was first proposed through the concept of lip-prints [3]. In fact, it is a challenging issue. Here an algorithm is proposed to extract features from the can be used for recognition of persons by using support vector machine [4]. The process of scanning and matching can occur through verification or identification. In verification, a one-to-one match takes place in which the user must claim an identity, and the biometric is then scanned and checked against the database. In identification, a user is not compelled to claim an identity; instead, the biometric is scanned and then matched against all the templates in the database. If a match is found, the person has been "identified."

## II. METHODS AND ALGORITHMS

### A. Local binary patterns (LBP)

Local binary pattern is a type of visual descriptor used for classification in computer vision [5]. LBP is the particular case of the Texture Spectrum model proposed in 1990. LBP was first described in 1994. It has since been found to be a powerful feature for texture classification; it has further been determined that when LBP is combined with the Histogram of oriented gradients (HOG) descriptor [6], it improves the detection performance considerably on some datasets. A comparison of several improvements of the original LBP in the field of background subtraction was made in 2015 by Silva et al[7].

The LBP feature vector, in its simplest form, is created in the following manner:

(1) Divide the examined window into cells (e.g. 16x16 pixels for each cell).

(2) For each pixel in a cell, compare the pixel to each of its 8 neighbors (on its left top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise.

(3) Where the center pixel's value is greater than the neighbor's value, write "0". Otherwise, write "1". This gives an 8-digit binary number (which is usually converted to decimal for convenience).

(4) Compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the center). This histogram can be seen as a 256-dimensional feature vector.

(5) Optionally normalize the histogram.

(6) Concatenate (normalized) histograms of all cells. This gives a feature vector for the entire window.

The feature vector can now be processed using the Support vector machine, extreme learning machines, or some other machine-learning algorithm to classify images. Such classifiers can be used for face recognition or texture analysis.

### B. Spatial Gray Level Dependence Matrices

SGLDM is a statistical method, which consists in constructing co-occurrence matrices to reflect the spatial distribution of gray levels in the region of interest [8]. SGLDM is based on the estimation of the second order conditional probability density g(i, j,d, ϴ)[9]. This means that an element at location (i,j) of the SGLD matrix signifies the probability that two different resolution cells which are in a specified orientation ϴ from the horizontal and specified distance d from each other, will have gray level values i and j respectively[10]. The angle is used to evaluate the direction of texture, and the application of several distance values can provide a meaningful description of the size of the periodicity texture. Thus for different ϴ and d values, different SGLD matrices result. The angle ϴ is usually restricted to values of 0, 45, 90, and 135°, and the distance d is limited to values restricted to integral multiples of pixel size [11]. In our work, we are using SGLDM approach.

## III. FEATURE EXTRACTION

Feature extraction in image processing is a technique of redefining a large set of redundant data into a set of feature vectors of reduced dimension [12]. Nucleus texture measurements were performed on the grayscale version of the nucleus images. Texture was defined as a function of the spatial variation in pixel intensities. Gray-level pixel distribution can be described by the second order statistics such as the probability of two pixels having particular gray levels at particular spatial relationships. This information can be depicted in two-dimensional gray-level co-occurrence matrices (GLCM), which can be computed for various distances and orientations.

some statistical measures to extract textural characteristics from the GLCM. Some of these features are as follows

**Contrast**: It is a measure of the local variations of gray levels present in an image. Images with large neighboring gray level differences are associated with high contrast. This parameter can also characterize the dispersion of the matrix values from its main diagonal.
Contrast is defined as follows:

$$cont = \sum_i \sum_j (i-j)^2 g(i,j)$$

Where g(i,j) corresponds to the elements of co-occurrence matrix ,ie the probability of moving from a pixel with gray level I to a pixel with gray level **j.**

**Homogeneity**: This parameter, called also Inverse Difference Moment, measures the local homogeneity of an image. It assigns larger values to smaller gray level differences within pixel pairs. This parameter has opposite behavior of the contrast. More the texture has homogeneous regions, more the parameter is high. Homogeneity is written as

$$\text{hom} = \sum_{i,j} \frac{1}{1+(i-j)^2} g(i,j)$$

**Energy:** This parameter is a measure of image homogeneity; it reflects pixel -pair repetitions .Homogeneous images have very few dominant gray tone transitions, which result into higher energy[16]. Energy is defined as follows:

$$ener = \sum_{i,j} (g(i,j))^2$$

**Entropy**: The feature entropy is a measure of non-uniformity in the image or region of interest. If the image is heterogeneous, many elements on the co-occurrence matrix have small values, which imply that entropy is very large. Entropy is inversely correlated to energy , it is given by the following expression:

$$ent = -\sum_i \sum_j g(i,j)\log(g(i,j))$$

**Mean**: The mean is determined by the homogenous brightness or darkness of the image. The more homogeneously bright the image is, the higher is its mean, and vice versa .The mean is written as:

$$mean = \sum_i \sum_j g(i,j)$$

**Variance**: It is a measurement of Heterogeneity and was correlated strongly with standard deviation.It characterizes the distribution of gray levels around the mean value calculated above. Therefore, variance increased when the gray levels values differed from their means. The expression of the variance is:

$$\text{var} = \sum_i \sum_j (i-mean)^2 g(i,j)$$

## IV.SVM FOR CLASSIFICATION

Classification is one of the most important tasks for different application such as text categorization, tone recognition, image classification, micro-array gene expression, proteins structure predictions, data Classification etc[13-18] .In our project we are using SVM (Support Vector Machine) for classification purpose. SVMs are set of related supervised learning methods used for classification and regression . They belong to a family of generalized linear classification. A special property of SVM is , SVM simultaneously minimize the empirical classification error and maximize the geometric margin. So SVM called Maximum Margin Classifiers. SVM is based on the Structural risk Minimization (SRM). SVM map input vector to a higher dimensional space where a maximal separating hyperplane is constructed. Two parallel hyperplanes are constructed on each side of the hyperplane that separate the data. The separating hyperplane is the hyperplane that maximize the distance between the two parallel hyperplanes. An assumption is made that the larger the margin or distance between these parallel hyperplanes the better the generalization error of the classifier will be . We consider data points of the form

$$\{(x1,y1),(x2,y2),(x3,y3),(x4,y4)\ldots\ldots\ldots.,(xn, yn)\}.$$

Where yn=1 / -1 , a constant denoting the class to which that point xn belongs. n = number of sample. Each xn is p-dimensional real vector. The scaling is important to guard against variable (attributes) with larger varience. We can view this Training data , by means of the dividing (or seperating) hyperplane , which takes

$$w . x + b = o \text{ ----- } (1)$$

Where b is scalar and w is p-dimensional Vector. The vector w points perpendicular to the separating hyperplanes. Adding the offset parameter b allows us to increase the margin. Absent of b, the hyperplanes is forsed to pass through the origin, restricting the solution. As we are interesting in the maximum margin, we are interested SVM and the parallel hyperplanes. Parallel hyperplanes can be described by equation

$$w.x + b = 1$$
$$w.x + b = -1$$

If the training data are linearly separable, we can select these hyperplanes so that there are no points between them and then try to maximize their distance. By geometry, We find the distance between the hyperplane is $2 / |w|$. So we want to minimize $|w|$. To excite data points, we need to ensure that for all I either

$w. x i– b \geq 1$ or $w. xi– b \leq -1$

This can be written as

$$yi( w. xi– b) \geq 1 , 1 \leq i \leq n \text{ ------}(2)$$

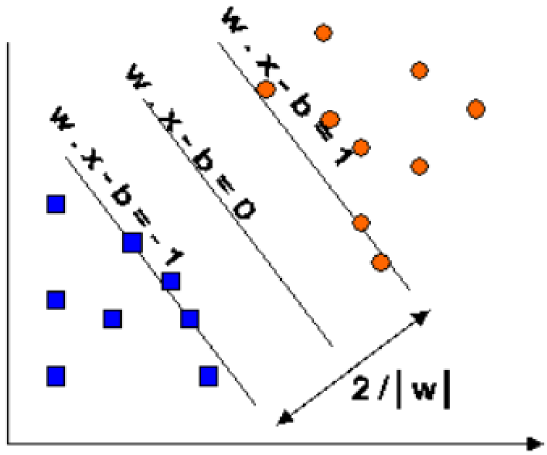


**Figure 1**. Maximum margin hyperplanes for a SVM trained with samples from two classes

Samples along the hyperplanes are called Support Vectors (SVs). A separating hyperplane with the largest margin defined by $M = 2 / |w|$ that is specifies support vectors means training data points closets to it. Which satisfy?

$$y\, j[w^T. \ xj+ b] = 1 , \quad i =1 \text{ -----}(3)$$

**(A) Model Selection For SVM**

Model selection is also an important issue in SVM [20]. Recently, SVM have shown good performance in data classification. Its success depends on the tuning of several parameters, which affect the generalization error. We often call this parameter tuning procedure as the model selection. If you use the linear SVM, you only need to tune the cost parameter C. Unfortunately, linear SVM are often applied to linearly separable problems. Many problems are non-linearly separable. For example, Satellite data and Shuttle data are not linearly separable. Therefore, we often apply nonlinear kernel to solve classification problems, so we need to select the cost parameter (C) and kernel parameters (γ,d) .We usually use the grid-search method in cross validation to select the best parameter set. Then apply this parameter set to the training dataset and then get the classifier. After that, use the classifier to classify the testing dataset to get the generalization accuracy.

## V. EXPERIMENTAL RESULTS

Experiments are performed on gray level images to verify the proposed method. 8 bits per pixel represent these images. Face images are used for experiments are shown in below figure

**Figure 2.** Input Image Database

The next step is applying face detection on the above images. It is performed by the voila and jonne's algorithm. The face-detected outputs are given below

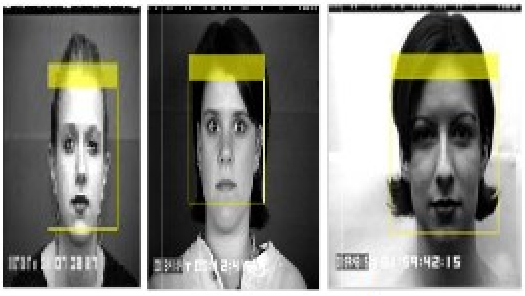

**Figure 3**. Detected faces

Then the lip region is extracted from above images by taking some approximations. For eliminating the noise and camera influences suitable filtering is applied. Then the proposed features i.e contrast, energy, homogeneity, mean, variance and entropy are extracted and then each person is distinguished using support vector machine.

## VI.CONCLUSION AND FUTURE WORK

Biometrics systems based on lip color and texture recognition are of great interest, but have received little attention in the scientific literature. This is perhaps due to the belief that they have little discriminative power. Thus, our experimental results show that by using spatial gray level dependence matrix algorithm along with support vector machine we can recognize person based on his lips. In future, the work can be done on an identification system that incorporates the features of both lips and speech. Accuracy can be improved by the use of other feature extraction techniques. Accuracy can also be improvised by incorporating several feature extraction techniques to form a unique one.

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