

## Dynamic Texture Feature Extraction Using Weber Local Descriptor

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### ABSTRACT

In numerous biometric applications, gender recognition from facial pictures plays a vital role. During this paper, we have a tendency to investigate Weber's native Descriptor (WLD) for gender recognition. WLD may be a texture descriptor that performs higher than alternative similar descriptors however it's holistic as a result of it's terribly construction. We have a tendency to extend it by introducing native abstraction information; divide a picture into variety of blocks, calculate WLD descriptor for every block and concatenate them. The gender from face options are classified by the minimum distance measurement and neural network.

**Keywords** - dynamic textures, WLD descriptor, neural network.

### I. Introduction

Our behavior and social interaction are greatly influenced by genders of people, we wish to interact with. There are a number of applications where gender recognition can play an important role. In improving human computer interaction systems; successful gender recognition system could have great impact. To make them be more human-like acting user-friendly. It is useful in applications including biometric authentication, high-technology surveillance and security systems, image retrieval and passive demographical data collections. We are not only able to tell who they are by only looking ones' faces. Also perceive a lot of information such as their emotions, ages and genders. Here we propose, powerful simple local descriptor which is robust. WLD descriptor consists of two components: orientation and differential excitation. The smaller size of the support regions for WLD makes it capture more local salient patterns. It is not arguable that feature of face is one the most important thing that characterizes human beings. WLD is computed around a relatively small region which is square (e.g., 3 X3). The description granularity of SIFT is much larger than that of WLD. SIFT is computed around a relatively large region (e.g., 16 X16). We can add some features to WLD to extend it so as to extract the multi granularity features with use of multi scale analysis techniques. WLD is computed in a finer granularity than SIFT. Furthermore texture provides a rich source of information about the natural scene. A texture adds better quality richness to a design for designers. For computer scientists, a texture is good and attractive because it helps to understand basic mechanisms that is under the subject of human visual perception Also it is an important component of use in image analysis technique that can be used for

solving a wide range of segmentation, applied recognition and synthesis problems. Firstly, the main and basic goal of texture research is grasping image content based on textural properties in images present in computer vision. Secondly, for retrieving visual information to develop automated computational methods. The delicate issues in understanding the goal practically include understanding human texture perception and deriving appropriate quantitative texture descriptions. Particularly, approaches regarding the main schools of analysis of texture, definitions of texture and those related applications are surveyed. An overview of research of texture during the advancement of this field in the past several decades is provided in this paper. The structure of the thesis and the motivation of this study are also presented.

### II. WEBER'S LAW DESCRIPTOR

It is a psychological law. It states that the change of a stimulus (such as lighting, sound) that we just notice is a constant ratio of the original stimulus. A human being would recognize it as background noise rather than a valid signal, when the change is smaller than this constant ratio of the original stimulus. The differential excitation component of the proposed Weber Local Descriptor (WLD) is computed for a given pixel. It is the ratio between the two terms: first is the intensity of the current pixel; the second is the relative intensity differences of a current pixel against its neighbours (e.g., 3 X3) square regions. We attempt to extract the local salient patterns in the input image, with the differential excitation component. In addition to this, current pixel's gradient orientation is also computed. For each pixel of the input image, we compute two

components of the WLD feature which are differential excitation and gradient orientation. we represent an input image (or image region) with a histogram by combining the WLD feature per pixel. We call a WLD histogram hereinafter. Hence We call WLD; a dense descriptor. The proposed WLD descriptor employs the advantages of SIFT using the gradient and its orientation in computing the histogram, smaller support regions. and those of LBP in computational efficiency. But WLD differs from Local Binary Pattern and SIFT. As mentioned above, the SIFT descriptor is a 2D histogram. This 2D histogram of gradient locations and orientations consisting of firstly, the additional dimension to the image gradient orientation and Secondly, two dimensions correspond to image spatial coordinates. Since SIFT is sparse descriptor, it computes only for the regions of interest (located around detected interest points) that have usually already been normalized with respect to scale and rotation. Using information in these sparsely located interest regions, texture classification with SIFT is performed. As WLD on the contrary, is a dense descriptor, computed for every pixel and depends on the magnitude of the centre pixel's intensity and both the Texture classification local intensity variation and with WLD is carried out using 2D WLD histograms.

A short literature review reveals that recent trends in feature selection for offline signature verification are based on grey level information and supplementary texture gray level information [5]. Another approach considers curvature of the most important segments and introduces a graph metric feature set [6]. Contour features have been used also to code and represent the directional properties of the signature contours [7]. Another interesting issue is that feature used in the analysis of writer verification and identification tasks could be employed in order to examine the signature image as a textural signal. Then, textural features could be used in order to represent the feature space [8].

Signature verification cannot be done by character recognition because the alphabets of signature cannot be read out separately and it appears as an image with some curves representing the writing style of an individual. So, a signature image can be considered as a special distribution of pixels representing writing style rather than a collection of alphabets.

This paper is organized as two sections:

1. Offline signature verification i.e., whether the signature is authenticated or un-authenticated.
2. Name identification by extracting the features of the signature using Local Binary Patterns and recognizing the name by using probabilistic neural network (PNN).

### III. FACE DETECTION

The task achieved by face detection systems is to be understood using following steps. To know how to exploit uniqueness of faces in name recognition, the first step is to detect and localize those faces in the images. One of popular research areas is face detection in which many algorithms have been proposed for it. Considering the face detection as a binary classification task, most of them are based on the same idea. The task is to decide whether it is a face or not, given a part of image. This is achieved by first transforming the given region into features and then using classifier trained on example images to decide if these features represent a human face. As faces show themselves having various sizes, appear in various locations and we also employ window-sliding technique. The idea in which the classifier classifies the portions of an image, at scales and all location, whether it is face or non-face.

### IV. GRAY SCALING

Signature image consists of pixels and each pixel has RGB values that mean each pixel is made of green red and blue color. By combining these we can get a new color. Each color has its value or intensity. These values lie in the range 0 to 255. For signature verification, the color of ink has no significance at all. Instead of doing this, two signatures must be compared. Hence all scanned images will be converted to grayscale images. A grayscale is an image in which the value of each pixel is a sample, that is, it varies only intensity information. Such Images are known as black and white images. These are composed exclusively of shades of gray, varying from white at the strongest intensity and black at the weakest intensity. Grayscale images are distinct from one-bit bi-tonal black and white images, which are images with only two colors, black and white (binary images). Grayscale images have many shades of gray in between.

### V. Feature Selection

The feature selection (or dimensionality reduction) module is employed as not all the detected features are useful. Here we choose only a subset of representative features. Doing feature selection gives us the relevant features and thus the more accurate result. Also give us an additional advantage of faster computation time as the dimensionality of data is reduced. The popular feature selection techniques often employed in name classification task are Principal Component Analysis (PCA), Independent Component Analysis (ICA), Ad boost and Genetic Algorithm.

### VI. Classification

With all necessary features have been extracted, the final task is to decide whether or not to represent female or male face by those features. There are obviously two decisions to make this is essentially binary classification task. To learn the decision boundary between these two classes, the classifier is trained on the female and male example face images. After that it take help of what it learn to take a decision on the given face images. Among the binary classifiers, the most popular classifiers which give better performance than the others are a variation of Support Vector Machine (SVM), a variant of Ada-boost and different Neural Network architectures. And among these classifiers, a number of comparative studies have been carried out and have suggested the best performance is obtained from the SVM.

### VII. RECOGNITION

One of the most successful techniques is the Principal Component Analysis (PCA) that is important in image recognition and compression. PCA is a statistical method under the broad title of factor analysis. The main purpose of PCA is to minimize the large dimensionality of the (observed variables); data space to the smaller intrinsic dimensionality of feature space (independent variables). It is needed to describe the data economically. This is the situation when there is a strong correlation between observed variables.. When you have obtained measures on a number of observed variables, principal component analysis is appropriate, wish to develop a smaller number of principal components that is the artificial variables. This will account for most of the variance in the observed variables. The principal components may then be used as criterion variables in subsequent analyses or predictor. In this first we have to obtain the energies of the gray scale image. Those energies include mean, covariance, Eigen values and Eigen vectors. After calculation of all the energies of data base images and the input image, Euclidean distance between these data base images and input test image have to be calculated. These results are sorted according to the images and stored into one variable. If the input image is matched with any one of the image in the data base it is recognized as the authorized signature otherwise it is recognized as the unauthorized one. This recognition is based on the Euclidean distance between the data base and test image in the process of PCA.

### VIII. NAME IDENTIFICATION

This section is divided into 2 parts:

1. Feature extraction using Local Binary Patterns.

2. Name analysis or identification using probabilistic neural network.

#### 8.1 Feature extraction using Local Binary Patterns:

The LBP approach codifies and collects into a histogram the occurrences of micro-patterns such as: edges, corners, spots etc. Recently, in different facial image analysis tasks such as: Face Recognition signature recognition, Facial Feature Extraction, Face Detection Facial Expression Recognition, Gender Classification, Facial Key point representation Face Authentication, the LBP representation has been successfully used.

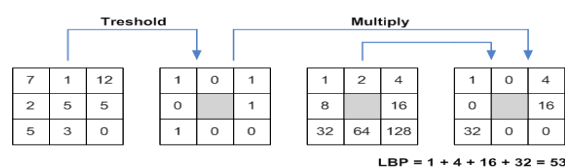
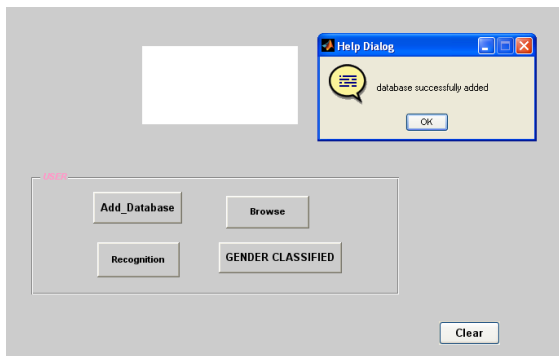


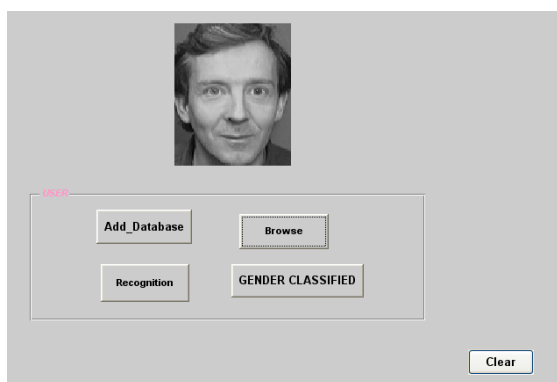
Fig.1. feature extraction using LBP

The native Binary Pattern (LBP) operator is outlined as gray level texture live during a native neighborhood. The foremost necessary property of the LBP operator is its invariability against monotonic grey level changes. Equally necessary is its machine simplicity. LBP operator describes the environment of a constituent. Every ILBP(x, y) code is puzzled out as follows: the eight neighboring pixels square measure binaries exploitation as threshold the middle grey level worth  $I(x, y)$ , generating a binary one if the neighbor is bigger than or adequate to the center; otherwise it generates a binary zero. The eight binary range square measure described by 8-bit range and saved in  $ILBP(x, y)$ , the vary that is  $0 \leq ILBP(x, y) \leq 255$ . Local binary pattern (LBP) may be a powerful feature projected to capture the feel in objects. Within the basic LBP technique, a grey scale image is processed specified a computer code is generated for every constituent within the image. This code encodes whether or not the intensities of the neighboring pixels square measure larger or but the present pixel's intensity. So, for example during a 3x3 neighborhood with the present constituent being the middle, a computer code of length eight is generated consisting of 0s and 1s, consistent with the relative intensities of the neighbors. A bar chart is then computed to count the quantity of occurrences of every computer code, describing the proportion of common textural patterns. The LBP technique is usually utilized in visual perception with sensible success and that we expected it to even be helpful in offline signature verification.

**8.2 Results and analysis:**



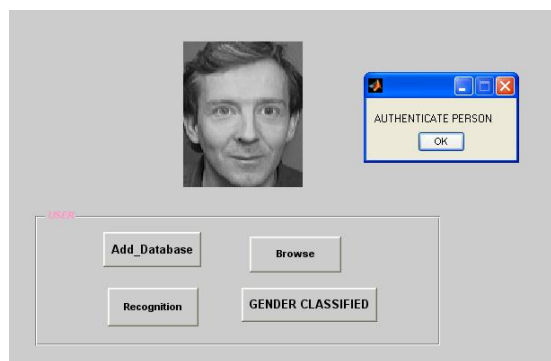
**Fig.2. data base creation**



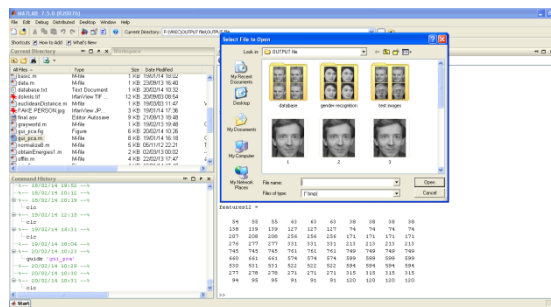
**Fig.3. Browse Image**

**IX. PROBABILISTIC NEURAL NETWORK**

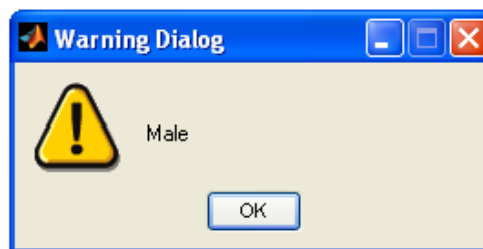
A PNN is predominantly a classifier since it can map any input pattern to a number of classifications. PNN is a fast training process and an inherently parallel structure that is guaranteed to converge to an optimal classifier as the size of the representative training set increases and training samples can be added or removed without extensive retraining. A consequence of a large network structure is that the classifier tends to be oversensitive to the training data and is likely to exhibit poor generalization capacities to the unseen data. In this paper, Probabilistic Neural Network is used to compare the features of input image with data base image which are obtained from the Local Binary Pattern.



**Fig.4. Recognition Person Original/Fake Identification**



**Fig.5. Genders Classified for Template Data Base**



**Fig.6. Gender Classified**

**CONCLUSION**

In this paper we have implemented two techniques, one is to verify the signature whether authorized or unauthorized by measuring the Euclidean distance of both input image and data base images and we compared this results using principle component analysis (PCA). The second one is name identification using local binary pattern (LBP) and probabilistic neural network (PNN). Defining the effective features which results in minimum deviation for an signature instance may aid to further improvement of the system accuracy. An extension to the approach would be implementation of more accurate distance measurement techniques like mahalanobis distance to verify the signature sample instead of Euclidean distance measure.

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