Development of a System to Detect Diabetes Mellitus via Facial Key Block Analysis

P. Georgia Chris Selwyna, P. Deepika, R. Deepika, H. Dhivya, R. Gowri Sankaran
Department of Biomedical Engineering, Velalar College of Engineering and Technology, Erode, Tamil Nadu, India

Abstract- **Millions of people die from Diabetes Mellitus every year. Recently, researchers have discovered that Diabetes Mellitus can be detected in a non-invasive manner through the analysis of human facial blocks. Although algorithms have been developed to detect Diabetes Mellitus using facial block color features, use of its texture features to detect this disease has not been fully investigated. In this paper, we propose a Principal Component Analysis (PCA) algorithm to detect Diabetes Mellitus based on facial block texture features. In previous work, Local binary Pattern is used which is not effective. In order to test the system performance, the facial images of 200 volunteers consisting of 100 Diabetes Mellitus patients and 100 healthy persons are captured and analyzed through this system. Based on the test result, the Computer-assisted Non-invasive Diabetes Mellitus Detection System through facial key block analysis is proven to be effective and efficient at distinguishing Diabetes Mellitus from Healthy patients in real time.**

Keywords: **Diabetes mellitus, Local binary pattern, Principal component analysis, facial block color features.**

I. INTRODUCTION

As reported by the International Diabetes Federation (ID-F), there are 387 million people with Diabetes Mellitus (DM) worldwide in 2014 [1]. This number means 1/20 people in 2014is suffering from DM. Compared with this number, there are limited medical facilities. For example, Xu et al. [2] estimated there were 113.9 million Chinese adults with DM in 2010, while the number of hospitals in China was 20,918 in 2010 [3]. The traditional method to diagnose DM is through a Fasting Plasma Glucose (FPG) test [4], which takes a blood sample from the finger tip of a patient. It is obvious that this method is invasive and can cause discomfort. After taking this blood sample, a FPG test requires a medical professional determine the test result [5]. In this paper, a DM detection system named Computer- assisted Non-invasive Diabetes Mellitus Detection System (C- NDMDS) is designed and developed to help medical profes- sionals quickly and easily to detect DM in real time. This system can decrease the workload of medical professionals, causes no discomfort to the patient through a non-invasive method, and makes better use of medical facilities.

According to Traditional Chinese Medicine (TCM) theory [6,7], various facial regions can reflect the health status of different inner organs. It is well known that DM can cause many types of complications including the dysfunction of various inner organs (such as kidney disease) [8–10]. Hence, the analysis of facial images (blocks adopted from TCM) can be used to help detect DM patient in a quantitative manner.

II. EXISTING METHOD

L.Bridges, Churchill Livingstone (2004), explained that the Face reading has been part of Traditional Chinese Medicine for many centuries, and Professor Lillian Bridges is a popular academic and international lecturer on the subject who gained her fascinating knowledge through her family line of Master Face Readers in China. Based on an understanding of the shapes, markings and features of a face, practitioners can learn about the health and life of a patient relating to the principles of Chinese medicine. In addition to understanding how the body's internal functions - physical, psychological and emotional - can be seen on a face, practitioners can also learn how to evaluate Shen to understand non-verbal expressions.

Dagher, R. Nachar (2006), analysed a fast incremental principal non- Gaussian directions algorithm, called IPCA-ICA, is introduced. This algorithm computes the principal components of a sequence of image vectors incrementally without estimating the covariance matrix (so covariance-free) and at the same time transforming these principal components to the independent directions that maximize the non-Gaussianity of the source. Two major techniques are used sequentially in a real-time fashion in order to obtain the most efficient and independent components that describe a whole set of human faces database. This procedure is done by merging the runs of two algorithms based on principal component analysis (PCA) and independent component analysis (ICA) running sequentially. This algorithm is applied to face recognition problem. Simulation results on different databases showed high average success rate of this algorithm compared to others

Zhao Lihong, GuoZikui (2011), focused mainly on the feature extraction method of adaptively weighted Block 2-Dimensional Principal Component Analysis. The block methods divide a large picture into several smaller sub-blocks to get the local discrimination information and reduce the computational complexity. Then, a weighted Euclidean distance classifying algorithm is proposed to extract features of face images, and the Euclidean distance classifier is used for classifying. The experiments show that the Adaptively Weighted Block 2-Dimensional Principal Component Analysis method has better performance than standard 2-Dimensional Principal Component Analysis.

In previous work, Local Binary Pattern (LBP) to be applied on the block texture feature ex- traction phase, as it was proven to be efficient at texture analysis. Before LBP was applied in CNDMDS, various parameter values of it were tested and the best one was selected which then finally used in feature extraction of this system. Finally, two traditional classifiers: k-Nearest Neighbor (k-NN) and Support Vector Machines (SVM) were tested and only the better one in DM classification was applied in CNDMDS. According to the experimental results, this system (CNDMDS) is not effective and efficient in DM detection and can be applied to detect DM, reducing the workload of medical professionals.

III. PROPOSED METHOD

In this paper, we propose a context-aware local binary feature learning (CA-LBFL) method for face recognition. Unlike existing learning-based local face descriptors such as discriminant face descriptor (DFD) and compact binary face descriptor (CBFD) which learn each feature code individually, our CA-LBFL exploits the contextual information of adjacent bits by constraining the number of shifts from different binary bits, so that more robust information can be exploited for face representation. Given a face image, we first extract pixel difference vectors (PDV) in local patches, and learn a discriminative mapping in an unsupervised manner to project each pixel difference vector (PDV) into a context-aware binary vector. Then, we perform clustering on the learned binary codes to construct a codebook, and extract a histogram feature for each face image with the learned codebook as the final representation. In order to exploit local information from different scales, we propose a context-aware local binary multi-scale feature learning (CA-LBMFL) method to jointly learn multiple projection matrices for face representation. To make the proposed methods applicable for heterogeneous face recognition, we present a coupled CA-LBFL (C-CA-LBFL) method and a coupled CA-LBMFL (C-CA-LBMFL) method to reduce the modality gap of corresponding heterogeneous faces in the feature level, respectively.

a) RGB TO GRAY SCALE

An RGB image can be viewed as three images(a red scale image, a green scale image and a blue scale image) stacked on top of each other. In MATLAB, an RGB image is basically a M*N*3 array of colour pixel, where each colour pixel is a triplet which corresponds to red, blue and green colour component of RGB image at a specified spatial location.

Similarly, A Grayscale image can be viewed as a single layered image. In MATLAB, a grayscale image is basically M*N array whose values have been scaled to represent intensities.

In MATLAB, there is a function called rgb2gray() is available to convert RGB image to grayscale image.

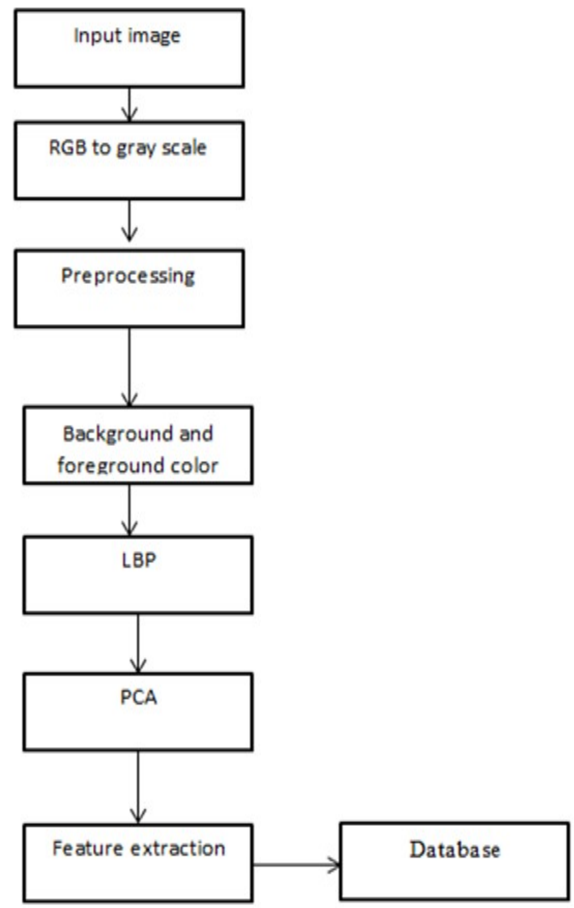

Fig 1. Processing system

b) PRE PROCESSING

Data sets can require preprocessing techniques to ensure accurate, efficient, or meaningful analysis. Data cleaning refers to methods for finding, removing, and replacing bad or missing data. Detecting local extrema and abrupt changes can help to identify significant data trends. Smoothing and detrending are processes for removing noise and linear trends from data, while scaling changes the bounds of the data. Grouping and binning methods are techniques that identify relationships among the data variables.

c) BACKGROUND AND FOREGROUND COLOR

The Foreground Detector compares a color or grayscale video frame to a background model to determine whether individual pixels are part of the background or the foreground. It then computes a foreground mask. By using background subtraction, you can detect foreground objects in an image taken from a stationary camera.

d) PRINCIPAL COMPONENT ANALYSIS

Principal component analysis(PCA) is a quantitatively rigorous method for achieving this simplification. The method generates a new set of variables, called principal components. Each principal component is a linear combination of the original variables. All the principal components are orthogonal to each other, so there is no redundant information. The principal components as a whole form an orthogonal basis for the space of the data.

GLCM (grey level co-occurrence method)

The GLCM is a tabulation of how often different combination of pixel brightness values (grey levels) occur in a image. Firstly, we create grey level co-occurrence matrix from image by using grey comatrix function in MATLAB software, from this we can calculate texture measures from the GLCM. The features extracted using method are contrast, correlation, energy, homogeneity.

e) FEATURE EXTRACTION

Feature extraction a type of dimensionality reduction that efficiently represents interesting parts of an image as a compact feature vector. This approach is useful when image sizes are large and a reduced feature representation is required to quickly complete tasks such as image matching and retrieval.

Feature detection, feature extraction, and matching are often combined to solve common computer vision problems such as object detection and recognition, content-based image retrieval, face detection and recognition, and texture classification.

Fig 2. Input image

Fig 3 Grayscale image

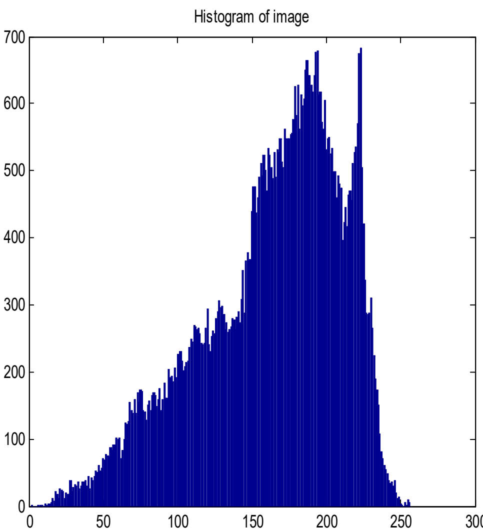

Fig 4 Histogram of the input image

Fig 5 Transformed image

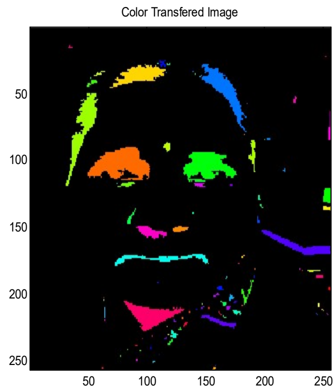

Fig 6 Color transferred image

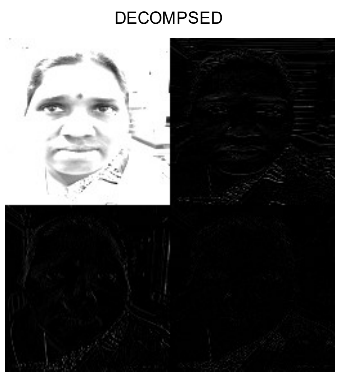

Fig 7 Decomposed image

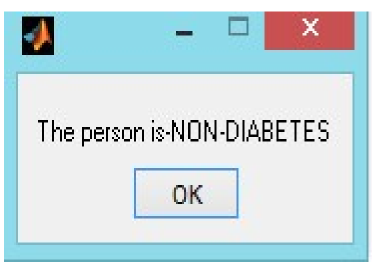

Fig 8 Result

IV. RESULTS AND DISCUSSION

The images are captured through web camera and they are preprocessed to filter out the noises and obtained filter image is undergone feature extraction. The real time captured image is compared with the trained images in classification.

In order to test the system performance, the facial images of Diabetes Mellitus patients and healthy persons are captured and analyzed through this system. Based on the test result, the Computer-assisted Non-invasive Diabetes Mellitus Detection System through facial key block analysis is proven to be effective and efficient at distinguishing Diabetes Mellitus from Healthy patients in real time.

V. CONCLUSION

DM as a chronic disease not only affects the daily life of people but also increases the workload of medical professionals. In this paper, a simple and efficient system named CNDMDS was designed and developed to help medical professionals to detect DM quickly and easily, which is also non-invasive and convenient for the patients. CNDMDS has two parts: (a) a non- invasive device used to capture facial images and (b) a software installed in the computer connected with this device detecting DM and showing the results in real time. It is well known that CNDMDS through facial key block analysis is a simple and efficient system which can detect DM correctly and quickly in real time. In our future work, we will improve this system and develop various feature extractors and classifiers in DM detection.

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