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Hyper Spectral Face Recognition using Gabor + KPCA

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Abstract: *Biometric security is challenging task in day to day life because it is difficult to avoid the fraud. In this research paper emerging biometric trait, i.e. Hyper Spectral Face is considered for human authentication system. There are various visible spectrum of electromagnetic spectral bands are considered for face recognition instead of only three RGB bands. Hyper Spectral gives band wise more finite detail information of face. It is very novel and more accurate than ordinary face recognition system. Hong Kong PolyU Hyper Spectral Face Database used for Face recognition. Kernel Principle Component Analysis (KPCA) algorithm gives prominent features of the Hyperspectral Face Dataset. Gabor + KPCA + Mahalabonis distance on the verification rate at 1% FAR on the evaluation set 89.74%.*

Keywords: *Hyperspectral, Face, Gabor, KPCA, Distance Measures*

I. Introduction

The Biometric is a process of human authentication system through their physical, behavioral or chemical properties. Face recognition is a biometric trait used to identify the person on his physical appearance. Face recognition is a very interesting area in biometrics, Seong G. Kong [1] shows the sensor imaging with different modalities. Dermal texture of skin is unique and stable throughout the life of a human being. The Dermal texture of facial skin can be used to discriminate between individual peoples. Skin based light reflection having random in nature but unique to every individual in that required higher spectral reflectance band.

There are various electromagnetic spectral bands are used for different purposes; in biometrics visible spectrum band is used because below the visible band radiation is very harmful to the human body, such as X-rays, ultraviolet, etc. Some re- searcher used Thermal IR imagery as an alternative source [2]. For face recognition visible spectrum is applied in which the range of electromagnetic energy of camera is 0.4–0.7µm.

The infrared spectrum comprises the reflected IR and the thermal IR Wave bands. The reflected IR band (0.7–2.4 µm) is associated with reflected solar radiation that contains no information about the thermal properties of materials. The near-infrared (NIR) (0.7–0.9 µm) and the short-wave infrared (SWIR) (0.9–2.4µm) spectra are reflective and differences in appearance between the visible and the reflected IR are due to the properties of the reflective materials. This radiation is for the most part invisible to the human eye. As the world is becoming increasingly more insecure, people are looking for new forms of security which are more reliable and less vulnerable against intruder attacks. One such emerging technology is the field of Biometrics. The main reason for the acceptance of the biometrics as a tool for security is its universality, distinctiveness, permanence and collectability. Main issues to be considered at the time of implementing a biometric system is performance, acceptability and circumvention.

II. Face Recognition

Face recognition is an active research area for pattern recognition and computer vision. It is a difficult and complex problem and due to its potential use in a wide variety of commercial and law enforcement applications including access control, security monitoring, and video surveillance. Unlike other biometric identification systems based on physiological characteristics, face recognition is a passive, non- intrusive system for verifying personal identity in a user-friendly way without having to interrupt user activity [1]. It has many application areas, i.e. human computer interaction, security, person identification [3, 4]. One of the factors that affect the performance of the recognition system is the training sample size [5- 7]. Sufficient number of training samples are always needed to train the classification system well [8]. If only one image per person is available, the recognition process gets more difficult. This problem is called one sample problem [9]. Traditional methods will suffer or fail when a single image per person is available [10–12]. Several algorithms have been proposed to overcome this difficulty [5, 13–17].

III. Methodology

3.1. Proposed Methodology

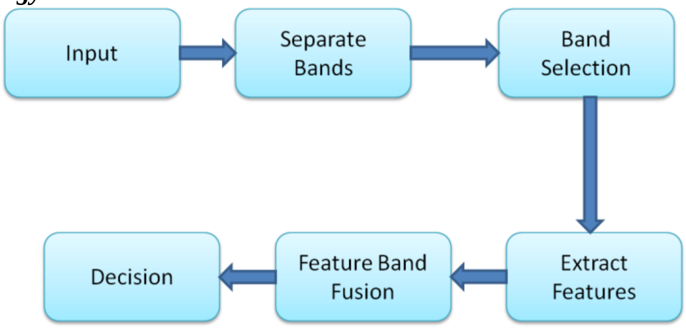

Figure 1. Hyper Spectral Face Recognition System

3.1.1 Hyper-Spectral Images.

Take the input as Hyper-Spectral face image. Hyper-Spectral image consist of 33 bands in the visible spectrum. Hyper-Spectral images from PolyU Hyper- Spectral face database (PolyU-HSFD).

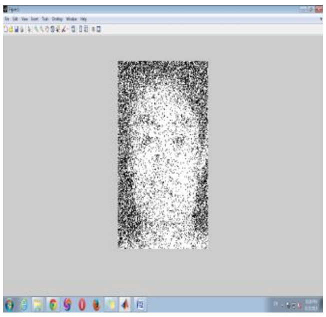

Figure 2. Single Spectral Band Image

3.1.2 Separation of Band.

After taking the input from the system separate 33 bands on the basis of band region, each band having certain reflection in a specific visible spectrum.

3.1.3 Band Selection for Face Feature Extraction

Feature extractions play an important role in finding any pattern. Face features extracted by using Gabor+KPCA technique. Features show the exact reflection and region of active spectra where we are interested from separate bands. Then formulate the fusion of features of all bands and make the single feature for a single image to take the decision.

3.1.4 Matching

The main outcome of the overall process is to find the person is genuine or not for that classification or distance matching techniques is used therefore we can match with the existing database template. Matching decision depending on the features is related to the person or not. In this research Mahcos similarity based distance applies to the feature set.

3.1.5 Gabor Filter

A filter bank consisting of Gabor filters with various scales and rotations is created. The filters are convolved with the signal, resulting in a so-called Gabor space which gives for KPCA as input vector.

3.1.6 Kernel Principal Component Analysis(KPCA)

KPCA is a nonlinear generalized PCA, which performs on an arbitrarily large dimension to select an appropriate feature space. There is no need to provide a number of features to select in advance like PCA, and it gives elucidation very clear when data is in high dimension [18].

KPCA algorithm performs following steps:

- ✓ Get the Data in the form of a matrix
- ✓ Performa Dot Product
- ✓ Diagonal K and normalize the Eigenvector
- ✓ Expansion coefficients
- ✓ Compute Projection Matrix

3.1.7 Mahalinobis Cosine (Mahcos)

Here m-by-n data matrix X, which is treated as m (1-by-n) row vectors x1, x2, ..., x_m, the various distances between the vector x_r and x_s are as follows:

$$\text{similarity} = \cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|}$$

IV. Result & Discussion

For this work The Hong Kong Polytechnic University Hyper-spectral Face Database (PolyU-HSFD) is used. This database included 300 Hyper-Spectral image cubes of 25 subjects. This database was collected in two different times and sessions on an average span of five months. The spectral range is from 400nm to 720nm with a step length of 10nm, total 33 bands.

Gabor + KPCA + Mahalabonis distance on Hong Kong PolyU Database and we got the rank one recognition rate of the experiments 46.15%. For the Verification/authentication experiments on the evaluation data the equal error rate on the evaluation set 4.91%, the minimal half total error rate on the evaluation set 3.53%, the verification rate at 1% FAR on the evaluation set 89.74%, the verification rate at 0.1% FAR on the evaluation set equals 2.56%, the verification rate at 0.01% FAR on the evaluation set 2.56%. Figure 4 & 5 indicates the accuracy & performance of the system. As compare to sidharth et.al. this is improved results.

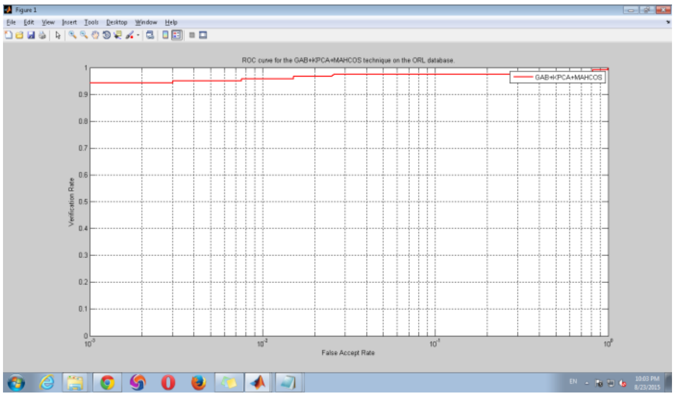

Figure 3. ROC Curve

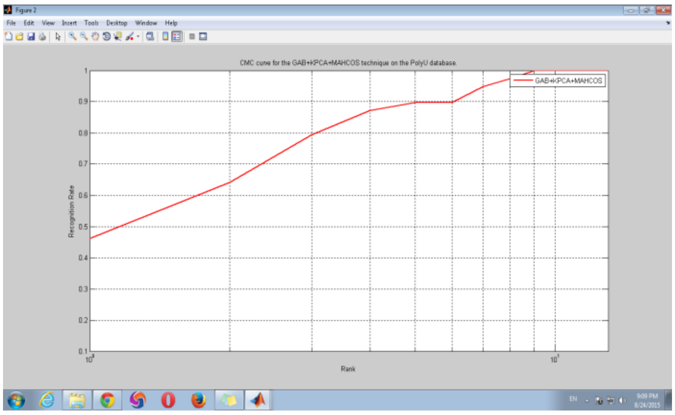

Figure 4. CMC Curve

V. Conclusion

Hyper Spectral Face Recognition novel emerging biometric trait is used. KPCA gives elucidation very clear when data is in high dimension. Gabor + KPCA + Mahalabonis distance on Hong Kong PolyU

Database the verification rate at 1% FAR on the evaluation set 89.74%, the verification rate at 0.1% FAR on the evaluation set equals 2.56%, the verification rate at 0.01% FAR on the evaluation set 2.56%.

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