International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395 -0056
Volume: 04 Issue: 03 | Mar -2017 www.irjet.net p-ISSN: 2395-0072

Night time face recognition at large standoff

Sonali Chhapre, Priti Jadhav, Ankita Sonawane, Paresh Korani

[1]*Student, Dept. of Computer Engineering, KKWIEER College, Maharashtra, India.*
[2]*Student, Dept. of Computer Engineering, KKWIEER College, Maharashtra, India.*
[3]*Student, Dept. of Computer Engineering, KKWIEER College, Maharashtra, India.*
[4] *Student, Dept. of Computer Engineering, KKWIEER College, Maharashtra, India.*

---***---

Abstract - *The face recognition in the night time situation becomes difficult, if the subject is at larger distance from the camera. Thus image quality degrades because of large standoff and low luminance at night time. To address this challenging issue of night time face recognition, an Augmented Heterogeneous Face Recognition (AHFR) approach is proposed. This approach is useful for cross-distance and cross-spectral face matching. In this project, high quality face images are recovered from degraded probe images using an image restoration method based on Locally Linear Embedding (LLE). Further this restored image is matched with images in gallery or database using a heterogeneous face matcher.*

***Key Words*: Cross Spectral, Cross Distance, Near Infrared (NIR), Visible Light(VIS), Long Distance Heterogeneous Face Database(LDHF-DB).**

1. INTRODUCTION

A primary modality for biometric authentication is FACE recognition and has received increasing interest in the recent years. Existing biometric systems are developed for cooperative user applications, such as access control, machine readable traveling document (MRTD), computer logon, and ATM. Such applications, requires a user to cooperate with the camera so as to have his/her face image captured properly. There are more general scenarios, such as face recognition for surveillance, where a person should be recognized without intentional or cooperative effort. To achieve reliable result, Face Recognition can be performed on intrinsic factors of face only. Among the several other factors, problems with uncontrolled environment lighting, is the issue to be solved for reliable face-based applications. A typical problem is that matching between near infrared (NIR) and visible light (VIS) face images in the situation that enrolment is finished with controlled indoor VIS face images, while authentication would be done using NIR face images to avoid the influence of the various environment illuminations. The sensing modality of NIR images is somewhat different than VIS images. These VIS images typically reside in face image databases usually maintained by the law enforcement agencies, such as the driver license databases, criminal records etc. Face recognition systems capable of performing cross-spectral (NIR probe to VIS gallery) and cross-distance (60 m, 100 m and 150 m probe to 1 m gallery) face matching are desirable in practical applications.

The cross-spectral (NIR vs. VIS) and cross-distance (60 m, 100 m, and 150 m vs. 1 m standoff) face matching problem for the nighttime face recognition at large standoff are addressed here . Here the term heterogeneous in the context of face images refers to the images captured in both daytime and nighttime at different distance (e.g., 1 m, 60 m 100 m, and 150 m). For example refer fig 1 given below which depicts NIR images that are captured at night time at a large standoff (e.g., 150 m) still contain some discriminative facial details. A Long Distance Heterogeneous Face (LDHF) database consisting of 1 m indoor, and 60 m, 100 m, and 150 m outdoor VIS and NIR images of 100 different subjects is used for performing the tests of the proposed system.

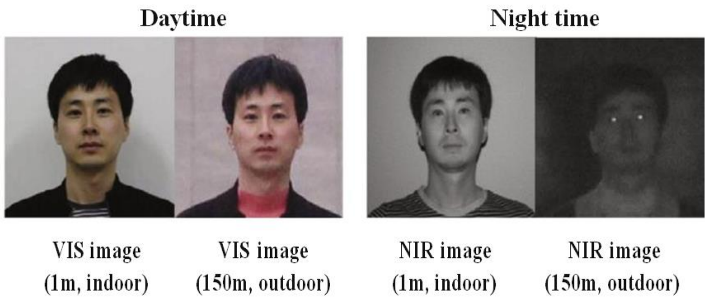

Fig -1: Visible light (VIS) & near-infrared (NIR) face images.

Considering the degraded quality of image due to large distance and low illuminance during nighttime, a high-quality probe face images is recovered from the degraded probe face images by using an Locally Linear Embedding (LLE) [ref] based image restoration method. Further a heterogeneous face matching [1] is used to match the restored face images to the database gallery face images.

2. BACKGROUND

2.1 NIR Images

The capability of surveillance systems is expanded by different image acquisition methods. These methods collect face images in different modalities than VIS, such as near-infrared (NIR), thermal, and SWIR (Short-Wave Infrared) images. In operational face recognition applications NIR images are widely used because of following reasons: (i) The NIR light is not visible to the human eyes and hence the surveillance operation can be somewhat covert. (ii) NIR images are less affected by surrounding temperature, emotional and health conditions of the subjects as compared to the thermal images. (iii) NIR illuminators are cheaper as compared to some other face imaging systems, such as thermal sensors. (iv) NIR illumination can easily penetrate glasses, allowing it to capture more details around the eyes. These advantages of NIR imaging system have motivated a number of studies on face recognition using NIR images.

2.2 Cross-spectral face matching

An approach to NIR face recognition is cross-spectral face recognition (or heterogeneous face recognition (HFR)) where the probe face image is NIR but the database gallery face image is VIS. In this approach the NIR and VIS face images are directly matched using modality invariant face representations. Heterogeneous face recognition methods are particularly useful for nighttime face recognition where the probe images are NIR images, but the enrolled face gallery images are typically VIS photos. A studies related to HFR by Klare and Jain [2] represented NIR and VIS face images using the histogram of oriented gradients (HOG) and LBP features. Maeng et al. [3] provides a method for normalizing VIS and NIR images using DoG filter, and extract features for cross-spectral and cross-distance matching.

2.3 Available Datasets

There are few databases collected for studying cross-spectral and cross-distance face recognition. Among these, only the NIR Mid-range dataset and LDHF database simultaneously covers the scenarios of cross-spectral (NIR vs. VIS) and cross-distance face matching. The NIR Mid-range dataset, at large standoff distance (30 m, 60 m, 90 m, and 120 m), only contains NIR images captured outdoors at nighttime, and there are no VIS images captured outdoors in daytime. It becomes difficult to analyze the differences between NIR and VIS images in face recognition at large distance. However, this dataset is not available in the public domain. Whereas, the LDHF database is available in the public domain and it includes both daytime VIS images and nighttime NIR images captured at various standoff distances (1 m, 60 m, 100 m, and 150 m). Fig 2 describes sample images of the LDHF database i.e. VIS images (top row), cropped VIS face images with grey scale (second row), NIR images (third row), cropped NIR face images (bottom row) at (a) 1 m, (b) 60 m, (c) 100 m, and (d) 150 m.

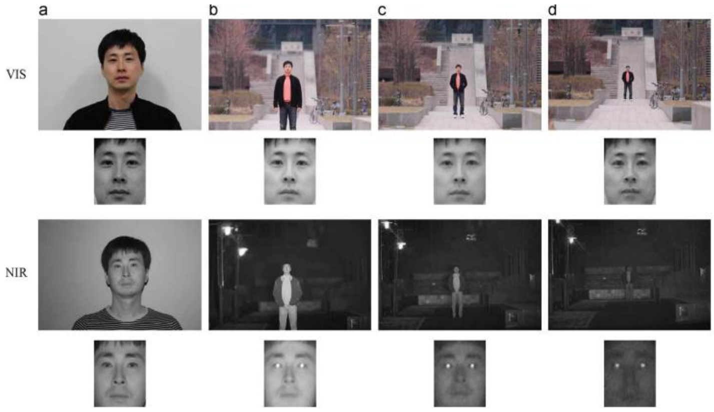

Fig -2: Example images of the LDHF database.

3. IMPLEMENTATION

In the night time face recognition, high quality face images need to be recovered from degraded probe images for security applications, which are mostly in night time scenarios when the subject is far away from the surveillance camera. The input image for the system can be either VIS or NIR type and it must be pre-processed using normalization techniques. Further image restoration is used for restoring the face image so that the image is enhanced and it helps in feature extraction and accurate matching. Later face matching is performed with available database. Thus the identity of the person in the image can be disclosed. Following figure 3 shows general implementation idea.

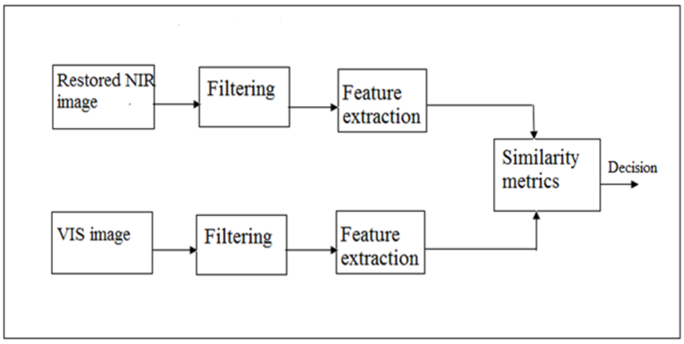

Fig -3: Overview for performing cross-spectral and cross-distance face recognition.

3.1 Normalization of image

The normalization phase consists of reducing the effect of scale, rotation, and translation variations by filtering the image. Initially for geometric normalization, the eye locations in both NIR and VIS face images are automatically detected. Then the face image is rotated and scaled so that the line connecting the two eyes is horizontal. Finally, all the face images are cropped to be of the same size using any of these cropping: tight face cropping (to remove the hair, forehead, ears, and jaw, and focus on the central facial region), medium face cropping (to include some portion of hair, forehead, and facial shape below the chin) or loose face cropping (to include most of the hair, ears, jaw, and the whole facial shape). A photometric normalization method which consists of noise filtering and contrast enhancement is applied on the images. A 3x3 median filtering is used to suppress the high frequency noise by preserving the facial details.

3.2 Image restoration

A learning based image restoration method is used based on a training set consisting of pairs of low-quality face images and their corresponding high-quality face images. This method is used to recover a high quality face image from a low quality (large standoff) face image. This learning is done with the help of a training set consisting of both low quality and respective high quality images. A local linear mapping between these images is obtained and used for recovering the high quality images. This requires two steps, Dictionary building based on k-means clustering [4] and image restoration based on LLE [5].

Each pair of low-quality and high-quality images are randomly sampled into n pairs of corresponding patches where each pair of patches comes from the same location in low-quality and high-quality face images (see Fig. 4). Later this set of patches from both low and high quality images constitutes the dictionary that is used to learn a locally linear mapping between the low-quality and high-quality patches.

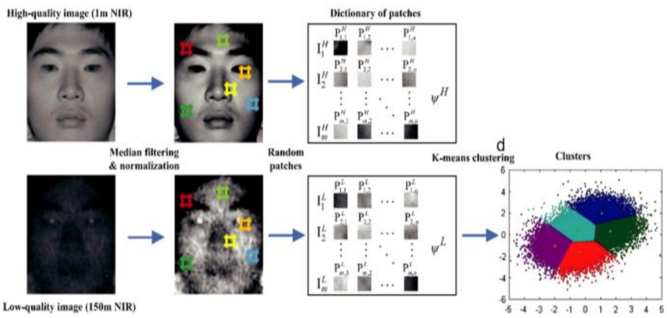

Fig -4: Overview of dictionary building process.

LLE approach is useful for mapping the patches from lower dimension to higher dimension thus providing image synthesis. Each local patch in the probe face image needs to be compared to all the n patches in the dictionary so as to determine a set of nearest-neighbor patches. To reduce the cost of comparison the low-quality patches are grouped into K clusters CL1, CL2, …, CLK using K-means algorithm [4] (see Fig. 4). Corresponding high-quality patches are similarly partitioned into K clusters CH1, CH2, …, CHK . As shown in Fig. 9, a low-quality face image is to be divided into overlapping patches of the same size used to build the dictionary. Considering a low-quality patch the closest cluster is identified using Euclidean distance. Then, using LLE [5], a set of weights are calculated for the reconstruction of low quality patch using its T number of neighboring patches in respective cluster. After the restoration of all the N patches of an input low-quality face image, the whole restored face image is obtained by averaging the overlapped regions of the restored patches.

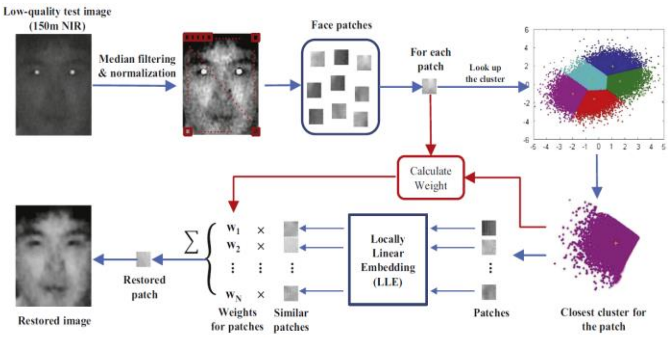

Fig -5: Image restoration based on LLE.

3.3 Feature extraction

Due to restoration, a high quality face images is obtained and a reduced modality gap between the VIS and NIR face images is observed. Now it becomes possible to use available heterogeneous face matchers which are developed for face matching at the same standoff (for both the VIS and NIR images). The heterogeneous face recognition (HFR) system that was developed in [1] can be used to match the restored face images at variable standoffs with the different database gallery face images. Difference of Gaussian (DoG) filter is used along with Scale Invariant Feature Transform (SIFT) [6] and Multiscale Local Binary Pattern (MLBP) [7] descriptors. Thus features are extracted from images. All the features extracted from overlapped patches are concatenated together to form a holistic representation of a face image. Histogram oriented graphs (HoG) can also be used as image descriptors.

3.4 Face matching

The modality gap between the VIS and NIR face images is reduced after restoration of high-quality face images. Because of this it becomes possible to use available heterogeneous face matchers developed for face matching at the same standoff (for both the VIS and NIR images) for performing face recognition. The heterogeneous face recognition (HFR) system that was developed in [1] can be used to match the restored face images at different standoffs with the 1 m VIS gallery face images or other VIS images too. A score level fusion can be used to calculate the matching score.

4. CONCLUSION

To address the issue of face recognition at night time the problem of cross-spectral (NIR and VIS kind of images) and cross-distance (images captured at various distances i.e. up to 150m) face matching is considered. An image acquisition system can be designed to collect face images at large standoff for both VIS images in daytime and NIR images at nighttime. Along with this imaging system, a database containing images of face can be used called Long Distance Heterogeneous Face (LDHF) that is publicly available for researchers. The performance of face recognition of the proposed method is improved because of the learning based face image restoration method.

REFERENCES

[1] B. F. Klare, A.K. Jain, Heterogeneous face recognition using kernel prototype similarities, IEEE Trans. Pattern Anal. Mach. Intell. 35 (2013) 1410–1422.

[2] B. Klare, A.K. Jain, Heterogeneous face recognition: matching NIR to visible light images, in: Proceedings of ICPR, 2010, pp. 1513–1516.

[3] H. Maeng, H.-C. Choi, U. Park, S.-W. Lee, A. K. Jain, NFRAD: near-infrared face recognition at a distance, in: Proceedings of IJCB, 2011, pp. 1–7.

[4] A.K. Jain, R.C. Dubes, Algorithms for Clustering Data, Prentice-Hall, New Jersey,

[5] S. T. Roweis, L.K. Saul, Nonlinear dimensionality reduction by locally linear embedding, Science 290 (2000) 2323–2326.

[6] D. Lowe, Distinctive image features from scale-invariant keypoints, Int. J. Comput. Vis. 60 (2004) 91–110.

[7] B. Klare, Z. Li, A.K. Jain, Matching forensic sketches to mugshot photos, IEEE Trans. Pattern Anal. Mach. Intell. 33 (2011) 639–646.