

Nighttime Face Recognition at Long Distance: Cross-distance and Cross-spectral Matching

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Abstract. Automatic face recognition capability in surveillance systems is important for security applications. However, few studies have addressed the problem of outdoor face recognition at a long distance (over 100 meters) in both daytime and nighttime environments. In this paper, we first report on a system that we have designed to collect face image database at a long distance, called the Long Distance Heterogeneous Face Database (LDHF-DB) to advance research on this topic. The LDHF-DB contains face images collected in an outdoor environment at distances of 60 meters, 100 meters, and 150 meters, with both visible light (VIS) face images captured in daytime and near infrared (NIR) face images captured in nighttime. Given this database, we have conducted two types of cross-distance face matching (matching long-distance probe to 1-meter gallery) experiments: (i) intra-spectral (VIS to VIS) face matching, and (ii) cross-spectral (NIR to VIS) face matching. The proposed face recognition algorithm consists of following three major steps: (i) Gaussian filtering to remove high frequency noise, (ii) Scale Invariant Feature Transform (SIFT) in local image regions for feature representation, and (iii) a random subspace method to build discriminant subspaces for face recognition. Experimental results show that the proposed face recognition algorithm outperforms two commercial state-of-the-art face recognition SDKs (FaceVACS and PittPatt) for long distance face recognition in both daytime and nighttime operations. These results highlight the need for better data capture setup and robust face matching algorithms for cross spectral matching at distances greater than 100 meters.

1 Introduction

There has been a tremendous growth in the number of installed surveillance cameras due to their ability to capture faces in a covert manner. Embedding face recognition capability in surveillance systems is gaining a lot of attention due to growing security concerns. As an example, there are over 4.2 million CCTV cameras in the United Kingdom, and there is one camera for every 32 persons [1]. Despite significant progress in automatic face recognition, there are many challenges in recognizing low resolution face images with unconstrained illumination and pose that are typically provided by surveillance cameras. While commercial off-the-shelf (COTS) face recognition systems have high recognition performance

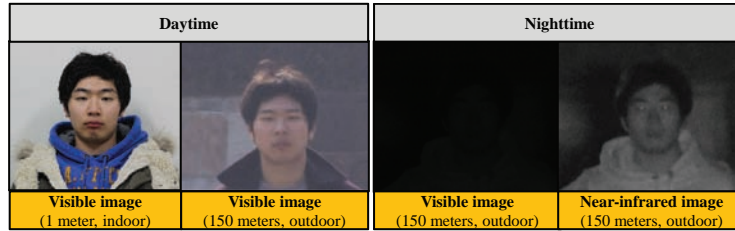


Fig. 1. Face images acquired at two different distances (1 meter and 150 meters), in two different lighting conditions (visible light and near-infrared light), and different environments (indoor and outdoor). Note that the image quality in the outdoor environment is generally lower than that in the indoor environment due to large camera standoff and unconstrained acquisition conditions.

in controlled scenarios, they perform rather poorly in surveillance environments, particularly when the images are acquired under unconstrained environments [2]. Insufficient illumination at nighttime and blurred or low resolution face image at a long distance are regarded as the most important challenges for face recognition in surveillance scenarios (Fig. 1).

Considering face recognition in nighttime, a special light source which can illuminate the subject’s face in the dark is needed. Among various types of lighting, the use of infrared source is the most commonly adopted method for nighttime face recognition. In particular, use of near-infrared (NIR) illumination for nighttime face recognition in surveillance scenarios has the following advantages [3], [4], [5]: (1) NIR illuminator is generally not visible to the human eye and keeps the surveillance operation covert; (2) NIR images are not affected by ambient temperature, emotional and health condition of the subject compared to thermal images; (3) lower price of NIR illuminator compared to thermal sensors; (4) NIR illumination can easily penetrate glasses; (5) NIR light is robust to variations in ambient lighting. So, it is not surprising that a number of research groups have studied face recognition using NIR illumination and have proposed various NIR face detection and recognition methods.

NIR face recognition approaches published in the literature can be categorized into three types: (i) directly using NIR images [6] [7] [8] [9] [10] [11] [12] [13], (ii) image synthesis from NIR to VIS [14] [15], and (iii) heterogeneous (cross-spectral) face recognition. Heterogeneous face recognition is generally required for nighttime surveillance because the enrolled face images in the gallery are usually mugshot face images (VIS) of good quality but the probe images are in NIR modality. In studies of heterogeneous face recognition, Yi et al. [16] proposed a canonical correlation analysis (CCA) based method to learn the correlation between NIR and VIS images from NIR/VIS face pairs. Liao et al. [17] presented a Local Structure of Normalized Appearance (LSNA) method to find common facial features in NIR and VIS face images by using a Difference-of-Gaussian (DoG) filtering for appearance normalization and Multi-scale Block local binary patterns (MB-LBP) for feature representation. Gentle AdaBoost was used for

selection of effective MB-LBP features; regularized linear discriminant analysis (R-LDA) was applied for subspace learning. Klare and Jain [18] proposed to use histograms of oriented gradients (HOG) feature descriptors in addition to LBP descriptors. This was followed by LDA to learn discriminative projections. Maeng et al. [19] proposed DoG-SIFT method for common feature extraction from VIS and long distance NIR images.

Table 1 summarizes major NIR face detection and recognition approaches that we have reviewed. However, most of the databases used for NIR face recognition contain faces that were captured in an indoor environment at a short distance (~ 1.5 meters). Further, little work has been done on cross-modality matching in outdoor and nighttime environments at a long distance (surveillance setting). Li et al. [12] showed that the performance of face recognition using NIR illumination is better than visible light in nighttime environment (poor lighting). Maeng et al. [19] also conducted experiments using NIR images captured in nighttime (completely dark conditions), but the databases used in both these studies were captured in an indoor environment. Bourlai et al. [20] report performance of various face recognition methods on their NIR face database captured in outdoor and nighttime environments, but they did not report any results on cross-spectral and cross-distance face matching.

Regarding face recognition at a distance (FRAD), a few research groups have collected databases of faces at long distance. Yao et al. [21] collected a face video sequence, UTK-LRHM, at a long distance (from 50 to 300 meters) with high magnification both in indoor and outdoor settings. Rara et al. [3] collected FRAD database in both indoor and outdoor environments. They used their own imaging system for collecting face images at distances up to 80 meters, but their database did not include NIR images at nighttime. To address this problem, Maeng et al. [19] collected the NFRAD database (Near-infrared Face Recognition at a Distance Database) which contains indoor visible and NIR facial images at a short distance (1 meter) and long distance (60 meters). Cross-modality (VIS to NIR) and cross-distance (short distance to long distance) matching experiments were performed using the NFRAD database. Experiments in [19] using NFRAD-DB showed that a noisy halo-like light pattern (Fig. 2(a)) caused by the NIR illuminator degraded the image quality, resulting in rather poor recognition accuracy. Bourlai et al. [20] also investigated a long distance NIR face database which contains visible light images in an indoor environment at a distance of about 1.5 meters, and NIR image in an outdoor environment at four different standoffs, i.e. 30, 60, 90 and 120 meters. They performed intra-spectral (VIS to VIS and NIR to NIR) and intra-distance matching for evaluating face recognition capabilities. However, they did not report cross-distance and cross-modality matching which is an important scenario for surveillance operations. Table 2 illustrates representative face databases captured at long distances.

The objective of this paper is to address cross-modality (NIR vs. Visible light) and cross distance face recognition in both daytime and nighttime environments. We have designed and configured an imaging system for collecting the Long Distance Heterogeneous Face Database (LDHF-DB) consisting of 100 subjects

Table 1. Representative NIR face recognition studies reported in the literature

Authors	Image modality	Imaging environment	Experimental setting	Method
Zhao and Grigat [10]	NIR images	Short distance ($\sim 1.5\text{m}$), indoors, facial expression variation	Intra-spectral	DCT-SVM
Huang et al. [4]	NIR images	Short distance ($\sim 1.5\text{m}$), indoors, pose & expression variation	Intra-spectral	ELBP-Adaboost
Shen et al. [11]	NIR images	Short distance ($\sim 1.5\text{m}$), indoors, pose, expression & illumination variation	Intra-spectral	DBC-Adaboost
Li et al. [12]	NIR images	Short distance (0.5 to 1m), indoors, illumination variation	Intra-spectral	LBP-Adaboost
Zhang et al. [13]	NIR images	Short distance (0.8 to 1.2m), indoors	Intra-spectral	Gabor-DBC
Bourlai et al. [20]	VIS and NIR images	Short (1.5m) and long distance (30 to 120m), indoors and outdoors	Intra-spectral	Bayesian-MAP
Yi et al. [16]	VIS and NIR images	Short distance ($\sim 1.5\text{m}$), indoors, pose & illumination variation	Cross-spectral	PCA/LDA-CCA
Chen et al. [14]	VIS and NIR images	Short distance ($\sim 1.5\text{m}$), indoors, expression & illumination variation	Cross-spectral	LBP-Synthesis
Wang et al. [15]	VIS and NIR images	Short distance ($\sim 1.5\text{m}$), indoors, pose, expression & illumination variation	Cross-spectral	LoG-Synthesis
Liao et al. [17]	VIS and NIR images	Short distance (0.7m), indoors	Cross-spectral	DoG-MB-LBP
Klare and Jain [18]	VIS and NIR images	Short distance (0.7m), indoors	Cross-spectral	HoG-LBP
Maeng et al. [19]	VIS and NIR images	Short (1m) and long distance (60m), indoors	Cross-spectral	DoG-SIFT

Table 2. Summary of long distance face image databases

Database	UTK-LRHM [21]	FRAD [3]	NFRAD [19]	[20]	LDHF-DB (this study)
No. of subjects	Indoor: 55; outdoor: 48	Outdoor: 97	Indoor: 50	Indoor and outdoor: 103	Indoor and outdoor: 100
Distance (standoff)	Indoor: 10 to 20m; outdoor: 50 to 300m	15 to 80m	1m and 60m	Indoor: 1.5m; outdoor: 30 to 120m	Indoor: 1m; outdoor: 60 to 150m
Image spectrum	VIS	VIS	VIS and NIR	VIS and NIR	VIS and NIR
Environment	Daytime	Daytime	Daytime and nighttime	Daytime and Nighttime	Daytime and nighttime
Format	Still images and video sequences	Still images	Still images	Video sequences	Still images
Resolution	640×480	4,752×3,168	3,872×2,592	752×582	5,184×3,456



Fig. 2. Nighttime NIR images at 60m acquired using (a) the NIR illuminator used in [19] and (b) an improved illuminator used in this paper. Notice the noisy light pattern around the head in (a) generated by the NIR illuminator in [19].

at a short distance (1m) as well as at long distances (60m, 100m, and 150m) in both daytime and nighttime. We integrate a telephoto lens with a camera which allows us to have autofocus capability to capture faces with high resolution. We also use an improved NIR illuminator for capturing higher quality of NIR images compared to [19] (Fig. 2). Our illuminator provides homogeneous NIR lighting without generating a halo like pattern, as shown in Fig. 2(b).

Compared to Bourlai et al.’s work [20], we collected outdoor face images in both daytime and nighttime, and increased the standoff distance using the improved LDHF imaging system. Short distance images were captured indoors, and long distance images were captured outdoors, simulating conditions similar to real surveillance scenario, where the gallery consists of short distance visible band images (mugshots) and the probe consists of long distance nighttime NIR face images. We performed two cross-distance face matching experiments on our

database, with intra-spectral matching in daytime and cross-spectral matching in nighttime. Experimental results show that while daytime face recognition even at long distances (up to 150m) is a relatively easy problem, matching visible light images at a short distance (1m) to NIR images at a long distance in nighttime ($> 60\text{m}$) is a challenging problem. Furthermore, the recognition performance drops significantly as the standoff distance increases from 60m to 150m.

2 LDHF Database Construction

2.1 LDHF Imaging system

The key component in NIR face recognition is a special purpose NIR image capture system [12]. Moreover, a special camera with high magnification is essential for long distance image capture. Therefore, we configured an imaging system for collecting visible light images and NIR images at a long distance using commodity components. For long distance images, we used a Canon EF 400mm F2.8L II IS USM telephoto lens (focal length is 400mm) coupled with Canon 600D DSLR camera for high resolution image capture, and two kinds of NIR illuminators for NIR image capture at nighttime. Following are the main requirements for the NIR imaging system [22]: (1) active NIR light should be nonintrusive to the human eye, (2) direction of the NIR lighting on the face should be fixed, and (3) active NIR light arriving at the camera sensor should override other light sources in the environment. Given these requirements, we used RayMax300 illuminator (with a fixed NIR wavelength of 850nm) which can emit strong and constant NIR rays up to a distance of 300m, is able to fix the light direction, and emits light which is not intrusive to human eyes. This illuminator is used in our system for collecting NIR images at a long distance in outdoor environments. Another illuminator we used is 24 IR LED built in a CCTV camera (GUARDCAM, SS91 IR24) which can also fix the light direction and is eye-safe. This illuminator is used for capturing NIR images at a short distance in indoor environments. The Canon 600D DSLR has a built-in IR/UV cut-off filter in the sensor, so we removed the IR/UV filter from the DSLR to capture NIR rays. Fig. 3 shows the imaging system used in the LDHF-DB collection.



Fig. 3. The proposed LDHF imaging system: (a) telephoto lens connected to a DSLR camera and (b) NIR illuminator.

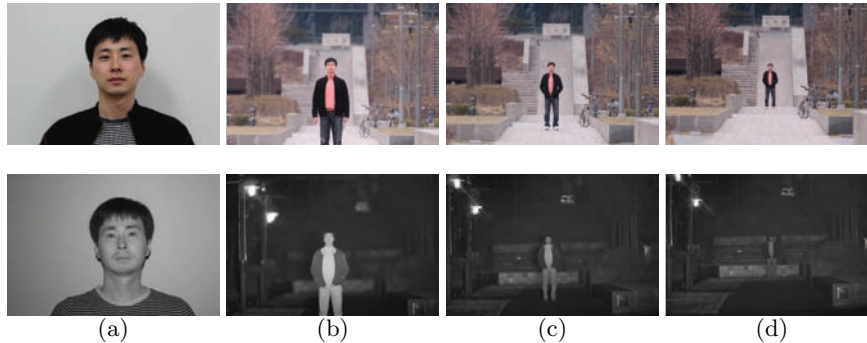


Fig. 4. Example images in the LDHF-DB: VIS (top) and NIR (bottom) images at (a) 1m, (b) 60m, (c) 100m, and (d) 150m.

2.2 LDHF Database

Using the LDHF imaging system, we collected a face database, called LDHF-DB, which contains both visible light and NIR face images at distances of 60m, 100m, and 150m outdoors and at a 1m distance indoors. We captured frontal facial images of 100 subjects (70 males and 30 females); for each subject 1 image was captured at each distance in daytime and nighttime. So there are totally 8 images for each subject, as shown in Fig. 4. The database was collected over a period of one month. All the face images of individual subjects were collected in a single sitting. Table 2 describes the details of the LDHF database, with a comparison to existing databases.

Visible light and NIR face images in the LDHF-DB contain frontal faces captured at each of the following distances: short distance (1m), and long distances (60m, 100m, and 150 m). Short distance (1m) visible light images were collected under a fluorescent light by using the DSLR camera with the Canon F1.8 lens, and NIR images were collected using the modified DSLR camera and NIR illuminator of 24 IR LEDs without visible light. Long distance (over 60m) VIS images were collected during the daytime using a telephoto lens coupled with a DSLR camera, and NIR images were collected using the DSLR camera with NIR light provided by RayMax300 illuminator. Long distance images might look subtly different from each other because of the weather conditions (fog and cloud). Fig. 4 shows example images in our database. All images of a subject are frontal faces without glasses, and collected in a single sitting. The image resolution is 5,184x3,456 pixels that are stored in the JPEG and RAW formats. The LDHF-DB will be made available to interested researchers.

3 Face Recognition

3.1 Preprocessing

NIR face images appear different from VIS face images. Further, NIR images become blurred as the stand-off distance increases. Long distance images in

LDHF-DB were captured outdoors, so background objects in images such as trees makes it difficult to automatically detect faces. To compensate for these problems, preprocessing is applied to images to reduce the appearance difference between NIR and VIS images, and enhance the image quality.

Preprocessing involves face detection, segmentation, histogram equalization, and gaussian smoothing. First, faces are detected, and then rotated based on the left and right eye positions in the horizontal direction. Images are resized to have a fixed distance (75 pixels) between the two eyes, and then cropped to 200×250 pixels as shown in Fig. 5. This is followed by Gaussian filtering ($\sigma = 2$) to remove the noise contained in high spatial frequencies. Fig. 5 shows the preprocessing scheme.

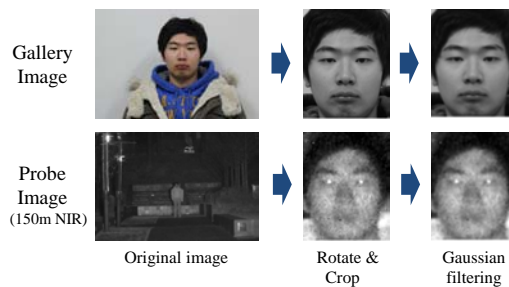


Fig. 5. Schematics of the proposed preprocessing method.

3.2 Feature representation and Matching

After normalizing face images through preprocessing, we used overlapping image patches to extract SIFT [23] features for face representation. We divided each image into 32×32 overlapping patches with a sliding step of 16 pixels in both the horizontal and vertical directions. A total of $11 \times 14 = 154$ image patches were sampled from the 200×250 face image. We applied the SIFT feature descriptor to describe each image patch as a d -dimensional vector which is normalized to sum to one. SIFT consists of two stages: (1) key point extraction, and (2) descriptor calculation in a local neighborhood. We skipped the key point extraction stage because we used a fixed grid for sampling the SIFT feature descriptors. In the descriptor calculation stage, gradients with both magnitude and orientation in each patch were calculated. Further, each patch was divided into 4×4 sub grids. An 8-bin magnitude-weighted gradient orientation histogram was calculated in each sub grid, and all histograms were concatenated to form a 128-dimensional ($4 \times 4 \times 8$) feature vector. Finally, we obtained 154 SIFT descriptors, each with a dimensionality of 128.

Given this face representation, we directly compute the Euclidean distance between the two feature vectors for VIS-VIS face matching which, as shown later,

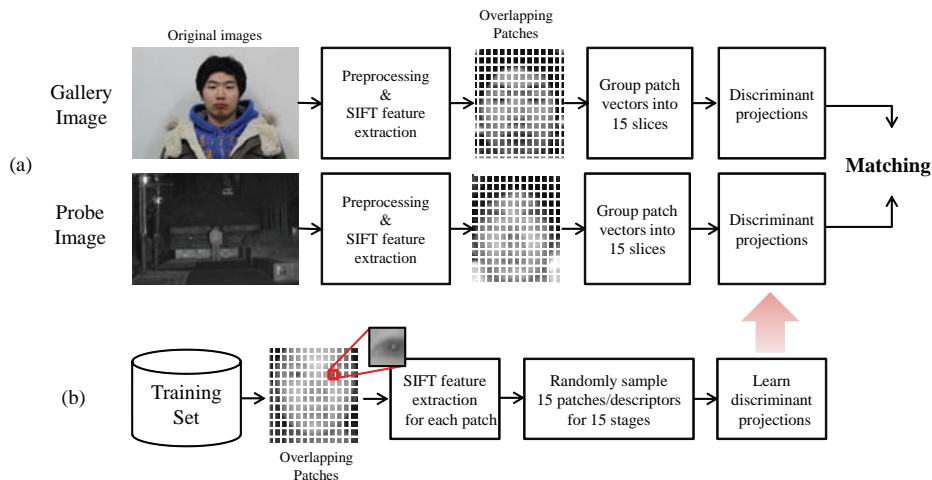


Fig. 6. Schematics of the face recognition process: (a) recognition stage and (b) training stage.

gives excellent results. On the other hand, for VIS-NIR face matching, due to its heterogeneous nature, we applied the random subspace method [18] to reduce the feature dimensionality and learn discriminant subspaces for heterogeneous face matching. This approach uses multiple random samplings of features from image patches, and applies LDA on each bag of features to learn the discriminative projection matrix. We used 15 random sampling stages; SIFT feature descriptors of 15 image patches were randomly sampled from the 154 available patches and concatenated into a single feature vector of 1,920 dimensions to represent the face image. At each stage, the mean class vector for each subject was computed using both the NIR and VIS images, and between-class and within-class scatter matrices were computed. Finally, by applying the LDA, we obtained a discriminative projection matrix for each random sampling stage. In our experiments, we used the CASIA HFB (NIR-VIS) face database [24], which contains 200 subjects, as a training set, and the NIR and VIS images in the LDHF-DB that we collected as the testing set. Finally, we obtained 15 LDA projection matrices of $1,920 \times 199$ dimensions. In the recognition stage, the feature vector of each image was first projected to these 15 different learned subspaces, and the projected vectors were concatenated into a single feature vector. The similarity between a pair of probe and gallery images was computed based on the Euclidean distance between their feature vectors. Fig 6 shows the proposed face recognition process for VIS-NIR face matching.

4 Experiments

Two types of face recognition experiments were performed: (1) Intra-spectral and cross-distance face matching and (2) Cross-spectral and cross-distance face

matching. According to the experimental setting, the LDHF-DB was divided into two subsets. This was intended to compare the long distance face recognition performances in daytime and nighttime. Faces in visible images and 1m NIR images were automatically detected. However, we manually located the NIR faces at distances of 60m and higher.

4.1 Intra-spectral and cross-distance face matching

In this experiment, only the VIS face images were used for face recognition. We used the 1m VIS images (100 images of 100 subjects) as gallery images, and the long distance VIS images (60m, 100m, and 150m VIS images) of 100 subjects as probe images. The images in this data set were normalized by preprocessing, followed by feature extraction as described earlier. The probe images were then directly matched against the gallery images. Intra-spectral and cross-distance matching for NIR images was not performed because of its limited utility in surveillance applications.

4.2 Cross-spectral and cross-distance face matching

In this experiment, both the VIS and NIR face images were used for face recognition. We used the same gallery as in the first experiment (1m VIS images), but now the long distance NIR images (60m, 100m, and 150m NIR images) of the 100 subjects served as probe images. The images in this data set were also normalized by preprocessing, followed by feature extraction. Both probe and gallery feature vectors were then transformed in the learned discriminant subspaces. The transformed probe features were then matched against the gallery features, via Euclidean distance.

To compare the performance of the proposed method, we used two commercial face matchers as baselines. In baseline experiments, Cognitec’s FaceVACS [25] and PittPatt [26] matchers were used.

4.3 Results

The matching performance of each experiment is illustrated as Receiver Operating Characteristic (ROC) curve (Fig. 7). From the results in Fig. 7, we can see that the proposed method, Gauss-SIFT, outperforms the two commercial matchers in both the experiments. In our preprocessing chain, the Gaussian filtering helps the appearance normalization in different spectral images and different standoff images so that similar features can be extracted for face images with the same identity across spectrum and standoff.

Intra-spectral and cross-distance face matching The ROC curves of the three face recognition methods are shown in Fig. 7 (a). The proposed method outperforms the two commercial matchers at 60m, 100m, and 150m VIS images. The true verification rate of the proposed method at 1% false acceptance rate is 100% for the 60m probe, 100% for the 100m probe, and 99% for the 150m probe.

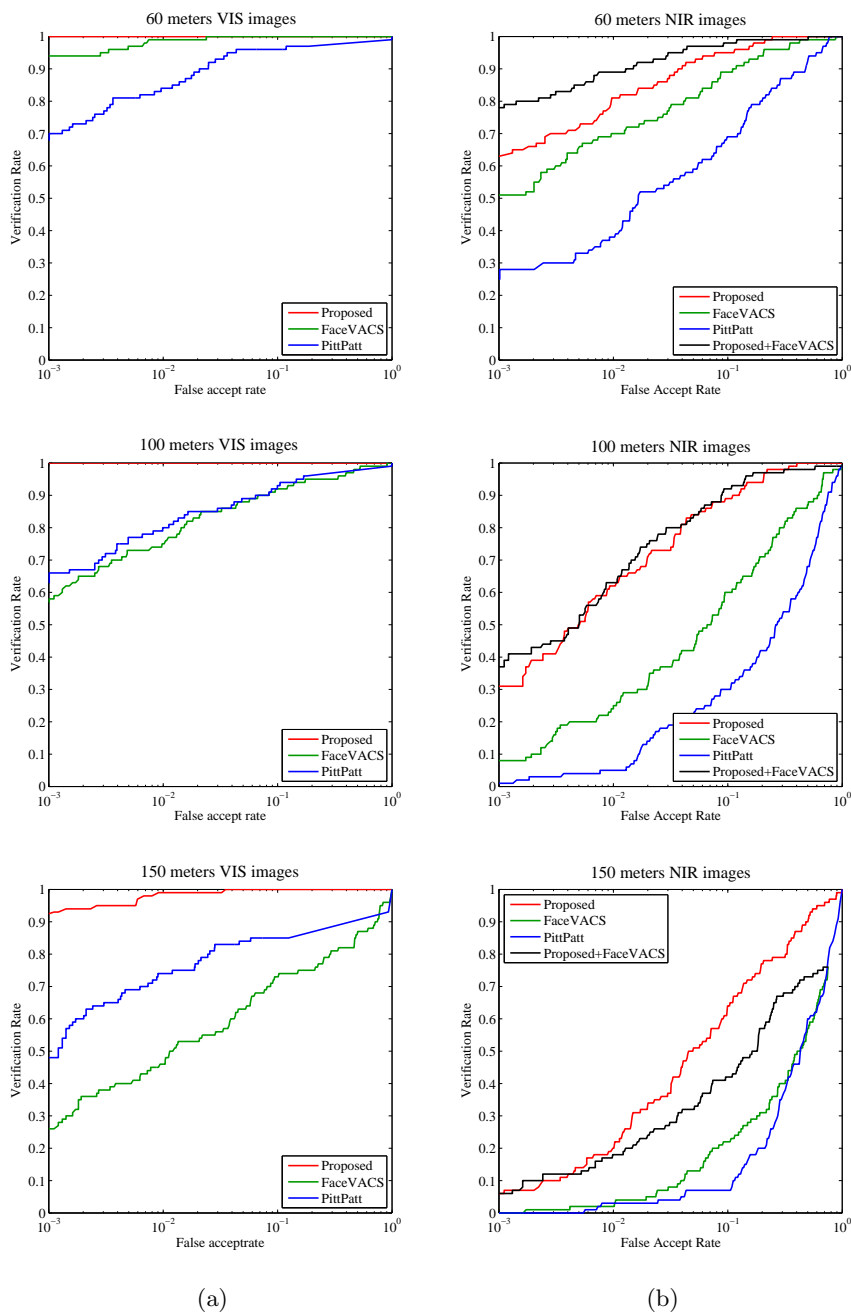


Fig. 7. ROC curves: (a) intra-spectral (VIS to VIS) and cross-distance (1m gallery to probes at 60m, 100m and 150m) matching results and (b) cross-spectral (VIS to NIR) and cross-distance (1m gallery to probes at 60m, 100m and 150m) matching results.

Cross-spectral and cross-distance face matching The ROC curves of the three face recognition methods are shown in Fig. 7 (b). Again, the proposed method outperforms the two commercial matchers at standoff of 60m, 100m, and 150m NIR images. The true verification rate of the proposed method at 1% false acceptance rate is 81% for the 60m probe, 61% for the 100m probe, and 20% for the 150m probe. A score-level fusion (min-max normalization on each score, followed by simple sum rule) of the proposed method and FaceVACS improved the true verification rate to 89% in the 60m case and 63% in the 100m case. However, the fusion scheme slightly degraded the performance (18% vs. 20%) in the 150m case. As expected, these cross-spectral matching results are significantly lower than the intra-spectral (VIS images) face matching at the corresponding distances. This is because long distance NIR images have different facial appearance from VIS images (such as bright eyes), and have lower image quality (blurred face and noise) due to poor lighting condition in nighttime compared to daytime. Fig. 8. (a) shows examples of gallery and probe images that were correctly recognized by the proposed method, and Fig. 8. (b) shows examples of gallery and probe images that were incorrectly recognized. Examples shown in Fig. 8 indicate that image quality degradation in nighttime at long distances pose significant challenges for state of the art face recognition methods.

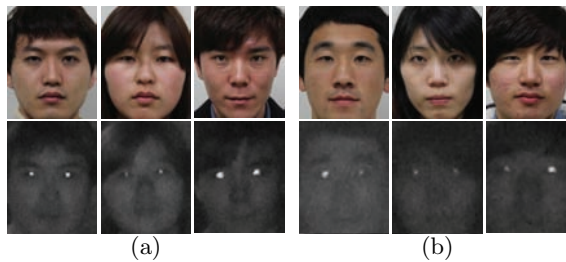


Fig. 8. Examples of NIR probe images (bottom) at 150m and the corresponding VIS gallery images (top): (a) correctly recognized pairs and (b) incorrectly recognized pairs by the proposed method.

5 Conclusions and Future work

We have addressed the problem of cross-spectral and cross-distance face matching in the context of nighttime surveillance operations. For this purpose, we built an image capture system to collect a face database which includes VIS images as well as NIR images at both short and long distances (1m, 60m, 100m, and 150m). Two types of experiments were performed: (i) intra-spectral and cross-distance face matching and (ii) cross-spectral and cross-distance face matching. In each experiment, we evaluated the performances of the proposed face recognition algorithm (Gauss-SIFT) and two state-of-the-art commercial face recognition match-

ers, FaceVACS and PittPatt. For both intra-spectral and cross-distance face matching and cross-spectral and cross-distance matching, the proposed method provides higher verification rates than FaceVACS and PittPatt. However, for cross-spectral and cross-distance face matching, the verification rates are significantly lower than the corresponding intra-spectral matching results. This is due to the degraded image quality of NIR images at large distances at nighttime. Our results highlight that nighttime face recognition at long distances is still a challenging problem that deserves further research.

Our future work will address the following two problems: (i) improving the NIR imaging system and enlarging the database size and (ii) improving cross-spectral and cross-distance face recognition rates. We plan to increase the size of the database to 200 subjects, and collect outdoor face images up to 200 meters in both VIS and NIR spectrums. We also plan to enhance the invariant feature extraction methods to overcome image distortion effects observed at long distances and image quality degradation in outdoor environments.

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