Evaluating the Efficiency of a Night-Time, Middle-Range Infrared Sensor for Applications in Human Detection and Recognition

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ABSTRACT

In law enforcement and security applications, the acquisition of face images is critical in producing key trace evidence for the successful identification of potential threats. In this work we, first, use a near infrared (NIR) sensor designed with the capability to acquire images at middle-range stand-off distances at night. Then, we determine the maximum stand-off distance where face recognition techniques can be utilized to efficiently recognize individuals at night at ranges from 30 to approximately 300 *ft*. The focus of the study is on establishing the maximum capabilities of the mid-range sensor to acquire good quality face images necessary for recognition. For the purpose of this study, a database in the visible (baseline) and NIR spectrum of 103 subjects is assembled and used to illustrate the challenges associated with the problem. In order to perform matching studies, we use multiple face recognition techniques and demonstrate that certain techniques are more robust in terms of recognition performance when using face images acquired at different distances. Experiments show that matching NIR face images at longer ranges (i.e. greater than about 300 feet or 90 meters using our camera system) is a very challenging problem and it requires further investigation.

1. INTRODUCTION

Biometric systems utilize physiological and behavioral characteristics to recognize or verify the identity of individuals.[1] Biometric products are currently used in several airports, in log-on devices for networked PCs, in e-commerce, e-banking and health monitoring. Although there are different biometric modalities that can be used (such as fingerprints, face, iris, retina, voice etc.), face is considered among the top choices because, unlike other modalities, it is easy to capture, it is non-invasive, and the face-based recognition (FR) technology is fairly accurate. Depending on the application, the face modality can be used either independently or in combination with other modalities in order to increase recognition performance.

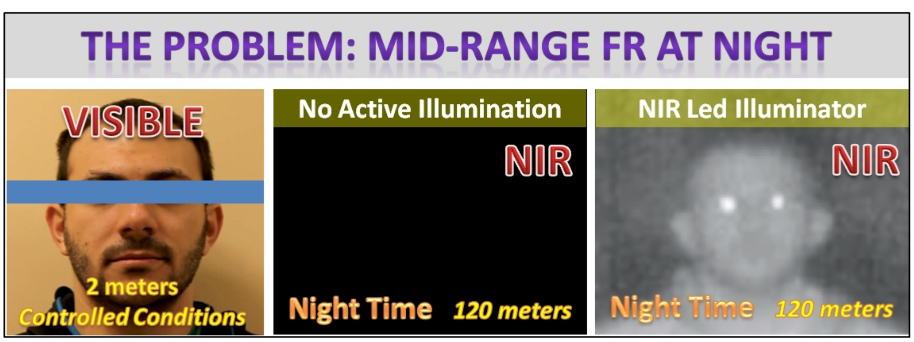

Figure 1. Illustrating the problem of facial recognition at night time and at mid-ranges, i.e., from about 70 and up to 400 feet (20 - 120 meters). We can see how a typical face image acquired under controlled conditions in the visible band look like vs. the mid-range image of the same subject at 120 meters without and with active illumination.

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When performing FR in controlled conditions, i.e. indoors, outdoors during day time, short ranges etc., the capabilities of the existing FR techniques can result in very high identification rates. However, when operating at night and at long ranges, using the standard FR techniques to achieve high identification performance results in a challenging problem (see Fig. 1). In this paper, we focus on such a scenario. For that purpose, a camera system is used that has the capability of delivering detailed surveillance assessment imagery at any outdoor illumination conditions (either daylight, low-light or no-light conditions). Due to its optical capabilities, our camera system enables detailed human assessment in complete darkness at long ranges (beyond 400 meters). However, in practice, even though the system operator can read text, numbers, and detect humans at long ranges (see Fig. 2), the system cannot automatically recognize humans via their faces because the image quality degrades as a function of standoff distance. This is due to a variety of factors including limited camera and active illumination capabilities, environmental conditions, and camera focus that needs to be continuous and automatic.

For the purpose of this study, a database in the visible (baseline) and NIR spectrum of 103 subjects is first assembled and used to illustrate the challenges associated with the problem. Then, a set of experiments is performed in order to demonstrate the possibility for mid-range face recognition, at night, in the NIR band. These experiments revealed that matching NIR face images at longer ranges (i.e. greater than 90 meters using our camera system) is a very challenging problem. Several FR techniques provided by the CSU evaluation system[2] are used to perform matching studies. The experimental results demonstrate that certain FR techniques are more robust in terms of recognition performance when face images at night are acquired across different distances.

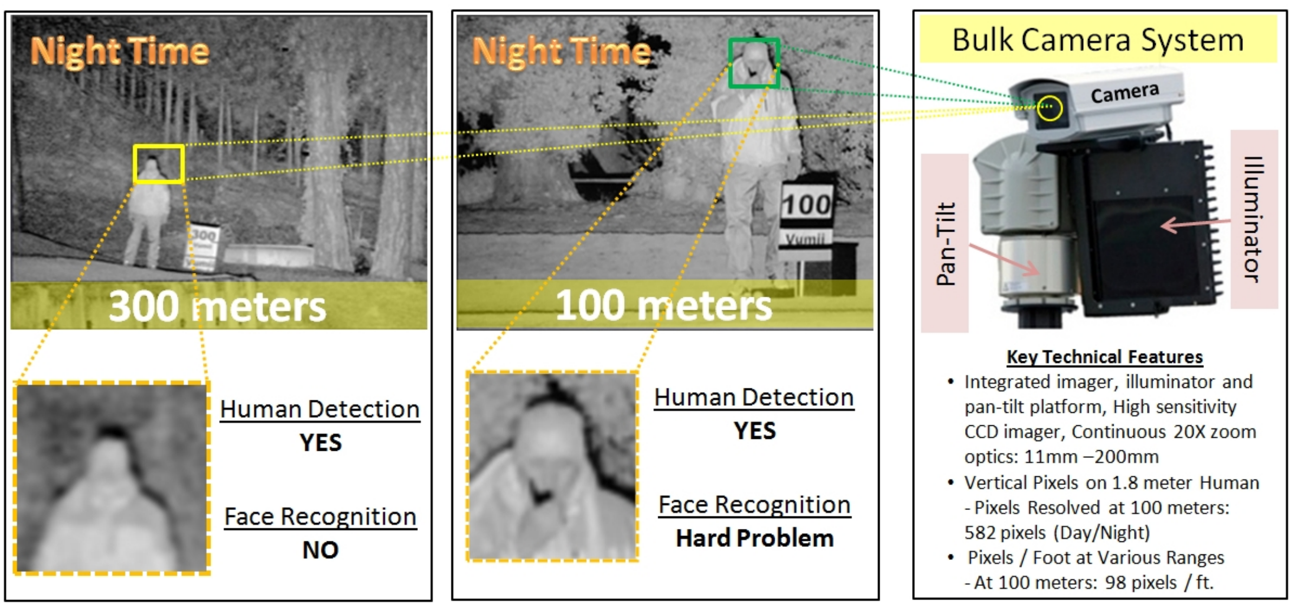

Figure 2. Overview of the NIR camera system with the capability to acquire face images day and night at mid-ranges, i.e., from about 70 and up to 400 feet (20 - 120 meters). We can see the challenges with night-time FR at mid-ranges: without active illumination FR is not possible, while with active illumination FR is possible but a very challenging problem, especially at standoff distances further than 60 meters.

1.1 Background Work

Face recognition is a field with considerable history of more than thirty years, and a somewhat outdated but quite complete review of the field can be found in.[3] Classic methods include Eigenfaces,[4] based on Principal Components Analysis (PCA), as well as variants,[5,6] Elastic Graph Matching,[7] Linear Discriminant Analysis[8] etc.

The difficulty of face recognition as a problem depends very much on the expected breadth of allowable variations for the faces to be recognized. Although controlled-condition uniform-background passport-photo-style snapshots are well within the capabilities of the current state-of-the-art, photos containing faces which are occluded, have large rotations, free illumination conditions, and significant facial expressions, can be difficult to be recognized.[3] Especially regarding the subject of interest of this paper, photos taken from long ranges, up to 50 meters or more, can also be quite problematic. For example, as they might contain very few pixels containing the face (low resolution), and also as the subjects are often in motion, and the facial pictures are blurred.[9] Thus, remote face recognition has its own special difficulties, and is a subject which has been systematically started to be tackled only quite recently, some representative papers being.[9–13]

In,[9] the authors provide a thorough analysis of the problems that remote-face identification needs to address, and then preliminary results are presented in which a baseline algorithm using PCA followed by LDA and an SVM is compared to a sparse representation-based algorithm on a home-grown remote face database (also in[10]). There is already a number of standard databases for evaluation of face recognition algorithms, including FERET,[14] FRGC/PVRT[15] etc. However, these databases consist of data collected from close ranges. Regarding longer-range databases suitable for evaluating remote-face algorithms, apart from the one described in,[9] there is also UTK-LRHM,[11] and in the same paper a comprehensive remote-face algorithm including stages for image enhancement and super-resolution is presented and applied to the database. Moving into the non-visible spectrum, and especially Long Wave Infrared, there is the example of,[12] which presents a case of long-range face-detection using infrared. Finally, a thorough analysis of system issues, and long-range facial image acquisition and image quality can be found in.[13]

1.2 Goals and Contributions

In this work we investigate face recognition on our assembled visible and NIR Database that consists of frontal face images of 103 subjects. All NIR face images were acquired at night time and at four different standoff distances (four distance-based datasets), i.e. 30, 60, 90 and 120 meters. Three different experiments have been performed. The *first* experiment investigates the matching of high quality face images obtained in the visible spectrum for the purpose of establishing baseline performance. We know that while low-light (e.g. outdoors, night time) NIR images would not affect recognition performance at short-ranges (30 meters or less using our camera system) when using active illumination, it will at longer ranges. Thus, in the *second* experiment we compare intra-distance NIR to NIR images for all distance-based datasets we assembled, while having the size of the training set fixed (i.e. 40%). The effect of training set size on system performance is studied in the *third* experiment. We know that matching NIR to visible images (heterogeneous problem) is a more challenging problem, but it is outside the scope of this paper.

1.3 Paper Organization

The rest of the paper is organized as follows. Section 2 presents the system design, Section 3 the FR matching techniques we used, and Section 4 the complete experimental set up and results. Finally, Section 5 describes the conclusions and the future plans.

2. NIGHT-TIME IMAGERY

The mid-range camera system used in this work is a Near-IR camera (provided by Vumii Imaging Inc.) that operates at 850 nm. It is a unique outdoor perimeter and border surveillance camera system, and its bulk version integrates (i) a NIR LED illuminator that is invisible to the human eye, (ii) a camera with high-magnification optics (continuous optical long-focal length zoom) placed on a precision pan-tilt platform (see Fig. 2).

A visible camera (i.e., Canon 5D Mark II) was also used to collect frontal face images that are necessary for the baseline FR experiments, after applying our automated eye detection method. What follows is a description of (a) the final camera system (operational system), (b) the live subject-capture setup that was used for the data collection activities we performed (we collected face images at different distances so as to perform face recognition studies), and (c) data preparation for FR studies.

2.1 Camera System for Mid-Range Imagery at Night

The original (bulk) camera system (acquired from Vumii Imaging Inc.) was not operational due to the absence of various hardware components and the associated software. We purchased those components, integrated them and utilized commercial software to be able to operate the camera. In practice, first, we acquired the necessary components in order to make the camera integrable with the computer. These include a power supply, video encoder, serial port (and other wiring adapters), communications cables, and other miscellaneous wiring materials.

Then, we connected the components together and tested their communication with the camera in order to get all the hardware working. In the third step, we utilized the necessary software to be able to make the camera operational (automatically move the pan-tilt, focus the camera, acquire images) via a graphical user interface. In the final step, we worked with the Mechanical Engineering Department at WVU and enclosed all camera components into an weatherproof enclosure. In Fig. 3 we can see each step we followed to prepare the camera system for the final collection of face images at night.

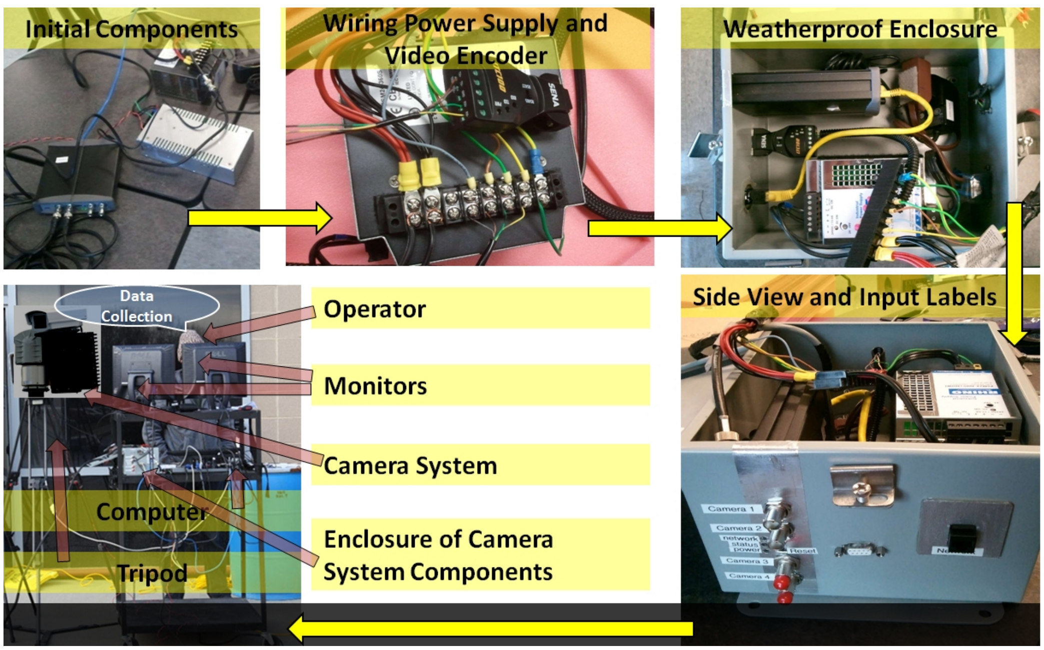

Figure 3. Overview of the steps and the components used to construct the final camera system and prepare it for data collection. Hardware components were combined and software was utilized to be able to acquire face images at mid-ranges.

2.2 Live Subject-Capture Setup

Two cameras were used in our live subject capture setup:

- **Canon EOS 5D Mark II**: This digital SLR camera has a 21.1-mega-pixel full-frame CMOS sensor with DIGIC 4 Image Processor and a vast ISO Range of 100-6400. It also has Auto Lighting Optimizer and Peripheral Illumination Correction that enhances its capability. In this work, Canon is used to obtain standard RGB, ultra-high resolution frontal pose face images in the visible spectrum.

- **Near Infrared Mid-Range Camera**: This NIR mid-range camera leverages a focused-beam array LED technology combined with an optimized imager, optics, and pan-tilt platform. The camera system provides high zoom magnification and long range surveillance capabilities in both day- and night-times environments. The main imaging characteristics include an 1/3" High Sensitivity Grayscale CCD with 752 x 582 (NTSC) effective pixels. The camera lens is capable for 20x continuous zoom (11-200mm), with a horizontal field of view (24.1-1.4 degrees). The camera also has an IR illumination source focused LED beam array (850nm) with an illumination power of 25w (max output).

The live face capture configuration we used is illustrated in Fig. 4, and includes the mid-range camera system (described above), a visible camera, a hygrometer, a light (lux) meter, and range finder (to digitally verify the precise distance at long ranges). Four standoff distances were considered to collect face images, i.e., 30, 60, 90 and 120 meters. The database was assembled outdoors at night time spanning over a time period of 20 days. Recordings of the faces of the subjects were taken with the mid-range camera. The temperature and humidity of the collection location were also recorded. Then, the subjects mug shots was also taken using the visible camera in an indoors controlled environment (useful data for baseline FR studies).

In the beginning of the session, the subjects were briefed about the data collection process after which they signed a consent document. In total, 103 subjects (69 male + 34 female) participated in this experiment, and the database has video sequences of full frontal mid-range NIR and visible face images of each subject, resulting in a total of 103×5 videos (103×4 NIR outdoors and 103 visible indoors) per subject. Demographic information of the data collection we performed in provided in Fig. 5.

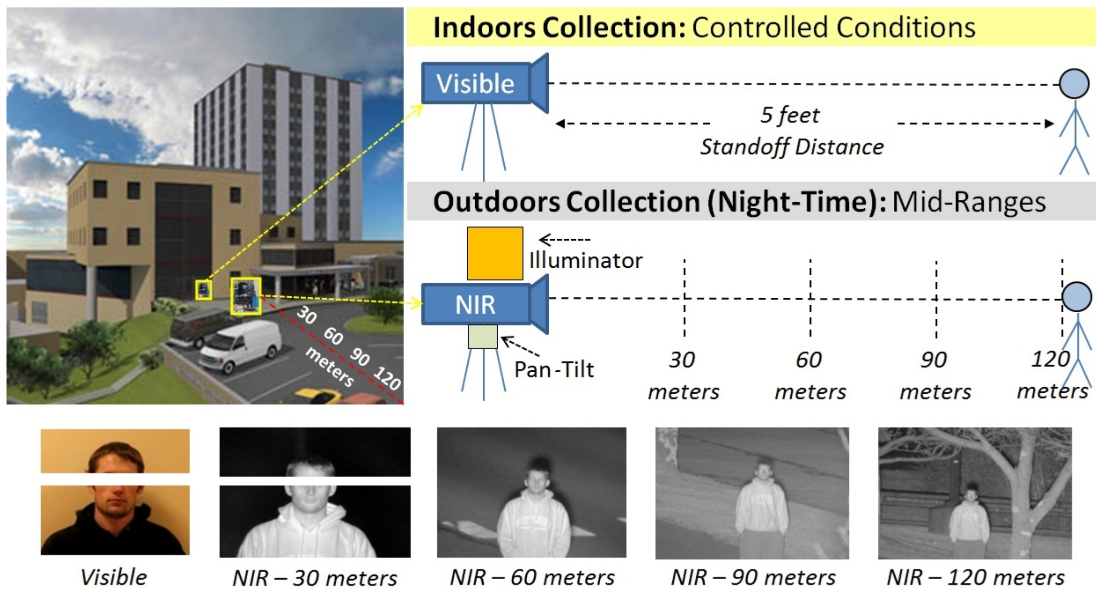

Figure 4. The live subject-capture setup using the visible and mid-range NIR cameras. At the bottom of the figure we can see face image samples acquired by our system.

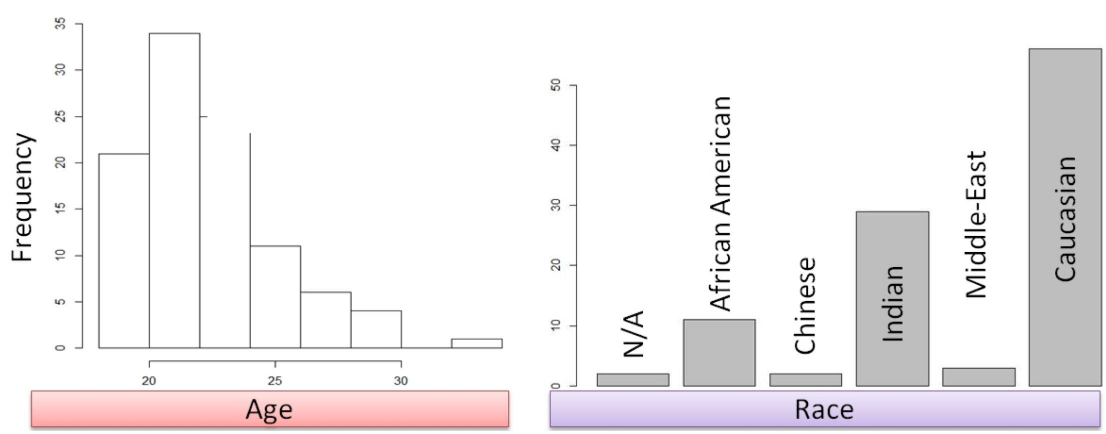

Figure 5. Demographic information of the collected data. We can see the age (left) and race (right) distribution.

2.3 Data Preparation for FR studies

The videos taken from the mid-range camera were recorded using commercial software provided by the video encoder. These video files of type ".asf" which were then converted to ".png" images. The videos taken with the Canon camera were of type ".mov" and were converted to ".png" images using Matlab* video processing libraries. Once all of the frames of each video had been converted, the participants' face images were then organized, e.g. all of the images from each individual distance were stored in their own distance folder. Visible and NIR face image at different distances were then post-processed.

During post-processing, the videos of each subject at various distances were split up into single framed images. Then, a script was used to randomly select 8 images of an individual per distance. All images are checked for quality (e.g., frames in which there is glare from car headlights in the background or the subject blinks were replaced by good quality face images). In the next step, we applied a set of pre-processing routines before we finally tested academic FR algorithms. These pre-processing steps and the FR studies we performed will be described below.

3. INTRA-SPECTRAL AND INTRA-DISTANCE MATCHING

In our intra-spectral (visible to visible, i.e., baseline, and NIR to NIR - intra-distance) experiments, we used both commercial and academic software. While the pre-processing routines employed by the commercial software are not known, the academic software employed the following pre-processing and face recognition methods.

- **Pre-Processing**: A geometric normalization scheme is applied to images acquired after automatic face detection and eye detection that was applied to the visible and NIR images acquired at 30 meters (good quality data). The eye detection method used is based on a template matching algorithm where the coordinates of the eye were automatically obtained.[16] For the rest of the data, no face detection or eye detection was performed because traditional techniques did not work when employing the face image datasets acquired at longer ranges than 30 meters. Thus, we manually annotated the eye locations of all face images on the challenging datasets.

  Then, a normalization scheme is employed that compensates for slight perturbations in the frontal pose, and consists of eye detection and sequence of normalization steps including integer to float conversion, geometric normalization (lines up human chosen eye coordinates), masking (crops the image using an elliptical mask and image borders such that only the face from forehead to chin and cheek to cheek is visible), histogram equalization (standard photometric normalization technique), and pixel normalization (scales the pixel values to have a mean of zero and a standard deviation of one). Eventually we have a set of canonical faces that are all warped to the same dimension of 150×130 pixels.[2] Figure 6 illustrates example face images before and after normalization at different distances.

- **Face Recognition Methods**: Both commercial and academic software were employed to perform the face recognition experiments. In terms of the commercial software we used the *Identity Tools G8* provided by L1 Systems†. This algorithm was used only for FR experiments in the visible spectrum to establish a baseline performance. In the academic software we used standard face recognition methods are provided by the CSU Face Identification Evaluation System,[2] including *Principle Components Analysis* (PCA),[4,17,18] *a combined Principle Components Analysis and Linear Discriminant Analysis algorithm* (PCA+LDA),[8] and the *Bayesian Intra-personal/Extra-personal Classifier* (BIC) using either the Maximum likelihood (ML) or the Maximum a posteriori (MAP) hypothesis.[19]

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*http://www.mathworks.com/products/matlab/
†www.l1id.com

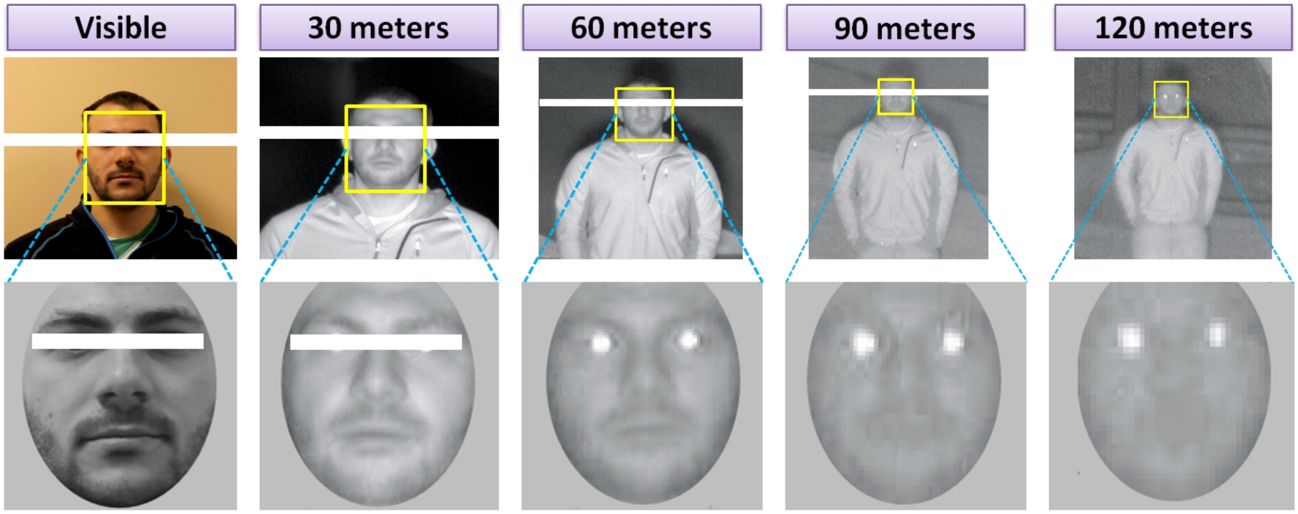

Figure 6. Example face images before and after geometric normalization (no photometric) in the visible band (band), and in the NIR band where images were acquired at different standoff distances ranging from 30 and up to 120 meters.

4. EXPERIMENTAL SCENARIOS

By using the visible and NIR images in the assembled database, four different types of face identification experiments were performed:

- (i) Visible vs. Visible (baseline using only L1 Systems commercial software)
- (ii) Intra-spectral, intra-distance NIR vs. NIR at all distances (fixed training and test sets)
- (iii) Intra-spectral, intra-distance NIR vs. NIR at all distances (variable training and test sets)

Scenarios (ii) and (iii) represent a challenging FR problem. In all scenarios eight random photos were selected from each subject per distance per to generate the training and test sets for the CSU Face Identification Evaluation System.

The *first* experimental scenario matches high quality images in the visible spectrum for the purpose of establishing a baseline for comparison. In the *second* experiment (i.e., homogeneous distance-based matching) we compare NIR gallery images acquired at a specific distance against NIR probe images acquired at the same distance with the gallery images. In this experiment the frontal face images of the participants were randomly broken into two groups where 40% of the subjects were used as the training set, and the images of the remaining subjects were used as the testing set. This process was repeated ten different times, using a random selection of the training/test sets each time.

In the *third* experiment (i.e., homogeneous distance-based matching) we compare NIR gallery images acquired at a specific distance against NIR probe images acquired at the same distance as the gallery images. The difference between this experiment and the second one is the variable training and test sets, i.e. the frontal face images of the participants were randomly broken into groups based on training set sizes using 20%, 40%, 60%, and 80% of the images, while the rest of the images were the testing set. Once more, this process was repeated ten different times, using a random selection of the training/test sets each time.

The identification performance of the system is evaluated through the cumulative match characteristic (CMC) curve. The CMC curve measures the $1 : m$ identification system performance, and judges the ranking capability of the identification system.

4.1 Baseline and Mid-Range Matching Results

In the results of the baseline experiments (where the matcher G8 from L1 Systems was used) we determined that with G8 the identification rate was 100% at Rank-1. Other texture based techniques (e.g., LTB, LTP) or appearance based (e.g., PCA, LDA) could be used. However, for practical purposes we did not perform experiments with those academic FR techniques because we have tested them in several baseline experiments[16, 20, 21] and they are known to achieve a lower performance (rank-1 identification rate) than L1 at ideal conditions.

In the second set of experiments, we compared NIR to NIR face images. For this purpose we employed the academic software (CSU Face Identification Evaluation System[2]) while the training set was fixed at 40%. The identification performance results are summarized in Fig. 7 (top row), where we can see the mean results after running each experiment 10 times, and Fig. 7 (bottom row) where we can see the box plot results across all distances when using all FR algorithms of CSU system. Experimental results illustrate that LDA followed by Bayesian ML achieve the best performance results across all distances. The consistency of LDA performance when operating in challenging conditions is not surprising (see work in[22]).

In the third set of experiments, we compared NIR to NIR face images and again employed the CSU academic software. In this set of experiment we varied the training set size to determine whether larger training sets will result in higher recognition performance independent of whether we are operating at 30 meters or 120 meters standoff distance. For that purpose (a) we randomly selected 20, 40, 60, and 80% of the images for training and the rest images were used for testing, and (b) this process was repeated ten different times. The identification performance results are summarized in Figs. 8 and 9.

There are three main conclusions here: (a) LDA and Bayesian ML FR techniques achieve the best performance results across all distances and conditions. (b) The closer the standoff distance we operate to acquire face images at night the better the identification performance, and (c) The higher the training set size the better the identification performance. In addition, we can see that even when using 20% vs. 80% training set size, identification performance is very high, i.e. with 20% training set size we have: about 99.5% (mean rank-1 score when using the Bayesian ML technique) at 30 meters, and about 93.5% (mean rank-1 score when using the LDA technique) at 120 meters. In comparison, with 80% training set size we have: 100% at 30 meters, and about 99.7% at 120 meters. These are the best rank-1 scores when using for both case the Bayesian ML technique.

5. CONCLUSIONS AND FUTURE WORK

We presented a systematic performance analysis of various standard face recognition algorithms on visible and NIR imagery at *night time environments* (all of the images of our study were collected outdoors at night). To facilitate our analysis, we first conducted a comprehensive data collection with a novel sensor system capable of acquiring NIR images at a video frame-rate of 30 frames per second at mid-range standoff distances that start from 30 and go up to 120 meters.

The data collection effort (face images of subjects were acquired with intra-personal variability) was designed to investigate the hypothesis that night time NIR imagery using a mid-range sensor and a focused-beam array LED technology would yield high recognition performance at short ranges that degrades as the distance of the target to the sensor increases.

Different scenarios were tested allowing us to gain some understanding of the shortcomings of the NIR spectrum on images captured at mid-range standoff distances with respect to the visible modality. As expected, intra-spectral (NIR) experiments result in a performance that reduces as a function of distance, especially at ranges greater than 90 meters where facial features become less prominent (due to various factor including atmospheric conditions). This is independent of the FR matcher used, although some matchers perform much better than others (e.g. LDA and Bayesian ML vs. PCA) across all scenarios investigated.

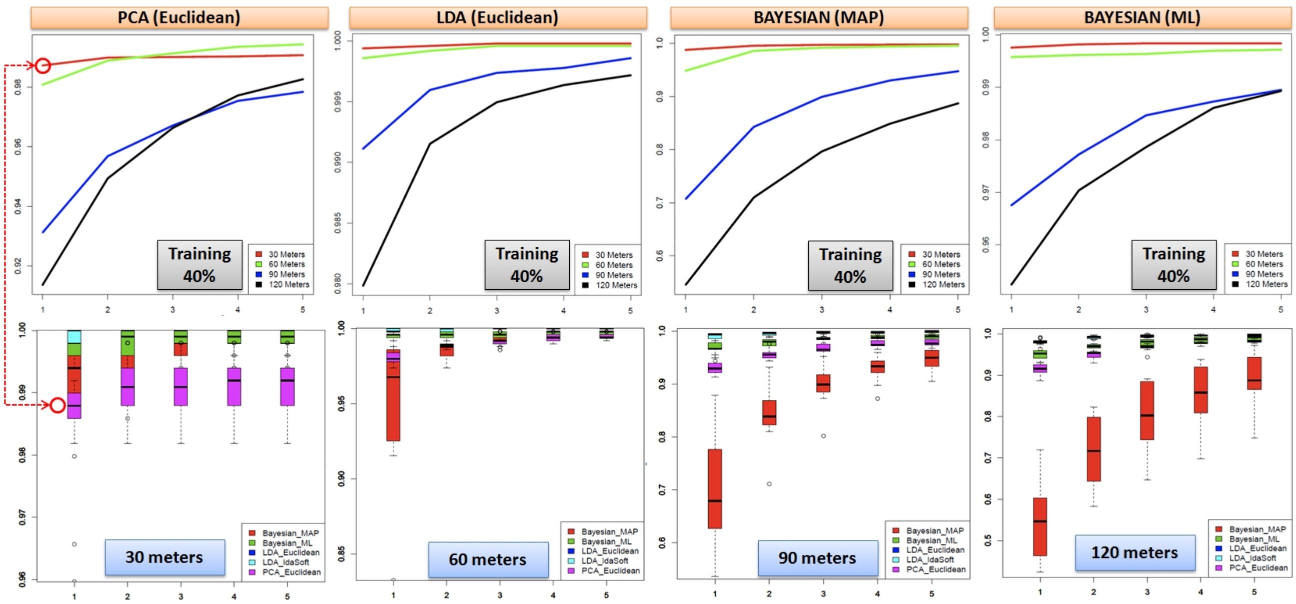

Figure 7. Experiment 2: Rank-1 to Rank-5 (x-axis) mean identification performance (y-axis) results [Top Row], and box plot results [Bottom Row] when using PCA, LDA, and Bayesian (ML or MAP) algorithms. We can see that LDA followed by Bayesian ML achieve the best performance results across all distances. We can also see the associate mean identification performance result at rank-1 (top to bottom row) when using the PCA algorithm.

When we operate at 30 meters standoff distance (using this particular camera system), identification performance on NIR imagery appears to be comparable to that of visible imagery (baseline) under certain conditions e.g., training set size 40% or greater and usage of LDA or Bayesian ML as a FR matcher. Thus, it appears that NIR modality holds great promise under reasonable operating conditions. Another benefit of using this NIR mid-range sensor is the possibility of obtaining the same recognition rates when face images are acquired in either day or night time environments.

The main disadvantages of our NIR mid-range system are its cost, the fact that our prototype was not a complete system (additional software plus hardware need to be purchased and then connected and tested so that the system can be operational), and finally, its size and weight (50.7 lbs or 23 kg).

5.1 Future Directions

Following our work, further experiments and data collections will be necessary to investigate more challenging scenarios, e.g., when subjects are wearing glasses, when data collection is performed at different sessions (for cross-session FR testing), or when face images are acquired opportunistically while the subjects are non-cooperative. We intend to expand our collection and analysis effort towards that direction.

It is also worth mentioning that a promising avenue for extensions, even more so applicable in the case of longer-range FR, has to do with the incorporation of context in the recognition process; i.e. utilizing image content outside the detected face (objects, other faces, environment, recognized text) or other sources of context, such as spatio-temporal information associated with the picture.

Examples of context-assisted recognition, albeit for objects and not for faces, are given in,[23] which is based on holistic context representations, while,[24] performs object detection by modeling the interdependence of objects, surface orientations, and camera viewpoint. However, none of these papers address the utilization of social context for face recognition. The only noteworthy exception is,[25] and for the more general case of partial or no identity information known.[26] In this paper, social context (knowledge of first-level friendship relations) is utilized in order to assist multi-face recognition, based on the strong correlation between co-occurrence of faces in photos and acquaintance of the individuals whose faces were captured. In the future, it would be interesting to see extensions of existing and future long-range recognition methods in order to incorporate different forms of contextual information.

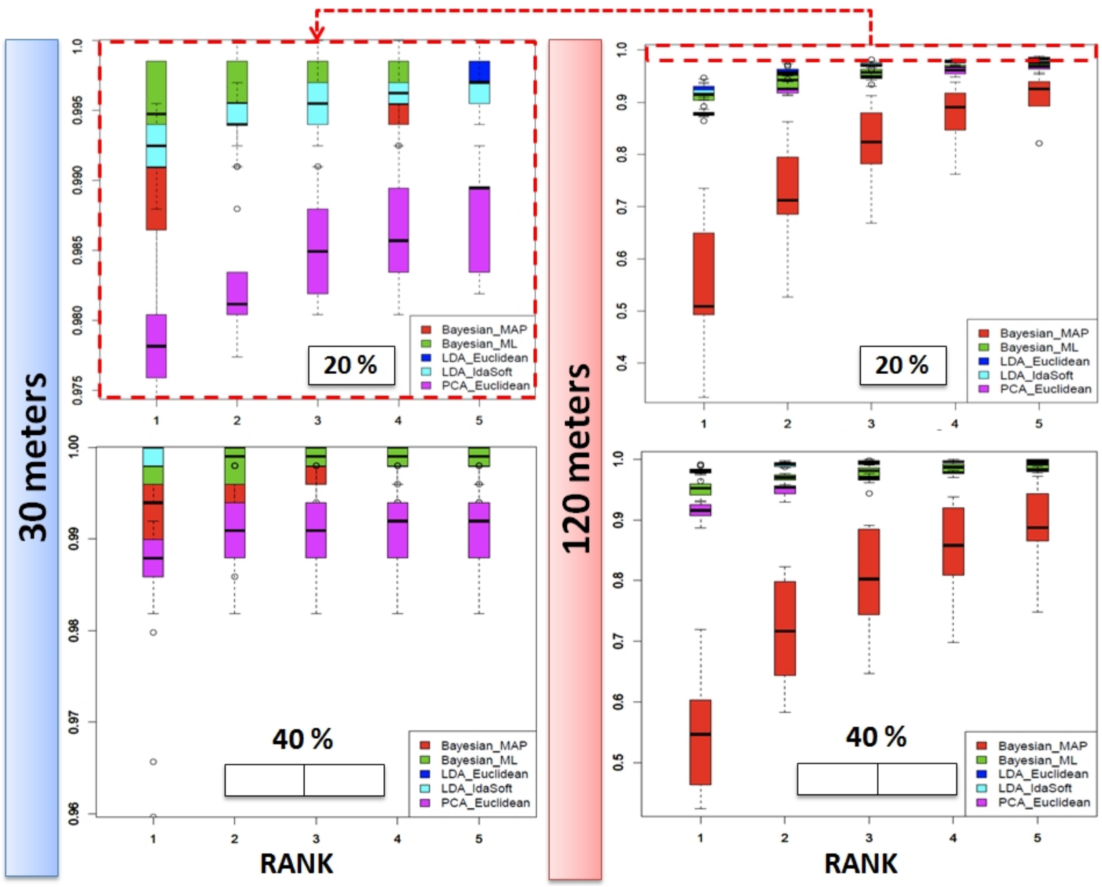

Figure 8. Experiment 3: Rank-1 to Rank-5 (x-axis) box plot identification performance (y-axis) results when using 20% [Top Row] and 40% [Bottom Row] training set size at two distance-based scenarios, i.e. when operating at 30 meters [Left Column] or at 120 meters [Right Column]. For these experiments we used the FR algorithms of the CSU academic software. We have also highlighted (red dotted line) the concentration of identification performance results (same training set size) when operating at 30 meters vs. 120 meters illustrating that the quality of the images and as a result the performance at short ranges is much better than at high ranges.

Acknowledgments

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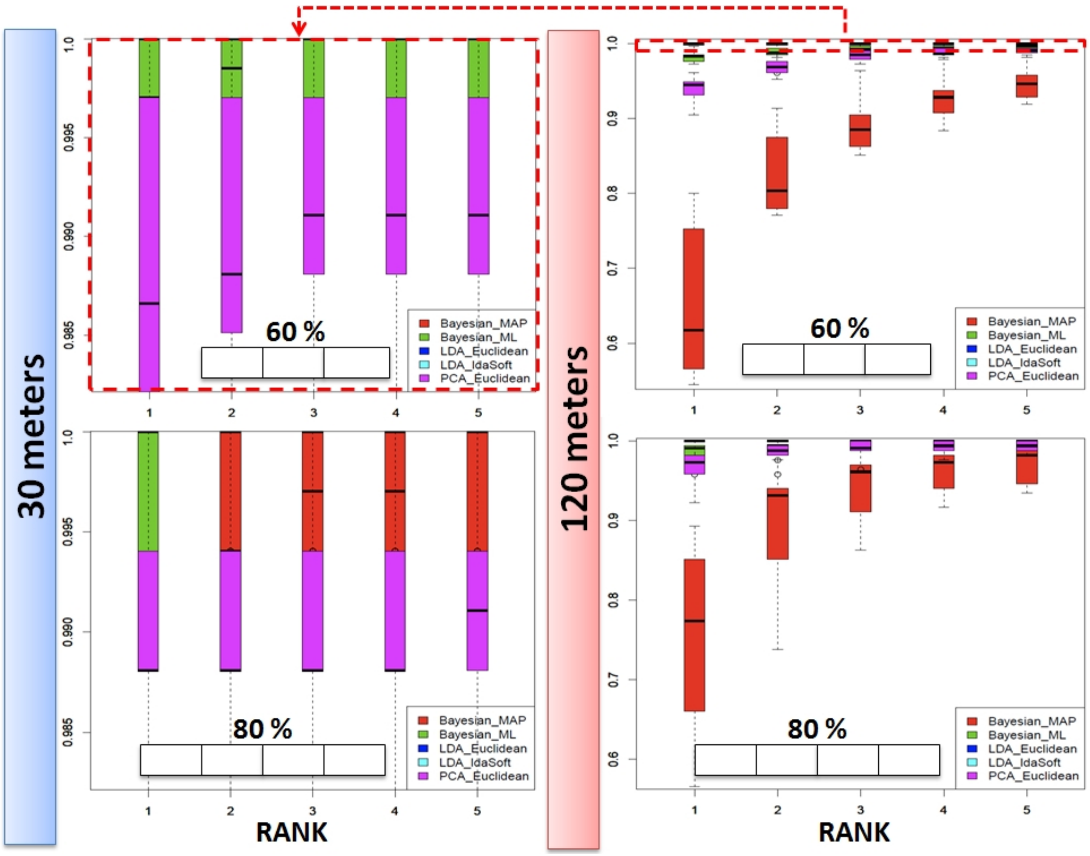

Figure 9. Experiment 3: Rank-1 to Rank-5 (x-axis) box plot identification performance (y-axis) results when using 60% [Top Row] and 80% [Bottom Row] training set size at two distance-based scenarios, i.e. when operating at 30 meters [Left Column] or at 120 meters [Right Column]. For these experiments we used the FR algorithms of the CSU academic software. We have also highlighted (red dotted line) the concentration of identification performance results (same training set size) when operating at 30 meters vs. 120 meters illustrating that the quality of the images and as a result the performance at short ranges is much better than at high ranges.

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