On Designing Practical Long Range Near Infrared-based Face Recognition Systems

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Abstract

Although automated face recognition (AFR) is a well-studied problem with a history of more than three decades, it is still far from being considered a *solved problem* for the case of difficult exposure conditions, such as during night-time, in environments with unconstrained lighting, or at large distances from the camera. However, in practical forensic scenarios, it is often the case that investigators operate in difficult conditions, where cross-session data need to be matched and where, [grouping of the data in the context of demographic information](#) (constitute the grouping in terms of gender, ethnicity) may be used in order to assist law enforcement officials, forensic investigators and security personnel in human identification practices. In this paper, we discuss the challenges in designing a practical near infrared (NIR) FR system and, more specifically, study the problems of intra-spectral, cross-spectral, i.e. VIS-NIR, intra-distance and cross-distance NIR FR, in indoors, outdoors, day-time and night-time environments. Furthermore, we

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propose the usage of a multi-feature scenario dependent fusion scheme that can enhance recognition performance. We also investigate which scenarios used, related to datasets, features useful for face matching or their combination, are most beneficial to the identification accuracy of NIR FR systems, when the gallery set is composed of either visible or NIR band face images. Thus, we illustrate that the selection of specific feature extraction techniques and their fusion are often the key design aspects that can turn practically non-functional systems to effective systems with real-world applicability. As a result, such a strategy can significantly extend the range of conditions under which automated NIR FR systems can operate.

Keywords: Forensics, Face Recognition, Near Infrared, Cross-Scenario Face Matching, [Demographic Information](#), Night-time, Long-Distance, Score Level Fusion.

1. Introduction

Face recognition systems have long been a very important tool for security applications. Databases of passport-style photos of millions of people have traditionally been part of the citizen records of most nations. Such photos are usually taken under highly controlled conditions; the light source and direction, face pose, standoff distance (i.e. the distance between the camera (source) and the face (target)), as well as the background, for example, are kept within tightly controlled limits. However, for both security-related as well as consumer-based applications of face recognition, the conditions of the materials to be used for training or testing a human recognition system are much more varied. The variability of illumination sources and background, as well as poses variation and even partial facial

12 occlusions, are usually the norm rather than the exception in freely-taken mate-
13 rial, such as surveillance videos, photos posted on the internet etc. Furthermore,
14 forensic material often needs to be taken in even harsher conditions: for exam-
15 ple, during night-time, or at moderately long distances from the subject, often
16 surpassing thirty meters (or about 100 feet) standoff distance.

17 Under such conditions, traditional face recognition approaches, such as those
18 based on Local Binary Patterns [1] or Linear Discriminant Analysis [2], often
19 provide unsatisfactory results, which can be practically unusable in a court of
20 law, where typically face-based evidence needs to be extremely accurate so that it
21 can provide to law enforcement officers a solid lead, to either identify or rule out
22 suspects. Thus, it is a fact that multiple directions toward improving the design of
23 more efficient and practical FR systems are being explored.

24 This work is an effort to investigate some of the challenges of unconstrained
25 face recognition by focusing on *three main directions* (see Fig. 1): (i) the usage of
26 both visible and near infrared sensors, (ii) dealing with challenging matching sce-
27 narios, where the problem domain is composed of: homogeneous or intra-spectral,
28 and heterogeneous or cross-spectral matching studies, while also the face images
29 are acquired using different cameras, at day-time or night-time conditions, indoors
30 or outdoors, at different standoff distances (up to more than 100 meters away) and
31 (iii) the usage of a multi-feature scenario depended fusion (MFSDf) face match-
32 ing scheme (our proposed approach), with and without the support of [grouping in](#)
33 [the context of demographic information](#), which can assist in improving FR per-
34 formance at the aforementioned challenging matching conditions.

35 One example pertaining to the *first two directions*, deals with the problem of
36 identifying people both at day-time and night-time environments, at variable dis-

Figure 1: Problem overview: *matching cross-scenario face data, in which the probe face images are captured in the near infrared band when operating under difficult conditions, is a very challenging task. In this study, we, first, investigate variable face matching scenarios using academic, commercial and our proposed system. In addition, we performed a study where the expectation is to improve FR performance by utilizing male and female groups in the context of demographic information of data in face matching studies.*

37 tances and illumination conditions. This can be accomplished by using various
 38 types of visible (e.g. with telephoto lenses) and infrared sensors (Near, Short-
 39 Wave, Mid-Wave, and Long-Wave IR), under either single-spectral or multi-spectral
 40 recognition settings [3, 4]. We also know that there are certain settings and config-
 41 urations that provide increased identification performance during night-time op-
 42 erations, when using passive IR sensors [3], active IR sensors [5] or visible band
 43 sensors that operate during day-time and at medium distances [6].

44 One example pertaining to the *third direction*, deals with the problem of im-
 45 proving identification performance using our proposed multi-feature (LBP, Gabor
 46 and HOG) scenario-dependent fusion scheme. Our proposed scheme is tested
 47 on two different dual-band face datasets collected as part of two separate studies
 48 [7, 8]. This is beneficial for the purpose of this study, since the subjects on each
 49 dataset are different and the faces of the subjects were captured under similar

50 conditions (i.e. in terms of standoff distance and overall environment) but using
51 different sensors (details will be provided in section 3.2).

52 The usage of [male and female groups in the context of demographic informa-](#)
53 [tion](#) of data is also considered. Filtering is performed before face matching for the
54 purpose of improving face recognition performance. A practical example where
55 one of the state-of-the-art FR commercial software was assisted by demographic
56 data to work efficiently is discussed in [9]. This is the case of the April's 2013
57 bomb attacks in Boston, U.S.A. where two men, shown in pixelated photos and
58 video footage, were suspected of involvement in the event. These suspects were
59 successfully face-based identified (as part of a proof of concept study after the
60 event), only when demographic filtering was used (e.g. age range and gender), as
61 a prior step to FR matching, i.e. a filtered search was performed where each probe
62 was only compared against gallery images with *similar* demographic data.

63 While all aforementioned directions are necessary when designing a FR sys-
64 tem, there are other problems that FR operators need to deal with. In practical
65 applications, one of the problems with human face-based recognition is that it is
66 often the case where the training material (i.e. the gallery dataset of face images,
67 normally captured in a controlled environment of a set of individuals enrolled in
68 the dataset) is only available in the visible spectrum (see Fig. 2). Thus, one needs
69 to perform the very challenging task of matching cross-scenario face images. One
70 way of attempting to deal with such a challenge is through photometric normaliza-
71 tion [10], utilizing algorithms such as contrast limited adaptive histogram equal-
72 ization (*CLAHE*) [11]. While such algorithms often are shown to improve iden-
73 tification performance, their capability in practical applications is limited due to
74 the fact that face images of suspects (probes), available from surveillance data,

are of low quality. The reasons are that such face images are captured using low quality sensors at the challenging conditions discussed above while also they need to be successfully cross-matched to the available mug shots, i.e. good quality face images (gallery), typically captured in the visible band.

Figure 2: Data collection scenarios of both visible and infrared face data, under controlled (top image) or uncontrolled (bottom image) conditions. The questions that need to be answered are (i) ‘what is the baseline FR performance when performing cross-scenario matching?’ and, (ii) ‘can FR benefit from [context of demographic information](#) of data for the face images collected by surveillance cameras?’

In this paper, motivated by the above state of affairs, we are presenting highly promising concrete quantitative results arising from the design and evaluation of a NIR FR system (in comparison with a conventional visible FR system) that operates at night-time and at long distances (both baseline and cross-scenario studies have been performed). In this paper we also present results arising from before (baseline) and after the usage of our proposed fusion approach, when (i) we used

85 either the same or different datasets for training and testing. All NIR face images
86 were collected outdoors at night time conditions, while the visible counterparts of
87 the NIR face images were collected either indoors or outdoors, (ii) we extended
88 the training set with more subjects and images, (iii) we deal with only male or
89 female subsets for performance evaluation. Hence, the overview of our work is to
90 study what are the effects of matching cross-scenario face data (collected at dif-
91 ferent conditions; using different sensors) have on the identification performance
92 of a NIR FR system, while we also investigate which conditions and scenarios,
93 associated with each face image captured, can further enhance recognition perfor-
94 mance.

95 For the rest of the paper, we will start by providing an overview of related ex-
96 isting background research, and then, describe our system, our proposed method-
97 ological approach and the results obtained. Next, we will provide a discussion,
98 including interesting observations as well as future directions, before proceeding
99 to a concise conclusion of our findings, which illustrates the benefits of our pro-
100 posed matching scheme and usage of [female and male groups in the context of](#)
101 [demographic information](#) of data towards improving FR performance.

102 **2. Background**

103 Automated Face Recognition is a field with considerable history, with major
104 publications having already started in the 80s. A somewhat outdated but quite
105 complete review of the field can be found in [5]. Classic methods include Eigen-
106 faces [12] as well as variants [13], Elastic Graph Matching [14], Linear Discrim-
107 inant Analysis [15], Kernel-Based methods, Hidden Markov Models [16], all the
108 way to more recent methods using sparse representations [17] and ensembles of

109 classifiers [18]. Apart from academic systems, a number of high-performance
110 commercially available systems also exist, such as FaceVACS [19], PittPatt [20],
111 Identity Tools G8 [21] and NeoFace by NEC (www.nec.com).

112 Regarding face recognition in difficult conditions, such as night-time or large
113 distances, infrared and multi-spectral imaging has provided promising results.
114 In [22], the Long-Distance Heterogeneous Face (LDHF) Database is presented,
115 which contains face images collected in an outdoor environment at distances of
116 1 meters, 60 meters, 100 meters, and 150 meters, with both visible light (VIS)
117 face images captured in daytime and NIR face images captured in nighttime. Re-
118 sults for intra-spectral as well as cross-spectral face matching are provided, and a
119 FR algorithm using SIFT and random subspaces is presented. However, the 100
120 meter and 150 meter ranges have quite poor results. In [23] a SWIR face recogni-
121 tion system is discussed that was used from the collection of multi-spectral data.
122 Cross-scenario matching experiments are discussed in [4]. There, both commer-
123 cial as well as academic FR algorithms are used, including LBP [1] and LTP
124 [24]. Also, a number of photometric normalization techniques are utilized, e.g.
125 CLAHE [11], single scale retinex with logarithmic (SSRlog) or with arc-tangent
126 transformation (SSRatan), in order to facilitate intra-spectral and cross-spectral
127 matching. Furthermore, datasets on SWIR and MWIR bands were collected, at
128 multiple progressive difficulty levels. Promising results regarding the utility of
129 other FR cross-scenarios, e.g. in the MWIR band is provided at [3].

130 When focusing only in NIR FR approaches published in the literature, we can
131 state that they can be grouped into the following main categories: (i) NIR FR:
132 Both gallery and probe sets are composed of only NIR images [25, 26, 27, 28, 29,
133 30, 31]. (ii) Image Synthesis: usage of image synthesis to convert NIR images to

Table 1: NIR FR literature, including the FR matching category, as well as the approaches, environment and standoff distances used (see also table at [8]).

Category	Literature	Approach	Indoors/Outdoors	Standoff Distances
Homogeneous FR NIR vs. NIR	Li et al., 2007 [29]	LBP, Adaboost	Indoors	0.5 ~ 1m
	Zhang et al., 2010 [28]	Gabor, DBC	Indoors	0.8 ~ 1.2m
	Huang et al. 2007 [26]	ELBP, Adaboost	Indoors	~ 1.5m
	Shen et al. 2012 [31]	DBC, Adaboost	Indoors	~ 1.5m
	Kang et al. [8]	Filtering, SIFT, MLBP	Indoors/Outdoors	1m, 60m, 100m, 150m
	Bourlai et al. [7]	CSU Face Matchers	Indoors/Outdoors	1.5m, 30m, 60m, 90m, 120m
Heterogeneous FR VIS-NIR	Yi et al. 2007 [38]	PCA-CCA	Indoors	~ 1.5m
	Liao et al. 2009 [39]	DoG, MB-LBP, G. Adaboost	Indoors	~ 1.5m
	Maeng et al. 2011 [22]	DoG-SIFT	Indoors	1m, 60m, 100m, 150m
	Klare & Jain 2013 [40]	MLBP, SIFT, LDA, Kernel	Indoors	0.8 ~ 1.2m
	Kang et al. [8]	Filtering, SIFT, MLBP	Indoors/Outdoors	1m, 60m, 100m, 150m
	Bourlai et al. [7]	CSU Face Matchers	Indoors/Outdoors	1.5m, 30m, 60m, 90m, 120m

visible ones, before FR experiments are conducted [32, 33, 34], and (iii) Cross-scenario FR: the probe face images are NIR, while the gallery face image are visible (typically mug shots collected indoors and at a fixed standoff distance, a case that is more realistic in a law enforcement scenario). In [7] (part of this study is discussed in this paper), a night-time, middle-range near infrared sensor is evaluated at four distances ranging from 30 to 120 meters, and results on both intra-spectral (visible to NIR) as well as intra-distance matching are provided. Thus, what we propose is an approach related to the first but mainly to the third category. Table 1 summarizes representative NIR FR approaches reported in the literature pertaining to the first and last category.

Examples of context-assisted FR include [35, 36], where sensed and inferred contextual meta-data are utilized in order to enhance recognition in camera-phone photos, as well as [37], where the interplay between people, events, and locations is utilized in order to create a unified recognition system.

148 From all the aforementioned published work in NIR FR, the closest paper to
 149 ours is [8]. The main differences are the following: (1) we used a NIR camera
 150 sensor with a NIR illuminator, while in [8] they used a visible camera with tele-
 151 photo lenses and a NIR illuminator. The developed system from [8], can capture
 152 better quality images at longer distances than our developed system. (2) The de-
 153 mographic data, time and period of collection are different. (3) A MFSDF face
 154 matching scheme is proposed that significantly improves the performance of face
 155 recognition system from the database collected under cross-distance and cross-
 156 spectral scenarios. (4) In our paper, we exploited further the cross-scenarios with
 157 the context of demographic information (gender class) and showed it is useful to
 158 improve face identification performance. (5) The database has video sequences of
 159 full frontal mid-range NIR and visible 232 face images of each subject, resulting
 160 in a total of 103×5 videos (103×4 NIR 233 outdoors and 103 visible indoors)
 161 per subject. *To the best of our knowledge, our study is the first in the literature*
 162 *where the NIR face images were captured using a NIR camera system with a NIR*
 163 *illuminator, outdoors, only at night-time (pitch black), at variable distances, and,*
 164 *the demographic information is also captured and used for identification in this*
 165 *database.*

166 What follows, is a description of baseline experiments, our proposed method-
 167 ological approach, including the NIR camera system used for the purpose of this
 168 study, the face image data collected. Then, we will discuss the FR algorithms
 169 tested for our same- and cross-scenario matching and we will proceed with the
 170 description of our new proposed method and the analysis that we carried out to-
 171 wards answering our main research questions as discussed in Section 1 and Fig. 2.

172 3. Methodological Approach

173 3.1. Night-Time Imagery

174 The mid-range camera system used in this work is a Near-IR camera (pro-
 175 vided by Vumii Imaging Inc.) that operates at 850 nm. It is a unique outdoor
 176 perimeter and border surveillance camera system, and its bulk version integrates
 177 (i) a NIR LED illuminator that is invisible to the human eye, (ii) a camera with
 178 high-magnification optics (continuous optical long-focal length zoom) placed on
 a precision pan-tilt platform (see Fig. 3).

Figure 3: 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.

179

180 3.2. Live Subject-Capture Setup and Datasets

181 Two cameras were used in our live subject capture setup: (a) Canon EOS 5D
 182 Mark II, i.e. a digital SLR camera that has a 21.1-mega-pixel full-frame CMOS
 183 sensor, and (b) a NIR mid-range imaging system that leverages a focused-beam

array LED technology combined with an optimized imager, optics, and pan-tilt platform. The camera also has an IR illumination source focused LED beam array (850nm). The live face capture configuration we used is illustrated in Fig. 4.

The *NIR database* was assembled outdoors at night time spanning over a time period of 20 days. Then, the subjects' mug shots was also taken using the visible

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.

camera in an indoors controlled environment. In total, 103 subjects (69 male + 34 female) participated in this experiment. The more detail information about the data preparation for FR studies is provided in [7].¹ Table 1 provides information about relevant work to ours, while Table 2 below compares the WVU, NIR Mid-Range and LDHF face databases for cross-distance and cross-spectral face matching. The pre-processing steps and the FR studies we performed will be described below, starting first, with our proposed multi-feature

¹*Data Release of the (WVU) NIR Mid-Range Face Dataset:* This is, currently, a private database with availability determined on a case-by-case basis. If interested in working with this database, please contact Thirimachos Bourlai, at ThBourlai@mail.wvu.edu.

Table 2: Summary of face image databases for cross-spectral and cross-distance matching using long range data. *Note: WVU database consists of video sequences for each subject. Still images were selected from those sequences to perform the FR studies. In this work 103×8 NIR outdoors (4 for gallery and 4 for probes) and 103 visible indoors face images per subject were used.*

Database	# Subjects	# Images	Sensors	Day/Night	Indoors/Outdoors	Distances
LDHF[8]	100	200	Visible	Day	Indoors	1m
	100	600	Telephoto, NIR illuminator	Day and Night	Outdoors	1m, 60m, 100m, 150m
NIR WVU[7]	103	$n \times 103$	Visible	Night	Indoors (mugshots)	1.5m
	103	$n \times 103$	NIR System	Night	Outdoors	30m, 60m, 90m, 120m

scenario dependent fusion scheme.

3.3. Multi-Feature Scenario Dependent Fusion

To perform cross-scenarios face matching, we propose a multi-feature scenario dependent fusion (MFSDF) scheme. It involves four main steps: (i) *Pre-processing of images with and without the usage of mask*, (ii) *Feature extraction using global and local descriptors, such as Gabor, HOG and LBP*, (iii) *Learning Subspace* (iv) *Fusion of scores based on a decision level scheme*.

Pre-processing: Geometric normalization of images is performed to compensate for slight perturbations in the frontal pose. We adopt two different methods: with and without the usage of a mask.

Normalization With Mask: To perform the normalization with mask, we use the technique developed from AFIES (more detail information is provided in [41]). A sequence of normalization steps are performed 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), and pixel normalization

Figure 5: Normalized elliptical face mask with a standard size of 130×150 pixels.

212 (scales the pixel values to have a mean of zero and a standard deviation of one).

213 Finally, cropped an elliptical face mask to a standard size of 130×150 pixels (see
214 Fig. 5).

215 **Normalization Without Mask:** When mask is not used, in order to localize the
216 face region, the two main steps of our approach include, eye detection and affine
transformation. First, the eye center positions are located and used to geometri-

Figure 6: Normalized face region with a standard size of 128×128 pixels.

217

218 cally normalize the images, based on the located eye coordinates, the canonical

219 faces are automatically generated by applying an affine transformation. Faces are
220 first aligned by placing the coordinates of the eyes in the same row, such that the
221 slope between the right and left eye is zero degrees. Finally, cropped the face
222 region to a standard size of 128×128 pixels (see Fig. 6).

223 **Feature Extraction:** (i) LBP: provides texture-based information. It is highly
224 discriminative, efficient and proved to performs well when used as part of a FR
225 system [24]. It performs well even when the background is not uniform and edges
226 are noisy. (ii) Gabor: features are used to extract face shapes and appearance. The
227 Gabor wavelets transformation provides desirable features and captures proper-
228 ties like spatial locality, spatial frequency and orientation selectivity. The features
229 extracted from Gabor filtered images are more robust to illumination and facial
230 expressions. In this work, we used 40 Gabor wavelets with the scale value ν lies
231 in range from $\{0, 1, 2, 3, 4\}$ and eight orientations μ in the range of $\{0, 1, \dots, 7\}$.
232 (iii) HOG: This is one of the most well-known local shape descriptors in com-
233 puter vision [40]. The main idea is to extract the local orientation information
234 rather than the magnitude of image patches. Images are divided into overlapping
235 or non-overlapping cells and neighboring cells consist of a local region that rep-
236 resented as a block. The local shape information (HOG features) is computed
237 for each block. The extracted features of blocks are concatenated into a vector x
238 (components of x are local features of image). We selected the cell size 8×8 and
239 block size 2×2 .

240 **Feature Subspace:** A set of features is based on LBP, Gabor and HOG methods
241 for NIR and VIS images. To reduce the dimensionality of the feature space, we
242 adopted the method used by Tan et al. [24], where they only used LBP and Ga-
243 bor image feature descriptors. In our work we extended the feature space to LBP,

244 Gabor and HOG and, further than that, used the KLDA learning based analysis
245 method to reduce the dimensionality problem.

246 **Fusion of scores:** It is based on decision level scenarios. We select 11 different
247 scenarios: (i) the first three scenarios are based on the usage of single feature de-
248 scriptor, namely the Gabor, HOG or LBP, (ii) the next six scenarios are based on
249 the usage of two features descriptors, using sum and weighted fusion schemes. In
250 the sum fusion scheme, we select three combinations: Gabor+LBP, Gabor+HOG
251 and HOG+LBP. In the weighted fusion scheme, we select combinations with two
252 features and, then, weights are assigned based on the performance of the indi-
253 vidual feature descriptor. (iii) The last two scenarios are based on all three fea-
254 ture descriptors, using the sum (Gabor+LBP+HOG) and weighted fusion scheme
255 where weights are assigned to each descriptor based on the performance scores
256 (distance scores). Finally, we performed an empirical evaluation in order to select
257 the scenario which provides us with best rank-1 scores.

258 3.4. Baseline Face Recognition Matchers

259 In our cross-scenario FR studies we used both commercial and academic FR
260 software. While the pre-processing routines employed by the commercial soft-
261 ware are not known, the academic software employed the following pre-processing
262 and face matching modules.

263 - **Pre-Processing:** This step is the same as the pre-processing step in Section 3.3.

264 - **Face Recognition Tools:** Both commercial and academic software were em-
265 ployed to perform the FR experiments. In terms of the commercial off-the-shelf
266 (COTS) software, we used the *Identity Tools G8* (www.11id.com) provided by L1
267 Systems. In the academic software we used standard FR methods are provided
268 by the Academic Face Identification Evaluation System (AFIES) CSU [41], in-

cluding *Principle Components Analysis* (PCA) [42, 43, 44], a combined *Principle Components Analysis and Linear Discriminant Analysis algorithm* (PCA+LDA) [45], and the *Bayesian Intra-personal/Extra-personal Classifier* (BIC) using either the Maximum likelihood (ML) or the Maximum a posteriori (MAP) hypothesis [46].

4. Face Recognition Studies

4.1. Matching Across Different Scenarios

We evaluate system performance using the CSU, the commercial and our proposed FR methods, and utilize the datasets briefly discussed in subsection 3.2. To check the efficiency of our system, we selected 5 different sets, with different training and testing combinations and an extended gallery dataset. We performed the following experiments:

Experiment 1: Visible vs. Visible (intra-spectral) face matching - it provides the rank-1 identification rates of a conventional FR system. For that purpose we use only a commercial software.

Experiment 2: NIR vs. NIR (intra-spectral) and intra-distance face matching at all distances available. The experiments performed were *30m vs. 30m* (baseline, best quality images for the camera sensor used), *60m vs. 60m*, *90m vs. 90m*, and *120m vs. 120m*.

Experiment 3: We also match cross-spectral and cross-distance images, i.e. the baseline visible images to NIR images captured at *30m*, *60m*, *90m* and *120m* respectively.

Experiment 4: We compare cross-distance images, i.e. the baseline NIR images (*30m*) to NIR images captured at *60m*, *90m* and *120m* respectively. Equal impor-

293 tantly, as a case study (see more information below) we also investigated whether
294 [demographic information](#) can assist in improving cross-distance and cross-spectral
295 FR performance.

296 **Experiment 5:** We extended the gallery data, using LDHF database collected
297 from [8]. For training based FR matchers (AFIES and proposed method), used
298 either the same or different datasets for training and testing. We extended the
299 training set with more subjects and images for the database collected under dif-
300 ferent environment conditions i.e. indoor or outdoor, different distances. We used
301 variable training sets but due to the page limitation of this paper we cannot include
302 and discuss all results.

303 While the main cross-scenario FR experiments (1-2) described above (Section 4.1)
304 are easy to understand, we provide more discussion on experiments 3, 4 and 5.
305 Here we investigate whether, the change in distance (*30 m to 60m, 90m and 120m*)
306 and sensor (gallery in VIS and Probe in NIR), affects the performance of face
307 recognition system.

308 We also propose the MFSDF face matching scheme to improve the identification
309 rank-1 performance of the system, for the database collected under un-controlled
310 conditions. We also investigate whether [demographic information](#), in particular
311 the gender class (male and female) and extended gallery data, contribute to FR
312 performance under certain conditions, and this has never been investigated in the
313 past, as we have commented above.

314 Please note that the identification performance of the system is evaluated through
315 the cumulative match characteristic (CMC) curve. The CMC curve measures the
316 $1 : m$ identification system performance, and judges the ranking capability of the
317 identification system.

318 5. Experimental Results

319 What follows is the description of two sets of FR experiments using a set
320 of commercial and academic face matching algorithms. In the first set of ex-
321 periments, no [grouping in the context of demographic information](#) is used. Our
322 experiments aim to illustrate how our baseline NIR FR system operates when
323 compared to a conventional visible FR system (where face images are captured
324 under controlled conditions). We need to know *what is the rank-1 identification*
325 *rate when matching NIR to NIR good quality, long range face images (30m vs.*
326 *30m)*. Finally, we need to know the extent of which the rank-1 identification rate
327 is affected when standoff distance increases. This is established by performing
328 intra- and cross-distance NIR FR matching when going from 30 meters and up to
329 120 meters away. Cross-spectral and cross-distance matching is also investigated
330 using the same commercial, academic and proposed algorithms. In the *second*
331 *set of experiments, i.e. Experiment as discussed in Section 4.1, we are trying to*
332 *determine whether the usage* [grouping in the context of demographic information](#)
333 can enhance recognition performance. Hence, we investigate which combinations
334 of available data are most beneficial to the identification accuracy of the NIR FR
335 system.

336 Table 3, depicts information about the total number of, datasets, cross-scenarios
337 and face recognition algorithms are selected. In this work, we have selected the
338 datasets with and without [the context of demographic information](#). For without
339 the context of demographic information, all data is used and with demographic
340 information gender class (male and female group) is used. For each dataset, we
341 have randomly divided the 50% data as training set and rest of data set is used as
342 testing set. [There is no overlap between the training and testing images. In each](#)

Table 3: Summary of total number of face recognition experiments are performed for each dataset, with and without [grouping in the context of demographic information](#). To perform the FR experiments, two FR cross-scenarios are selected cross-distance (CD) and cross-spectral (CS).

Datasets	Train/Test Datasets	# Scenarios	AFIES, COTS and Proposed MFSDF	# Total Experiments
All	4	3 CD + 4 CS	6 + 1 + 2	252
Male	4	3 CD + 4 CS	6 + 1 + 2	252
Female	4	3 CD + 4 CS	6 + 1 + 2	252

experiment, the subjects that used in training, were not used for the testing. This process is repeated several different times, using random selection of training and testing set each time. Two cross-scenarios are selected: CD and CS. For CD NIR vs. NIR face matching is performed for 3 sets: *30m vs. 60m*, *30m vs. 90m* and *30m vs. 120m*. For CS VIS vs. NIR face matching is performed for 4 sets: *1.5m vs. 30m*, *1.5m vs. 60m*, *1.5m vs. 90m* and *1.5m vs. 120 m*. Cross-scenarios are investigated using academic, commercial (non-training based) and the proposed MFSDF face matching scheme. In table 3 we can see the total number of face matching experiments performed for each dataset.

5.1. [Baseline and Matching Results Before Grouping in the Context of Demographic Information](#)

Inter-Distance Matching: In this, we compare NIR to NIR, intra-distance face images. The experiments performed were *30m vs. 30m* (baseline, best quality images), *60m vs. 60m*, *90m vs. 90m*, and *120m vs. 120m*. For this purpose we employed G8 (COTS) and the academic software (AFIES) [41]) while the training set size was varied to determine whether larger training sets will result in higher

Table 4: In this table we investigate the *intra-spectral*, *intra-distance* matching scenarios without demographic information: experimental results when running all CSU FR algorithms when using 20%, 40% and 60% of the NIR data for training and the rest data (80%, 60% and 40% respectively) for testing. When CSU was used, the experiments were run 10 times and the rank-1 scores presented here are the means. G8 was also tested for each scenario. Note that there is one case (90m) where rank-1 was about 38% vs. 59% with the 120m data. This was because the experiment was run once and we noticed that some 90m face images selected for matching were more heavily affected by background noise (e.g. passing cars and illumination) due to the time of the collection.

FR Algorithm	Intra-Spectral (NIR vs. NIR), Intra-Distance Matching (Rank-1)											
	30 m			60 m			90 m			120 m		
	20%	40%	60%	20%	40%	60%	20%	40%	60%	20%	40%	60%
Bayesian MAP	0.9898	0.9879	0.9952	0.9042	0.9486	0.9491	0.9546	0.9778	0.9962	0.9240	0.9617	0.9815
Bayesian ML	0.9950	0.9976	0.9979	0.9943	0.9958	0.9973	0.9467	0.9675	0.9833	0.9164	0.9524	0.9975
LDA Euclidean	0.9923	0.9994	1.000	0.9905	0.9986	1.000	0.9617	0.9911	1.000	0.9229	0.9798	1.000
LDA lda-Soft	0.9922	0.9994	1.000	0.9892	0.9984	1.000	0.9598	0.9907	1.000	0.9200	0.9817	1.000
PCA Euclidean	0.9794	0.9873	1.000	0.9639	0.9008	0.9872	0.9107	0.9313	0.9476	0.8782	0.9137	0.9405
G8	0.9564			0.6942			0.3738			0.5923		

359 recognition performance independent of whether we are operating at 30 meters or
360 120 meters standoff distance. Hence, (a) we randomly selected 20, 40, 60% of the
361 images for training and the rest images were used for testing, and (b) this process
362 was repeated 10 times. The identification performance results of intra-spectral
363 experiments are summarized in Table 4.

364 Based on the results of the baseline experiments, we determined that the results
365 from AFIES outperformed the COTS software, where the identification rate is
366 37% for 90m and 59% for 120m (see Table 4).

367 **Cross-Distance Matching:** In this experiment, we compared cross-distance face
368 images, i.e. the baseline NIR face images (30m) were compared to NIR images
369 captured at 60m, 90m and 120m respectively. The intra-spectral, cross-distance
370 experiments are summarized in Table 5, Fig. 7 (*NIR 30m vs. NIR 60m*) and Fig. 8

Table 5: In this table we investigate the *intra-spectral*, *cross-distance* matching scenarios (without demographic filtering): experimental results when running all FR algorithms using 50% of the NIR data for training and the rest of the data for testing. For each algorithm including, AFIES, COTS and proposed MFSDF face matching scheme, the experiments were run several times and the rank-1 scores presented here are the means.

FR Algorithm	Intra-Spectral (NIR vs. NIR), Cross-Distance Matching (Rank-1)		
	30 vs. 60 m	30 vs. 90 m	30 vs. 120 m
	50%	50%	50%
AFIES			
Bayesian MAP	0.85	0.52	0.36
Bayesian ML	0.86	0.60	0.38
LDA Euclidean	0.88	0.61	0.38
LDA lda_Soft	0.88	0.64	0.40
PCA Euclidean	0.68	0.27	0.20
PCA MahaCosine	0.86	0.68	0.46
COTS	0.16	0.02	0.01
Proposed Methods			
MFSDF Without Mask	0.89	0.66	0.55
MFSDF With Mask	0.90	0.68	0.54
Fusion of MFSDF (best set)			
With and Without Mask	0.93	0.81	0.64

(NIR 30m vs. NIR 90m and NIR 30m vs. NIR 120m).

Based on the results, we determined that proposed method and AFIES achieves similar identification results for NIR 30m gallery matched against NIR 60m probe. The rank-1 score is 88% for AFIES (LDA-EUC and LDA lda-soft) and 93% from the proposed method (fusion of mask and non-mask). On the other hand, identification results are very low using COTS software, where the rank-1 score accuracy is 16%. For both 90m and 120m NIR probe images, proposed approach achieves significant improvement compared to AFIES. For example for 90m rank-1 score is

Figure 7: *Intra-spectral, cross-distance matching scenarios for NIR 30m (Gallery) against NIR 60m (Probe)*: Performance of baseline face recognition and proposed MFSDF face matching scheme for cross-distance images (without demographic information). Each algorithm was run several times and here rank scores are presented from best performing set.

379 81% when using our proposed method, when compared to only 68% from AFIES
 380 (PCA MahaCosine). For 120m, AFIES achieves 46% identification rate, while the
 381 proposed method achieves 64% rank-1 accuracy.

382 The CMC curves for the first 5 ranks, for the best performed set out of ran-
 383 domly selected sets, are represented in Figs. 7 and 8. The best rank-1 scores

Figure 8: Intra-spectral, cross-distance matching scenarios for NIR 30m against NIR 90m (Left) and NIR 30m against NIR 120m (Right) (without grouping in the context of demographic information): Each algorithm was run several times and here the rank scores are presented from best set.

Table 6: In this table we investigate the *cross-spectral*, *cross-distance* matching scenarios (without [grouping in context of demographic information](#)): experimental results when using 50% of the data for training and the rest for testing. Experiments were run several times and rank-1 scores presented here are the means.

Gallery: VIS 1.5m vs. FR Algorithms	Intra-Spectral (NIR vs. NIR), Cross-Distance Matching (Rank-1)			
	NIR 30 m	NIR 60 m	NIR 90 m	NIR 120 m
	50 %	50 %	50 %	50 %
AFIES				
Bayesian MAP	0.19	0.15	0.21	0.15
Bayesian ML	0.18	0.16	0.23	0.13
LDA Euclidean	0.19	0.20	0.13	0.11
LDA lda_Soft	0.19	0.22	0.13	0.12
PCA Euclidean	0.08	0.08	0.07	0.08
PCA MahaCosine	0.12	0.10	0.09	0.01
COTS	0.48	0.03	0.02	0.01
Proposed Methods				
MFSDf Without Mask	0.56	0.34	0.21	0.16
MFSDf With Mask	0.50	0.37	0.23	0.16

384 achieved using our method are 77% (no mask), 75% (with mask) and 81% for
385 fusion of mask and no mask for the 90m (see Fig. 8) and 64% for fusion of mask
386 and no mask method for 120m probe.

387 **Cross-Spectral Matching:** We compared visible to NIR face images captured
388 at 30m, 60m, 90m and 120m. For cross-spectral, experiments are summarized in
389 Table 6 and Fig. 9 (*VIS vs. NIR 30 m and VIS vs. NIR 60m*). In all tables we can
390 see the mean rank-1 identification rates when using AFIES, COTS and proposed
391 MFSDf system.

392 Based on the results, we determined that proposed method achieves better

(a) AFIES (*VIS* vs. *NIR 30m*)

(b) AFIES (*VIS* vs. *NIR 60m*)

(c) Proposed With Mask

(d) Proposed With Mask

(e) Proposed Without Mask

(f) Proposed Without Mask

(g) AFIES and COTS vs. Proposed

(h) AFIES and COTS vs. Proposed

Figure 9: Cross-spectral, cross-distance matching scenarios for VIS 1.5m (Gallery) against NIR 30 m (Probe) (Left) and VIS 1.5m (Gallery) against NIR 60 m (Probe) (Right).

393 performance results compared to AFIES and COTS system, for gallery at *30m*
394 and probe at *60m*, the identification rank-1 accuracy is 56% (without mask) from
395 proposed method, 19% from AFIES and 48% from COTS. Our proposed method
396 achieves significant improvement over the academic and commercial method for
397 *60m* and *90m* distance. For *60m*, the identification accuracy is, 37% for proposed
398 MFSDF, 22% for AFIES and 3% from COTS. For *90m*, the identification accuracy
399 is, 44% for proposed MFSDF, 23% for AFIES and 2% from COTS. For *120m*,
400 results are similar from proposed and AFIES (15%) and very low performance
401 results from COTS.

402 The CMC curves for first 5 ranks, for the best performing set out of randomly
403 selected 4 different sets, are represented in Fig. 9. The identification accuracies
404 are 58% for without mask, 52% for with mask from proposed system, 21% for
405 AFIES and 51% for COTS.

406 COTS system provided us with good results only for one case, where we
407 matched the gallery images against *NIR 30m*. The main reason for better per-
408 formance of commercial system is that images are still with good quality. In our
409 work, we collected the database under un-controlled conditions at long distances
410 (for example at *60m*, *90m* and *120m*). The poor quality of the images (at long
411 distances) results in poor performance of the COTS system.

412 In order to examine the effectiveness of FR algorithms, each experiment is re-
413 peated several times (i.e. each time a different training set was randomly selected)
414 for cross-scenarios using academic, commercial and proposed face recognition
415 methods. To see the performance variation between three FR matchers, we first
416 plotted the boxplots. In Fig. 10, where the first 2 figures are for cross distance,
417 and rest of the 4 figures are for cross spectral face matching.

418 In this we compared the rank-1 score from proposed method with AFIES. For
419 COTS, it performed well only for *VIS 1.5m* vs. *NIR 30m* and scores are very low
420 for rest of the 7 sets when gallery data (*NIR 30m*, *VIS 1.5m*) is compared against
421 probe data (*60m*, *90m*, *120m*) as represented in Table 5 for cross distance and Ta-
422 ble 6 for cross spectral experiments.

423 Based on the mean and variance of boxplots, the matching accuracy from pro-
424 posed method (using either with or without mask), for *NIR 30m* vs. *NIR 90m*, is
425 overall higher from proposed method compared to AFIES. For *NIR 30m* vs. *NIR*
426 *120m* and from cross-spectral (all the 4 cases c, d, e and f), our proposed method
427 outperformed AFIES.

428 5.2. Matching Results from Grouping in the Context of Demographic Information

429 The use of [demographic information](#) (gender class) is proposed to improve the
430 performance of face recognition systems. In our work, three different face recog-
431 nition experiments are conducted: AFIES, COTS and proposed MFSDF method.
432 For each FR cross-scenario, experiments are conducted, for example for cross-
433 distance, *NIR* vs. *NIR (30m to 60m, 90m and 120m)* and for cross-spectral *VIS*
434 vs. *NIR (1.5m to 30m, 60m, 90m and 120m)*. Each experiment is repeated several
435 times for two FR cross-scenarios. For each demographic group (male and female),
436 in total 63 FR experiment are conducted considering two FR cross-scenarios as
437 represented in Table. 3.

438 **Demographic-based Cross-Distance Matching:** For cross-distance scenario, based
439 on the results for male class, for *60m* and *90m* (probe images), we determined that
440 identifications results are similar for proposed and AFIES method. From proposed
441 method, the rank-1 score accuracy is 94% for *60m* and 81% for *90m* as shown in
442 Table.7. For *120 m* distance, our proposed method performs better and the rank-1

(a) NIR 30m vs. NIR 90m

(b) NIR 30m vs. NIR 120m

(c) VIS 1.5m vs. NIR 30m

(d) VIS 1.5m vs. NIR 60m

(e) VIS 1.5m vs. NIR 90m

(f) VIS 1.5m vs. NIR 120m

Figure 10: Box-plots for cross-distance using intra-spectral and cross-spectral matching scenarios after running each experiment several times.

Table 7: In this table we investigate the *intra-spectral*, *cross-distance* matching scenarios for database after the usage of [the context of demographic information](#): experimental results when running all FR algorithms using 50% of the NIR data for training and rest of the data for testing. For each algorithm including, AFIES, COTS and proposed MFSDF, the experiments were run several times and the rank-1 scores presented here are the means.

FR Algorithm	Intra-Spectral (NIR vs. NIR), Cross-Distance Matching (Rank-1)		
	30 vs. 60 m	30 vs. 90 m	30 vs. 120 m
	50%	50%	50%
MALE DATA			
AFIES			
Bayesian MAP	0.92	0.69	0.40
Bayesian ML	0.93	0.74	0.47
LDA Euclidean	0.93	0.69	0.45
LDA Ida_Soft	0.93	0.69	0.47
PCA Euclidean	0.79	0.39	0.28
PCA MahaCosine	0.94	0.79	0.52
Proposed Methods			
MFSDF Without Mask	0.92	0.78	0.57
MFSDF With Mask	0.92	0.71	0.52
Fusion of MFSDF (best set)			
With and Without Mask	0.94	0.81	0.71
FEMALE DATA			
AFIES			
Bayesian MAP	0.78	0.53	0.38
Bayesian ML	0.82	0.56	0.42
LDA Euclidean	0.74	0.47	0.38
LDA Ida_Soft	0.75	0.46	0.39
PCA Euclidean	0.56	0.21	0.17
PCA MahaCosine	0.84	0.61	0.49
Proposed Methods			
MFSDF Without Mask	0.65	0.51	0.44
MFSDF With Mask	0.71	0.47	0.41
Fusion of MFSDF (best set)			
With and Without Mask	0.82	0.74	0.54

443 score accuracy is improved from 52% to 71%.

444 Based on the results for female class, for *60m* (probe images), we determined
445 that identifications results are similar for proposed method and AFIES. From pro-
446 posed method, the rank-1 score accuracy is 82% for *60m* as represented in Table.7.
447 For *90 m* and *120 m*, our proposed method performs better and the rank-1 score
448 accuracy is improved from 61% to 74% for *90m* and 49% to 54% for *120m*.

449 **Demographic-based Cross-Spectral Matching:** For cross-spectral scenario,
450 based on the results for male class, we determined that proposed system outper-
451 formed both the commercial and academic software for all four cases including,
452 when gallery images (*VIS 1.5m*) matched against probe images (*NIR 30m*, *NIR*
453 *60m*, *NIR 90m* and *NIR 120m*). For *30m*, identification performance is improved
454 from 34% (AFIES), 51% (COTS) to 61% (Proposed). For *60m*, identification
455 performance is improved from 33% (AFIES), 3% (COTS) to 46% (Proposed) and
456 26% (AFIES), 2% (COTS) to 29% (Proposed) for *90m*. The rank-1 score accuracy
457 for *120m* is improved from 18% (AFIES) to 30% (Proposed).

458 Based on the results for female class, for *NIR 30m*, COTS system performs
459 better than both academic and proposed system. The [demographic information](#)
460 and good quality of the images is the main reason for better performance of com-
461 mercial system. The results for (AFIES) and proposed method are similar in per-
462 formance. Moreover, for each of these three FR matchers (AFIES, COTS and
463 proposed MFSDf), performance of the system is not improved and rank-1 scores
464 are close to results without any [grouping in context of demographic information](#).
465 In some of the cross scenarios, FR system did not perform well and the rank-1
466 score is decreased (after grouping of the data into female class) from 23% (with-
467 out grouping in the context of demographic information) to 18% (AFIES) for *NIR*

Table 8: In this table we investigate the *cross-spectral*, *cross-distance* matching scenarios for database after the usage of [grouping in the context of demographic information](#): experimental results when running using 50% of the data for training and the rest data for testing. Experiments were run several times and the rank-1 scores presented here are the means.

VIS 1.5m vs. FR Algorithm	Cross-Spectral (VIS vs. NIR), Cross-Distance Matching (Rank-1)			
	NIR 30 m 50%	NIR 60 m 50%	NIR 90 m 50%	NIR 120 m 50%
MALE DATA				
AFIES				
Bayesian MAP	0.34	0.33	0.18	0.14
Bayesian ML	0.31	0.29	0.19	0.14
LDA Euclidean	0.30	0.27	0.25	0.17
LDA lda_Soft	0.32	0.28	0.26	0.18
PCA Euclidean	0.17	0.15	0.15	0.08
PCA MahaCosine	0.20	0.26	0.18	0.14
COTS	0.52	0.03	0.02	0.02
Proposed Methods				
MFSDF Without Mask	0.47	0.39	0.24	0.23
MFSDF With Mask	0.51	0.39	0.23	0.25
Fusion of MFSDF (best set) With and Without Mask	0.61	0.46	0.29	0.30
FEMALE DATA				
AFIES				
Bayesian MAP	0.30	0.25	0.17	0.12
Bayesian ML	0.31	0.22	0.17	0.12
LDA Euclidean	0.26	0.21	0.18	0.14
LDA lda_Soft	0.27	0.23	0.18	0.12
PCA Euclidean	0.20	0.13	0.11	0.11
PCA MahaCosine	0.19	0.16	0.12	0.23
COTS	0.65	0.08	0.08	0.03
Proposed Methods				
MFSDF Without Mask	0.26	0.22	0.18	0.19
MFSDF With Mask	0.32	0.27	0.26	0.16

(a) AFIES (VIS vs. NIR 30m)

(b) AFIES (VIS vs. NIR 60m)

(c) Proposed With Mask

(d) Proposed With Mask

(e) Proposed Without Mask

(f) Proposed Without Mask

(g) AFIES and COTS vs. Proposed

(h) AFIES and COTS vs. Proposed

Figure 11: Cross-spectral matching scenarios for Male Data, VIS 1.5m (Gallery) against NIR 30 m (Probe) (Left) and VIS 1.5m (Gallery) against NIR 60 m (Probe) (Right).

468 90m, 56% (without demographic information) to 32% (proposed) for NIR 30m
469 and 37% to 27% (proposed) for NIR 60m of the system.

470 Based on the results, we conclude that (for all three FR matchers), female class
471 is more challenging to match in comparison to male class (with grouping in the
472 context of demographic information) and all data (without grouping). Klare et al.
473 [47] reported that, factors such as, use of cosmetics and small size of female face,
474 results in higher within-class variance and affects the identification performance
475 of system and supported our findings.

476 5.3. Face Matching With Extended Gallery Data

477 In this we used Long Distance Heterogeneous Face Database (LDHF) database
478 collected from Kang et al. [8], with 100 subjects to extend the gallery data. LDHF
479 data contains VIS and NIR images at distance of 1m, 60m, 100m and 150m. To
480 perform cross-distance face matching experiments, NIR images collected at dis-
481 tance from 1m to 150m are selected. For cross-spectral, VIS images at a distance
482 of 1m and NIR images at a distance of 1m, 60m, 100m and 150m distance are
483 selected. We repeated the same set of experiments, performed with and with-
484 out the usage of the context of demographic information using cross-distance and
485 cross-spectral face matching scenarios.

486 For cross-distance face matching, results are presented in Table 9. Based on
487 the results, we concluded that for 60m, identification rank-1 performance is higher
488 for AFIES system compared to our proposed system for with and without the us-
489 age of grouping in the context of demographic information. For 90m and 120 m,
490 our proposed system achieves better performance results than AFIES. For exam-
491 ple, the rank-1 score accuracies at 90m and 120m distances are 42% and 30% (All
492 Data), 48% and 36% (Male Class) and 25% and 20% (Female Class) respectively.

Table 9: In this table we investigate the *intra-spectral*, *cross-distance* matching scenarios with and without [grouping in the context of demographic information](#), with extended gallery: experimental results when running all FR algorithms using LDHF data for training and our data for testing.

FR Algorithm	Intra-Spectral (NIR vs. NIR), Cross-Distance Matching (Rank-1)		
	30 vs. 60 m	30 vs. 90 m	30 vs. 120 m
	50%	50%	50%
ALL DATA			
AFIES			
Bayesian MAP	0.77	0.34	0.12
Bayesian ML	0.78	0.38	0.20
LDA Euclidean	0.69	0.35	0.20
LDA lda_Soft	0.36	0.11	0.07
PCA Euclidean	0.58	0.21	0.09
PCA MahaCosine	0.67	0.31	0.17
Proposed Methods			
MFSDf Without Mask	0.71	0.42	0.30
MALE DATA			
AFIES			
Bayesian MAP	0.84	0.43	0.30
Bayesian ML	0.84	0.42	0.30
LDA Euclidean	0.75	0.39	0.15
LDA lda_Soft	0.37	0.15	0.05
PCA Euclidean	0.65	0.23	0.11
PCA MahaCosine	0.73	0.32	0.18
Proposed Methods			
MFSDf Without Mask	0.80	0.48	0.36
FEMALE DATA			
AFIES			
LDA Euclidean	0.44	0.11	0.17
LDA lda_Soft	0.11	0.05	0.09
PCA Euclidean	0.41	0.13	0.15
PCA MahaCosine	0.46	0.13	0.07
Proposed Methods			
MFSDf Without Mask	0.45	0.25	0.20

Figure 12: *Cross-spectral matching scenarios for VIS 1.5m against NIR 30m (top) and VIS 1.5m against NIR 60m (bottom) with extended gallery set (with grouping in context of demographic information).*

493

494 For cross-spectral scenario, we conducted face matching experiments using 5
 495 different sets. For *Set1*, LDHF data base is used for training and our database
 496 for testing. *Set2*, where our database is used for training and LDHF database for
 497 testing. *Set3* to *Set 5* are based on selection of both the databases to train the
 498 system (our and LDHF data) and rest of the data for testing. For example for *Set3*
 499 LDHF data is used for testing, in *Set4* our data is used for testing and, finally, in
 500 *Set5* both are used for testing (non-overlapping of training/testing).

Table 10: Measure of statistics (mean, median, minimum and maximum) for attained image quality scores: experimental results when visible images are used as reference images and long distance images (NIR 60m) as query images.

IQA Methods	UIQ		SSIM		FSIM	
Data Type	LDHF	OUR	LDHF	OUR	LDHF	OUR
Mean	0.88	0.73	0.43	0.28	0.74	0.68
Median	0.90	0.74	0.43	0.28	0.75	0.68
Minimum	0.66	0.44	0.34	0.12	0.69	0.59
Maximum	0.95	0.80	0.53	0.39	0.80	0.75

Based on the results, we conclude that the best performance results are achieved from *Set3*, where both LDHF and our data is used for training and only LDHF database is used for testing. The main reason for better performance for *Set3* is the quality of the images. To verify our face recognition results, a number of image quality assessment (*IQA*) methods are used. Since image quality indicators have been used in FR experiments before, providing valuable information, we decided to use them in this paper. For example, universal image quality (*UIQ*) was used in FR experiments [48, 49], structural similarity index method (*SSIM*) [50] and feature similarity index for image quality (*FSIM*). The visible images collected under controlled conditions (*VIS 1.5m*) are used as reference images. The images collected at a distance of 60m in NIR band are selected as query images. The quality score values are lies between 0 and 1.

Experimental results showed that for LDHF database (100 subjects), quality scores mean value is 0.88 for *UIQ*, 0.43 for *SSIM* and 0.74 for *FSIM*. On the other hand, for our database (103 subjects), quality scores mean value is 0.73 for *UIQ*, 0.28 for *SSIM* and 0.68 for *FSIM*. The statistical analysis results for quality scores (for both the databases) are presented in Table 10.

518 6. Discussion and Conclusions

519 The night-time mid-range NIR dataset represents a very challenging real-
520 world FR scenario. We conducted a comprehensive data collection with a sensor
521 capable of acquiring NIR images at standoff distances ranging from 30-120m. The
522 data collection effort (face images of subjects were acquired with intra-personal
523 variability) was designed to investigate the hypothesis that night time mid-range
524 NIR imagery would yield high recognition performance at short ranges that de-
525 grades as the distance of the target to the sensor increases. Different scenarios
526 were tested, allowing us to gain some understanding of the shortcomings of such
527 a FR scenario. As expected, intra-spectral (NIR) intra-distance experiments re-
528 sulted in a performance that reduces as a function of distance, especially at ranges
529 greater than 90 meters, where facial features become less prominent due to var-
530 ious factors including atmospheric conditions. Generally, all rank-1 rates appear
531 high (some matchers perform much better than others, e.g. LDA and Bayesian
532 MAP vs. PCA), but this can be explained by the fact that we were matching same
533 session data. When cross-distance matching experiments were performed and the
534 gallery set is composed of either NIR or visible face images, we determined that
535 the closer the standoff distance we operate to acquire face images at night the bet-
536 ter the identification performance is. In addition, the higher the training set size,
537 better is the identification performance.

538 We performed the identification experiments for three types of cross-scenarios:
539 (i) intra-distance and intra-spectral, (ii) cross-distance and intra-spectral, and (iii)
540 cross-spectral and cross-distance. We proposed a multi-feature scenario depen-
541 dent fusion face matching scheme and evaluated the performance improvement by
542 comparing with available academic and commercial systems. [Our results provide](#)

543 important evidence towards whether the proposed system can be taken into reality.
544 The main requirements for a real time face recognition system are: it should be
545 able to do the recognition for the database collected in challenging environments,
546 and, less time consuming for example can match the query data within seconds.

547 First, it is clear that our proposed method (MFSDF) can enhance the auto-
548 mated FR performance for the cross-scenarios. In the experimental results, it was
549 shown that the proposed system provides better performance results than both
550 AFIES and COTS systems, for cross distance (particularly for 30 vs. 90m and
551 120m) which initially resulted in the lowest accuracy using the COTS system.
552 For cross spectral scenarios, proposed system achieves better rank-1 score accu-
553 racy, particularly for VIS 1.5m vs. 30m, where the lowest accuracy recorded from
554 the AFIES system and for VIS 1.5m vs. NIR 60m the lowest accuracy recorded
555 from the COTS system. This suggests that our proposed method increases the FR
556 performance of our biometric system.

557 Second, through our experiments using grouping in the context of demo-
558 graphic information of the data, where we filtered the data based on gender class
559 (male and female), it was shown that male class provides improvement in the re-
560 sults for cross-distance and cross-spectral scenarios. On the other hand, female
561 class is more challenging to perform the face matching for all the matchers used
562 in this work as expected. We have a valid reason for the poor performance using
563 female class, for example the factors like facial makeup, size of face etc. With
564 extended gallery with more variation in the training data (including data collected
565 under different conditions like sensors, distances), where LDHF data is used for
566 training and our data for testing and vice versa, both the databases are used for
567 training and testing, it was shown that, it will improve the robustness of the face

568 recognition method as expected.

569 Third, We proposed a system that is efficient in comparison to the available
570 traditional methods. The time elapsed to run the cross-scenario experiments in-
571 cluding the training and testing part, is few seconds (e.g. 3 to 4 seconds). When
572 compared to our proposed system, the traditional FR systems used and tested were
573 much slower - it took hours to run the same set of experiments. At present, the pro-
574 gramming platform used to develop the proposed system is Matlab. In the future
575 we plan to use C++ so that we can develop a capability for real-time processing.

576 Beyond the concrete results and methods that were presented, there exist many
577 fruitful avenues for future extensions. For example, one could experiment with
578 more demographic filters like age, ethnicity etc. Most importantly, though, one
579 could investigate an important practical consideration: in our experiments, we
580 have performed this grouping in the context of demographic information manu-
581 ally. However, in autonomous practical systems, these have to be obtained au-
582 tomatically. Obtaining demographic information automatically is thus a fruitful
583 area for future research towards wider applicability of automated face recognition
584 systems that can perform well under difficult conditions.

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and with mask (Fig. 5) based on normalization technique developed from AFIES (more detail information is provided in the section 3.3 on pages 13-14).