Can we match Ultraviolet Face Images against their Visible Counterparts?

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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. However, face recognition (FR) for face images captured using different camera sensors, and under variable illumination conditions, and expressions is very challenging. In this paper, we investigate the advantages and limitations of the heterogeneous problem of matching ultra violet (from 100 nm to 400 nm in wavelength) or UV, face images against their visible (VIS) counterparts, when all face images are captured under controlled conditions.

The contributions of our work are three-fold; (i) We used a camera sensor designed with the capability to acquire UV images at short-ranges, and generated a dual-band (VIS and UV) database that is composed of multiple, full frontal, face images of 50 subjects. Two sessions were collected that span over the period of 2 months. (ii) For each dataset, we determined which set of face image pre-processing algorithms are more suitable for face matching, and, finally, (iii) we determined which FR algorithm better matches cross-band face images, resulting in high rank-1 identification rates. Experimental results show that our cross spectral matching (the heterogeneous problem, where gallery and probe sets consist of face images acquired in different spectral bands) algorithms achieve sufficient identification performance. However, we also conclude that the problem under study, is very challenging, and it requires further investigation to address real-world law enforcement or military applications. To the best of our knowledge, this is first time in the open literature the problem of cross-spectral matching of UV against VIS band face images is being investigated.

Keywords: Ultra-Violet (UV) Imaging, Face Recognition, Image Preprocessing, Intra-spectral, Cross-spectral, Distance Metrics.

1. INTRODUCTION
Biometric data enhances defense and security capabilities for identification of humans in day and night, and in variable weather and environmental conditions. Automated face recognition systems have become increasingly an important tool for security applications. Depending on the application, face can be used either independently or in combination with other modalities in order to increase recognition performance.

There are a number of practical issues that still need to be solved with FR systems. When designing such a system, one has to deal with a variety of problems that arise from each module of the overall system, i.e. data collection, transmission, data storage, signal processing and decision making. The data collection module has its own challenges. For example, FR systems perform well with frontal faces captured under controlled conditions (indoors, short standoff distance, sufficient illumination). The problem becomes more complicated (system performance can degrade) when face images are captured under variable illumination conditions, expressions and poses.

Another challenge is when data collection is performed using sensors that operate at different spectral bands (VIS, UV, infrared (IR)). Differences in appearance between images sensed in the VIS and the UV band...
are due to the properties of the object being imaged. Ultraviolet radiation is similar to visible light in all the physical aspects, the UV region has wavelengths lower than that of visible light. Due to the fact that UV and VIS bands are close, and both UV and visible face images can be captured using high quality camera sensors, the study of face recognition using data from those bands is expected to have promising results.\textsuperscript{11}

It is a fact that different sensors and wavelengths reveal different characteristics of a scene (e.g., in our dual band system, the features of a face).\textsuperscript{2} UV imagery generates a more complete image (e.g., human face) and in the case of UV face images, interesting facial features and texture are revealed. Therefore, the UV band may take advantage of information (facial features) that might go unobserved. However, it may also provide less qualitative information in comparison with visible band face imaging systems as shown in Fig. 3.

The UV band is positioned within the electromagnetic spectrum between the X-ray and the VIS band. The UV band ranges from 100 nm to 400 nm, and consists of the three bands: the long wave UV-A band that ranges from 315 nm to 400 nm, the medium UV-B that ranges from 280 nm to 315 nm and the short wave UV-C band that ranges from 100 nm to 280 nm. The UV-C band is of little significance, since most of the atmosphere readily absorbs this radiation.\textsuperscript{12} The UV-A light source, such as metal-halide lamp, is primarily used for dentistry and tanning purposes.\textsuperscript{13, 14} In addition, the light sources such as, pharos excimer laser and xenon chloride (XeCl) excimer laser, producing UV-B, are used for the treatment of skin diseases (such as the atopic dermatitis). The germicidal lamps producing UV-C are used for sterilization, a well proven technology for the destruction of air-borne bacteria, viruses and mold spores in scientific labs, medical facilities and processing industries.\textsuperscript{15} Another advantage of the usage of UV sensors is human body (patients) monitoring and therapeutic treatment programs.\textsuperscript{14, 16}

In this work, we have used a face imaging system designed by Faraghan Medical Camera systems\textsuperscript{18} for the purpose of collecting face images and conducting a FR study. The system is blocking the VIS and IR, only to capture UV face images contained in a standard xenon flash tube. We are not using any additional UV emitting light source (only UV from standard camera flash) in our experimental system. The specific UV filter used is allowing the UV wavelength range from 320-385 nm, and that is the one used to capture the face images for the purpose of our study.

1.1 Human Safety Measures

Before considering face matching studies, either same-spectral (matching UV against UV face images), as well as cross-spectral (matching VIS face images against their UV counterparts), it is crucial to understand the impacts of UV radiations on humans, in terms of their skin as well as eye safety.\textsuperscript{14, 16}

Skin Safety: The longest UV wavelength (UVA), can penetrate the middle layer of skin (dermis) but only at very high radiant exposures. The middle UV wavelength (UVB) can penetrate the outer layer of the skin (epidermis) and can causes skin burns, erythema etc.\textsuperscript{19} The shortest UV wavelength (UVC) has the maximum risk. However, natural UVC rarely reaches the earth. It is typically blocked by the ozone layer of the atmosphere.

![Figure 1. Spectral band representation for UV band and sub-bands UV-V, UV-A, UV-B and UV-C.\textsuperscript{17}](image-url)
before reaching the earth.\textsuperscript{20}

\textbf{Eye Safety:} The human eye is most sensitive to UV-C band in range from 265 nm to 275 nm. The UV-C most part is absorbed by the ozone layer.\textsuperscript{14,16} But, this band is easily found in Welder’s arc light. Commercial sources, such as mercury or germicidal lamps and short exposure to this band can cause cataract and DNA damage to biological surfaces.\textsuperscript{21}

The UV-A band, i.e. in the range from 300 to 400 nm (long wave), cannot perceived or sensed by humans directly, as human eye lenses block most of the radiation within this range. The short wavelengths are blocked by the cornea.

\section*{1.2 Related Work}

Ortiz et al.,\textsuperscript{15} developed a system for the analysis of dermatological aspects of a human body. In this system, the authors used three image sensors including: VIS, UV and IR light sensors to capture the database. The collected database was used for processing, analysis of skin surfaces and finally, for the treatment of the skin.  

Cooksey et al.,\textsuperscript{22} performed the reflectance measurements of human skin body in the range from UV band to IR band. A commercial spectrophotometer was used to collect the reflectance from each subject’s skin (forearm) within the band ranging 250 nm to 2500 nm. The results obtained in this work, served as a reference for optical properties of skin and provided help in the development of digital and physical tissue phantoms.

Fulton et al.,\textsuperscript{14} proposed a system where the authors utilized a UV camera to improve the appearance of a photo-damaged area and other skin conditions. In their work, they reported that images captured from an UV camera provides qualitative information to detect the pigment changes, melasma, vitiligo and other skin changes in human face. Based on their study, they concluded that UV cameras should become an integral component of a medical pre-screening system that is capable of detecting skin damage in the human body due to the sun.

Burgener et al.,\textsuperscript{12} proposed the risks and benefits associated with the exposure to the UV band in biological cabinets. In that work, the authors provided the information related to the guidelines and limitations for the use of UV band in safety cabinets. William et al.,\textsuperscript{21} proposed an iris recognition system using hyper-spectral signatures. There, the authors evaluated that spectral diversity can be used as a unique biometric identifier. In their system, three bands were selected VIS, UV and NIR in order to conduct biometric identification study.

Rickman et al.,\textsuperscript{11} proposed a system for biometric identification where human recognition is performed when matching UV to UV images. In that system, both gallery and probe images were collected in the UV band and thus, a UV database was generated. The identification was performed based on the detected skin region area including subject’s cheek, hand and forehead etc. However, the authors were focused only on same-spectral matching. In this paper we focus on both same-spectral and cross-spectral face matching studies.

\section*{1.3 Goals and Contributions}

In this paper, we study the problem of same-spectral and cross-spectral face recognition in heterogeneous environments, where the two bands used for the identification studies are VIS and UV. More specifically, we investigate the advantages and limitations of matching UV face images against UV as well as UV to VIS images, when the face images of either band were captured under controlled conditions. To the best of our knowledge, this is first time in the open literature the problem of FR using UV and VIS band face images is being investigated under homogeneous and heterogeneous matching scenarios.

The contributions of our work are three-fold; (i) We used a camera sensor designed with the capability to acquire UV images at short-ranges, and generated a dual-band (VIS and UV) database that is composed of multiple, full frontal, face images of 50 subjects. Two sessions collected span over the period of 2 months. (ii) For each dataset, we determined which set of face image pre-processing algorithms are more suitable for face matching, and, finally, (iii) we determined which FR algorithm better matches cross-band images, resulting in high rank-1 identification rates.

Three different experiments are performed. The first is focused on matching high quality face images captured in the VIS spectrum for the purpose of establishing a baseline. The second experiment compares facial images captured in UV band and the third experiment compares UV to VIS band face images. Experimental results show
that our proposed cross spectral matching (the heterogeneous problem, where gallery and probe sets have face images acquired in different spectral bands) algorithms achieve good identification performance for the database at hand.

1.4 Paper Organization
The rest of this paper is organized as follows. Section 2 presents the system design and the complete experimental set up. Section 3 provides a summary of the face recognition algorithms employed and the experiments conducted. Section 4 presents the experimental results while conclusions are drawn in Section 5.

2. SYSTEM DESIGN AND DATABASE
In this study, we have used an experimental system designed and developed by Faraghan Medical Camera Systems. The designed system uses the following components:

2.1 Imaging System
- **Canon Digital Rebel XT**: This digital SLR camera has a 8.0-megapixel full-frame CMOS sensor with DIGIC 4 image processor and a vast ISO range of 100-6400. It also has an auto lighting optimizer and peripheral illumination correction that enhances its capability. In this work, the Canon DSLR (Fig. 2) is used to obtain standard RGB, ultra-high resolution frontal pose face images in the VIS spectrum. The camera is TTL (through the lens) driven, meaning the flash will be adjusted based on a pre-flash measure of the amount of light reflected back from the subject through the lens. Subject distance and ambient light are also therefore taken into consideration.

- **Canon Macro Twin Lite MT-24EX**: This Flash is an extremely flexible and very easy to use. It can be rotated over an 80 degree angle around a lens, in 5 degree increments. It includes, full E-TTL flash control with compatible EOS camera (exposure compensation, flash exposure lock and ratio control of left-right flash tubes) and focusing lamps. The flash output for Canon MT-24 has a maximum power of guide number 72 feet at ISO 100, which means that a target of 18 feet away will be correctly illuminated with an aperture of f/4 (72 = 18 × 4) using a sensitivity of ISO 100. The flash heads form a triangle with the base formed by the two flashes and the subject chin cup at the third vertex. This is demonstrated in Fig. 2.
• **Filters:** In our experimental set up, Faraghan UV filters are used in the wavelength range from 320-385 nm. Both the UV filters and diffuser filters are located on the top and bottom pockets of the flash case. Filters are flipped (up/down) to capture the images in the UV and VIS bands (flip down for UV and up for VIS).

The aforementioned system components were used to assemble the WVU UV Face dataset.

### 2.2 Databases

The face images collected from the developed system are shown in Fig. 3. The database was assembled in two sessions spanning over a time period of 2 months. In the beginning of first session, the subjects were briefed about the data collection process. In total, 50 subjects participated in this experiment. Each session of the dataset has 4 frontal face images of each subject, resulting in a total of 400 images (200 images in UV and 200 in VIS). For each subject, we obtained images with and without employing a UV filter.

![Figure 3. Database collected from the designed system, VIS images (left) and UV images (right).](image)

The database collected from Type 1 to Type 6 skin types, according to the Fitzpatrick skin type classification scale. The Fitzpatrick scale is a semi-quantitative scale, made of six skin photo types and depends on the basal complexion, amount of melanin pigment and inflammatory response to UV. Based on this scale, Skin Type 1 (pale white skin), are those who always burn easily (sunburns) but do not tan at all. Skin Type II (fair skin), are those who burn easily and tan with difficulty, and Type III (darker white skin) who burn and tan moderately. Skin Type IV (brown skin), are those who burn minimally, Type V (dark brown skin) are those who burn rarely and Type VI (black skin type) who are almost never burn but tan readily. In Fig. 3, the top row images are collected from skin type I, II and III. The center row images are collected from skin type V and bottom row images are captured from skin type VI.

### 3. METHODOLOGY

In this section, we discuss the algorithms used for pre-processing both visible and UV face images. First, we applied geometric normalization on all visible and UV face images, using the manually annotated eye centers. Then, a specific photometric normalization technique was applied after performing an initial empirical study
(to determine which PN technique is more useful for achieving high rank-1 scores). Finally, we tested various face recognition techniques (including PCA, KPCA, KDA, KFA, LBP and LTP) and distance metrics such as Euclidean, Cosine Similarity and Cosine Mahalanobis, before concluding which combination of image pre-processing approaches, face matching algorithms and distance metrics result in the highest rank-1 scores when performing either same-spectral or cross-spectral matching experiments.

What follows is a brief description of the algorithmic steps applied in the intra-spectral and cross-spectral face matching studies conducted.

3.1 Pre-Processing Method

1. Geometrical Normalization: The geometric normalization scheme compensates for slight perturbations in the frontal pose. It is composed of two main steps, eye detection and affine transformation. The eye center positions are first located by manual annotation and are used to geometrically normalize the images. Based on the located eye coordinates, the canonical faces were automatically constructed by applying an affine transformation.\(^7\) Faces are first aligned by placing the coordinates of the eyes in the same row such that the slope between the right and left eye is zero degrees. Finally, all the faces are canonicalized to the dimension of 111×121 pixels.

2. Photometric Normalization: In terms of photometric normalization and in order to facilitate cross-spectral UV matching, we employed the contrast limited adaptive histogram equalization (CLAHE) technique. CLAHE operates on local regions (8×8 for our experiments) in the image and applies histogram equalization, illustrated in equation (1), to each sub-region.\(^7\)

![Geometrically Normalized Images](image)

![Photometrically Normalized Images](image)
\[ f(n) = \frac{(N - 1)}{M} \times \sum_{k=0}^{n} h(k) \]  

Here, \( M \) and \( N \) are the number of pixels and grey level bins in each sub-region, and \( h \) is the histogram of each sub-region. To increase contrast without amplifying noise, CLAHE redistributes each histogram such that the height falls below the clip limit threshold (0.01 in our experiments). More specifically, grey level counts beyond the clip limit are uniformly redistributed among the grey levels below the clip threshold. Finally, each sub-region is combined using bilinear interpolation. CLAHE normalized imagery is illustrated in Fig. 5.

### 3.2 Face Recognition Experiments

To perform the face recognition experiments, standard FR methods, including appearance based (linear and non-linear subspace projection)\textsuperscript{27–29} and texture based methods, were employed.

**Appearance-Based Methods:** We used the following appearance based methods, including: Principle Components Analysis (PCA)\textsuperscript{30, 31} and the Linear Discriminant Analysis (LDA) algorithm.\textsuperscript{32} We also used an extension of PCA that is kernel based Principle Components Analysis (KPCA) method.\textsuperscript{33} In addition, the Kernel Fischer Analysis (KFA) a kernelized version of LDA method is used.\textsuperscript{34} PCA method considers only the variance of the training images to construct the subspace. Whereas, the LDA algorithm aims to improve the performance of FR systems, by considering both inter and intra class variations of the training samples to construct the subspace and maximizing function represented in equation (2).\textsuperscript{35} In this equation, \( S_B \) represents the between class covariance matrix and \( S_W \) is the within class covariance matrix. The kernel based methods are defined as kernelized versions of linear (PCA and LDA) analysis methods. Kernel based method allows the learning of the non-linear mappings. The data in the kernel based method are mapped to a new feature space \( F \) via some function \( \phi \), while the maximizing function used is provided in equation (3).

\[
J(w) = \frac{w^T S_B w}{w^T S_W w} \tag{2}
\]

\[
J(w) = \frac{w^T S_B^\phi w}{w^T S_W^\phi w} \tag{3}
\]

To find the distance scores, we used the Euclidean (EUC) and City Block Distance (CTB) methods. Finally, to measure the similarity scores, the Cosine Similarity (COS) and the Cosine Mahalanobis (MAHCOS) similarity methods were used.

**Texture Based:** Local Binary Patterns (LBP) and Local Ternary Patterns (LTP) methods considered to be standard texture based face recognition methods.\textsuperscript{36–38} These methods are used to get the appearance and texture information and is invariant to change in illumination conditions. It is highly discriminative, efficient method and perform well for the FR systems. LBP method performs well even when the background is not uniform and edges are noisy.\textsuperscript{39} It can filter out noise using the uniform patterns.\textsuperscript{36, 37} The LBP operator works as a local 3\( \times \)3 neighborhood around each pixel, thresholding the pixels in the neighborhood at the location of the central pixel. This creates a binary pattern as a local image descriptor. A drawback to LBP is that it is sensitive to noise in areas such as cheeks and foreheads. Because of this we also use LTP, which is more resistant to noise in these areas because it uses a 3-valued pattern instead of a binary pattern for the local image descriptor. For all experiments conducted, we used two different similarity measures for both LBP and LTP matching. The first was the chi-squared distance, and the second was the distance transform.

### 4. EXPERIMENTAL RESULTS

In this section we will discuss our cross-spectral matching experiments when three different sets of face matchers are used. The first set, is when we are using the PCA and KPCA algorithms. The second set is, when using the LDA and KFA methods for performance evaluation. Finally, the third set is, when we are using texture based face matchers such as the LBP and LTP algorithms. Finally, we investigate whether texture based approaches are more beneficial for cross-spectral matching in terms of performance when compared to using the PCA and LDA algorithms.
4.1 PCA and KPCA based Approaches

Fig. 6(a), shows the extent to which the performance of our FR system is improved by using PCA and KPCA methods. Based on the rank 1 scores obtained, it was determined that performance is improved when we applied the Mahalanobis cosine distance measure method. Our experimental results, demonstrate that when the PCA+MAHCOS method is employed, better results are obtained. In practice, a 39% rank 1 score was achieved when using the PCA+MAHCOS approach, while only a 5% was achieved for PCA+COS and an 8% for PCA+CTB. When the Kernel based method was used, namely the KPCA, the rank-1 score further improved to 42% when KPCA was combined with the MAHCOS distance metric. All results when using either the PCA or KPCA algorithms in combination with a set of different distance metrics can be found in Figs. 6(a) and 6(b).

![Fig. 6. Rank 1 identification performance results, for cross-spectral matching.](image)

4.2 LDA and KFA based Approaches

Fig. 7(a), shows the extent to which the performance of our FR system is improved by using the LDA method. Based on the rank 1 scores obtained, it was determined that system performance was improved when linear discriminant based methods were applied. Our experimental results demonstrate that when the LDA method is

![Fig. 7. Rank 1 identification performance results for cross-spectral matching.](image)
employed, better results are obtained when compared to PCA and KPCA.

More specifically, a 61% rank 1 score when using the LDA+MAHCOS approach, while the rank-1 identification rate was further improved to 65% when using the KFA + MACHOS method. All results when using either the LDA or KFA algorithms in combination with a set of different distance metrics can be found in Figs. 7(a) and 7(b).

4.3 LBP and LTP based Approaches

The baseline intra-spectral matching experiments conducted including: VIS-VIS and UV-UV, resulted in 100% rank 1 score when using the LBP and LTP methods. This is demonstrated in Fig. 8(a). Fig. 8(b), shows the extent to which the performance of our FR system is improved by using texture based LBP and LTP methods. Based on the rank 1 scores obtained, it was determined that system performance in terms of rank-1 identification rate was improved when texture based methods are applied. More specifically, our experimental results demonstrate that when the LBP/LTP descriptors are employed, better results are obtained. These methods result in 88% rank

(a) Geometrical Normalization.
(b) Geometrical Normalization + CLAHE.

Figure 9. Rank 1 identification performance results for cross-spectral matching.
1 scores for LBP-CHI, 90% for LBP-DT, 88% for LTP-CHI and 90% for LTP-DT (see Fig. 8(b)). These scores are a significant improvement over the previously studied PCA and KPCA methods, i.e., a 55% improvement in comparison to when using the PCA method and a 42% improvement for using the KPCA method.

Fig. 9(b), shows that CLAHE had a positive impact on the matching of cross-spectral face images. We determined that the rank-1 score reached to 98% for either the LTP-DT and LBP-DT methods when applied both geometric and photometric normalization using CLAHE as part of the preprocessing of both the visible and UV face images. In Fig. 9(a), we can see that the best results when using only geometric normalization are achieved for LBP-DT method. Finally, in Fig. 9(b) we can see that LBP-DT is still the best method when geometric normalization is combined with adaptive histogram equalization.

5. CONCLUSION

In this work, we investigated the advantages and limitations of matching UV against UV as well as UV against VIS face images. We presented a systematic performance analysis of various standard face recognition algorithms on visible and ultra-violet imagery. To facilitate our analysis, we first conducted a comprehensive data collection with a novel sensor system capable of acquiring UV images under controlled environment conditions. The data collection effort (face images of subjects were acquired with intra-personal variability) was designed to investigate the hypothesis that UV imagery would yield high recognition performance.

Different scenarios were tested allowing us to gain some understanding of the shortcomings of the UV spectrum with respect to the visible modality. As expected, cross-spectral experiments resulted in reduced performance, before and after pre-processing using appearance based methods. This is most probably due to the fact that only visible band face images were used for training while UV face images were used for testing. On the other hand, identification results achieved significant improvement using texture based methods. Our experimental results show that when the texture based approaches such as, LBP/LTP descriptors are employed, better results are obtained for cross-spectral matching in terms of performance when compared to using appearance based methods (PCA, LDA, KPCA and KFA). It is concluded that the performance accuracy (in terms of rank-1 identification rate) reached 90%. Based on our experimental results, we concluded that CLAHE had a positive impact on the matching of cross-spectral face images. We determined that the rank-1 score reached to 98% for either the LTP-DT and LBP-DT methods when both geometric and photometric normalization (using CLAHE) was applied to both the visible and UV face images. Thus, it appears that the UV modality holds great promise under reasonable operating conditions. In particular, there should be emphasis on recognition of individuals in the UV region, as UV imagery generates a more significant face image and therefore can take the advantage of information (facial features) that might go unobserved using the conventional VIS spectrum systems.

In the future, we are planning to improve the quality of our work by further investigating appearance based approaches, using more balanced training data in terms of bands used, and considering lightening variations. In addition, further experiments and data collections will be necessary to investigate more challenging scenarios, e.g., when subjects are wearing glasses, or when images are acquired outdoors. We intend to expand our collection and analysis effort towards that direction.

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