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Extended Spectral To Visible Comparison Based On Spectral Band Selection Method For Robust Face Recognition

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***Abstract*— Multi-spectral imaging has recently acquired significant attention in biometrics based authentication due to it's potential ability to capture spatio-spectral images across the electromagnetic spectrum. Especially, in the case of facial biometrics, multi-spectral imaging has shown significant promising results under unknown/varying illumination environment. However, the challenge arises when surveillance cameras provide the visible images while the enrollment are spectral band images. In order to address the backward/cross compatibility of probing visible images from regular surveillance cameras against the high quality spectral band images in enrollment, development of robust algorithms are required. In this paper, we present a new approach of selecting optimal band based on highest correlation coefficients of individual feature vectors from bands in comparison with feature vectors from visible images of respective individual classes for robust recognition performance. The proposed approach of band selection is validated on a newly collected face database of 168 subjects whose face images are collected in 9 different spectral bands and correspondingly their visible images from a regular camera operating in visible spectrum. The extensive set of experiments conducted on the new database with selected single band and multiple spectral bands in enrollment data versus the visible probe image has indicated the significance of the band selection. The new approach of spectral to visible matching with the proposed band selection method shows significant Rank-1 recognition rate of 94.04% supporting the applicability of proposed method.**

I. INTRODUCTION

Physiological and behavioral mode of biometric traits such as face, finger, iris, voice, gait, etc., have remarkably proven the the strength in real time access control for biometric authentication. Among all the biometric traits, authentication system based on facial biometric trait is popular mainly due to the non-invasive nature of the image capture that allows to capture face images in covert manner at varying stand-off distance[1]. However, the traditional face recognition system suffers under unknown or varying illumination condition which significantly affects the recognition performance[2]. Multi-spectral imaging for facial biometrics has recently gained significant attention due to it's property of capturing spatio-spectral information across the electromagnetic spectrum [3]. Further, the use of multi-spectral imaging extracts the discriminant complementary information across different spectrum (such as reflectance and emittance) to provide robust information [4]. The availability of multi-spectral imaging technology across the broad spectrum facilitates the flexibility of using information from different wavelength that can span from visible to active infrared [5].

The unique reflectance property of individuals constitute the characteristic feature that makes multi-spectral imaging more appropriate approach in the robust facial biometrics recognition. Hence, ample amount of literature can be found stressing the significance of multi-spectral face recognition under various controlled or uncontrolled scenarios (for example, night time face recognition at large varying stand-off distance under unknown illumination, for presentation attack detection, face liveness detection, etc)[6][1].

However, Automatic Border Control (ABC) systems operate by comparing the face image (or template) stored in the electronic passport with the live capture of photo to authenticate the legitimate user of the passport. Since the ABC systems are installed in the indoor conditions with the artificial lighting, the variation of the light intensity during the day and night scenario will result in varying performance of the ABC systems. This fact was extensively studied on the prototype commercial ABC system (MORPHO WAY) that indicated the variation in the performance of the ABC system proportionately to the change in light intensity [7]. This fact motivated us to consider the scenario of using extended-spectral face images as the possible enrolment sensors for the precise application by considering it's robustness against the varying illumination.

Although, the face images captured in extended-spectra produces highly reliable performance, the challenge remains in matching the newly captured images from extended spectra against the images collected in traditional manner such as visible images in passport, visible images from typical surveillance cameras. To achieve good performance in comparing extended spectral image against visible images, it is necessary to develop algorithms that are agonistic to spectral changes or algorithms that are able to adapt to spectral changes. Further, it has to be noted that most of the earlier works are focused on either of two spectral bands or a number of narrow spectral bands (n) i.e., hyperspectral imaging (hyperspectral imaging captures overlapping spectral bands images) or discrete/disjoint spectral bands (usually called extended multi-spectral imaging [8]).

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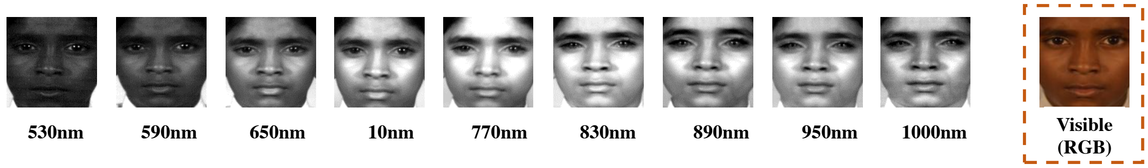

Fig. 1: Multi-spectral facial database @ 9 spectral bands and Visible image

Motivated by limited works on matching visible images against the extended-spectral images and severity of problem, in this work, we investigate different protocols of spectral band matching against the visible images. We further find their suitability to address the comparison of real-time visible images (typically in Red, Green and Blue (RGB) channel) from regular surveillance systems to spectral images in enrollment set. However, the key challenge is that the spectral band information consists of number of overlapping or disjoint bands while the visible images are captured in wide spectral band i.e. visible spectrum in the range from 400nm to 700nm resulting in images of approximated red, green and blue response range of color-filter array.

To achieve robust performance for spectral band to visible image comparison, one can fuse all spectral bands in the enrollment dataset and probe against the visible images. The demerit of such an approach is that all the different bands are to be processed to obtain the optimally fused image and the resulting image may not be very similar to the image obtained in visible spectrum. Further, fusion of image may lead to the slit distortion (or blurring) due to the misalignment of individual intra-spectral bands. Another approach is to enroll all spectral bands to match against the visible image, but the drawback of such approach is that it allows the possibility of false matching that affect the performance of the system and computation expenses due to increase in the number of spectral bands in the enrollment dataset. This further increases the computation time and redundancy in adjoining spectral bands. Alternatively, one can think of selection methods such that a set of highly informative spectral bands for every individuals in the dataset can be chosen.

In this work, we present a spectral band selection based on correlation mapping function that computes the amount of relationship between individual spectral band and visible image. The correlation coefficients obtained from the function gives the best possible relationship of each spectral band with respect to visible images, that make best possible selection of spectral band for the processing. Unlike, the common way of selecting it straight from the image, we employ the band selection based on the extracted feature vectors of individual spectral bands in comparison to feature vector of visible image. The advantage of selecting at feature level is that it contains the most discriminative characteristic features from different bands rather than at image level that contains more redundant information that affects the appropriate band selection. We selected the spectral bands based on the maximum correlation coefficient values corresponding to features from visible image.

In order to evaluate the proposed approach, we have created a new database of face images acquired from 168 subjects using a extended spectral camera and corresponding visible images using regular DSLR camera. Specifically, we have collected images in nine spectral bands operating in the range of $530nm$ to $1000nm$ wavelength in two different sessions corresponding to enrollment. In the similar manner, we have also collected face images from corresponding 168 subjects using a regular DSLR camera of high resolution for the probe set. A set of extensive experiments are carried out to demonstrate the applicability of proposed approach to carry out spectral to visible face image matching. Further, we also present a comparative analysis to the state-of-the-art techniques when single spectral band is employed in the enrollment to match against visible image. To best of our knowledge, this is the first of it's kind study which will contribute to spectral band selection for the robust performance of spectral to visible image matching. The key contributions of this work can be summarized as:

- Presents a new approach of matching extended spectral band images to visible images for face recognition to address the circumstances when probe images are only available in the visible spectrum (color image) while the enrollment is available in spectral bands.
- Presents a band selection approach for every individual class based correlation of extracted features from the individual spectral band against the features from visible image.
- Presents a new database of 168 subjects whose face images are captured in 9 different spectral bands in two sessions along with the visible images of the corresponding subjects in the visible spectrum.
- An extensive experimental evaluation to demonstrate the applicability of proposed approach of matching spectral bands against the visible images based on the band selection approach.

In the reminder of this paper, section II describes the new database of extended spectral and visible face images collected. Section III introduces the proposed approach of band selection for enrollment to probe against visible images. Section III-A briefly explains the feature extraction and classification method used in performance analysis. Further, Section IV presents the experimental evaluation and obtained results along with key observations. In the end, section V provides final conclusive remarks .

II. Extended Multi-spectral Face Database

This section presents the details of the newly collected database of face images in visible and extended spectral bands with 9 different wavelength which we hereafter refer as $SpecVis$ face database signifying the spectral and visible bands respectively. As indicated by the name, the $SpecVis$ database consists of two subsets of database acquired from 168 subjects. The details of each of the subset of database is provided in the following subsection. Of the 168 subjects in the $SpecVis$ database, 96 subjects are male and rest of the 72 subjects are female.

A. Spectral Subset of SpecVis Face Database

Spectral face images of 168 subjects constitute the spectral subset of the $SpecVis$ face database. In order to capture the face images in the spectral bands, we have employed a custom-built extended multi-spectral sensor [8] that can capture images in nine spectral bands, specifically operating in narrow bands of $530nm, 590nm, 650nm, 710nm, 770nm, 830nm, 890nm, 950nm, 1000nm$. The face images in each of the spectral band is collected in two different sessions for each subject resulting in 2 enrolment images across 9 bands. Thus, the enrolment set consists of 3024 images (168 $Subjects$ $\times$ 2 $Samples$ $\times$ 9 $bands$).

B. Visible Subset of SpecVis Face Database

In order to simulate the process of matching the spectral images against the visible images, we have also collected face images of all 168 subjects using a regular visible camera. Specifically, we have employed a high resolution Nikon D3200 DSLR camera. This subset of the database consists of 168 face images in total.

TABLE I: $SpecVis$ database description

	Visible Subset	Spectral Subset
Subjects	168	168
Bands	3 (RGB)	9
Samples per subject	1	2
Total Images	168	3024

The detailed composition of the $SpecVis$ database is presented in the Table I and the Figure 1 depicts the sample face images captured across 9 bands along with the image captured in Visible spectrum using DSLR camera.

C. Pre-processing of Data

The face images are collected with the cameras having larger field of view and thus, the images also consist of the background scene. In order to obtain the necessary information alone, i.e., face region, we have employed eye coordinate based normalization to localize the face. Further, the geometric alignment using affine transform is carried out to account for slight perturbation in the facial image which usually results in the sequential image capture in the case of spectral band image. The normalized and aligned face is then cropped and enhanced using a simple technique of histogram equalization to increase the visibility of details in the face part. Finally, the localized face region is then resized to size of 120×120 pixels resolution to reduce the computation time.

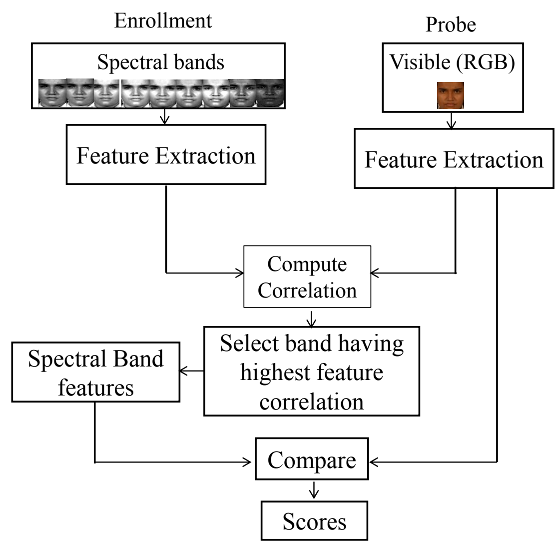

Fig. 2: Feature extraction method for face recognition

III. Proposed Band Selection Approach

Figure 2 shows the face recognition approach in employed in this work. Unlike the traditional face recognition where the reference and the probe image come from same spectrum, in this work, the reference images are captured using spectral bands and the probe image comes from visible spectrum. For the set of spectral band images, we compute the features and similarly, we compute the feature vectors (ref subsection III-A) for the probe visible images. For each set of band versus the visible image, we compute the correlation values. Further, based on the correlation values, we choose best bands from the spectral image corresponding to visible image. Finally, the comparison score is obtained by comparing the features from chosen band and features from visible image. Figure 3 presents the detailed illustration of proposed spectral band selection approach employed in this work.

As illustrated in Figure 3, we employ correlation based approach to select the best spectral bands from the enrolled set. We select the spectral band image for individual class based on the highest correlation of the features extracted from spectral bands against the features extracted from visible image. Most of the approaches of band selection are usually based on entropy and wavelet energy which work well when enrollment and probe set belongs to the same spectrum [9]. However, such approaches perform poorly in the case when there is a spectral gap (or modality gap) that

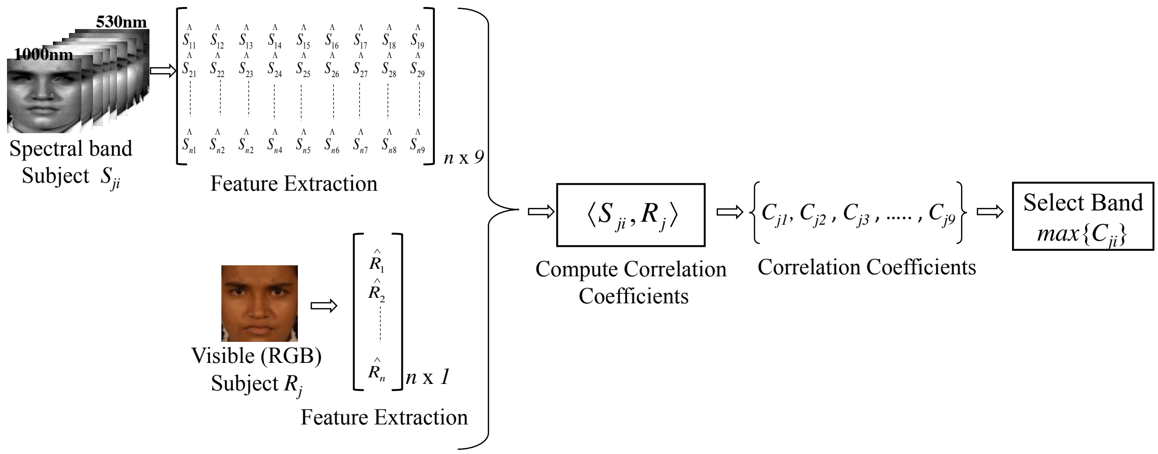

Fig. 3: Proposed approach of spectral band selection

exist between enrollment and probe sets (usually, in the case of cross spectral matching). In such cases, the correlation based technique plays an important role which makes use of enrollment and probe set to select the final spectral band.

Let the set of spectral images corresponding to different bands of $530nm, 590nm, 650nm, 710nm, 770nm, 830nm, 890nm, 950nm$ and $1000nm$ be represented as S where:

$$S = \{S_1, S_2, S_3 \ldots S_9\}$$

Given the spectral band face image S_i for $i = 1...9$ corresponding to 9 different spectral bands, and R_j for $j = 1, 2, ..., 168$ be the visible image corresponds to different subjects. We extract the feature vectors for 9 spectral bands and the visible image to compute the correlation coefficients between spectral bands and visible image of individual class. It has to be noted that the visible image is converted to gray image before extracting the features.

Let the $\hat{S}_i$ for $i = 1...9$ be the extracted spectral band feature vector of dimension $1 \times n$ and $\hat{R}_j$ for $j = 1, 2, ..., 168$ be the extracted visible feature vector for 168 subjects of dimension $1 \times n$. We compute the correlation coefficient by using Pearson's correlation coefficient [10] illustrated in the following Equation 1:

$$C_{\hat{R}_j \hat{S}_i} = \frac{\sum_{d=1}^{n} (\hat{R}_j^d - \mu_j)(\hat{S}_i^d - \mu_i)}{\sqrt{(\sum_{d=1}^{n} (\hat{R}_j^d - \mu_j)^2)(\sum_{d=1}^{n} (\hat{S}_i^d - \mu_i)^2)}} \quad (1)$$

where parameter μ_j and μ_i are the mean feature vector of visible image and mean feature vector of the spectral band respectively. These are shown in equation 2 as follows:

$$\mu_j = \frac{1}{d} \sum_{d=1}^{n} \hat{R}_j^d \ ; \quad \mu_i = \frac{1}{d} \sum_{d=1}^{n} \hat{S}_i^d \quad (2)$$

The final correlation coefficient between spectral bands and visible image is illustrated as:

$$C_{\hat{R}_j \hat{S}_i} = \{C_{\hat{R}_j \hat{S}_1}, C_{\hat{R}_j \hat{S}_2}, \ldots C_{\hat{R}_j \hat{S}_9}\}$$

Further, we make the selection of the spectral bands that contains most significant information as well as show close correlation with visible image based on the highest correlation coefficients.

$$E_j \left\{ \hat{S}_i \right\} = arg\ max\{C_{\hat{R}_j \hat{S_{j1}}}, C_{\hat{R}_j \hat{S_{j2}}}, \ldots C_{\hat{R}_j \hat{S_{j9}}}\} \quad (3)$$

From the Equation 3 we select the spectral band having maximum correlation with visible image. Finally, the experimental evaluation is conducted using state of the art face recognition algorithm for performance analysis. Further, to provide baseline evaluation, we enrol multiple samples from spectral bands consecutively in the decreasing order of correlation coefficients.

A. Feature Extraction Methods and Classifier

In order to perform band selection based on the feature correlation, we have employed four state-of-the-art local and global feature extraction methods that include: Histogram of Oriented Gradient (HoG)[11], GIST[12] and Log-Gabor transform [13] and Binarized Statistical Image Features (BSIF)[14]. These feature extraction methods have proven their significance in the literature for improved performance. Further, we have employed Collaborative Representation Classifier (CRC)[15] [16] for efficient classification of these dominant and discriminative features. A brief overview of each of these methods are given in the section below.

Histogram of Oriented Gradients (HOG): HOG is the feature descriptor method gives structural information embedded in the given image. The important aspect of HOG is to compute the magnitude of gradient vectors to efficiently extract the direction in which the prominent edge are present. Further, the magnitude information of all the edge is placed in nine bins of histogram with each bins of size 20 degree spanning from 0 to 180 degrees. In our case, for image size of 120×120 pixels, we obtain the histogram of gradient vector from 196 blocks (4 histogram for each blocks) having 50% overlap in each of these blocks. Thus final HOG descriptor obtained after concatenating each of the nine bins of histogram one below the other to get feature vector of size 1×7056.

GIST: The GIST descriptor provides robust features for face recognition, utilizing Gabor filters of different scale and orientation to obtain the feature map [12]. In the current work, we employ 32 Gabor filters that include 4 different scales and 8 different orientations that allow us to obtain 32 feature maps which contains sufficient feature information. Further, these obtained feature maps are divided into 4×4 spatial dimension to get 16 sub-feature maps which are then averaged to obtain the final feature dimension of size 512.

Log-Gabor transform: This is another feature extraction method that operates in similar lines with the GIST descriptor using banks of filters operating in different scale and directions. As compared to the GIST, Log-Gabor obtains the feature matrix by concatenating each of the feature matrix on holistic image. In this method, we employ 32 filters of 4 different scales and 8 different orientation on our image 120x120 size to get the final feature descriptor for image i.e $(32\ filters)\ x\ (120 \times 120)\ =\ 460800$ feature dimension. Further, to reduce the computation time while preserving the most dominant features, we downsample the feature vector to reasonable feature size of 76800.

Binarized Statistical Image Features (BSIF): BSIF obtain the features from image using a set of filters learnt using natural images (BSIF)[14]. The set of filters are convoluted with the image followed by simple binarisation. Further, the binarized images are combined together using a simple binary-to-gray conversion strategy. In this work, we employ a filter of size 17×17 with a bit-length of 12. The obtained responses are represented in histogram of size 4096 in our work.

Collaborative Representation Classifier: For efficient classification of the histogram based feature vectors obtained by the different feature extraction methods mentioned above, we employ probabilistic collaborative representation based classifier (ProCRC), which maximize jointly the likelihood ratio of test sample with other classes and final classification of features is obtained by confirming the maximum likelihood of test sample image with the other classes [16].

In this paper, the set of histogram feature vectors selected based on the proposed band selection method using above methods for all the images from the reference set that correspond to selected spectral bands. The features are further used to learn the collaborative sub-space $\mathscr{C}$ [16]. In order to obtain the comparison scores, we make use of the regularised Least Square Regression on the learnt spectral feature vectors versus the probe feature vectors stemming from visible image [16] as formulated by:

$$\widehat{F} = argmin_{\alpha} \left\| \hat{R} - \mathscr{C}\alpha \right\|_2^2 + \lambda \left\| \alpha \right\|_2^2 \quad (4)$$

where the $\hat{R}$ is the feature vector of the probe image, $\mathscr{C}$ is the learned collaborative subspace, α is coefficient vector and λ is the regularization parameter. The distance obtained is used as the comparison score to obtain the biometric performance.

IV. Experimental Results

This section of paper presents the experimental protocols introduced in the evaluation for matching spectral band to visible image using state of the art face recognition algorithms. The results are presented in terms of Rank-1 recognition accuracy in this work. The quantitative validation results are presented on our proposed band selection method that select the most significant spectral bands of the individual class based on the highest correlation coefficients between the feature vectors of spectral bands and feature vectors of visible image of respective individual class. In order to evaluate the proposed approach of band selection, we consider the data from Session 1 and Session 2 independently. The data from each of the session is considered to select the bands based on the proposed approach and matched against the features from probe image.

Table II indicates the recognition rate at rank 1 for both Session 1 and Session 2 of the dataset using four different feature extraction algorithms along with a robust classifier with our proposed approach. Further, in order to illustrate the performance across the various algorithms when multiple bands are selected, we incrementally add bands with correlation coefficients from highest to lowest. The key observations from the obtained results are outlined below:

1) The proposed approach of selecting highest correlating bands results in consistently higher recognition rate.
2) BSIF-ProCRC obtains the maximum recognition rate of 94.04$\%$ as compared to the other feature extraction methods. Further, lowest performance is observed from HOG-ProCRC with 61.90$\%$ recognition rate.
3) A reasonable performance is obtained with only single selected band enrolled as compared to the multiple spectral bands in the enrollment which signifies that single spectral band is sufficient to get the optimum performance rather than increasing computation and comparison time by simply using multiple spectral bands.

As it can be noted from Table II, the recognition rate increases almost linearly as the number of spectral bands are added in the enrollment based on our proposed method and after a certain number of bands, the recognition rate decreases due to higher number of spectral bands. The key intuitions for such a behaviour can be asserted as below:

1) Best classification can be obtained when only few spectral bands are enrolled that gives significant discriminative information of the class. But as the number of bands are increased, there is a possibility of decreasing interclass separation which could result in poor performance (one can see the decrease in the recognition rate when all nine spectral bands are enrolled as shown in both the Table II).
2) Further, with increase in the number of spectral bands, the possibility of overlapping correlation coefficient

TABLE II: The recognition rate at Rank-1 when number of bands in the enrollment dataset increases

Session	Algorithm	Number of bands in enrollment (Selected using proposed method)								
		1	2	3	4	5	6	7	8	9
Session 1	HOG-ProCRC	61.90	62.50	65.48	67.86	64.29	66.07	68.45	67.26	65.48
	GIST-ProCRC	69.05	73.21	79.76	82.14	82.74	79.76	81.55	84.52	85.12
	logGabor-ProCRC	70.83	75.60	78.57	77.38	79.17	78.57	77.38	76.79	76.19
	BSIF-ProCRC	88.69	91.66	91.66	93.45	92.26	94.04	94.04	92.26	91.66
Session 2	HOG-ProCRC	51.19	60.71	60.12	58.33	61.31	60.12	60.12	61.90	60.12
	GIST-ProCRC	64.88	76.19	74.40	79.76	76.79	78.57	79.76	80.36	77.38
	logGabor-ProCRC	61.90	66.07	71.43	71.43	70.83	73.81	73.21	76.19	75.00
	BSIF-ProCRC	87.50	91.07	92.26	91.07	91.67	91.67	91.07	91.67	88.69

TABLE III: The recognition rate at Rank-1 when number of bands in the enrollment dataset fused using Wavelet Transform

Session	Algorithm	Number of fused bands in enrollment							
		2	3	4	5	6	7	8	9
Session 1	HOG-ProCRC	30.95	26.19	28.57	29.76	25.60	25.00	25.00	25.60
	GIST-ProCRC	50.60	50.00	48.81	41.67	38.10	39.29	39.29	37.50
	logGabor-ProCRC	44.64	41.07	41.67	40.48	42.86	43.45	43.45	45.83
	BSIF-ProCRC	74.40	69.64	67.86	55.95	50.60	52.38	52.38	62.50
Session 2	HOG-ProCRC	23.81	20.24	20.83	17.26	17.86	17.86	17.86	22.02
	GIST-ProCRC	42.26	42.26	36.90	35.12	30.95	36.31	36.31	37.50
	logGabor-ProCRC	45.83	41.67	38.69	32.74	38.10	36.90	36.90	36.90
	BSIF-ProCRC	66.07	55.36	50.60	48.21	42.26	43.45	43.45	50.60

with other inter-class increases. For instance, it can be seen from the Figure 4 that performance from BSIF-ProCRC for single selected spectral band in the enrollment corresponding to 650nm selected for subject 1 results in high feature correlation coefficient (C=0.68) with the visible image that results in perfect match with the genuine individuals. Whereas for the non matched subject 2 the selected spectral band was 710nm with correlation coefficient (C=0.47) and such low correlation results in the interclass miss-match.

Thus, spectral band to visible image match shows the applicability of the proposed protocol that can address the real life application of surveillance application. Further, band selection approach shows the improved performance with feature correlation technique.

For comparison of baseline results with our proposed technique, we have computed the spectral band fusion with wavelet transform based on the highest entropy value of each band. We compute the fused spectral band image by averaging the wavelet coefficients obtained after decomposing it from 2-level Discrete Wavelet Transform (2DWT). For efficient decomposition of wavelet coefficient, we employ Haar mother wavelet [17]. The results presented in Table III indicates that the proposed method reasonably outperforms the fusion results for all state-of-the-art face recognition methods. This further signifies the importance of our proposed method.

Fig. 4: Example that shows the face match and not match with the genuine subjects

V. CONCLUSIONS

With the growing importance of multi-spectral/extended-spectral imaging in the facial biometrics to obtain robust performance, spectral to visible image matching remains challenging. In order to address the backward compatibility of using color visible images from regular surveillance cameras against the high quality spectral band images, robust algorithms are required. In this work, we have presented a new approach of matching spectral band images against visible images by exploring the feature level correlation between visible image and extended-spectral bands. Thus, the proposed method can choose a set of spectral bands from the extended-spectral bands to improve the performance while matching with the visible image.

Extensive set of experiments on a newly collected face database ($SpecVis$) of 168 subjects has indicated a high Rank-1 recognition rate of 94.04% with the proposed approach. Based on the obtained results, it is noted that, rather than using a single best selected band, at-least three spectral bands can be used that are selected based on the correlation measure with the probe visible image.

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References

[1] F. Nicolo and N. A. Schmid, "Long range cross-spectral face recognition: Matching swir against visible light images," *IEEE Transactions on Information Forensics and Security*, vol. 7, no. 6, pp. 1717–1726, 2012.

[2] G. Bebis, A. Gyaourova, S. Singh, and I. Pavlidis, "Face recognition by fusing thermal infrared and visible imagery," *Image and Vision Computing*, vol. 24, no. 7, pp. 727 – 742, 2006.

[3] T. Bourlai and B. Cukic, "Multi-spectral face recognition: Identification of people in difficult environments," in *Intelligence and Security Informatics (ISI), 2012 IEEE International Conference on*, 2012, pp. 196–201.

[4] R. S. Ghiass, O. Arandjelovi, A. Bendada, and X. Maldague, "Infrared face recognition: A comprehensive review of methodologies and databases," *Pattern Recognition*, vol. 47, no. 9, pp. 2807 – 2824, 2014.

[5] M. Uzair, A. Mahmood, and A. Mian, "Hyperspectral face recognition with spatiospectral information fusion and pls regression," *IEEE Transactions on Image Processing*, vol. 24, no. 3, pp. 1127–1137, 2015.

[6] Z. Zhang, D. Yi, Z. Lei, and S. Z. Li, "Face liveness detection by learning multispectral reflectance distributions," in *Face and Gesture 2011*, 2011, pp. 436–441.

[7] R. Raghavendra, K. B. Raja, B. Yang, and C. Busch, "Automatic face quality assessment from video using gray level co-occurrence matrix: An empirical study on automatic border control system," in *2014 22nd International Conference on Pattern Recognition*, 2014, pp. 438–443.

[8] N. T. Vetrekar, R. Raghavendra, and R. S. Gad, "Low-cost multi-spectral face imaging for robust face recognition," in *2016 IEEE International Conference on Imaging Systems and Techniques (IST)*, 2016, pp. 324–329.

[9] R. Raghavendra, S. Venkatesh, K. Raja, F. Cheikh, and C. Busch, "Mutual information based multispectral image fusion for improved face recognition," in *12th International Conference on Signal-Image Technology and Internet-Based Systems (SITIS -2016)*, 2014, pp. 438–443.

[10] J. L. Rodgers and W. A. Nicewander, "Thirteen ways to look at the correlation coefficient," *The American Statistician*, vol. 42, no. 1, pp. 59–66, 1988.

[11] R. Basri and D. W. Jacobs, "Lambertian reflectance and linear subspaces," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25, no. 2, pp. 218–233, 2003.

[12] P. E. Pochi, J. S. Strauss, and D. T. Downing, "Age-related changes in sebaceous gland activity," *Journal of Investigative Dermatology*, vol. 73, no. 1, pp. 108 – 111, 1979.

[13] J. A. Iglesias-Guitian, C. Aliaga, A. Jarabo, and D. Gutierrez, "A Biophysically-Based Model of the Optical Properties of Skin Aging," *Computer Graphics Forum*, 2015.

[14] J. Kannala and E. Rahtu, "Bsif: Binarized statistical image features," in *Proceedings of the 21st International Conference on Pattern Recognition (ICPR2012)*, 2012, pp. 1363–1366.

[15] R. R. Anderson and J. A. Parrish, *Optical Properties of Human Skin*. Boston, MA: Springer US, 1982, pp. 147–194.

[16] S. Cai, L. Zhang, W. Zuo, and X. Feng, "A probabilistic collaborative representation based approach for pattern classification," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 2950–2959.

[17] G. Pajares and J. M. de la Cruz, "A wavelet-based image fusion tutorial," *Pattern Recognition*, vol. 37, no. 9, pp. 1855 – 1872, 2004.