Exploring Convolutional Neural Network for Multi-spectral Face Recognition

Anish K. Prabhu, Narayan Vetrekar, and R. S. Gad(✉)

Department of Electronics, Goa University, Taleigao-Plateau, Goa, India
{elect.anishprabhu,elect.ntvetrekar,rsgad}@unigoa.ac.in
https://www.unigoa.ac.in

Abstract. Multi-spectral face recognition has procured noteworthy consideration over a most recent times because of its potential capacity to acquire spatial and spectral information over the electromagnetic range, which cannot be obtained using traditional visible imaging techniques. With the advances in deep learning, Convolutional Neural Network (CNN) based approach has become an essential method in the field of face recognition. In this work, we present two face recognition techniques using face image at nine unique spectra ranging from Visible (VIS) to Near-Infra-Red (NIR) range of the electromagnetic spectrum. This paper is based on the application of using CNN as feature extractor along with Support Vector Machine (SVM) and k-Nearest Neighbor (k-NN) as a classifier on the images of nine different spectra ranging from 530 nm–1000 nm. The obtained performance evaluation results show highest $Rank-1$ recognition rate of 84.52% using CNN-KNN, demonstrating the significance of using CNN extracted features for improved accuracy.

Keywords: Face recognition · Multi-spectral imaging · Convolutional Neural Network · Support Vector Machine

1 Introduction

Biometrics is one of the widely developed area of bio-engineering, as it is the computerized technique of recognizing individuals depending on a physiological or behavioral traits. The biometric system based on physiological or behavioral traits consists of fingerprint, voice, gate, signature, iris, retina, face, etc. Among these available biometric systems, face recognition has gained noteworthy attention in the field of biometric, due to which it has found its applicability in various sectors such as surveillance, authentication, secure access control, law enforcement, border security, etc. Face recognition is receiving significant attention mainly due to its non-invasive method of face image acquisition that allow to capture face image at different stand-off distance [8]. In spite of all these advantages of face biometric over other biometric traits, the performance of face recognition system is hampered by the variations in illuminations, expressions,

B. Deka et al. (Eds.): PReMI 2019, LNCS 11941, pp. 606–613, 2019.
https://doi.org/10.1007/978-3-030-34869-4_66

poses, background, occlusion, etc. [3]. The effect of variations in illumination conditions is well addressed by employing multi-spectral face imaging, thereby makes use of more than one electromagnetic spectrum (For instant Thermal and visible broad spectrum). The principle behind utilizing multi-spectral imaging is to extract complementary discriminant information over various spectrum bands (reflectance and/or emittance) for improved performance [5]. One of the main characteristic features that make multi-spectral imaging more appropriate approach to obtain robust face recognition is its ability extract distinctive features of the individuals.

The majority of work available in the literature have employed various tools and techniques to perform face recognition across multi-spectral range. Li et al. [7] have employed Local Binary Patterns (LBP) to extract the textural features from Near-Infra-Red (NIR) face images, which is based on rotation invariance and robustness image blur but this approach poses serious limitation when there is change in the face location in an image due to head movement. However, the limitation of variation in the pose was addressed in the method proposed by Zhang et al. [13] by using the potential of Gabor-Directional Binary Code (GDBC) for multi-spectral face recognition. In another work, Farokhi et al. [4] introduced a methodology based on Zernike moments and Hermite kernels (ZMHK) to address the limitation of face detection problem in NIR face images, thereby obtaining an effective and superior face detection. Although, the above methods have presented the promising results, but they are highly dependent on manual feature selection process. In the recent times, various deep learning techniques have been utilized in the face recognition domain working across visible and Near-Infra-Red (NIR) spectrum. Zhang et al. [14] proposed Convolutional Neural Network (CNN) architecture for NIR images, with improved face recognition rate as compared to GDBC and ZMHK methods mentioned above. In another work, CNN based model mainly identified as NIRFaceNet was proposed by Peng et al. [10] worked on NIR face images of Chinese Academy of Sciences' Institute of Automation (CASIA) NIR database. In the similar line with the previous work, a CNN based model also known as (a.k.a.) DeepFace [11] was trained on four million facial images, proposed by Facebook's Artificial Intelligence (AI) group to perform face recognition in visible wavelength range.

The previous works have shown limited attention towards the use of deep learning technique for multi-spectral face recognition domain, with few works centered towards NIR face recognition. In this work, we present a deep learning based approach to automatically extract features from Visible (VIS) as well as Near-Infra-Red (NIR) face images using CNN and then processing independently the extracted feature sets with Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) classifiers for multi-spectral face recognition. The experimental evaluation results in the form of recognition rate at $Rank-1$ is presented on multi-spectral face database of 6048 images collected across nine narrow spectral band images corresponding to 530 nm, 590 nm, 650 nm, 710 nm, 770 nm, 830 nm, 890 nm, 950 nm, 1000 nm spanning from 530 nm to 1000 nm spectrum range. In the due course of time the major contributions can be summarized as follows:

- Explore the potential of Convolutional Neural Network (CNN) to extract the individual spectral band features for robust performance on the multi-spectral face database i.e. *SpecVis* having face images of 168 subjects across nine spectral bands.
- Use of pre-trained network *Alexnet* [6] as a feature extractor of face images across *nine* spectral bands ranging from 530 nm–1000 nm and Support Vector Machine (SVM), k-Nearest Neighbor (k-NN) as classifiers.
- Experimental results in the form of recognition rate at $Rank-1$ across individual spectral band for improved performance accuracy.

In the reminder of the paper, Sect. 2 describes the multi-spectral face database employed and the preprocessing techniques used, Sect. 3 presents the proposed method of feature extraction based on Convolutional Neural Network (CNN) processing independently with two different methods such as Support Vector Machine (SVM) and k-Nearest Neighbor (k-NN) using multi-spectral face database of 168 subjects, Sect. 4 presents the detailed experimental evaluation protocol and related experimental results along with major observations, and final conclusive remarks along with future work is summarized in Sect. 5.

2 Database

This section of paper explains the details related to the publicly available database *SpecVis* [12] utilized in our work for performance analysis. The database comprises of 168 subjects collected using in-house custom-build multi-spectral imaging sensor across nine narrow spectrum bands including 530 nm, 590 nm, 650 nm, 710 nm, 770 nm, 830 nm, 890 nm, 950 nm, 1000 nm spanning from Visible to Near-Infra-Red spectrum range. The 168 subjects consists of 96 male and 72 female collected in two sessions with two samples each. Between each sessions a time difference of about 1 to 3 weeks is maintained during the data collection. In total, 6048 sample multi-spectral images are collected which corresponds to 168 Subjects $\times$ 2 Sessions $\times$ 2 Samples $\times$ 9 Bands = 6048 Samples. Table 1 summarizes the total number of samples collected.

Table 1. *SpecVis* database describing total number of sample images

Subjects	Sessions	Samples	Bands	Total images
168	2	2	9	6048

2.1 Pre-processing of Images

Images acquired using multi-spectral sensor have a broader field of view, which in turn includes the background scene apart from the facial data. Hence, we pre-process the multi-spectral facial images that includes face normalization and

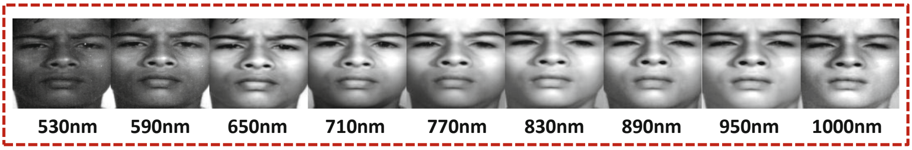

Fig. 1. Multi-spectral face database across nine narrow spectral bands

enhancement. In case of normalization, we used eye-coordinate based approach to detect the facial region and then perform translation and rotation correction to perform geometric alignment. Following the normalization technique, we employ contrast enhancement to improve the facial features. Further, the cropped facial image is resized to a common 120 × 120 uniform dimension before performing feature extraction and classification. Figure 1 illustrates the multi-spectral facial database after performing pre-processing technique.

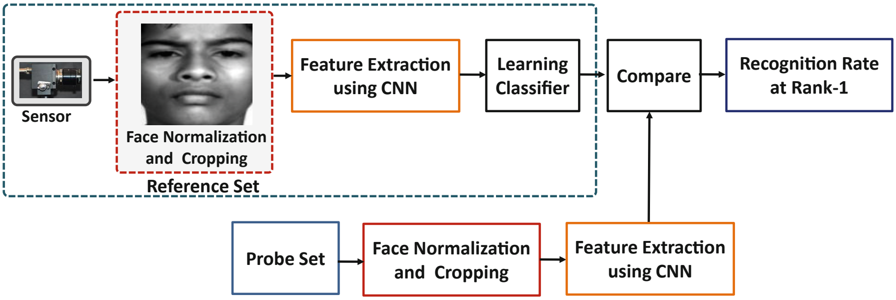

Fig. 2. Proposed method to extract CNN based features corresponding to individual spectral bands and classification

3 Methodology

This section presents the details about the feature extraction method and classification approach employed in this work for multi-spectral face recognition. The methodology consists of reference set and probe set. For reference set, we first perform the individual spectral band face normalization and cropping (Refer Sect. 2.1), followed by CNN based feature extraction, which further processed to learn the classifier. During the probe set, the respective individual spectral bands processed to compare it against the learned reference set to obtained recognition rate at $Rank-1$. Figure 2 presents the illustration of feature extraction and classification approach employed in this work. Further, the details related to the proposed method is explained using following sub-sections: Feature extraction and classification.

3.1 Feature Extraction

CNN has had pivotal outcomes over the previous decade in several fields such as face recognition, fingerprint recognition, voice recognition, character recognition, image processing, etc., related to feature extraction and pattern recognition for robust performance [2,9]. This accomplishment of CNN has provoked researcher community to build larger models to tackle complex problems which were impractical with classical Artificial Neural Networks (ANN). One of the most critical aspects of CNN is that it can also be used as a feature extractor as it acquires unique and complex features when the input image propagates into the deeper layers of the network.

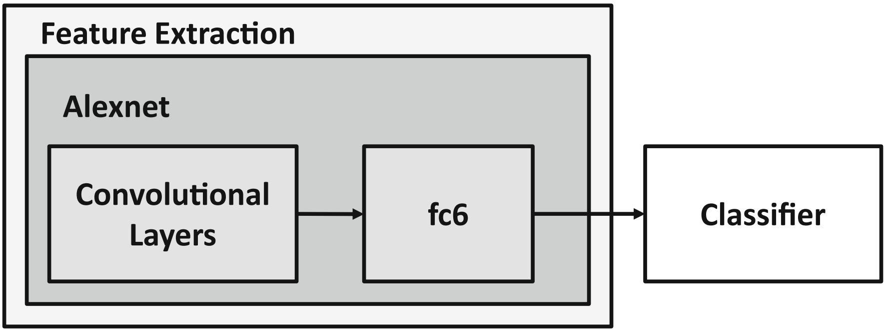

Fig. 3. Feature extraction using CNN and classification

Figure 3 depicts the implementation of pre-trained CNN model Alexnet as a feature extractor. On the pre-processed multi-spectral images of face region in each band, we apply an existing pre-trained CNN model i.e. Alexnet proposed by Krizhevsky et al. [6]. Alexnet comprises of 5 convolutional layers and 3 fully-connected layers. We extract the feature set from the first fully-connected layer (feature layer 'fc6') of the pre-trained Alexnet model. The same procedure is followed for remaining of the nine spectral bands to compute the feature vector. For each of the nine bands, we calculate the feature vector for the training set by the use of deep learning technique.

3.2 Classification

The next step of the proposed method is to efficiently perform the classification based on the feature vector generated by pre-trained Alexnet model (Discussed in The previous Sect. 3.1). In this paper, we have employ independently the multi-class Support Vector Machine (SVM) [1] and K-Nearest Neighbor (k-NN) classifier separately across individual spectral bands to compute improved recognition rate at $Rank-1$. SVM and k-NN classifiers are broadly utilized in the past for robust classification accuracy.

4 Experimental Results

In this segment of the paper, we present experimental evaluation protocol and quantitative results using multi-spectral facial database of 168 subjects across nine spectral bands. Specifically, we first extract features using pre-trained Convolutional Neural Network (CNN) and then learn the classifier independently using Support Vector Machine (SVM) and k-Nearest Neighbor (k-NN) classifier. The $Rank-1$ recognition rate is obtained independently across individual spectral band using proposed methods and compared against the state-of-the-art multi-spectral face recognition methods.

Table 2. Rank-1 recognition rates (%) across individual nine spectral bands using state-of-the-art methods and proposed methods.

Algorithm	Individual spectral band								
	530 nm	590 nm	650 nm	710 nm	770 nm	830 nm	890 nm	950 nm	1000 nm
LBP-SVM	17.26	25.3	59.52	59.82	42.86	39.29	40.48	35.12	42.86
LBP-KNN	20.24	27.68	61.01	59.23	44.05	41.07	40.18	35.71	49.11
CNN	56.55	63.1	65.48	61.9	59.23	50.6	67.56	63.69	66.07
CNN-SVM	60.71	72.62	76.49	77.08	72.02	73.81	76.19	74.7	79.46
CNN-KNN	66.37	79.46	80.65	84.52	76.79	78.87	80.95	80.65	82.14

4.1 Evaluation Protocol

In this section, we explain the experimental evaluation protocol followed for multi-spectral face recognition in this work. We split the *SpecVis* database into two sets: reference set and probe set. Reference set consists of 168 subjects along with their samples corresponding to session-1 data and probe set consists of respective 168 subjects along with their samples corresponding to session-2. Since the performance is obtained across individual spectral bands, the protocol remains same while computing the recognition rate at $Rank-1$ across individual spectral bands.

4.2 Observations

Based on the evaluation protocol, we present our results across state-of-the-art methods and proposed method. Table 2 summarizes the $Rank-1$ recognition rate obtained across individual spectral bands. From the obtained results, we make our major observations as follow:

- The overall $Rank-1$ recognition rate across individual spectral bands shows reasonable performance using the proposed method.
- The highest recognition rate of 84.52% is obtained for CNN-KNN approach using 710 nm spectrum band and the lowest performance of 17.26% recognition rate is obtained with LBP-SVM using 530 nm spectrum band.

- Of the classification method used in proposed approach, CNN-KNN outperforms CNN-SVM across all the individual spectral bands.

To summarize, the proposed method based on extracting CNN features for multi-spectral facial database improves the performance accuracy across individual spectral band compared to the state-of-the-art methods, demonstrating the significance of employing CNN based feature extraction.

5 Conclusion

Face recognition is always a challenging task under varying illumination conditions. In recent times, due to the advancement in sensing technologies, multi-spectral imaging have shown greater potential to under varying illumination conditions to perform better. Although, multi-spectral imaging across individual spectral bands obtains the discriminative feature information, the performance of individual bands are not consistent using state-of-the-art texture descriptor methods. Hence, in this paper, we present the CNN based feature extraction technique along with two independent classifiers such as Support Vector Machine (SVM) and k-Nearest Neighbor (k-NN) to obtain an improved performance across individual spectral bands. The results in the form of recognition rate at $Rank - 1$ is obtained based on the publicly available $SpecVis$. The observed results demonstrated the consistent improvement in the recognition rate across individual spectral band. Proposed method of CNN-KNN has appeared as the algorithm with highest rank-1 recognition rates across all nine bands. Also, the recognition rate of 84.5% for the 710 nm band is the highest rank-1 recognition rate obtained using CNN-KNN approach.

Acknowledgement. This work is supported by University Grant Commission, India (Grant No. 40-664/2012 (SR)).

References

1. Ahuja, Y., Yadav, S.K.: Multiclass classification and support vector machine. Glob. J. Comput. Sci. Technol. Interdisc. **12**, 14–20 (2012)
2. Albawi, S., Mohammed, T.A., Al-Zawi, S.: Understanding of a convolutional neural network. In: 2017 International Conference on Engineering and Technology (ICET), pp. 1–6, August 2017
3. Bebis, G., Gyaourova, A., Singh, S., Pavlidis, I.: Face recognition by fusing thermal infrared and visible imagery. Image Vis. Comput. **24**, 727–742 (2006)
4. Farokhi, S., Sheikh, U.U., Flusser, J., Yang, B.: Near infrared face recognition using Zernike moments and hermite kernels. Inform. Sci. **316**, 234–245 (2015)
5. Ghiass, R.S., Arandjelović, O., Bendada, A., Maldague, X.: Infrared face recognition: a comprehensive review of methodologies and databases. Pattern Recogn. **47**(9), 2807–2824 (2014)
6. Krizhevsky, A., Sutskever, I., Hinton, G.E.: ImageNet classification with deep convolutional neural networks. Neural Inform. Process. Syst. **25** (2012)

7. Li, S.Z., Chu, R., Liao, S., Zhang, L.: Illumination invariant face recognition using near-infrared images. IEEE Trans. Pattern Anal. Mach. Intell. **29**(4), 627–639 (2007)
8. Nicolo, F., Schmid, N.: Long range cross-spectral face recognition: matching SWIR against visible light images. IEEE Trans. Inform. Forensics Secur. **7**, 1717–1726 (2012)
9. Patel, R., Yagnik, S.B.: A literature survey on face recognition techniques. Int. J. Comput. Trends Technol. (IJCTT) **5**, 189–194 (2013)
10. Peng, M., Wang, C., Chen, T., Liu, G.: NIRFaceNet: a convolutional neural network for near-infrared face identification. Information **7**, 61 (2016)
11. Taigman, Y., Yang, M., Ranzato, M., Wolf, L.: DeepFace: closing the gap to human-level performance in face verification. In: 2014 IEEE Conference on Computer Vision and Pattern Recognition, pp. 1701–1708, June 2014
12. Vetrekar, N.T., Raghavendra, R., Raja, K.B., Gad, R.S., Busch, C.: Extended spectral to visible comparison based on spectral band selection method for robust face recognition. In: 2017 12th IEEE International Conference on Automatic Face Gesture Recognition (FG 2017), pp. 924–930, May 2017
13. Zhang, B., Zhang, L., Zhang, D., Shen, L.: Directional binary code with application to polyu near-infrared face database. Pattern Recogn. Lett. **31**(14), 2337–2344 (2010)
14. Zhang, X., Peng, M., Chen, T.: Face recognition from near-infrared images with convolutional neural network. In: 2016 8th International Conference on Wireless Communications Signal Processing (WCSP), pp. 1–5, October 2016