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Detecting Disguise Attacks on Multi-spectral Face Recognition Through Spectral Signatures

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***Abstract*—Presentation attacks on Face Recognition System (FRS) have incrementally posed challenges to create new detection methods. Among the various presentation attacks, disguise attacks allow concealing the identity of the attacker thereby increasing the vulnerability of the FRS. In this paper, we present a new approach for attack detection in multi-spectral systems, where face disguise attacks are carried out. The approach is based on using spectral signatures obtained from a spectral camera operating in $eight$ narrow spectral bands across the Visible (VIS) and Near Infra-Red (NIR) ($530nm$ to $1000nm$) spectrum and learning deeply coupled auto-encoders. The robustness of the proposed approach is validated using a newly collected spectral face database of subjects conducting both bona fide (i.e. real) presentations and disguise attack presentations. The database is designed to capture 2 different kinds of attacks from 54 subjects, amounting to a total number of 6480 samples. Extensive experiments carried on the multi-spectral face database indicate the robust performance of proposed scheme when benchmarked with three different state-of-the-art methods.**

***Index Terms*—Biometrics, Spectral Face Imaging, Spectral Signature, Disguise Detection**

I. Introduction

Biometric systems have favored face biometrics over other modalities due to it's non-intrusive nature of image capture at varying stand-off distances. Despite the advancements, face recognition systems in recent times are challenged by number of ways such as presentation attacks [1], verification after plastic surgery [2] and disguise attacks [3]–[6]. The goal of the disguise attack is to conceal the identity of the subject using accessories to avoid being recognized by the biometric system. Figure 1 illustrates such an attempt by a subject employing accessories. The examples show variations in appearance of the face with accessories such as moustache and beard. While a moustache or beard could be the natural result of long-term ageing of the biometric characteristic, the scope of this work is to detect short-term concealment modifications of the appearance reached with artificial accessories. Such inconspicuous attacks lead to a simple change in the visual perception and thus subjects can deliberately remain elusive from being recognized for instance in a border control scenario.

A. Related Works

Earlier work in this direction have focused on two main themes: face recognition under disguise and detection of face disguise attacks [7]. In this work, we focus on the disguise face detection that has received considerable interest in the

Fig. 1: Variations in facial appearance of same individual under Disguise: (a) Normal Face, (b) Normal beard, (c) Long beard

biometric community. Among earlier works to detect disguise attacks, we can find approaches that are inspired by the traditional holistic mechanism of Principle Component Analysis (PCA). The approach was utilized by a number of researchers and applied independently on parts of a face such as upper and lower half or left and right half of the face image, to detect the partial disguise attack (it has to be noted that these studies were further limited to detect sunglasses and scarf accessories) [8]–[10]. The performance of these works depend heavily on how much of the eye and mouth regions are covered and they are reported to perform poor when these regions are occluded. Several other works [11], [12] have used various facial skin regions to explore the differences in skin color to detect whether the face is disguised or not, which follows the works of detecting the disguise attacks using artificial make-up. Again these approaches do not fully meet real world conditions, where skin color varies strongly under varying illumination conditions, and thus limiting the use of such disguise detection approaches. Nonetheless, the application of texture based methods to extract local and global features has indicated a robust approach for addressing the disguise detection problem [7], [9]. Most of these above studies are based on the visible spectrum images, stemming from the AR database [9], Yale [13] and synthetic databases [14]. It was only recently that the thermal imaging along with texture based methods for disguise detection was investigated [3]. The drawback of this work is that the texture descriptor is used to distinguish the disguise face patches, which limits it's use-case for thermal spectrum images that contains only emittance information (heat map), rather than the texture data. Further Wang et. al. [4] have presented the argument that some of the sample images in the database are covered with too much of disguise accessories, which are not realistic in real world.

Based on the available work, it is noted that the majority of the work is reported on the visible spectrum, especially for occlusions detection that can be easily detected by the naked eyes. Thus, the applicability of these methods are limited in a real-life scenario, for instance, the border control with a human operator. With the evolving technology, multi-spectral FRS are already deployed for the border control applications [15] and these facts have motivated us to pursue the multi-spectral disguise detection. The work gains significance particularly for detecting disguise attacks in multi-spectral FRS which are normally difficult to detect for an human observer with naked eyes.

B. Our Contributions

To the best of our knowledge, the spectral properties [16] of multi-spectral imaging is not explored to detect a disguise face attacks on multi-spectral FRS. In principle, a multi-spectral imaging sensor extracts the characteristic spatio-spectral data across Visible (VIS) and Near Infra-Red (NIR) spectrum based on the reflectance properties of an object. Spectral imaging technique acquires complementary image information (i.e. reflectance or emittance) across various disjoint spectral bands such that the characteristic discriminative features can be obtained.

Inspired by such key advantages of multi-spectral imaging, it is our assertion that the spectral information from multi-spectral imaging can be used to distinguish bona fide face images from disguise face images (covered with accessories). Learning and detecting such differences from the photometric reflectance properties across various spectrum bands will lead to different feature vectors for artificial accessories in contrast to bona fide presentations. It has to be noted that a bona fide presentation is an interaction of the biometric capture subject and the biometric data capture subsystem in the fashion intended by the policy of the biometric system, meaning that face region has not been altered or occluded to conceal identity. For instance, the photometric spectral reflectance characteristics of the artificial accessories (beard/moustache) differs from a real/natural face (beard/moustache) that can be attributed to the artificial materials used to generate the artificial accessories. We therefore, attempt to address such identity concealer attacks by exploiting spectral information obtained across various individual bands captured from the face region.

Further, artificial disguise accessories (beard/moustache) can be generated using different kinds of materials that includes human hair, crepe wool, and fur. One can obtain natural beard using natural human hair, but the fine textural nature of human hair makes it difficult to manipulate facial characteristics with genuine look [17]. Further, the limited availability and the high cost of human hair makes it less popular among the identity concealers [17]. Material fur does not give more realistic appearance; hence it's use case is very limited. Crepe wool on the other hand provides more natural looking beard, close to real human hair and availability at low-cost, makes it attractive for usage in carrying out disguise attacks. Attributed to this factor and specifically to be close to realistic attacks, we construct a new face disguise database with disguise attack attempts that are carried out using the artificial crepe wool material on the multi-spectral camera. The newly constructed database is comprised of 54 subjects captured in eight different bands with two types of disguise attacks with normal (Refer Figure 1(b)) and long beard (Refer Figure 1(c)). To the best of our knowledge, this it the first unique database, which has been collected so far to simulate the realistic operating conditions of multi-spectral camera and close to reality attacks.

Considering the significance of spectral imaging and at the same time the vulnerability towards attacks, we present a robust approach of disguise attack detection by exploring the concept of spectral signatures. Precisely, we extract the spectral signature of moustache regions for $bonafide$ presentation of the subject (individuals without disguise accessories) and disguise presentation attempt by the subject (individuals with disguise accessories). The set of extracted features are presented to deeply coupled autoencoders to classify bona fide and disguise samples. We further benchmark the performance against the state-of-the-art feature extraction methods to present the significance of our proposed method for disguise attack detection in multi-spectral imaging. The key contributions of this work can be highlighted as below:

- Presents a new approach to detect disguise attacks by exploring the spectral signature and learning a deeply coupled autoencoder to distinguish $bonafide$ and $disguise$ presentations.
- Presents a newly acquired spectral disguise face database captured in $eight$ narrow spectral bands including $530nm$, $590nm$, $650nm$, $710nm$, $770nm$, $890nm$, $950nm$, $1000nm$ across Visible (VIS) and Near Infra-Red (NIR) spectrum. The database comprises of 6480 face images captured under various disguise variations and to best of our knowledge, this is the first and largest database captured using $eight$ spectral bands for disguise attacks. The database is publicly available for the research purpose along with the publication of this article.
- Extensive experiments are carried out on the newly constructed database that shows the significant improvement in performance when compared with three different existing methods.

The rest of the paper is organized as follows: Section II presents in detail the proposed approach to detect disguise based on spectral signatures. Section III presents the description of our newly collected spectral disguise face database. Section IV presents the experimental results for disguise detection and Section V presents the conclusive remarks.

II. Proposed Method: Spectral Signature Based Disguise Detection

The proposed method explores the spectral signature approach for disguise attack detection. Figure 2 illustrates the framework employed in this work. Considering the fact that

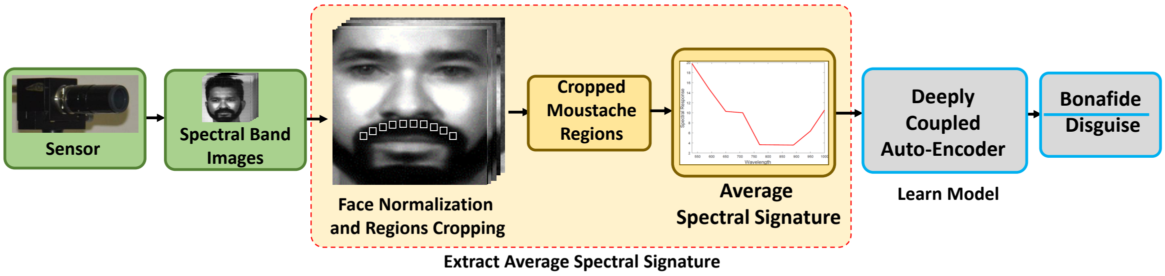


Fig. 2: Proposed approach based on spectral signature for $Disguise$ detection

the effect of disguise is confined only to certain regions (depending upon the type of disguise) in the face, we focus our approach to process a region of interest from the face image. In this work, we specifically focus on two common type of attacks with *normal beard* and *long beard*. In case of attacks with *normal beard*, the attacks are carried out with partly covered cheeks and moustache region while in the attacks with *long beard*, the face is covered densely on selected parts of cheeks and moustache region. Since the attack is more confined to cheek and moustache region and showing more visibility in the moustache region (refer Figure 2 and Figure 3 for face detection region on normal and long beard respectively) has motivated us to choose only moustache region to extract relevant information to detect attacks while reduce the computation complexity in processing full face image. However, one can argue that the disguise can be presented only in the cheek region while keeping the moustache region unaltered with natural hair. However, it is indicated in [18] that disguise on the cheek region has lesser contribution in degrading the performance of the FRS due to disguise. This further justifies our choice of choosing the moustache region alone.

Given the multispectral image, we first perform the face detection and normalisation using the approach based on face landmark detection [19] for automatically cropping both face and the moustache region. Specifically, the landmarks of mouth region is utilized to obtained the coordinates corresponding to the center of mouth, which further is used to automatically locate and crop 10 regions of moustache, each of size 11×11 pixels. The proposed approach extracts various regions of moustache in a block based manner and concatenates them before obtaining an average spectral signature. The average spectral signature obtained for both bona fide and disguise individuals used to learn a deeply coupled autoencoder to detect disguise attacks.

Let the spectral band image S_λ be represented by Equation 1 as follows:

$$S_\lambda = \{S_1, S_2, S_3 \ldots, S_8\} \quad (1)$$

where, $\lambda = \{1, 2, 3, \ldots, 8\}$ represents individual spectral bands corresponding to $530nm$, $590nm$, $650nm$, $710nm$, $770nm$, $890nm$, $950nm$ and $1000nm$ wavelength. These spectral band represents the reflectance or emittance information across the VIS-NIR ($530nm$ to $1000nm$) spectrum.

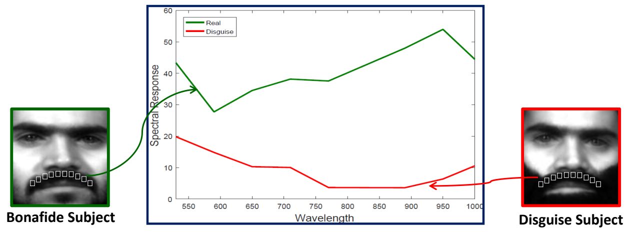


Fig. 3: Illustration of differences in the spectral characteristics for moustache regions of bona fide and disguise presentations

In this work, we represent the bona fide and disguise samples using spectral reflectance vectors, that are extracted from the facial moustache region. It is our assertion that an artificial moustache has different photometric reflectance characteristics compared to the bona fide moustache. Figure 3 shows the normalized face image, when disguise attacks are carried out using long-beard. Further, Figure 3 also presents reflectance under disguise attacks in moustache region for attacks with beard alongside the bona fide image and this further justifies our assumption of obtaining different profile of spectral signatures extracted from face moustache region corresponding to bona fide and disguise presentation. We therefore consider the cropped region from region corresponding to moustache $s_{i\lambda}$ in the spectral domain which can be represented by Equation 2 as:

$$s_{i\lambda} = \{s_{i1}, s_{i2}, s_{i3}, \cdots, s_{i8}\} \quad (2)$$

where, $i = \{1, 2, 3, \ldots, 10\}$ represents the cropped regions of S_λ. In order to simplify the computation, we concatenate all the regions in respective spectral bands The size of each spectral band after concatenation of 10 regions become 11×110. The concatenated region for a spectral band is represented using Equation 3.

$$h_\lambda(x, y) = [s_{1\lambda}(m, n) \parallel s_{2\lambda}(m, n), \parallel \cdots \\ \cdots s_{3\lambda}(m, n) \parallel \cdots, \parallel s_{10\lambda}(m, n)] \quad (3)$$

where, (m, n) represents the coordinates of each region before concatenation and (x, y) represents the final coordinates after concatenating the all 10 regions. Further, the average spectral characteristic is computed for these concatenated regions. Let the average spectral signature be denoted by φ_λ and mathematically represented in the Equation 4

$$\varphi_\lambda = \frac{1}{x \times y} \sum_{p=1}^{x} \sum_{q=1}^{y} h_\lambda(x_p, y_q) \quad (4)$$

The average spectral signature φ_λ obtained from Equation 4, is used as a feature vector of size 1×8 to learn the Deeply coupled autoencoder model. The autoencoder has two main functional components namely: encoder and decoder. Encoder maps φ_λ to vector E as follows:

$$E_l = h^l(w^l * \varphi_\lambda + b^l) \quad (5)$$

where, l indicate the l^{th} layer, h^l denote the transfer function on the encoder, while w^l is the weighting matrix and b^l is a bias vector.

Then, the decoder maps the encoded representation E back into an estimate of the original input vector φ_λ as follows:

$$\hat{\varphi_\lambda} = h^{l+1}(w^{l+1} * \varphi_\lambda + b^{l+1}) \quad (6)$$

The cost function is represented as the superposition on mean square, weight regularization and sparsity regularization as follows:

$$C = \frac{1}{N} \sum_{n} \sum_{k} (\varphi_\lambda^{kn} - \hat{\varphi_\lambda}^{kn}) + \lambda * \Sigma_{weightsregularisation} + \beta * \Phi_{Sparsityregularisation} \quad (7)$$

Where, n indicates the number of samples and k indicates the dimension of each sample in the training data, λ is the coefficient for the L_2 regularization term and β is the coefficient of the sparsity regularization term.

In this work, we learned a deep autoencoder with two layers connected in a cascade fashion. The first autoencoder is trained in an unsupervised manner using a training data that represent the spectral signatures from bona fide and disguise presentation attack. The output of the first autoencoder is connected to the second autoencoder. We then train a softmax layer to perform the classification in a supervised manner to have a deep network formed by coupling two autoencoders along with the softmax layer. Further, the fine tuning is also carried out by training a developed deep network in a supervised fashion to improve the robustness. Given the spectral signature corresponding to the test sample, we compute the similarity scores by testing with the trained deep network.

III. Spectral Disguise Database

In this section, we present the description of our spectral disguise face database collected and introduced with this work. The database is comprised of 54 subjects captured in *eight* narrow spectral bands corresponding to $530nm, 590nm, 650nm, 710nm, 770nm, 890nm,$ $950nm$ and $1000nm$ covering the VIS-NIR spectrum. The subjects contributing to this database are all male participants between the age of 20 to 50 years. We have considered only male subjects not to introduce the bias in the experiments especially with the proposed method which is purely based on the moustache region. Further, all the subjects in the bona fide presentation have naturally grown moustache and 22 subjects out of 54 subjects have naturally grown beard. Thus, considering female subjects into bona fide presentation set without a moustache and disguise presentation with a moustache will not serve the purpose of disguise classification, rather it becomes the classification problem of detecting subjects with and without moustache which is beyond the scope of this work.

The data collected is categorized into bona fide set (normal captured samples - without disguise), and two variants of disguise that includes wearing normal-beard and long-beard. Figure 4 illustrates the face images collected without disguise and with disguise variations. Under each category, we have captured 5 sample images per subject in one session, which corresponds to 54 Subjects$\times$ 5 Samples$\times$ 8 Bands = 2160 sample images. This will result in a total of $2160 \times 3 = 6480$ samples.

The newly constructed database has the following unique features, when compared with existing disguise databases:

- First multispectral face disguise database collected using a single camera with eight narrow spectral bands across the Visible (VIS) and Near Infra-Red (NIR) ($530nm$ to $1000nm$).
- Introduces unique characteristic reflectance or/and emittance information by exploring band level data (*eight* spatio-spectral band), when compared to the publicly available disguise data with a limited number of bands (either single band (visible), or two bands (visible and thermal)).
- The attention was given towards building the database with challenging disguise attacks such as Normal-beard and long-beard (Figure 4(b and c)), in which most of the face is concealed to avoid being recognized by face recognition system. However other disguise variations such as hairstyle, varying cap or hat, etc., are avoided in this work, which usually does not have a significant impact on the FRS, considering the presence of face detection software together with face quality estimation, which normally eliminate these unwanted regions before processing.
- Further, with the expert supervision, the spectral disguise database is captured in a realistic scenario, making it difficult even to detect with naked eyes of human observer. This is the unique dataset which has been collected so far and shall be made publicly available at: http://www.nislab.no/biometrics_lab/msfd_db. For the vulnerability analysis please refer supplementary material.

IV. Experiments and Results

In this section, we present the results of the proposed scheme on the newly constructed face disguise database using the multispectral sensor with eight different spectral bands in visible and near-infrared range. The performance of the proposed scheme is compared with the three different existing methods such as PCA-SVM [10], Intensity and Texture Encoder (ITE)-SVM [3] and Gabor features-PCA-SVM [20]. To

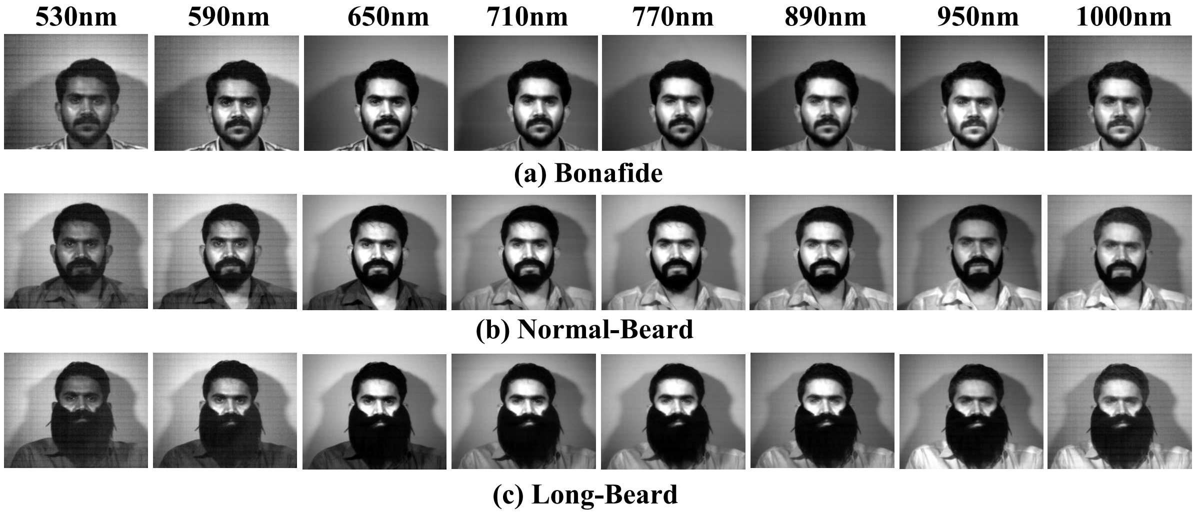
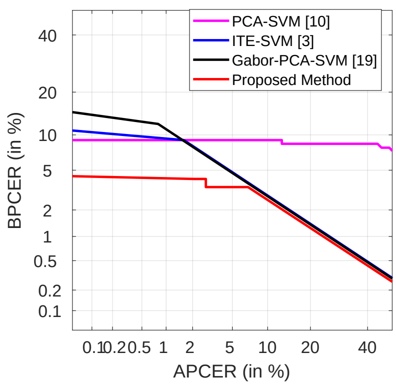
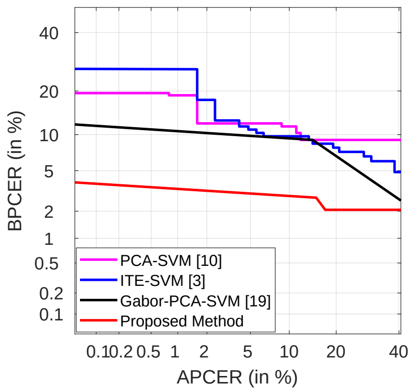


Fig. 4: Sample spectral band images across $eight$ bands:(a) bona fide facial images (without disguise) and (b) disguise attack $(Normal - beard)$ (c) disguise attack $(long - beard)$



(a) Disguise detection - long beard



(b) Disguise detection - normal beard

evaluate the performance of the proposed algorithm, we divide the whole database of 54 subjects to have two independent sets namely: *training* and *testing* set. The training set consists of 25 subjects that results in 25 subjects $\times$ 8 Spectral bands $\times$ 5 samples = 1000 samples independently with bona fide, disguise with normal bread and disguise with long beard. The testing set is comprised of 29 subjects that results in 29 subjects $\times$ 8 Spectral bands $\times$ 5 samples = 1160 samples independently with bona fide, disguise with normal bread and disguise with long beard. The training and testing partition was repeated *m* times (where $m = 10$) using Holdout cross-validation and there is no overlapping between these two subsets. Finally, the performance is reported by averaging the results obtained over all 'm' trails.

A. *Results and discussion*

This section presents the quantitative results of the proposed method and existing methods for the multispectral face disguise attacks. The proposed method is compared with three different state-of-the-art methods. The state-of-the-art methods are developed either on only visible band [10], [20] or to work independently on both visible and thermal spectrum [3]. However the proposed method is based on the computing the spectral signature that utilizes the average intensity values in the moustache region of the face across all spectral bands. Thus in order to have a fair benchmark of the existing schemes with the proposed method, we evaluate the performance of existing methods on the fused image that is obtained from all eight spectral bands using wavelet-based average fusion technique [21].

TABLE I: Quantitative performance of the proposed scheme on long beard disguise attack

Algorithms	D-EER	BPCER @	
		APCER = 5%	APCER = 10%
PCA-SVM [10]	8.94	15.85	9.42
ITE-SVM [3]	5.34	4.94	3.29
Gabor-PCA-SVM [20]	6.46	4.94	3.29
Proposed Method	**3.44**	**3.86**	**3.07**

Figure 5a and Table I shows the quantitative performance of the proposed scheme on the disguise detection when presented with long beard disguise attack. It can be noted from the obtained results that the proposed method has indicated the best performance, when compared to that of the existing schemes. The proposed method shows a performance of Detection-Equal Error Rate (D-EER) of 3.44% and a BPCER = 3.86% @ APCER = 5% and BPCER = 3.07% at APCER = 10%. Figure 5b and Table II shows the quantitative performance of the proposed scheme on the disguise detection, when presented with normal-beard disguise attacks. It can also be noted that the proposed method shows the best performance, when benchmarked to existing schemes. Thus based on the obtained results, the important observations are:

1) The proposed method shows the best performance in detecting both normal and long beard face disguise attacks, when compared with the existing schemes.
2) Existing methods shows the degraded performance on the normal beard disguise, when compared to long beard disguise. This indicates the difficulty in detecting the normal beard as the occlusion of the face region is less, when compared to that of the long-beard disguise attack. In addition, our database is collected to have a natural normal beard for about 22 subjects that have also contributed to the degraded performance of the state-of-the-art scheme.
3) The proposed method has indicated the consistent performance on both normal and long beard disguise detection that can be attributed to the robustness of the spectral signature in quantifying the characteristics of natural beard with an artificial beard.

TABLE II: Quantitative performance of the proposed scheme on normal beard disguise attack

Algorithms	**D-EER**	**BPCER @**	
		APCER = 5%	**APCER = 10%**
PCA-SVM [10]	11.05	13.22	12.61
ITE-SVM [3]	9.64	11.74	9.66
Gabor-PCA-SVM [20]	11.74	9.86	9.14
Proposed Method	**3.79**	**3.82**	**3.69**

V. CONCLUSION

With increasing vulnerability of the FRS towards disguise attacks, FRS demand the need for robust methods to detect such attacks. In the recent times, spectral imaging has obtained significant attention due to it's ability to capture the information beyond the visible spectrum. This has resulted in deploying several multi-spectral face recognition systems in the real-life scenarios. In this paper, we have presented a new approach for disguise detection by exploring the spectral signature. More specifically, we have used the average spectral signature of bona fide and disguise presentation attempts of moustache regions to learn the signatures using deeply coupled autoencoder to classify bona fide and disguise samples in a robust manner. We have also introduced a new multispectral face disguise database comprised of 54 subjects in 8 spectral bands with 2 different disguises consisting of normal beard and the long beard. This is the first of it's kind database with 8 spectral bands that are made available to the public for research purpose. Extensive experiments are carried by comparing the performance of the proposed scheme with the three different existing schemes. The proposed method has indicated the consistently high performance in detecting both normal and long beard disguise attacks on multi-spectral FRS.

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