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Time-Frequency Features of Laplacian Decomposition

Kiran B. Raja, R. Raghavendra, Christoph Busch
{kiran.raja; raghavendra.ramachandra; christoph.busch} @hig.no
Norwegian Biometrics Laboratory, Gjøvik University College, 2802 Gjøvik, Norway

***Abstract*—Smartphones are gaining popularity as a biometric authentication device for many applications like banking and e-commerce. While multiple smartphone manufacturers providing phones with new features, consumers venture to try new phones or use multiple devices to sign into secure applications leading to a situation, in which they have to deal with data emerging from various smartphones along with manifold capture conditions. Recognition processes involving such cross-smartphone data leads to degraded biometric performance. In this work, we propose a novel technique to extract texture features from the periocular region by decomposing the images into Laplacian pyramids of various scales and obtain frequency responses in different orientations. Further, we propose to encode the features sparsely as a means to increase the cross-smartphone authentication using periocular region. From the extensive set of experiments conducted on a publicly available smartphone periocular database, we demonstrate the improvement using the proposed feature encoding and comparison for authentication scenarios. An average gain in Equal Error Rate of around 10 % is achieved while the best gain of 16 % is obtained for various comparisons as compared to previously reported verification scores. The obtained gain in performance indicates the applicability of the proposed feature extraction technique for real-life authentication scenarios employing data from different smartphones in the visible spectrum.**

***Keywords*-Visible spectrum; iris recognition, periocular recognition, cross-smartphone, feature extraction**

I. Introduction

Smartphones with advanced features have led the consumers to opt for frequent upgrades or change of brand of smartphones. At the same time, many of the accounts for banking or e-commerce allow sign-in from multiple devices as long as they are registered for. Growing popularity of biometric-based authentication [1], [2], [3], [4], [5], [6] in such services is impacted by device-dependent biometric data capture. Essentially, the freedom to sign-in from different devices leads to biometric data originating from multiple personal devices for the same individual. As a consequence a decreased cross-sensor authentication performance is observed, which is not desired by any consumer using biometrics authentication for secure applications.

Although many works have explored different biometric characteristics such as face [1], finger photo [2], [3], knuckle print for identification [4] on smartphones, recent works have indicated strong preference for face, periocular and iris-based authentication on smartphones [5], [6], [7], [8]. However, owing to the limited visibility of the iris texture in the visible spectrum for a large sector of population, periocular biometrics is strongly preferred [9]. Periocular biometrics in smartphone-based authentication is deemed to provide good performance for secure applications [10], [11], [12], [13]. Motivated by the performance of periocular biometrics on smartphone authentication, in this work, we attempt to improve the verification performance. Specifically, we look into the aspect of cross-smartphone periocular verification employing the publicly available database [5], [14]. Further, we also propose a new feature extraction method to obtain texture features from the periocular region by decomposing the images into Laplacian pyramids of various scales and obtain frequency responses in different orientations. To make it robust and with the intention to achieve a good verification performance, we propose to represent the features sparsely for comparison. We then demonstrate the improved verification performance and compare it against well-known feature extraction techniques used in other works.

The rest of the paper is organized as follows: Section II gives a brief overview of the cross-smartphone periocular verification scheme. Section III discusses the proposed feature encoding of texture features and algorithm employed for classification. Section IV provides the details of the database, experiments and protocol for evaluating cross-smartphone periocular biometrics. Section V discusses the obtained results for the proposed method followed the conclusive remarks of this work in Section VI.

II. Cross-smartphone Periocular Verification

In a typical cross-smartphone periocular verification set-up, the reference and probe data is captured on two different smartphones. In such a situation, the necessity for cross-smartphone evaluation arises whereas if the data comes from one and the same smartphone but different cameras or illumination, the impact of varying imaging conditions should be studied. The challenges in handling such varying conditions of illumination and camera specifications along with the different smartphones are illustrated in Figure 1. The images from two sample subjects from the database are illustrated in Figure 1(a) and Figure 1(b) corresponding to iPhone and Samsung respectively. The left and right part of both Figure 1(a) and Figure 1(b) provides the overview of the challenging nature of the database. The impact of varying illumination conditions in imaging and the change of the interaction of the capture subject with the smartphone can be clearly

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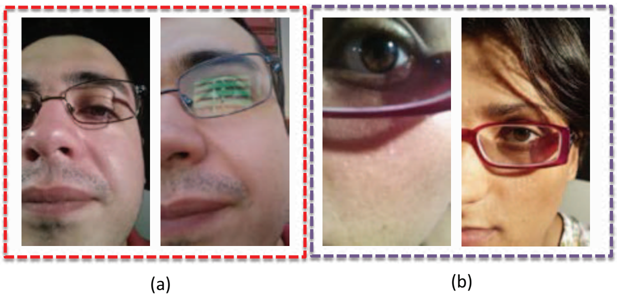


Figure 1: Sample images of two subjects captured under varying conditions. Left part of (a) provides the image captured using iPhone in indoor illumination while right part of (a) provides the image captured in outdoor illumination. Similar variations can be seen in (b) for the images obtained using Samsung phone.

seen. Such magnitude of changes in images for periocular verification in the visible spectrum intuitively degrades the biometric performance as reported in earlier work [9]. To overcome such degraded performance, in this work we propose a robust feature extraction method leading to improved verification performance.

As this work intends to improve the performance of cross-smartphone periocular verification, we employ the verification framework as depicted in the Figure 2. Unlike for a regular periocular recognition pipelines in our work, as indicated in the Figure 2, the enrolment and probe data comes from either different smartphones or from the same smartphone but was captured under different conditions in the visible spectrum. Once the periocular image is obtained, we extract the texture features using the proposed feature extraction technique as discussed in Section III. The obtained features are represented sparsely, and the comparison is performed. Based on the obtained comparison score, a subject is either verified or rejected.

III. Proposed Periocular Feature Extraction Method

The proposed algorithm for the feature extraction is motivated the technique used for presentation attack detection (a.k.a, spoof detection) [15] and is based on the decomposition of each image into Laplacian pyramids of multiple scales. Each of the resulting images at the specific scale is used to obtain a Short-Term-Fourier-Transform (STFT) response in four different orientations. The response corresponding to 4 different orientations is encoded as a single response image, and the features are obtained by taking the histogram as described in this section.

The Laplacian pyramid localizes the image features in both space and frequency domain [16]. The Laplacian pyramid can also be used as an alternative to a series of band-pass filtered images sampled successively at sparser representations [16]. The amount of edge information in any natural image contributes to the frequency information of that particular image [17]. A series of high-pass and low-pass filtering operations on images provides such information. Owing to the structural similarity of many images of the similar kind, one can expect similar responses for all such images when they are filtered with high-pass and low-pass filters. Such similar signatures of images will lead to a degraded classification performance. Further, cross-smartphone periocular images provide very low verification performance due to different camera specifications and characteristics along with varying capture conditions.

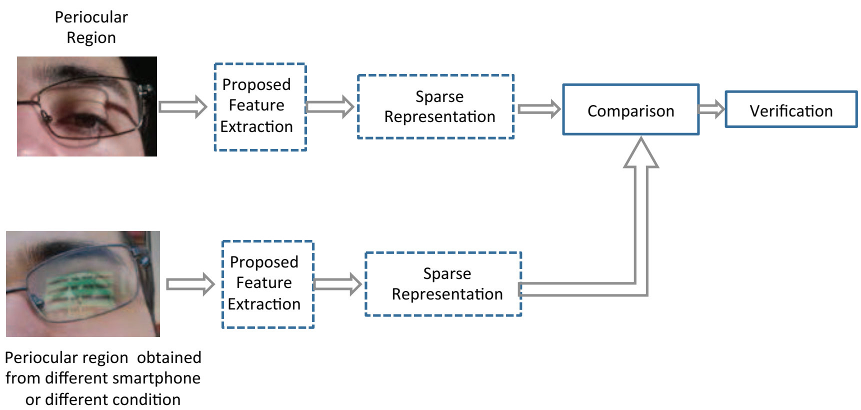


Figure 2: Illustration of scheme for cross-smartphone periocular recognition framework. The probe data may originate from same smartphone under different imaging conditions or different smartphone altogether.

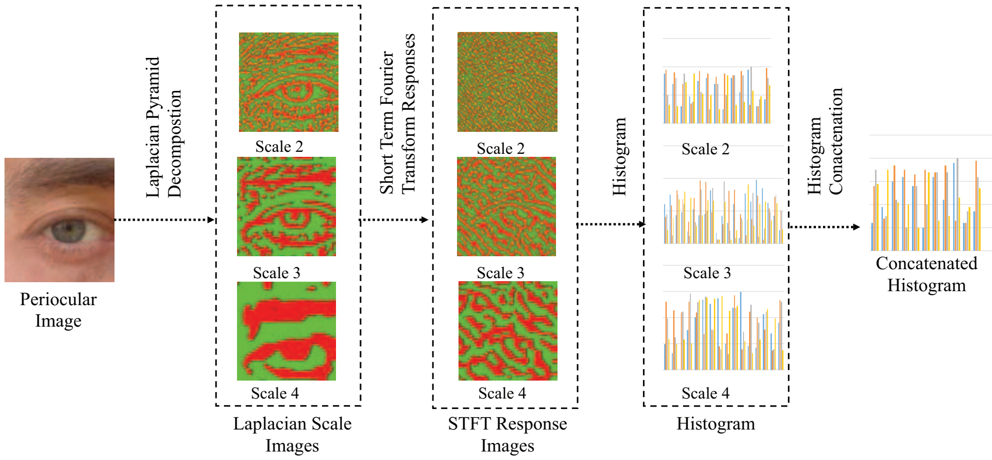


Figure 3: Illustration of proposed feature extraction method; The periocular image is decomposed into Laplacian pyramids of scale 4 and corresponding STFT response maps are obtained in each scale. [*Note: Only scales from 2 to 4 are used in this work. Images from all scales are resized to uniform size and depicted with pseudo-color maps for the purpose of illustration only].

Obtaining higher classification rates for such data relies heavily on the obtaining unique signatures. One way to obtain unique signatures of an image is by decomposing it to Laplacian pyramids. The decomposed pyramids enhance the uniqueness of the signature of the image at different scales. Unique signatures along different scales should intuitively reduce the cross-smartphone periocular image classification error rate. Thus, even though the image stems from different cameras, the underlying scale-space information remains fairly consistent leading to higher verification performance.

To localize unique image signatures independent of device it originates from, we employ Laplacian pyramids of 4 different scales with a binomial filter kernel of size 9. Laplacian pyramid decomposition separates the lower and higher frequency in well-defined components. Although, the frequency content of the image is well localized using Laplacian Pyramids, the orientation information of each frequency content is not obtained. The orientation information of each frequency component boosts the uniqueness of the image.

Thus, the obtained low pass and high pass filtered image at each scale is used to localize the orientation information of each frequency component with the aid of Short-Term-Fourier-Transform (STFT) analysis. In our work, we have employed four significant orientations ($\phi = \{0°, 45°, 90°, 135°\}$) to obtain the STFT responses.

The periocular images in this work are resized to 256×256 which yields 4 different scale images Laplacian Pyramid. Although, the Laplacian Pyramid image at different scales is expected to provide the unique signature, the very first level contributes redundant features due to the first level of filtering operation, and this would inherently result in redundant information for classification leading to lower performance. Based on empirical trials, we have discarded images at decomposition level 1 and retained the rest of the 3 scales, which are further analyzed for frequency information using STFT.

If an image at a particular scale s of the Laplacian pyramid is represented by I_s, we obtain the STFT response of the image. The STFT of the image at scale s, which is represented by F_s is the image resulting to response of frequency components in four different orientations such that $\phi = \{0°, 45°, 90°, 135°\}$. The filter response obtained from each orientation are separated for real and complex values subsequently. Each of the responses denoted by b is finally encoded to form the final response map as given by FR_s where i corresponds to different orientation angles given by $\phi = \{0°, 45°, 90°, 135°\}$.

$$FR_s = \mathrm{Re}(\sum_{i=1}^{4}(b_i) * (2^{(i-1)})) + \mathrm{Im}(\sum_{i=1}^{4}(b_i) * (2^{(i-1)})) \tag{1}$$

The feature vector FV, of the image at a particular scale s is formed by obtaining the histogram of the response map at scale FR_s.

$$FV_s = \sum_{i=0}^{255}\{FR_s\}_i \tag{2}$$

The final feature vector for the periocular image is formed by concatenating the feature vectors of images from scale 2 to n and orientation $\phi = \{0°, 45°, 90°, 135°\}$. The final feature vector FV_f can be represented as :

$$\begin{aligned} FV_f = \{&FV_{s=2,\phi=0°}, FV_{s=2,\phi=45°}, \\ &FV_{s=2,\phi=90°}, FV_{s=2,\phi=135°}, \\ &..., FV_{s=n,\phi=0°}, FV_{s=n,\phi=45°}, \\ &FV_{s=n,\phi=90°}, FV_{s=n,\phi=135°}\} \end{aligned} \tag{3}$$

The final feature vector given by Equation 3 is used to represent the image for classification purposes.

Figure 3 presents the framework for feature extraction. This indicates that In the current work, we have employed three scales starting from 2 to 4. The given periocular image is decomposed into Laplacian pyramids. The STFT response maps are obtained for different scale images. Further, the histogram of these images are obtained. All the histograms from different STFT response maps are concatenated to form the final feature vector. It can be observed from the figure that subtle texture information in the image along various orientations and scales are prominently visible with the Laplacian decomposition, which are further enhanced by the STFT response maps. The obtained feature vector with histogram concatenation is used for verification.

A. Feature classification

Given the histogram features of the image as in Equation 3, we further enhance the uniqueness of the histogram signature by sparse representation. The sparsely represented feature vector is classified by representing it as a L_1 minimization problem. The steps in the classification can be outlined as:

1) Given the class of enrolment samples for a particular subject, we extract the feature vector as described by Equation 3 and construct a training class T. A similar training class is constructed for each subject in the gallery.

$$T = [T_1, T_2, ..., T_C] \in R^{N(n_u.C)} \tag{4}$$

where n_u denotes the number of training samples for each class and N indicates the dimension of the feature vector defined by Equation 3 for C subjects.

2) Given the feature vector of the probe image T_e, one can assume a linear relation between training class images (T) and probe image (T_e) as:

$$T_e = T \times \alpha \tag{5}$$

where, $\alpha = [\alpha_1, ..., \alpha_{1n_u} \; |, | \; \alpha_2, ..., \alpha_{2n_u} \; |, | \; \alpha_C, ..., \alpha_{Cn_u}]$

3) The established relation of linear combination between T and T_e can be modeled as a l_1 minimization problem such that:

$$\hat{\alpha} = \arg \min_{\alpha' \in R^N} \|\alpha'\|_1 Te = T\alpha' \tag{6}$$

4) Compute the reconstruction error corresponding the test image and training images.

$$err(y) = \|Te - \Pi_C(\alpha')\|_2 \tag{7}$$

where y represents the number of test images and Π represents the whole training classes.

5) The minimum reconstruction error for a particular class is treated as the comparison score for such test image.

IV. Experiments and Protocol

Owing to the fact that smartphones are used for authentication in various situations and also to consider a situation where the enrolment data for an application such as secure banking is captured using a phone that is different than the one used for verification, we evaluate cross-smartphone verification performance in the lines of our earlier work [18]. To clearly mark the gain in the performance with the proposed technique, we provide the comparison against the best verification performance provided earlier.

A. Database

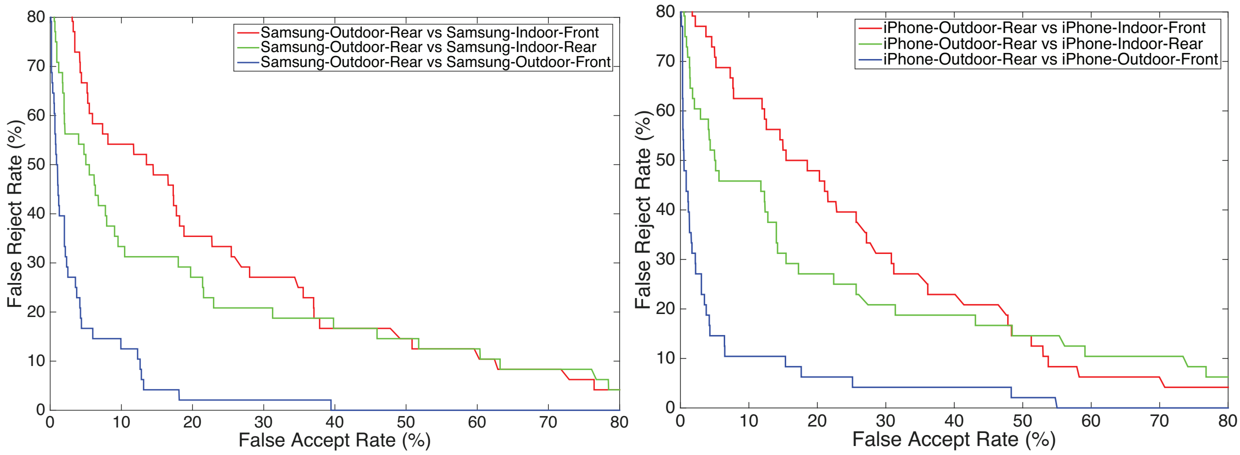
We have employed the publicly available smartphone periocular database provided by BIPLab [5], [14]. The dataset consists of periocular images from 75 subjects captured using *iPhone* 5 and *Samsung Galaxy S*4. The images are acquired using both frontal and rear camera in both indoor and outdoor illuminations. Moreover for each subject images are captured with the two phones using both cameras under the two different illumination conditions. To have the fair comparison of the performance under various conditions, a subset of the whole database has been employed in this work as some subjects do not have the data in all different capture conditions. We have employed 50 unique periocular instances with four samples for each capture condition for both smartphones.

1) Cross-smartphone Evaluation Protocol: Considering the possibility of using any smartphone to capture the image for verification under any illumination, in this work, we retain the protocol proposed in the earlier work [9]. Under the protocols proposed earlier, the enrolment images stem from a particular smartphone captured in a particular illumination while probe images come from the same/different smartphone under different/same illumination. As each subject has four samples provided, we consider them as enrolment for one set of particular acquisition condition and use the other four images from different acquisition conditions as the probe. For instance, if the reference images are captured in outdoor illumination using the frontal camera of iPhone, the probe images for the same subject is captured using the frontal camera of Samsung phone under outdoor illumination. Assuming multiple attempts to gain access, we consider the minimum scores obtained from 4 individual comparisons to final results of this work.

2) Feature Extraction Methods: In the current work, we have proposed a novel method for periocular verification. Further, to provide a comparison against the frequently used feature extraction techniques, we have employed two other feature techniques - Local-Phase-Quantization (LPQ) [19] and Binarized Statistical Image Features (BSIF) [20], [13]. BSIF filters of size 17×17 are employed in this work based on the empirical trials. Sparse Representation Classifier described in Section III-A is used for classification of features obtained from BSIF, LPQ and the proposed feature extraction method.

V. Results and Discussion

To indicate the gain in the performance for periocular verification feature extraction technique, we provide the results of the well used methods in the periocular verification scenario. All results in this work are reported with the Equal Error Rate (EER) as a measure for the verification performance.



(a) Samsung Dataset

(b) iPhone Dataset

Figure 4: Detection Error Tradeoff (DET) obtained using the proposed algorithm. (a) presents the DET curves of Samsung dataset and (b) presents the DET curves of iPhone dataset.

A. Samsung Dataset Evaluation

Table I provides the verification performance of the dataset obtained using Samsung smartphone. It can be observed from the Table I that images acquired in outdoor illumination using the rear camera to capture the reference images and images from other capture conditions are used as probe images. The outdoor illumination was chosen for the reference as these images are of highest quality in the employed dataset. The presented table indicates the gain in performance in very high order. An average gain of around 12 % is observed for the complete set of verification performance as compared against BSIF based verification. The highest gain can be seen for the comparison corresponding to images obtained in outdoor conditions using the frontal and rear camera that is around 16%. The Detection Error Trade-off (DET) performance of the proposed algorithm is provided in the Figure 4 (a) depicting lower EER.

Table I: Comparison table of EER (%) for proposed method versus previously reported benchmark results for Samsung data

Reference	Probe	LPQ	BSIF	Proposed
Outdoor Rear	Indoor-Front	44.63	37.69	**27.54**
	Indoor-Rear	37.63	25.00	**22.01**
	Outdoor-Front	35.32	25.26	**12.38**

B. iPhone Dataset Evaluation

Table II provides the verification performance of the dataset obtained using the iPhone smartphone. Similar to the previous section, images acquired in outdoor illumination using the rear camera are employed as reference as they correspond to images with superior quality in the employed dataset. The images from the other capture conditions are used as probe images. Table II presents the obtained performance gain. An average gain of around 8 % is observed for the complete set of verification performance as compared to the BSIF based verification. The highest gain can be seen for the comparison corresponding to images obtained in outdoor conditions using the frontal and rear camera that is around 10 % as compared to the BSIF based verification. The DET performance curves of the proposed algorithm are provided in the Figure 4 (b) indicating lower EER and thus higher verification performance.

Table II: Comparison table of EER (%) for proposed method versus previously reported benchmark results for iPhone data

Reference	Probe	LPQ	BSIF	Proposed
Outdoor-Rear	Indoor-Front	37.81	41.28	**31.02**
	Indoor-Rear	35.61	29.16	**23.00**
	Outdoor-Front	20.76	16.06	**10.31**

C. Cross-smartphone Evaluation

Along the lines of our previously published results [9], in this work we present the comparisons of data captured in a particular scenario from one smartphone versus the data captured in the exact scenario from a different smartphone. For instance, the data collected using iPhone frontal camera in outdoor illumination is compared against data captured using Samsung frontal camera in outdoor illumination.

Table III presents the verification performance of the proposed method and compares it to existing benchmark results[18]. The obtained performance using the proposed approach is on average 4 % higher as compared to verification results based on the BSIF technique. The best performance gain can be observed in data captured using the frontal camera in indoor illumination, which results in a gain in terms of EER equals 7 %. Figure 5 presents the DET performance curves for verification carried out on data acquired in the similar conditions but different smartphones. The lower EER in the graphs signify the applicability of proposed algorithm for cross-smartphone periocular verification.

Table III: Comparison table of EER (%) for proposed method versus previously reported benchmark results for data captured under similar settings but different cameras

Reference	Probe	LPQ	BSIF	**Proposed**
iPhone Outdoor Rear	Samsung Outdoor Rear	12.12	16.22	**12.5**
iPhone Outdoor Front	Samsung Outdoor Front	18.97	8.50	**8.35**
iPhone Indoor Rear	Samsung Indoor Rear	16.68	10.41	**8.33**
iPhone Indoor Front	Samsung Indoor Front	20.05	16.64	**10.39**

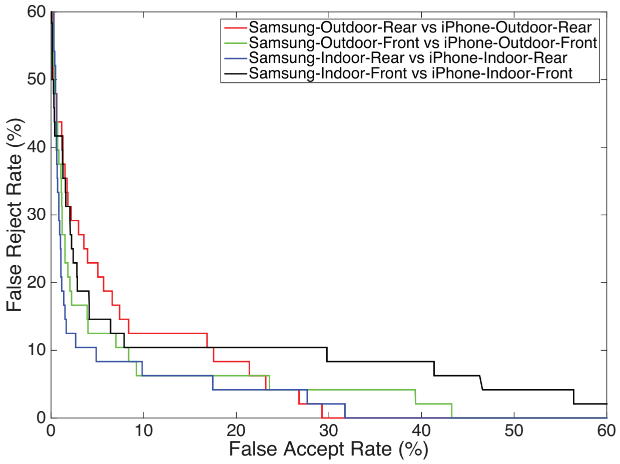


Figure 5: Detection Error Tradeoff (DET) obtained for cross-smartphone comparisons using proposed algorithm.

D. Discussion

The proposed method has consistently provided higher performance as compared to the existing state-of-art results using a single feature extraction technique. The obtained gain in performance is clearly indicating the significance of the proposed feature extraction technique. The complexity of the dataset comes with the blur, non-uniform illumination and the pose of the face while acquiring the images. The proposed technique has addressed these challenges using the combination of the proposed feature extraction technique and sparse representation. A possible extension of the proposed feature extraction technique along with fusion approaches may further reduce the verification error rate.

VI. Conclusion

The growing popularity of smartphones as biometric authentication sensor along with the possibility of using different devices for signing into secure applications leads to a situation of having the data that stems from different smartphones. As the users of such secure applications are not constrained to a particular location that is ideal to acquire biometric data, one has to anticipate lower biometric performances. To deal with such lower performances, in this work, we propose a new feature extraction technique that is based on Laplacian decomposed frequency responses that are sparsely represented. The proposed feature extraction technique is evaluated on various cross-smartphone data and the results obtained show the robust nature of the algorithm. The proposed algorithm has provided a gain of around 10 % in EER for is obtained for various comparisons as compared previously reported verification scores while the best gain obtained is around 16 %. The higher gain obtained from the proposed approach advocates the reliable and robust nature of the algorithm that is device and imaging condition agnostic.

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