Improving Fingerprint Interoperability by Integrating Wavelet Entropy and Binarized Statistical Image Features

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Abstract: Assuming that a large recognition system based on fingerprints will allow one sensor type at its creation and throughout its lifetime is not realistic. The vendor diversity on the market accentuates the need to make these systems interoperable, i.e., able to compare fingerprints collected using different devices with comparable high accuracy. In this paper, we propose a learning-based scheme for enhancing interoperability between optical fingerprint sensors. Different features (i.e. image quality, texture) and signal domains (space and frequency) are utilized to compensate for the variations in cross-sensor recognition performance of a commercial matcher. Specifically, we consider Binarized Statistical Image Features (BSIF) and characteristics derived from the Discrete Wavelet Transform (DWT). DWT is able to preserve spatial information of an image when performing frequency analysis while BSIF has shown to be an effective local descriptor for images with unusual characteristics. Experiments are carried out on a data set consisting of fingerprints obtained from 494 users acquired using four different optical devices. Results show a significant reduction in error rates compared to the baseline as well as improved performance compared to previous research.

Keywords: Fingerprint, Interoperability, Wavelet.

1   Introduction

Fingerprint recognition is widely deployed in governmental, military and commercial applications, with a number of different vendors offering a wide range of solutions. This creates a competitive market for these products. An important application regards the national system Integrated Automated Fingerprint System (IAFIS) which maintains the largest biometric database in the world containing fingerprints pertaining to more than 70 million individuals [4]. "What if a local police department decides to use a different mobile fingerprint scanner?" Regardless of existing standards that specify image resolution and support the creation of "qualified product list", a reasonable answer is that the introduction of a new sensor may reduce overall matching performance. Different sensors, even if they belonging to the same technology, create different raw data[5]. Interoperability is the ability of a recognition system to integrate different acquisition devices without a significant degradation of matching performance.

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   [4]http://www.fbi.gov

   [5]http://ftp.jrc.es/EURdoc/21585-ExeSumm.pdf

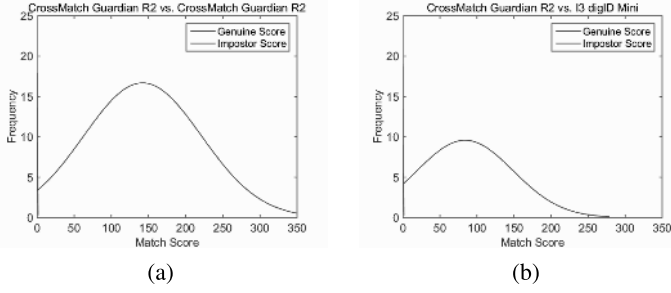(a)   (b)

Fig. 1: Performance of traditional match score in both the intra and inter-device scenarios: (a) Matching performance where gallery and probe images are obtained with the same device; (b) Matching performance where gallery and probe images are obtained with different devices.

User interaction process, acquisition technology type and sensor characteristics represent the main categories of sensor related distortions and variations. In this study, we consider touch sensors which are affected by skin elasticity and pressure exerted by the finger when it is placed on the sensor surface. Optical devices produced by different manufacturers usually present physical differences between units (i.e., lenses). Ridges and valleys which compose the fingerprint pattern create contrast in the image: ridges are in contact with a glass platen and when the surface is illuminated the light is reflected at the valleys and absorbed at the ridges [Ma03b]. Fig. 2 shows how visually different fingerprint images can be pertaining to the same finger acquired using different devices of the same optical sensor technology.
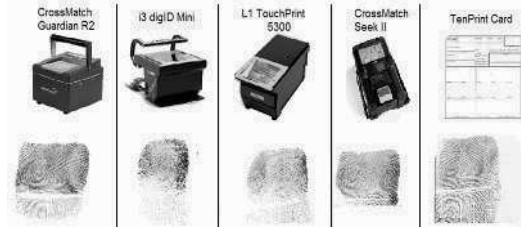

Fig. 2: The same fingerprint captured across five different devices.

The goal of this paper is to compensate for distortions due to device diversity and reduce its impact on the performance of the overall fingerprint recognition system. Specifically, we focus on interoperability issues between *optical sensors*. Abrupt changes and several discontinuities featuring the ridge / valley pattern can be effectively examined further through a multi-resolution perspective, which allows to examine textural patterns of small size and low contrast at high resolution and high contrast patterns from a coarser view [We10]. DWT is particularly efficient to represent signals with localized changes. In this work, for the first time in the realm of fingerprint interoperability enhancement problem, we consider characteristics derived from the Discrete Wavelet Transform (DWT). Additionally, we extract Binarized Statistical Image Features (BSIF). Device diversity creates texture variation and BSIF ia a local image descriptor which efficiently encodes texture information. Such a descriptor is based on binarized responses to linear filters learnt from natural

images using Independent Component Analysis (ICA). These features are then fused with matching features such as image quality, minutiae count and match score to train a classifier to discriminate between genuine and impostor fingerprint pairs in the cross-sensor domain.

The proposed approach is evaluated on fingerprints acquired from 494 participants at West Virginia University using four high resolution optical sensors and the traditional ink-based method. The proposed algorithm significantly improves match rates compared to the baseline. The paper is organized as follows. Section 2 describes the existing approaches for mitigating interoperability between fingerprint sensors. Section 3 presents the features exploited in the proposed method. Section 4 discusses experimental results. Section 5 draws our conclusions.

2   Related Work

In 2004, Jain and Ross discussed the sensor interoperability issue as one pertaining to matching images acquired using different sensor technologies [RJ04]. Experiments were carried out using an optical and a capacitive fingerprint sensor with same the same resolutions, 500 dpi, but different scanning areas. The intra-sensor Equal Error Rate (EER) was 6.14% on data collected using the optical device and 10.39% using the capacitive one. The matching was more accurate with a larger scanning area which allows the extraction of more minutiae points. The cross-sensor performance was significantly lower; the reported EER was 23.13%. In 2006, Ross and Nadgir modeled variations due to sensing diversity as non-linear distortions and they proposed a calibration scheme in which such distortions are represented by Thin-Plate Splines [RN06]. The knowledge of corresponding points between images is used to model the relative distortions. Control points (i.e., minutiae points) are manually selected; therefore, their method is not completely automated. Translation parameters are determined by aligning centroids of the two images, while the rotation is estimated through the orthogonal matrix computed using singular value decomposition (SVD). In their approach, matching is performed by distorting minutiae of one sensor based on the built deformation model before comparing them to those of the other sensor. This procedure significantly improved inter-sensor matching performance. However the achieved error rates do not make the final system appealing for real applications.

In 2010, Poh *et al.* designed a Bayesian Belief Network (BBN) to model the relationship between image quality, match score and device. In their work, the device d used for testing is unknown and the BBN estimates its posterior probability $p(d|q)$ given the quality measure q [PKB10]. Quality estimates are then clustered and each cluster is associated to one of the devices. This approach does not explicitly model the influence of the device. In 2013, Lugini *et al.* statistically analyzed how match scores change across different optical devices [Lu13]. Results of the Kendall's rank correlation test pointed out that there is a significant difference between sensor pairs and that the change is not symmetric when inverting the two devices. Marasco *et al.* proposed a learning-based approach to improve cross-device performance [MLC13]. They extracted quality and intensity-based

characteristics of fingerprint images acquired using four different commercial optical devices and scanned ink rolled prints. The defined set of characteristics was concatenated with the match score into a feature vector used for training a pattern classifier. Later, they investigated the impact of age and gender across different optical devices and matching algorithms [MLC14, Ma14].

3   The Proposed Approach

The goal of the proposed system is to verify if two fingerprints pertain to the same identity by taking into account variations in the images related to device diversity. The architecture of the proposed enhancement scheme is illustrated in Fig. 3. In the proposed architecture,
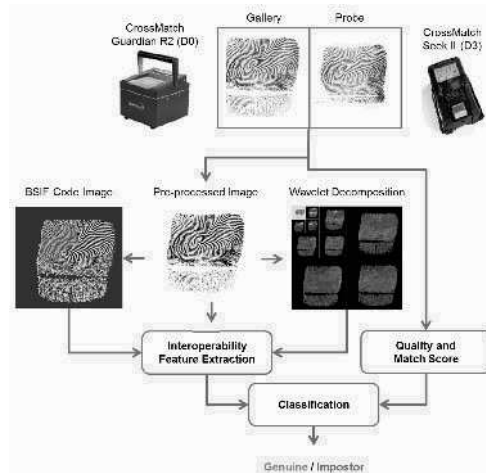

Fig. 3: Proposed architecture in which interoperability features are extracted from processed images and fused with quality features and match score. A classifier is trained with the resulting feature set to distinguish between genuine matches and impostors.

pre-processing is performed to enhance ridge regions of raw fingerprint images. Features that make use of the spatial and frequency information provided through DWT and BSIF are extracted and fused with matching features taken from raw images. This combined feature set is provided as input into a classifier trained through supervised learning to produce a match classification between two fingerprints, the probe and the other from the gallery, as either a genuine match or non match (impostor).

3.1   Feature Extraction

Natural images can be modeled as non-stationary signals, characterized by patterns of long period at low frequencies (e.g., background), and short-period patterns at high frequencies (e.g., discontinuities, edges). The latter, although they represent a relatively small percentage in the image, have a high information content. Unfortunately, the techniques which

resort to cosine transform disperse over a large number of coefficients the information relative to the discontinuities. In the proposed approach, the variation points in the image are analyzed as locations of contours and are quantified through the Wavelet Transform, which possesses several interesting properties: *i)* it can analyze signals with time-varying characteristics, due to its good time-frequency location abilities; *ii)* it provides a representation of *resolution* at different scales, referred to as *multi-resolution* representation, which naturally offers a hierarchical view of information; *iii)* it is easily realizable through a filter bank. The Discrete Wavelet Transform (DWT) of a one-dimensional signal decomposes it into a set of basis functions obtained by shifting and scaling versions of the prototype (mother) wavelet. The signal is passed through a series of low- and high-pass filters, each one followed by a down sampler [We10].

Wavelet Entropy. Entropy expresses the degree of uncertainty associated with a random variable [Ma13]. In this study, the random variables of interest represent the average amount of information generated by the distributions of the wavelet coefficients related to approximation and details at the various decomposition levels. The coefficients represent how closely the wavelet is correlated with each specific section of the image. We compute the Shannon Entropy (SE) and the Log Energy Entropy (LEE) of the wavelet coefficients C generated at different scales by different sections of the image as described above. Shannon entropy in time domain can measure signal uncertainty. Spectrum entropy based on Shannon entropy can be considered as an estimate of signal complexity. Wavelet entropy measures, based on wavelet analysis, represent the complexity of the signal in both time domain and frequency domain [ZYXG06]. Our investigation involves the computation of entropy measures, log energy and Shannon entropy, related to the coefficients of the approximation as well as the horizontal, vertical and diagonal details generated through a 6-level Discrete Wavelet Decomposition.

In our final feature set, entropy calculations between fingerprint pairs for each coefficient matrix at each level are represented as unsigned differences. Figure 5 (a) shows the SE value difference distributions across genuine and impostor pairs acquired from the level one decomposition and Figure 5 (b) shows the LEE value difference distributions. Using entropy measures beyond the first level of resolution did not show any improvement in the separation of genuine and impostor pairs. By focusing on the first level of the DWT, the proposed system requires less processing time for feature calculation.

For this particular algorithm, we select Daubechies db8 with 8 vanishing moments as the mother wavelet, see Fig. 4 (a). The associated low- and high- pass filters are represented in Fig. 4 (b) and (c), respectively. In this work, the entropy measures are obtained by using the algorithm proposed by Coifman and Wickerhauser [CW92].

- Log Energy Entropy (LEE) of C:

$$LEE(C) = \sum_{i,j} (log_2(C_{i,j})) \qquad (1)$$

- Shannon Entropy (SE) of C:

$$SE(C) = -\sum_{i,j} C_{i,j} log_2(C_{i,j} + \varepsilon)$$

(2)

where i and j index C the wavelet coefficient matrix.

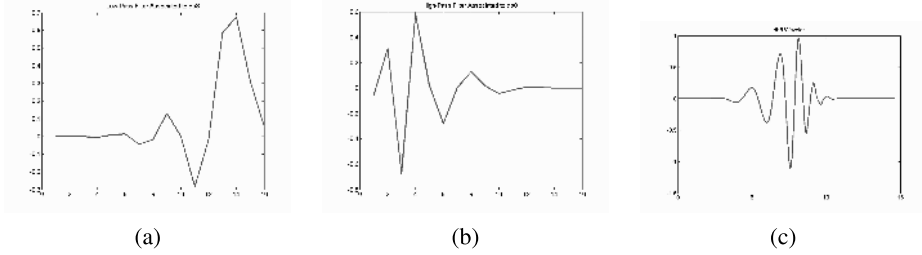(a)   (b)   (c)

Fig. 4: Debauchies analysis filters: (a) low-pass filter and (b) high-pass filter create the transformation performed in this study. The filters are designed for 16 coefficients. X axis indicates the coefficient number, while the Y axis indicates the corresponding value for that specific coefficient number. These filters are associated to the Daubechies wavelet function shown in Figure (c), the mother wavelet selected in this work.

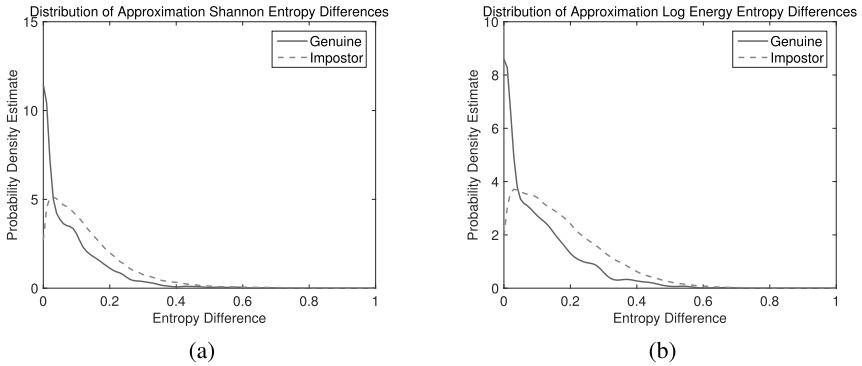(a)   (b)

Fig. 5: Shannon Entropy (SE) and Log Energy Entropy (LEE) value differences related to the level one wavelet decomposition coefficients: (a) SE from the approximation image; (b) LEE from the approximation image.

Binarized Statistical Image Features (BSIF). Local image descriptors have become a standard tool for providing image features in computer vision tasks. Methods such as local binary pattern (LBP) and local phase quantization (LPQ) calculate a binary code to represent each pixel in an image. This code is a description of a pixel's neighborhood obtained by convolution with a set of linear filters[6]. Binarized statistical image features (BSIF) is a method of local image description. It uses linear filters learned from a training set of natural images to produce a binary code for each pixel [KR12]. This creates a contrast to

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[6]http://www.ee.oulu.fi/ jkannala/bsif/bsif.html

the manually predefined filters in LBP and LPQ [OPM02, Mä03a]. While not specifically designed to counteract the effects of variations introduced by blur and rotation, BSIF has shown comparable performance to local descriptors that have been designed with such considerations. Due to robustness, we explore BSIF in the context of fingerprint interoperability. The number of bits used to represent each pixel is determined by the number of filters in the chosen set. The value of each bit, b_i, is calculated as a binary response of its associated filter, W_i, to the surrounding image region, X, at a threshold of zero.

$$s_i = \sum_{u,v} W_i(u,v) X(u,v) \tag{3}$$

The binarized feature $b_i = 1$ when $s_i > 0$, and $b_i = 0$ otherwise. Fig. 6 shows the result of each filter in the 5 bit set on a single fingerprint image.

Resulting coded images are represented as a normalized histogram with a number of bins equal to the number of possible values encoded by the number of bits at each pixel. This can result in large feature vectors even when using as little as 5 bits, the smallest pre-learned filter sets provided. For this reason we investigate more compact representations of the histograms based on the frequency values present. We also consider the Euclidean distance between the BSIF histograms of a pair of fingerprints being compared. Fig. 7 shows the distribution of these measures between genuine and impostor fingerprint pairs.

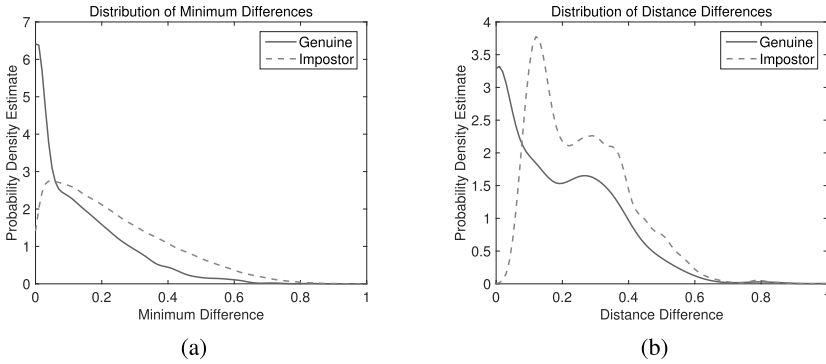Fig. 6: Result of convolution with each filter in the pre-learned 5 bit 11x11 filter set.

Fig. 7: Features that summarize BSIF histograms: (a) Minimum frequency of BSIF histograms across devices ; (b) Euclidean distance between image histograms.

Image Quality measures the degree of usefulness of a biometric sample for automated recognition. The quality of captured biometric data directly impacts the effectiveness of the matching process [GT07]. Image quality takes into account skin conditions (e.g., dryness, wetness, cuts) and sensor conditions (e.g., noise, size). The NFIQ value assigned to

a fingerprint image is a scalar in the range 1-5, where 1 represents the highest quality.

Minutiae Count indicates the number of minutiae extracted from a fingerprint image and it represents an indicator of quality as well. Most fingerprint matchers use minutiae points for recognition. A minutiae point (i.e., ridge ending or ridge bifurcation) is represented as a triplet $\mathbf{m} = [x,y,\theta]$ that indicates minutiae location co-ordinates and angle [RJN11].

Match Score indicates the degree of similarity between fingerprints computed as a function of the number of corresponding minutiae. Minutiae are paired if they are within a predefined distance threshold and the angle between their directions is within a predefined angle threshold.

We have also fused alignment (see Figure 8), intensity-based statistics (see Figure 9), pattern noise, image gradient features extracted according to the procedure presented in [MLC13].
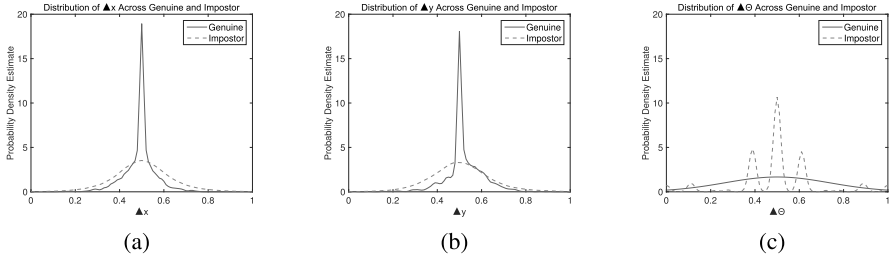

Fig. 8: Alignment parameters obtained from Generalized Hough Transform of fingerprint image pairs: (a) Δx ; (b) Δy ; (c) $\Delta\theta$.
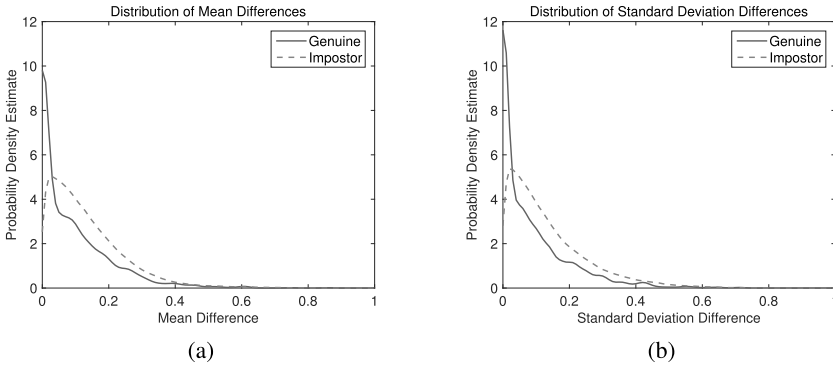

Fig. 9: Gray level statistic differences between fingerprint pairs: (a) Mean; (b) Standard Deviation.

4   Experimental Results

4.1   Data set

The data set used in this study consists of fingerprints pertaining to 494 users. Images were collected using four live-scan devices (D0-D3) and ink-based ten-print cards (D4), as illustrated in Table 1. For each live-scan device, users sequentially provided two sets of fingerprints, each made up of: rolled individual fingers on both hands, left slap, right slap, and thumbs slap. No quality check was applied during acquisition. Match scores were

Tab. 1: Characteristics of the Live-scan devices used for the fingerprint acquisition carried out in this study.

	Manufacturer	Model	Resolution (dpi)	Image size (pixels)	Capture area (mm)
D0	Cross Match	Guardian R2	500	800 x 750	81 x 76
D1	i3	digID Mini	500	752 x 750	81 x 76
D2	L1 Identity Solutions	TouchPrint 5300	500	800 x 750	81 x 76
D3	Cross Match	Seek II	500	800 x 750	40.6 x 38.1
D4	Ten Print Scans	-	500	800 x 715	-

generated for *right index fingers only*, using the commercial matcher Identix BioEngine Software Development Kit. Impostor match scores were generated by dividing users in groups of 100 and matching the fingerprints within the same group.

4.2   Procedure

With the exception of device IDs, the proposed interoperability-related features represent a comparison between fingerprint pairs. They have been incorporated with quality measures and match scores. Although a Pearson's coefficient correlation analysis has been carried out for feature selection, best results were obtained using the entire set of 26 attributes. The considered features designed to capture variations due to sensor diversity do not appear to be linearly related to each other.

Prior to classification, all features are normalized between 0 and 1 through the use of min-max scaling. Classification makes use of a Random Forest due to its overall resistance to the effects of overfitting as well its success in previous work in comparison to other classifiers. A validation set was used to select both the number of trees in the forest and how many features would be randomly selected at each decision split. Specifically, in order to achieve the best results in the fewest number of trees, we performed final testing on a model composed of 500 trees with 13 features selected randomly at each split. **In all experiments, the subjects are mutually exclusive among training, validation and testing**. Specifically, subjects are partitioned as follows: 25% for training, 25% for validation and 50% for testing. In this work, feature extraction and classification algorithms are implemented using Matlab Version R2015a.

The performance of the proposed method is evaluated by using False Match Rate (FMR) and False Non-Match Rate (FNMR) metrics. FMR corresponds to the proportion of instances where an impostor is incorrectly labelled as a genuine match with respect to the total number of impostor comparisons. FNMR corresponds to the proportion of instances where a genuine match is incorrectly labelled as an impostor with respect to the total number of genuine comparisons.

4.3   Results

Figure 10 (a) shows the results of the selected Random Forest classifier on the final set of features. The proposed approach obtains a FMR of 0.004% and a FNMR of 4.454% when tested on fingerprint pairs from users not seen by the classifier during training. Figure 10 (a) shows the Detection Error Tradeoff (DET) curve related to the proposed algorithm compared to the DET computed by using only the match score, serving as a baseline, both in cross-sensor matching. For intra-sensor performance see Figure 3 in [MLC13] where the same database is used. Classification in Random Forests is done by majority voting within the forest of generated trees, which yields a single operating point. Specifically, a pair is declared to be a match if more than 50% of votes agree for that. Instead, the DET pertaining to the proposed approach was obtained by considering the percentage of trees that voted for a pair of fingerprints being a match.

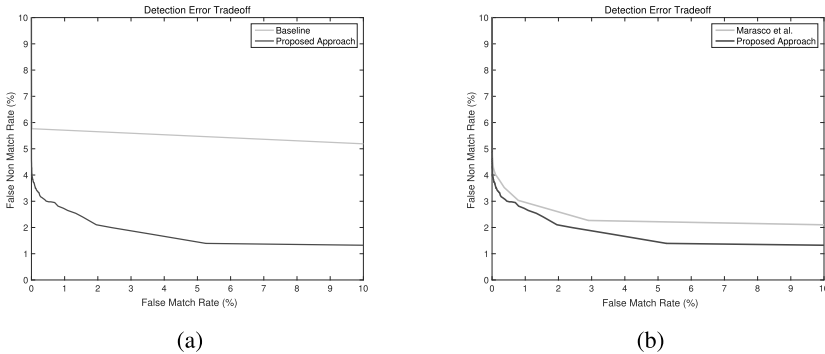(a)   (b)

Fig. 10: (a) Comparison of the results obtained with the proposed approach with the Detection Error Tradeoff with the baseline of a thresholded match score. (b) Comparison of the Detection Error Tradeoff curve obtained from the proposed method with that obtained by using the features and classifier presented in [MLC13] on the same training and testing set.

We additionally see an improvement over the results of [MLC13] when we apply the previous method to a data set with fingerprint pairs that are mutually exclusive between training, validation and testing. Figure 10 (b) shows the DET obtained from our model compared to the DET obtained by using the previously used feature set and classifier on the same training and testing split that we used. We further illustrate improvements over previous methods by comparing FNMR when FMR is held constant. Table 2 shows the results for each of the previously discussed DETs evaluated at a FMR of 0.01%.

Tab. 2: False Non-Match Rates obtained by each method when False Match Rate is held equal at 0.01%.

Method	FNMR (%)
Match Score	5.77
Marasco et al. [MLC13]	4.73
Proposed Method	4.24

5   Conclusions

The goal of this paper is to improve fingerprint interoperability by applying novel features in parallel to the traditional matching. Specifically, we combine spatial and frequency-based features extracted from DWT and BSIF analysis with previously proven intensity- and quality-based fingerprint image characteristics. We employ a classification scheme that fuses these features with match scores to develop a model for improving inter-device match rates. The model was evaluated on a set of fingerprint pairs comprised of images captured from 494 subjects across five devices. Results show a significant improvement over baseline rates in both False Match Rates and False Non-Match Rates. The proposed algorithm improves the FNMR from approximately 4.7% to 4.2% compared to previous results when FMR is held to 0.01% and subjects between training and testing are mutually exclusive.

We believe that our approach will allow further scalability of intra-sensor fingerprint matching to a much larger number of fingerprint sensors and much larger user populations as well. Additionally, our plan is to study image focusing provided by each device as feature to exploit for interoperability purpose. Furthermore, the learning-based nature of the proposed enhancement scheme requires an investigation into practical ways to introduce new sensors into the system and their impacts on performance.

References

[CW92]   Coifman, R.; Wickerhauser, M.: Entropy-based Algorithms for Best Basis Selection. IEEE Transactions on Information Theory, 38(2):713–718, 1992.

[GT07]   Grother, P.; Tabassi, E.: Performance of Biometric Quality Measures. IEEE Transactions on Pattern Analysis and Machine Intelligence, 29(4):531–543, 2007.

[KR12]   Kannala, J.; Rahtu, E.: BSIF: Binarized Statistical Image Features. 21st International Conference on Pattern Recognition (ICPR), pp. 1363–1366, 2012.

[Lu13]   Lugini, L.; Marasco, E.; Cukic, B.; Gashi, I.: Interoperability in Fingerprint Recognition: a Large-Scale Study. Workshop on Reliability and Security Data Analysis (RSDA), Budapest, pp. 1–6, June 2013.

[Mä03a]   Mäenpää, Topi: , The Local Binary Pattern Approach to Texture Analysis: Extentions and Applications, 2003.

[Ma03b]   Maltoni, D.; Maio, D.; Jain, A.; Prabhakar, S.: Handbook of Fingerprint Recognition. Springer, 2003.

[Ma13]   Marsico, M. De; Nappi, M.; Riccio, D.; Tortora, G.: Entropy-based Template Analysis in Face Biometric Identification Systems. Signal, Image and Video Processing, 7(3):493–505, 2013.

[Ma14]   Mason, S.; Gashi, I.; Marasco, E.; Lugini, L.; Cukic, B.: Interoperability between Fingerprint Biometric Systems: An Empirical Study. International Conference on Dependable Systems and Networks, 23:26th, 2014.

[MLC13]   Marasco, E.; Lugini, L.; Cukic, B.: Minimizing the Impact of Low Interoperability between Optical Fingerprint Sensors. Biometrics: Theory, Applications and Systems (BTAS), pp. 1–8, 2013.

[MLC14]   Marasco, E.; Lugini, L.; Cukic, B.: Automatic Enhancement of Interoperability between Optical Fingerprint Sensors. NIST International Biometric Performance Testing Conference (IBPC), 2014.

[OPM02]   Ojala, T.; Pietikainen, M.; Maenpaa, T.: Multiresolution Gray-scale and Rotation Invariant Texture Classification with Local Binary Patterns. IEEE Transactions on Pattern Analysis and Machine Intelligence, 24(7):971–987, 2002.

[PKB10]   Poh, N.; Kittler, J.; Bourlai, T.: Quality-Based Score Normalization With Device Qualitative Information for Multimodal Biometric Fusion. IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans, 40(3):539–554, 2010.

[RJ04]   Ross, A.; Jain, A.: Biometric Sensor Interoperability: A Case Study in Fingerprints. International ECCV Workshop on Biometric Authentication, pp. 134–145, 2004.

[RJN11]   Ross, A.; Jain, A.; Nandakumar, K.: Introduction to Biometrics: A Textbook. Springer, 2011.

[RN06]   Ross, A.; Nadgir, R.: A Calibration Model for Fingerprint Sensor Interoperability. SPIE, 6202, 2006.

[We10]   Weeks, Michael: Digital Signal Processing Using MATLAB & Wavelets. Jones and Bartlett Learning, 2010.

[ZYXG06]   Zheng-You, H.; Xiaoqing, C.; Guoming, L.: Wavelet Entropy Measure Definition and Its Application for Transmission Line Fault Detection and Identification. International Conference on Power System Technology, pp. 1–6, 2006.