

Advancing Surface Feature Encoding and Matching for More Accurate 3D Biometric Recognition

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Abstract—Accurate and efficient feature descriptors are crucial for the success of many pattern recognition tasks including human identification. Existing studies have shown that features extracted from 3D depth images are more reliable than those from 2D intensity images because intensity images are generally noisy and sensitive to illumination variation, which is challenging for many real-world applications like biometrics. Recently introduced 3D feature descriptors like *Binary Shape* and *Surface Code* have been shown improved effectiveness for 3D palm recognition. However, both methods lack theoretical support for the construction of the feature templates, which limits their matching accuracy and efficiency. In this paper, we further advance the *Surface Code* method and introduce the *Efficient Surface Code*, which describes whether a point tends to be concave or convex using only one bit per pixel. Our investigation also reveals that the discriminative abilities of the convex and concave regions are not necessarily equal. For example, line patterns on human palms and finger knuckles are expected to reveal more discriminative information than non-line regions. Therefore, we also propose a weighted similarity method in conjunction with the *Efficient Surface Code* instead of the traditional Hamming distance adopted in both *Binary Shape* and *Surface Code*. Comparative experimental results on both 3D palmprint and 3D finger knuckle databases illustrate superior performance to the aforementioned state-of-the-art methods, which validates our theoretical arguments.

Keywords — *Biometrics, Feature Description, 3D Palmprint*

I. INTRODUCTION

Research on feature description is critical for accurate and efficient automated biometric system. An advanced feature descriptor should be accurate, efficient, and meet the following requirements: (i) capable of extracting discriminative information, which is invariant for genuine match pairs but different for imposter match pairs; (ii) tolerant to illumination and pose variations among genuine match pairs; (iii) containing the minimum amount of information needed to discriminate the expected number of classes; and (iv) providing theoretical support and physical interpretation for further investigation.

Discriminative biometrics features can be extracted from 2D intensity images or 3D depth images. However, the formation of intensity images is dependent on surface reflection properties, surface orientation, illumination, and sensor noise. By contrast, 3D depth images are generally more reliable, because physical depths are not affected by pose and illumination variations.

The relevant literature has illustrated that extracting features from 3D depth images offers promising results. *Shape index* [1]

describes local shape information and is particularly useful to produce a stable description of nine well-known surface types [2]. *Surface Code* [5] representation adopts information of surface types and encodes a pixel into one of the nine surface types. However, this method requires four bits per pixel, which is quite inefficient. Furthermore, the use of Hamming distance for matching the four-bit codes lacks adequate theoretical support. Another more recent descriptor, *Binary Shape* [8], uses ordinal measurements for encoding 3D surface features. This method has been found quite efficient and accurate. However, only incorporating the general ordinal representation for 3D images may not produce the best distinctive surface feature, because other information (e.g. orientation) may also be useful.

In this paper, we build on the *Surface Code* feature descriptor and introduce *Efficient Surface Code*. In addition, we also propose a weighted similarity approach in conjunction with *Efficient Surface Code* to address the limitations of the traditional Hamming distance. Our feature descriptor encodes the concave and convex points with much smaller template sizes for efficient matching. Our comparative experimental results to be presented in this paper have achieved superior performance and demonstrated the effectiveness of our approach for 3D palmprint and 3D finger knuckle biometric recognition.

Two key contributions from this paper can be summarized as follows:

(1) In view of the limited efficiency of, and the lack of theoretical support for, the discretization of *shape indexes* associated with *Surface Code* [5] and *Finger Surface Code* [6], we have developed an *Efficient Surface Code* feature descriptor which reduces the template size from four-bit to one-bit per pixel. This advancement enables a more accurate and efficient description of the concave and convex surface details for discriminative feature extraction.

(2) Our investigation also indicates that the discriminative abilities of the convex and concave regions on biometric surfaces are not necessarily equal. For example, line patterns on human palms and finger knuckles generally contain more discriminative information than non-line regions. We therefore propose a weighted similarity method in conjunction with *Efficient Surface Code* as a compelling alternative for the popular Hamming distance measure adopted in both *Binary Shape* [8] and *Surface Code*. Our comparative experimental results demonstrate the effectiveness of the proposed method.

The rest of this paper is organized into five sections. Related work in the literature is reviewed in Section II before our proposed approach is introduced in Section III. Comparative

experimental results are presented in Section IV and discussed in Section V. The key conclusions of this paper are summarized in Section VI.

II. RELATED WORK

Development of distinctive feature description using 2D intensity images has attracted extensive efforts in the literature. For examples, feature descriptors using *Local Binary Patterns* (LBP) [14, 15], *Improved LBP* (ILBP) [16], *1D Log-Gabor Filter* [17] and *Phase Only Correlation* (BLPOC) [18] are shown to be effective for person recognition. Zheng et al [19] extracted 3D features from a single 2D contactless image and introduced *Difference of Normal* (DoN) feature descriptors for more accurate palmprint matching. These studies have shown that local variations, global statistical information, ordinal measurements, and some physical characteristics such as curve orientations can be used to discriminate identities. Several research efforts [5-6, 8, 19-22] underlines the effectiveness of human identification using 3D information from the popular 2D biometric identifiers.

Existing work shows that extracting features from 3D depth images produces promising results. *Shape index* [1] is a well-known 3D feature in the literature. It captures the local 3D shape information computed from the curvatures of a point on a surface and can approximately describe nine well-known surface types with a scalar value from 0 to 1 [2]. This feature is shown to be highly stable and discriminative in many research work [2-6]. Woodard and Flynn [3] employed *shape index* features extracted from finger knuckle range images for personal identification. Zhang et al [4] employed *shape type* (ST), a feature similar to *shape index*, for 3D palmprint identification.

Surface Code [5] is a binary representation of *shape index* information. This method discretizes the *shape index* values into nine parts non-linearly, with these parts corresponding to the nine defined surface types. Since four bits are required to encode nine information levels, four binary images are generated as the templates for matching. During the matching stage, the four binary images are considered equally. Hamming distance between a pair of templates will be computed for all pixels and the mean among all pixels is the dissimilarity score. *Finger Surface Code* [6] is proposed specifically for extracting features on finger surfaces. Its discretization method is slightly different from *Surface Code*.

On the other hand, ordinal information is also shown to be robust against illumination, contrast and misalignment variations and effective for complex palmprint recognition [19]. Reference [8] details the development of an efficient 3D feature descriptor (*Binary Shape*) for biometric images, which encodes the local variations of depth details as the discriminative features. The sign of the response from an efficient filtering operation represents the feature value, which is of one bit. Therefore, one binary image is generated for each 3D image. Similar to *Surface Code*, *Binary Shape* also adopts Hamming distance for computing the matching scores. This method is efficient and quite accurate. However, such generalized binary features in 3D biometric images may not be the best distinctive surface feature and other information (e.g. local 3D or surface normal orientation) deserves careful consideration.

III. EFFICIENT SURFACE CODE AND WEIGHTED SIMILARITY

In this section, we first analyze the discretization steps in *Surface Code* and *Finger Surface Code*, and identify the effective components. We then propose *Efficient Surface Code* feature descriptor. This is followed by an analysis on the importance of white and black pixels in binary feature descriptors and our proposal of a weighted similarity method.

A. Discretization on Surface Code and Finger Surface Code

Any point on a 3D hand biometric surface can be categorized into one of the nine surface types [2]. *Surface Code* [5] describes each of the nine surface types, with the help of *shape index*, into a four-bit feature representation. Table I shows the mapping between ranges of *shape index* and the individual code representations of *Surface Code*. The matching score between a pair of templates are computed by using Hamming distance. *Finger Surface Code* [6] is a modification of *Surface Code* with a different discretization method. Table II shows the mapping between ranges of *shape index* and the code representations of *Finger Surface Code*. Similarly, this method also generates four-bit codes and employs Hamming distance for the matching.

In order to begin with this analysis, the information encoded in each binary feature descriptor is first examined. Figure 1 (a) and (b) show such sample binary feature images which are encoded using *Surface Code* and *Finger Surface Code*. Images in the first two rows belong to the same subjects while those in the third row are from different subjects. Each column presents one-bit images, with the left most being the most significant bit. It is obvious that human specialists can only distinguish the subjects by observing the second bit image of *Surface Code* or the first bit image of *Finger Surface Code*. Binary images for the remaining bits may only contain noise. To further justify this argument, the information from each bit image is further explored.

Table III illustrates the corresponding range for each bit image. For example, the white pixels of the fourth bit image of *Surface Code* correspond to ranges 2-3, 6-7, 10-11, and 14-15, while the black pixels correspond to the remaining ranges. Suppose, the *shape index* of a point in template A falls in range 3 and that in template B falls in range 11, they share the same value for the fourth bit image of *Surface Code*. This arbitrary grouping approach is not expected to encode useful information and the bit images may not be necessary.

Another problem with these two representations lies in the use of Hamming distance. For example, when Hamming distance is used for *Surface Code*, the distance is 1 between level 1 (0001) and level 5 (0101) but 4 between level 7 (0111) and level 8 (1000). These resulting distances cannot correctly represent the actual difference between different levels. This limitation also exists in *Finger Surface Code* [6].

B. Efficient Surface Code

The above analysis of the feature representations suggests that not all four binary images may be needed. More importantly, the use of Hamming distance raises issues for further investigation. We therefore introduce a new discretization method which is more effective and efficient. It

TABLE I. CODE CONVERSION TABLE FOR SURFACE CODE

Meaning	Spherical Cap	Trough	Rut	Saddle Rut	Saddle	Saddle Ridge	Ridge	Dome	Spherical Cap							
Range ^a	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Level	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Code	0000	0001	0010	0011	0100	0101	0110	0111	1000	1001	1010	1011	1100	1101	1110	1111

^a *Shape index* is evenly divided into 16 ranges. Range 1 represents *shape index* [0, 0.0625].

TABLE II. CODE CONVERSION TABLE FOR FINGER SURFACE CODE

Meaning	Spherical Cap	Trough	Rut	Saddle Rut	Saddle	Saddle Ridge	Ridge	Dome	Spherical Cap							
Range ^a	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Level	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Code	0000	0001	0010	0011	0100	0101	0110	0111	1000	1001	1010	1011	1100	1101	1110	1111

^a *Shape index* is evenly divided into 16 ranges. Range 1 represents *shape index* [0, 0.0625].

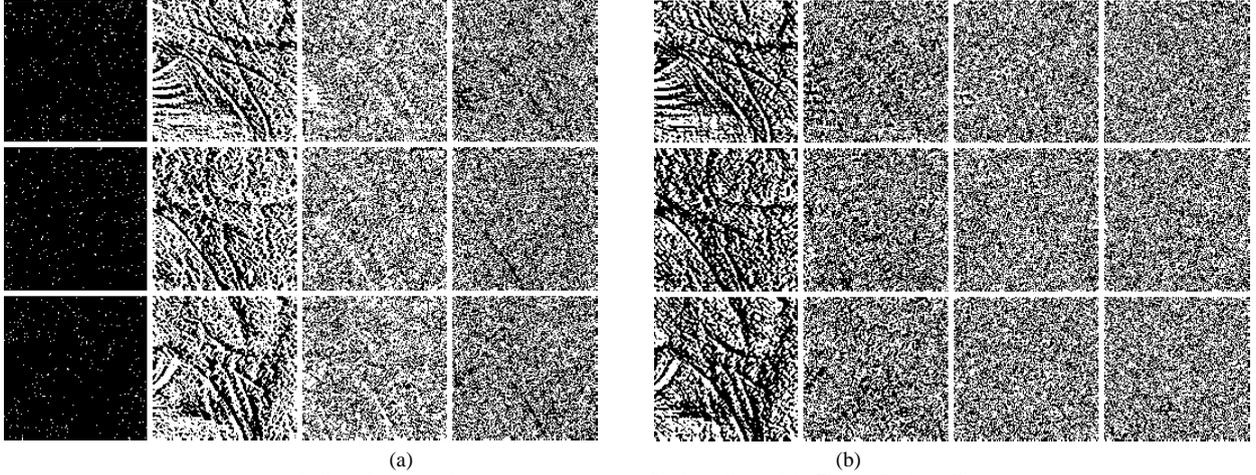
Fig. 1. Sample binary feature images of (a): *Surface Code*; (b): *Finger Surface Code*

TABLE III. CORRESPONDING RANGE FOR EACH BIT IMAGE

Bit images	Bit-1	Bit-2	Bit-3	Bit-4
Range for <i>Surface Code</i>	16	8-15	4-7, 12-15	2-3, 6-7, 10-11, 14-15
Range for <i>Finger Surface Code</i>	10-16	5-9, 14-16	3-4, 7-9, 12-13, 16	2, 4, 6, 8-9, 11, 13, 15

can be observed that the second bit of *Surface Code* and the first bit of *Finger Surface Code* contains useful discriminative information (white pixels corresponding to ranges 8-15 and ranges 10-16 respectively). This implies that the discriminative information can be interpreted as whether the *shape index* falls in the range above 8 or below 9 (equivalent to a *shape index* value of 0.5). With the support of the histogram of the *shape index* distribution of 1770 3D palm images presented in Figure 2, it is observed that the most discriminative information lies in the concave and convex regions, which corresponds to the line patterns on human skin. Therefore, it is judicious to discretize *shape index* into only two levels. Let ESC denotes *Efficient Surface Code*.

$$ESC = \begin{cases} 0, & SI < 0.5 \\ 1, & SI \geq 0.5 \end{cases} \quad (1)$$

This discretization also accords with the suggestion of using two classes in [8]. Sample 3D depth images from palmprints and finger knuckles, as well as the corresponding binary feature images are shown in figure 3 and figure 4, respectively.

C. Importance of white and black pixels

In biometric recognition problems such as iris, palmprints and finger knuckle recognition, binary images are generally preferred and used as templates for matching. Hamming distance is widely adopted for computing dissimilarities between two binary images. This well-known distance measure is effective when all the values in the coding space encode equally important information for discriminative identities. However, whether all the values in the coding space encode equally important information depends on the choices of feature extraction, discretization and binarization methods. Therefore,

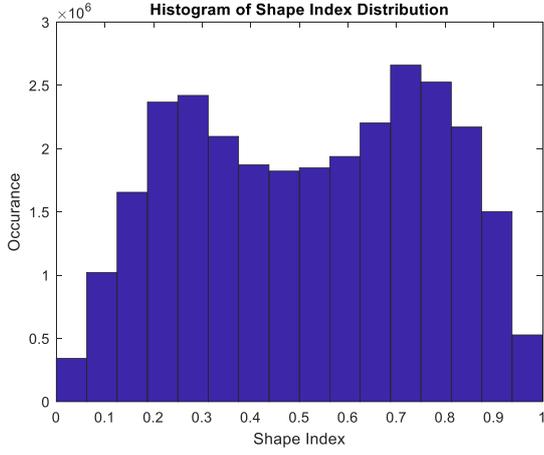


Fig. 2: Histogram of *shape index* distribution of 1770 3D palm images

such an equal probability or maximum entropy assumption may not be always true. For our discussion, white pixels of *Efficient Surface Code* represent concave pixels while black pixels represent convex pixels.

We performed new experiments to validate this argument. Since manual alignments of genuine image pairs are required for this experiment, only ten genuine image pairs and ten imposter image pair were used. Although the small dataset may not be representative, the results indicate a good possibility that the white and black pixels are of different importance. Comprehensive experimental results presented in the experimental section have helped to validate our argument.

Let the number of white and black pixels in template X be $NW(X)$ and $NB(X)$ respectively. Let the number of white and black matching pixels between templates A and templates B be $NWM(A,B)$ and $NBM(A,B)$ respectively. We defined the white pixel matching rate ($WPMR$) and the black pixel matching rate ($BPMR$) for matching template A and template B as follows:

$$WPMR(A, B) = \frac{2 * NWM(A, B)}{NW(A) + NW(B)} \quad (2)$$

$$BPMR(A, B) = \frac{2 * NBM(A, B)}{NB(A) + NB(B)} \quad (3)$$

We found that the genuine image pairs had an average $WPMR$ of 0.5067 and an average $BPMR$ of 0.6954. The corresponding values for the imposter image pairs were 0.3892 and 0.6105. Apparently, the matching rates for the genuine image pairs are higher than those for the imposter image pairs. Furthermore, the increment of $WPMR$ is more significant than that of $BPMR$. Therefore, it is reasonable to conclude that white pixels are more important for this dataset.

D. Weighted Similarity

Since discriminative information from palmprints and finger knuckle patterns lies in the irregular line patterns corresponding to the concave/white pixels representation in the respective feature map, it is reasonable to argue that a match between a concave pair offers a higher level of confidence than a match between a convex pair. Hence, we propose a more effective similarity measure which can judiciously consider the individual importance of features in the coding space for computing the matching scores. Our suggestion also accords

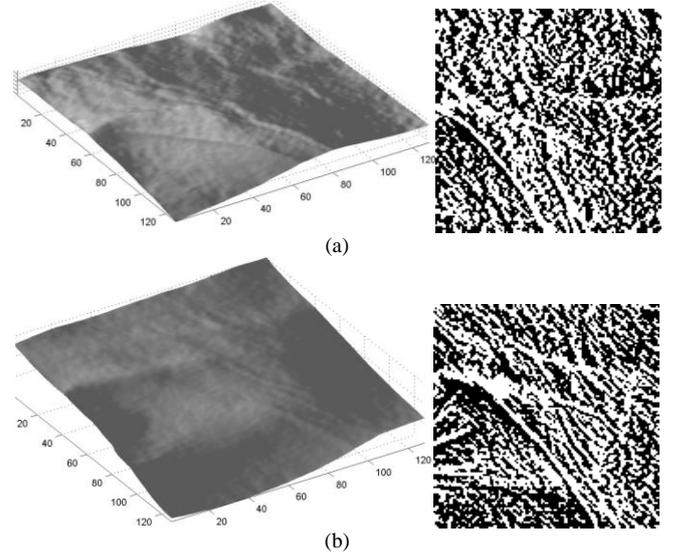


Fig. 3: (a) and (b) shows sample 3D palmprint images and the binary features extracted using *Efficient Surface Code*

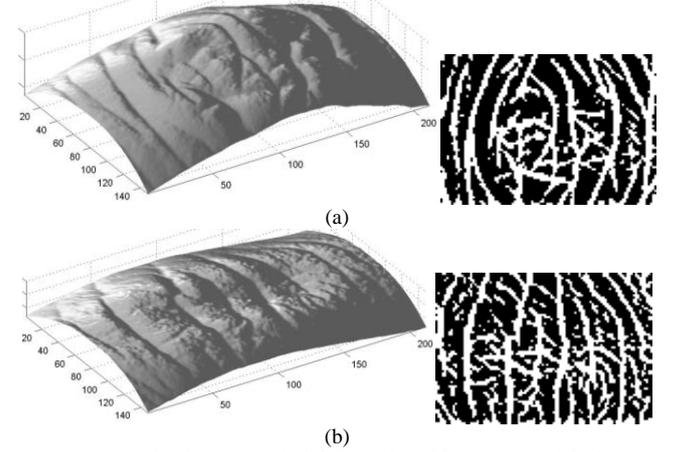


Fig. 4: (a) and (b) shows sample 3D finger knuckle images and the binary features extracted using *Efficient Surface Code*

with the *azzoo* similarity measure [9]. For a pair of template A and template B with dimension $M \times N$, the matching score computed using Hamming distance (HD) is:

$$score = \frac{1}{M \times N} \sum_{y=1}^N \sum_{x=1}^M HD(A(x, y), B(x, y)) \quad (4)$$

$$HD(a, b) = \begin{cases} 1, & \text{if } a \neq b \\ 0, & \text{if } a = b \end{cases} \quad (5)$$

where $a, b \in \{0, 1\}$. We introduce the Weighted Similarity (WS) function to replace HD by as follows:

$$score = \frac{1}{M \times N} \sum_{y=1}^N \sum_{x=1}^M WS(A(x, y), B(x, y)) \quad (6)$$

$$WS(a, b) = \begin{cases} w_1, & \text{if } a = b = 1 \\ w_2, & \text{if } a = b = 0 \\ w_3, & \text{if } a \neq b \end{cases} \quad (7)$$

where $a, b \in \{0, 1\}$. For $w_1=0, w_2=0, w_3=1$, WS is exactly equals to HD . For convenience, we represent distance measure for similarity instead of dissimilarity. When $w_1=1, w_2=1, w_3=0$, WS represents the Hamming similarity measure. In order to

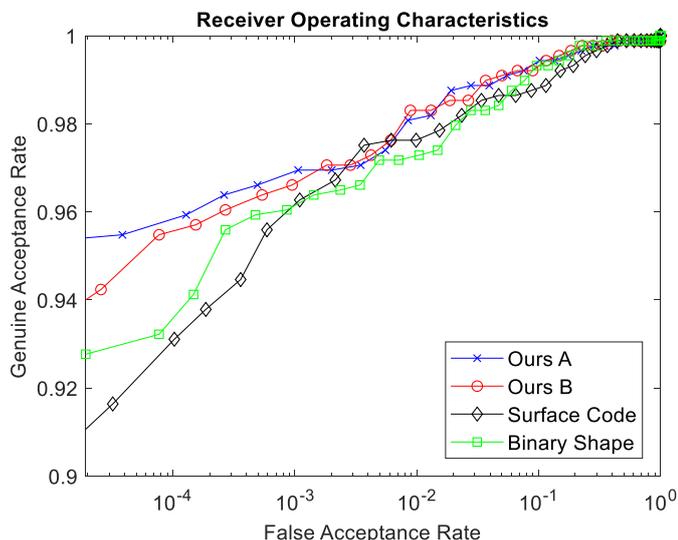


Fig. 5: Comparative ROCs on PolyU contactless 2D/3D palmprint database

simplify the equation for efficient optimization, we can rewrite the equation for the Simplified WS (*SWS*) function as follows:

$$SWS(a, b) = \begin{cases} 2 - s, & \text{if } a = b = 1 \\ s, & \text{if } a = b = 0 \\ 0, & \text{if } a \neq b \end{cases} \quad (8)$$

Parameter s controls the significance of one of the coding pairs. Hamming distance is a special case when s is set to be 1. If the four possible scenarios ($ab \in \{00, 01, 10, 11\}$) are equally likely, the expected similarity score will be 0.5, which is independent of the parameter s . Since it is possible that the coding spaces may not encode equally important information, the weighted similarity can also be adopted for other useful applications.

IV. EXPERIMENTS AND RESULTS

The effectiveness of our proposed method was evaluated on the PolyU contactless 2D/3D palmprint database and a 3D finger knuckle database, which contain 3D images for extracting features required by *Efficient Surface Code*.

The PolyU contactless 2D/3D palmprint database [5] is publicly available and contains 1770 palmprint images from 177 subjects in two sessions. There are five 3D images for each subject per session. This contactless 3D palmprint database is acquired from only from one hand (right hand palms) and was preferred to avoid adverse influence from the correlation [7] between the palmprint features between left and right palmprint images. We have evaluated our proposed method using 177 subjects with two sessions, each with five images. The first session images were used as the training set, and the second session images were used as the testing set, yielding 885 (177×5) genuine and 155760 ($177 \times 176 \times 5$) imposter matching scores. To account for the translation variations in this database, the templates were shifted with vertical and horizontal translations. The maximum score was considered as the final score. Figure 5 illustrates comparative performance using ROC curves, which compares our proposed methods with the two state-of-the-art methods *Binary Shape* [8] and *Surface Code* [5]. Ours (A) refers to our *Efficient Surface Code* with simplified

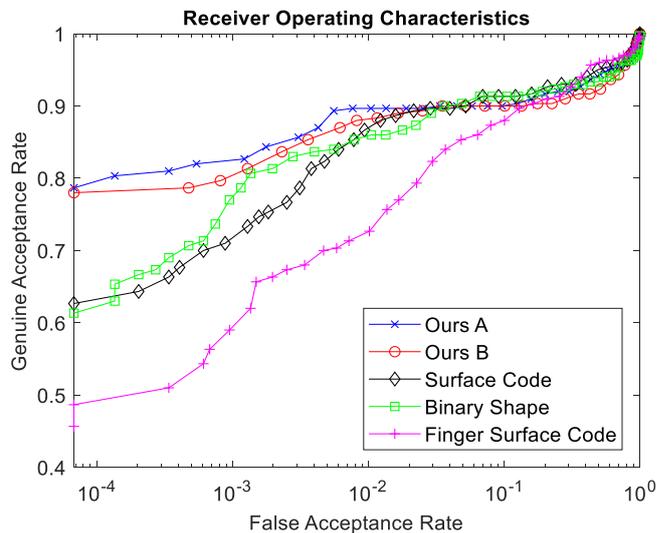


Fig. 6: Comparative ROCs on PolyU contactless 2D/3D finger knuckle database

weighted similarity ($s = 0.78$). Ours (B) refers to using the templates generated from *Binary Shape* [8] with simplified weighted similarity ($s = 0.87$). The observed improvement in performance is more evident for high security applications, where a very small false acceptance rate is expected.

The 3D finger knuckle database has been developed by us and contains 600 forefinger images from 50 subjects with two sessions. There are six 3D depth images for each subject per session. The first session images were used as the training set, while the second session images were used as the testing set, resulting in 300 (50×6) genuine and 14700 ($50 \times 49 \times 6$) imposter matching scores. Since there are large translation and rotation variations in this database, the templates were shifted with rotation, vertical and horizontal translations. The maximum score was considered as the final score. Figure 6 illustrates comparative performance using Receiver Operating Characteristics (ROC) curves, which compared our proposed methods with the state-of-the-art methods. Ours (A) refers to our *Efficient Surface Code* with simplified weighted similarity ($s = 0.75$). Ours (B) refers to using the templates generated from *Binary Shape* [8] with simplified weighted similarity ($s = 0.7$). The observed improvement in performance is more evident for high security applications, where a very small false acceptance rate is expected.

V. DISCUSSION

Although the parameter s in our experiments was empirically selected, it can also be estimated from the feature templates. White pixels corresponding to the line regions were found to be more important than the black pixels corresponding to the non-line regions. Meanwhile, the total number of white pixels was smaller than the total number of black pixels in the feature templates. Therefore, there is a correlation between the importance of white/black pixels and the number of the respective pixels. The parameter s can be estimated from the total number of white and black pixels in the feature templates.

Our experimental results indicated that the performance improvement for the finger knuckle matching was more pronounced than that for the palmprint matching. This is due to the noise existing in the palm images (Figure 4) which

influenced the decision from concave/convex pixels and resulted in the performance degradation. Noise removal algorithms can therefore be further incorporated for denoising the 3D palm images.

In order to further investigate the effectiveness of weighted similarity measure, we also evaluated the performance of our method using *Efficient Surface Code* on the PolyU 2D/3D Palmprint database [10] (contact based), denoised mean curvature images (MCI) employed in Li et al [11], log-Gabor filter based templates from IIT Delhi iris database [12], templates from even Gabor filter with morphological operators on PolyU finger image database [13] and DoN feature descriptors [19] on 2D images of the PolyU contactless 2D/3D Palmprint database. In all these analyses, the observed improvements were not significant, and this could be attributed to the fact that the importance of white and black pixels generated from the above methods may have similar weights, especially when the images are noisy. Therefore, the *Efficient Surface Code* would produce comparable performance to Hamming distance measures for those binary template images. These findings also support our theoretical arguments that weighted similarity is useful when the white and black pixels in the binary images templates encode information with different importance, which is demonstrated in our palmprint and finger knuckle experiments.

VI. CONCLUSIONS AND FURTHER WORK

This paper has proposed a new feature descriptor, *Efficient Surface Code*. This feature descriptor can efficiently encode concave and convex surface details and has been shown to be useful for accurately matching palmprint and finger knuckle images. This discriminative feature descriptor produces templates with one bit per pixel, which are four times smaller than those produced by *Surface Code* [5].

We have also introduced a weighted similarity measure for more accurately matching two binary feature images. The white and black pixels in some binary images do not necessarily encode information with equal importance. In our experiments, concave regions in palmprint and finger knuckle images were found to be more useful than the convex regions for accurate person identification. Our experimental results have indicated that our proposed methods can significantly outperform state-of-the-art methods for matching these biometric images. Despite the superior experimental results presented in this paper, sophisticated methods for the computation of the parameter s requires further investigation and is suggested for further work.

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