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Research on Lossless Compression Algorithms of Low Resolution Palmprint Images

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Abstract: In this study, lossless grayscale image compression methods are compared on public palmprint image databases. Effect of lossy compression algorithms on biometric samples has been well studied. However, lossless compression algorithms on the compression ratios have little been appreciated. In this study, we review and the stateofart lossless compression algorithms and investigate the performance using different when processing palmprint sample data. In particular, including those based on transformation (integer transform based in the JPEG , JPEG2000 and JPEG XR system, as well as the SPbased transform coding method), based on predictive lossless compression algorithms (LJPEG, CALIC and JPEGLS), dictionarybased compression methods (PNG UHA,7z and RAR). To gain a better and reliable result, these lossless compression algorithms are employed to test on different palmprint databases. Based on the testing results using an open palmprint image database, analysis and comparison, CALIC gives high compression ratios in a reasonable time, whereas JPEGLS is nearly as effective and very fast. The performance shows that a guide is given to choose which lossless palmprint image compression algorithm. At last, to find better solutions on how to improve lossless compression performance, we give some examples and suggestions.

Key words: Biometric traits, comparison efficiency, lossless image compression, palmprint image

INTRODUCTION

Biometric traits are widely applied in local and remote authentication systems for advances of biometric recognition technologies. With the increasing usage of biometric systems the question arises naturally how to store and handle the acquired sensor data, for example, storing biometric sample data in smart ID card and transmitting biometric data to the center database in the crime scenes. Palm print image based personal authentication is one of the most useful biometrics technologies. As palm print images contain more information of the identity than fingerprint images, it is likely that palm print image based personal authentication is able to obtain a higher accuracy. Because the storage of original palm print images requires a large amount of memory, it is crucial to explore the optimal compression algorithm of palm print images. The transfer time of palm print images depends on the size of the compressed images. The practical usefulness of a Picture Archiving and Communication System (PACS) presupposes that transfer operations must fulfill reasonable time requirements. For example, Allinson *et al*. (2007) presented details of experiments to establish the optimum form of compression that provides realistic transmission times and yet does not affect the utility and integrity of the U.K. Fingerprint Service in searching for latent identifications and in archiving unidentified latents on the U.K. national Automatic Fingerprint Identification System (AFIS). Wavelet Scalar Quantization (WSQ) was developed by the FBI, Los Alamos National laboratory and the National Institute of Standard Technology (NIST) specifically to reduce the media storage requirements of the FBI expanding AFIS facility by providing lossy compression over the range 10:1 to 20:1 (Bradley *et al*., 1993). JPEG2000 and SPIHT are correctly predicted by PSNR to be well suited compression algorithms to be employed in iris recognition systems (Matschitsch *et al*., 2007).

As we know, during in the lossy compression stage, some of information would be lost and this would reduce the recognition accuracy. And different image lossy compression is based on different principles and different biometric samples contain different structure information, therefore, many researchers have investigated the different lossy compression algorithms to choose the best

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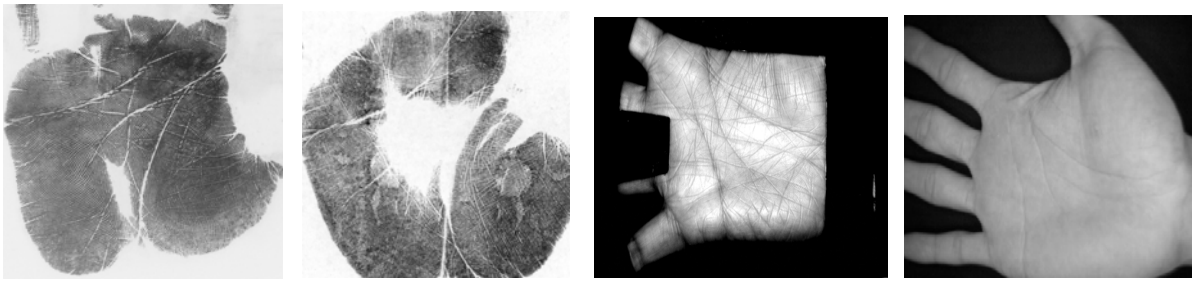


(a) (b) (c) (d)

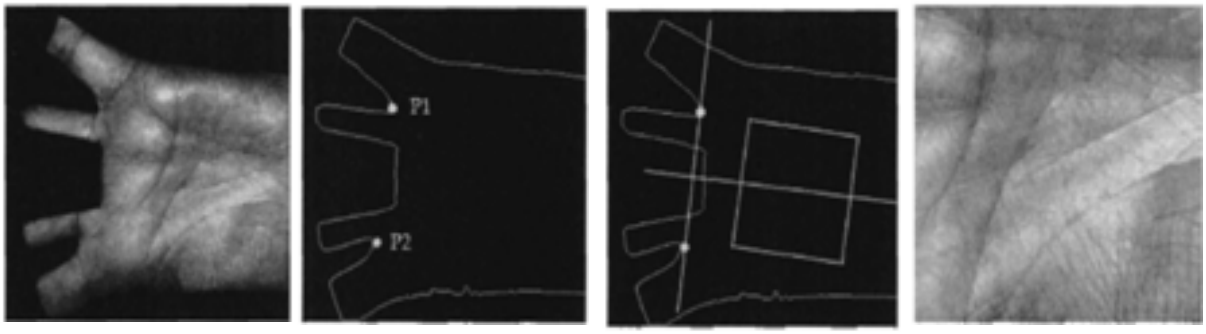
Fig. 1: Some orignal palmprint samples, (a) Highresolution palmprint image, (b) Latent palmprint at the scene of the crime, (c) A sample image from PolyU database, (d) A sample palmprint images from CASIA database

algorithm for the right biometric samples. The JPEG and JPEG 2000 are both the existing lossy compression standards. For natural images. The JPEG2000 standard compression system has superiority performance than JPEG system both in PSNR (Peak signaltonoise ratio) values and visual quality at the same compression ratio. However, according to our research results, the JPEG200 based compression system effect on palmpint recognition is serious than the JPEG based system, though the PSNR of reconstructed palmprint images based on JPEG2000 system is higher than that of JPEG (Li *et al.*, 2010). In addition, the implementation of JPEG2000 is more complexity than JPEG. A significant amount of study exists on using compression schemes in biometric systems. However, the attention is almost exclusively focused on lossy techniques since in this context the impact of compression to recognition accuracy needs to be investigated. Researchers have also investigated effects of lossy compression on biometric recognition have been investigated. The impact of different lossy compression algorithms (JPEG, JPEG2000, SPIHT and so on) on recognition accuracy of selected fingerprint and face recognition systems have been investigated (Funk *et al.*, 2006). Daugman and Downing (2008) explored the effect of severe image compression on iris recognition performance. Kurt *et al.* (2011) studied effects of JPEG XR compression on iris recognition systems under different settings.

However, the lossless image compression on the biometric image has little been concerned. Different biometric images have different main features, for example, the main feature of fingerprint images are their minutiaes, valley and ridge lines (He *et al.*, 2007) while the features of face image mainly exists in their low subspace (Zhao *et al.*, 2003). For lowresolution palmprint image, the features mainly include line and rich texture information (Zhang *et al.*, 2003), therefore, orientation optimized competitive coding (Yue *et al.*, 2009) and BOCV (binary orientation cooccurrence vector, (Guo *et al.*, 2009) obtain nearly the stateoftheart performance in palmprint recognition field. The performance of different biometric traits using the lossless compression algorithm are not are not exactly same. According to Georg *et al.* (2009), JPEG2000 (lossless mode) is suitable for iris images and PNG is suitable for fingerprints DB3. However, computational demand of these lossless schemes is higher than JPEGLS. One of the few results on applying lossless compression techniques exploits the strong directional features in fingerprint images caused by ridges and valleys. A scanning procedure following dominant ridge direction has shown to improve lossless coding results as compared to JPEGLS and PNG (Johan *et al.*, 2003). However, until now, there has not been researched on which lossless compression method is suitable to compress the palmprint image. In this study, by testing on palmprint database, analysis and comparison, we make a conclusion that the JPEGLS system is suitable for lossless palmprint image compression for its compression efficiency and speed.

MATERIALS AND METHODS

Palmprint images: There are mainly employed two categories in the palmprint recognition system. One is high resolution, in which the structure of a high resolution palmprint is similar to the fingerprint, such as Fig. 1a, b, similar to fingerprint image, Fig. 1a is captured by highresolution device and Fig. 1b is extracted from the scene of the crime and can be used to verify the crime person. The other is lowresolution, in which the initial recognition algorithms are inspired from the IrisCode (Kong, 2007), such as Fig. 1c, d, can be downloaded from website http://www4.comp. polyu.edu.hk/~biome trics/ and Fig. 1d can be from The Chinese Academy



(a) (b) (c) (d)

Fig. 2: The main steps of preprocessing, (a) original image, (b) Identify two key points to build a coordinate system, (c) Extracting the central part as a subimage and (d) Preprocessed result

of Sciences Institute of Automation (CASIA)(http://www.cbsr.ia.ac.cn/).

Preprocessing: Preprocessing is used to align different palm prinit images and to segment the central parts for feature extraction. To improve the accuracy of palm print recognition system, a lot of preprocessing algorithms have been proposed to be invariant to orientation and translation of palm on scanner which makes the system robust to orientation and translation of placing hand onscanner. The palm print recognition process starts with preprocessing and extracting central region of interest (ROI) from the palm print images obtained. It is important to define a coordinate system that is used to align different palm print images for matching. To exact the central part of a palm print, for reliable feature measurements, most of the preprocessing algorithms employ the key points between fingers to set up a coordinate system.

Furthermore, Han detects points in the middle of fingers and constructs lines passing through finer tips and the points to setup a coordinate system (Han 2004). All these approaches utilize only the information on the boundaries of fingers, while Kumar *et al.* (2003) propose to use all information in palms. They fit ellipse to a binary palm print image. According to the orientation of the ellipse, a coordinate systems, central parts of palm prints are segmented. Most of the preprocessing algorithms segment square regions for feature extraction, but some of them segment circular and half elliptical regions (Poon *et al.*, 2004).

Liambas and Tsouros (2007) produce an innovative approach for detecting the region of interest in palm print identification, from a highly noisy image, using a combinatorial algorithm. The existing research faces some critical issues such as noise, shadows, illumination variance, scars, rings, hand disorientation, disability (missing fingers) and different age group samples. All above inconvenient points are overcome by the proposed technique, in the preprocessing phase of palm print verification. Based on the distance between valley points adjacent to index finger and ring finger, Badrinath *et al.* (2011) proposed an robust technique to extract palm print either from left or right hand image acquired under non constrained environment. It also can classify hand image into either right or left hand.

As illustrated in Fig. 2, preprocessing involves generally the following steps:

- Binarizing the palm images
- Extracting the contour of hand and/or fingers and detecting the key points
- Establishing a coordination system and extracting the central parts

Figure 2a illustrates the key points and Fig. 2d shows a preprocessed image. In this study, palmprint is orientated and the ROI, whose size is 128 28, is cropped. The first and second steps in all the preprocessing algorithms are similar. However, to detect the key points between fingers has several different implementations including tangentbased approach (Zhang *et al.*, 2003). Tangentbased approaches have several advantages. They depend on a very short boundary around the bottom of fingers. Therefore, it is robust to incomplete fingers (as in the disabled) and the presence of rings. In this study, we employ this preprocessing algorithm in our experiment.

Lossless image compression algorithms: The goal of image compression is to achieve total decorrelation of the data. In information theory an entropy encoding is a lossless data compression scheme that is independent of the specific characteristics of the medium. Two of the most common entropy encoding techniques are Huffman

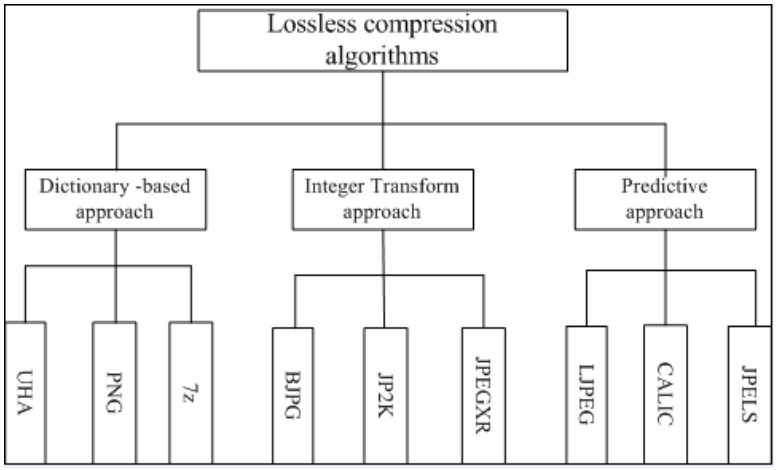


Fig. 3: The category of lossless image compression

coding and arithmetic coding. However, the main redundancy in the image is the space and visual redundancy. Only using the entropy encoding can not gain better compression ratio. The lossless image compression ratio can be roughly classified into three kinds according to different reduced redundancy mechanism, as illustrated in Fig. 3. The first one is dictionary based compression coders, such as 7z, UHA, RAR and PNG format picture. The second one is transformed based image compression coders, such as JPEG (binary implementation. lossless version), JPEG2000, JPEG XR and S+P transform. The last one is predictive scheme and entropy coding used on the prediction error compression coders, such as CALIC, JPEG_LS, LJPG (lossless JPEG).

A dictionarybased coder, also sometimes known as a substitution coder, is a class of lossless data compression algorithms which operate by searching for matches between the text to be compressed and a set of strings contained in a data structure (called the 'dictionary') maintained by the encoder. When the encoder finds such a match, it substitutes a reference to the string's position in the data structure. A list of lossless image compression based on dictionary algorithms is reviewed as follows. dictionary based schemes, in which strings of symbols are replaced with shorter (more probable) codes Dictionary based schemes (such as ZIP) are widely used for text compression. Schemes for computed graphic image compression widely used on the Internet (such as GIF, TIFF LZW and PNG) are also dictionary based.

- **7Z and ZIP:** uses LZMA as compression procedure which includes an improved LZ77 and range encoder. 7z uses LZMA as compression procedure which includes an improved LZ77 and ranger encoder .We use the 7ZIP software applying options a mx9. ZIP uses the DEFLATE algorithm, which is can also realized by the 7ZIP software. The 7z software can be download from http://downloads. sourceforge.net/sevenzip/7za920.zip.
- **UHA:** Supports several algorithms out of which ALZ2 has been used (option uharc a m3). ALZ2 is optimized LZ77 with an arithmetic entropy encoder. UHA is downloaded from ftp://ftp.sac.sk/pub/sac/ pack/uharc 06b. zip.
- **PNG:** Portable Network Graphics (PNG) is a W3C recommendation for coding of still images which has been elaborated as a patent free replacement for GIF, while incorporating more features than this last one (W3C, 1996). It is based on a predictive scheme and entropy coding. The entropy coding uses the Deflate algorithm of the popular Zip file compression utility, which is based on LZ77 coupled with Huffman coding. The PNG compression testing software is developed based on libpng version 1.4.5 and zlib 1.2.3 It can be downloaded from the website http:// www.libpng.org/ pub/png/libpng.html

The transform based image compression systems are original developed in a lossy way (Fig. 4). With the Discrete Wavelet Transform (DWT) realized in a lifting scheme (Sweldens, 1996), the integertointeger transformation is employed firstly in integer wavelet transform (Daubechies and Sweldens, 1998), then in the Integer Discrete Cosine Transform (IDCT) (Liang and Tran, 2001) and Lapped Biorthogonal Transform (LBT) (Tu *et al.*, 2008). Therefore, the JPEG (Binary DCT version), JPEG 2000 (Integer DWT) and JPEG XR (LBT) are also supporting the lossless image compression. The procedure of They are showed as follows.

- **JPEG (lossless version):** Different from the standard JPEG, the JPEG lossless version takes place of the

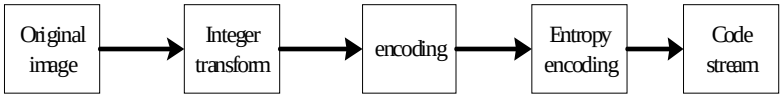


Fig. 4: The flow of transform based lossless image compression approach

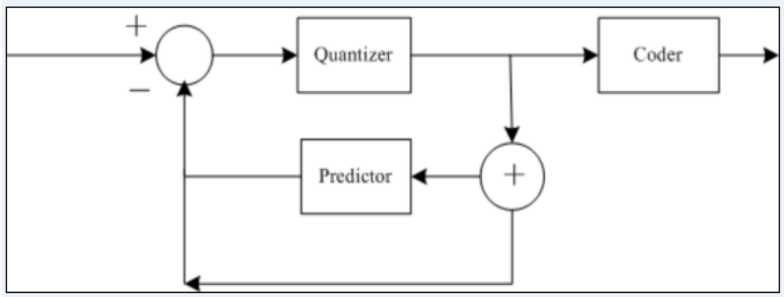


Fig. 5: The flow of predictive lossless image compression approaches

binary DCT (Integer DCT) instead of traditional DCT. The JPEG (Lossless Mode, binary DCT can be download from http://thanglong.ece.jhu.edu/~jliang/

- **JP2K (JPEG2000):** As noted previously, is the next ISO/ITUT standard for still image coding. In the following, we restrict the description to Part I of the standard, which defines the core system. Part II will provide various extensions for specific applications, but is still in preparation. JPEG 2000 is based on the DWT and provides for lossless coding by performing with either the reversible Le Gall (5, 3) taps filter in the transform stage. The JPEG 2000 software (http : // www . kakadus of tware .com) version 2.3.2or http://www.ece.uvic.ca/~frodo/jasper/software/jasper1.900.1.zip
- **S+P transform:** For lossless image compression, similar to the wavelet transform, Said and William A. Pearlman proposed an integer multiresolution transformation, which was called S+P transform (Said and Pearlman, 1996). The new transformation is similar to the subband decomposition, but it uses only integer operations. A codec uses this transformation to yield efficient progression up to lossless recovery. http://www.cipr.rpi. edu/research/ SPIHT/EW_Code/lossless.zip
- **JPXR (JPEG XR):** The "Information technology JPEG XR image coding system Reference software ISO/IEC 291995" is used to apply this most recent ISO still image coding standard, which is based on the Microsoft HD format. JPEG XR stages in the following, please consult the standard or related publications with respect to this issue (Dufaux *et al.*, 2009). It is exactly invertible in integer arithmetic and hence supports lossless image representation. For experimentation, we use the official JPEGXR reference software 1.8 (as of September 2009, the parameters DC, LP and HP band as used in the default settings) (http: //www .itu. int/rec/ TRECT. 835201001 I/en) (ITUT Rec. T.835 | ISO/IEC 291995, "Information TechnologyJPEG XR Image Coding System Part 5: Reference Software," 2010)

In the prediction based lossless data compression schemes, they often consist of two distinct and independent components: modeling and coding as illustrated in Fig. 5. In general, the predictor consists of a fixed and an adaptive component. It often performed through decorrelation, context modelling and entropy coding of the prediction error. Most modern research into lossless compression involves predictive schemes with statistical modeling. The older JPEG lossless and the new JPEGLS schemes are in this class.

- **JPEGLS (JPLS):** Is the latest ISO/ITUT standard for lossless coding of still images. It reference encoder LOCO using Median edge detection and Subsequent predictive and Golumb encoding (in two modes: Run and regular modes) (Weinberger *et al.*, 2000). JPEGLS is the latest ISO/ITUT standard for lossless coding of still images. It also provides for earlossless compression. This algorithm was designed for lowcomplexity while providing high lossless compression ratios. Software implementations of JPEGLS for various platforms are available at the web site http://www.hpl.hp. com/loco/.
- **CALIC:** a Context based, Adaptive, lossless image codec is a compression technique based on the pixel context of the present pixel to be coded (i.e., the

Table 1: Experimental performance under different lossless compression algorithms

		Time(s)		Compression ratio		Size (bytes)		Bpp (bit per pixel)	
	Lossless compression algorithms	Original	Roi	Original	Roi	Original (853,758,768)	Roi (135,365,424)	Original	Roi
Dictionary based	7z	120	824	2.5672	1.4398	94,017,301	332,570,031	3.1163	5.5564
	Zip	112	117	12.0139	1.25531	07,837,726	423,928,344	3.9724	6.3731
	UHA	406	2292	2.6691	1.3939	97,110,171	319,872,062	2.9973	5.7391
	PNG	750	1473	2.2123	1.4806	91,424,309	385,909,420	3.6161	5.4031
Transform based	BJPG	786	998	1.7768	1.2209	110,870,683	480,510,441	4.5025	6.5524
	JP2k (Jas)	1283	2577	2.2190	1.4674	92,246,938	384,743.990	3.6052	5.4517
	JP2K (Kdu)	993	1492	2.5077	1.4894	90,884,079	340,448,279	3.1901	5.3712
	S+P	1110	3374	1.3923	1.5180	89,174,517	613,191,321	5.7458	5.2702
	JPXR	746	1133	1.9237	1.4520	93,226,311	443,805,144	4.1586	5.5096
Context based	JPLS	760	923	2.3773	1.4886	90,937,109	359,122,394	3.3651	5.3743
	CALIC	1131	2013	2.5541	1.5319	88,366,427	334,271,440	3.1322	5.2224
	LJPEG	768	1063	1.8823	1.48799	0,975,583	453,568,355	4.2501	5.3766

setting of the pixels of some predetermined pattern of neighbour pixels) (Wu 1997). The method is capable of learning from the errors made in the previous predictions and in this way it can improve its prediction adaptively when the compression proceeds. The final set of prediction errors is coded by arithmetic or Huffman coding. The executive software can be from ftp://ftp.csd.uwo.ca/pub/from_wu/.

- **Lossless JPEG (LJPG):** was developed as a late addition to JPEG in 1993, using a completely different technique from the lossy JPEG standard (Pennebaker and Mitchell 1993). It uses a predictive scheme based on the three nearest (causal) neighbors (upper, left and upperleft) and entropy coding is used on the prediction error. At the time of this writing, the Independent JPEG Group lossless JPEG image compression package, a free implementation of the lossless JPEG standard, is available by anonymous ftp from ftp://ftp.cs.cornell.edu/pub/multimed/ljpg. The library, LibJPEG with default Huffman tables and PSV = 1 is employed in our study.

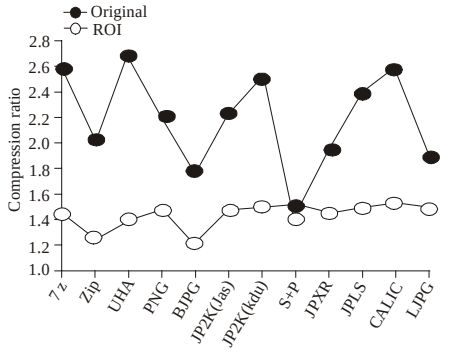
RESULTS

There are no enough samples to test the high resolution palm print images. The images of CASIA palm print database have been compressed in a standard jpg format. Therefore, in order to make the results more trust, we only use Hong Kong Polytechnic University (PolyU) Palm print Database to conduct the experiments. The PolyU Palm print Database contains 7752 grayscale images in BMP image format, corresponding to 386 different palms. In this database, around 20 samples from each of these palms were collected in two sessions, where around 10 samples were captured in the first session and the second session over a period of two months, respectively. The light source and camera focus have also been changed to test the robustness of any technique. The resolution of all the original palmprint images is 384 84 pixels at 75 dpi.

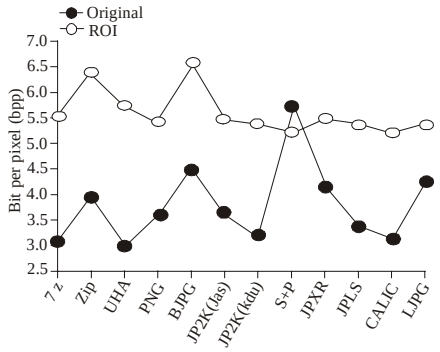
In order to obtain clear and better understanding on how to storage the palmprint images, we make experiments with palmprint images both on original size and its ROI part. The results have been generated on a ThinkPad PC with an Intel Pentium 4 processor (2.1 GHz) and 2 GB RAM configured with Microsoft Windows 7 Home Basic system, visual C++ 6.0. To obtain the speed performance under the same conditions all the lossless image compression programs are recompiled on using Visual C++.

Compression efficiency: The palmprint database contains 7752 images, each size of image is 384*284, therefore, the size of original palmprint database is 853758768 bytes. After these images are cropped, the size is reduced down to 135365424 bytes. Based on Table 1, we plot the Fig. 6, which illustrates the compression ratio using different lossless image compression methods. From Fig. 6, In general, the compression ratio of original palmprint database is larger than ROI parts. In the original palmprint image, as illustrated in Fig. 2, most of the original palmprint image is the black background, which is easy to compress and represent. In Fig. 6, the compression ratio variation trend of UHA and S+P are not corresponding to the other lossless compression algorithms. For the S+P transform, according to Said and Pearlman (1996), the performance of S+P is nearly the best in compression ratio during the majority images and it is also verified in the average of ROI palmpint parts. But, when testing on the original palmprint database using the S+P transform, the compression ratio reaches the worst one. That is partly that the S+P transform can not deal very well with the boundary of palmprint background.

The 7z was developed for the general file for compression. And it is not very suitable for image

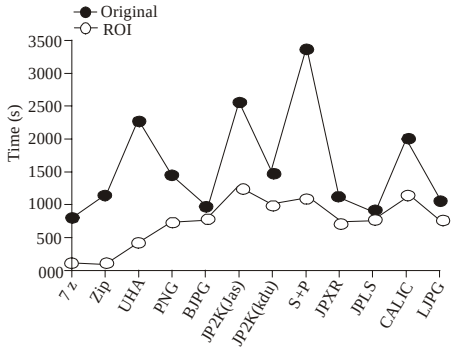


(a)

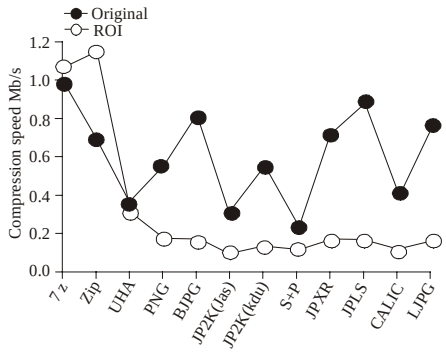


(b)

Fig. 6: Image compression efficiency of different lossless algorithms, (a) compression ratio, (b) bit per pixel



(a)



(b)

Fig. 7: Compression speed of different lossless algorithms, (a) time, (b) compression speed

compression. In contrast, the UHA can gain better compress performance which processing the original palmprint background information. The BJPG, which just uses the binary DCT version instead of traditional DCT, not surprisingly, the compression efficiency is the lowest in the employed algorithm except the S+P transform. The SP is not suitable for compression the images including a lot of background information, though it gain nearly the best compression performance for ROI images. Relatively speaking, the CALIC, JPLS, JP2k (Jas, Kdu) lossless image compression algorithms are stable and have also better performance. In a word, according to the palmprint images of both original and ROI part, the CALIC achieves the best compression ratio. From Fig. 6a, we observe a range of 1.21.6 for the ROI parts using the presented lossless image compression techniques. For the original palmporint image, the range of compression ratio is 1.62.7.

Compression speed: According to Fig. 7, the 7z and zip methods which employed in the 7z software are nearly the fastest algorithms. One reason is that the 7z software is optimized implemented in Assembly Language. The size of original palmprint database is six times larger than that of ROI (853758768/135365424 = 6.3071), however, the increased handling time is not always corresponding to the increased image size. For example, the handling time of BJPG and JPLS employed on PolyU palmprint database is just a little larger than that of processed ROI images. In the original palmprint image database, the handling speed is: 7z > JPLS >BJPG >LJPEG >JPEGXR >ZIP>PNG>JP2k (kdu)>CALIC>UHA>JP2K (Jas)>S+P. After extracted palmprint ROI parts, the compared handling speed is: Zip > 7z > UHA > JPXR >PNG > JPLS > LJPG>BJPG>JP2K (Kdu)>SP>CALIC> JP2K (Jas).

From Fig. 7, The dictionarybased algorithms (zip, 7z, UHA, PNG) have nearly the fast speed (the running time of JPXR is little longer that of the PNG. The 7 z software which is open software and always improved by the engineers, therefore, the processing speed is the fastest of all. The following speed is the predictionbased algorithms, such as JPLS and LJPG. The computational complex of arithmetic encoding is higher than the Huffman encoding and Glomb encoding algorithms. And

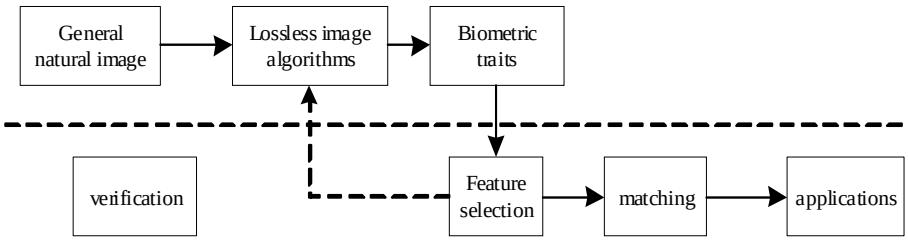


Fig. 8: Possible solution to improve the lossless image compression

compared with Huffman coding, the computational complex of Golomb is lower. Therefore, the speed of JPLS is faster than that of LJPG. The LJPG is faster than that of CALIC, in which the last stage arithmetic coding takes much time.

The last ones are the transformedbased algorithms, such as S+P transform and JP2K. In the BJPG system, which inherits the JPEG standard compression system, the images firstly is divided into 8×8 blocks and the Huffman coding is employed in the last stage. Therefore, the computational complex of BJPG is less than that of JP2k, which is based on the DWT and timeconsuming arithmetic coding. Inspired by the MPEG block based techniques, the JPEG XR, which is originally developed for the longrange image, takes advantage of a liftingbased reversible hierarchical lapped biorthogonal transform and block based encoding algorithm. The transform requires only a small number of integer processing operations for both encoding and decoding. The block based encoding algorithm is using a Variable Length Coding (VLC) lookup table approach in which a VLC table is selected among a small set of fixed predefined tables. And therefore, the running efficiency of the JPEG XR is higher than that of BJPG.

Overall, JPLS, LJPEG and PNG show nearly the same compression ratio. However, the JPLS has an advantage in the compression speed. Therefore, considering the best compromise between compression results and time consuming, the employment of JPLS in biometric palmprint systems can be recommended for most scenarios which confirm the standardization done in ISO/IEC 19794.

DISCUSSION

Many Lossless compression algorithms have been proposed until now. For images, there are three related lossless image compression standards, JPEG2000, JPEGLS and JPEG XR. And the PNG is also the common image format. However, there have not been developed a compression scheme which is used for biometric images. Though there is WSQ for fingerprint images, it was developed in 1996, 17 years ago and its performance is less than JP2K (Allinson *et al.*, 2007). And a lot of new schemes have been proposed during these periods. With the increasing accuracy in the biometric verification in many areas, it is very demanding to choice a proper coding algorithm to save and transmit these biometric samples.

Different biometric traits have different intrinsic characters. Therefore, we should find the best performance image compression for some specific biometric traits and corresponding to compression algorithms. According to the present research, for fingerprint, the minutiae as the main fingerprint characters can distinguish different fingers well. And the minutiae based approach in fingerprint recognition system has gain the best performance. The appearance based approach (PCA, LDA, *et al*.) has successfully used in face recognition. In iris recognition system, the texture feature and encoding, which is developed by Daugman (1993), has been used in commercial field. For lowresolution palmprint image, the distinguishing features mainly include line and rich texture information. When compressing these images, we should note these different features.

For pamprint, how to improve compression performance according to the features of palmprint needs further be developed. As illustrated in Fig. 8, we can improve the lossless image compression via the feature guided compression schemes. The following three algorithms can be improve the special image lossless compression performance. By using orientations, estimated from the linear symmetry property of linear neighbourhoods in the fingerprint, Johan *et al.* (2003) developed a scanning algorithm which follows the ridges and valleys. Compared to JPLS, using ridge scanning and recursive Huffman the gain is 10% in average. Nathanael and Mahmoud (2007) proposed a novel true twodimensional dictionary based grayscale lossless image compression scheme and the compression performance of the proposed scheme outperforms and surpasses any other existing dictionarybased lossless compression scheme. based on a twochannel LMS adaptive filter bank, Ruşen *et al*. (2001) proposed a lossless image compression algorithm and obtained higher compression ratios. Bekkouche *et al.* (2008) presented an adapted generalized lifting scheme in which the predictor is built upon two filters, leading to taking advantage of all this available information. For satellite images and textures, the generalized lifting schemes obtained a slightly noticeable (about 0.05 to 0.08 bpp) coding gain compared to the

others that permit a progressive coding in resolution. Inspired by the above algorithms, how to further improve the palmprint lossless image compression performance is our next research area.

CONCLUSION

To provide a comparison of the efficiency for palmprint images that can be expected from a number of recent as well as most popular still lossless image coding algorithms, we test different lossless image algorithms on an open palmprint image database. According to the testing results, JPEGLS is the stateofart fastest codec while the CALIC is the stateofart highest compression ratio for both original palmprint and its ROI part On average. The compression ratios with the four best methods (CALIC, S+P, JPEGLS) does not reach 2. Therefore, a topic for discussion is whether a limited and selective application of lossy compression techniques could be allowed in palmprint imaging. This is specifically the case for JPEGLS which exhibits the best compression results and very low computational demands.

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