Finger Vein Image Compression with Uniform Background

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ABSTRACT
We propose to replace the background data in finger vein imagery by uniform gray data and implications on (i) achieved lossless compression performance and (ii) obtained recognition accuracy in case of lossy compression are determined to employ 2 public datasets. Results indicate that replacement of original background by uniform one is definitely profitable for lossless compression, while the lossy case with impact on recognition accuracy has to be handled with caution as introduced sharp edges between finger area and background lead to artifacts which in turn degrade recognition performance. After having smoothed those areas, recognition performance is improved when replacing background for all settings.

CCS Concepts
• Theory of computation→Design and analysis of algorithms →Data structures design and analysis→Data compression.
• Computing methodologies→Artificial intelligence→ Computer vision→Biometrics.
• Computing methodologies→Computer graphics→Image compression.
• Information systems→Data management systems→Data structures→Data layout→Data compression.
• Information systems→Information retrieval→Document representation→Content analysis and feature selection.

Keywords
Finger vein recognition; lossless compression; lossy compression; uniform background.

1. INTRODUCTION
Compression has become an almost integral part of biometric systems and is covered by the ISO/IEC 19794 standard suite on Biometric Data Interchange Formats (ISO/IEC 19794-9:2011 for vascular data). According to the standard, either lossy compression (JPEG, JPEG_LS, and JPEG2000, see clause 8.3.13) or lossless compression (JPEG_LS, and JPEG2000) can be applied. Lossless compression is usually faster and does not interfere with the recognition accuracy of the system. Lossy compression is employed due to the much more significant data reduction achieved. However, the distortions introduced by compression artifacts may interfere with subsequent feature extraction and may degrade the matching results. Therefore, it is highly profitable to look into the best-suited compression methodology for a given biometric modality or even dataset, and to look further into possible interference between compression technology and feature extraction/template generation algorithms.

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Compression impact on vein-based biometric recognition schemes has not yet been investigated in sufficient depth. So far, available results focus at compressing the finger vein imagery as it has been acquired, i.e. as discussed in [1], where three ISO/IEC still image compression standards have been applied to a single public finger vein data set. Eventual interference of a collection of feature extraction /template generation schemes with different types of compression artifacts has been studied in detail. [2] completes this work by considering distinct application scenarios comparing to utilise probe data in uncompressed or compressed form, respectively and by considering two datasets in experimentation. Results have indicated that the optimal compression scheme depends on the target compression ratio as well as on the employed recognition algorithms. [3] considers a specific additional application scenario in which gallery data is pre-compressed with JPEG and JPEG2000 and the best compression scheme for a probe sample is determined for different target compression ratios (settings in which two different compression techniques are involved have been termed "inhomogeneous").

In this paper, we aim to improve finger vein data compression by concentrating the available bit-budget to the areas relevant for recognition (i.e. the finger area). When looking at typical finger vein data, it is obvious that the background (i.e. non-finger area) of the imagery does not contribute to the recognition process as it shows some (constant) parts of the scanning device only. Thus, we propose to replace these non-uniform background data (containing some visible parts of the sensor and mostly dark areas representing the finger-placement support with varying gray scales and corrupted by noise) by a constant gray value which should be compressed more efficiently than the original background (note that a related idea has been developed for iris recognition where eye-lid, as well as sclera data, has been replaced by constant gray data with the same aim [4]: "... so that the [...] compression did not waste bytes on non-iris pixels"). Section 2 introduces the still image compression standards as considered in this work and briefly reviews the finger vein recognition algorithms as used in the paper. In Section 3 we first explain the experimental settings (including the two finger vein datasets used in experimentation) and subsequently discuss the results of a large corpus of experiments. Section 4 presents the conclusions of this paper.

2. IMAGE COMPRESSION AND FINGER VEIN RECOGNITION

In this work, we consider three different ISO/IEC *lossy image compression* standards and a non-standardised technique for increasing compression ratio (i.e. ratio between original file size and file size after compression, shown on the x-axis in plots) up to 110 using the respective default configurations unless stated otherwise:

JPEG (JPG): The well-known (ISO/IEC IS 10918-1) DCT-based method. By adjusting the divisors in the quantisation phase, different compression ratios can be achieved. We adjust the quality parameter iteratively to achieve a file size closest to the desired compression ratio. The Matlab implementation is used.

JPEG 2000 (J2K): This wavelet-based standard (ISO/IEC IS 15444-1) is also a part of the DICOM standard where it replaced lossless JPEG compression. Results typically do not generate block-based artifacts as the original DCT-based JPG standard. J2K facilitates explicit rate control, i.e. target bitrates are met with high accuracy. We use JJ2000 version 5.1 available at https://code.google.com/p/jj2000/. For J2K, we additionally employ three variants of region of interest coding (ROI, i.e. the pixels corresponding to the finger): First, the classical variant where all the ROI data is coded into the bitstream before the background data ("J2K (ROI)"); second, where also resolution Level 0 of the background is encoded together with the ROI data (``J2K (Start Level 0)"); and third, where the first 4 resolution levels of the background is encoded with the ROI data ("J2K (Start Level 4)").

JPEG-XR (JXR): Is based on Microsoft's HD Photo and is known to produce higher quality than JPEG, but provides faster compression than JPEG 2000. In the default configuration, the Photo Overlay/Overlap Transformation is only applied to high pass coefficients prior to the Photo Core Transformation (ISO/IEC IS 29199-2). We adjust quantisation levels iteratively to achieve a target bitrate closest to the desired one. Software available at https://jxrlib.codeplex.com/ is used in experiments.

BPG: The "Better Portable Graphics" algorithm is based on a subset of the H.265 (HEVC, ISO/IEC 23008-2) video compression standard. We adjust quantisation levels iteratively to achieve a target bitrate closest to the desired one. The employed software can be downloaded from https://bellard.org/bpg/.

For *lossless compression*, we have used the lossless settings of JXR, Lossless JPEG (Ll_JPEG), GIF, PNG, JPEG_LS and ZIP with default configuration (compare [5] for descriptions and results for lossless iris image compression).

For *finger alignment*, we use a method adapted from Lee et al. [6] which simply masks out background pixels (setting them to 0). This already indicates clearly, that background information does not contribute to recognition as it is masked out at this stage. This is followed by a normalisation step, i.e. rotation compensation as done in [7]. For *image enhancement*, we apply **CLAHE** [8] as the final stage of High-Frequency Emphasis Filtering (**HFE**) which was originally proposed for hand vein image enhancement [9].

To foster reproducible research, we have only included *feature extraction* techniques in this study for which basic implementations are available (partially based on Matlab).

Maximum Curvature (**MC** [10]) aims to emphasise only the centre lines of the veins and is therefore insensitive to varying vein width. The first step is the extraction of the centre positions of the veins. For this purpose, the local maximum curvature in the cross-sectional profiles, based on the first and second derivatives, are determined. Afterwards each profile is classified as being concave or convex where only local maxima in concave profiles indicate valid centre positions of the veins. Then a score according to the width and curvature of the vein region is assigned to each centre position, which is recorded in a matrix called locus space. Due to noise or other distortions, some pixels may not have been classified correctly at the first step, thus the centre positions of the veins are connected using a filtering operation. Finally, binarisation is done by thresholding using the median of the locus space.

For matching the binary feature images we adopted the approach in [11] and [10]. As the input images are not registered to each other and only coarsely aligned (rotation is compensated), the correlation between the input image and in x- and y-direction shifted versions of the reference image is calculated. The maximum of these correlation values is normalised and then used as the final matching score.

In contrast to MC, the SIFT key-point [12] based technique uses information from the most discriminative points as well as considering the neighbourhood and context information of these points by extracting key-points and assigning a descriptor to each key-point. We employ additional key-point filtering as described in [13], where keypoints close to the finger/background boundary are discarded in addition to eventual background keypoints.

For MC the software of **B.T**. Ton [1] is used, while for SIFT feature extraction and matching software is used as provided by VL_Feat SIFT [2].

3. EXPERIMENTS

3.1 Experimental Settings

For experimental evaluations in this paper, we use the following two publicly available finger-vein datasets (note that datasets with a larger share of background will be able to benefit more from our approach, still, our two datasets share approximately the same background fraction) :

UTFVP: University of Twente Finger Vascular Pattern Database (UTFVP) [14], consisting of a total of 1440 images, taken from 60 subjects, 6 fingers per subject and 4 images per finger. The images have a resolution of 672×380 pixels with 8-bit greyscale depth and are stored in uncompressed form.

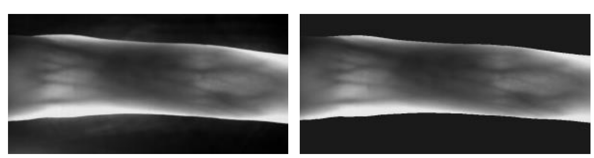


Figure 1. Originaland background replaced with uniform gray (UTFVP).

[1] Publicly available on MATLAB Central: http://www.mathworks.nl/matlabcentral/fileexchange/authors/57311

[2] http://www.vlfeat.org/

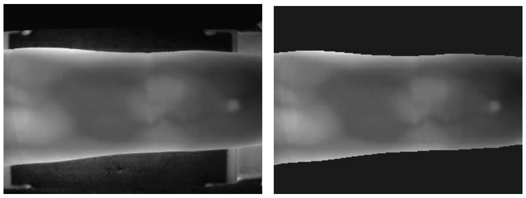


Figure 2. Original and background replaced with uniform gray (SDUMLA-HMT).

SDUMLA-HMT: The finger-vein subset of this multi-modal dataset consists of 3816 images, taken from 106 subjects, 6 fingers per subject, and 6 images per finger and was collected at Shandong University, Jinan, China [15]. Images are of resolution 320 × 240 pixels with 8-bit grey level and are also stored in uncompressed form.

The test procedure of the FVC2004 [16] was adopted to determine the EER (shown on the y-axis in plots). While we have also computed ZeroFNMR values and generated corresponding plots, space limitations prevent us from showing those. However, these exhibit the same trends as seen in the EER data.

In Figures. 1 and 2, we visualise the effect of replacing the background with uniform gray data for both datasets considered. This is achieved by finding the maximal gradient between background and finger area, and setting the background to a value of 0.1 (given the 8-bit grayscale data is mapped to [0,1]) to match the average luminance of the original background as closely as possible.

3.2 Experimental Results

In Table 1 we illustrate the gain achieved when replacing the background by uniform gray in case of applying a set of lossless compression schemes. It is evident, that for both datasets and all compression algorithms, the average file size is reduced by introducing a uniform gray background. However, the extent of improvement is fairly different.

Table 1. Lossless Compression (average file size)

	UTFVP		SDUMLA-HMT	
	Original	**Unif. Gray**	**Original**	**Unif. Gray**
Ll_JPEG	350 KB	297 KB	90 KB	59 KB
GIF	191 KB	113 KB	47 KB	28 KB
PNG	110 KB	101 KB	45 KB	25 KB
JXR	109 KB	80 KB	27 KB	22 KB
JPEG_LS	298 KB	168 KB	69 KB	39 KB
ZIP	240 KB	166 KB	57 KB	33 KB

While for some cases, we observe a file size reduction by almost a factor of 2 (e.g. JPEG_LS for UTFVP or PNG for SDUMLA), other cases are much less spectacular (e.g. PNG for UTFVP or JXR for SDUMLA). This means, that in fact, it is possible to achieve significant gain by this simple conversion to a uniform background, however, this strongly depends on the compression scheme and the dataset considered. Without testing the actual configuration, a prediction of the corresponding gain is not possible.

Subsequently, we investigate the effect of using the data with a uniform gray background in case lossy compression is applied. We start by discussing the different JPEG2000 variants. Figure. 3, applying MC to the UTFVP data set, displays a superior behaviour for the variant with a uniform gray background (always the red curve) up to compression ratio 40, for higher ratios the original data provides higher recognition accuracy.

When changing the recognition algorithm to SIFT but staying with the same data set the situation changes in a way that there is no setting left where the uniform background data gives a superior performance (not shown).

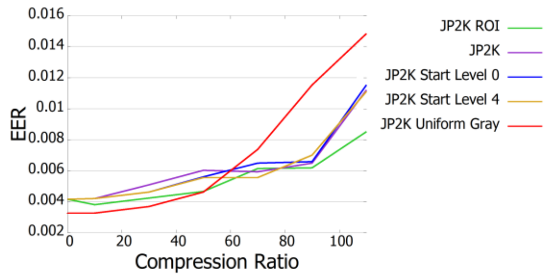


Figure 3. Recognition accuracy of MC (EER) on UTFVP data under JPEG2000 compression.

Staying with SIFT, but changing the dataset to SDUMLA as shown in Figure. 4, again the uniform background does not give better results, but the very poor behaviour as seen at high compression ratios on the UTFVP data cannot be observed.

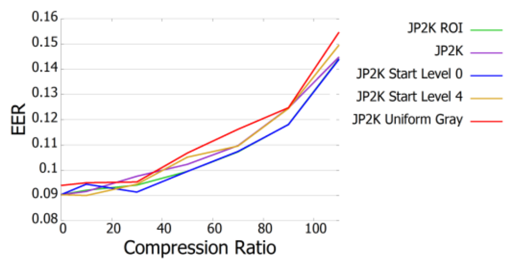


Figure 4. Recognition accuracy of SIFT (EER) on SDUMLA data under JPEG2000 compression.

Finally, when applying MC recognition to the SDUMLA data as shown in Figure. 5, we get superior recognition accuracy for the uniform grayscale background data across the entire range of considered compression ratios.

These four example settings, all considered with JPEG2000 variants, already show that using a uniform background does not necessarily enhance our recognition results. There are cases where this happens (only observed for MC recognition), but in some cases, we observe even significant result degradation (e.g. high compression ratios when using SIFT on the UTFVP data). Some variant of J2K ROI coding is typically better than simple J2K, but not significantly so. In the following, we provide some additional examples using other compression techniques.

Figure. 6a documents, that in some settings, the gain in recognition accuracy can be tremendous. Under BPG compression, we do not observe a significant reduction of recognition accuracy for increasing compression ratios at all when working on UTFVP data with the uniform grayscale background, while the original data exhibits the expected behaviour.

On the other hand, Figure. 6.b shows that by only changing the compression scheme to JXR, recognition accuracy gets drastically reduced for the uniform grayscale background data as compared to the original one for compression ratios larger than 70.

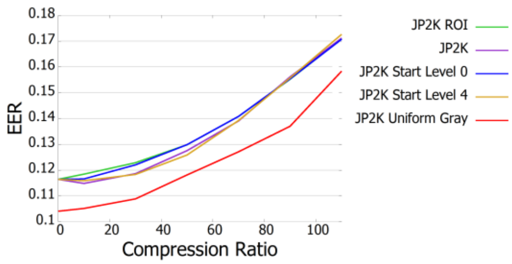
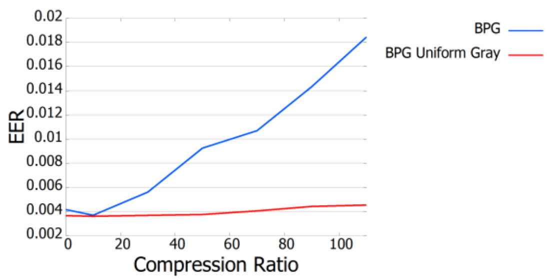
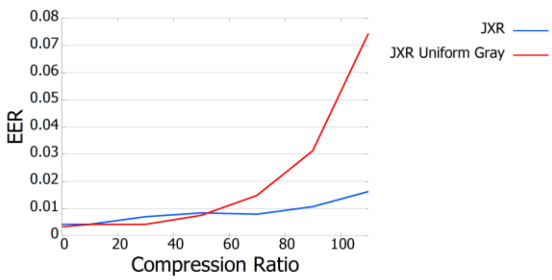


Figure 5. Recognition accuracy of MC (EER) on SDUMLA data under JPEG2000 compression.



(a) BPG



(a) JXR

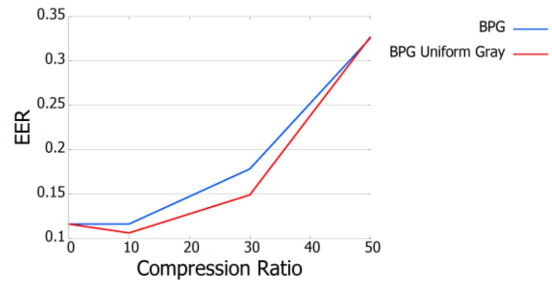
Figure 6. Recognition accuracy of MC (EER) on UTFVP data.

Even the typically poor results of JPEG compression can be mitigated slightly by using uniform grayscale background data as shown in Figure. 7.a, however, when changing the recognition algorithm from MC to SIFT (as shown in Fig. 7.b), this advantage is lost again.

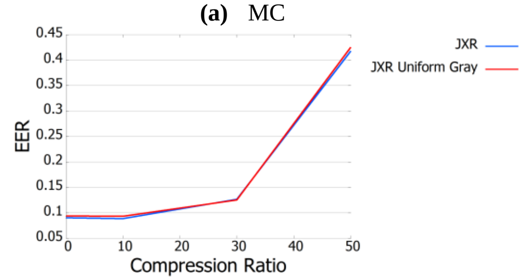
Overall, it has to be clearly stated that the advantage of setting the background to uniform gray scale as seen with lossless compression cannot be transferred in a straightforward manner to the case of lossy compression. Especially for high compression ratios and when applying SIFT recognition, recognition accuracy gets (partially significantly) worse when using gray background.

The observed effects in the lossy compression case, being somewhat unexpected, can be explained as follows: The artificial uniform background, introducing ragged edges between background and finger tissue data as present in the original data (see Figures. 1 and 2 for these edges compared to the original data), leads to compression artifacts at this boundary.

Thus we face recognition problems in some configurations, mostly seen at high compression ratios. This affects background removal and subsequent SIFT-based recognition more severely as compared to MC since these artifacts generate keypoints randomly, while artificial high curvature data as detected by MC are generated to a lesser extent. A way to circumvent this effect is to smoothen the artificial boundary to mitigate the generated compression artifacts which has proven to result in improved recognition performance for artificial gray background in all settings.



(a) MC



(b) SIFT

Figure 7. Recognition accuracy (EER) on SDUMLA data under JPEG compression.

4. ACKNOWLEDGMENT

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5. CONCLUSION

The experimental compression evaluations conducted in this paper indicate that it is beneficial to replace the original background in finger vein imagery by uniform gray values. This is the case for lossless compression, but for lossy compression also settings do exist where recognition accuracy is worse as compared to using original background data. These effects are caused by compression artefacts at the border between finger tissue and background and result from the sharp edge as generated when introducing the uniform background. A smoothening of the boundary (as also suggested for iris [4]) leads to more consistent results. We would like to point out the excellent performance of BPG on uniform gray background data, obviously facilitated by the excellent intra-prediction applied in this algorithm.

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