Robustness Evaluation of Hand Vein Recognition Systems

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***Abstract*—Hand vein recognition systems are more robust against external influences which degrade the image quality like dust or dirt on the sensor or skin surface conditions than fingerprint ones. We investigate the robustness of several hand vein feature extraction and matching schemes against different types of image distortions, related to conditions occurring during the acquisition of hand vein images. These distortions correspond to sensor defects, bad system design and problems in the use of the sensor. The impact on the recognition accuracy is quantified in terms of the EER and compared across the different schemes and different types of distortions.**

I. Introduction

Hand vein recognition systems gain more and more attention nowadays as they provide several advantages over the well established fingerprint ones. Hand vein recognition is more robust against skin surface conditions like dust, dirt, cuts, moisture than fingerprint recognition and can thus be used in scenarios where fingerprint systems cannot because of environment or finger surface conditions.

However other issues might affect the image quality and therefore the recognition accuracy of hand vein systems. These include misplacement of the hand, compression, noise, transmission errors, blurring and sensor ageing related pixel defects. Different strategies have been proposed to assess the robustness of fingerprints, e.g. benchmarking tests like the fingerprint verification contests (FVC [1]) and the BioSecure evaluation framework [2]. An alternative approach is to generate synthetic fingerprints (SFinGe [3]) or to artificially degrade real fingerprint images (in [4] StirMark is used). However for hand and finger vein recognition systems there are neither benchmark data sets nor robustness evaluation results available, except our previous work on the impact of sensor ageing on the recognition performance of finger vein recognition [5].

The main goal of this work is to evaluate the robustness of hand vein recognition systems (different feature extraction and matching schemes) against certain kinds of image degradations related to capturing conditions occurring in practice. We use the same methodology as proposed in [4], i.e. generating the degraded data sets based on a data set captured at the University of Salzburg. StirMark is used to apply image distortions to hand vein images where appropriate and generate degraded data sets. Additionally we generate several "aged" data sets using our image sensor ageing simulation algorithm [5].

Utilizing StirMark and the image sensor ageing simulation algorithm to generate these data sets has several advantages. First of all the tests are reproducible if their parameters are known and the test data set is available. Further it becomes feasible to isolate specific external influences from others if there is the need to investigate the impact of a specific type of influence. Moreover it is possible to systematically simulate different strengths of distortions corresponding to different levels of external influence, which may not only be a tedious and time-consuming work but also hardly possible to achieve using real data.

Section 2 briefly describes image sensor ageing related pixel defects and presents the StirMark toolkit's image manipulations we utilized. Section 3 gives a short review of the evaluated preprocessing, feature extraction and matching schemes and explains the experimental setup. It continues with the experimental results on the degraded data sets and a short discussion. Section 4 concludes this paper and gives an outlook on future work.

II. Image Degradations

A. Image Sensor Ageing

In principle a hand vein scanner consists of an infrared light source and an image sensor. An image sensor is an electronic device, containing an array of photosensitive cells, also called pixels, which captures the incoming light and transforms it into an electric signal. The pixels may become defective due to ageing effects. Defective pixels appear as spiky shot noise in the output images. Pixel defects are permanent, their number increases linearly with time, they are randomly distributed over the sensor area and they do not appear in clusters [6].

Defective Pixel Types: there are two main types of in-field pixel defects, hot and stuck pixels [7], [6]. Both are showing different characteristics than at manufacturing time. Example aged hand vein images can be seen in figure 1.

A **stuck pixel** has always the same arbitrary but fixed output value independent of the incoming illumination and exposure settings.

A **hot pixel** adds a light independent offset to the pixel's output which increases linearly with exposure time.

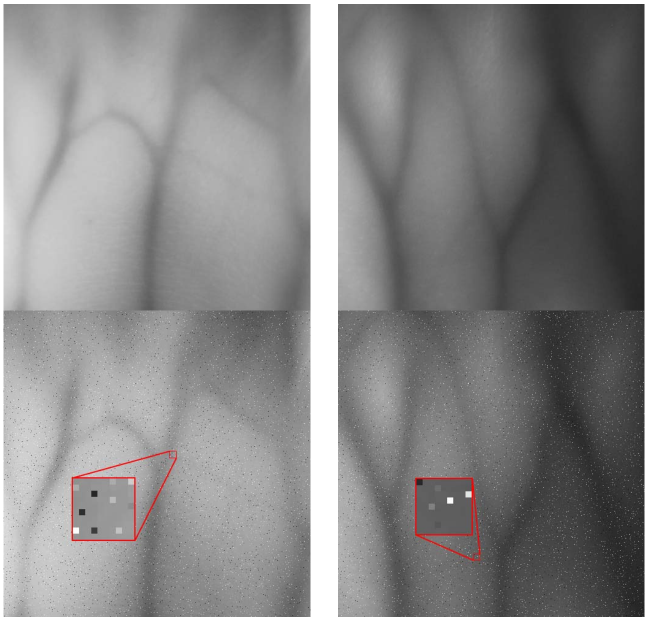
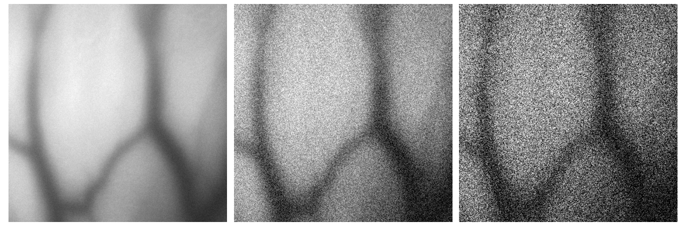
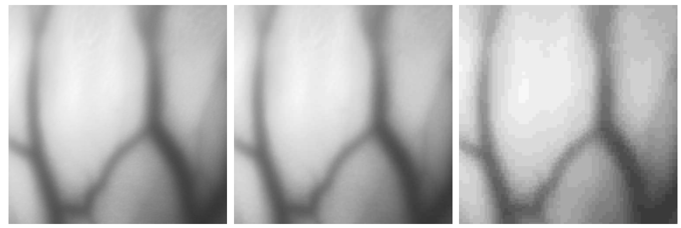


Figure 1: Sample aged images, top: original images, bottom: aged images containing 10000 hot and 10000 stuck pixels generated by the ageing simulation algorithm



(a) Level 1 (b) Level 7 (c) Level 15

Figure 2: Additive noise



(a) Level 80 (b) Level 50 (c) Level 10

Figure 3: JPEG compression

B. The StirMark Toolkit

Fabien A. P. Petitcolas et al. [8] developed a benchmark test in the context of robustness evaluation for digital image watermarking methods, called StirMark (Currently version 4.0 of the toolkit is available at http://www.petitcolas.net/fabien/watermarking/stirmark/). It provides specific types of perturbations which are pre-defined and their intensity can be adjusted via a given set of parameters for each type.

In the following we describe the StirMark image manipulations which are chosen to be appropriate for hand vein images and used during the experiments. Not all manipulations provided by StirMark are suitable to simulate natural acquisition conditions. For each manipulation the relation to realistic hand vein capturing scenarios which could be modelled thereby is outlined. The example images shown have been generated by applying the respective StirMark manipulations. The different kinds of manipulations have different meanings in the context of a biometric system and can be grouped into several classes: Sensor ageing related pixel defects and the remove lines and columns correspond to a defective sensor. JPEG compression influences result from a bad system design. Median cut filtering and additive noise are due to defects on the use of the sensor.

Median Cut Filtering results in non directional blur, additionally corrupting the clarity of the vein structure. This sums up small hand movements during the image acquisition and in general blurry vein structures due to the interaction of the infrared light with different types of tissue inside the finger. The size of the filter mask can be set from 1 to 15.

Additive Noise simulates noise that might naturally appear in hand vein images due to dust, graining caused by the acquisition equipment itself (e.g. thermal sensor noise), shot noise due to high ISO setting or other errors introduced during processing, storage and transmission of the acquired images. This noise is added to the input image. Its amount can be adjusted by a single parameter ranging from 0 to 100 where 0 means "none" and 100 means "completely random image". Some example images can be seen in figure 2.

Remove Lines and Columns corresponds to errors in hand vein images resulting either from transmission/processing or errors of the biometric sensor while reading the hand vein image (might not be able to read the whole hand and miss or skip some lines). This could be caused by a defective image sensor suffering from dead lines/columns. This manipulation removes lines and columns from the input image. The amount can be adjusted by a single parameter k which corresponds to the frequency of removing lines, where k means "remove 1 line in every k lines". The dimensions of the output image are reduced.

JPEG Compression is applied to the hand vein images in order to save storage space. It is lossy and leads to a general loss in sharpness, reduced edge clarity, loss of colour detail and introduces compression artefacts (blocking and ringing artefacts). This leads to a reduced visibility and breaking of the vein lines. The higher the compression the more severe the artefacts become. The quality level can be set from 0 to 100 where lower numbers indicate higher compression. Figure 3 shows some example JPEG compressed images.

III. Experiments

At first a brief overview of the evaluated preprocessing, feature extraction and matching methods are given. Then the hand vein data set and the test protocol are outlined. Subsequently, our experimental results with respect to the different schemes and types of image degradations are presented and discussed.

To improve the visibility of the vein pattern we use **High Frequency Emphasis Filtering** (HFE), **Circular Gabor Filter** (CGF) and simple **CLAHE** (local histogram equalisation) as **preprocessing**.

Different binarisation type **feature extraction** and one key point based technique are used. **Repeated Line Tracking** (RLT), **Maximum Curvature** (MC) and **Wide Line Detector** (WLD) aim to extract the vein pattern from the background resulting in a binary image, followed by a comparison of these binary images. For RLT, MC and WLD the MATLAB implementation by B.T. Ton (publicly available on MATLAB Central: http://www.mathworks.nl/matlabcentral/fileexchange/authors/57311) is used. In addition **Local Binary Patterns** (LBP) and a simple **Adaptive Binarisation** (AB) are evaluated as representatives of binarisation type feature extraction methods. **Matching** the binary feature images is done using a correlation measure, calculated between the input images and in x- and y-direction shifted and rotated versions of the reference image. Moreover a **SIFT** based technique with additional key-point filtering is used. AB, LBP and the preprocessing techniques as well as the SIFT(based on VL_Feat SIFT: http://www.vlfeat.org/) approach are custom implementations. For more details on the preprocessing, feature extraction and matching methods please refer to [9].

Hand Vein Data Set: A custom subset of the hand vein data set collected at the University of Salzburg [10] is used. Our custom data set contains only images captured using transillumination and includes images of 100 hands, 3 images per hand. This is a relatively low number of images to derive profound statements. Thus we plan to extend the whole data set in the future to include more subjects and also more images per subject/hand.

Image Sensor Ageing related pixel defects are simulated using our algorithm proposed in [5]. Although in practice only very few defective pixels occur under normal conditions, we use a defect rate of 1000 hot and 1000 stuck pixels per year over a period of 10 years during our experiments to account for higher radiation environments or other external stress imposed to the sensor.

EER Determination is done according to the FVC2004's [11] test procedure, resulting in in 300 genuine matches and 4950 impostor matches (3×100 images).

A. Experimental Results

From table I it can be clearly seen that MC and SIFT achieve the best baseline EER and show the highest robustness against all tested distortions.

Figure 4 shows from top to bottom the results for an increasing number of hot, stuck and combined hot and stuck pixels. In general hot pixels have less influence than stuck pixels. The influence on SIFT and MC is almost negligible up to 20000 defective pixels. AB is influenced starting from 6000 defects. WLD, RLT and LBP are affected starting from several hundred defects, especially for stuck and hot and stuck pixels combined. But in practice more than several hundred defects are very unlikely to occur and most of the scheme are robust against such a number of defects. Thus hand vein recognition systems are robust against a realistic number of pixel defects occurring in practical applications.

EER	MC	SIFT	WLD	RLT	LBP	AB
Baseline	0.013	0.02	0.073	0.044	0.297	0.157
5000 Hot	0.015	0.031	0.101	0.063	0.323	0.163
5000 Stuck	0.015	0.027	0.143	0.09	0.337	0.166
10000 Hot + Stuck	0.016	0.029	0.161	0.103	0.35	0.174
Noise level 1	0.023	0.036	0.24	0.143	0.37	0.223
Noise level 3	0.127	0.159	0.477	0.276	0.443	0.374
Noise level 15	0.457	0.294	0.527	0.49	0.457	0.5
RML 1 in 100	0.014	0.023	0.079	0.047	0.317	0.157
RML 1 in 30	0.02	0.017	0.107	0.103	0.36	0.18
RML 1 in 10	0.077	0.03	0.227	0.263	0.433	0.243
Median Filter 3	0.013	0.027	0.076	0.033	0.287	0.15
Median Filter 9	0.013	0.02	0.163	0.033	0.287	0.15
Median Filter 15	0.013	0.03	0.27	0.043	0.337	0.166
JPEG 90	0.013	0.026	0.07	0.043	0.3	0.157
JPEG 50	0.02	0.02	0.123	0.07	0.354	0.167
JPEG 15	0.066	0.118	0.363	0.21	0.45	0.28

Table I: EER for baseline performance and degraded images

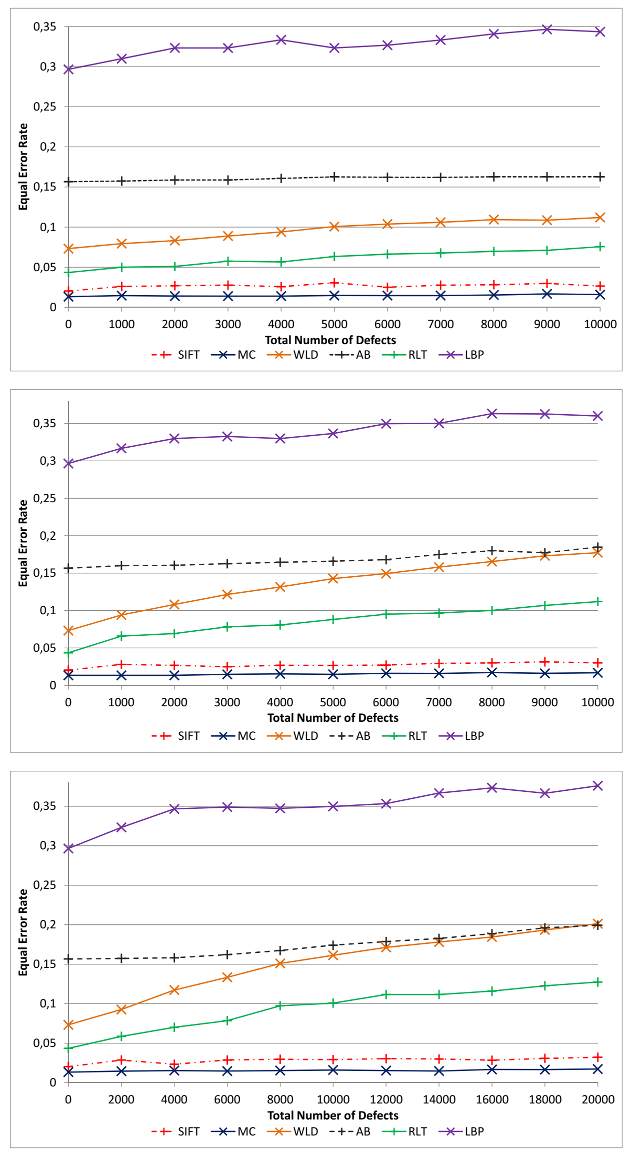


Figure 4: EER for hot, stuck and both, hot and stuck pixels combined

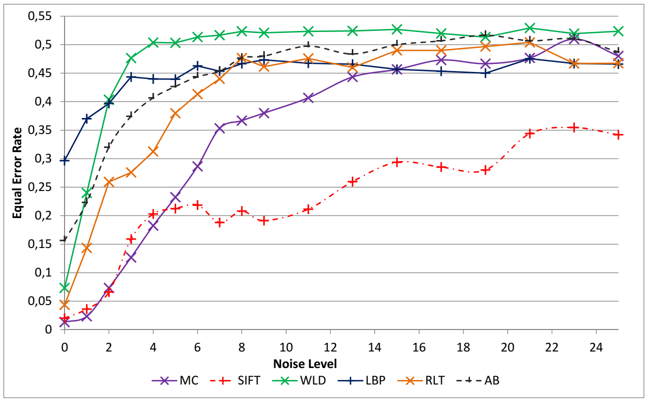


Figure 5: EER for additive noise test

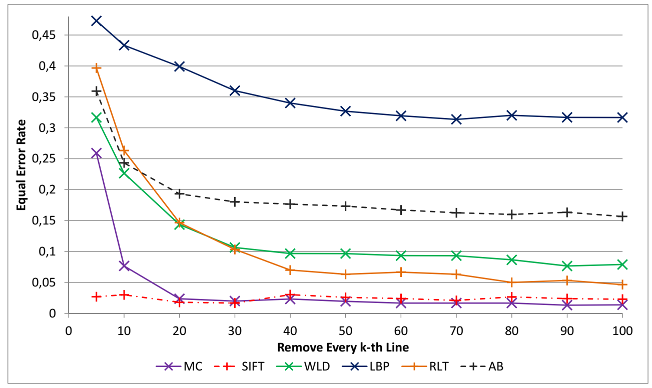


Figure 7: EER for remove lines

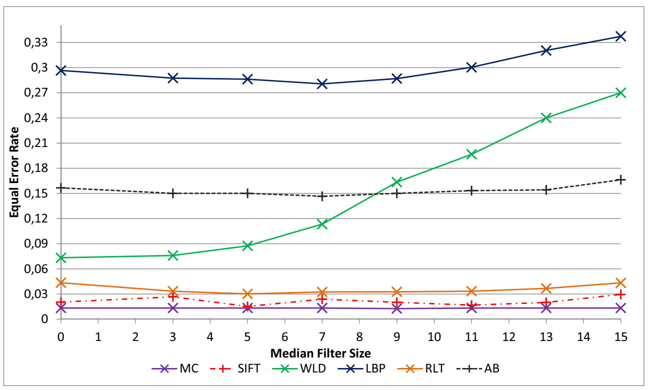


Figure 6: EER for median cut filtering test

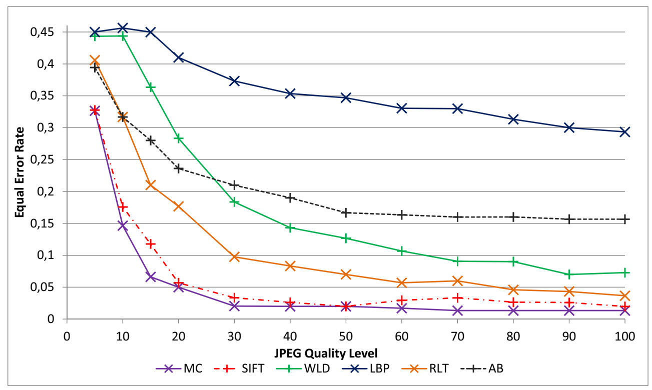


Figure 8: EER for JPEG compression

If additive noise is applied to the images, each of the tested schemes suffers significantly, which can be seen in figure 5. It has the most severe impact among all of the tested image manipulations. At a noise level of 5 except for SIFT and MC there is no meaningful recognition possible any more.

The difference between sensor ageing related pixel defects and additive noise is that the defective pixels caused by ageing always have the same fixed locations and characteristics in all output images. Random noise varies from image to image in both, its location and characteristics. The results clearly show that additive noise has a much more severe impact than sensor ageing. This might be due to the type of noise content introduced to the images but more likely due to the different amount of noise that is added. The average PSNR of images with 10000 defects is 24.92. The average PSNR of all images with noise level 1 is 28.28 and for noise level 7 it is 15.3.

Median cut filtering corresponds to blur. As figure 6 shows, MC is completely insensitive to this type of distortion. SIFT shows quite a good robustness too, except some variations. Actually all schemes except WLD show an improvement in their EER if slight median cut filtering is applied.

Figure 7 shows the excellent robustness of SIFT against the removal of lines even up to every 5th line is removed. MC is robust against the removal of lines up to 1 in 20 lines are removed. WLD, RLT and AB are affected more and LBP is affected most. Removing only a few lines does not “destroy” the vein lines, i.e. it is unlikely to break them. It shortens them and makes them thinner which has only a minor impact on the actual vein structure. If more lines are removed, vein lines may get broken or disappear completely.

Figure 8 shows the very high stability of MC against JPEG compression down to a quality level of 30. AB is only slightly affected down to a quality level of 50, from there its EER increases rapidly. The performance of SIFT decreases at first but at a quality level of 50 it is equal to its baseline performance. WLD, RLT and LBP are not robust against JPEG compression at all. All schemes are severely affected below a quality level of 20.

IV. Conclusion

We assessed the robustness of hand vein recognition systems against several image distortions related to real acquisition conditions. Therefore we generated several test data sets using different StirMark image manipulations and a sensor ageing simulation algorithm. Our experimental results clearly show a large variability in the robustness of the different schemes against the tested types of image distortions. The performance on unperturbed data and even the performance on lower strength levels of the perturbations cannot predict general robustness properties. This necessitates the need for a standardised test tool or common test data sets for the evaluation of hand vein recognition systems like they are available in fingerprint recognition.

Our experiments are a first step towards a systematic robustness evaluation for hand vein recognition. These first results are only theoretical but they provide a basis for further investigations. In practice not only a single kind of distortion will occur but several conditions distorting the images. Our first goal was to have a look at the single distortions and their influence on the recognition performance. Future work will include tests with combined distortions and also more specific image manipulations to be able to exactly model different acquisition conditions occurring in real applications. E.g. the influence of background illumination and constricted or dilated placement of the hand has to be investigated. In addition we will perform further tests on other public available data sets and more feature extraction and matching schemes.

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