# A High Quality Finger Vascular Pattern Dataset Collected Using a Custom Designed Capturing Device

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## Abstract

*The number of finger vascular pattern datasets available for the research community is scarce, therefore a new finger vascular pattern dataset containing 1440 images is presented. This dataset is unique in its kind as the images are of high resolution and have a known pixel density. Furthermore this is the first dataset which contains the age, gender and handedness of the participating volunteers as meta data.*

*The images have been captured using a custom designed capturing device. The various aspects of designing this capturing device are addressed in this paper as well.*

*To confirm whether this new dataset is in fact an important contribution some performance figures in terms of EER of several published state-of-the-art algorithms using this new dataset and an existing dataset from the Peking University are presented. Using this new dataset EERs down to 0.4% have been achieved.*

## 1. Introduction

The vascular pattern of the finger is advertised as a promising new biometric, characterised by very low error rates, good spoofing resistance and a user convenience that is equivalent to that of fingerprint recognition. Though this new form of biometrics is already commercially deployed, it still lacks a strong scientific base. This is due to industrial protectiveness, which restricts the ability to verify claimed performances. In order to compare existing algorithms a standardised testing method is needed and more datasets should be made available to researchers.

In order to stimulate the academic research on vascular pattern recognition this paper will present a new finger vascular pattern dataset which has been made available to other researchers[1]. The presented dataset is unique in its kind as it provides high resolution images together with demographics about the volunteers. Another contribution of this paper is the performance verification of several published algorithms using both the newly collected dataset and an existing dataset collected by the Peking University.

The new dataset has been collected using a custom designed capturing device, the various aspects of designing this capturing device are also covered in this paper.

As a final note it should be mentioned that in this paper the term *vascular pattern* is used instead of the more popular *vein*. This is done because the term vein might imply that only veins are captured by the capturing device, which is of course not true as both veins and arteries are captured, hence the name vascular pattern is preferred.

## 2. Acquisition Setup

A custom transillumination device type has been designed to capture the finger vascular pattern [9]. This type of capturing device has been chosen for its simplicity, robustness and the fact that external light interferences have little influence on the captured images. A downside of this type of capturing device is the reduced user convenience because the finger is partially obscured during the capturing process. All finger vascular pattern capturing devices are based on the fact that blood has a higher absorbency than surrounding tissue in the near-infrared spectrum. A schematic cross-section of the capturing device can be seen in Figure 1. The USB light-box is responsible for regulating the individual LED intensities and is encapsulated in the capturing device for the ease of portability. The overview also shows the slanted mirror indicated in green and the top plate containing the eight LEDs. The total length of the realised capturing device is 50 cm and the maximum height is 15 cm. The constructed capturing device consists of three main components; a light source, a camera and a mirror. These components will be described briefly in the successive paragraphs.

[1] http://www.sas.el.utwente.nl/home/datasets

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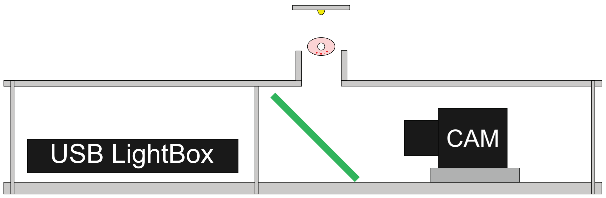
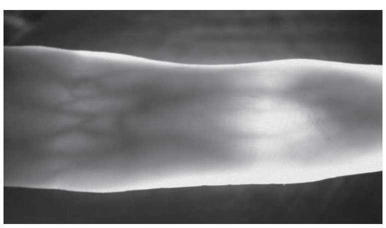
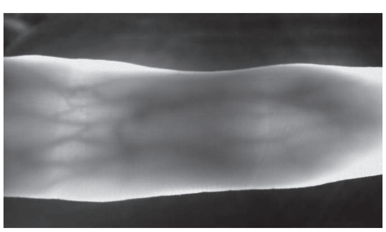



Figure 1: Schematic cross-section of the capturing device

**Light source** This the most important part of the capturing device since it determines the intensity of the captured image. Eight SFH4550 near-infrared LEDs produced by Osram with a wavelength of 850 nm are used to transilluminate the finger. This LED type has been chosen because it has a small angle of half intensity, which means more power can be coupled into the finger. Each individual LED intensity is regulated using a simple control loop in such a way that a uniform intensity along the finger is obtained in the captured image. This control loop is also necessary to cope with varying thicknesses along the finger and between persons. The benefit of this simple control loop can be seen in Figure 2 it clearly shows the over exposure in the non-regulated case.



(a) Eight equal LED intensities



(b) LED intensities regulated by control loop

Figure 2: Benefit of the control loop to adjust the individual LED intensities

**Camera** The camera used to capture the images is a BCi5 monochrome CMOS camera with firewire interface produced by C-Cam technologies. The camera has been fitted with a Pentax H1214-M machine vision lens with a focal length of 12 mm. This lens is fitted with a B+W 093 infrared filter which has a cut off wavelength of 930 nm. The filter is used to block out any interfering visible light. The camera is used in 8 bit mode with a resolution of $1280 \times 1024$ pixels.

**Mirror** To minimise the height of the capturing device a mirror is used to place the camera in the horizontal plane. A NT41-405 first surface mirror produced by Edmund Optics has been used for this purpose. The reason for choosing a first surface mirror is to avoid distortions in the captured image. A conventional mirror has its reflective layer protected by glass. The refractive indices of glass and air differ which means distortions will occur in the captured image. The final constructed capturing device can be seen in Figure 3.

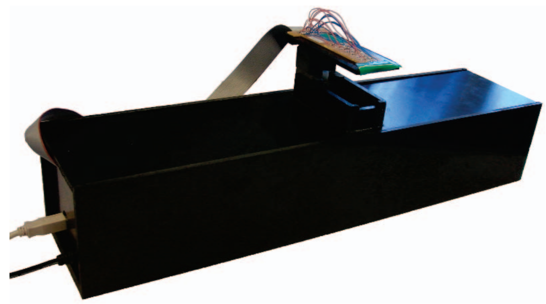
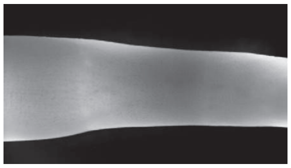


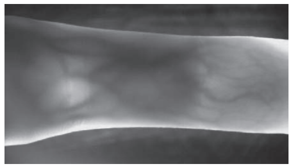
Figure 3: Realised finger vascular pattern capturing device

## 3. Description of Dataset

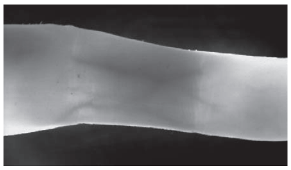
The collected dataset contains 1440 finger vascular pattern images in total which have been collected from 60 volunteers at our university during the 2011–2012 academic year. Images were captured in two identical sessions with an average time lapse of 15 days. For each volunteer the vascular pattern of the index, ring and middle finger of both hands has been collected twice at each session. This means that each individual finger has been captured four times in total. The captured images have a resolution of $672 \times 380$ pixels and have a pixel density of 126 pixels per centimetre (ppcm). The images are stored using the lossless 8 bit grey scale Portable Network Graphics(PNG) format. The percentage of male volunteers was 73% and the percentage of right handed volunteers was 87%. The dataset represents a young population with 82% of the volunteers falling in the age range of 19–30, the remaining volunteers were older than this. Some sample images from the collected dataset can be seen in Figure 4. The quality of the collected images varies from person to person, but the variation in quality of the images from the same person is small. The width of the visible blood vessels range from 4–20 pixels which corresponds to vessel widths of approximately 0.3–1.6 mm. These vessel widths are approximate numbers because the pixel density was determined assuming a flat surface.



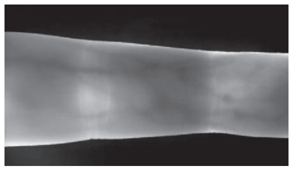
(a) Female, age 24



(b) Male, age 32



(c) Male, age 20



(d) Female, age 31

Figure 4: Sample images of the left hand ring finger from the collected dataset.

## 4. Results

To illustrate and rank the quality of the collected dataset the performance of a few published algorithms was evaluated. These algorithms have been applied to the novel collected dataset and the V4 finger vein database from the Peking University [8] which has been used as a reference. The performance of the algorithms is measured in terms of Equal Error Rate (EER). The experiments also investigate the merit of adaptive histogram equalisation (AHE) as a preprocessing step.

Each directory of the Peking dataset contains between four and eight images of the same finger. For the experiments only directories containing exactly eight images have been used, this accounts for 153 directories out of the available 200 directories. For this dataset it is not known which fingers belong to the same person.

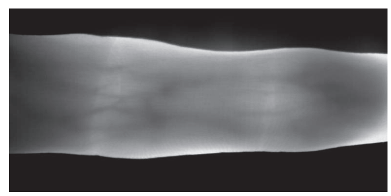
For both datasets 10% of the fingers have been used for tuning the various parameters of the algorithms. For the Peking dataset the valid directories are sorted ascending by filename and the first 10% are used for parameter tuning. For our dataset ten percent of the *fingers* have been selected by taking the first finger of the first volunteer, the second finger of the second volunteer . . . the first finger of the seventh volunteer. This method of selecting the training set has been chosen to get a larger variation in the quality of the vascular pattern images. The other 90% of both datasets has been used to determine the actual performance of the algorithms.

The exact number of genuine and imposter experiments done for both the parameter tuning and the actual determination of the performance are given in Table 2.

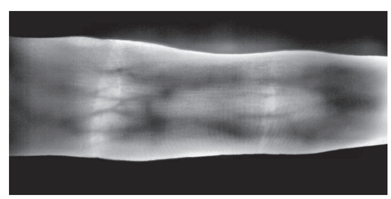
| dataset | #fingers | genuine | imposter |
|---|---|---|---|
| *Parameter tuning* | | | |
| Peking | 15 | 420 | 6720 |
| Our | 35 | 210 | 9520 |
| *Actual performance experiment* | | | |
| Peking | 138 | 3864 | 604992 |
| Our | 325 | 1950 | 842400 |

Table 2: Number of genuine and imposter tests performed.

For all of these experiments fingers were treated as identical individual identities, for example left hand index fingers were matched with right hand middle fingers. Two performance experiments are done per dataset, one with and one without adaptive histogram equalisation as preprocessing step. This preprocessing step is done using Matlab's `adapthisteq()` function with the default parameters set. The effect of applying an adaptive histogram equalisation to a vascular pattern image can be seen in Figure 5.



(a) Original image



(b) Adaptive histogram equalisation

Figure 5: Effect of adaptive histogram equalisation

To ensure that only image regions containing finger are matched with each other a binary mask is used. This mask is created by first determining the edges of the finger in the image using the method described by Lee [5] et al. and then filling in the area between these edges.

The edges detected in the previous step are used to normalise the image using the method described by Huang et al. [2]. This method tries to estimate a rotation and a translation based on the detected finger edges. After these parameters have been estimated they are used to define an affine image transformation which aligns the finger to the centre of the image. This affine transformation is also applied to the binary mask.

| | original paper | best reported | Peking | | Our | |
|---|---|---|---|---|---|---|
| | | | no AHE | with AHE | no AHE | with AHE |
| Normalised cross-correlation [3] | 0.0 | - | 14.7 | 9.8 | 3.1 | 1.9 |
| Maximum curvature [7] | 0.0 | 2.7 [2] | 1.2 | 1.3 | 0.4 | 0.4 |
| Repeated line tracking [6] | 0.2 | 5.0 [4] | 6.8 | 5.9 | 0.9 | 1.2 |
| Principal curvature [1] | 0.4 | - | 2.7 | 2.2 | 0.8 | 0.4 |
| Wide line detector [2] | 0.9 | - | 4.7 | 2.7 | 1.5 | 0.9 |

Table 1: Performance expressed in terms of EER(%) of several algorithms for both datasets, both with and without adaptive histogram equalisation (AHE) as a preprocessing step.

The output of each of the algorithms, except the normalised cross-correlation, is a binary template indicating the position of a blood vessel. Two binary templates are compared with each other by using the method described by Miura et al. [6]. An incidental side effect of using the binary finger region mask is that the shape of the finger is also indirectly taken into account when comparing two templates.

The final verification results are shown in Table 1 which indicates that our dataset performs significantly better in all cases and that adaptive histogram equalisation is beneficial in most of the cases.

The two methods proposed by Miura et al. have been tested by other researchers using their own collected datasets. One of them is Huang et al. [2] who has achieved an EER of 2.8% for the maximum curvature method and an EER of 5% for the repeated line tracking method. Another one is Choi et al. who has achieved an EER of 3.6% for the maximum curvature method. The last one is Kumar and Zhou [4] who achieved an EER of 8.3% for the repeated line tracking method and achieved an EER of 2.7% for the maximum curvature method. The mentioned EERs from Kumar and Zhou are the average EER of the middle and index fingers. The best reported performance figures of these two methods are mentioned in Table 1 as well.

## 5. Conclusions

A new finger vascular pattern dataset containing 1440 high quality images is presented to the research community. Despite the low number of 60 volunteers which participated the major contribution of this dataset is the addition of demographic data such as gender, age and handedness. Another contribution is the high quality of the captured images and the known pixel density of the images. Furthermore the data is collected in two identical sessions with a time lapse of approximately two weeks. Because of the high quality of the captured images this new dataset can pave the way for the research of high security cooperative applications. The performance evaluation using existing algorithms has shown that equal error rates down to 0.4% can be achieved by using this new dataset.

## 6. Future Work

The use of the vascular pattern of the finger as a biometric is still not as mature as other biometric traits such as 2D face recognition. To reach an equal maturity there is still a lot of research needed.

This future research should include the collection of larger datasets together with demographic data of the volunteers. These larger datasets will enable researchers to report performance figures with a higher confidence. It will also enable the research of factors such as age, gender, ethnicity and time lapse on the performance. The research community would also greatly benefit from standardised testing methods and datasets because only then results of different algorithms can be compared with each other in a comparative manner.

The biometric performance can further be improved by fusing other finger traits such as the crease pattern of the finger and the shape of the finger. An advantage of finger shape is that it is already present in the captured image. The crease pattern can be captured simultaneously with the vascular pattern by using a 'hot-mirror'. This type of mirror will pass visible light and reflect near-infrared light, it has already been used by Lee et al. [5] for a single trait sensor.

The current control loop which adjusts the LED intensities is still rather crude and leaves space for further improvements in terms of speed and image intensity uniformity. Preliminary results have shown that the relation between the intensity in the captured image and the intensity of the LED is as good as linear.

Fingers are often assumed to be exchangeable identities when performing performance experiments. This is a doubtful assumption as it has been noticed that ring and index fingers tend to curve towards the middle finger. Future research should be done to see whether this assumption can be justified.

An important aspect when designing a biometric system for high security cooperative applications is liveliness detection of the user to avoid spoofing. One possible liveliness indicator is the presence of a heart pulse of the user. A preliminary study has shown that the pulse can be extracted by looking at the local mean grey value within a sequence of finger vascular pattern images. For this study an image sequence was created by capturing an image every 10 ms. The local mean grey value as function of time of this image sequence is given in Figure 6. The period between the

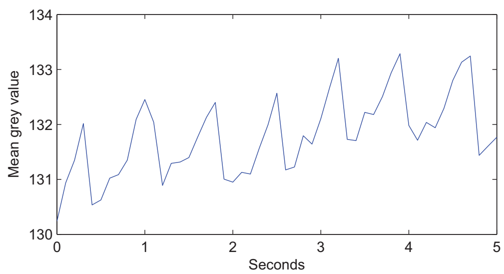



Figure 6: Local mean grey value of an image sequence

peaks in the plot is 7 ms which corresponds to a heartbeat of 86 beats per minute.

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