Mobile Wrist Vein Authentication Using SIFT Features

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Abstract. Biometrics have become important for authentication on modern mobile devices. Thereby, different biometrics are differently hard to observe by attackers: for example, veins used in vein pattern authentication are only revealed with specialized hardware. In this paper we propose a low cost mobile vein authentication system based on Scale-Invariant Feature Transform (SIFT). We implement our approach as vein recording and authentication prototype, evaluate it using a self recorded vein database, and compare results to other vein recognition approaches applied on the same data.

Keywords: Mobile authentication, wrist veins, NIR, SIFT features

1 Introduction

Modern mobile devices have access to, store, and process much private information, including messaging (email, SMS), contacts, access to private networks (VPN, WiFi), or even mobile banking. Thus, many devices provide local device access protection mechanisms, such as PIN, password, or fingerprint authentication. With those the authentication secret could be observed by attackers and used in replay attacks. However, some biometrics are more difficult to observe by attackers, as they largely remain hidden without using special sensors. For example, observing biometric information is harder for vein than for face authentication. By combining multiple such biometrics, also including weak biometrics like gait, strong and reliable mobile authentication can be achieved [3].

One biometric authentication less explored with mobile devices is vein authentication, which has gained popularity outside the mobile environment for being contactless. As skin largely absorbs the visible spectrum of light, veins mostly remain hidden in normal conditions, which prevents vein from being reliably observed in this spectrum. Light in the (NIR) or infrared (IR) spectrum has maximum depth of penetration of skin tissue. Hence, veins are illuminated with NIR/IR light and captured using cameras with optical NIR/IR bandpass filters [11,14]. Most vein authentication approaches use finger, hand dorsal, palm, or wrist vein patterns [13,15], with vein capturing devices designed for medical and security fields of research [6]. For mobile users wrist veins have the advantage of being relatively easy to access – which could be used e.g. with smart-watches, thereby not requiring any additional effort or changes in user behavior.

In this paper we investigate mobile wrist authentication using SIFT features. Our main contributions are a) development of a low cost wrist vein capturing device, b) using SIFT features for vein authentication, and c) evaluation of our approach using a new wrist vein database with 120 wrist vein images from 30 participants.

2 Related Work

Different approaches to vein visualization, recognition, and authentication have been proposed for medical and security purposes [2,8]. In this section we provide an overview of approaches most important to mobile vein authentication. In [13] NIR (800 nm) and far infrared (FIR, 800-1400 nm) light is used to acquire vein pattern images of the wrist, back, and palm of the hand. The capturing device is mounted on a board with a charge-coupled device (CCD) camera with IR filter and NIR lamp. After image acquisition, they use skeletonization to obtain vein patterns and perform matching by measuring the Hausdorff distance (LHD) between different patterns. Within a similar setup [10] uses fast spatial correlation for matching hand vein patterns in vein authentication.

In [9] wrist veins are captured using a physical structure and NIR illumination. They collect a database of 5 samples from the left and right hand for each of 50 subjects. Evaluation is done comparing nine different state-of-the-art vein matching techniques. Results indicate that Log-Gabor and Sparse Representation Classifier (LG-SRC) are the models with the best vein matching performance. [7] uses a local threshold for vein segmentation and 2D correlation coefficient for classification of obtained vein patterns. They evaluate on a self-recorded database of 1200 wrist images acquired from 50 volunteers for both left and right hands.

Finally [6] describes the design, development and initial evaluation of mVein-Vision, a mobile medical application for assisting and improving venipuncture. The application is implemented on a standard mobile device and intended to be a low cost alternative to commercial NIR devices. In contrast to our work, they only focus on vein detection and visualization as educational and clinical tool.

Summarizing, previous work does not yet combine wrist vein authentication with mobile environments. Therefore, our goal is to build and evaluate a mobile wrist vein authentication system, for which we propose to combine a low cost mobile vein capturing system with SIFT features for vein authentication.

3 Wrist Vein Authentication Based on SIFT Features

We present a low cost, mobile wrist vein authentication system, utilizing the visualization principle adopted from [6]. Our approach consists of three constituent parts (Fig. 1a) vein visualization and data collection using NIR illumination, b) vein image enhancement to obtain clear vein patterns, and c) vein authentication based on vein pattern matching using SIFT features.

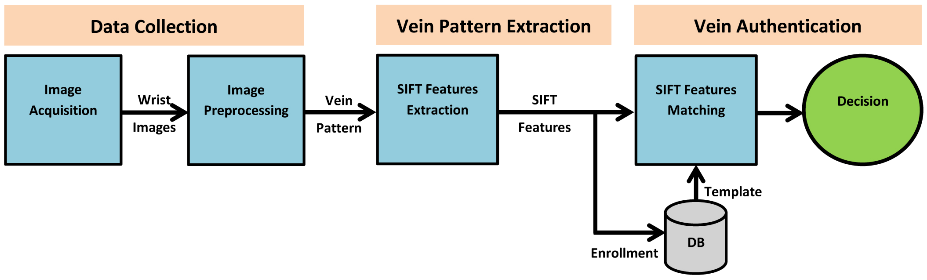


Fig. 1. Constituent parts of our approach to mobile vein pattern authentication.

3.1 Wrist Veins Capturing

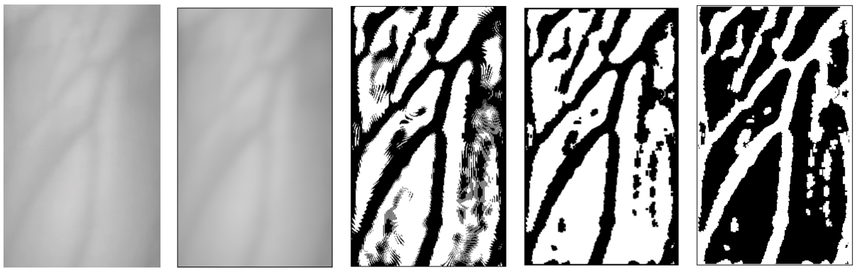
Considering the good results of [7] we adopt their approach of using a low cost CCD camera with NIR illumination for vein capturing. As we operate in a mobile environment, wrists cannot be assumed to be placed in front of the sensor in a fixed or uniform position. This freedom of positioning implies three challenges that need to be addressed for successful vein authentication: non-uniformness in shift, rotation, and scale of sensor data. One could use hand pegs (cf. [9]) to address shift and rotation. However this would make capturing images in a mobile environment overly cumbersome. Consequently, we instead use a region of interest (ROI) of about 5.8×9.7 cm size when capturing vein images. Users position their wrist accordingly inside the ROI, then the image is cropped to only contain information within the ROI.

3.2 Image Preprocessing

After obtaining vein images (Fig. 2a) we adopt preprocessing from [7] to increase quality and visibility of vein patterns. We apply a 3×3 median and Gaussian Blur filter to reduce noise (Fig. 2b), image binarization and a 15×15 mean auto local threshold (Fig. 2c), morphological closing to reduce outliers and sharpen veins (Fig. 2d), and pixel inversion to obtain veins as white and background as black pixels (Fig. 2e).

3.3 Wrist Vein Feature Extraction and Matching

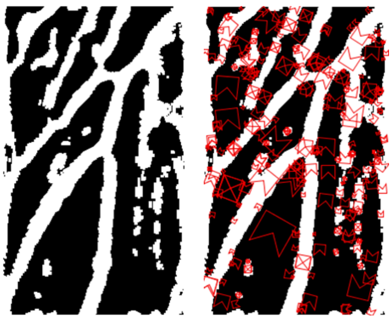
After preprocessing vein pattern images we derive features to distinguish individuals based on their vein patterns. Such vein patterns could be slightly scaled



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

Fig. 2. Vein image preprocessing: sample after applying cropping (a), filtering (b), auto local threshold (c), morphological closing (d), and pixel inversion (e).

and rotated to each other, resulting from the freedom of wrist position during capturing vein images. Thus, we use a SIFT features based matching algorithm [1] to extract and match features in a scale and rotation invariance manner (Fig. 3). Moreover, SIFT features have not yet been used for wrist vein recognition, but for extracting image characteristics in object recognition, movement detection, and image registers, and have proven to work for finger vein and face recognition [4,5].



(a) (b)

Fig. 3. Preprocessed vein pattern sample (a) and its extracted SIFT features (b).

Using the similarity between SIFT features of two vein patterns we derive if those are actually from the same person. For two samples I_A, I_B with corresponding SIFT features $S_a\{f_{A1}, f_{A2}, ..., f_{An}\}$ and $S_b\{f_{B1}, f_{B2}, ..., f_{Bm}\}$, our first step is to calculate a list of matching SIFT features L_{ab} between S_a and S_b: $L_{ab} = \{f_{A1} - f_{B3}, f_{A3} - f_{A2}, ...f_{An} - f_{Bm}\}$. L_{ab} already contains suitable matches between SIFT features of the two samples – based on which we propose to enhance the accuracy of feature matching by going one step further. We propose to use the Euclidean distance of all possible pairs of SIFT features of S_a and S_b, to ensure matched features in L_{ab} actually have the minimum distance compared to all other possible matches using the same features. Using the obtained L_{ab}, for each proposed matched pair of features ($f_{Ai} - f_{Bj}$ with $i \in [1, n]$ and $j \in [1, m]$), we calculate the Euclidean distance of these features $D(f_{Ai} - f_{Bj})$ to all other features $D(f_{Ai} - f_{B1}), D(f_{Ai} - f_{B2}), \ldots, D(f_{Ai} - f_{Bm})$. If thereby $D(f_{An} - f_{Bm})$ is the minimum distance we say that $f_{An} - f_{Bm}$ are a feature match (Eq. 1):

$$\forall x : D(f_{Ai} - f_{Bj}) < D(f_{Ai} - f_{Bx}) \Rightarrow \text{feature match} \tag{1}$$

After obtaining all matching features between two vein patterns, the number of matches C_{ab} is used together with a predefined threshold τ as similarity between those patterns. If $C_{ab} \geq \tau$ we conclude that those patterns are originated by the same person, and by different people otherwise.

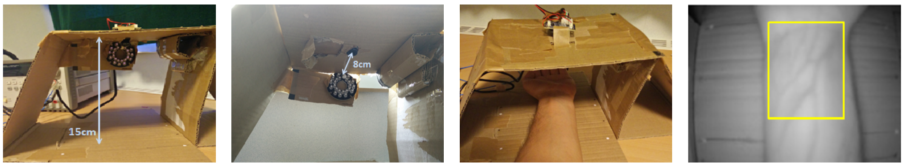
So far our approach acts in a 1:1 vein pattern comparison manner: it requires one sample to enroll users and one further sample to perform authentication. To improve authentication accuracy we propose to instead use majority voting with N vein pattern samples for both enrollment and authentication. Thus, during authentication, comparisons between N enrollment samples $I_{A,n}$ and N authentication samples $I_{B,m}$ result in N^2 individual results $C_{ab,i}$. We apply a majority voting like approach over all $C_{ab,i}$ to obtain an overall authentication result. Such can be done using mean, median, standard deviation, or similar, based on individual results. In our approach we compare using the mean and median with $N = 4$ samples, thereby on $N^2 = 16$ individual comparison results. The obtained similarity $\overline{C_{ab}}$ of two vein pattern samples is used with a threshold τ to decide if they were originated by the same person. If $\overline{C_{ab}} \geq \tau$ we say the samples are from the same person, respectively from different people otherwise.

4 Evaluation

To evaluate our approach we built a wrist vein capturing device and recorded a wrist vein dataset. Our device consists of three main parts (Fig. 4): a cluster of 24 LEDs emitting NIR light (880 nm), a CCD camera with an optical NIR bandpass filter (700-1000 nm), and an open physical structure. The camera is placed about 15 cm above of the wrist, with the LED array being about 8 cm away from the camera and about 17 cm from the capturing point – emitting light with an angle of about 62° to the wrist. Using this setup we obtained a reasonable illumination of wrist veins (Fig. 4d). The aim of our physical structure is to ease recording and emulate a mobile device equipped with NIR hardware. Using an open physical structure thereby provides for more realistic data in the mobile environment than frequently used closed box recording approaches with absolute darkness except the NIR illumination. Using our recording setup we simulate users placing their wrists inside a ROI frame on mobile devices. We record 4 vein image samples of the right wrist from 30 participants, which results in a total of 120 vein images.

4.1 Evaluation Setup

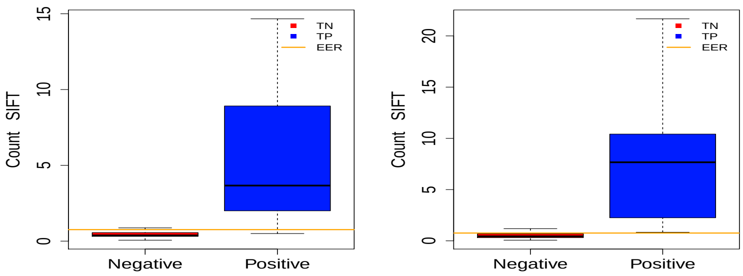
We apply image preprocessing, wrist vein feature extraction, and matching as explained in section 3 to our dataset. We then partition the preprocessed data



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

Fig. 4. Capturing device camera position (a), NIR LEDs position (b), hand position (c), camera view with ROI (d).

using gallery independence to evaluate our approach independently of participants in training data. We select 50% = 15 users for training our model and use the remaining 50% as held-back test set for exclusively testing the final model. The threshold $\tau = 0.760$ to separate true matches (P) and false matches (N) is based on the model's equal error rate (EER) from the training partition (Fig. 5a): we thereby obtain the same error for the P an N class during training. We then use τ with the test partition: as this data is originated by yet unseen participants we can derive how our system performs on new and unknown users.



(a) (b)

Fig. 5. Training Positive (blue) and Negative (red) classes distribution with derived EER threshold (orange) (a), testing Positive (blue) and Negative (red) classes distribution with evaluated EER threshold (orange).

4.2 Results and Model Comparison

We evaluate a number of different models using our dataset. The first three use our approach based on SIFT features: SIFT, SIFT mean, SIFT median. The first uses 1 sample for enrollment/authentication, the others 4 samples – and either mean or median with majority voting. For comparison, we further test three models based on 2D Cross Correlation: CC, CC mean, CC median [7]. The core difference to our SIFT based models is that instead of using SIFT feature similarity, those models use cross correlation similarity as underlying metric.

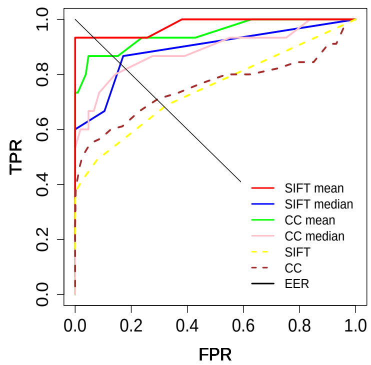


Fig. 6. Performance of our approach for different configurations.

Table 1. Performance of our approach including the decision threshold τ used with the EER.

Model	AUC	Acc.	EER	τ
SIFT Mean	0.980	0.858	0.072	0.760
SIFT Median	0.890	0.742	0.153	0.010
SIFT	0.705	0.636	0.319	0.010
CC Mean	0.950	0.775	0.143	0.100
CC Median	0.890	0.758	0.175	0.100
CC	0.710	0.631	0.292	0.100

Results indicate that using majority voting is in general preferable over using similarity measures of single samples for enrollment and authentication (Tab. 1). When comparing mean and median based majority voting, mean leads to better results for both SIFT and CC based models. When comparing SIFT and CC based models, SIFT models obtain overall better results (visible in both area under the ROC curve (AUC) and EER), which we assume originates from the SIFT features matching progress being more scale and rotation invariant. Thereby, the overall best performing approach is using a SIFT mean model, which resulted in an AUC of 0.98 and an EER of 0.072. However, we cannot conclude that our SIFT approach is completely rotation and scale invariant, as some strongly similar but different features still match. A possible approach to further increase the rotation invariance would be to compute different (de)rotations of captured vein images during authentication [7], which bears the drawback of being a computationally intensive task. Tab. 2 states a comparison of our results to approaches from previous and related approaches which used different dataset for evaluation.

Table 2. Performance of our approach in comparison to related approaches.

Model	EER
SIFT Mean	0.072
SIFT Median	0.143
LG-SRC [9]	0.016
Multiscale Match Filter [9]	0.134
2D Correlation [7]	0.038

Our approach having a lower overall authentication accuracy may be caused by different reasons: our approach does not use a closed physical structure which would prevent ambient illumination from non-NIR light sources, and only use 4 vein pattern samples for enrollment and authentication (in contrast to 5 and 12 samples with [7,9]).

5 Conclusions and Future Work

Wrist vein authentication is promising for multiple fields of application, including mobile environments. In the future wrist vein authentication could be included in e.g. smart watches and wristbands and combined with other unobtrusive authentication approaches to obtain strong yet user friendly mobile authentication.

In this paper we focused on a mobile wrist vein authentication system based on a low cost capturing device, which can be adapted to suit mobile environments. We proposed a novel matching approach based on SIFT features that gave promising results (EER=0.072) when using 4 vein images for enrollment and authentication. In the future our approach could be improved in terms of data recording capabilities: due to the freedom of the wrist, rotation needs to be addressed accordingly. Though this could be solved by trying different image rotations, such would cause a huge computational overhead. Further, addressing completely free illumination conditions [12] and human influence, such as different skin colors, light penetration, or vein behavior with sports could be investigated.

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