VID: Vein-Based Identification for Interactive Systems Using Thermal Imaging

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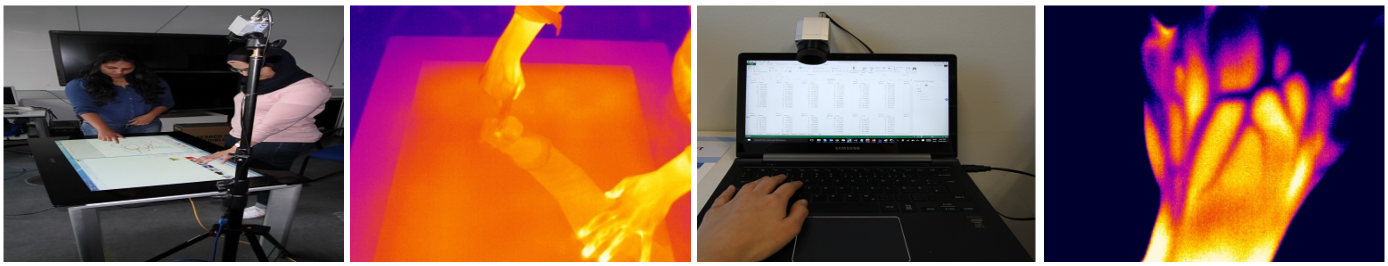

(a) (b) (c) (d)

Figure 1. (a) Interactive tabletop prototype, (b) Thermal View from the top mounted camera, (c) laptop concept prototype, and (d) the thermal view of the attached camera.

ABSTRACT

A body of recent work recognized the need of more transparent usable authentication mechanism. To be truly usable, authentication should be seamless and require no explicit actions from the user. Biometric authentication is a promising approach as biometric characteristics can be used to simultaneously identify and authenticate the user. In this paper we investigate using veins on the back of the hand for contactless and seamless authentication. We implemented a vein-based authentication mechanism by combining thermal imaging and computer vision. Through a study we show that the approach achieves a low false-acceptance rate and a low false rejection rate. It is invariant to changes of the hand pose as well as to changes of the environment. Being accurate, and invariant, vein-based authentication has the potential to be used to seamlessly authenticate users of desktop computers and tabletops. We demonstrate the potential of the approach through two prototypes that require no explicit action from the user.

Author Keywords

Thermal Imaging, Interactive Surfaces, User Authentication, User Identification, Collaboration

ACM Classification Keywords

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INTRODUCTION

Previous work recognized the limitations of current authentication mechanisms. A recent survey of the password habits among American consumers, for example, concludes that the average consumer takes minimal action to secure online accounts [7]. Prior work further showed that only few users use a PIN for their mobile device [15] and passwords are frequently re-used and forgotten [9]. Abdulwahid et al. conclude that robust authentication mechanisms are needed that operate in a transparent, continuous, and user-friendly fashion [3]. In search for usable and secure authentication mechanisms a large number of approaches have been proposed. A promising direction is biometric authentication [12]. Biometric authentication identifies a user using physiological or behavioral characteristics [13]. One of its major advantages is that there is no need to remember a PIN, a password or another kind of secret key.

Current biometric authentication mechanism typically requires the user to perform an explicit action. Fingerprint authentication, for example, requires to put a finger on a fingerprint sensor and iris scanner requires to look into a camera. Another biometric authentication approach is the use of vein-patterns of the palm dorsal. Using vein patterns underneath the human skin has several advantages. Every person has a unique pattern of veins, which is stable from the age of ten and unique even for twins [1]. As veins have a different temperature than the surrounding skin [6], thermal cameras can capture these patterns from a distant without interfering with the user's current task as shown in Figure 1.

Previous work demonstrated the potential of vein-based authentication for controlled setups, temperatures and, specific hand poses [20]. To become truly usable, it is necessary that users are casually authenticated without paying attention to the authentication mechanisms. In this paper we demonstrate an approach that has the potential to enable seamless vein-based authentication. The approach combines a commercial thermal camera with hand detection and vein-recognition algorithms. We conducted a user study with 29 participants in which we show that (1) the developed system enables pose-invariant authentication and by reinviting 15 participants to an outdoor session we show that (2) the system is robust despite changes of temperature and environment. We present two concepts that demonstrate the potential for transparent, continuous and user-friendly authentication.

RELATED WORK

We identified two strands of related work to our research: (1) seamless user authentication and identification using biometric information, (2) thermal imaging as a sensing technology.

Physiological Biometric Authentication

The uniqueness of the person's biometrics has been used to identify and authenticate users [5, 12]. Biometrics are classified into behavioral and physiological biometrics [22]. Behavioral biometrics relay on the behavioral cues to authenticate users, for instance their touch and keystroke patterns

Physiological biometrics is based on "something you are" and includes person's physiological information such as iris, face, voice, fingerprint, and hand geometry [19]. Various systems have been proposed which leverage these physiological information to identify users. A recent example is Bodyprint [11] that uses body parts like ear, finger, fist, and palm prints on a mobile phone touchscreen as an authentication scheme. Veins patterns are another biometric feature that has been proposed for identification and authentication. Since these pattern are unique for each users and stable for a lifetime [1], they are well suited as a biometric id. For example, finger veins can be captured under IR-lights [4] or vein pattern on the palm using VGA [20] or near IR imaging [10].

Researchers also explored using thermal (far IR) imagining to extract the veins on the palm [14, 21]. As veins have different temperature than the surrounding skin [6], they are visible to thermal cameras without any additional illumination sources. Vein triangulation and knuckle shapes are used to differentiate between users. Previous work, however, used a fixed hand pose recorded in controlled environments and even reported the inapplicability for outdoors environment. Being robust to pose variations and environment is, however, necessary to enable seamless and thereby usable identification and authentication.

Thermal Imaging for Sensing Interaction

Due to the advantages that thermal imaging provides, including robustness to illumination and color changes, it has been recently been proposed as a sensing technology for interactive systems [2, 16, 18]. This is achieved by integrating thermal imaging and existing computer vision techniques to improve touch or gestural interaction. The advantages of thermal imaging are utilized to overcome common RGB and depth cameras' limitations. Larson et al., used heat traces caused by fingers touching a surface and detected pressure for interaction on surfaces [16]. Sahami Shirazi et al. proposed thermal reflection to expand the interaction space beyond the camera direct field-of-view [18]. Abdelrahman et al. investigated the material properties supporting both touch and mid-air gestural interaction using thermal imaging as sensing technology [2]. Overall, thermal cameras are promising sensors for a range of interactive systems [18] that would naturally benefit from seamless identification and authentication.

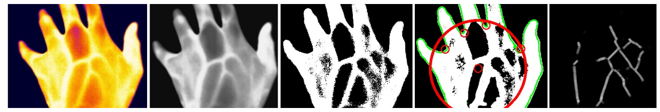

Figure 2. The first five steps of the vein extraction algorithm. After capturing an image from the camera, it is filtered and converted to grayscale, an adaptive threshold is applied, the region of interest is extracted and finally the veins are extracted.

VID: VEIN IDENTIFICATION

Identifying and authenticating users on the fly while interacting with interactive system is still a challenging task. We propose using a thermal camera that is already used for creating interactive systems [2, 16, 18] to identify and authenticate users based on their vein pattern. Previous work shows that thermal imaging is well suited to detect vein pattern in a static setting by taking a thermal image of the user's hand while sitting in an controlled environment [21]. We focus on interactive systems that are controlled using different gestures and are deployed at different environment.

We propose a vein-based authentication approach, called VID. Using thermal imaging, the approach consists of a recognition pipeline that extracts vein patterns and authenticate users. For testing the approach we use an Optris PI450[1] contactless thermal camera. It has a $62° \times 48°$ field-of-view, 382×288 optical resolution, and temperature sensitivity of 40 mK. It should be noted that the temperature resolution is the most important criteria due to the small temperature differences between veins and the body.

Recognition Pipeline

For extracting the hand veins, we are using the OpenCV library[2] for image processing and features extraction. We apply in total *six* steps to a thermal image stream to a identify a user as shown in Figure 2.

1. Image extraction: First, an image is extracted from the livestream of the thermal camera. This is currently done every 10 seconds but can be adopted to get faster identification.

2. Noise filtering: A 5×5 median filter is applied to smooth the image. The output is converted to grayscale and a 2D Gaussian filter is applied to further remove high frequency noise. Then, the image is normalized for better thresholding.

3. Thresholding: Extracting the veins (temperature contrast) using global thresholding did not yield in good results, as the vein-skin contrast changes over the hand. Hence, we use adaptive thresholding. The threshold value changes dynamically across the image with a kernel size 13×13. After this step, the result is a binary image of a user's hand.

[1] http://www.optris.com/thermal-imager-pi400

[2] OpenCV: http://opencv.org/

Figure 3. The setup used for the study. The indoor setting is shown on the left and the outdoor setting on the right.

4. Region Of Interest (ROI) extraction: Our ROI covers the palm dorsal. To extract it, we detect the hand by finding the largest contour in the image. We compute the hand contour (depicted in green in Figure 2), convex hull, convexity defects, and the hand center (red circles in Figure 2). The ROI is computed to be the circle around the hand's center and a radius that is the distance between the center to farthest convexity defects. Hence, we can automatically compute the ROI without restriction to the angle of approach of the hand nor it's orientation.

5. Veins Extraction: After identifying the ROI, we segment the veins pattern and applied a morphology operation to reduce the thickness of the veins to a single pixel. Thus, the resulting image consists only of thin lines representing the veins. We use these images as features for our classification approach.

6. Vein Classification: For matching the extracted vein patterns, we calculated the Hausdorff distance [8] as a measure of similarity between two vein pattern. Based on a distance threshold, we determine the matching veins pattern using a nearest-neighbor approach.

STUDY

To evaluate our VID approach, we conducted a user study in which we focused on two crucial aspects important for interactive systems. First, we investigated four different postures that are typically used when interacting (Figure 4) and, second, we looked into two different environmental settings, namely, indoors and outdoors. We chose these settings since we strive to have different setups that are especially challenging (e.g., for interaction in public spaces).

Participants & Procedures

We recruited 29 participants (14 female, with an average age of 23 years, $SD = 3.6$) using our university's mailing lists. All participants were students studying different majors. We setup our VID system next to a table. The thermal camera was mounted on a tripod and faced toward the surface from a distance of 90 cm to capture the participant's hand (see Figure 3) similar to an interactive tabletop setup. The light and temperature conditions of the setup was constant during the whole study with ambient temperature of 23°C, 37°C for the indoors and outdoors setups respectively.

After welcoming the participants, we described the goal of the study and handed out consent forms as well as demographic questionnaires. We introduced the four different hand poses (Figure 4), but did not restrict them during the study with regards to neither the angle nor orientation of their hand. The study was conducted over two sessions in two days. During the first day, we captured thermal videos of the all participants' hands in 4 different poses indoors. The order of the performed poses were randomized per participant. We recorded a thermal video of 30 seconds length for each pose. We deliberately chose to record videos rather than doing live authentication because of the reproducibility of our evaluation. The study took approximately 20 minutes per participant. The second day, 15 of the participants where re-invited to repeat the same poses using the same setup but outdoors, aiming to evaluate the environmental influence on our system. The procedure was identical to the first day.

Results

We replayed the recorded videos to assess our proposed approach. Our analysis included the evaluation of the influence of (1) different hand poses, and (2) environmental changes on the authentication accuracy.

Analyzing Hand Pose

In the first step, we analyzed the influence of the different hand poses. We trained our system using fourfold cross validation with one specific hand pose in each fold. For each user, we had 9 recordings of 3 hand poses in the training set and 3 recordings of one hand pose in the test set. Next, we used this data to determine the False Rejection Rate (FRR).

In the second step, we calculated the False Acceptance Rate (FAR). We followed the same approach as above but left additionally one participant completely out of the training set. Thus, this unknown potential user (attacker) tried to authenticate with all poses (i.e., with 12 recordings). We repeated this procedure for all participants.

Based on the computed FAR and FRR, we calculated the Equal Error Rate (EER) which is typically used to quantify the goodness of an authentication system [12]. The results of

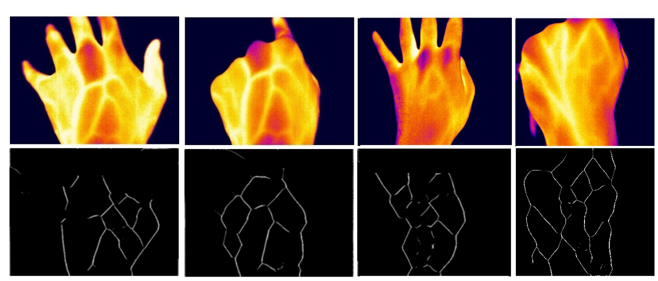

Figure 4. Thermal view and extracted veins pattern for the four hand poses. first 2 left poses from 1 user and the other 2 from another user. Showing the uniqueness of individual's vein patterns.

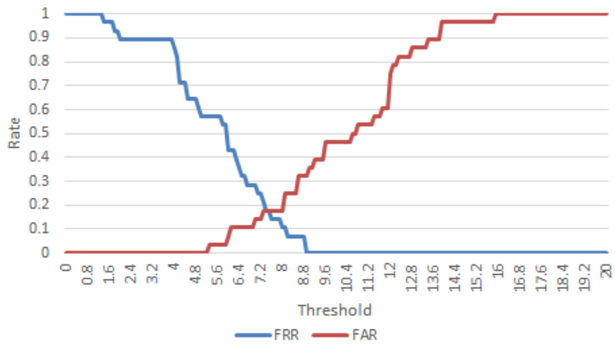

Figure 5. False Acceptance and the False Rejection Rate against different acceptance threshold values for the 29 participants with different hand poses.

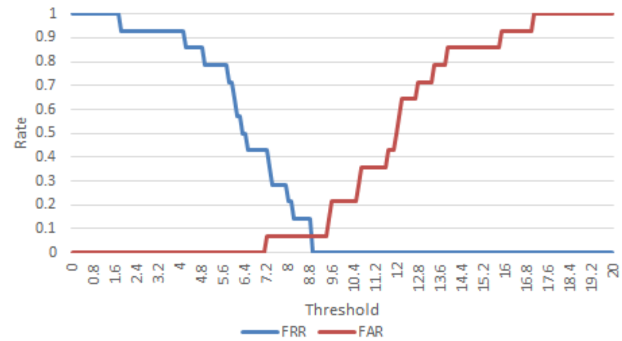

Figure 7. False Acceptance and the False Rejection Rate against different acceptance threshold values for the 15 participants in in- and outdoors settings.

the FRR and FAR against different threshold values are depicted in Figure 5. We achieved an EER of 17%. Over total 29 users, with the acceptance threshold of 9, this authentication scheme can achieve an identification accuracy up to 100%.

Analyzing Environmental and Temporal Influences

We further investigated the influence of the environmental and temporal changes. We used the recordings from the 15 participants that have been re-invited on the second day of the study. We trained our system using cross validation with one setup and session in each fold. In contrast, we used the recordings from the first day for training the users and the recordings from the 2nd day for querying. The FAR and FRR are computed using the same procedure described earlier. Figure 6 depicts the results of the FRR and FAR. We achieved an EER of 7%. With the acceptance threshold equal to 9, we achieved an identification accuracy of 100%.

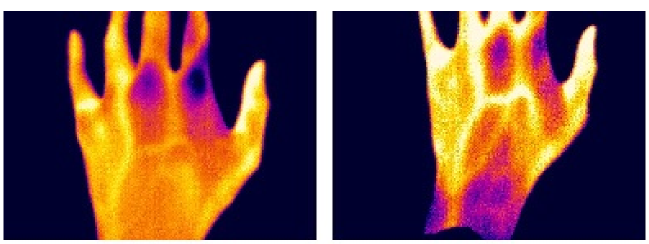

Figure 6. Thermal view of the vein pattern for the same user indoors (left) and outdoors (right).

APPLICATION SCENARIOS

We envision two different application scenarios in which our approach can implicitly identify and/or authenticate users.

Tabletop Multiuser Identification. Realizing interactive tabletops using thermal imaging yields several advantages such as the possibility to detect the amount of pressure applied on the surface or the traces made by the user [16]. In addition to that, our approach might enrich such a system by providing user identification so that multiple users are able to interact at the same time and the system is capable of differentiating them (Figure 1a). Further, it is possible to easily differentiate between input from the left and right hand since their veins pattern differs for the same user. This could be used to extend the gesture space, where the hand used to perform the gesture specify the action performed. For instance, if the user authenticate with the left hand the system logs him/her in to the public account and if the user uses the right hand it logs into the private account.

Laptop Authentication. Since thermal cameras are becoming smaller[3], we envision that the integration of this type of cameras into the display of a laptop will become a reality. Having a thermal camera that faces down the keyboard as shown in figure 1c, our system is able to track who is using the laptop and can reject the access for unknown users to specific information. At the same time, it preserves the privacy of the user since thermal imaging is perceived as a temperature sensor, which is more accepted compared to RGB ones.

DISCUSSION AND CONCLUSION

The results of the conducted study, highlights the potential of using veins patterns as bases of implicit biometric authentication for interactive systems. We show that it's possible to distinguish users regardless of their hand pose and the ambient temperature of the surroundings with an EER that is on par with recently proposed approaches [11]. Hence, a convenient, usable, continuous authentication scheme can be considered. It doesn't interrupt the user's task, as it seamlessly capture the veins on the palm dorsal. It also address hygiene issues, as the veins are captured in a contactless manner. Relying on the vein pattern underneath the skin makes it tolerant to skin conditions such as grease and wet hands. However, user acceptance should be investigated, as user have concerns about the storage of their physiological biometrics [17].

Relying on biometric features, as replacement of passwords and token, enhances the convenience of authentication. Users usually interact with devices like laptops and interactive tabletop without occluding the back of their hand. Thus, deploying thermal camera, which currently become affordable and small, to capture their veins pattern allows user identification and authentication. It is seamless, contactless, and continuous authentication scheme. Based on the approach proposed the user identification can be up to 100% precision with different hand poses both in indoors and outdoors settings.

[3]http://www.flir.com/

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