Development of Mobile-Based Hand Vein Biometrics for Global Health Patient Identification

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Abstract— For many health services in developing countries, patient identification is a fundamental need. In countries where no standard form of identification is available, this problem is exacerbated by a lack of literacy and also frequent errors in spelling and consistency. To address this need, we implemented two low-cost hand vein scanner devices for use with mobile devices. The first scanner device employs the internal camera of the an Android smart phone along with a rechargeable infrared light (850nm) and an external optical filter; and the second scanner device employs a low-cost webcam, with integrated LEDs (940nm) and optical filter, which is powered directly from the Android tablet. A single mobile app was developed for use with both scanner devices with the ability to adjust scanner settings, capture hand palm images, and annotate patient data. As an initial test of our scanner designs, we collected hand scans from 51 university students aged 18-34 using an IRB-approved protocol, and data was processed using a 2D-PCA biometric algorithm implemented on a PC using MATLAB software. Using the standard FAR-FRR curve for biometric analysis, we were able to achieve an Equivalent Error Rate (EER) of 6.3% for the phone camera scanner, and 4.2% for the webcam scanner design. These results compare favorably with other published biometrics studies and demonstrate the potential of low-cost biometric devices that can be integrated with mobile phones and tablets.

Fig. 1. Early prototypes of vein scanner device exploring how biometric device may be used.

I. INTRODUCTION AND MOTIVATION

The ability to properly identify a patient is a basic need for maintaining patient medical records and providing health care services over time. While the emergence of digital information technology and mobile devices are now enabling electronic medical records, many developing countries unfortunately lack a reliable national or local identification system. This lack of infrastructure is compounded by the prevalence of illiteracy on the part of the patient and by inconsistent training and spelling errors on the part of the health workers.

The challenge of patient identification also extends to more developed countries, where medication errors and benefits fraud are also a concern. Although electronic smart cards eliminate the errors caused by human data entry, such cards are not always carried by the patient or can be stolen.

The need for improved technologies for patient identification, access control, and secure financial transactions has thus created an obvious interest in biometric technologies, which derive a unique identification code from physical biometric features of the patient, without the need for a separate identification card [1]. In fact, in recent years, the national government of India, for example, has begun to deploy a national identification system, known as “Aadhaar,” that is linked to biometric information including the face image, fingerprint, and iris scan [2]. Other new biometric measures have also been explored over the past decade, including the use of hand vein patterns [3] and electrocardiogram signatures [4]. Many of these biometric data can also be combined with digital smart card identification systems to enable even more secure and robust systems [5].

Given the growing use of mobile devices in global health, there is a need to choose a biometric technology that can be readily integrated with mobile devices. While fingerprint scanners have been used with laptop computers in the past (e.g. IBM Thinkpad T60) and more recently integrated into the
commercial mobile phones (e.g. Apple iPhone 5s), the use of fingerprints as a means of patient identification has been limited in part by cultural stigma surrounding the use of fingerprints, and also limited by the variation in fingerprint data due to scratches on the skin surface, often seen in people who work in rural areas. As a result, other biometric measures have been explored.

Considering the great advances in the resolution and sensitivity of CMOS cameras now found in modern smart phones and tablets, two biometric methods, iris scan [6] and palmar vein scan [3], have emerged as leading candidates for use in patient identification which could potentially be implemented using mobile devices. Commercial biometric products employing iris and vein scanning have begun to emerge for use in facilities such as schools, hospitals and military buildings [7, 8]. However, these devices are relatively expensive (several hundred US$), are not designed to integrate with mobile devices, require significant computational resources, and require the purchase of expensive proprietary software. Other devices are currently in development at startup companies [9].

For certain markets, such as global health clinics, where expensive commercial systems cannot be used, it is useful to consider if low-cost biometric devices and algorithms can be designed specifically for use with mobile phones and tablets. While, the iris scan and vein scan devices both require infrared illumination, some smart phones (e.g. Samsung Galaxy S5, HTC One) are already equipped with infrared LEDs for use as television remote control devices, and can be evolved to support either palmar vein or iris biometrics. A clip-on phone attachment is also quite feasible and is currently being explored by a startup company for iris biometrics [10].

In this paper, we specifically focus on palmar vein patterns as a low-cost biometric and explore its potential integration with mobile devices.

II. CAPTURING THE HUMAN HAND VEIN PATTERN

A. Illumination and Optical Properties of the Human Hand

Proper illumination is needed in order to enhance the appearance of blood vessels in the hand. Some early vein detection methods [11] employed far-infrared thermal imaging (FIR) in order to detect small temperature differences between the blood vessels and the surrounding tissue. However, newer lower-cost methods [12] employ near-infrared (NIR) illumination and make use of the fact that near-infrared light is absorbed more strongly by human blood than the surrounding tissue, and thus appears darker.

In the visible light region (390-700nm), the optical appearance of skin is dominated by light scattering and light absorption (dominated by melanin pigment), which obscure the appearance of smaller blood vessels in the hand. As the wavelength is increased further, the tissue optical scattering and melanin optical absorption are reduced significantly, thus enabling a better contrast between the blood vessels and surrounding tissue [13]. While dorsal veins (i.e. back of hand) are sometimes used for vein biometrics, the use of palmar veins are much preferred for global health applications, since the hand palms contain far less melanin and are more consistent across racial differences.

Within the blood vessel, the light absorption of oxygenated and de-oxygenated hemoglobin are equal at 800nm wavelength (isosbestic point), and exhibit a local maxima at approximately 920-940 nm, then approach zero above 1200 nm. In this wavelength range, the light absorption from oxygenated blood is actually higher than that of de-oxygenated blood; however, the blood vessel walls of veins are also somewhat thinner than those of arteries, which may enhance the appearance of veins. Nevertheless, the human hand contains a variety of blood vessel types, including veins, arteries and shunts; therefore the designation of specific blood vessels as “veins” or “arteries” may actually be irrelevant for the purpose of biometric imaging.

Based on these observations, ignoring any limitations of the camera, and ignoring the presence of other tissues (e.g. transcutaneous fat, which has optical absorption in the 920 nm range), the preferred wavelength for biometric illumination is thus approximately 920-940 nm. Of course, it should also be noted that human skin is not fully transparent in the NIR region; thus, a near-infrared image of a hand contains some surface skin features (creases/wrinkles) as well as subsurface features (e.g. blood vessels).

B. Camera Properties

Standard hardware used for recording infrared or low-light images make use of charge-coupled device (CCD) cameras. However, the cameras found in modern consumer smart phones and webcams are manufactured using the standard silicon CMOS process which is less sensitive to infrared light. Furthermore, most consumer cameras, including smart phones, also contain an infrared filter blocking which is used to improve color rendition for photographs. While most modern CMOS cameras (depending on pixel size) can produce a relatively bright image throughout the near infrared range (to 1000 nm), the presence of the IR blocking filter dramatically reduces the transmission of light above approximately 900nm. In this paper, we explore the use of both an unmodified mobile phone camera (containing IR blocking filter) and a low-cost webcam with the infrared filter removed.

C. Image Processing and Data Analysis

Over the past decade, a wide variety of algorithms and image processing techniques have been published for vein biometrics, many of which have been adapted from hand palm biometric methods [14]. These algorithms may be organized into the following categories:

1) Hand orientation and Image registration: A common need in vein biometrics is to normalize the image and correct for any misalignments due to the degree of freedom given to the user for hand placement. A variety of algorithms have been developed to automatically measure the orientation of the hand and apply the appropriate amount of rotation to the raw image [15, 16]. Other methods include the use of feature-extraction algorithms which are invariant to small changes in rotation or translation [17, 18]. Certain algorithms use the
entire hand image, while others select a specific region of interest (ROI) to perform the analysis.

2) Blood vessel extraction: While both vein and skin features can be used for biometric analysis, certain methods make extensive use of image processing in order to extract and separate the blood vessel segments from the surrounding tissues. Such methods include various algorithms to perform edge detection, contour generation, and line segment generation.[19-23] Once the vein contours are defined, specific minutae can be defined and used as features for matching and classification [24].

3) Biometric data classification and matching: In order to compare or classify different hand scan images, various algorithms are used depending on the features employed. Methods using general image features often make use of so-called “sub-space analysis” which maps image features into a separate mathematical space (matrix) with appropriate basis vectors that better describe differences between images. Examples include principle components analysis (PCA), independent components analysis (ICA), and linear discriminant analysis (LDA) [25, 26]. The similarity between two images or hand scans can then be calculated by computing the distance between two images in the multi-dimensional space. Methods that extract vein contours and minutae generally make use of various Hausdorff distance metrics [27] to determine similarity or can also be analyzed through PCA/ICA methods as well. Several methods exist to translate the extracted features into a digital code, which can then be analyzed using standard coding metrics, such as Hamming distance [28].

III. DEVICE IMPLEMENTATION

The design goals of our scanner prototypes was to minimize the number of external parts and minimize cost. The use case we had in mind was a health worker who would be scanning a patient’s hand with the phone or tablet. Our initial design concepts, shown in Figure 1, consisted of simply a phone with infrared LED, or a simple plastic stand that would hold the phone and a rechargeable infrared light.

Comparing our conceptual model with two actual commercial vein scanning devices (Figure 2), we observed a practical need for a hand guide, to maintain a proper distance and orientation of the hand, and also an opaque shroud for the purpose of blocking external infrared light from lamps or sunlight.

Two scanner designs were constructed, and are described below:

A. Scanner #1: phone camera

The first scanner design is shown in Figure 4, and consists of an opaque plastic lightbox which contains a rechargeable infrared light.

User design: Although the preferred operation of the scanner may be to place the hand over the scanner, with the phone at the bottom of a plastic box, it would not possible to operate the mobile phone scanner software. As a result, scanner #1 was designed such that the phone would be placed over a small opening on the top of the box, with the camera facing down and leaving the front side phone screen accessible to the person operating the scan software. The person being scanned would then insert his/her hand into the bottom opening of the light box, with the palm facing up. A metal peg was mounted on the bottom plate of the scanner in order to help guide the hand and avoid rotation.

Choice of mobile device: For this study, a very compact Android phone was used (Sony Experia Mini Pro). Since the manufacturer (Sony) has extensive experience with digital cameras and camcorders, the camera on this phone has good low-light capability and better focus control than most Android phones. The internal infrared blocking filter of the phone was
not removed, since this procedure is risks damage to the phone, and would not be practical in an actual deployment.

Choice of illumination: Several different illumination wavelengths and optical filters were tested. Sample images are shown in Figure 3. In order to minimize the amount of light scattering from the skin, it is desirable to maximize the illumination wavelength. However, it was discovered that as the operating wavelength exceeded 900nm, the phone camera image became quite dim and noisy (Figure 3C). As a result, the operating frequency of 850 nm was chosen. A commercial photographic LED light with 16 LEDs was retrofitted with the 850nm infrared LEDs.

Choice of optical filter: The purpose of the optical filter is to block any visible light that may scatter from the skin and only transmit infrared light. Since the sensitivity of the smart phone camera is diminished in the infrared range, it was important that a high quality infrared filter be used in order to maintain a clear image and minimize attenuation. In order to meet these requirements, an optical quality 2cm X 2cm Kodak Wratten filter (#87) was used, which is specified to have a cut-off wavelength in the range of 740-795nm. Although these thin film filters are relatively expensive (~US$50), a single filter can be cut with scissors into 9-12 pieces in order to make multiple scanners, so the per-unit cost is approximately $5.

The total cost of scanner #1 was approximately US$45, which the largest cost being the LED light with rechargeable battery (US$35).

B. Scanner #2: external webcam

The second scanner design is shown in Figure 5, and also consists of an opaque plastic lightbox. However the camera and the illumination were provided by an external webcam, described below.

User design: Although for certain biometric applications, such as logging into your phone, the preferred operation might be to simply wave your hand over the phone, this interaction did not seem appropriate for the scenario of a health worker and a patient. Since the health worker generally needs access to the phone screen in order to operate the phone software (clinical software application), it may not always be convenient for the imaging device to be co-located with the user interface. With this in mind, scanner #2 was designed to use an external imaging device – in the form of a webcam – that is tethered to the mobile device used by the health worker. This device enables much greater flexibility in how the scanner could be used.

Choice of webcam and shroud: A Gearhead 1.3 Megapixel Nightvision model WC1100BLU USB webcam was used. The standard price for this webcam is less than US$10. The primary advantage of this web cam, aside from low cost, is that the web cam contains six internal LEDs, which are also USB powered from the phone/tablet, thus avoiding the need for any additional battery. The webcam was mounted with epoxy into a plastic shroud and base, made from plastic food containers, with the inside surface painted black. The internal infrared blocking filter of the webcam was also removed.

Choice of mobile device: For the mobile device a low-cost Android tablet was chosen (Nexus 7 2012 model, ~US$129., refurbished), which contains an integrated USB Host driver that supports webcams and is able to provide USB power to the webcam using a standard USB On-the-Go cable. The tablet...
also has the added advantage of providing a bigger screen for the health worker interface.

Choice of illumination: With the internal infrared filter removed, the low-cost web cam provided a clear image with reasonable brightness for all wavelengths tested (up to 1000nm). It was decided to choose 940nm as the operating wavelength, were the hemoglobin light absorption has a local maximum. The web cam was retrofitted with 940nm LEDs, and the resistors in the LED drive circuit were adjusted to provide a proper drive current of a 1-3 mA per LED. It should also be noted that this model webcam also include a potentiometer at the rear of the webcam to provide brightness adjustment for the LEDs.

Choice of optical filter: A Kodak Wratten filter (#87C) was chosen with a cut-off wavelength of 790-855nm. In order to minimize the amount of filter material needed and provide protection, the filter was cut into a small 5mm diameter disk and inserted directly into the webcam between the focusing lens and the CMOS imaging chip. Care was taken to properly focus the webcam at the location of the hand plane.

The total parts cost of scanner #2, not including the Android tablet, was only US$15.

C. Mobile Phone Software

A single mobile phone application was developed for both scanner devices using the standard Android JAVA SDK, which provides an interface for a health worker to enter the patient’s name or Identifier code, and capture biometric scans. The mobile app was designed to save data in multiple formats, including JPG and RGB, and the file names automatically included the patient’s ID code with each successive image filename automatically incremented. This provided a convenient platform for data collection and record-keeping.

A unique feature of our mobile application is the ability to automatically detect the presence of an external web cam that has been plugged in, allowing the user to select which camera to use for the image capture. The mobile software also exposes all the camera settings, such as the brightness level, which can also be adjusted by the user, if needed.

Although both scanners and the mobile app support several different image resolutions, we wanted to minimize the image size in order to minimize the memory requirements and computational processing required for the biometric data analysis. The image size chosen for scanner #1 was 180 X 150 pixels; and the image size for scanner #2 was 176 X 144 pixels.

Demonstration videos of both scanners are available online:

Scanner #1: https://www.youtube.com/watch?v=f0JMJq2-EiU
Scanner #2: https://www.youtube.com/watch?v=bYB5DMyaJI

IV. EXPERIMENTAL STUDY

A. Experimental Design and Data Collection

In order to test the scanner devices, a biometric study was conducted, with the approval of the university IRB committee. Fifty one subjects participated in the study, with ages ranging from 18 to 34, with 62% female. The study protocol consisted of acquiring 8-10 hand scan images from each participant on each scanner device. In order to measure hand placement variation, participants were required to completely remove their hand after each scan and then re-place their hand on the scanner. Although we considered including a third scanner device in the form of a commercial hand vein scanner, we discovered that the commercial hand scanners do not provide access to the raw image data in order to use for comparison; therefore the commercial device was not included.

B. Data Analysis

The primary steps of data analysis are summarized below:

1) Image Preprocessing: A minimum amount of preprocessing was applied to each image, and consisted of a 0.5 pixel smoothing, 15-pixel high-pass filter, and a uniform contrast adjustment applied uniformly to all images, as shown in Figure 6. No vein contour extraction algorithm was used, and no correction was provided for misaligned or rotated hands.

2) Construction of Feature Matrix: For our image processing, we implemented a standard 2D-PCA sub-space analysis [25]. In this case, the working sub-space is defined by calculating the eigenvectors of the covariance or “scattering” matrix which is constructed from all of the images in the training set. A set of coefficients, or “feature matrix” can then be derived for each sample image by projecting the image onto these eigenvectors.
3) Measuring Distance and Matching Criteria: Four training images were used for each participant enrolled in the study, and their corresponding feature matrix coefficients saved as "training data." For each new incoming "test image," the feature matrix of the test images is compared to each of the training data by calculating a Euclidian distance metric in the sub-space. Depending on a predefined threshold, the image is then designated as a "Match" (Accepted) or "No-Match" (Rejected).

V. RESULTS AND DISCUSSION

A. Data statistics

For each scanner, a total of 478 images were analyzed from 51 participants. Of these, 204 images (4 per subject) were used as training data, 51 images (1 per subject) were used as validation data, and 223 images (4 or 5 per subject) were used as test data.

B. False Accept Rate (FAR) vs False Reject Rate (FRR)

The results from both scanner devices are shown in Figure 5, with scanner 1 results plotted in red, and scanner 2 results plotted in blue. Both curves have a good basic square shape and approach the origin within a few percent. The point at which FAR=FRR, also known as the Equivalent Error Rate (EER) is 6.3% for scanner #1 and 4.2% for scanner #2, which compares favorably to other published vein biometric studies using similar 2D-PCA algorithms.

We can see from the curves that the False Reject Rate for scanner #1 (phone camera) is slightly higher than that of scanner #2 (webcam). One contribution to this error rate may be the fact that scanner #1 operated at a shorter wavelength and provided slightly less distinct vein patterns. However, the more likely cause is the fact that the mechanical design for scanner #1 provided greater freedom for the scanned hand to move; therefore, in some instances, if the hand is misaligned, the algorithm can produce a false reject.

C. Potential Applications and Threshold Setting

For those not familiar with biometric device statistics, it is worth noting that the exact operation point along the FAR-FRR curve depends on the threshold setting and the desired application. Sometimes articles or ads for biometric devices will provide an FAR or FRR statistic without providing EER or showing the complete FAR-FRR curve, which can be misleading. For example, if the matching criteria threshold is set very high, then FAR approaches zero (very few imposters will be counted as a match), but the risk of being falsely rejected (FRR) is increased. Conversely, if the threshold is set low, then the occurrences of FRR will approach zero, but the risk of an imposter getting a false match (FAR) will increase. For high security applications (e.g. access to medical records), most biometric devices are set to operate in the region where FRR is nearly zero; whereas for convenience applications (e.g. checking out library books) we may want to avoid the inconvenience of false reject and wish to operate in the region where FAR approaches zero. The results from both biometric scanner devices here demonstrate a reasonable EER and exhibit low FRR and low FAR over a practical range of threshold settings.

VI. CONCLUSIONS AND FUTURE WORK

We have successfully demonstrated the imaging capability of two biometric scanner designs based on mobile devices, with Equal Error Rates (EER) of 6.3% and 4.2%, respectively, which are within range of other biometric technologies and can be suitable for certain identification applications, or as a means of verification in places where identification infrastructure is lacking.

These results were also achieved using very small image sizes of 180 X 150 pixels, and 176 X 144 pixels, respectively, in order to demonstrate feasibility for implementation of the entire algorithm on a mobile phone. The two scanner device designs also have a very low materials cost (US$45, and US$15, respectively), with the second scanner design also eliminating the need for an external power source.

Through careful selection of the illumination frequency and optical filters, sufficient image quality was possible without the need for significant image enhancement. In addition, the mechanical design of the scanners helped minimize errors due to hand misalignment and obviated the need for extensive image processing to perform auto-correction.

The EER of these devices can perhaps be further improved through more advanced and efficient PCA algorithms [26] without additional computational burden. This is currently being explored.

We hope that low-cost designs such as these, which minimize cost and algorithmic complexity will soon enable affordable and scalable biometric devices that can serve the needs of the global health community.
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REFERENCES


[9] https://www.quixter.se


