Anisotropic diffusion filter for dorsal hand vein features extraction

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Abstract— In this paper, we present an competent approach for dorsal hand vein features extraction from near infrared images. The physiological features characterize the dorsal venous network of the hand. These networks are single to each individual and can be used as a biometric system for person identification/authentication. An active near infrared method is used for image acquisition. The proposed approach uses an anisotropic diffusion technique for contrast enhancement and morphological filtering to extract the venous network.

Index Terms— Dorsal hand vein, biometric, anisotropic diffusion filter, feature extraction.

I. INTRODUCTION

THIS last years, the research community show an increasing interest to biometrics. Although, the biometrics commercial products was born during this decade which is driven by security issues.

Biometrics has several modalities, they are classified in three principal techniques: biological technique as AND[1]; physiological technique as fingerprint[2], face[3], iris[4] and hand[5]. And finaly the behavioural technique: as keystroke [6], gait [7]. Most of the works was made in the visible spectrum. In this last years, some research start interesting in the non-visible spectrum like infrared images used in the hand vein identification/authentication.

Infrared thermography (IRT), thermal imaging, and thermal video are examples of infrared imaging science. That imagery produced as a result of sensing electromagnetic radiations emitted or reflected from a given target surface in the infrared position of the electromagnetic spectrum (approximately 0.72 to 1,000 microns). Many researchers used the thermal imaging for face and hand authentication, they got efficient results. Although the infrared imaging is less expansive and present too efficient results for that it was used in the both hand [9] and face [8] recognition.

In this paper, we present a work about the use of active near infrared imagery for the feature extraction of dorsal hand vein. This features shaped the dorsal venous network of the hand. This last is used for person identification/authentication. Many works was made for this feature extraction. Especially, [10] who used single triangulation of hand vein images and simultaneous extraction of knuckle shape information. In [11], the palm and dorsal veins are considered as texture samples being automatically extracted from the user's hand image. A 2D Gabor filter is employed for texture feature extraction. When [12], present the enhancement's step of the SAB11 Data Base for adaptive feature extraction method of the dorsal hand vein biometrics; which is the discrete wavelet transform.

The following sections present the idea behind the extraction of the venous network and the image processing steps to extract the resulting features from near infrared images.

II. DORSAL HAND VEIN FEATURES

the most important features that can be extracted from the back of the hand are so called dorsal venous network. The dorsal venous network of the hand is a network of veins formed by the dorsal metacarpal veins (Figure 1.[13]). In anatomy, the ulnar veins are venae comitantes for the ulnar artery. They mostly drain the medial aspect of the forearm. They arise in the hand and terminate when. Dorsal venous architecture In 82% of 300 individuals a large vein passed proximally from the center of the concavity of the dorsal venous arch to terminate in 65% in the cephalic vein, and in the remaining 17% in the basilic vein. These venous network are unique to each individual for that it is used as a biometric technique for person identification/authentication.

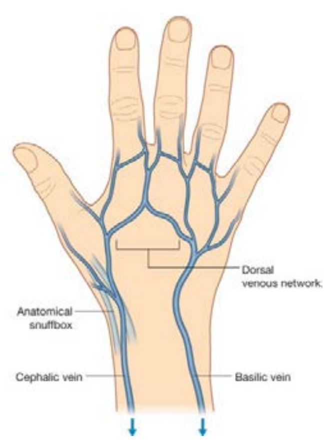


Figure 1: Dorsal Hand Veins | Varicose Veins [13]

The absorption of the skin to certain wavelengths in the near infrared spectrum allows us to extract these features. Many works resumed the research made in this field. The work presented in this paper is based on the SAB'11 and

SAB'13 database. This is database acquired from a biometric infrared device representing hundreds of dorsal hand veins samples; for male and female of different ages; sensitive to the infrared 850-900 nm waves [14]. This spectrum is indented for the current feature extraction because of the blood oxy-hemoglobin is higher than deoxy-hemoglobin and skin water. Which allow to the near infrared light to penetrate the skin and to be absorbed by the blood of the veins Figure 2.

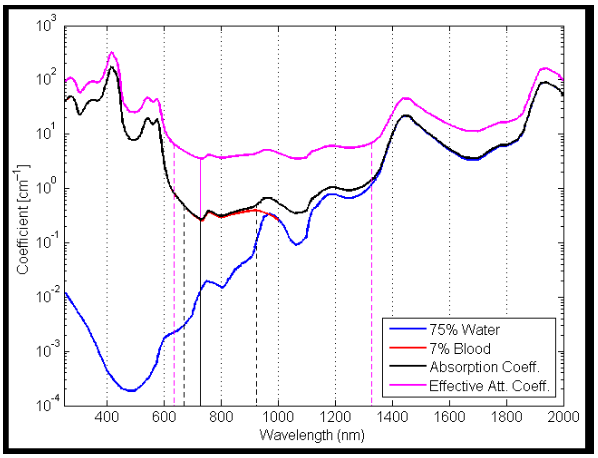


Figure 2 : Spectra for veins (SvO2 ≈ 60%). Absorption coefficient: λmin = 730 nm; NIR window = (664 - 932) nm. Effective attenuation coefficient: λmin = 730 nm; NIR window = (630 - 1328) nm.

To get the extraction features characterizing the venous network, we suggest the following steps that are summarize in the block diagram of Figure 4:

1. Improve contrast enhancement; using the anisotropic diffusion [15][16][17].
2. Get the feature extraction by the hat morphological filtering [18][19].

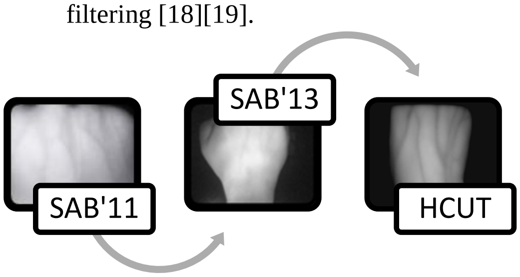


Figure 3: Samples of the infrared dorsal hand vein images from SAB'13.

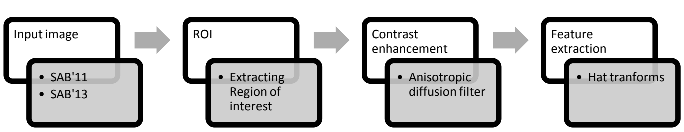


Figure 4:Block diagram of proposed system

III. CONTRAST ENHANCEMENT

In physiological hand biometrics, the quality of an image is determined by two criteria, namely hand (background) and veins (stripes). Backgound result from isotropic inhomogeneities of the density distribution, whereas stripes are an anisotropic phenomenon caused by adjacent veins pointing in the same direction. Anisotropic diffusion filters are capable of visualizing both quality-relevant features instantaneously. For getting an appropriate parameter choice, we can achieve isotropic smoothing at clouds and diffuse in an anisotropic way along veins in order to enhance them. However, if one wants to visualize both features separately, one can use a fast pyramid algorithm based on linear diffusion filtering for the background, whereas stripes can be enhanced by a special nonlinear diffusion filter which is designed for closing interrupted lines.

Perona and Malik propose a nonlinear diffusion method for avoiding the blurring and localization problems of linear diffusion filtering [20][21]. They apply an inhomogeneous process that reduces the diffusivity at those locations which have a larger likelihood to be edges. This likelihood is measured by $|\nabla u|^2$. The Perona-Malik filter is based on the equation:

$$\partial_t u = div(g(|\nabla u|^2)\nabla u) \qquad (1)$$

And it uses diffusities such as:

$$g(s^2) = \frac{1}{1+s^2/\lambda^2} \quad (\lambda > 0) \qquad (2)$$

The proposed diffusion process encourages intraregion smoothing. The mathematical framework for anisotropic diffusion is given by the equation below:

$$\frac{\partial}{\partial t} I(\bar{x},t) = \nabla^{\circ}\left(c(\bar{x},t)\nabla I(\bar{x},t)\right) \qquad (3)$$

Where:

$I(\bar{x},t)$: image;

$\bar{x}$: image axes (i.e. (x,y));

t : iteration step;

$c(\bar{x},t)$: diffusion function; [20] proposed two functions Equation (4) and (5):

$$c_1(\bar{x},t) = \exp\left(-\left(\frac{|\nabla I(\bar{x},t)|}{k}\right)^2\right) \qquad (4)$$

$$c_2(\bar{x},t) = \frac{1}{1+\left(\frac{|\nabla I(\bar{x},t)|}{k}\right)^{1+\alpha}} \quad | \propto > 0 \qquad (5)$$

k is the diffusion constant.

IV. FEATURE EXTRACTION

Feature extraction describes the relevant shape information contained in a pattern so that the task of classifying the pattern is made easily by a formal procedure. In pattern recognition and in image processing, feature extraction is a special form of dimensionality reduction. The main goal of feature extraction is to obtain the most relevant information from the original data and represent that information in a lower dimensionality space. Features represent important components of the venous network from the enhanced image. Knowing that only the central area of the image is interesting, we extract a ROI for the feature extraction input. After what, we apply mathematical morphology to extract the veins network.

Top-hat transform is an operation that extracts small elements and details from given images. There exist two types of top-hat transform: The white top-hat transform is defined as the difference between the input image and its opening by some structuring element; the black top-hat transform (sometimes called the *bottom-hat* transform) is defined dually as the difference between the closing and the input image. Top-hat transforms are used for various image processing tasks, such as feature extraction, background equalization, image enhancement, and others.

First, we apply top and bottom hat transforms to extract the desired features basing on a suitable structuring element B that is bigger than the width of the subcutaneous vessels in the image.

The algorithm is based on combining image subtraction with openings and closings results in **top-hat** and **bottom-hat** transformations. The ***top-hat*** transformation of a gray-scale image *f* is defined as *f* minus its opening:

$$T_{hat}(f) = f - (f \circ b) \quad (6)$$

Similarly, the ***bottom-hat*** transformation of a gray-scale image *f* is defined as the closing of *f* minus *f*:

$$B_{hat}(f) = (f \bullet b) - f \quad (7)$$

Then we substract the two obtained image. The structure element B in our experiments in a disk diameter 4

The top and the bottom hat transforms are given below:

$$I_f = B_{hat}(I, B) - T_{hat}(I, B) \quad (8)$$

V. EXPERIMENTAL RESULTS

Our experiments were lead on the SAB'13 [14] database with a All in one HP machine; that's configuration is Intel (R) Core (TM) i3-3240 CPU @3.40GHz 3.40GHz. The SAB'13 database was conducted with a built biometric dorsal hand vein device which is based on a camera that has a good sensitivity in the near infrared spectrum. A lighting system with hundreds infrared Led's emitting in the spectrum 850nm were used. In this paper, we proposed techniques which allow us to get the extraction of wanted vein network features.

The previous works shows that the uniqueness of the network vein let us use this modality as way to get person identification/authentication. Knowing that for each context and image, the central area of the image is the most interest part to use.

In our tests we start first across all the used databases with different variations in the diffusion constant and number of iterations until finding the efficient result, with below parameter. The results are shown in Figure 5.

IM - gray scale image (MxN).

Num_iter - number of iterations.

Delta_t - integration constant (0 <= delta_t <= 1/7).

Usually, due to numerical stability this parameter is set to its maximum value.

Kappa - gradient modulus threshold that controls the conduction.

Option - conduction coefficient functions proposed by Perona & Malik:

1 - c(x,y,t) = exp(-(nablaI/kappa).^2), privileges high-contrast edges over low-contrast ones according to Equation 4.

2 - c(x,y,t) = 1./(1 + (nablaI/kappa).^2), privileges wide regions over smaller ones according to Equation 5.

Where:
num_iter = 180;
delta_t = 1/7;
kappa = 100;
option = 2;

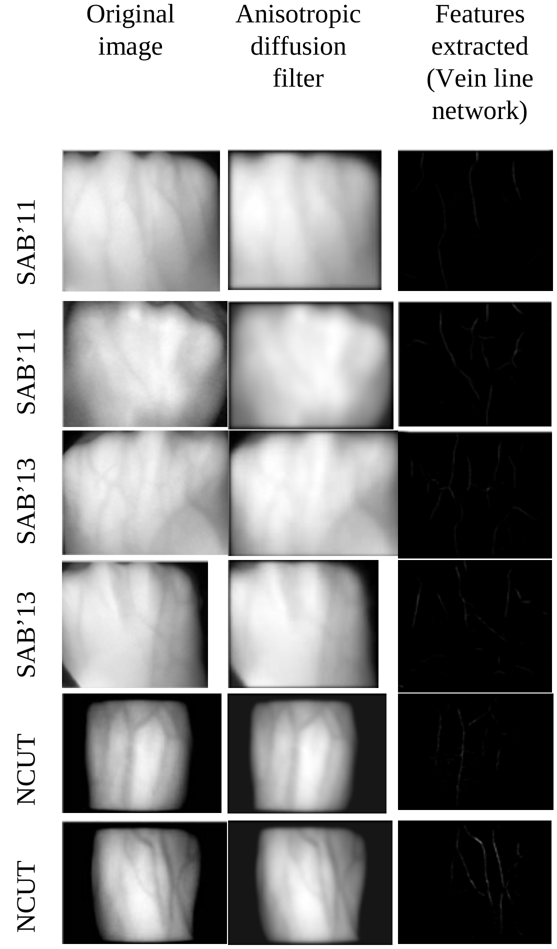
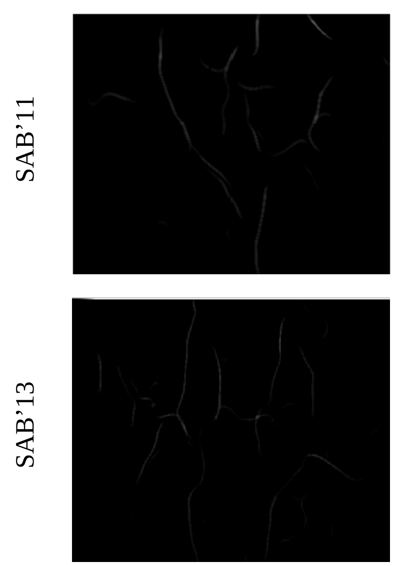


Figure 5: Dorsal hand vein results for three databases.

The Figure 5, show more the efficiency of the diffusion filter used for getting rapidly and efficiently the dorsal venous network. Nest figure 6, permit to see more the results.



NCUT

Figure 6: Anisotropic diffusion filtered image

VI. CONCLUSION

In this work we propose a new technique for extracting dorsal hand vein as physiological features in the aim of biometric recognition. In this work, we used the built database of near infrared dorsal hand with the corresponding features; known more as SAB'11, SAB'13 and NCUT Benchmark. These features represent the subcutaneous dorsal venous network of the hand, although the superficial veins forming the median antebrachial vein of the dorsal hand. With the proposed technique, we get efficient results for our tests for the extraction of the required features. Those features are important in their use in biometric applications for getting person identification/authentication.

As perspectives, for eventual future work we propose to explore more robust pattern matching techniques suitable for the current application which is person identification/authentication.

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