Dorsal Hand Vein Image Contrast Enhancement Techniques

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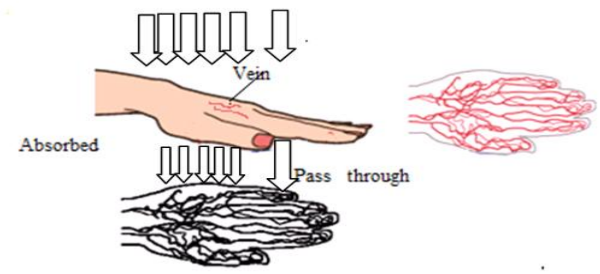
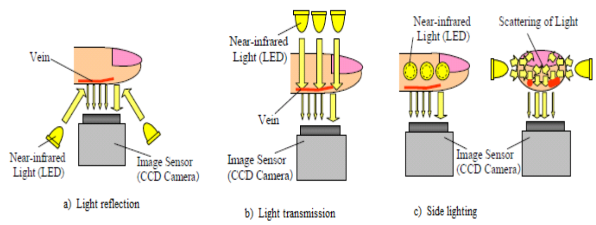
Abstract
The hand-vein pattern is one of the human biometric signatures that can be used for personal verification. The first task of a verification process using hand-vein patterns is extracting the pattern from an infrared hand vein image. An image of hand vein acquired by near-infrared (NIR) imaging device usually suffers from low contrast and noise due to non-illumination and thickness of the hand skin. This makes subsequent processing such as segmentation difficult. In this paper, a proposed approach is processed to improve the quality of hand vein image. Comparative analysis on a test image using different contrast enhancement algorithms has shown the effectiveness of the proposed method and its limits.
Keywords: *Image enhancement; Hand Vein; Biometrics; Infrared Imaging*.

1. Introduction

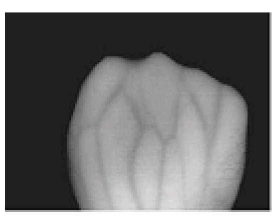
Biometrics is the science of identifying a person using their physiological or behavioral features [1]. Recently, vein pattern biometrics has attracted increasing interest from research communities. The human vascular structure is individually distinct and appears to be time invariant. Human blood vessels are formed during the embryo stage with a variety of differentiating features, rendering each pattern unique, and their patterns remain relatively constant over one's lifetime. A unique network of veins and arteries exists in every hand and finger of each human being. However, blood vessels are not exposed, and the intricate network pattern is usually not observable within the visible light wavelength. An individual's identity can be authenticated using vein patterns in one's hands and fingers, and those patterns are located just under the surface of the skin and can be clearly mapped with low-cost, high-resolution CCD cameras. The camera sensor of a vein pattern recognition (VPR) device is able to detect and recognize the vein pattern through the hemoglobin that actively flows in the individual's veins; those veins appear as a pattern of dark lines against a light (fig.1). Vein pattern imaging visualizes the vein network patterns by exploiting the optical characteristics of hemoglobin. The absorption images of the hemoglobin in deoxygenated veins differ markedly from the absorption images of oxygenated arteries. The venous blood carries waste such as carbon dioxide and it has a bright red color, and veins in one's hand are located closer to the surface than the arteries. VPR technology further refines the raw pattern images by applying illumination control and by employing advanced contrast-enhancement techniques. As a result, individuals can be rapidly verified against a stored reference template, providing very fast and robust biometric authentication. Most VPR systems use a set of light-emitting diodes (LEDs) to generate near-infrared light. Vein biometric systems record subcutaneous infrared absorption patterns to produce unique and private identity verification templates. The optical unit controls the lighting dependent on the illumination surrounding it. The light emitted from the LEDs penetrates the hand and enables the CCD camera to generate vein pattern images. The difference in the absorption of near-infrared light between veins and other body tissue is significant enough to produce a readily discernible sensor image of the vein pattern. After veins absorb the light rays, the veins appear as dark images to the camera, while the smaller, oxygenated arteries are less visible to the camera's sensor. The vein pattern is digitized into a binary form, and then the data are extracted, encrypted, and stored as a template [2].In NIR image acquisition, the dorsal hand vein image usually have poor contrast, non-uniform gray level and noise as the acquisition is affected by luminous intensity and thickness of the back of hand skin. Image enhancement is a process to bring out details that are hidden in an image, or to improve the quality of an image. Contrast enhancement not only serves to improve the image, but it is also useful in segmenting the image. In this work, five image enhancement algorithms have been implemented .The paper is organized as follows. Section 2 gives the related works on existing methods of enhancement vein images. In section 3, we present the proposed method to improve quality of hand images. Section 4 presents the enhancement performance measure and experimental results. Finally, Section 5 gives some concluding remarks to the paper.



a) Hand vein pattern



b) Three methods for capturing vascular pattern images of the finger [3].



c) Hand vein image

Fig. 1 Near-infrared light imaged by a CCD camera.

2. Hand Vein Image Processing Stages

The pre-processing of the acquired image plays an important role in feature extraction. A common step is the removal of noise from the image; this can be done by using a low-pass filter or an edge-preserving filter [4]. Another preprocessing step which is done often is to downscale the captured image [5]. This downscaling will save computation time, but the downside is that information might be lost. A common pre-processing step which is often done is image restoration [6]; this is done to compensate for varying light intensities in the captured image. In this work, five image enhancement algorithms have been implemented. Their capabilities at improving the quality of hand vein images are then compared. The five investigated algorithms are:

- Histogram Equalization (HE).
- Contrast Limited Adaptive Histogram Equalization (CLAHE).
- Frangi Filter.
- Radon like features method.
- Newtonian Operator (NO).

2.1 Histogram Equalization (HE)

Histogram equalization is a technique by which the gray-level distribution of an image is changed in such a way as to obtain a uniform (flat) resulting histogram, in which the percentage of pixels of every gray level is the same[7]. To perform histogram equalization, it is necessary to use an auxiliary function, called the transformation function, $T(r)$. Such transformation function must satisfy two criteria [8]:
1. $T(r)$ must be a monotonically increasing function in the interval $0 \leq r \leq L-1$.
2. $0 \leq T(r) \leq L-1$ for $0 \leq r \leq L-1$.
The most usual transformation function is the cumulative distribution function (cdf) of the original probability mass function, given by

$$s_k = T(r_k) = \sum_{j=0}^{k} \frac{n_j}{n} = \sum_{j=0}^{k} p(r_j) \qquad (1)$$

where s_k is the new (mapped) gray level for all pixels whose original gray level used to be. r_k The inverse of this function is given by

$$r_k = T^{-1}(s_k) \quad \text{for } k = 0, 1, \ldots, L-1 \qquad (2)$$

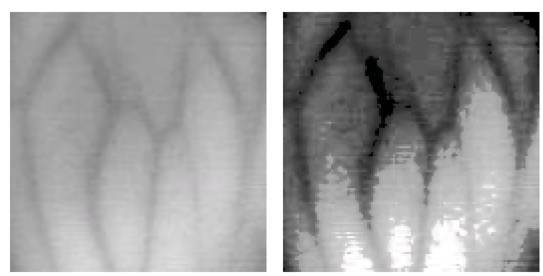


Fig. 2 Contrast enhancement results from hand vein image using HE.

2.2 Adaptive histogram equalization (AHE) CLAHE

Adaptive histogram equalization (AHE) differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast of an image and bringing out more detail. However, AHE has a tendency to overamplify noise in relatively homogeneous regions of an image. A variant of adaptive histogram equalization called contrast limited adaptive histogram equalization (CLAHE) [9,10] prevents this by limiting the amplification.

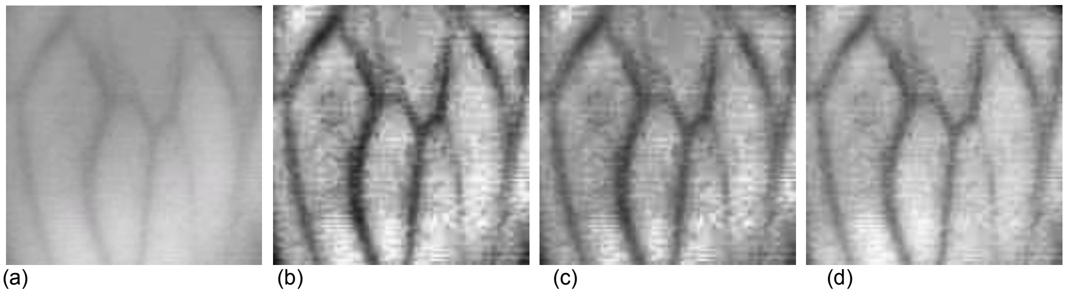


Fig. 3 Contrast enhancement of NIR vein pattern images: ROI for the hand image in Fig. 1(c); results from hand vein image using CLAHE (b) Distribution uniform (tiles7; clip level 0.02) (c) Distribution exponential (tiles7 ; α = 0.4;CL 0.02) (d) Distribution Raleigh(tiles7 ; α = 0.4;CL 0.02).

2.3 Frangi Filter

Frangi filter, is a method used for measure of "vesselness" in vascular application. In [11] Frangi introduced three measures to describe structure in images:

$$R_B = |\lambda_1|/\sqrt{|\lambda_2\lambda_3|}\,, R_A = |\lambda_2|/|\lambda_3| \quad (3)$$

and

$$S = \|H\|_F = \sqrt{\sum_i \lambda_i^2}, \quad (4)$$

which quantify deviation from a blob-like structure, the difference between platelike and line-like structures, and background noise, respectively. These measures were combined in a vesselness function as:

$$V^{Frangi}(\sigma, x) = \begin{cases} 0 & \lambda_2, \lambda_3 > 0 \\ \left(1 - \exp\left(-\frac{R_A{}^2}{2\alpha^2}\right) . \exp\left(-\frac{R_B{}^2}{2\beta^2}\right) . \left(1 - \exp\left(-\frac{S^2}{2c^2}\right) & otherwise \end{cases} \quad (5)$$

With α, β *and* c real-valued positive user defined parameters.

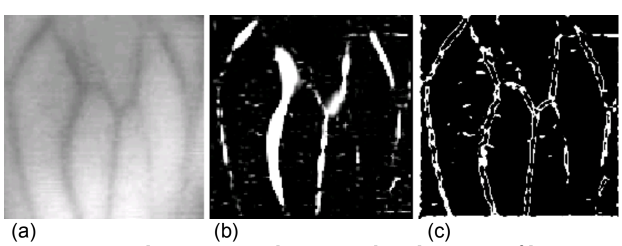


Fig. 1 Hand vein image enhancement based on Frangi filter: (a) Original hand vein image ;(b) ,(c)images processed by Frangi filter.

2.4 Radon like features

The Radon Transform (RT) [15] is a technique used extensively in tomography applications. It is defined by the integrated function $f(x, y)$ on a line L that is characterized by an intercept *m* and a slope *z*:

$$R(m, \tau)[f(x, y)] = \int_{-\infty}^{+\infty} f(x, m + \tau y)dx \quad (6)$$

The Radon Back-projection, inverse of the above described transform, is then used to reconstruct the original image. Radon-Like features (RLF)[12], which retains the central idea from the Radon Transform , processing an image (a 2D function, I(x; y) along a line (l, parameterized by t, i.e. l(t) = (x(t); y(t))),but instead of collapsing I(x;y) along l into a scalar value via integration (as in Eq. 6), RLF distribute some desired information derived from I(x, y) among various line segments along l. The line segments are defined by a set of salient points, called knots, along l. If the set of knots along l is given as ($t_{1,\ldots,}t_n$), value of Radon-Like feature at a point p along l between (x(ti); y(ti)) and (x(ti+1); y(ti+1)) is given by

$$\Psi(p, l, t_i, t_{i+1})[I(x, y)] = T(I, l(t)), \; t \in [t_i, t_{i+1}], \quad (7)$$

where T can be any desired function, called the extraction function.

As an example:

$$T_1(f, (l(t)) = \|l(t_{i+1}) - l(t_i)\|_2; t \in [t_i; t_{i+1}] \quad (8)$$

The extraction function T1 assigns all the pixels between the knots , t_i and t_{i+1} the value equal to the distance between them.

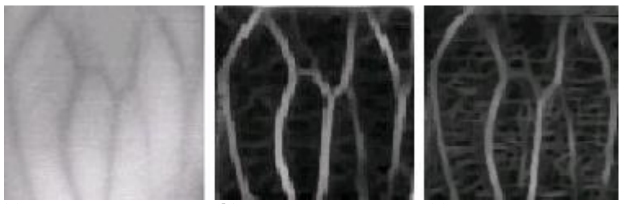
In our scheme for hand vein enhancement, the knots and the extraction function for Radon-Like features use the following transformation of the input image I(x, y):

$$R(x, y) = max \, \Delta \, G(\sigma, \phi) * I(x, y), \quad (9)$$

where σ and ϕ are the scale and the orientation of the boundary enhancing Gaussian-Second-Derivative (GSD).The knots for Radon-Like features are defined using an edge map of $R(x, y)$and the extraction function, T_2, is given as

$$T_2(I, l(t) = \frac{\int_{t_i}^{t_{i+1}} R(l(t))\partial t}{\|l(t_{i+1}) - l(t_i)\|} \,, t \in [t_i, t_{i+1}] \quad (10)$$

where l is the line along which features are obtained. This extraction function assigns all the pixels between the knots t_i and t_{i+1} along l the mean value of function R along l between the same two knots.



(a) (b) (c)
Fig.5 Example of hand vein image processed by RLF method a)original hand vein image(ROI);(b) RLF,(c)image processed by NO then RLF.

3. Newtonian Operator (NO)

This method [13] can be considered as member of convolution filters set but presents the originality of the adaptive found of convolution mask coefficients. The grey level distribution of pixels in the neighborhood of the current pixel is considered as $1/r^2$ distribution, which was deduced from the Newtonian model, where r is a hybrid distance which involves the spatial information and the luminance one. A neighborhood operation takes the values of pixels in the neighborhood of a point, performs some operations with them, and writes the results back on to the point. The grey level intensities inside the neighborhood window, can be calculated through the following formula:

$$g_i(t) = g_0 + \frac{1}{2}k\left(\sum_j \frac{g_j \Delta g_{ij}}{\left(\Delta g_{ij}^2 + d_{ij}^2\right)^{3/2}}\right)t^2 \qquad (11)$$

The variation of $g_i(t)$ is a parabola, the grey level of the pixel «*i*» can increase if $\Delta g_{ij} > 0$, decrease if $\Delta g_{ij} < 0$ or stay unchanged if $\Delta g_{ij} = 0$. We adapt this equation for enhancing the contrast by temporal sampling and fixing rate. The processes could be iterative. That is,

$$g_i(t+1) = g_i(t) + \frac{1}{2}k\sum_j \frac{g_j \Delta g_{ij}}{\left(\Delta g_{ij}^2 + d_{ij}^2\right)^{3/2}} \qquad (12)$$

$$g_i(t+1) = g_i(t) + \frac{1}{2}kS_{ij} \qquad (13)$$

$$S_{ij} = \sum_j \frac{g_j \Delta g_{ij}}{\left(\Delta g_{ij}^2 + d_{ij}^2\right)^{3/2}} \qquad (14)$$

S_{ij} could be a gradient or Laplacian operator.

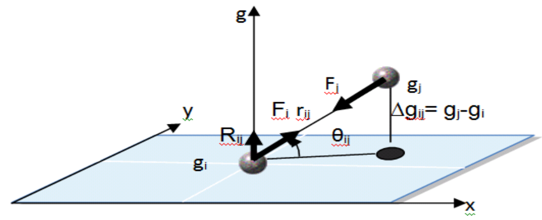
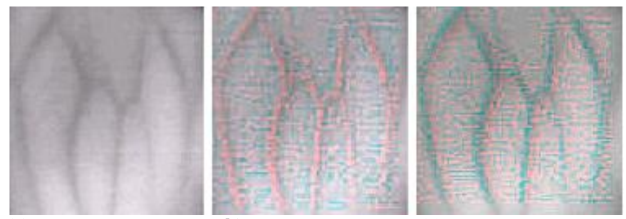


Fig.6 Tri-dimensional representation enhancing



(a) (b) (c)
Fig.7 Contrast enhancement results from hand vein image using newtonian operator (NO). (a)original hand vein image (ROI)(b), (c) the enhanced image (k=-8)and(k=+8);

4. Enhancement performance measure and experimental results

Evaluation of images, after processing, is an important step for determining how well the images are being processed. Quality of image is usually assessed using image quality metrics which can be categorized into subjective assessment, involving humans to evaluate the image quality and objective assessment that measures the image quality automatically. The goal of objective quality evaluation is to obtain a quantitative measure which gives the quality of the image in a manner consistent with human perception and subjective analysis should match with objective assessment values.

Unfortunately, most of the commonly used metrics cannot adequately describe the visual quality of the enhanced image. There is no universal measure, which specifies both the objective and subjective validity of the enhancement for all types of images. Contrast, brightness and sharpness are the three basic parameters that control the quality of an image. An image can be described by means of first order statistics of gray values of the pixels inside a neighborhood. Examples of such features extracted from the image histogram are mean, standard deviation (SD) and entropy. The second order features are based on gray level co-occurrence matrix (GLCM)[14] and it is one of the most popular methods for pixel variation statistics. Some of the second order statistical features are entropy, contrast, homogeneity, energy and correlation of the gray level pixels, defined as

$$Entropy = -\sum_i \sum_j P(i,j) \log P(i,j) \qquad (15)$$

$$Contrast = \sum_i \sum_j (i-j)^2 \, P(i,j) \qquad (16)$$

$$Homogeneity = \sum_i \sum_j \frac{P(i,j)}{1+|i-j|} \quad (17)$$

$$Energy = \sum_i \sum_j P(i,j)^2) \quad (18)$$

$$Correlation = \sum_i \sum_j \frac{(i-\mu_i)(j-\mu_j)}{\sigma_i \sigma_j} P(i,j)) \quad (19)$$

where i and j are two different gray levels of the image, P is the number of the co-appearance of gray levels i and j. Contrast returns a measure of the intensity difference between a pixel and its neighbor over the whole image. Homogeneity measures the similarity of gray-scale levels across the image. Thus, larger the changes in the gray-scale, the higher the GLCM contrast and lower the homogeneity.

Energy measures the overall probability of having distinctive gray-scale patterns in image. Correlation returns a measure of how correlated a pixel is to its neighbor over the whole image and it measures the joint probability of occurrence of the specified pixel pairs.

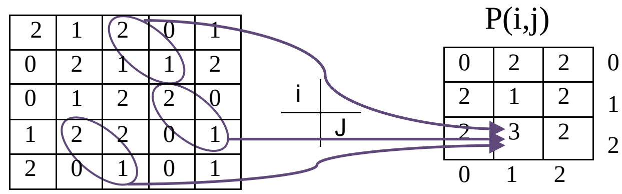


Fig: (a) A 5 x 5 image with three gray levels 0, 1, and 2. (b) The gray-level co-occurrence matrix for d = (1,1).

Table.1 image quality measures for the enhancement technique

	Frangi Filter		Radon Like Features		CLAHE			HE	Newtonian Operator	
	(b)	(c)	(b)	(c)	(b)	(c)	(d)		(c)	(b)
Contrast	0.11	1.8	0.43	0.74	0.32	0.40	0.46	0.49	0.80	1.46
Homogeneity	0.94	0.8	0.85	0.97	0.90	0.88	0.85	0.90	0.76	0.84

5. Conclusion

In this paper, five methods for hand vein image enhancement have been presented. Many image enhancement schemes like Histogram Equalization (HE), Contrast Limited Adaptive Histogram Equalization (CLAHE),Frangi-filter, Radon-like features (RLF), Newtonian Operator (NO), have been implemented and compared. The performance of all these methods has been analyzed and a number of practical experiments of images have been presented. From the experimental results, it is found that all the techniques yield different aspects for different parameters. The efficiency of the proposed method is promising even if the test database used in the experiments is quite small. We intend to define a more significant database confirming our first preliminary results.

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