Towards finger-vein image restoration and enhancement for finger-vein recognition

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ABSTRACT

Biometric recognition based on human finger-vein patterns is an emerging technique and has been receiving increasing attention. Due to light attenuation in biological tissue, the collected finger-vein images are often seriously degraded. This makes finger-vein feature representation unreliable, and inevitably impairs the accuracy of finger-vein recognition. Exploring suitable ways of finger-vein image restoration and enhancement is indispensable for finger-vein based personal identification. In this paper, we first analyze the intrinsic factors causing the degradation of finger-vein images, and propose a simple but effective scattering removal method to improve the visibility of finger-vein images. Moreover, to handle venous region enhancement problem effectively, a directional filtering method based on a family of Gabor filters is proposed. Finally, a Phase-Only-Correlation strategy is used to measure the similarity of the enhanced finger-vein images. Experiments performed on a large finger-vein image database show that the proposed method is effective and reliable in finger-vein image restoration and enhancement.

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1. Introduction

Finger-vein recognition as an accurate and fraud-proof biometric technique has drawn increasing attention from biometrics community in recent years [30,38,60,8,78,76,59,23,32,75,71,70,64,36,55,46,18,65,66,63,62,72,33,34,49,53,69,68,67,74,31]. Compared with conventional biometric traits, e.g., face, iris, fingerprint, palmprint, finger-vein is high live and forgery-proof by itself, high acceptable by users, and very convenient to use. This distinctly differentiates finger-vein from the classical traits and promotes its utilization in many security applications.

In embryology, the formation of vascular tissues is subject to a combined action of both deterministic and random processes in embryogenesis [21,43]. The inherent stochastic mechanism of vascular development is a key factor that directly causes the randomness of finger-vein networks, which therefore makes the finger-vein pattern highly unique and stable as a biometric pattern.

In anatomy, the finger-veins used for biometrics are superficial veins that present between the two layers of superficial fascia without accompanied arteries [57]. Owing to the opaqueness of skin layer, the superficial veins embedded in subcutaneous tissue cannot be visualized clearly by visible light. Hence, for vein imaging, the near infrared (NIR) light (700–900 nm) is often adopted in real applications since the NIR light can be absorbed by the hemoglobin in blood [79]. Especially, the finger-vein images can be captured in a contactless and non-invasive way using a NIR transillumination imaging device.
since the NIR light can penetrate through the human fingers, which is of great importance for user friendliness in practical application.

Unfortunately, it is impossible to capture finger-vein images with high visibility in practice. The biological tissue is highly heterogeneous and behaves as a multiple scattering medium in NIR imaging [1], which inevitably results in the deterioration of image resolution. Therefore, the finger-vein images are always degraded seriously because of multiple scattering interaction in biological tissue [54].

The degradation of finger-vein images brings a big challenge for finger-vein recognition since finger-vein network features cannot be exploited reliably when the separability is poor between the venous and non-venous regions. Over the past years, many efforts have been devoted for finger-vein image enhancement. Histogram equalization based algorithms were used to enhance the contrast of finger-vein images [60,78]. Wang et al. [59] combined the fuzzy and the retinex theory together to enhance the near-infrared vein images. Pi et al. [46] used edge-preserving filter and elliptic high-pass filter together to denoise and enhance some small blurred finger veins. Gao et al. [18] combined the traditional high frequency emphasis filtering algorithm and the histogram equalization to sharpen the image contrast. Oh and Hwang [44] proposed a homomorphic filter incorporating morphological subband decomposition to enhance the dark blood vessels. Lee et al. [34] and Rosdi et al. [49] used Gaussian-based high-pass filters to enhance the contrast of finger-vein images. Considering the variations of vein-coursing directions, Yang et al. [70,64,65] used different oriented filtering strategies to highlight the finger-vein texture. Although these methods can enhance finger-vein images to some extent, their performances were considerably undesirable in terms of visibility improvement since none of these methods treats the key issue of light scattering in finger-vein image degradation.

Strong scattering occurring in biological tissue during imaging is the main reason causing contrast deterioration in finger-vein images [7,2]. Considering light transport in skin tissue, Lee and Park used an depth-dependent point spread function (D-PSF) to address the blurring issue in finger-vein imaging [32,33]. This method is encouraging in finger-vein visibility improvement, however, D-PSF was derived for handling degraded issues in transcutaneous fluorescent imaging manner but not in transillumination manner [52]. Thus, the performance of D-PSF on light scattering suppression is still unsatisfying for finger-vein images since, in transillumination, light attenuation (absorption and scattering) arises not only from the skin but also from other tissues of the finger, such as bone, muscles, and blood vessels [6,61]. Moreover, estimating biological parameters properly is also a difficult task for D-PSF based image deblurring in practice. To deal with scattering issue, a scattering removal method based on a biological optical model was proposed in our previous works [62,69]. However, our previous method did not take into account the effects of background illumination, and only provided a rough method of scattering estimation. Hence, traditional scattering removal methods still cannot handle the finger-vein restoration problems effectively and reliably.

In this paper, instead of developing an elegant method of finger-vein feature analysis, we focus on two fundamental problems: multiple scattering removal and venous region enhancement, which is directly related to the usability and stability of finger-vein trait in human identification. The main contributions of this paper are the following:

1. A new biological optical model is proposed to reasonably describe the process of finger-vein image degradation.
2. A new scattering removal method is proposed to effectively improve the visibility of finger-vein images.
3. A new Gabor based filtering method is proposed to enhance venous regions as well as suppress fake veins and noises.

The remainder of this paper is organized as follows. In Section 2, we briefly introduce a homemade finger-vein imaging system. The proposed biological optical model is presented in Section 3. Section 4 details the proposed method in finger-vein image restoration. In Section 5, a Gabor-based method is proposed for venous region enhancement. Experimental results are reported in Section 7. Section 8 summarizes this paper.

2. Finger-vein image acquisition

To obtain finger-vein images, we have designed a homemade finger-vein imaging system, which can automatically capture a finger-vein image, as shown in Fig. 1(b). An open window (70 × 25 mm²) centered in the width of imaging plane is set for finger-vein imaging. The luminaire is a NIR light-emitting diode (LED) array at a wavelength of 760 nm, and in NIR transillumination, a CCD sensor is placed underneath a finger, as shown in Fig. 1(a).

To localize the ROIs from finger-vein images, a simple but effective method proposed in our previous work [66,68] is used here, as shown in Fig. 1(c). From Fig. 1(c), we can see that veins cast dark “shadows” on the imaging plane while the surrounding tissue (e.g., fat) presents a bright background. These shadows called “angiogram” in medical imaging actually create the finger-vein imageries in NIR transillumination.

Some finger-vein ROIs of one subject at different instants are listed in Fig. 1(d). We can notice from Fig. 1(d) that the sample ROIs have little intra-class variation, which obviously is beneficial for accurate finger-vein recognition.

3. Weighted biological optical model

According to diaphanography in modern medicine, finger-vein imaging is a kind of optical transillumination modality [14]. In this manner, the NIR lights penetrating through a human finger can be refracted, absorbed and scattered by the
biological tissue [6,61,13]. Since the biological tissue can be viewed as a complex heterogeneous optical medium, the NIR lights suffer from significant scattering in addition to absorption when they propagate into this medium [14,3]. That is, light scattering dominates in finger-vein imaging. This phenomenon is similar to that of visible light propagating in fog [50], which can greatly reduce the definition of imaging scenes. Thus, image degradation is inevitable for finger-vein imaging owing to multiple light scattering in biological tissue. Undoubtedly, image restoration using scattering removal is helpful to improve the quality of finger-vein images.

From the biophotonics point of view, as the incident light propagates through biological tissue, the transmitted light is composed of three components—the ballistic, the snake, and the diffuse photons [47], as shown in Fig. 2. Ballistic photons, or coherent photons, travel through a scattering medium in a straight line. Snake photons experience some slight scattering, but still propagate in the forward or near-forward direction. Diffuse photons, or incoherent photons, undergo multiple scattering and experience random paths in biological tissue.

Obviously, to visualize the objects embedded in biological tissue, the ballistic photons with propagation direction preservation can form sharp shadows on the imaging plane, whereas the multiple scattered diffuse photons can inevitably reduce the contrast of the shadows as well as giving rise to the unwanted, incoherent imaging background [48]. That is to say, the multiple scattering is the most unfavorable factor that leads to image blurring in optical transillumination imaging.

According to tissue optics, the transmitted light observed at skin surface can also be simply decomposed into the direct attenuation component and the scattering component, as shown in Fig. 3. The former represents the non-scattered light composed mainly by the ballistic photons, which obeys the Beer–Lambert law in reducing the object radiation over the traversing medium [7,24]. And the latter represents the scattered light composed by the diffuse and snake photons, which emerges randomly and can be only investigated statistically. Specially, the proportion of scattered radiation increases with depth because a deeper object tends to suffer more influence of the scattered radiation.

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For the direct attenuation component, its intensity on the imaging plane is mainly determined by the non-scattered light. So, assuming that $\mu_1$ and $\mu_2$ denote the optical absorption and scattering coefficients, based on the Beer–Lambert law, we can obtain

$$I_0(x) = I_0(x)e^{-\mu_1d},$$

where the vector $x$ represents the spatial coordinates $[x, y]$, $I_0(x)$ represents a finger-vein image free of degradation, $d$ is the object depth in a biological medium, $\mu = \mu_1 + \mu_2$ is called transport attenuation coefficient, and $I_0(x)$ denotes the transmitted intensity after absorption and scattering. Noticeably, due to the heterogeneity of skin tissue and the spatial randomness of vein distribution, both the transport attenuation coefficient $\mu$ and the depth $d$ vary spatially in the tissue medium, that is, $\mu = \mu(x)$ and $d = d(x)$. So, $T(x) = e^{\mu(x)d(x)}$ is often called non-scattered transmission map (NSTM) [7], which describes the optical transmissivity of a given biological tissue.

For the scattering component, due to the randomness of the scattered light, it can be regarded as the background illumination on the whole, and only a part of the background illumination can arrive at the imaging plane. For intuitively understanding this point, Fig. 4 gives a schematic illustration that intuitively describe this phenomenon. In Fig. 4, $s$ represents an original source, $p$ is the observation of $s$ on the imaging plane, $H$ denotes a small column in the skin tissue corresponding to a beam from the object point $s$ to a point $p$ on the image plane (each pixel corresponds to a small column), the neighbor points $(s_i, i = 1, 2, \ldots, n)$ around $s$ are viewed as the local background radiation sources, which would emit radiation and produce a scattering component along $H$.

Let the original intensity of a neighbor point $s_i$ be $I_0(s_i)$, then the direct transmitted radiation of this point, that is the non-scattered radiation, should be $I_0(s_i)T(s_i)$. According to the energy conservation principle, the scattered radiation of this point is $(1 - T(s_i))I_0(s_i)$. Generally, the distribution of scattering energy is not uniform in a local block $\Omega(s)$ since the skin medium is inhomogeneous. However, it is affirmative that (1) the directions of scattered light rays are random due to the high density of biological cells, and (2) the nearer $s_i$ to $s$ is, the higher the probability of the scattered light into column $H$ is. Hence, a 2D Gaussian function $g(s)$ has been used to approximately model the distribution of the scattered energies in $\Omega(s)$ [11,17],

$$g(s) = \frac{1}{\sqrt{2\pi}\sigma_s} \exp\left(-\frac{(I_i(s_i) - I_i(s))^2}{2\sigma_s^2}\right),$$

where $I_i(s_i) = (1 - T(s_i))I_0(s_i)$, $I_i(s)$ and $\sigma_s$ respectively denote the local mean value and the local standard deviation of the scattered energies in $\Omega(s)$.

In this sense, the local average background illumination can be represented by $I_i(s)$ whose value is closely related to the local optical properties of skin tissue. Imaginably, $I_i(x)$ describes a local background illumination map (LBIM) over a whole finger-vein image, and not all local background illumination can enter into the column $H$. So, let $x_1$ be a probability weight, similar to Koschmieder model [27,41], the proposed weighted biological optical model (WBOM) is defined as
where $\mathbf{z}_1 < 1$, and the last term, $\mathbf{z}_1(1 - T(x))I_r(x)$, represents the approximate scattering component that emerges from the skin surface and makes an adverse contribution towards finger-vein imaging. Obviously, different from the environmental illumination in the atmosphere, $I_r(x)$ varies spatially because of the high heterogeneity of skin tissue. Compared with our previous model proposed in [69], the proposed WBOM is superior to BOM since the weighted factor $\mathbf{z}_1$ can representatively describe the forward probability of the scattered energies. Compared with our previous method proposed in [62,69], the WBOM is more reasonable for describing the scattering phenomenon in biological tissue.

Given $I_r(x), \mu(x)$ and $d(x)$, we can easily compute $I_0(x)$ which represents the intrinsic intensity of a finger-vein image without scattering corruption. However, not only is the attenuation coefficient $\mu(x)$ of human skin tissue inconsistent, but the thickness $d(x)$ also varies with different individuals. Hence, solving $I_0(x)$ via Eq. (3) is an ill-posed problem since $I_r(x), \mu(x)$ and $d(x)$ all cannot be evaluated properly in practice. Instead of directly computing $I_0(x)$, in the following, we first estimate $I_r(x)$, and then $T(x)$ according to the observation $I(x)$.

### 4. Finger-vein image restoration

In WBOM, only the observation $I(x)$ is determined. So, it is an important task of how to estimate LBIM $I_r(x)$ and NSTM $T(x)$ by $I(x)$ for scattering removal. In this section, a novel method based on Anisotropic Diffusion And Gamma Correction (ADAGC) is proposed for estimating LBIM and NSTM effectively.

#### 4.1. Local background illumination map estimation

Computing $I_r(x)$ via Eq. (2) directly is a difficult task in practice since the intensity $I_r(x)$ is indeed unavailable. Hence, in this section, a local background illumination estimation method is proposed for $I_r(x)$ approximation.

First, the finger-vein images are transformed into their negative versions. In the observation $I(x)$, veins appear shadows due to light absorption, which makes vein information sensitive to illumination adjustment. On the contrary, in the negative versions, the venous regions turn brighter than their surroundings, veins thus can be regarded as luminous objects. Moreover, in this situation, the skin tissue can be approximately treated as the only opaque layer that blurs vein objects during imaging. This is beneficial for background illumination estimation.

Second, we have to use the local observation in $\Omega(p)$ to estimate $I_r(x)$ in $\Omega(s)$, as shown in Fig. 4. According to Section 3, we know that the scattered light is also attenuated exponentially, which degrades it to zero rapidly due to the high heterogeneity of skin layer. Thus, the scattering information should dwell locally in the observation.

Third, anisotropic filtering techniques should be suitable for background illumination estimation [19,28]. The heterogeneity of skin tissue determines that the transport behavior of the scattered NIR light is anisotropic in skin layers, and such transport results in anisotropic diffusion of light in imaging. So, using anisotropic filtering process can model this kind of optical anisotropic diffusion process in finger-vein imaging.

Based on the above discussion, we rewrite the proposed WBOM as

$$\tilde{I}(x) = \tilde{I}_0(x)T(x) + \mathbf{z}_1(1 - T(x))\tilde{I}_r(x), \quad (4)$$

where $\tilde{I}(x), \tilde{I}_0(x)$ and $\tilde{I}_r(x)$ represent the negative versions of $I(x), I_0(x)$ and $I_r(x)$, respectively. Next, we detail the process of background illumination estimation.

Let $W \subset \mathbb{R}^2$ and $\tilde{I}(x, t) : W \rightarrow \mathbb{R}^2$ be a family of images in the scale-space, the anisotropic diffusion proposed in [45] is defined as
\[
\frac{\partial \tilde{I}(\tilde{x}, t)}{\partial t} = \text{div}(c(\tilde{x}, t) \nabla \tilde{I}(\tilde{x}, t))
\]  

(5)

where \( t \) is the process ordering parameter or iteration number, \( \nabla \) is the gradient operator, \( \text{div} (\cdot) \) denotes the divergence operator and \( c(\tilde{x}, t) \) represents the diffusivity of the process. To preserve significant information (e.g., edges) as well as reduce noise during image diffusion, \( c(\tilde{x}, t) \) is usually chosen as a function of the image gradient. Since the NIR light is scattered anisotropically in skin tissue, and its randomness can be approximately modeled using 2D Gaussian distribution, Gaussian-based functions are reasonable for modeling \( c(\tilde{x}, t) \). Hence, similar to Eq. (2), we define
\[
c(\tilde{x}, t) = \frac{1}{\sqrt{2\pi}\sigma_p} \exp \left(-\frac{\| \nabla \tilde{I}(\tilde{x}, t) \|^2}{2\sigma_p^2}\right),
\]  

(6)

where \( \| \cdot \| \) denotes the norm operator, and \( \sigma_p \) is the standard deviation of pixels in \( \Omega(p) \), which controls the sensitivity to salient contents in finger-vein images during anisotropic diffusion.

Thus, a family of smoothed images can be generated, which consists of the transformed versions of an original image that are degraded consecutively in a backward manner. With the increase of iteration \( t \), the anisotropic-diffused finger-vein image can gradually approximate to the inhomogeneous background illumination.

Let \( \tilde{I}_t(\tilde{x}) \) be the last member of a family of diffused finger-vein images, then the LBIM can be estimated by
\[
\tilde{I}_t(\tilde{x}) = \begin{cases} 
\tilde{I}_0(\tilde{x}), & \tilde{I}_t(\tilde{x}) < \tilde{I}(\tilde{x}) \\
\beta \tilde{I}_t(\tilde{x}), & \text{otherwise}
\end{cases}
\]  

(7)

where \( \beta (\leq 1) \) is a controlling factor that suffices \( \tilde{I}_t(\tilde{x}) < \tilde{I}(\tilde{x}) \).

In Fig. 5, we list some diffusion results under different number of iterations \( t \), where the size of \( \Omega(p) \) is \( 9 \times 9 \). We can clearly see from Fig. 5 that the diffused images become more and more smoothing with increasing \( t \) gradually, and the significant information of the finger-vein image content can be mostly preserved. This shows that the anisotropic diffusion process can represent the characteristics of light transporting in skin tissue.

4.2. Non-scattered transmission map estimation

The NSTM is often viewed as an intrinsic characteristic function of the transmitted information that describes the internal composition of a given kind of biological tissue in imaging [7]. From NSTM \( T(\tilde{x}) \), we can therefore observe most of the finger-vein information. Unfortunately, the proposed WBOM is non-analytical for computing \( T(\tilde{x}) \) via Eq. (4), although \( \tilde{I}_t(\tilde{x}) \) has been estimated reasonably in Section 4.1.

It is certain that both the background illumination and the transmission map must be present in the observation \( \tilde{I}(\tilde{x}) \). To compute \( T(\tilde{x}) \), we should make use of the observation \( \tilde{I}(\tilde{x}) \) again. Here, we first give an explicit expression of \( T(\tilde{x}) \), then try to find a suitable method to estimate it reliably. Based on Eq. (4), we can obtain
\[
T(\tilde{x}) = \frac{\tilde{I}(\tilde{x}) - \alpha_2 \tilde{I}_\alpha(\tilde{x})}{\tilde{I}_0(\tilde{x}) - \alpha_1 \tilde{I}_\alpha(\tilde{x})}
\]  

(8)

Obviously, \( T(\tilde{x}) \) cannot be computed directly by Eq. (8) since \( \tilde{I}_0(\tilde{x}) \) is unknown, but it is confirmed that \( \tilde{I}_0(\tilde{x}) \) must be brighter than \( \tilde{I}(\tilde{x}) \) because \( \tilde{I}_0(\tilde{x}) \) is a clear image free of absorption and scattering corruption.

**Fig. 5.** Anisotropic diffusion. (a) An original finger-vein image \( \tilde{I}(\tilde{x}) \). (b) The negative version \( -\tilde{I}(\tilde{x}) \). (c), (d) and (e) denote the diffused image \( \tilde{I}_t(\tilde{x}) \) with \( t = 10, 20, 30 \), respectively. Here, \( \Omega(p) \) is a \( 9 \times 9 \) block.

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Thus, a corrected image in brightness based on \( \hat{I}(\hat{x}) \) should be approximate to \( \hat{I}_0(\hat{x}) \). To obtain a brighter finger-vein image, therefore, a nonlinear Gamma correction method [15,51] is used here, which is defined as

\[
\hat{I}_r(\hat{x}) = 255 \left( 1 - (I(\hat{x})/255)^{\gamma} \right).
\]

If \( \gamma < 1 \), then \( \hat{I}_r(\hat{x}) > \hat{I}(\hat{x}) \), that is, \( \hat{I}_r(\hat{x}) \) is brighter than \( \hat{I}(\hat{x}) \), as shown in Figs. 6(a) and 5(b). In this sense, \( \hat{I}_r(\hat{x}) \) is approximate to \( I_0(\hat{x}) \). However, directly using \( I_r(\hat{x}) - \alpha_1 I_r(\hat{x}) \) for computing \( T(\hat{x}) \) must increase the estimation error since the brightness of \( I_r(\hat{x}) \) cannot be higher than that of \( I_0(\hat{x}) \). To reduce the residual variations in the denominator of Eq. (8), the weight \( \alpha_1 \) of \( I_r(\hat{x}) \) should be changed. So, we define

\[
\hat{I}_0(\hat{x}) - \alpha_1 \hat{I}_r(\hat{x}) \approx \hat{I}_r(\hat{x}) - \alpha_2 \hat{I}_r(\hat{x}),
\]

where \( \alpha_1 \geq \alpha_2 \), and \( \alpha_1 \) should be much lower than \( \alpha_1 \). Thus, the NSTM can be estimated by

\[
T(\hat{x}) \approx \frac{\hat{I}(\hat{x}) - \alpha_1 \hat{I}_r(\hat{x})}{\hat{I}_r(\hat{x}) - \alpha_2 \hat{I}_r(\hat{x})}.
\]

Compared with the backward estimation of \( \hat{I}_r(\hat{x}) \), \( T(\hat{x}) \) is estimated approximately in a forward manner. Fig. 6(b) illustrates the estimated NSTM. We can clearly see from Fig. 6(b) that most of the finger-vein information is exhibited apparently. This shows that the NSTM can be estimated properly in this way.

4.3. Image restoration

Given the estimates of \( \hat{I}_r(\hat{x}) \) and \( T(\hat{x}) \), the proposed WBOM turns analytical for computing \( \hat{I}_0(\hat{x}) \). Consider that the residual errors in Eq. (11) must result in noise in \( T(\hat{x}) \), and \( T(\hat{x}) \) should be locally smooth since both the object depth \( d(\hat{x}) \) and the attenuation coefficient \( \mu(\hat{x}) \) cannot vary greatly in the skin tissue, the averaging filter, mask size same as \( \Omega(p) \), is used for making \( T(\hat{x}) \) smooth in advance of computing \( \hat{I}_0(\hat{x}) \), as shown in Fig. 6(c).

Thus, according to the estimates of \( \hat{I}_r(\hat{x}) \) and \( T(\hat{x}) \), and based on Eq. (4), we can conveniently implement finger-vein image restoration by

\[
I_0(\hat{x}) = 255 - \hat{I}_0(\hat{x}) = 255 - \frac{\hat{I}(\hat{x}) - \alpha_1(1 - T(\hat{x}))\hat{I}_r(\hat{x})}{T(\hat{x})}.
\]

In Figs. 6(d) and (e), we list the restored \( \hat{I}_0(\hat{x}) \) and \( I_0(\hat{x}) \). From Fig. 6(e), we can clearly see that the scattering effect is removed effectively as well as significantly improving the visibility of the finger-vein network. This shows that the proposed WBOM is effective in modeling the process of finger-vein image degradation, and the proposed ADAGC is very convincing in LBIM and NSTM estimation.

Undoubtedly, the restored image still indicates an approximate representation of a clear finger-vein image free of scattering, since the anisotropic property of light transport in heterogeneous tissue cannot be modeled exactly. Therefore, noise introduction is inevitable in this restoration procedure, as shown in Fig. 6(e). Aiming to further enhance the venous regions and reduce noises in the restored images, a Gabor-based method is introduced in the next section.

![Fig. 6](image-url)

Fig. 6. Transmission map estimation and image restoration. (a) The Gamma correction image, here \( \gamma = 0.6 \). (b) Transmission map \( T(\hat{x}) \) with \( \alpha_1 = 0.98 \), \( \alpha_2 = 0.5 \). (c) The smoothed \( T(\hat{x}) \) by the averaging filter with a \( 9 \times 9 \) mask. (d) The restored image \( \hat{I}_0(\hat{x}) \) by the median filter with a \( 3 \times 3 \) mask. (e) The restored image \( I_0(\hat{x}) \) corresponding to (d).
5. Venous region enhancement

The band-pass property of Gabor wavelet and its capability of selecting directions make Gabor transformation very suitable for noise reduction and local content-specific feature analysis in image processing. So, Gabor wavelets with various scales and orientations have been successfully employed in a wide range of image analysis applications.

5.1. Gabor wavelet family

Let \( \Delta \phi \in [1, 1.5] \) be the half-amplitude frequency bandwidth in octaves \([12,10]\), a family of admissible self-similar Gabor wavelets with d.c. subtraction can be expressed as \([35]\)

\[
G^k_m(x) = \frac{\omega_m}{\sqrt{2\pi}v} \exp \left(-\frac{\omega^2_m}{2v^2} |A\bar{x}_h|^2\right) \cdot \exp(jf_m\bar{x}_h) - \exp(-v^2/2),
\]

where \( j = \sqrt{-1}, v = \sqrt{2\ln2}(2^{\Delta\phi} + 1)/(2^{\Delta\phi} - 1). A = \text{diag}[1, \lambda]^k \) is a 2 \times 2 diagonal matrix that defines the anisotropy of Gabor wavelets, \( k = 1, 2, \ldots, N \) is the orientation index, \( m = 1, 2, \ldots, M \) is the scale index, \( f_m = [\omega_m, 0] \) is a variable vector denoting the \( m \)th center frequency of the complex exponential, \( \theta \) denotes the orientation of a Gabor wavelet.

The redundancy of a family Gabor wavelets in frequency domain will be tremendous if some parameters (e.g., \( \omega_m, \lambda \)) are chosen improperly. To maximally reduce the redundancy in frequency domain, any two adjacent family members should be tangent in half-amplitude profiles, as shown in the right of Fig. 7. Hence, the following rules between Gabor parameters should be observed \([35,29]\),

\[
\left\{
\begin{array}{l}
\lambda \approx \sin \left(\frac{\pi}{2N}\right) \sqrt{\ln2}
\theta_{k+1} = \theta_k + \pi/N
\omega_{m+1} = \omega_m \frac{\sqrt{2\ln2}}{\pi}\sqrt{\ln2}
\end{array}ight.
\]

The rules expressed by Eq. (14) facilitate the Gabor family design. Thus, given the parameters \( \Delta \phi, \omega_1, M \) and \( N \), a family of even Gabor wavelets with minimum redundancy can be generated automatically. Fig. 7 shows a family of even Gabor wavelets, where the contours correspond to the half-amplitudes of Gabor responses in frequency domain.

5.2. Inter-scale multiplication operation

Using Euler formula, a Gabor wavelet can be decomposed into two parts: real and imaginary. The real part, usually called even Gabor wavelet, is suitable for ridge detection \([73]\), while the imaginary part, usually called odd Gabor wavelet, is suitable for edge detection \([80]\). Since veins present ridges, even Gabor wavelets are desirable for the purpose of venous region enhancement.

Let \( U^k_m(x) \) be a Gabor transformed image, then we can obtain

\[
U^k_m(x) = \text{Re}(G^k_m(x) \otimes I_0(x)),
\]

where the symbol “\( \otimes \)” denotes 2D convolution, and \( \text{Re}(\cdot) \) indicates the real part of Gabor transformation. For a given scale \( m \), the value of \( U^k_m(x) \) must be at its maximum when a tunable Gabor wavelet simultaneously and locally matches the
orientation and width of a vein ridge. Hence, let $E_m(\tilde{x})$ denote a Gabor image with optimal responses over all possible orientations, we then can obtain

$$E_m(\tilde{x}) = \max_{\eta \in [0, \pi]} \langle U^k_m(\tilde{x}) \rangle.$$  \hfill (16)

However, $E_m(\tilde{x})$ inevitably contains much unwanted information (e.g., false ridges) in a certain scale, although we have minimized the redundancy of Gabor wavelets in the frequency domain. This is ascribed to the structure of even Gabor wavelets. An even Gabor wavelet is composed of a main excitatory lobe (MEL), two secondary excitatory lobes (SEls) and two inhibitory lobes (InLs). Thus, there are always some trivial things generated and strengthened by SEls and InLs in 2D convolution operation.

To suppress these unwanted information effectively, we propose an inter-scale multiplication operation (ISMO), which is defined as

$$E(\tilde{x}) = \prod_{m=1}^{M} E_m(\tilde{x}).$$ \hfill (17)

Here, $E(\tilde{x})$ is called the Gabor-enhanced image. Thus, the optimal responses of even Gabor wavelets in $M$ scales and $N$ orientations can be simultaneously achieved using ISMO. This is very suitable to enhance vein vessels with diameter and orientation variations. Furthermore, mutual inhibition of SEls and InLs in inter-scales is utilized successfully by product operation, which just serves for unwanted information suppression.

Note that we have proposed a Multiscale Multiplication Rule (MSMR) for this purpose in our previous work [68]. Compared with MSMR, some negative values can be remained in ISMO but not in MSMR, and we think that “Inter-scale Multiplication Operation” is more proper than “Multiscale Multiplication Rule” in representing the meaning of the proposed algorithm in false information suppression. So, we use ISMO here to substitute MSMR.

6. Finger-vein image matching

In this section, the phase-only-correlation (POC) measure proposed in [25] is simply used for handling the finger-vein image matching problem based on the Gabor-enhanced finger-vein images.

Assume that $E_a(\tilde{x})$ and $E_b(\tilde{x})$ are two Gabor-enhanced finger-vein images, and $F_a(\tilde{u})$ and $F_b(\tilde{u})$ represent their 2D DFT, respectively, according to the property of Fourier transform, we know

$$E_a(\tilde{x}) \circ E_b(\tilde{x}) = \iff F_a(\tilde{u}) F_b(\tilde{u}),$$ \hfill (18)

where “$\circ$” denotes a 2D correlation operator, and $\tilde{u}$ represents the coordinates in frequency domain. Detailed description about Eq. (18) can be found in [25,26]. Based on Eq. (18), we can compute the cross phase spectrum as

$$R(\tilde{u}) = \frac{F_a(\tilde{u}) \bar{F}_b(\tilde{u})}{\|F_a(\tilde{u})\| \|F_b(\tilde{u})\|} = e^{i \phi(\tilde{u})}.$$ \hfill (19)

Let $\psi(\tilde{x}) = \text{IDFT}(R(\tilde{u}))$, thus, $\psi(\tilde{x})$ is called a POC function. The POC function has a sharp peak when two Gabor-enhanced finger-vein images are similar, whereas it will be near zero for those from different classes, as shown in Fig. 8. Moreover, the POC function is somewhat insensitive to image shifts and noises. This is helpful for accurately measuring the similarities in finger-vein image matching.

![Fig. 8. POC function. Left: $\psi(\tilde{x})$ of two identical finger-vein images. Right: $\psi(\tilde{x})$ of two different individual finger-vein images.](image-url)
It is worth pointing out that, to robustly handle accurate image matching problem, band-limited phase-only-correlation (BLPOC) function has also been proposed in [25] and widely used for image matching in practice [26, 39, 77, 37]. Compared with POC, BLPOC is more reliable in measuring the similarities between two images. However, traditional POC is yet more convincing than BLPOC in investigating the qualities of images. This is because the matching result based on POC is more sensitive to image quality than that of BLPOC. Hence, the POC function still can be used as a simple and effective measure to objectively evaluate the performance of the proposed method in scattering removal and venous region enhancement.

7. Experiments and discussions

In this section, extensive experiments are conducted to prove the validity of the proposed method in finger-vein image restoration and venous region enhancement.

7.1. Finger-vein image database

Although many finger-vein recognition problems have been discussed in a lot of literature, the common finger-vein image database is still vacant for algorithm comparison. The finger-vein images used in our experiments are all from a homemade finger-vein image acquisition system, as shown in Fig. 1. The captured finger-vein images are 8-bit gray images with a resolution of 320 × 240, and all segmented ROIs are resized to 100 × 180 considering finger variations in profile and size. Here, a total of 100 individuals provided their vein imageries (forefinger, middle finger and ring finger) of two hands, and each finger has 15 images across three sessions. We collected five images per session with twenty-day interval between sessions. Therefore, we have built a database containing 9000 (100 × 6 × 15) finger-vein images.

7.2. Standard deviation map

This section is closely related to Section 4.1. In Section 4.1, we do not detail the parameter \( \sigma_p \) in Eq. (6). However, \( \sigma_p \) is a very important parameter in shape description of the used 2D Gaussian function \( c(x, t) \). In this section, we will give a further discussion about \( \sigma_p \) for clear understanding.

Based on the discussion in Section 3, we know that scattering is a universal physical phenomenon when light propagates inside an optical medium, such scattering effects can directly result in blurred vision. That is, for finger-vein image enhancement, scattering removal is definitely a nontrivial step in practical applications.

Unfortunately, the scattered light is weakened quickly within the human skin layer due to the high heterogeneity of the skin tissue. In the skin tissue, the scatterers are not only various but also very dense, which makes the skin medium effective on damping the scattered NIR light. Therefore, the behavior pattern of the scattered light spatially holds locality and randomness. To describe this kind of light scattering behavior, a Gaussian function \( c(x, t) \) defined by Eq. (6) is used in Eq. (5). Under the constraint \( c(x, t) \), the family of the diffused images has the capability of locally preserving the scattering pattern as well as modeling the scattering randomness in background illumination estimation procedure.

For a given finger-vein image, the statistic \( \sigma_p (p = \tilde{x}) \) related to \( \Omega(p) \) determines the variations of \( c(\tilde{x}, t) \) in shape during the diffusion process. Obviously, \( \sigma_p \) is not constant but variable since the pixels contained in \( \Omega(p) \) spatially vary with the center point \( p \) over an image. Hence, \( \sigma_p \) represents a standard deviation map (SDM) corresponding to a given finger-vein image. Moreover, the SDM varies not only with the block size of \( \Omega(p) \) but with individual finger-vein images, as shown in Fig. 9.

The SDM stays relatively stable during the anisotropic diffusion process. Due to the introduction of the gradient map \( \| \nabla I(x, t) \| \), the salient information contained in a finger-vein image also is added as a restrictive condition for constraining the diffusion evolution, which is beneficial for diversity preservation of image contents. Hence, the SDM evolves smoothly and slowly in the diffusion process, as shown in Fig. 10. Compared Fig. 10(d) with Figs. 10(a)–(c) respectively, we can clearly observe that the SDM changes very little though the diffusion step is twice more than before. This is undoubtedly desirable for \( c(\tilde{x}, t) \) to actually embody the light scattering properties in LBIM estimation. Note that, to compute the standard deviations near the image boundaries properly, the original finger-vein images are margined in advance by replicating pixels around image boundaries.

7.3. Parameter setting in scattering removal

From Section 4, we know that four parameters, \( x_1, \beta, \gamma \) and \( x_2 \), participate in the process of finger-vein image restoration. Determining the values of these parameters reasonably is therefore very important for reliable scattering removal in finger-vein images. Before value assignment for these parameters, some following coarse rules should be observed:

- \( x_1 \) should be a bigger number but less than one. Although the direction of the scattered light is highly random due to the heterogeneity of the skin tissue, the multiple scattering is dominated by near forward scattering events in biological tissue [7, 2]. So, the probability of the scattered light towards the camera is higher.

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\( b \) should also be a bigger number but less than one. In NIR spectrum, scattering is predominant over absorption [58]. The intensity of a diffused image using Eq. (5) cannot be much lower than that of the original image.

\( c \) should not be assigned a too small value. Gamma correction is a nonlinear method for image illumination adjustment [15,51]. Traditionally, the pixels will become brighter if \( c > 1 \), otherwise they are darker (\( c < 1 \)) or unchanged (\( c = 1 \)). Since the vein objects appear shadows in finger-vein images, making \( c \) less than one is beneficial to emphasize the venous regions. However, finger-vein images will be distorted apparently if the value of \( c \) is too small.

\( a_2 \) should be much smaller than \( a_1 \). The NSTM is a decaying exponential function with a maximum value of 1 at \( d(\bar{x}) = 0 \) or \( \mu(\bar{x}) = 0 \). So, the value of Eq. (11) must be less than one. Moreover, \( I_{\gamma}(\bar{x}) \) cannot be totally substituted by \( I_q(\bar{x}) \). Thus only assigning a smaller value to \( a_2 \) can make Eq. (10) desirable for approximating the denominator of Eq. (8).

In addition, \( b > a_1 > \gamma > a_2 \) is necessary for scattering removal in finger-vein images. In the transillumination manner, the captured images or observations actually represent the complex interactions between the biological tissue and the NIR light. So, for LBIM estimation, if \( b < a_1 \), the estimated background illumination will vary more locally, which is inconsistent to the

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**Fig. 9.** Standard deviation maps. (a) Two finger-vein images. (b)–(e) show SDMs when \( \Omega(p) \) is \( 9 \times 9, 13 \times 13, 17 \times 17 \) and \( 21 \times 21 \), respectively.

**Fig. 10.** Standard deviation map evolution. (a) \( t = 10 \). (b) \( t = 20 \). (c) \( t = 30 \). (d) \( t = 60 \). Here, \( \Omega(p) \) is \( 17 \times 17 \).
light scattering properties in biological tissue. From Eq. (10), we can clearly see that $a_1$ must be bigger than $a_2$ in order to suffice the approximate equation, and only when $\gamma$ is also bigger than $a_2$, we can ensure that the NSTM is estimated properly. However, if $\gamma$ is too small (close to 0), then $\tilde{I}_f(x)$ must be distorted greatly. Hence, among these four parameters, $\beta$ should be the biggest, $a_2$ should be the smallest, and $a_1$ and $\gamma$ are two middle terms for $a_1 > \gamma$.

From Eq. (7), we can see that only some diffused pixels whose values are bigger than their observations are controlled by the parameter $\beta$. In order not to affect the diffusion state, the value of $\beta$ should be as large as possible while $\beta < 1$ holds. The parameter $a_1$ is used to indicate a probability of forward scattering events, so assigning a big value less than one to $a_1$ is rational for forward scattering probability description. Different from $\beta$ and $a_1$ which related to the scattering phenomenon, $\gamma$ and $a_2$ are used to estimate the difference between $I_0(x)$ and $I_f(x)$ such that making $\gamma > a_2$ is beneficial for NSTM estimation without image distortion due to Gamma correction. Furthermore, the size of $\Omega(p)$ is an important parameter in finger-vein image restoration, since the SDM varies with $\Omega(p)$, as shown in Fig. 9.

Thus, it is clear that $a_1$, $\beta$, $\gamma$, $a_2$ and $\Omega(p)$ are jointly contributive to scattering removal in the real situation. Considering the above discussion, let $\beta = 0.995$, $a_1 = 0.98$, $\gamma = 0.6$, $a_2 = 0.5$, then some image restoration results are listed in Fig. 11, where the sizes of $\Omega(p)$ vary from $9 \times 9$ to $21 \times 21$ with step 4. From Fig. 11, we can observe that the multiple scattering effects can be removed effectively from finger-vein images, and the noises from restoration procedure decrease with the increase of $\Omega(p)$ in size. Considering the trade-off between scattering removal and computing cost, $\Omega(p)$ is set to a $17 \times 17$ block in our application.

7.4. Parameter setting in Gabor wavelets

The optimal Gabor response to a specific image processing requirement is directly determined by the values of Gabor parameters. Although the Gabor functions are widely used in various image analysis tasks, different tasks need different Gabor parameter settings. For finger-vein image processing, the Gabor parameters should be set properly to make the proposed ISMO work effectively in venous region enhancement and suppress the unwanted information (i.e., false veins and noises).

Here, we first determine the value of the initial frequency $\omega_1$ of a Gabor wavelet family. From Eq. (13), we can see that the standard deviation of the 2D Gaussian envelop is determined by

$$\sigma_m = \frac{\nu}{\omega_m}.$$  

![Fig. 11. Finger-vein image restoration. (a) Original finger-vein images. (b)–(e) show the restored results when $\Omega(p)$ is $9 \times 9$, $13 \times 13$, $17 \times 17$ and $21 \times 21$, respectively. Here, $\beta = 0.995$, $a_1 = 0.98$, $\gamma = 0.6$ and $a_2 = 0.5$.](image-url)
\( \sigma_m \) represents one spatial scale of a Gabor wavelet, which determines the size of the receptive field of a neuron \([22,20]\). If a spatial stimulus is close to the receptive field in size, a visual cell will have an optimal response compatible to the stimulus \([42]\). In finger-vein images, the stimuli are veins, so \( \sigma_m \) should match the diameters of veins. Besides, the half-amplitude frequency bandwidth \( \Delta \phi \) is also an important factor in governing the response of the 2D Gabor function. Neurophysiological research reveals that most visual cells have the values of \( \Delta \phi \) between 1 and 1.5 octaves in macaque V1 \([12,40]\). However, for a given task in computer vision, \( \Delta \phi \) is usually constant.

In our previous works \([72,67]\), we found that the Gabor function performed well in finger-vein feature exploitation when \( \Delta \phi = 1.2 \) octaves and \( \sigma_1 = 8 \) pixel-widths. This is because the resolution of the used image sensor is 320 \( \times \) 240 in our image acquisition device and the segmented ROI is 100 \( \times \) 180. So, for the finger-vein images captured by our imaging device, the widths of veins were all less than 8 pixel-width. Let \( \Delta \phi = 1.2 \) and \( \sigma_1 = 8 \), then we can obtain

\[
\omega_1 = \frac{\sqrt{2 \ln 2}}{\sigma_1} \left( \frac{2^\Delta \phi + 1}{2^\Delta \phi - 1} \right) = 0.3741.
\]

Based on Eq. (14), we can iteratively compute the center frequencies for the rest of the Gabor family members.

Then, the numbers of \( M \) and \( N \) should be set properly for generating a desirable family of Gabor wavelets in venous region enhancement. The proposed ISMO can perform well in mutual inhibition of SELs and InLs for \( M = 3 \), as shown in Fig. 12, which benefits false vein suppression, but not well in ridge enhancement and noise reduction if the orientation number \( N \) is selected improperly. This is due to the fact that the anisotropy of the Gabor wavelet family varies with the orientation number \( N \), as shown in Fig. 13. In order to find the optimal \( N \), a lighting image with high quality is used for testing since the lightning ridges are similar to the finger-vein ridges in shape and orientation, as shown in Fig. 14(a). Let \( N = 4, 6, 8, \) and 10, the enhancement results by ISMO are illustrated in Figs. 14(b)–(e), respectively. By visual comparison, we can see that Fig. 14(c), that is \( N = 6 \), seems best in lightning ridge representation, but the Gabor wavelet family corresponding to Fig. 14(c) cannot deal with the noises effectively, as shown in the middle row of Fig. 15. Compared with the middle row, the bottom row of Fig. 15 is better in suppressing Gaussian, speckle, salt and pepper and poisson noises, that is, the Gabor wavelet family with 8 orientations works better in noise reduction than that with 6 orientations. This does not mean that increasing the orientation number \( N \) can improve the ridge representation, as shown in Fig. 14(e), where the ridge distortion becomes noticeable when \( N \) is up to 10.

Furthermore, Fig. 14 also clearly illustrates that no false ridges are created by ISMO. This shows that ISMO is loyal to the original ridge information. Hence, considering the trade-off between unwanted information suppression and ridge information representation, a Gabor wavelet family with \( \Delta \phi = 1.2, \sigma_1 = 8, M = 3 \) and \( N = 8 \) should be optimal for venous region enhancement in finger-vein images.

7.5. Comparisons on enhancement methods

For finger-vein image processing the current methods can be categorized into two main groups: image restoration and image enhancement. Here, the proposed method is compared with several common approaches in these two aspects. For finger-vein image restoration, PSF-based and dehazing-based methods are often used to deblur finger-vein images considering light scattering. These two methods pay different attentions to image degradation. In terms of light transporting in...
biological tissue, the former regards the finger-vein imaging system as a shift-invariant linear system, which describes the macro-optical properties of the biological tissue, whereas the later mainly focuses on the propagating behaviors of photons within the tissue, which describes the micro-optical properties of the biological tissue.

Some restored results are illustrated in Fig. 16, where the used original images are shown in Fig. 11(a). PSF-based restoration results are listed in Figs. 16(a) and (b), and dehazing-based restoration results are listed in Figs. 16(c)–(e). Although Fig. 16(b) performs better than Fig. 16(a) in image restoration, vein information loss and scattering residue in Fig. 16(b) are still more apparent compared with Fig. 16(e). Moreover, the traditional dehazing method shown in Fig. 16(c) and the improved dehazing method shown in Fig. 16(d) are also unsatisfying in scattering removal despite a little achievement on contrast improvement. Hence, the proposed method is more desirable than these current methods in terms of scattering removal and vein information preservation.

**Fig. 13.** Gabor wavelet families. (a)–(d) show Gabor wavelet families with $M = 3$, and $N = 4, 6, 8$ and 10, respectively. Here, $\Delta \phi = 1.2$ and $\omega_1 = 0.3741$.

**Fig. 14.** Ridge enhancement. (a) A lightning image. (b)–(e) show enhancement results using the proposed ISMO with different Gabor families that respectively correspond to Figs. 13(a)–(d).

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Fig. 15. Noise suppression. (a)–(d) illustrate the enhancement results using the proposed ISMO for Gaussian, speckle, salt & pepper and poisson noises, respectively, where noises are added up to 20% respectively in (a), (b) and (c). The middle and bottom rows respectively correspond to two Gabor wavelet families with six and eight orientations at three scales.

Fig. 16. Image restoration comparison. (a) PSF-based method using a single skin layer [32,34]. (b) PSF-based method using multiple skin layers [63]. (c) A dehazing method [27]. (d) An improved dehazing-based method [62,69]. (e) The proposed method, WBOM + ADAGC.

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Fig. 17. Histogram-based method comparison. (a) Gray-level-grouping (GLG) method [5]. (b) Morphological based histogram equalization [9]. (c) Histogram template equalization (HTE) [60]. (d) Histogram transformation based on local standard deviation [4].

Fig. 18. Venous region enhancement comparison. (a) Circular Gabor-based method [70]. (b) Hessian-based method [16, 56]. (c) Single-scale Gabor-based method [71]. (d) Nonsubsampled directional-based method [65]. (e) The proposed ISMO method.
For finger-vein image enhancement, histogram-based and filtering-based methods are often used in practice. Histogram-based methods are widely used in image processing for image quality improvement. For finger-vein images, filtering-based methods usually works better than histogram-based methods in venous region enhancement because the finger-veins have their own special texture, and the filtering-based methods are more flexible to adapt to this specific texture. This cannot be achieved desirably by histogram modification. Fig. 17 illustrates some results enhanced by four classical histogram-based methods, which shows that the enhanced finger-vein images are still considerably undesirable for further vein feature analysis.

Certainly, the directional filtering techniques are more advisable for vein ridge enhancement because the vein courses randomly vary in orientation. Fig. 18 illustrates some vein ridge enhanced results, where the used finger-vein images are the restored versions shown in Fig. 16(e). From Fig. 18, we can clearly see that the circular Gabor-based method shown in Fig. 18(a), and the Hessian-based method shown in Fig. 18(b) are not well practicable in vein ridge enhancement as well as noise suppression. Moreover, if the family of Gabor wavelets is not designed properly, the enhanced results are still undesirable, as shown in Fig. 18(c), where many false veins are generated due to the effects of SELs and InLs.

For more reliable vein ridge representation, we proposed an improved vein ridge enhancement method in [65] based on the combination of the nonsubsampled directional decomposition and the Hessian-based filtering, as shown in Fig. 18(d). However, we can also clearly see from Fig. 18(d) that not only the vein shapes but also some thin veins cannot be described undistortedly and effectively though the veins are represented smoothly and noises are suppressed successfully. Compared with Fig. 18(d), Fig. 18(e) is more convincing in real finger-vein network representation, and the vein-depth variations are also presented clearly, which is more true in describing the spatial distributions of vein networks in fingers. Hence, Fig. 18(e) is preferable to Fig. 18(d) in vein ridge enhancement.

The proposed algorithm is implemented using MATLAB R2010a on a standard desktop PC which is equipped with a Core i5-2400 CPU 3.10 GHz and 2.99 GB memory. For each step of processing a finger-vein image, the running time is listed in Table 1. We can clearly see from Table 1 that LBIM estimation step costs more time compared with the subsequent steps. So, if a fast method is used to well estimate LBIM, the total time cost can be saved greatly. Certainly, algorithm implementation in C++ can further increase the computation speed.

### 7.6. Finger-vein image matching test

In this section, the finger-vein image matching test is implemented for giving a more accurate evaluation of the proposed method’s performance. In our previous works [75,72], we found that the finger-vein images from different fingers could be viewed as from different individuals because each finger is sufficient for personal identification. Therefore, the database is expanded to 600 subjects and 15 finger-vein images per subject. For finger-vein matching on this database, the number of genuine attempts is 63,000 (600C₁⁵), and the number of imposter attempts is 40,432,500 (15 × 5C₁⁵).

The original images are first processed by respectively using the methods in Figs. 16 and 18. Then the phase-only-correlation (POC) function is used for measuring the finger-vein image matching scores. Based on the matching scores, the false non-match rates (FNMRs) and the false match rates (FMRs) are computed at different thresholds. Thus, we can obtain different receiver operating characteristic (ROC) curves corresponding to different methods in Figs. 16 and 18. Note that the histogram-based methods shown in Fig. 17 are not used in finger-vein image matching due to their bad performance on finger-vein image enhancement.

The ROC curves corresponding to the methods in Figs. 16 and 18 are respectively shown in Figs. 19 and 20, where EERs (equal error rates) are the error rates when FNMRs and FMRs are equal. From Fig. 19, we can clearly see that the restored finger-vein images using the proposed method have the best performance of ROC curves and obtain the lowest EER. This indicates that the randomness and uniqueness of finger-vein networks can be effectively represented by the proposed finger-vein image restoration method. Hence, based on the restored finger-vein images, effectively strengthening the randomness and uniqueness of the vein networks is undoubtedly very important for further improving the accuracy of finger-vein recognition. In this aspect, the proposed ISMO performs well, as shown in Fig. 18. Also, from Fig. 20, we can clearly observe that the EER of the ISMO method is the lowest. Moreover, the finger-vein images after ISMO also provide a better ROC curve than the restored images based on WBOM plus ADAGC. This shows that the uniqueness of finger-vein features can be represented reliably and effectively using the proposed algorithm.

Table 2 shows the ERRs under the POC measure for performance comparison of the aforementioned methods. Besides the proposed method that can contribute the lowest ERRs in image restoration and segmentation, dehazing based methods are more suitable than PSF based methods in finger-vein restoration, and Gabor based methods are superior to the other directional filter methods in finger-vein enhancement.
8. Conclusion

In this paper, we have addressed some important problems in finger-vein image restoration and enhancement. First, based on the optical properties of the biological tissues, we proposed a weighted biological optical model for describing the degradation of finger-vein images. Second, a new anisotropic diffusion method with standard deviation map constraint was proposed to estimate the local background illumination maps in a backward way. Third, the non-scatter transmission maps were estimated in a forward way based on the observations with the help of Gamma correction. Fourth, we proposed a new method to facilitate the Gabor wavelet family design. Based on this method, a family of even Gabor wavelets with minimum redundancy could be created automatically. Finally, an inter-scale multiplication operation was proposed for venous region enhancement as well as unwanted information suppression. Extensive experimental results on a large finger-vein image database showed that the proposed algorithm was effective and reliable in finger-vein restoration and enhancement.

However, the real imaging process in transillumination manner actually is blind for us except the image observation, although the theory of tissue optics has been established long before. Simply based on the image observation, it is impossible to restore the original information completely. The way out of the problem is to estimate the original images by the observations as reasonably as possible, where the proposed method gives a meaningful attempt towards the ultimate solution.

Table 2
Equal Error Rates of different methods using the POC measure.

<table>
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<th>Image enhancement EERs</th>
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Fig. 19. ROC curves of different finger-vein restoration results.

Fig. 20. ROC curves of different finger-vein enhancement results.

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References


