Visibility Restoration via Smoothing Speed for Vein Recognition*

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SUMMARY A novel image enhancement method for vein recognition is introduced. Inspired by observation that the intensity of the vein vessel changes rapidly during the smoothing process compared to that of background, the value of a pixel changes with a speed, which is inversely proportional to the size of the region it belongs to, during the smoothing process. Yang and Yang [3] proposed to adopt the multi-channel Gabor filters to efficiently highlight blood vessels. They employed a set of center frequencies with multiple orientations and scales to accurately preserve the detailed shape of vein patterns. Due to its promising results, Gabor filter-based preprocessing schemes have been popularly utilized [4], [5] for vein recognition. However, filtering outputs often dilute the nonlinearity of vein structures, which results in the performance drop of vein recognition. On the other hand, authors of [6] proposed to employ the concept of dehazing, which aims at removing the scattered airlight from foggy images, for vein image enhancement. They demonstrate that reducing the scattered radiance generated by the skin tissue provides the clear vein structures similar to the dehazing effect.

In this letter, a novel method for improving the quality of vein images is proposed. The key idea of the proposed method is to highlight the vein structure via a smoothing-speed weight. Since vein shapes are generally thin and long, the pixel intensity in the vein region changes fast during the smoothing process while that of background (i.e., skin tissue) stays consistently. Therefore, the intensity difference between the original image and its smoothed version, so-called smoothing speed, can be adopted to distinguish vein regions from their surroundings. Based on this, the proposed smoothing speed is finally applied to the original image as a restoration weight for efficiently emphasizing vein regions. To confirm the performance improvement in terms of the proposed enhancement method, the local binary pattern (LBP)-based template matching scheme [7] is adopted as the baseline algorithm, which has been popularly employed for vein recognition [4], [8].

2. Proposed Method

The rationale behind the proposed method is that the value of a pixel changes with a speed, which is inversely proportional to the size of the region it belongs to, during the smoothing process. Since blood vessels yield the small scale space due to their thin and elongated shapes while background tissues are generally flat (i.e., large scale space), the noticeable difference between two regions can be efficiently captured in the scale space. From this point of view, the image smoothing is firstly conducted by utilizing the nonlinear diffusion technique formulated as follows [10]:

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where $I$ denotes the input image and $k$ indicates the iteration index. To preserve the underlying structure of the input image (e.g., edges and corners) during the smoothing process, we propose to adopt the total variation flow for the diffusivity function $g(\cdot)$, which is defined as $g(z) = 1/(z + \xi)$ [11]. According to the property of the total variation flow, small-scale components diffuse fast while pixels belonging to a flat region (i.e., large-scale space) change slowly. Therefore, it is thought that the smoothing speed of each pixel can be easily estimated by computing the difference between the pixel value of the original image and its smoothed version. Specifically, the smoothing speed at each pixel position $(x, y)$ can be simply defined as follows:

$$
s(x, y) = |u^k(x, y) - u^0(x, y)|,
$$

where $M$ denotes the total number of iterations for smoothing, which is adaptively determined according to the difference between smoothing spaces, i.e., $d = (\sum_{x,y} |u^k(x,y) - u^{k-1}(x,y)|)/N$ where $N$ is the total number of pixels. In our implementation, diffusion is stopped when the condition $d < 1.0$ is satisfied. Some examples of the smoothing speed map are shown in Fig. 1. As can be seen, blood vessels yield the large value of the smoothing speed compared to background in various vein images.

In the following, the proposed smoothing speed is subsequently applied to the original image as a weight value for accurately highlighting the vein region, which is formulated as

$$
\tilde{I}(x, y) = \frac{1}{s(x,y) + \tau} I(x, y),
$$

where $\tau$ is a positive number and it controls the effect of the smoothing speed to the final representation $\tilde{I}$. Since pixels belonging to vein regions have large values of $s(x, y)$ in (2), the weight term makes them more darker while those in background have mostly small $s(x, y)$ values (around zero), which forces pixels maintaining the original brightness. Therefore, it is thought that the proposed weight is effective to efficiently improve the contrast between vein regions and background. It should be emphasized that this control term $\tau$ also has an ability to relax corruption of textures, which enables to efficiently preserve the meaningful textural information of vein images. It is noteworthy that the larger $\tau$ tends to dilute the effect of the smoothing speed, thus the textures of the original image are revealed more strongly in the final representation. Results of the vein enhancement according to various $\tau$ values are shown in Fig. 2. It is easy to see that vein patterns are successfully revealed by the proposed method and the larger $\tau$ value allows more textures of the original image to be involved into the enhanced result as mentioned. Note that the value of $\tau$ is set based on extensive experiments explained in the next section.

For efficient implementation, the additive operator splitting (AOS) [12] scheme is adopted for solving (1) in the proposed method, which is defined in a semi-implicit manner and formulated as follows:

$$
u^{k+1} = 0.5((I - 2\Delta t \cdot D_x(u^k))^{-1} + (I - 2\Delta t \cdot D_y(u^k))^{-1})u^k,
$$

where $D_x$ and $D_y$ are the diffusion matrices for horizontal and vertical directions, respectively (for more details, see [12]). The $\Delta t$ denotes the time step. It is noteworthy that the time step can be set to be arbitrarily large (e.g., $\Delta t = 10$) since the AOS scheme guarantees the stability regardless of the size of the time step. Therefore, it efficiently improves the processing speed compared to the conventional Euler-based scheme while maintaining the edge-aware characteristic. The enhanced vein images by the proposed method are subsequently input to the recognition framework, which is constructed based on the local textural patterns. The detailed procedure will be explained in the following section.

### 3. Experimental Results

In this section, the proposed enhancement method has been tested based on the CASIA multispectral palm vein database [13], which is most popularly employed for the performance evaluation of palm vein recognition. Specifically, the CASIA multispectral palm vein database is composed of total 7,200 images obtained from 100 people. Each person test 36 times for each hand with six wavelength illuminators, i.e., 460nm, 630nm, 700nm, 850nm, 940nm, and white.
light, respectively. Since the vein is apt to absorb the long-wavelength illuminations, sample images captured with the 940nm illuminator are generally used for the performance evaluation of vein recognition. As a basic recognizer, the local binary pattern (LBP)-based method [4], [8] is adopted for our experiments as mentioned, which first extracts the region of interest (ROI) whose size is 180 × 180 pixels as shown in Fig. 3 and computes features in each sub-region of ROI. After that, concatenated features are finally fed into the similarity metric. To demonstrate the efficiency of the proposed method in a qualitative manner, we compare ours with other representative enhancement methods, which are CLAHE [1], M-Gabor [3], and dehazing [6]. Some examples of enhancement results in terms of each method are shown in Fig. 3. Even though previous methods are effective in revealing blood vessels compared to the original image, they amplify the background noise as well (see cyan rectangles and their enlarged versions in the bottom part of Fig. 3). In contrast to that, the proposed method successfully highlights the vein regions without yielding unnecessary patterns in tissue regions.

To analyze the effect of the vein enhancement in a quantitative manner, the performance improvement by each enhancement method is evaluated based on ROC curves (i.e., accuracy @ false acceptance rate (FAR)) and corresponding results are shown in Fig. 4. To do this, images of the left hand are employed. For enrollment, the third sample among six 940nm-wavelength images of the left hand is used. Then, matching scores for 500 true pairs (i.e., five trial images × 100 people) and 59,400 false pairs (i.e., six trial images × 100 people × 99 enrollment images) are computed. Note that six trial images are used for the case of false matchings while five trial ones are employed for true matchings (one is dedicated for enrollment). The histogram intersection is employed for computing the similarity score between two feature vectors generated by LBP descriptors as introduced in [4], [8]. As can be seen, the proposed method efficiently improves the performance of vein recognition compared to other previous approaches. Note that the relaxation parameter $\tau$ used in (3) is set to 1.0 based on the experiment for analyzing the performance variation according to different $\tau$ values as shown in Table 1. Table 2 shows the performance improvement at the level of FAR = $10^{-4}$ (i.e., 0.01%) achieved by each enhancement scheme. The processing speed of the proposed method is about 8 fps averaged on 6,000 images, which is evaluated based on a single PC (Intel i7 2.5 GHz CPU and 64 GB RAM without parallel processing). From various experimental results, it is thought that the proposed method is helpful for improving the reliability of vein-based authentication systems.

### 4. Conclusion

In this Letter, a novel image enhancement method for vein recognition has been proposed. The key idea of the proposed method is to apply the smoothing speed as a weight...
for visibility restoration, which is relatively fast in the vein region due to its thin and long shape. The relaxation factor is also adopted to consider the textural information for the final representation. Based on various experimental results, it is confirmed that the smoothing speed-based enhancement successfully leads to the performance improvement for vein recognition.

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