Comparative Studies on Multispectral Palm Image Fusion for Biometrics

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Abstract. Hand biometrics, including fingerprint, palmprint, hand geometry and hand vein pattern, have obtained extensive attention in recent years. Physiologically, skin is a complex multi-layered tissue consisting of various types of components. Optical research suggests that different components appear when the skin is illuminated with light sources of different wavelengths. This motivates us to extend the capability of camera by integrating information from multispectral palm images to a composite representation that conveys richer and denser pattern for recognition. Besides, usability and security of the whole system might be boosted at the same time. In this paper, comparative study of several pixel level multispectral palm image fusion approaches is conducted and several well-established criteria are utilized as objective fusion quality evaluation measure. Among others, Curvelet transform is found to perform best in preserving discriminative patterns from multispectral palm images.

1 Introduction

Hand, as a tool for human to percept and reconstruct surrounding environment, is most used among body parts in our daily life. Due to its high acceptance by the human beings, its prevalence in the field of biometrics is no surprising. Fingerprint[1], hand geometry[2], palmprint[7][8], palm-dorsa vein pattern[3], finger vein[4] and palm vein[5] are all good examples of hand biometric patterns. These modalities have been explored by earlier researchers and can be divided into three categories:

- Skin surface based modality. Examples are fingerprint and palmprint. Both traits explore information from the surface of skin and have received extensive attention. Both of them are recognized as having the potential of being used in highly security scenario;
- Internal structure based modality, which extracts information from vein structure deep under the surface for recognition. Although new in biometric family, the high constancy and uniqueness of vein structure make this category more and more active nowadays[3][9];
- Global structure based modality. The only example of this category is hand geometry. Hand geometry is a good choice for small scale applications thanks to its high performance-price ratio.

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No matter which category of modality one chooses to work on, a closer look on the skin appearance benefits. Physiologically, human skin consists of many components, such as Cells, fibers, veins and nerves, and they give skin a multi-layered structure. At the outermost layer, numerous fine furrows, hair and pores are scattered over the surface of skin, while veins, capillaries and nerves form a vast network inside[6]. Optical study has demonstrated that light with longer wavelength tends to penetrate the skin more deeply, for example, near infrared light from 600nm to 1000nm typically penetrates the skin to about 1-3 mm. Therefore different visual contents, with different optical properties, are detected with incident light of different wavelengths[11]. The uniqueness of human skin, including its micro, meso and macro structures, is a product of random factors during embryonic development. Enlighten by the success and fast development of above mentioned hand based biometrics, each of them reflecting only one aspect of hand, we believe that best potential of biometric feature in the hand region is yet to be discovered.

The purpose of this work is to exploit the correlative and complementary nature of multispectral hand images for image enhancement, filtering and fusion. Take palmprint and vein for example, the common characteristics of two modalities is that they both utilize moderate resolution hand imagery and they share similar discriminative information: line-like pattern. On the other hand, the intrinsic physiological nature makes the two traits holding distinctive advantages and disadvantages. More precisely speaking, palmprint is related to outermost skin pattern, therefore, its appearance is sensitive to illumination condition, aging, skin disease and abrasion etc. In contrast, hand vein pattern, as an interior structure, is robust to the above mentioned external factors. However, vein image quality varies dramatically across the population and in case of blood vessel constriction resulting from extremely cold weather. Several advantages can be obtained by fusing the two spectral hand images. First of all, a more user-friendly system can be developed by alternatively combining the two traits or choosing the appropriate one for recognition according to corresponding imaging quality; secondly, forgery is much more difficult for such an intelligent system and hence the system is more secure; and finally, the recognition performance might be boosted.

In this work, we designed a device to automatically and periodically capture visible and near infrared spectral images. Two sets of lights are turned on in turn so that palmprint and vein images are captured. With the images at hand, we validated the idea of image fusion. Several pixel level image fusion approaches are performed to combine the original images to a composite one, which is expected to convey more information than its inputs.

The rest of this paper is organized as follows. The hardware design of image capture device is presented in Section 2, followed by a brief introduction of the four methods in Section 3. The proposed fusion scheme is introduced in Section 4 and Section 5 includes experimental results as well as performance evaluation. Finally, conclusion and discussion are presented in Section 6.

2 Hardware Design

Fig. 1 illustrates the principal design of the device we developed to capture images in both visible (400-700nm) and near infrared (800-1000nm) spectra. The device works under a sheltered environment and the light sources are carefully arranged so that the palm region is evenly illuminated. An infrared sensitive CCD camera is fixed at the bottom of the inner encloser and connected to a computer via USB interface. An integrated circuit plate is mounted near the camera for illumination and different combinations of light wavelengths can be accomplished by replacing the circuit plate. By default, the two sets of lights are turned on in turn so that only expected layer of hand appears to camera. When illuminated with visible light, image of hand skin surface, namely, the palmprint is stored. while when NIR light is on, deeper structure as well as parts of dominant surface features, for example the principal lines, are captured. Manual control of the two lights is also allowed by sending computer instruction to the device. A pair of images captured using the device is shown in Fig. 2(a)-(b), where (a) is palmprint image and (b) is vein image. It is obvious that the two images emphasize on quite different components of hand.

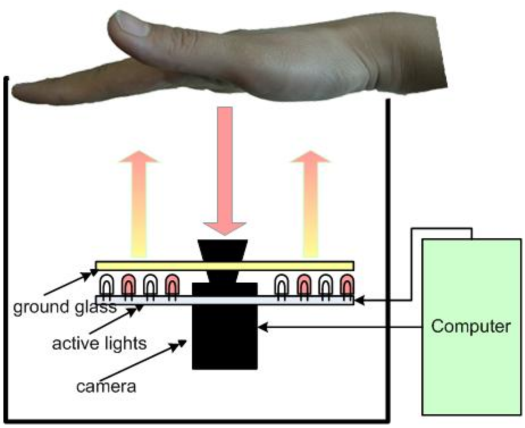


Fig. 1. Multispectral palm image capture device, where LEDs of two wavelengths is controlled by computer

3 Image Fusion and Multiscale Decomposition

The concept of image fusion refers to the idea of integrating information from different images for better visual or computational perception. Image fusion sometimes refers to pixel-level fusion, while a broad sense definition also includes feature-level and matching score level fusion. In this work, we focus on pixel level fusion because it features minimum information loss.

The key issue in image fusion is to faithfully preserve important information while suppress noises. Discriminative information in palmprint and vein, or more specifically principal lines, wrinkle lines, ridges and blood vessels, all takes form of line-like patterns. Therefore, the essential goal is to maximally preserve these patterns.

In the field of pixel-level fusion, multiscale decomposition (MSD), such as pyramid decomposition and wavelet decomposition, is often applied because it typically provides better spatial and spectral localization of image information and such decorrelation between pyramid subbands allows for a more reliable feature selection[19]. The methods utilized in this paper also follow this direction of research, while evaluation measures are applied to feature level representation rather than intensity level to accommodate the context of biometrics. We selected four multiscale decomposition methods for comparison.

Gradient pyramid can obtained by applying four directional gradient operators to each level of Gaussian pyramid. The four operators correspond to horizontal, vertical and two diagonal directions respectively. Therefore, image features are indexed according to their orientations and scales.

Morphological pyramid can be constructed by successive procedure of morphological filtering and sub-sampling. Morphological filters, such as open and close are designed to preserve edges and shapes of objects, which make this approach suitable for the task presented here.

Shift invariant digital wavelet transform is a method proposed to overcome the wavy effect normally observed in traditional wavelet transform based fusion. It is accomplished by an over-complete version of wavelet basis and the downsampling process is taken place by dilated analysis filters. In our implementation, Haar wavelet is chosen and decomposition level for the above mentioned three methods is three.

Curvelet transform is a bit more complex multiscale transform[12][13][15][14] and is designed to efficiently represent edges and other singularities along curves. Unlike wavelet transform, it has directional parameters and its coefficients have a high degree of directional specificity. Therefore, large coefficients in transform space suggests strong lines on original image.

These methods are not new in the field of image fusion[16][17][18][19][21], . However, earlier researchers either focus on remote sensing applications, which involves tradeoff between spectral and spatial resolution, or pursue general purpose image fusion scheme. This work is the one of the first applications that adopt and compared them in the context of hand based biometrics.

4 Proposed Fusion Method

Our fusion method is composed of two steps, namely, a preprocessing step to adjust dynamic ranges and remove noises from vein images and a fusion step to combine information from visible image and infrared image.

4.1 Preprocessing

When illuminated with visible light, images of skin fine structures are captured. Contrast to the behavior in visible wavelength, cameras usually have a much lower sensitivity to infrared lights. Therefore, cameras tend to work at a low luminance circumstance and AGC(Auto Gain Control) feature takes effect to maintain the output level. This procedure amplifies the signal and noises at the same time, producing noisy IR images.

The first stage of preprocessing is to distinguish between the two spectra. The relative large difference between camera responses to the two wavelengths makes NIR images constantly darker than visible image, in consequence the separation is accomplished simply via an average intensity comparison.

Followed is a normalization step to modify the dynamic range of vein image so that the mean and standard deviation of vein image equals to that of the palmprint image. The underlying reason is that equal dynamic range across source images helps to produce comparable coefficients in transform domain.

Finally, bilateral filtering is undertaken to eliminate noises from infrared images. Bilateral filtering is a non-iterative scheme for edge-preserving smoothing [10]. The response at x is defined as an weighted average of similar and nearby pixels, where the weighting function corresponds to a range filter while the domain component closely related to a similarity function between current pixel x and its neighbors. Therefore, desired behavior is achieved both in smooth regions and boundaries.

4.2 Fusion Scheme

According to the generic framework proposed by Zhang et. al.[19], image fusion schemes are composed of (a) Multiscale decomposition, which maps source intensity images to more efficient representations; (b) Activity measurement that determines the quality of each input; (c) Coefficient grouping method to determine whether or not cross scale correlation is considered; (d) Coefficient combining method where a weighted sum of source representations is calculated and finally (e) Consistency verification to ensure neighboring coefficients are calculated in similar manner. As a domain specific fusion scheme, the methods applied in this work can be regarded as examples of this framework.

For each of the multiscale decomposition methods mentioned in Section 3, the following scheme is applied:

Activity measure - A coefficient-based activity measure is applied to each coefficient, which means that the absolute value of each coefficient is regarded as the activity measure of corresponding scale, position and sometimes orientation;

Coefficient combining method - Generally speaking, no matter what kind of linear combination of coefficient is adopted, the basic calculation is weighted sum. We utilized the popular scheme proposed by Burt[20] to high frequency coefficient and average to base band approximation.

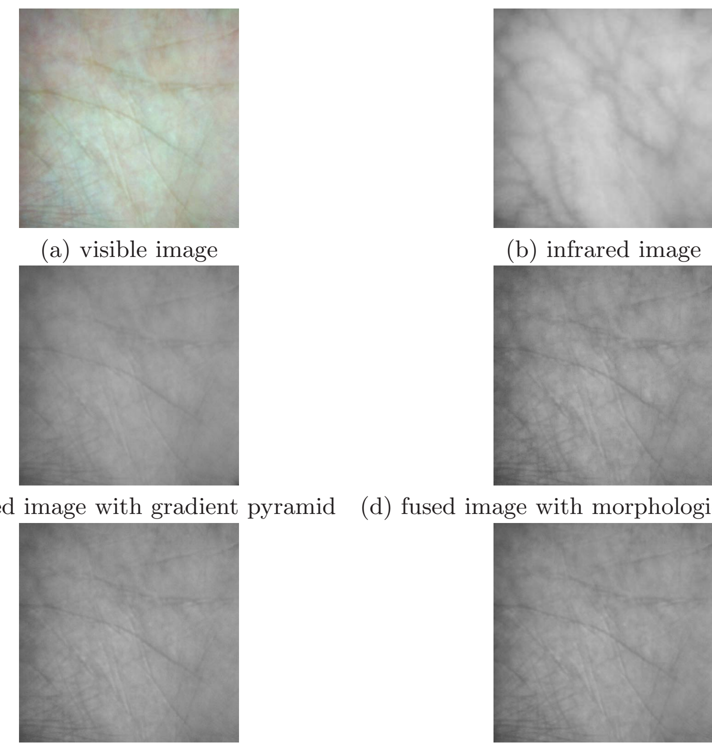
Consistency verification - Consistency verification is conducted in a blockwise fashion and majority filter is applied in local window of 3 by 3 in case that choose max operation is taken in coefficient combination.

5 Experimental Results

To evaluate the proposed fusion scheme, we collected a database from 7 subjects. Three pairs of images are captured for both hands, producing a total number of 84 images.

5.1 Subjective Fusion Quality Evaluation

The proposed scheme is applied to each pair of visible and NIR images and the resulting fused images by the four decomposition methods are subjectively examined. Fig. 2 demonstrates such an example. Morphological pyramid, although produces most obvious vein pattern on fused images, sometimes introduced artifacts. Other three methods seem to perform similarly to human eyes, thus objective fusion quality evaluation is necessary for more detailed comparison.



(a) visible image

(b) infrared image

(c) fused image with gradient pyramid

(d) fused image with morphological pyramid

(e) fused image with shift-invariant DWT

(f) fused image with Curvelet transform

Fig. 2. Palmprint and vein pattern images captured using the self-designed device as well as the fused images

5.2 Objective Fusion Quality Evaluation

Many fusion quality evaluation measures have been proposed[22][23] and we choose four of them for our application.

Root Mean Square Error(RMSE) between input image A and fused image F is originally defined in Eq. 1.

$$RMSE_{AF} = \sqrt{\frac{\sum_{i=1}^{N}\sum_{j=1}^{N}[A(i,j)-F(i,j)]^2}{N^2}} \tag{1}$$

Mutual information(MI) statistically tells how much information fused image F tells about the input image A. Suppose that $p_A(x)$, $p_F(y)$ and $p_{AF}(x,y)$ denote marginal distribution from A, F and joint distribution between A and F respectively. Mutual information between A and F is defined as Eq. 2.

$$MI_{AF} = \sum_x \sum_y p_{AF}(x,y) log \frac{p_{AF}(x,y)}{p_A(x)p_F(y)} \tag{2}$$

Universal image quality index(UIQI) was proposed to evaluate the similarity between two images, and is defined in Eq. 3. The three components of UIQI denote correlation coefficient, closeness of mean luminance and contrast similarity of two images or image blocks A and F respectively.

$$UIQI_{AF} = \frac{\sigma_{AF}}{\sigma_A\sigma_F} \cdot \frac{2\mu_A\mu_F}{\mu_A^2+\mu_F^2} \cdot \frac{2\sigma_A\sigma_F}{\sigma_A^2+\sigma_F^2} = \frac{4\sigma_{AF}\mu_A\mu_F}{(\mu_A^2+\mu_F^2)\cdot(\sigma_A^2+\sigma_F^2)} \tag{3}$$

The above mentioned general purpose criteria are usually applied to intensity image. However, in order to predict the performance of proposed method in the context of biometrics, we apply these measures to feature level representation. In the field of palmprint recognition, the best algorithms reported in literature are those based on binary textual features[7][8]. These methods seek to represent line-like patterns and have been proved to be capable of establishing stable and powerful representation for palmprint. We utilized a multiscale version of *Orthogonal Line Ordinal Feature* (OLOF) to fused image as well as palmprint image for feature level representation and the average results on collected database are shown in Table 1. Textural features are not suitable for vein image due to the sparse nature of true features and widespread of false features. From Table 1, we can obviously find that Curvelet transform based method outperforms other methods in that it maintains most information available in palmprint. The disadvantage of Curvelet transform is that it takes much longer time in calculating coefficients.

We also adopted average local entropy to estimate the information gain from palmprint to fused image and the result is shown in Fig. 3. Curvelet transform based approach is the only one which conveys more information than the original palmprint representation. Thus we can safely draw the conclusion that Curvelet transform based method results in richer representation and is more faithful to source representations. The superior performance of Curvelet transform mainly

Table 1. Objective Fusion Quality Evaluation

	$RMSE_F^{Palm}$	MI_F^{Palm}	$UIQI_F^{Palm}$	Time Consumption(s)
Gradient Pyramid	0.4194	0.3300	0.5880	**0.5742**
Morphological Pyramid	0.4539	0.2672	0.4800	1.2895
Shift-Invariant DWT	0.4313	0.3083	0.5583	1.9371
Curvelet Transform	**0.3773**	**0.4102**	**0.7351**	18.6979

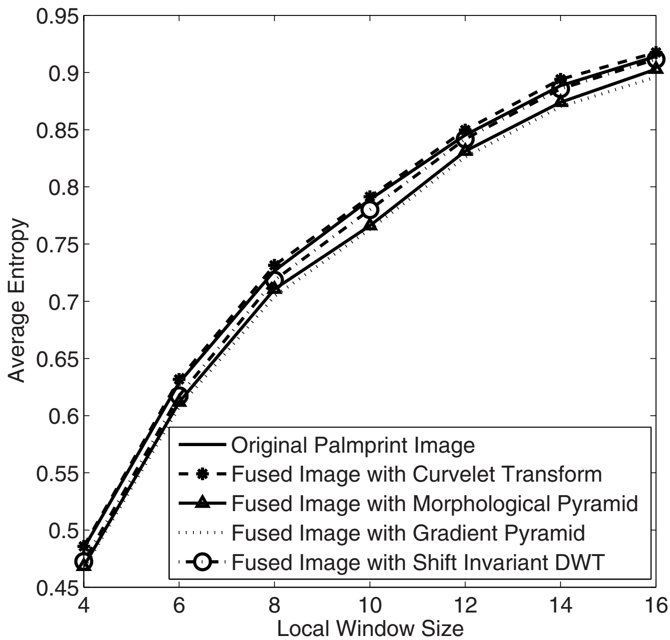


Fig. 3. The average local entropy of fused image with regard to window size

results from its built-in mechanism to represent line singularities. Gradient pyramid performs next to Curvelet transform, which suggests its good edge preservation capability and low orientation resolution compared with Curvelet transform. Morphological pyramid method introduces too many artifacts which contribute most to performance degradation.

6 Conclusion and Discussion

In this paper, we proposed the idea of multispectral palm image fusion for biometrics. This concept extends the visual capability of camera and will improve user-friendliness, security and hopeful recognition performance of original palmprint based biometric system. Several image fusion based approaches are evaluated in the context of discriminative features. Experimental results suggest that Curvelet transform outperforms several other carefully selected methods in terms of well established criteria.

Further work along proposed direction will include the followings:

- Image collection from more spectra. The results presented in Section 5 have proved the superior performance of Curvelet transform in combining palmprint and vein images. To explore the best potential of hand biometrics, we will improve device to capture images from more spectra. Although line-like pattern is dominant on palmprint and vein images, they are not necessarily suitable for other components. Thus more schemes need to be studied based on examination of meaningful physiological characteristics of each skin component.
- Recognition based on fused image. Currently, the database is not large enough to produce convincing recognition performance. A well defined database will be collected in the near future and the proposed method will be tested and also compared with other level fusion;

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