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A gradient-based combined method for the computation of fingerprints' orientation field

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ABSTRACT

Estimation of fingerprint orientation fields is an essential module in automatic fingerprint recognition system. Many algorithms based on gradient have been proposed, but their results are unsatisfactory, especially for poor image. In this paper, a gradient-based combined method for the computation of fingerprints' orientation field has been proposed. In our method, we first calculate the first level orientation fields with three different size blocks; and then combine these first level orientation fields together to form the second level orientation field; finally, use the iteration based method to predict orientation. All experiments show that, compared to the prior works, our method is more robust against noise while preserving the accuracy and is capable of predicting.

1. Introduction

Accurate automatic personal identification is critical in a wide range of application domains such as smartcard, electronic commerce, and automated banking. Biometrics, which refers to identifying an individual based on his or her physiological or behavioral characteristics, is inherently more reliable and more capable in differentiating between an authorized person and a fraudulent imposter than traditional methods such as knowledge-based [password or personal identification number (PIN)] and token-based [passport or driver license]. Among all biometric traits, fingerprints have one of the highest levels of reliability [1] and have been extensively used by forensic experts in criminal investigations [2], so designing an automatic fingerprint identification system (AFIS) with high accuracy has very important significance.

Although automatic fingerprint recognition has been extensively studied and has received good performance on small database, there still exist some critical issues such as long processing time on large databases and low matching rate on poor image. To solve these problems, improvements on fingerprint classification and identification are needed. As a global feature of fingerprint, orientation field which describes the local direction of the ridge-valley pattern, plays a very important role in both topics mentioned above.

During the past years, lots of methods have been proposed for calculating fingerprints' orientation fields, which can be broadly categorized as gradient-based approaches [3–6], filter-bank based approaches [7,8], and model-based approaches [9–13]. Filter-bank based methods are resistant to noise, but their results are not very accurate because of the limited number of filters, furthermore, they are also known to be computationally expensive due to the comparison of all filters' outputs. Model-based methods try to consider the global constrains and regularities of orientation fields except for the areas around singular points [12], so they are able to predict orientation fields for the large noise areas, but almost all model-based methods depend on accurate extraction of singular points, and for the poor fingerprint images, it is a hard work. At the same time, model-based methods often can not give out accurate orientation fields for the areas with high-curvature ridges, such as the areas near singular points. Compared with the two kind methods mentioned above, gradient-based methods are more accurate and subtle, and therefore become one of the most popular methods for the computation of fingerprints' orientation fields. However, they are sensitive to noise.

For overcoming the defect of gradient-based methods, [4] proposed a hierarchical scheme to dynamically adjust the estimation windows, they introduced a concept of *consistence*, which means the deviation between the current block orientation and other blocks orientation around it. If the *consistency level* is above a certain threshold, then the current block orientation is re-estimated at a lower resolution level until it is under a certain level. Wang et al. [5] also proposed a weighted averaging method, the basic idea is to

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conduct redundant estimation for each target block, following this idea, they design a weighted averaging scheme operated on the target blocks directly. Both of the two methods have made good improvements, but for poor fingerprint images, especially for images with large noise areas, their results are still not very satisfying.

In this paper, we aim to propose a new gradient-based method for the computation of fingerprints' orientation fields. Comparing with the previously proposed gradient-based approaches, our method will not only possess the advantage of high accuracy, but also be more robust against noise and be capable of predicting.

2. Related work and analysis

In this section, we will focus on the discussion about the basic gradient-based method introduced by Kass and Witkin [3], which has been adopted by many researchers, such as [14–18]. The basic gradient-based approach estimates fingerprints' orientation fields with the following hypothesis: within a limited block area, the orientations of all pixels should almost be the same, so we can employ the block-orientations to replace the pixel-orientations. The reason for using block-orientations is that: they are more robust against noise than pixel-orientations. The main procedure contains the following three steps:

1. Divide the input fingerprint images into blocks of size $W \times W$, and calculate all pixels' gradient vectors $[G_x(x,y),G_y(x,y)]^T$ in each block with the following description:

$$[G_x(x,y),G_y(x,y)]^T = \left[\frac{\partial I(x,y)}{\partial x},\frac{\partial I(x,y)}{\partial y}\right]^T = \begin{bmatrix}\frac{I(x+1,y)-I(x-1,y)}{2}\\ \frac{I(x,y+1)-I(x,y-1)}{2}\end{bmatrix} \quad (1)$$

where $I(x,y)$represents gray-scale value of point (x,y).

2. Square all pixel-gradient vectors, and calculate block gradient vectors $[G_{Bx},G_{By}]^T$ by using the following formulas:

$$[G_{Bx},G_{By}]^T = \left[\sum_{x=1}^{W}\sum_{y=1}^{W}G_{sx}(x,y),\sum_{x=1}^{W}\sum_{y=1}^{W}G_{sy}(x,y)\right]^T \quad (2)$$

in this expression,

$$G_{sx}(x,y) = G_x^2(x,y) - G_y^2(x,y) \quad (3)$$

$$G_{sy}(x,y) = 2G_x(x,y)G_y(x,y) \quad (4)$$

here $[G_{sx}(x,y),G_{sy}(x,y)]^T$ refers to squared gradient vectors.

3. Compute the ridge-valley orientation $\theta(0 \leqslant \theta < \pi)$ which is perpendicular to gradient direction by using the following description:

$$\theta = \frac{1}{2}\pi + \frac{1}{2}\begin{cases}\tan^{-1}\left(\frac{G_{By}}{G_{Bx}}\right) & G_{Bx} > 0\\ \tan^{-1}\left(\frac{G_{By}}{G_{Bx}}\right)+\pi & G_{Bx} < 0 \cap G_{By} \geqslant 0\\ \tan^{-1}\left(\frac{G_{By}}{G_{Bx}}\right)-\pi & G_{Bx} < 0 \cap G_{By} < 0\end{cases} \quad (5)$$

For measuring the reliability of estimation, [3] proposed a concept called *coherence*, which is defined below:

$$Coh_B = \frac{\left|\sum_{x=1}^{W}\sum_{y=1}^{W}(G_{sx}(x,y),G_{sy}(x,y))\right|}{\sum_{x=1}^{W}\sum_{y=1}^{W}|(G_{sx}(x,y),G_{sy}(x,y))|} \quad (6)$$

Obviously, if all squared gradient vectors point to exactly the same direction, the value of Coh_B will be 1; if all squared gradient vectors are equally distributed in all directions, Coh_B will be 0; In between the two extreme situations, Coh_B will vary between 0 and 1.

Now, we are going to take some further discussions about this method:

We first give out another expression of gradient vectors which is shown below:

$$[G_x(x,y),G_y(x,y)]^T = r[g_x(x,y),g_y(x,y)]^T \quad (7)$$

in this expression,

$$r = \sqrt{G_x^2(x,y)+G_y^2(x,y)} \quad (8)$$

$$[g_x(x,y),g_y(x,y)]^T = \left[\frac{G_x(x,y)}{r},\frac{G_y(x,y)}{r}\right]^T \quad (9)$$

here r is the module which means the length information, and $[g_x(x,y),g_y(x,y)]^T$ is the normalized gradient vector which represents the vector's direction information. After that, we replace the gradient vectors in Eqs. (2)–(4) with this new forms, and the result are:

$$\begin{bmatrix}G_{Bx}(x,y)\\ G_{By}(x,y)\end{bmatrix} = \begin{bmatrix}\sum_{x=1}^{W}\sum_{y=1}^{W}r^2(x,y)g_{sx}(x,y)\\ \sum_{x=1}^{W}\sum_{y=1}^{W}r^2(x,y)g_{sy}(x,y)\end{bmatrix} \quad (10)$$

with

$$g_{sx}(x,y) = \frac{G_x^2(x,y)-G_y^2(x,y)}{r^2(x,y)} \quad (11)$$

$$g_{sy}(x,y) = \frac{2G_x(x,y)G_y(x,y)}{r^2(x,y)} \quad (12)$$

where $[g_{sx}(x,y),g_{sy}(x,y)]^T$ is the normalized squared gradient vector.

From the result given by (10), we can conclude that the essence of the basic gradient-based method is computing the weighted average for all normalized squared gradient vectors within a block, where the weighting coefficient for each normalized squared vector is its corresponding squared length. In [6], the author considered that 'the length has the effect that strong orientation has a higher vote in the average orientation than weaker orientation', which means the gradient vector's orientation strength is growing with its length, the gradient vector with longer length will play a more important role. At the same time, there is another reverse viewpoint [17,18], they both considered that: the motivation of calculating block gradient vector is utilizing its direction information to estimate block orientation, hence, the block orientation should merely decided by pixel's direction information, and has no relationship with the length information.

For comparing the two viewpoints' influence on orientation results more directly, we have done lots of comparative experiments between the results of 'before normalizing' and 'after normalizing' with the basic gradient-based method. Further more, for testing the effect of normalization on other methods, we also do the same experiments with the weighted averaging method. All results of the both methods show that: for the areas with good quality, the estimated orientations of 'before normalizing' and 'after normalizing' are almost the same, but for the noise areas, especially for the edges of noise areas, the 'after normalizing' orientations are more accurate than 'before normalizing'. Due to the limitation of the space, we just give out one group contrastive results for both the two methods. As is shown by Fig. 1 (the red points in (d–h), and the red points in the rest figures in this paper represent the orientation of their corresponding blocks can not be calculated, since their block gradient vectors $[G_{Bx},G_{By}]^T$ (which are calculated by formula (2)) are $[0,0]^T$, and the orientation can not be computed by using formula (5)), comparing (d), (e) with (c), we can find that: around the edges of noise areas, the basic gradient-based method is seriously affected, but after normalizing, the result is more accurate, at the same time, the rest area results of (d) and (e) are nearly the same. Comparing the results of (g) and (d), we can find that the effect of length is diffused, and the orientation results around noise