Commentary: Contactless and Pose Invariant Biometric Identification Using Hand Surface

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1. Introduction

Biometric identification by hand or finger is now the most commonly used and most accepted method of identification. But with the increase in use, some problems have been exposed and need to be solved. The existing hand identification methods can be roughly divided into three categories through image acquisition methods. The first and widely used is the method based on constrained and contact imaging. But constrained imaging caused limited ambiguous information and contact imaging caused the hygiene issue. In recent years, the main research trend is to cancel contact and using unconstrained imaging. Therefore, the other two methods are based on constrained and contactless imaging and unconstrained and contactless imaging. The latter is what this article wants to achieve. There are already ways to achieve, however, they assume that the user's hand is parallel to the set up which is actually not always the case in real life. They also have bad performance with large pose variance even using more stable points. The author proposes a method using 3-D recognition to detect a single point to estimate the pose of the hand rather than detecting multiple points in 2-D methods. Direction information can be used to correct the pose and intensity images of hand. In addition, since rotating the hand will greatly change the geometry and contour of the hand, it is more accurate to used palmprints for recognition. Therefore, the author proposed a dynamic fusion strategy to combine palmprints. The approach proposed by the author can effectively improve the accuracy of hand identification with large pose variance and it is more user-friendly, which will increase the commercial value and also have a certain value for future biological features research.

2. Methods

For the normalization of 3-D and 2-D pose, using Otsu's threshold to get a binary image and morphology to eliminate noise firstly. Here, erosion first and dilation can be used to eliminate small objects, separate objects at minute points and smooth the boundary of larger objects without changing their area significantly. Next is how to recognize the palm. The author first used contours to find the roots of small ring finger and middle finger, connect them, and then draw a vertical line and a circle. The circled place is the palm. But it has limitations because of the reliance on finger boundaries. If the fingers overlap, the palm cannot be accurately recognized. Therefore, the author used another method, which simply calculating the distance between pixels in the hand and the contour. Find the maximum value and set it to the palm of the hand. Although the center points obtained from different angles of the same hand using this method are not necessarily the same. These center points have little error and can be seen close to the real center of the hand. Once we got a set of 3-D points, using iterative reweighted least squares (IRLS) to fit it because the proportion of outliers increase when the part of the circle to be fitted is occluded. The standard least squares method is unreliable. IRLS can solve the above problems to a certain extent, which introduces a weight function based on least squares residual and threshold. After calculating the set of points close to the center of palm, we can get the 3-D direction of hand by calculating the normal vector. Then calculate the rotation angle and correct the original image. But some parts that are invisible or occluded will have holes after posture correction. The author used bicubic interpolation to solve the hole problem. It can calculate the pixel value of the corrected image by adding the 16 weighted nearest pixels of the original image. This method of normalization is a good choice, because it basically solves the interference of hand posture on hand recognition. But it still has a weakness that if the rotation angle of the hand is really large, the resulting holes will not be filled, and a part of the resulting image will be missing.

In the feature extraction process, the first approach is 3-D palmprint. Palmprint is a very unique feature. It can be distinguished by its depth and curvature. The author used an existed method called SurfaceCodes calculating the shape index for the point on the palm [1]. The second approach is 2-D palmprint. What used in the paper is six Gabor filters with different directions [2], giving the main direction for each pixel and encode them. Calculating the Hamming distance between the encoded data to judge the similarity. 3-D hand geometry features extracted from cross-sectional finger segments [3]. Obtain the geometric features of the hand like finger's length from the image to form a feature vector. Calculating the Euclidean distance between the vectors to judge the similarity. In this part, the author did not propose new functions. And both two 3-D extraction functions are good, but 2-D extraction functions are simple and have some weakness. For example, the size of the same hand after correction at different angles may change. It is not accurate to obtain the geometric features directly from the binary image. It is better to get different features different weights.

In the dynamic fusion process, Because of the aforementioned low accuracy of using geometric features, the author proposed that geometric features are not applicable and directly dynamic combine 3-D palmprint, 2-D palmprint and Cross sectional 3-D Finger features. Give different weights for them and combine the scores. This method is a good choice, because it solved the problem of shape feature and improved the performance of hand matching.

3. Results

To evaluate the approach, the author used a dataset where each user has five different poses of hand. Users can use different rotation angles for the poses. By analyzing the rotation angles obtained by applying the proposed method, we can see that the mean rotation angles about x axis are much higher than the mean rotation angles about y axis. It is because the image volume of scanner and human habits. To evaluate the performance of posture correction, compare the matching score distribution of true and false users before posture correction and after posture correction. It can be clearly seen that after correction, the overlap area and EER are significantly reduced both for 2-D palmprint and 3-D palmprint. It also increases the performance of 2-D and 3-D geometry where 3-D is better using ROC curves. To evaluate the performance of dynamic fusion, using the sum rule to combine the matching scores. Compare the EER of it to the EER computed by other combination of matchers. It is obviously that dynamic fusion always has a best performance than others.

It can be seen from the evaluation results that using 3-D to recognize opponents for posture correction can indeed improve the accuracy and performance of detection. But I think the evaluation method is not comprehensive. It did not consider, for example, the different imaging environment and relatively extreme posture. Also, there is no comparison of the final recognition accuracy between the proposed method and another method. This evaluation can only prove that the proposed method can improve performance, but there is no method to prove that this method is better than other methods. It is better to use the same dataset applying different methods which may make a more convincing case.

4. Conclusions

This paper proposed a hand identification based on unconstrained and contact-free imaging using 3-D recognition and dynamic fusion. This method improves the performance and also reduce the projection deformation problem caused by the contact-free imaging. But it still has some weaknesses. This method can only solve part of the problem caused by pose variance, problems caused by difficult pose are still here. For example, using posture correction cannot solve the problem caused by large overlapped hand poses. The holes cannot be filled. Although the lack of some parts of the image does not affect the use of dynamic fusion. However, Dynamic fusion in this method is partly dependent on palmprint recognition. In many cases, palm prints cannot be clearly identified such as poor imaging environment, very shallow palmprints or some poses which cannot get clear palmprints. In these cases, palmprints become useless. In my opinion, combining geometric feature is a way to solve this problem.

At the same time, the use of 3-D increases the cost and reduces the acquisition rate, which makes it difficult to use commercially. This method shows that using dynamic fusion combining features always has better performance than directly sum the matching score consistently. This can be applied to other biological recognition and further researches.

References

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