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An Effective Multi-Biometrics Solution for Embedded Device

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***Abstract*—Biometric solution for embedded device gained significant attention in the commercial and research sectors over recent years. Combining multiple biometrics may enhance the performance of personal verification system in accuracy and reliability. This paper presents a new multi-biometric verification solution aimed at implementing on an embedded system within a wide range of applications. The system combines the voiceprint and fingerprint biometrics and makes decision at score level. Fusion strategy is based on score normalization and support vector machine (SVM) classifier. We tested the performances of SVM using three kernel functions for system adaptation. Experimental result demonstrates that proposed multi-biometric verification approach achieves 1.0067% equal error rate (EER) that can be deployed in majority of embedded devices such as PDA and smart cell phone for user's identity verification.**

***Keywords*—Voiceprint, Fingerprint, SVM, Multi-biometrics, Embedded Device, EER, Score-level fusion**

I. INTRODUCTION

Attributed to the identity-based nature of verification, biometric has gained much attention over recent years particularly, for its potential role in information and forensic security [1].Because of the noise introduced in both acquiring and processing procedures, the constraint of the environment and the robustness of the algorithm, a sole biometric usually can not be able to provide a satisfying result [2]. A possible way to alleviate this problem is to design multi-model recognition system which combines results of different biometrics together [3].In [4] a multi-model recognition system employing face, iris, online signature and off-line handwriting was designed, and after integration the overall error rate has been lower than that of a single biometric verification system for both verification and identification. In [5] a multi-modal biometric identification system based on iris and face is developed, it has advantages of iris recognition with low error rate and face recognition with human-friendly.

Although there has been a substantial amount of work done on combining different biometrics for a variety of purposes, however, not much work has focused on the combination of fingerprint and voiceprint. Wang, etc compared 13 combination methods in the context of combining the voiceprint and fingerprint recognition system in two different modes: verification and identification in [6], and the experimental results show that Support Vector Machine are superior to other schemes. However, the matching scores generated from fingerprint and voiceprint verifiers are heterogeneous because they are not on the same numerical range, which may negatively affect fusion results using SVM. What's more, the performance of SVM with different kernel functions and parameters is not mentioned in [6], which remains a problem in the implement of an actual system.

With the fast development of mobile communication devices such as PDA and multifunctional mobile phone, there are high demands for owner's identity verification. The fingerprint and voiceprint system can be easily applied to the mobile applications to overcome a number of inherent difficulties of the standalone classifier system without much cost increase [6]. However no work has focused on the combination of fingerprint and voiceprint into such an embedded system.

An effective multi-biometrics solution for embedded device is given in this paper. The contributions of this paper are as follows:

- We applied the SVM with score normalization to the fingerprint-voiceprint biometric fusion and compared the results to the SVM fusion used alone [6]. Results show that the normalization can improve the performance of SVM used for score classification.
- The performances of SVMs based on three kernel functions are tested, and the function with the best performance is selected as the fusion method of the multi-biometrics solution for embedded device.
- We describe the development of multi-biometrics verification on an ARM9-core based embedded system. Fingerprint and voiceprint are fused in score level fusion using SVM and score normalization. The design and implementation of hardware and software are given in details. The system has the functions of fingerprint and voice enrollment, verification and security level configuration.

The software of the system can be applied to the mobile devices such as PDA and mobile phone using the Windows CE operation system equipped with microphone and fingerprint sensor. Thus voice can be captured through the built-in microphone and fingerprint can be captured by fingerprint sensor. Verification can be accomplished by comparing the fusion score with the adjustable threshold.

Compared with traditional multi-biometrics verification system, the embedded system of multi-biometrics has advantages of low-cost and simple-to-use. Fingerprint and voiceprint biometric algorithms, which belong to no-violation and initiatively method, do not interfere the person being identified and does not violate person's privacy, so it's easily accepted.

The rest of the paper is structured as follows. Section II introduces the fingerprint and voiceprint verifiers used in our system. Section II outlines the proposed method for fusion of fingerprint and voiceprint. Section III describes the design and implementation of multi-biometric system, and Section IV shows experimental results. Conclusions and future are given in Section V.

II. BIOMETRIC VERIFIERS

A. Fingerprint Verifier

For fingerprint verification implementation, a full-function fingerprint identification system-on-chip (SOC) PS1802 produced by Synochip Corporation [7] is employed. PS1802 is a high-performance general purpose DSP controller with full-function Fingerprint Identification.

A critical step in fingerprint verification system is to automatically and reliably extract minutiae from the captured fingerprint images. PS1802 fingerprint modal uses a commercial minutia extraction algorithm, including image preprocessing, binarization, thinning and minutia finding, and the output image of each process is given, as we can see form Fig. 1. With these minutia features, an alignment-based elastic matching algorithm is used.

Figure 1. Output images of PS1802 modal's minutia extraction algorithm.

B. Voiceprint Verifier

The voiceprint recognition system is content dependent; it accepts a voice sample for up to 10 seconds and enrolls the user in less than 4 seconds. The speech recordings used for feature extraction were utterances of a 4-digit PIN in English. The recording speech is divided into several small segments with a fixed length. Then a 34-dimensional feature vector calculated using 20ms Hamming windows with 10ms shift. Each feature vector consists of (concatenated):

a) *the Mel Frequency Cepstral Coefficients (size 16)*;
b) *the energy coefficient (size 1)*;
c) *the energy coefficient (size 1)*;
d) *the delta energy (size 1).*

The number of feature vectors between users and presentations may differ.

With these feature vectors, we train the code book for each speaker with VQ (vector quantization) [8].

III. MULTIPLE BIOMETRICS FUSION METHOD

Information fusion in biometrics is possible at the sensor, feature, score or decision levels [9]. Previous works from the biometric literature [1, 10] showed that fusion at the score level is the most preferred approach, because score-level fusion allows fusing two modalities without requiring knowledge of the individual systems or access to the extracted features. Also, having much more information than that available at the decision level, allows for more flexible fusion approaches.

As to fuse fingerprint and voiceprint verification systems, a score vector $\boldsymbol{X}(x_1, x_2)$ representing the score output of multiple verification systems was constructed, where x_1 and $x2$ correspond to the score obtained from the fingerprint and voiceprint verification system respectively. Then the identity verification problem turns to be 2 dimensional score vector $\boldsymbol{X}(x_1, x_2)$ separated into two classes, genuine or impostor.

Obviously, the identity verification problem is a typically binary classification problem, i.e. accept (genuine) or reject (imposter). SVM is well known as a two-class problem classifier with high performance [11, 12]. So, in this paper, we adopted SVM as the fusion strategy of the fingerprint and voiceprint identity verification system.

A. Score Normalization

In typical statistical learning fusion literature when SVM was used for fusion no normalization for the scores/data is usually performed. However in this paper we have proved that score normalization have a very significant impact on enhancing the results accuracy.

In our approach, the raw scores from fingerprint and voiceprint match system are normalized before they can be inputted into SVM. These score can be normalized by max-min method as following:

$$x = \frac{x - min}{max - min} \tag{11}$$

where *min* and *max* are the minimum and the maximum values of these scores.

B. Support Vector Machine

Support vector machine (SVM) is based on the principle of structural risk minimization. It aims not only to classifies correctly all the training vectors, but also to maximize the margin from both classes. The optimal hyperplane classifier of a SVM is unique, so the generalization performance of SVM is better than other methods that possible lead to local minimum [11, 12]. In reference [6], SVM was compared with other fusion methods of fingerprint and voiceprint, and its performance was the best. And in this paper, we pay attention to the performance of SVM with different kernel functions. The detailed principle of SVM is not showed in this paper, and it can be seen in reference [11, 12]. And three kernel functions of SVM used in our study are:

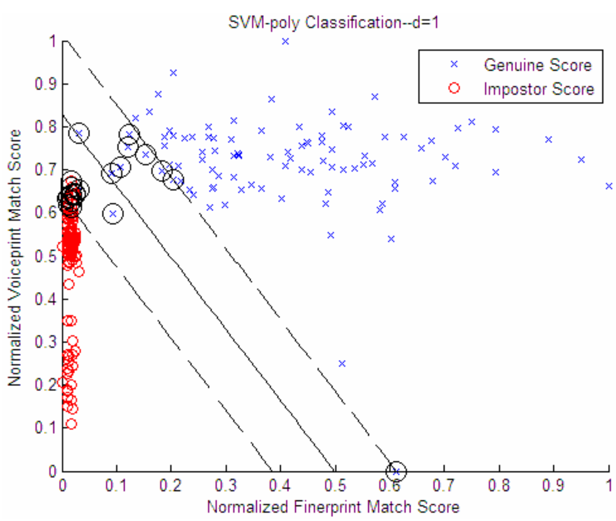
$$\text{Polynomials: } K(x, z) = (x^T z+1)^d, d>0 \tag{1}$$

$$\text{Radial Basis Functions: } K(x, z) = exp\left(-g\, ||x-z||^2\right) \tag{2}$$

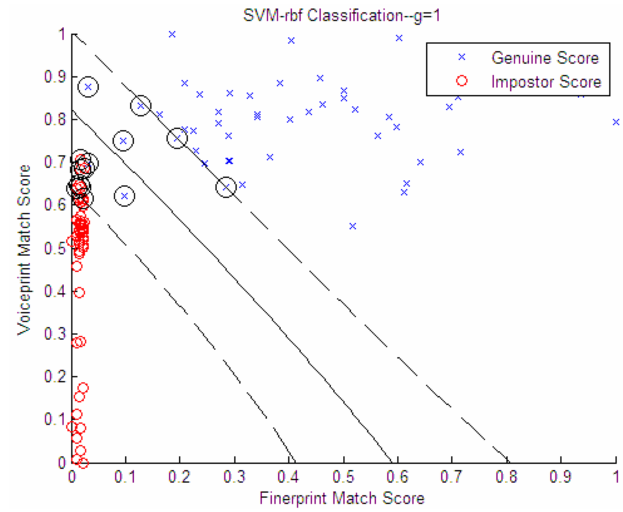
$$\text{Hyperbolic Tangent: } K(x, z) = tanh\left(\beta x^T z+\gamma\right) \tag{3}$$

In order to select the best kernel function for our system, we test the performances of SVMs based on three kernel functions mentioned above, and the results can be seen at the following figures.

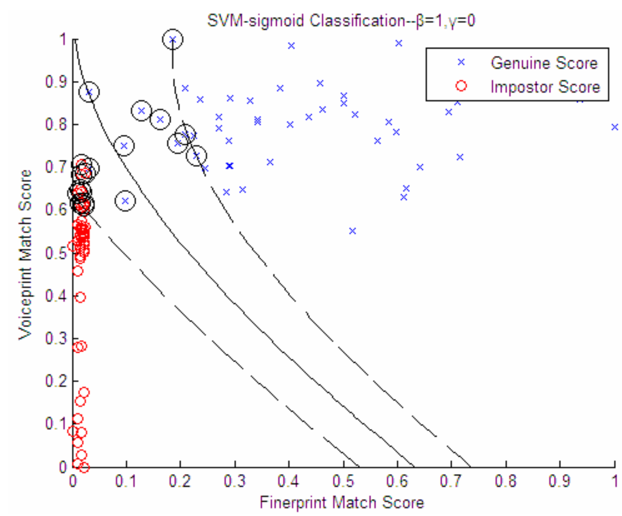
Fig.2 shows different SVMs with different kernel functions separating genuine and impostor of fingerprint and voiceprint after normalization. We can see that three SVMs can all separate the two classes correctly. Their performances are similar; however, the number of support vectors and the difficulty to adjust parameters of kernel function are different. In our experiment, the SVM-poly is easier to be trained than SVM-RBF and SVM-sigmoid; the latter two need more patience during training period. Moreover, the classification error of the SVM-poly is the lower (0.3%) than the other tow ones (0.4% and 0.5%), which makes Polynomials kernel function our final choice.



(a) SVM-Poly



(b) SVM-RBF



(c) SVM-Tanh

Figure 2. SVM Classification results with different kernel functions.

IV. MULTI-BIOMETRIC SYSTEM DESIGN AND IMPLEMENTATION

A. System Frame and Design Scheme

The multi-biometric verification system is composed of three sub-systems, fingerprint sub-system, voiceprint sub-system and score level fusion sub-system.

This embedded platform adopts an ARM9-Core based S3C2440A microprocessor and the Microsoft Windows CE operation system. An external module PS1802 produced by Synochip Corporation is employed as fingerprint sub-system whilst the voiceprint sub-system uses the microphone of the developing board to capture voice biometric samples. System software is developed by using Microsoft Embedded Visual C++. The system frame is shown in Fig.3.

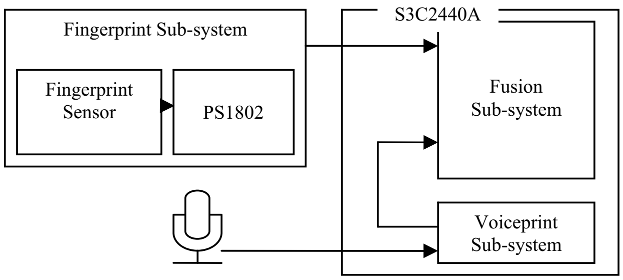


Figure 3. The frame of multi-biometric verification system.

B. Hardware Architecture

The S3C2440A is a 32-bit RISC microprocessor made by Samsung Company [13]. It is a powerful processor with an ARM 920T RISC core, working at up to 400MHz. It has a 128 kilobyte on-chip Flash and a 64 kilobyte on-chip Static RAM. Moreover, the processor chip is as compact as 14mm×14 mm in size. It can be operated in two low power working modes which make itself the first choice for developing portable devices [13].

To meet the demand of the audio capturing of voiceprint, the IIS-bus interface model with a UDA1341 audio CODEC is adopted. The Universal Asynchronous Receiver and Transmitter (UART) model is used as interface to fingerprint model PS1802. The technics concerning the voiceprint recognition and multi-biometrics fusion algorithm have been used in the system. Fig. 4 shows the hardware structure of the multi-biometrics embedded system.

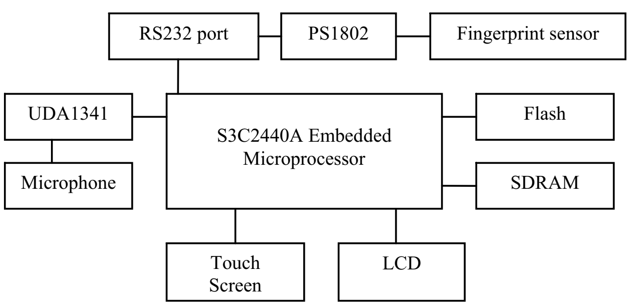


Figure 4. The hardware structure of ARM-based multi-biometric verification system.

C. System Software Implementation

A multi-biometric verification system works in two models: enrollment model and verification models. In the off-line enrollment model, an enrolled fingerprint image and voice signal is preprocessed, and the features are extracted and stored into the on-board memory or the external SD card. In the on-line verification model, the similarity between the enrolled features and the features of real-time captured fingerprint image and voice signal are examined, giving two match scores. After fusing the two scores using SVM, decision can be determined by comparing the fusion score with the threshold. Fig.5 shows the working models and data flow of a multi-biometric verification system.

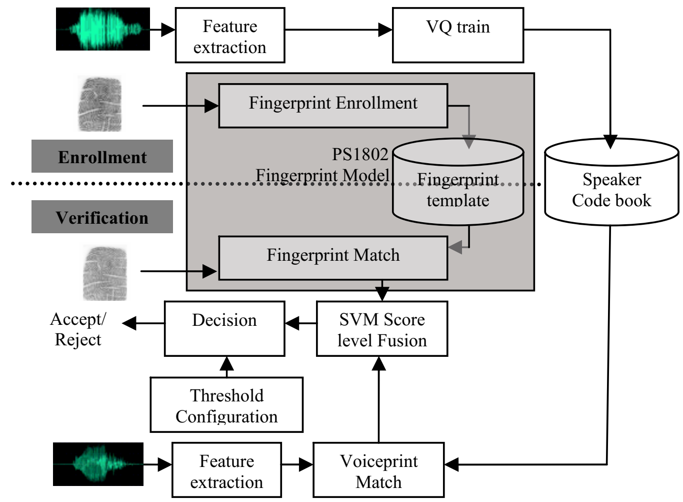


Figure 5. The working models and data flow of a multi-biometric verification system.

All algorithms are implemented with C/C++, and loaded within the flash memory. The training data (or model) are generated in ARM, and then save them into the flash memory. And these data are used to verify the user's identity.

V. PERFORMANCE EVALUATION

A. Evaluation Database and Protocol

Here To test the biometric verification performance of proposed system, 300 users (200 male and 100 female) are invited to construct the multimodal database and participate experiment trials. For every user 2 pairs of testing sample are captured. A pair of testing sample contains a voice sample for 2~10s at a sampling frequency of 16 kHz/s and a fingerprint image at the resolution of 256×288.

The constructed multimodal database consists of 600 records corresponding to 300 users (2 records each subject). In our experiments, the 300 subjects are divided into two sets: 50 subjects (100 records) as training data to estimate the parameters of SVM, the remaining 250 subjects (500 records) as the test data to evaluate the performance of the trained system.

In the testing stage, we have $250\times249=62250$ negative instances for computing the false acceptance rate (FAR), while the instances for false rejection rate (FRR) 250.

The performance of the verification system can be represented by the ROC (receive operating characteristic) curves, which plot probability of FAR versus probability of FRR for different values of the decision threshold. The point on the ROC defined by FAR=FRR is the EER point. Finally, the experiment results (ROC and EER) based on the test data, as well as some comparisons, are presented as follows.

B. The Recognition Performance

1) Comparison with unimodal methods: The goal of the multimodal fusion is to achieve better precision and reliability of human verification than single biometrics. In order to prove the effectivity of our proposed method, we present a comparison with the unimodal methods (only one modality used).Fig. 6 shows the ROC curves and EER of the following biometric systems: only fingerprint verification, only voiceprint verification and the proposed multimodal verification.

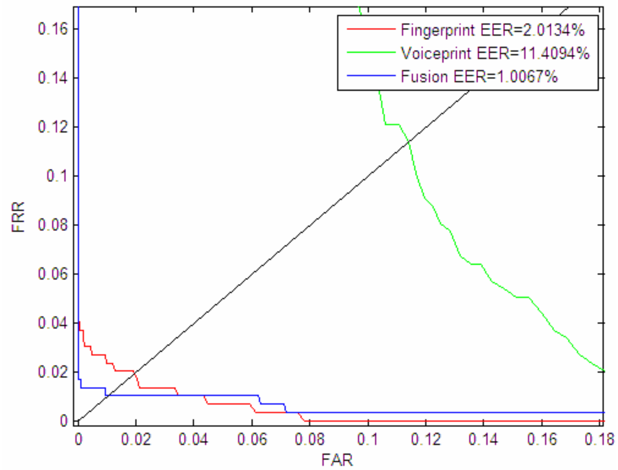


Figure 6. ROC curves of unimodal method and the proposed method.

As can be seen from Fig. 6, fingerprint recognition usually has a high verification performance, and it can achieve the performance of 2.0134% EER. Actually, fingerprint should have better verification performance if the quality fingerprint image captured is high enough, however it's not the crucial problem we discuss here. Voiceprint recognition is less reliable than fingerprint. But when two biometrics are combined using our proposed method, we can achieve a performance of 1.0067% EER. This brings obvious performance improvement compared with the unimodal biometric methods. This means that multimodal biometric method is an effective way to improve human identification accuracy.

2) Comparison with score normalization: To test the normalization's impact for SVM fusion, in the experiments, we compared the SVM fusion with SVM combining normalization. Fig. 7 gives the ROC curves and EERs of the two methods.

As we can see, the normalization improves the EER of SVM fusion from 1.3353% to 1.0067%, which means score normalization have a significant impact on enhancing the results accuracy.

The idea behind combining SVM and score normalization may result from the fact that SVM technique is itself making some sort of score normalization while trying to transform the problem from non-linearly separable problem to a linearly separable one. We can realize from this that the enforced normalization which we are suggesting in this paper is doing part of the SVM job in a more effective way leaving less decisions and work for the SVM to handle.

3) Comparion of different kernels: We test the recognition performances of SVMs based on three kernel functions mentioned above, and the results can be seen at the following figure. Fig. 8 gives the ROC curves and EER of SVM fusion using different kernels: poly, RBF and Tanh kernels.

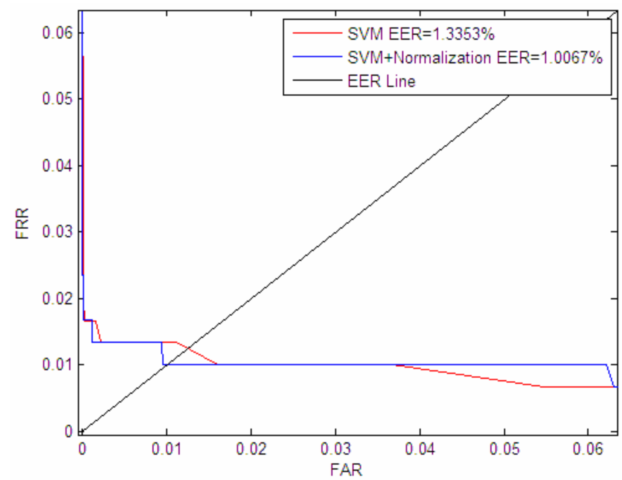


Figure 7. ROC curves of SVM fusion and SVM with score normalization .

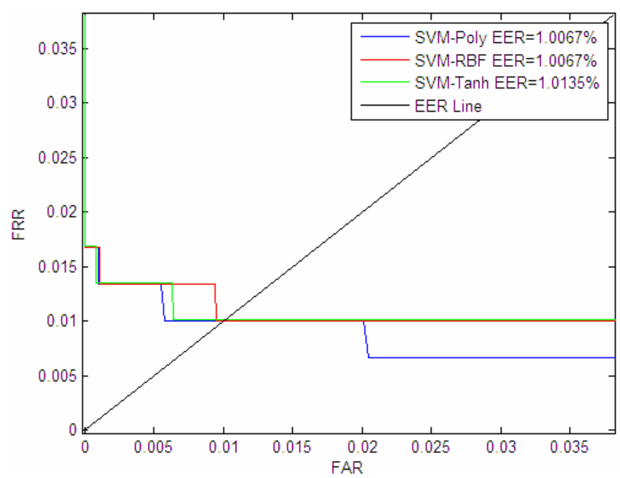


Figure 8. ROC curves of SVM fusion with different kernels .

We can see that their performances are similar. Poly kernel outperforms the other two, the RBF is middling (although the EER is equal to that of Poly, the FRR is higher when the FAR is not in the EER line), and Tanh is a shade worse. Notice that the computational complexity of SVM is independent of the dimensionality of the kernel space where the input feature space is mapped. And the high computational burden is required both in training and testing phase. Fortunately, in our experiments, only a relatively small number of training data is enough. Just those points near to the support vectors or near to the hyperplane are inputted into SVM, of course, the hyperplane was not known at beginning, so just estimated it. From Fig.2, we see that the SV numbers of the three kernels are all no more than 30, so the computation quantum is not large during testing phase too.

C. The Real-time Performance

To test the processing time of our algorithm on different platforms, we tested our algorithm on Desktop PC with

Windows XP operating system and S3C2440A microprocessor with Windows CE operating system. As Table 2, we could see that the processing speed of Desktop PC (P4/3.0GHz, 2G-RAM) was more than three times faster than that of S3C2440A, but the latter is still acceptable for real-time application (a few seconds).

TABLE I. COMPARATIVE PROCESSING TIME ON DESKTOP PC AND EMBEDDED SYSTEM (UNIT: MS)

	Desktop PC	***Embedded system***
Voiceprint feature extraction	1034	3530
Voiceprint VQ training	975	3301
Voiceprint match	893	2904
Fingerprint enrollment	160	522
Fingerprint match	492	1320
SVM classification	1530	4387

Furthermore, in order to achieve the less computational time we can complement the multimodal method in the following ways: firstly, with the quick development of microelectronics, faster processors can been used to speed up the identification system; secondly, the verification modules of different modalities can been executed simultaneously by utilizing multiple processors technology especially in the embedded system, which can save more computational time.

VI. CONCLUSION AND FUTURE WORK

The biometrics verification system based on embedded system has many advantages including small size, less calculating, relatively high speed, and stable performance. Combining multiple biometrics may enhance the performance of personal verification system in accuracy and reliability. In this paper, we proposed a new embedded multi-biometric verification system for mobile devices. This system combines fingerprint and voiceprint in score level. Our experiment results suggest that it has acceptable real-time performance in recognition rate; therefore it can satisfy the needs for portable embedded devices with high accuracy and reliability.

In the coming future, the embedded multi-biometric verification recognition system will be widely used in security check-up, ID confirmation, entrance guard system, intelligent attendance check. Note that our embedded system framework can also be applied to other biometrics such as face, iris, etc with the video port of the S3C2440A, although this paper considered fingerprint and voiceprint only. In future work, we plan to develop face, voiceprint and fingerprint algorithms and smart dynamic fusion strategies on embedded devices like mobile phones, PDA, etc.

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