Multi-Biometric System For Newborn Recognition

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Abstract

The use of biometrics as a tool for authentication for adults has come into existence in all the application areas. Similarly, the identification of newborn is becoming a necessity to avoid baby swapping, mixing, child kidnapping and illegal adoptions in hospitals. Hence, a newborn personal authentication system is proposed for this issue based on multi biometrics. The biometric traits considered are the footprint of the newborn and the fingerprint of the mother. An appropriate fusion scheme is implemented to overcome the drawbacks of a single modality. The experimental results are promising and prove to be an effective system.

Keywords: Biometrics; Fusion; Match score-level; Multibiometrics; Newborn

1. Introduction

Biometrics is a field of technology that uses automated methods for identifying or verifying a person based on physiological or behavioral traits. The term comes from the Greek words bios (life) and metrikos (measure). A biometric system is essentially a pattern-recognition system that recognizes a person based on a feature vector derived from a specific biological characteristic that the people possess. Biometrics is a good and feasible choice to deal with this task considering several factors, i.e., easy usage, fast processing, and low cost, good accuracy, etc. Physiological biometric identifiers include fingerprints, hand geometry, ear patterns, eye patterns (iris and retina), facial features, and other physical characteristics. Behavioral identifiers include voice, signature, key stroke, and others. Recently, apart from the conventional hard biometrics, a new class of soft biometrics is also emerging. These include height, weight, gender of the person, color of the clothes, hair color, etc. By using biometrics it is possible to establish an identity based on `who you are'. Depending on the application, a biometric system typically operates in one of two modes: verification or identification [1]. There is no doubt that biometric is one of the most important and effective solutions for this task.

In recent years, biometric authentication has seen considerable improvements in reliability and accuracy, with some biometrics offering reasonably good overall performance. However, even the most advanced biometric systems are still facing numerous problems, some inherent to the type of data and some to the methodology itself. In particular, biometric authentication systems generally suffer from imprecision and difficulties in person recognition due to noisy input data, limited degrees of freedom, intra class variability, non universality, and other factors that affect the performance, security, and convenience of using such systems [2]. Multibiometrics is a relatively new approach to biometric knowledge representation that strives to overcome the problems by consolidating the evidence presented by multiple biometric traits/sources. The combination of different systems can improve the security level of only one system. Multi-biometric systems can significantly improve the recognition performance in addition to improving population coverage, deterring spoof attacks, increasing the degrees of freedom, and reducing the failure-to-enroll rate. Although the storage requirements, processing time, and computational demands of a multi-biometric system can be higher than that for a unimodal biometric system, the aforementioned advantages present a compelling case for deploying multi-biometric systems in real-world large-scale authentication systems [3].

The unimodal biometric employs single biometric trait (either physical or behavior trait) to identify the user. Example: Biometric system based on fingerprint or iris or Voice or hand geometry etc. A biometric system that consolidates the information from multiple sources is known as multimodal biometric system. Example: Biometric system based on face and hand or finger and speech, etc.

The key to successful multi-biometric system is in an effective fusion scheme, which is necessary to combine the information presented by multiple biometric sources. The amount of the information available for fusion decreases after each level of processing in a biometric system. The raw data represents the richest set of information, while final decision contains just an abstract level of information. The system requires an integration scheme to fuse the information obtained from the individual modalities. In a multimodal biometric system that uses different biometric traits, fusion can be done at four different levels of information [4], and these levels correspond to four important components of a biometric system. Those four important modules are: (1) Sensor module, (2) Feature extraction module, (3) Matching module, and (4) Decision-making module. The fusion thus can take place at the sensor level, feature extraction level, matching score level, or decision level. Further in many practical multimodal biometric systems, early levels of information such as raw data or feature sets may not be available or even if they are available they may not be compatible for fusion. In such cases information obtained at later levels like match score level or decision level can be employed as it is ease to fuse and all commercial devices provide access to scores and decisions. In the rest of this section, we will focus on the newborn issues and developing a multi-biometric system. In Section 2, we will discuss about the need for multi-biometric newborn recognition and the databases used. Section 3 will discuss the previous work carried out for the same. Section 4 will illustrate the fusion scheme employed. Section 5 will summarize the results of the experiments in terms of recognition rates. The results indicate that fusing individual modalities improves the overall performance of the biometric system. Section 6 discusses insights on multi-biometric knowledge system design for an effective newborn recognition system using score-level fusion.

2. Newborn Recognition

The rising cases of infant abduction, illegal adoptions, child swapping inside the hospitals after birth, baby girl killing pose threats to the society. The measures to prevent such incidents must be effective, timely and robust. The currently followed practices in hospitals after birth of a newborn are to take impressions of the footprint of the baby along with the fingerprint of the mother and stored in a ledger with the date, time regarding the birth as shown in figure 1a. Another method is tying an identity band (ID) around the hand or ankle of the infant as shown in figure 1b. But these methods are not effective as described in [5]. To overcome those drawbacks biometrics based identity verification is proposed which uses online image acquisition, electronic processing and storage. Hence an online method is used rather than the conventional offline ink & paper method.

Figure 1. a. Inked footprints b. Id band

2.1. Footprint database

There are no available newborn footprint databases in the web. Hence, our own newborn footprint database is created. The newborn's footprint images are captured using a digital SLR (DSLR) camera, whose type is Canon EOS 7D as shown in figure 2 Since there is no available newborn footprint database, the images must be captured in real time. The image capturing work was done in the Primary Health Center (PHC), Medavakkam, which is one of the Government run hospitals in India. After getting the legal permission from the health services officials, the images were captured. When capturing images, two persons are needed. One person is the author of the paper whose task is to pacify and hold the foot of the newborn and the other person is a well qualified professional photographer to take pictures of the newborn foot.

Figure 2. Canon DSLR camera

A black cloth was wrapped around the ankle to facilitate image segmentation. All the images were collected in one session during the first 2 days following birth. After we explained some knowledge about the importance and significance about Newborn's biometrics to newborn's parents, they consented that we can capture footprint images once. In image acquisition stage, a crucial problem is to select an opportune time to capture images. If a newborn is hungry, crying or suffering from any minor illness, he/she will ceaselessly move his/her hands, feet, and whole body. In this time, it is difficult to hold and capture footprint images with desirable quality. On the contrary, if a newborn is calm or sleeping, the task of image capturing will become easy. In this paper, all images were captured when newborns were calm or sleeping. The sample footprint database is shown in figure 3.

Figure 3. Footprint database

2.2. Fingerprint database

The fingerprint of the newborn mother is also collected by means of a fingerprint scanner. The fingerprint scanner used is digital Persona U.are.U 4500 Reader, USB fingerprint reader as shown in figure 4. The images were captured simultaneously from the infant and the mother.

Figure 4. Fingerprint reader

The sample fingerprint images collected are shown in figure 5.

Figure 5. Fingerprint database

The database consists of 40 newborn-mother biometric images and from each newborn and his/her mother 6 footprint and 6 fingerprint images were collected respectively. Hence, the database consists of 480 (240+240) images which are stored together with the name of the mother and birth details like date and time of birth.

3. Previous work

The use of online footprint over the other traits like face, fingerprint, ear, and palm print for the newborn is well discussed in [5]. Also the drawbacks of offline method are explained in [5-6]. Our previous works include biometrically recognizing the newborn using footprint feature which involves online image capture from two different types of background conditions [5]. After getting insights from the unimodal system, we developed a multimodal system by including another biometric trait. Hence, the newborn identity verification was carried out using serial mode of integration of both the footprint (newborn) and fingerprint (mother) [7]. The method of retrieval and verification was done to establish the identity with N+ 1 computation.

4. Proposed work

Now we adopt a more rigorous approach which involves the multi-biometric system to be exploited fully to render a decision over the newborn identity claim. An effective fusion scheme is implemented to fuse the information available from the multi-biometric sources and optimally give the final decision. The block diagram of the proposed system using match score level fusion is shown in figure 6.

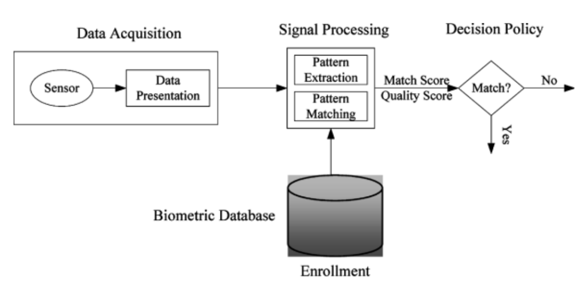

Figure 6. Proposed system

4.1. Fusion schemes

As indicated in Figure 7 there are four ways in which information from multiple sources are combined such as sensor level, feature level, match score level and decision level [4].

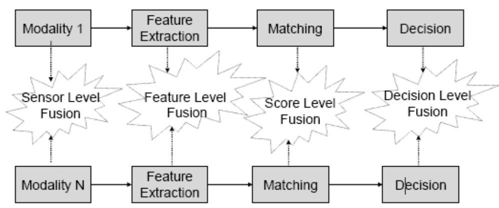

Figure 7. Levels of fusion

4.1.1. Sensor level fusion. This is also known as integration at pre classification/matching level with the available raw data of a particular trait from various biometric sources or various samples from a single source. In a palmprint there are 4 different regions namely: upper palm, lower palm, thenar and hypothenar [8]. Hence multiple samples of palm print can be collected by a single sensor and fused at sensor level. But it requires some preprocessing such as sensor calibration and data registration before performing the fusing [4].

4.1.2. Feature level fusion. Prior to classification/matching, integration of information takes place. It refers to combining different feature vectors that are obtained by either using multiple sensors or employing multiple feature extraction algorithms on the same sensor data [9]. When the feature vectors are homogeneous (e.g., multiple hand geometry impressions of a user's hand) it can be concatenated easily. When the feature vectors are non homogeneous (e.g., feature vectors obtained using different feature extraction techniques, or feature vectors of different biometric modalities like voice and iris), it is difficult to consolidate information as the feature sets are incompatible.

4.1.3. Score level fusion. Integration of information happens after the classification/matcher stage. Fusion at the matching score level can be approached in two distinct ways. In the first approach the fusion is viewed as a classification problem, while in the second approach it is viewed as a combination problem. In the classification approach, a feature vector is constructed using the matching scores output by the individual matchers; this feature vector is then classified into one of two classes: "Accept" (genuine user) or "Reject" (impostor). In the combination approach, the individual matching scores are combined to generate a single scalar score which is then used to make the final decision. Since the matching scores generated by the different modalities are heterogeneous, normalization is required to transform these scores into a common domain before combining them [9].

4.1.3. Decision level fusion. Integration of information at the abstract or decision level can take place when each biometric matcher individually decides on the best match based on the input presented to it. It is too rigid since only a limited amount of information is available at this level [9].

Therefore, integration at the matching score level is generally preferred due to the ease in accessing and combining matching scores.

4.2. Score normalization schemes

The simplest normalization technique is the Min–max normalization. Min–max normalization is best suited for the case where the bounds (maximum and minimum values) of the scores produced by a matcher are known. In this case, we can easily shift the minimum and maximum scores to 0 and 1, respectively. However, even if the matching scores are not bounded, we can estimate the minimum and maximum values for a set of matching scores and then apply the min–max normalization [10].Given matching scores $\{S_k\}$, k=1,2,..,n the normalized scores are given by equation 1:

$$S' = S_k - \min\{S_k\} / (\max\{S_k\} - \min\{S_k\}) \quad (1)$$

where S' is the normalized score. The other normalization methods like Decimal scaling, Z-score, Double Sigmoid function, Tanh estimators are discussed in [10] and shown in table 1.

Table 1
Summary of normalization techniques

Normalization technique	Robustness	Efficiency
Min–max	No	High
Decimal scaling	No	High
z-score	No	High
Double sigmoid	Yes	High
Tanh-estimators	Yes	High

4.3. Fusion rules

1. *Non-probabilistic rules:* Normalized score for user i (i=1, 2, 3,…,I, where I is the total number of individuals in the database) by matcher m(m=1,2,3,….,M, where M is the total number of matchers) is denoted as n^m_i and f_i is the fused score[11].
    a. Simple Sum: Scores of all matchers are summed for all users.
    b. Min-Score: Minimum score is selected from user I from any of the classifiers M.
    c. Max-Score: Maximum score is selected from user I from any of the classifiers M.
    d. Matcher Weighting: Weights are assigned to all matchers based on exhaustive assignment.
2. *Probabilistic rules:* No score normalization is required prior to the fusion. Probability directly provides the value between (0, 1). But Probability estimation error is a problem in this method as in [11].
    a. Product rule
    b. Min rule
    c. Max rule

5. Integrating footprint and fingerprint

The match score level fusion is employed which uses combination approach with min-max normalization and non-probabilistic fusion rule i.e. weighted-sum rule.

5.1. Footprint recognition

The captured footprint is pre-processed to remove the unwanted background. The various pre-processing steps are [5, 7]:

- Particle Filter
- Clamp Function
- Gray Scale Image Segmentation
- Morphology
- ROI Extraction

The next step involves extracting discriminating features based on texture information from the footprint. A Gabor filter with proper setting of its parameters is used to extract the information. This extracted information is stored as patterns in the database [5]. These are known as the training/gallery images. A similarity measure is used to find the match between the test/probe pattern to the training/gallery pattern. Higher scores between patterns represent greater similarity such that they belong to the foot of the same infant.

5.2. Fingerprint recognition

A fingerprint is the pattern of ridges and furrows (valley) on the surface of a fingertip. Ridges are the lines on the tip of one's finger. The unique pattern of lines can either be loop, whorl, or arch pattern. Valleys are the spaces or gaps that are on either side of a ridge. The most important features in fingerprints are called the minutiae, which are usually defined as the ridge endings and the ridge bifurcations [12]. A ridge ending is the point, where a ridge ends abruptly. A ridge bifurcation is the point, where a ridge forks into a branch ridge as shown in figure 8.

Figure 8. a. Ridge ending b. Ridge bifurcation

The captured fingerprints must be pre-processed to segment the unwanted regions [7]. The estimation of the ridges is followed by an effective minutiae extracting algorithm that involves ridge map, thinning and post processing using morphological functions. Now, the minutiae are represented in a format that stores the x, y co-ordinates along with the orientation angle information [7]. An alignment based elastic string pattern matching is used and a similarity measure is the performance metric used.

5.3. Score-level fusion

The newborn footprint identification is done and the scores generated by this module is fused with the scores generated by the second classifier, i.e. fingerprint of the mother. Even though both the scores are similarity measures normalization is required since the range of both the scores are different. The footprint scores are in the interval (0, 1) whereas the fingerprint scores are in the interval (0, 1000). Hence, min-max normalization is used as described in section 4.2. Now the fingerprint scores are normalized so that they are transformed onto a common interval i.e. (0, 1).

An appropriate fusion rule like sum rule-based fusion is used. The procedure for sum rule-based fusion is stated as [13] and given in equation 2:

$$f_i = \Sigma_I\ i\ foot\ score*(n) + i\ finger\ score*(1-n) \quad (2)$$

where n is the weight multiplied to each of the matcher such that the addition of weights in all the classifier is unity, and i=1,2,3,…,I is the number of users. Also, *i foot score* are confidence/accuracy (%) from the foot scores file. *i finger score* are normalized matching (%) from the finger scores file. Based on some preliminary results, we decided to use equal weights in our experiments. In the next step, the fused score f_i will be compared to a pre-specified threshold t. We declare that the newborn baby belongs to the corresponding mother if $f_i \geq t$, otherwise, we declare that he or she is an impostor.

6. Experimental results

A newborn footprint database is established. In total, the database contains 240 images from 40 newborns' captured at the Primary Health Center, Medavakkam-Chennai, India. Six images were collected from the right foot of each newborn. In accordance with that a fingerprint database is also established from the corresponding 40 mothers of the newborn using an USB fingerprint reader. Six impressions of thumb were collected from every one of them. Totally, the database consists of 480 images (240+240). One image is selected for training for both the modalities and the rest of the images were for testing. Hence, there are 40 training images each for both footprint and fingerprint. Similarly, there are 200 images each for both footprint and fingerprint. The experiments were conducted on a personal computer with an Intel Pentium B960 processor (2.20 GHz) and 4.0G RAM configured with Microsoft XP and LabVIEW 11.0 software. The system is graphical-user-interface based and menu driven. The necessary image preprocessing can be easily done by selecting the image directory. The time taken to give a decision over the claim is few seconds.

The recognition performance of the footprint, fingerprint systems when operated as unimodal systems and when fusion is performed is shown as a comparison in figure 9. The performance of any biometric system is usually represented by the ROC (Receiver Operating Characteristic) curve. An ROC curve plots, parametrically as a function of the decision threshold, the rate of "false positives" (i.e. impostor attempts accepted) on the x-axis, against the corresponding rate of "true positives" (i.e. genuine attempts accepted) on the y-axis [10].

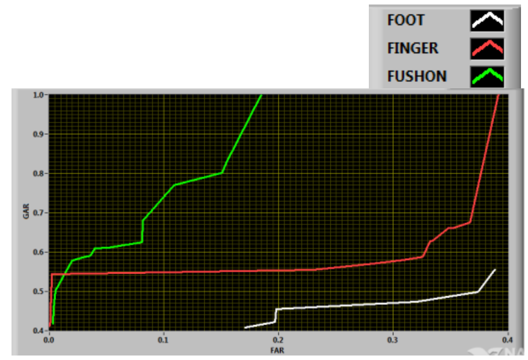

Figure 9. ROC curve

If imposter scores exceed the threshold it results in a false accept, while genuine scores that falls below the threshold results in a false reject. Then, FAR of a biometric system can be defined as a fraction of scores exceeding the threshold. Similarly, FRR may be defined as a fraction of genuine scores falling below the threshold. Then, we can define GAR as a fraction of genuine scores exceeding the threshold. Hence, in our experiment we calculate the GAR at 0.1% to 0.4% FAR.

Compared to the unimodal system, the fusion results are more efficient. At 0.1% FAR, there is 75% genuine acceptance accuracy which is much higher than the footprint and fingerprint systems.

9. Conclusion

In this paper, we have presented a detailed description in designing a multi-biometric system for newborn recognition. In addition to this, we have also presented a brief review of our related work in designing an appropriate biometric system for the identity verification of the newborn. Since the work presented in this paper focuses on data fusion at the match score level experimental results obtained by the unimodal biometric systems and serial mode are not presented here. They can be seen on [5] and [7] respectively. Experimental results show that the efficacy and the performance speed is also considerably increased for the multimodal biometric fusion system proposed the results are promising. Multimodal biometric data fusion of several biometric modalities combines the information provided by each unimodal modality to obtain a final decision. It has been demonstrated that multimodal fusion increases the robustness of the recognition system to obtain a recognition decision even when one or more of the biometric decisions cannot be accomplished. A fusion scheme applied as early as possible in the recognition system is more effective. The performance of sum rule-based fusion depends on the choice of normalization technique.

Hence this method is a low cost solution to the newborn violence rather than the expensive DNA procedure.

In the future, we will adapt a better image acquisition protocol by deploying high resolution scanners to collect the footprints and the number of images in the database will also be increased. We are also trying to implement the system using VLSI based FPGAtechnology.

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References

[1] Anil.K.Jain, Ross A, Prabhakar S (2004) “An introduction to Biometric recognition”, *IEEE* Trans.Circuits System Video Technology Special Issue Image Video based Biometrics 14(1) 4–20

[2] Md. Maruf Monwar, and Marina L. Gavrilova,” Multimodal Biometric System Using Rank-Level Fusion Approach”, *IEEE* Trans on system, man, and cybernetics—Part B: cybernetics, 39(4), Aug 2009 pp-867-578

[3] M. P. Down and R. J. Sands, “Biometrics: An overview of the technology, challenges and control considerations,” *Inf. Syst. Control J.*, vol. 4, pp. 53–56, 2004.

[4] G Hemantha Kumar and Mohammad Imran,”Research Avenues in Multimodal Biometrics”, *IJCA* Special Issue on “Recent Trends in Image Processing and Pattern Recognition”RTIPPR, 2010.

[5] S.Balameenakshi. S.Sumathi,” Biometric Recognition of Newborns: Identification using Footprints”, *Proceedings of 2013 IEEE International Conference on Information and Communication Technologies (ICT 2013),* 737-742, Tamilnadu, India

[6] Hai-Yang Cai, *et al* “Newborn Footprint Recognition using Orientation Feature”, Neural Computing & Applications: 1-9, Dec ICIC 2010.

[7] S.Balameenakshi, S.Sumathi and R.Rani Hemamalini,”Identity Verification of Newborn Using Biometrics”, *International Journal of Engineering Research and Applications (IJERA*) ISSN: 2248-9622 National Conference on Advanced Communication & Computing Techniques (NCACCT-19 March 2013, Chennai)

[8] Peter, W. I. L. D. "Single-sensor hand and footprint-based multimodal biometric recognition."

[9] Anil Jain, Karthik Nandakumar, Arun Ross,” Score normalization in multimodal biometric systems”, *Pattern Recognition* 38 (2005) 2270 – 2285

[10] Horng, Shi-Jinn, et al. "An improved score level fusion in multimodal biometric systems." *Parallel and Distributed Computing, Applications and Technologies, 2009 International Conference on*. IEEE, 2009.

[11] Sahoo, Soyuj Kumar, Tarun Choubisa, and Mahadeva Prasanna SR. "Multimodal biometric person authentication: A review." *IETE Technical Review*29.1 (2012): 54.

[12] L. Hong, A.K.Jain, S. Pankanti, and R. Bolle, “An identity authentication system using fingerprints,” *Proc. IEEE*, vol. 85, no. 9, pp.1365–1388, Sep. 1997.

[13] Utkarsh Gupta et al,“Score Level Fusion of Face and Finger Traits in Multimodal Biometric Authentication System” *IJCA* Proceedings on International Conference and workshop on Emerging Trends in Technology (ICWET 2012) *(ICWET2/Number 4 (ISBN: 973-93-80864-50-9))*