Neural networks for Multibiometrics – Review on Issues, Applications, Challenges and Research Areas

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Abstract

RecentAdvances in the field of Information Technologymakes Information Security an inseparable part of it. In order to deal with security, Authentication plays an important role. This paper presents a review on the biometric authentication techniques and some future possibilities in this field. Biometric authentication systems makes use neural networks for the training and verification phase. The fusion of multiple biometrics helps to minimize the system error rates. Fusion methods include processing biometric modalities sequentially until an acceptable match is obtained. This paper is an overview of Neural networks for multibiometrics, challenges in the progress of multibiometrics using neural networks, the main research areas and its applications to develop the security system for high security areas.

Keywords: Unimodal, Multibiometrics, ANN

1. INTRODUCTION

Information securitydeals with the assurance of confidentiality, integrity and availability of information in all forms. There are many tools and techniques that can support the management of information security. But system based on biometric has evolved to support some aspects of information security. Biometric authentication supports the facet of identification, authentication and non-repudiation in information security.Biometric authentication has grown in popularity as a way to provide personal identification. Person’s identification is crucially significant in many applications and the hike in credit card fraud and identity theft in recent years indicates that this is an issue of major concern in wider society. Individual passwords, pin identification or even token based arrangement all have deficiencies that restrict their applicability in a widely-networked society. Biometric is used to identify the identity of an input sample when compared to a template, used in cases to identify specific people by certain characteristics. Possession based: using one specific "token" such as a security tag or a card and knowledge-based: the use of a code or password. Standard validation systems often use multiple inputs of samples for sufficient validation, such as particular characteristics of the sample. This intends to enhance security as multiple different samples are required such as security tags and codes and sample dimensions. So, the advantage claimed by biometric authentication is that they can establish an unbreakable one-to-one correspondence between an individual and a piece of data.

Biometric systemsbased on single source of information are called unimodal systems. Although some unimodalsystems [2] have got considerable improvement in reliability and accuracy, they often sufferfrom enrollment problems due to non-universal biometrics traits, susceptibility to biometricspoofing or insufficient accuracy caused by noisy data [3].Hence, single biometric may not be able to achieve the desired performance requirement inreal world applications. One of the methods to overcome these problems is to make use ofmultimodal biometric authentication systems, which combine information from multiplemodalities to arrive at a decision. Studies have demonstrated that multimodal biometricsystems can achieve better performance compared with unimodal systems.

This paper presents the review of neural networks for multibiometrics. This includes applications,challenges and areas of research in multimodal biometrics. The different fusion techniques ofmultimodal biometrics have been discussed. The paper is organized as follows. A detailed literature has been presented in Section 2 followed by Multialgorithm and multi sample approach in Section 3 whereas need of multibiometrics and details of Multibiometrics are illustrated in Section 4 and Section 5 respectively.Artificial Neural Networks along with its architecture is discussed in Section 6. Applications of Neural Networks in Multibiometrics are illustrated in Section 7, whereas Challenges and research areas are given in Section 8. Summary and Conclusions are presented in the last section of the paper.

2.LITERATURE SURVEY

Combining several systems has been investigated in patternrecognition [1] in general; in applications related to audiovisualspeech processing [3]; in speech recognition–examples of methods are multi-band, multi-stream , front-end multi-feature approaches and the unionmodel [9]; in the form of ensemble [10]; in audio-visual personauthentication; and, in multi-biometrics [12], [13], [14],[15], [16] (and references herein), among others. In fact, oneof the earliest worksaddressing multimodal biometric fusionwas reported in 1978 [17]. Therefore, biometric fusion has ahistory of 30 years.Recent advances in multi-biometrics have been focusing onquality-based fusion, e.g., [18], [19], [20], [21], [22], wherethe quality associated with the template as well as the querybiometric sample are taken into account in decision levelfusion. For this purpose, a plethora of quality measures haverecently been proposed in the literature for various biometricmodalities, e.g., fingerprint [23], [24], iris [25], face [26],speech [27], signature [28], and classifier-dependent measure(confidence) [29], [30]. The proposed quality measures, ingeneral, aim to quantify the degree of excellence or conformanceof biometric samples to some predefined criteria knownto influence the system performance. For instance, for theface biometrics, these assess image focus, contrast and facedetection reliability.

In quality-based fusion, the match scores of biometric samplesof higher quality are given more important consideration,i.e., higher weights, in order to compute the final combinedscore. There are two ways quality measures can be incorporatedinto a fusion classifier, depending on their role, i.e.,either as a control parameter or as evidence. In their primaryrole, quality measures are used to modify the way a fusionclassifier is trained or tested, as suggested in the Bayesianbasedclassifier called “expert conciliation” [18], reducedpolynomial classifier [31], quality-controlled support vectormachines [19], and quality-based fixed rule fusion [32]. Intheir secondary role, quality measures are often concatenatedwith the expert outputs to be fed to a fusion classifier, asfound in logistic regression [20] and the mixture of GaussiansBayesian classifier [21].

Other notable work includes the use of Bayesian networksto gauge the complex relationship between expert outputsand quality measures, e.g., Maurer and Baker’s Bayesiannetwork [33] and Poh*et al.*’s quality state-dependent fusion[34]. The work in [34] takes into account an array ofquality measures rather than representing quality as a scalar.By means of grouping the multi faceted quality measures, a fusion strategy can then be devised for each cluster of qualityvalues.Other suggestions include the use of quality measures toimprove biometric device interoperability [35], [36]. Such anapproach is commonly used in speaker verification [37] wheredifferent strategies are used for different microphone types.

Last but not least, another promising direction in fusion isto consider the reliability estimate of each biometric modality.In [38], the estimated reliability for each biometric modalitywas used for combining symbolic-level decisions, whereasin [39], [40], [41], [30], score-level fusion was considered.However, in [39], [40], [41], the term “failure prediction” wasused instead. Such information, derived solely from the expertoutputs (instead of quality measures), has been demonstratedto be effective for single biometric modalities [39], fusionacross sensors for a single biometric modality [40], and acrossdifferent machine learning techniques [41]. In [30], the notionof reliability was captured by margin, a concept used in largemarginclassifiers [42]. Exactly how the reliability is definedand estimated for each modality, and how it can be effectivelyused in fusion, are still open research issues.

3. MULTI ALGORITHM AND MULTI SAMPLE APPROACH

Multi algorithm approach employs a single biometric sample acquired from single sensor. (Figure 1)Twoor more different algorithms process this acquired sample. The individual results arecombined to obtain an overall recognition result. This approach is attractive, both from an application and research point of view because of use of single sensor reducing dataacquisition cost. The 2002 Face Recognition Vendor Test has shown increased performancein 2D face recognition by combining the results of different commercial recognition systems[4]. Gokberk et al. [5] have combined multiple algorithms for 3D face recognition. Xu et al. [6]have also combined different algorithmic approaches for 3D face recognition.

Multi sample or multi instance algorithms use multiple samples of the same biometric. Thesame algorithm processes each of the samples and the individual results are fused to obtainan overall recognition result. In comparison to the multi algorithm approach, multi sample hasadvantage that using multiple samples may overcome poor performance due to one samplethat has unfortunate properties. Acquiring multiple samples requires either multiple copies ofthe sensor or the user availability for a longer period of time. Compared to multi algorithm,multi sample seems to require either higher expense for sensors, greater cooperation fromthe user, or a combination of both. For example, Chang et al. [7] used a multi-sampleapproach with 2D face images as a baseline against which to compare the performance ofmulti-sample 2D + 3D face.

4. NEED OF MULTIBIOMETRICS

Most of the biometric systems deployed in real world applications are unimodal which rely onthe evidence of single source of information for authentication (e.g. fingerprint, face, voiceetc.). These systems are vulnerable to variety of problems such as noisy data, intra-classvariations, inter-class similarities, non-universality and spoofing.

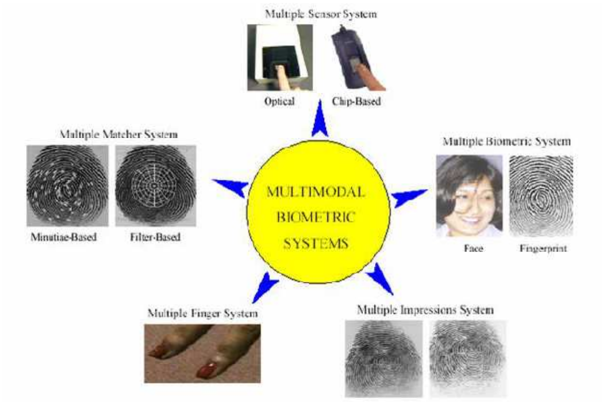

Figure 1: Fusion in multibiometric system

t leads to considerably highfalse acceptance rate (FAR) and false rejection rate (FRR), limited discrimination capability,upper bound in performance and lack of permanence [8]. Some of the limitations imposed byunimodal biometric systems can be overcome by including multiple sources of information forestablishing identity. These systems allow the integration of two or more types of biometricsystems known as multimodal biometric systems. These systems are more reliable due to thepresence of multiple, independent biometrics. These systems are able to meet thestringent performance requirements imposed by various applications. They address theproblem of non-universality, since multiple traits ensure sufficient population coverage. Theyalso deter spoofing since it would be difficult for an impostor to spoof multiple biometric traitsof a genuine user simultaneously. Furthermore, they can facilitate a challenge – responsetype of mechanism by requesting the user to present a random subset of biometric traitsthereby ensuring that a ‘live’ user is indeed present at the point of data acquisition.

5. MULTIBIOMETRICS

The term “multimodal” is used to combine two or more different biometric sources of a person(like face and fingerprint) sensed by different sensors. Two different properties (like infraredand reflected light of the same biometric source, 3D shape and reflected light of the samesource sensed by the same sensor) of the same biometric can also be combined. Inorthogonal multimodal biometrics, different biometrics (like face and fingerprint) are involvedwith little or no interaction between the individual biometric whereas independent multimodalbiometrics processes individual biometric independently. Orthogonal biometrics areprocessed independently by necessity but when the biometric source is the same and different properties are sensed, then the processing may be independent, but there is at leastthe potential for gains in performance through collaborative processing. In collaborativemultimodal biometrics the processing of one biometric is influenced by the result of anotherbiometric.

A generic biometric system has sensor module to capture the trait, feature extraction moduleto process the data to extract a feature set that yields compact representation of the trait,classifier module to compare the extracted feature set with reference database to generatematching scores and decision module to determine an identity or validate a claimed identity.In multimodal biometric system information reconciliation can occur at the data or featurelevel, at the match score level generated by multiple classifiers pertaining to differentmodalities and at the decision level. Biometric systems that integrate information at an early stage of processing are believed tobe more effective than those which perform integration at a later stage. Since the feature setcontains more information about the input biometric data than the matching score or theoutput decision of a matcher, fusion at the feature level is expected to provide betterrecognition results. However, fusion at this level is difficult to achieve in practice because thefeature sets of the various modalities may not be compatible and most of the commercialbiometric systems do not provide access to the feature sets which they use. Fusion at thedecision level is considered to be rigid due to the availability of limited information. Thus,fusion at the match score level is usually preferred, as it is relatively easy to access andcombine the scores presented by the different modalities [2].

Rukhin and Malioutov [10] proposed fusion based on a minimum distance method forcombining rankings from several biometric algorithms. Fusion methods were compared byKittler et al. [11], Verlinde et al. [12] and Fierrez-Aguilar et al. [13]. Kittler found that the sumrule outperformed many other methods, while Fierrez-Aguilar et al. [13, 14] and Gutschovenand Verlinde [15] designed learning based strategies using support vector machines.Researchers have also investigated the use of quality metrics to further improve theperformance [16, 14, 17–21].Many of these techniques require the scores for different modalities (or classifiers) to benormalized before being fused and develop weights for combining normalized scores.Normalization and quality weighting schemes involve assumptions that limit the applicability ofthe technique. In [22], Bayesian belief network (BBN) based architecture for biometric fusionapplications is proposed. Bayesian networks provide united probabilistic framework foroptimal information fusion. Although Bayesian methods have been used in biometrics [16,23–25], the power and flexibility of the BBN has not been fully exploited.

Brunelli et al. [26] used the face and voice traits of an individual for identification. A Hyper BFnetwork is used to combine the normalized scores of five different classifiers operating on thevoice and face feature sets. Bigun et al. [16] developed a statistical framework based onBayesian statistics to integrate the speech (text dependent) and face data of a user [27]. Theestimated biases of each classifier are taken into account during the fusion process. Hongand Jain associate different confidence measures with the individual matchers whenintegrating the face and fingerprint traits of a user [28]. They also suggest an indexingmechanism wherein face information is used to retrieve a set of possible identities and thefingerprint information is then used to select a single identity. A commercial product calledBioID [29] uses the voice, lip motion and face features of a user to verify the identity. AloysiusGeorge used Linear Discriminant analysis (LDA) for face recognition and Directional filterbank (DFB) for fingerprint matching. Based on experimental results, the proposed systemreduces FAR down to 0.0000121%, which overcomes the limitation of single biometric systemand proves stable personal verification in real-time [30].

6.ARTIFICIAL NEURAL NETWORK

Artificial Neural Network (ANNs) has a large appeal to many AI researchers. A neural network can be defined as model of reasoning based on the human brain. The brain consists of a closely interconnected set of nerve cells or basic information-preprocessing units, called neurons. The human brain incorporates nearly 10 billion neurons and 60 trillion connections, synapses between them [Shepherd, 1990]. By using multiple neurons simultaneously, the brain can perform its functions much faster than the fastestcomputers in existence today [Negnevitsky,2002].

6.1 Architecture

A multilayer perceptron is a feed-forward neural network with one or more hidden layers. Typically, the network consists of an input layer of source neurons that at least one hidden layer of neurons and an output layer of neurons (Figure 2). The input signals are propagated in a forward direction on a layer-by-layer basis. The backpropagation algorithm perhaps is the most popular and widely used neural paradigm.

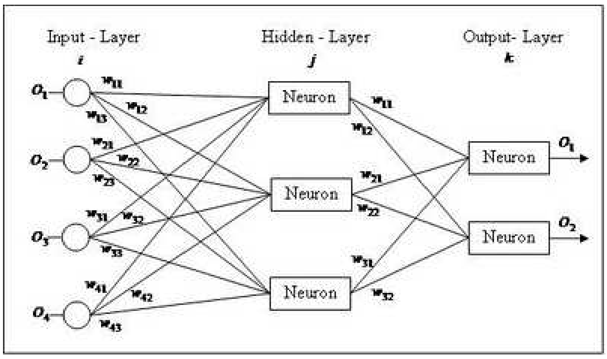

Figure 2: Feed-forward Neural Network

It based on the generalized delta rule proposed by research group in 1985 headed by Dave Rumelhart based at Stanford University, California, USA.

Before the network can be used, it requires target patterns or signals as it a supervised learning algorithm. Training patterns are obtained from the samples of the types of inputs to be given to the backpropagation neural network and their targets are identified by the researchers. The objective of the algorithm is to find the next value of adaptation weight which is also known the Generalized Delta Rule (G.D.R).

The hidden layer weights are adjusted using the errors from the subsequent layer. Thus, the errors computed at the output layer are used to adjust the weight between the last hidden and the output layer. Likewise, an error value computed from the last hidden layer outputs are used to adjust the weight in the next to the last hidden layer and so on until the weight connections to the first hidden layer are adjusted. In this way, errors are propagated backwards layer by layer with corrections being made to the corresponding layer weights in an iterative manner. The process is repeated a number of times for each pattern in the training set until the total error converges to a minimum or until some limit is reached in the number of training iterations completed [Patterson, 1999].

6.2 The Activation Function

The activation function has the characteristics of continuity, differentiability and non-decreasing uniformity. There is several activation functions used in neural network. There is several activation functions used in the neural network. Binary sigmoid and bipolar sigmoid are generally used in the neural network training. The binary sigmoid which has a normalized range within 0 and 1 and bipolar sigmoid is normalized within -1 to +1 are used in backpropagation training.

7. APPLICATIONS OF NEURAL NETWORKS IN MULTIBIOMETRICS

The neural network has the ability of storing theinformation of the continuous quantity. The detailinformation of the continuous quantity can be calculatedfrom the whole network, and also determine the wholenetwork.The paper by Garris*et al.* provides an overview of theNN-based approaches to optical character recognition (OCR).They also provide an end-toendOCR recognition system based on an enhanced multilayerperceptron (MLP) classifier.The paper by Phillips presents a face identification algorithmthat automatically processes an unknown image by locatingand identifying the face. His algorithm is based on designing anet ofmatching pursuit filters optimized for face detection andidentification. For identification, the filters find features thatdifferentiate among faces, whereas, for detection, the filtersencode the similarities among faces. This algorithm has beenevaluated on three sets of images. The first set was imagesfrom the FERET data base (a well-known benchmarking dataset for face recognition). The second set was infrared andvisible images of the same people. This demonstration wasdone to compare performance on infrared and visible imagesindividually, and on fusing the results from both modalities.The third set was mugshot data from a law enforcementapplication.

The defense and intelligence communities require automated methods capable of rapidlydetermining an individual's true identity as well as any previously used identities and pastactivities, over a geospatial continuum from set of acquired data. A homeland security andlaw enforcement community require technologies to secure the borders and to identifycriminals in the civilian law enforcement environment. Key applications include bordermanagement, interface for criminal and civil applications, and first responder verification.

Enterprise solutions require the oversight of people, processes and technologies. Networkinfrastructure has become essential to functions of business, government, and web basedbusiness models. Consequently securing access to these systems and ensuring one'sidentity is essential. Personal information and Business transactions require fraud preventsolutions that increase security and are cost effective and user friendly. Key application areasinclude customer verification at physical point of sale, online customer verification etc.

Designing biometric sensors, which automatically recognize the operating environment(outdoor / indoor / lighting etc) and communicate with other system components toautomatically adjust settings to deliver optimal data, is also the challenging area. The sensorshould be fast in collecting quality images from a distance and should have low cost with nofailures to enroll [IJBB5].

The multimodal biometric systems can be improved by enhancing matching algorithms,integration of multiple sensors, analysis of the scalability of biometric systems, followed byresearch on scalability improvements and quality measures to assist decision making inmatching process. Open standards for biometric data interchange formats, file formats,applications interfaces, implementation agreements, testing methodology, adoption ofstandards based solutions, guidelines for auditing biometric systems and records andframework for integration of privacy principles are the possible research areas in the field.

8. CHALLENGES AND RESEARCH AREAS

Architectures There is a huge space of different fusionarchitectures that has not been explored. The range of possibleconfigurations encompassing serial, parallel and hybridstructures is immense. While the parallel fusion strategy ismost commonly used in multimodal biometric fusion, thereare additional advantages in exploring serial fusion, where theexperts are considered one at a time. It offers the possibilityof making reliable decisions with only a few experts, leavingonly difficult problems to be handled by the remaining experts.

Fusion strategies An important consideration when adoptinga fusion strategy is to consider the statistical dependencyamong the expert outputs. For instance, in intramodal fusion,several experts may rely on the same biometric sample and sohigher dependency is expected among the expert outputs. Onthe other hand, in a multimodal setting, the pool of expertsis likely to be statistically independent. In [20], three typesof frameworks are proposed in order to solve a multimodalfusion problem involving intramodal experts.

The first frameworksimply assumes independence, in which case the fusionclassifier reduces to a Naive Bayes one.

The second frameworkconsiders dependency of experts in an intramodal setting (allobserving the same biometric modality) whereas ignores thedependency at the multimodal setting, hence realizing a twostagefusion process. Finally, the third framework makes noassumption about the expert outputs.

Expert selection Expert selection can be cast as a featureselection problem, as illustrated in [48]. However, directly applyingsuch technique to biometric authentication is difficult.In Section III, for instance, we have seen that the optimal setof experts found using a development population of users maynot be the best for the target users. The phenomenon, knownas “Doddington’s menagerie”, relates to the fact that eachexpert is affected by the differences in the ability of the users’biometric models to represent their respective identities.

Thesediverse abilities have been characterized in Doddington*etal.* [49] by associating different animal names with the users,such as sheep and goats. Thus, a much more robust criterion,taking into account of Doddington’s menagerie, must beconsidered in expert selection. Another issue is raised by thecost considerations. Conciliating both the operational cost andperformance into a single criterion proves to be a difficult task.A special problem of expert selection, called dynamic expertselection arises naturally in the serial fusion architecture. Indynamic expert selection, a fusion classifier may decide whichexpert is *most informative* to query even before the datais acquired. In the recent Multimodal Biometric benchmarkevaluation, organized by the Biosecure (EU-funded) project 2,dynamic fusion strategy proved to be very promising inachieving good performance while minimizing costs.

9. SUMMARY AND CONCLUSIONS

This paper presented the various issues related to multimodal biometric systems. Bycombining multiple sources of information, the improvement in the performance of biometricsystem is attained. Various fusion levels and scenarios of multimodal systems are discussed.Neural network solutions like Support vector machine(SVM) helps to get Fusion at the match score level that is the most popular due to the ease in accessing andconsolidating matching scores. Template security is critical to the integrity of a biometricsystem. Fuzzy vault and Fuzzy extractor are provided as solution to template security. Performance gain is pronounced when uncorrelated traits areused in a multimodal system. The challenges faced by multimodal biometric system andpossible research areas are also discussed in the paper.

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