Hybrid Neural Networks in Generic Biometric System: A Survey

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Abstract

There are numerous definitions of hybrid systems that vary from one another in terms of the methods suggested. In general, hybrid systems can be characterised as combining two or more distinct approaches to create a fusion system that depends on the merged approaches. Sequential, auxiliary, and embedded hybrid systems are different types of hybrid systems. In general, in order to use biometrics, there must be a way to record the chosen distinguishing attribute. Preprocessing is then utilised to enhance the input. Then, for processing and storage, the most distinguishing features are extracted, encoded, and added to a suitable representation template. By comparing query inputs to templates that have been stored, it is possible to identify the subject under examination. Biometric systems have been employed by numerous industries.

Keywords: Hybrid systems; Biometrics; Auxiliary; Embedded systems.

1. Introduction

Traditionally, for security applications, the utilisation of keys by which the people carry to open a secure application in a physical environment may be limited to loss or falsification. Furthermore, smart cards may be lost or changed. Therefore, biometrics such as fingerprint, iris, and face are the most common and more secure authentication processes as shown in Figure 1 [1].

Generally, biometrics can be classified into physiological biometrics and behavioral biometrics. The physiological biometrics are always with the person alive such as eye, face, finger, palm, hand geometry, etc. While the behavioural biometrics such as voice or speech recognition, and signature recognition depends dynamically on the behavioural characteristics of the person as Shown in Figure 2 [2,3].

In a biometric system, four parameters need to be taken into account. Performance is the first variable, and it refers to the recognition accuracy and speed that can be achieved, the resources needed to achieve the desired recognition accuracy and speed, as well as the operational and environmental variables that affect the accuracy and speed [4–6].

The second parameter, acceptability, measures how ready people are to accept using a specific biometric trait (identifier) in their day-to-day lives. The third parameter, circumvention, measures the ease with which the system can be deceived using dishonest means. Finally, the cost is always a factor and must be considered along with the life-cycle cost of system upkeep. There are some significant characteristics [7].

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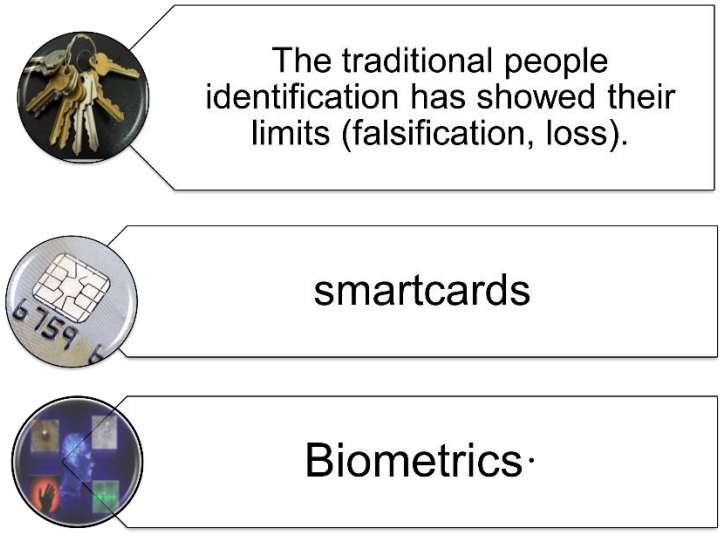

Figure 1: Traditional authentication methods vs biometrics

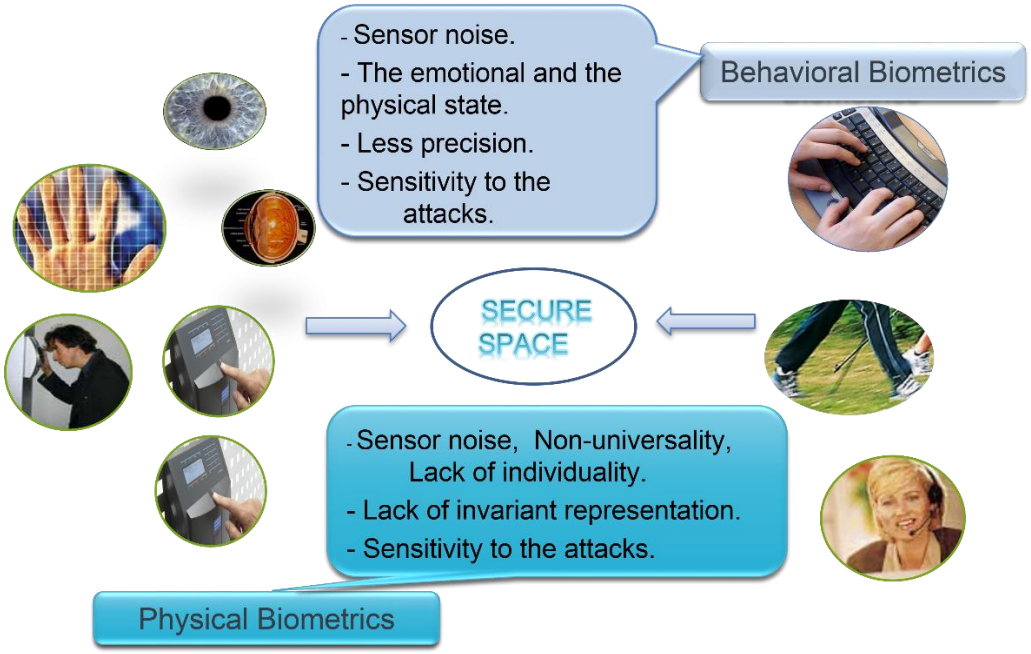

Figure 2: The physical and behavioral biometric characteristics

Table 1: Biometric prosperities.

Parameters	Properties
Universality	The quality ought to exist in everyone.
Distinctiveness	There should be enough distinction between any two people in terms of the trait.
Permanence	Over time, the characteristic should be sufficiently invariant (concerning the matching criterion).
Collect-ability	The attribute can be quantitatively measured.
User-friendliness	The technology must be easy to use, the scanning process must not be obtrusive, and people must be prepared to accept it.
Accuracy	The accuracy of the system must be high enough and depending on how the system is used, there must be a balance between the FAR (False Accept Rate) and FRR (False Reject Rate).

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2. Related Work

Data collection in a general biometric system begins with the measurement of a behavioral or physiological feature. A sensor needs to see the user's characteristics. Any biometric characteristic that is presented to the sensor introduces a behavioral/physiological component, which can differ greatly between users, applications, the test lab, and the operating environment. The convolution of (a) the biometric measure; (b) the manner in the measure is presented; and (c) the technical feature of the sensor, is the output of the sensor, which is the input data upon which the system is created.

The method by which some biometric systems, but not all, capture data at one site but store and/or process it at another is known as transmission. Before transmission, compression may be necessary due to the high volume of data that will be sent. The process of compression and expansion typically results in a loss of quality in the restored signal, with weight loss getting worse as the compression ratio rises. In an open system, transmission and compression techniques ought to be standardised.

Segmentation, feature extraction, quality control, and pattern matching are the four divisions that can be made in signal processing. Finding the biometric pattern within the transmitted signal is the process of segmentation. In general, feature extraction is a type of non-reversible compression, which means that the extracted features cannot be used to recreate the original biometric image. Even after being separated from the broader signal, the raw biometric pattern still has non-repeatable aberrations from the system's representation, sensor, and transmission processes. In certain systems, feature extraction comes first, then transmission, to use up less bandwidth.

Templates or models created by registered users will be kept in a database and paired with incoming feature samples by the pattern matcher. The database could be disseminated on smart cards, cards that can be read optically, or cards with magnetic strips that are carried by each user who has signed up for the system doing the (one-to-one) matching. If the system uses (one-to-N) matching with N more than 1, as it does in identity or "PIN-less verification" systems, then the database will be centrally located. The decision subsystem carries out system policy by controlling the database search, identifying "matches" or "non-matches" based on proximity or similarity measurements obtained from the pattern matcher, and eventually making a "accept/reject" decision-based on system policy. All biometric systems can be described by the general model as shown in Figure 3, which can be divided into five subsystems: data collection, Transmission, signal processing, decision, and data storage.

In this step, comparisons between the biometric photographs entered and the images saved in the database are made. The biometrics of the individual is photographed for person identification, and the previous procedures are used to obtain the biometric code. Following that, one of the comparison methods is used to compare the input biometric code to codes in the database. Verification, identification, and detection processes are therefore included in the biometric authentication processing system depicted in Figure 4. While the procedure of verification is used to check a person's existence by determining whether it is on the database by comparing the codeword resulting from feature extraction with the existence codeword on the database (i.e., one to one matching),

By comparing the input person keyword with the keywords recorded in the database, the identification process decides whether the persons are present in the database (one to many matching). The detection process is a technique for human identification that checks a database to see if a person is real or not, as well as looking at the most typical biometric traits [8].

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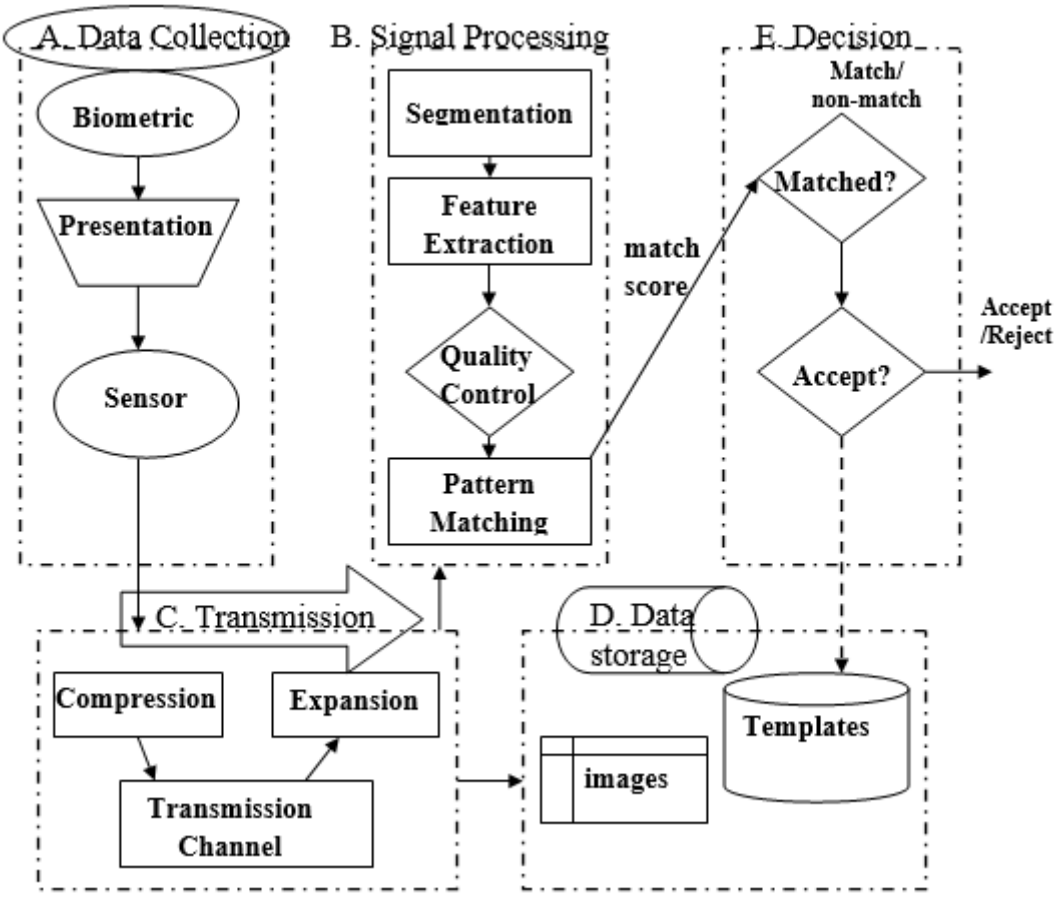

Figure 3: A generic biometric system's parts

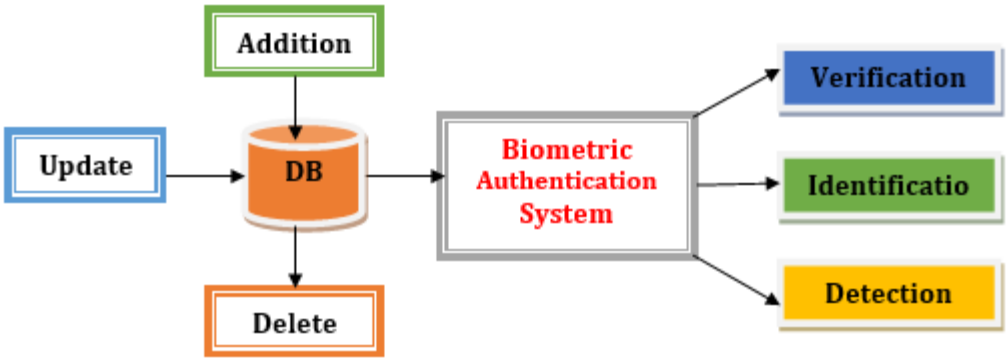

Figure 4: Biometric Authentication System

3. Hybrid Neural Networks

Because they produce several local minima while looking for a global optimum point, neural networks (NNs) with a lot of hidden neurons are typically challenging to train. Conventional algorithms, including correlation, PCA, partial least squares analysis, fast Fourier transform (FFT), and wavelet transform, are efficient instruments for locating and strengthening unique features in the information that may be more condensed and ordered than the raw data itself [9].

The preprocessed data will undergo a nonlinear transformation if the NN is smaller. For instance, a data collection with 1024 components can be broken down into 200 elements, which can then be supplied into 200 input neurons as forms, locations, intensities, ratios, and slopes. This hybrid neural network (HNN) will be very effective and reliable.

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A NN with over 65,000 input neurons and up to 4.3 109 global connections in the first layer is needed to associate the entire image in order to perform pattern recognition on a high-resolution image in parallel, such as a 256 256 pixel image. Making a ship of a board with this kind of interconnection capability to do parallel pattern recognition is beyond the capabilities of modern VLSI technology.

As seen in Figure 5, an HNN identifies objects by combining preprocessing methods (as the first layer) and NN algorithms. Reading the photographs into the computer in grayscale format and digitising them for computer processing are the first steps in image preparation. The images then go to the processing steps, where edge enhancement, normalisation, and smoothing are carried out. Any noisy artifacts are eliminated during smoothing. By removing background bias signals, normalisation enhances the contrast of the image. In the initial process, edge enhancement starts to extract some of the unique aspects of each image. The next step involves NN training and identification using the signals that have been analysed. To represent the feature windows from preprocessing, the input neurons are aggregated.

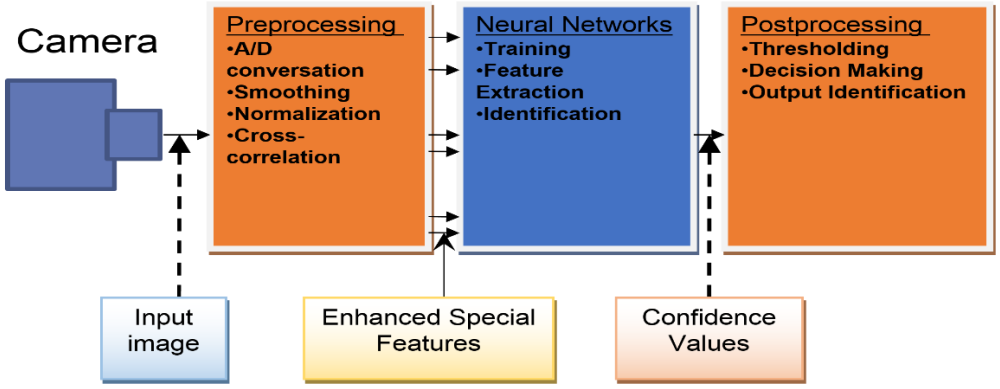

Figure 5: Schematic diagram of an HNN-based pattern recognition system

Pattern recognition techniques are traditionally divided into three groups: statistical (or decision-theoretic), structured, and artificial intelligence-based approaches. Classification is the main application of decision-theoretic approaches. Assigning an unknown input pattern to one of M classes is the goal of pattern classification. An N-dimensional feature vector is used to represent a single pattern.

The explicit use of structural information in pattern recognition is the fundamental concept in structural pattern recognition. The hierarchical composition of a complex pattern based on simpler sub-patterns and numerous relations that may exist between distinct sub-patterns and/or distinguishing traits are two significant factors that are modeled using structural information. The recognition process for syntactic methods, a significant subgroup of structural approaches, is based on examining input patterns. Matching is the second subclass of the structural approach, where a finite number of pattern prototypes are kept as structural representations based on strings, trees, or graphs rather than N-dimensional feature vectors.

Pattern classes are viewed as abstract notions and specific patterns as instances of those patterns in artificial intelligence-based methodologies. In order to represent pattern classes, knowledge characterising them must be stored explicitly. Some artificial intelligence-based methodologies include first-order predicate calculus logic employing resolution refutation as an inference mechanism, production systems controlled by forward- and/or backward-chaining control strategies, and semantic networks.

There are advantages and disadvantages to every technique. Statistical, structural, and artificial intelligence-based methodologies are occasionally used to get around these restrictions. A hybrid strategy is a name for this outcome. Different hybrid techniques exist, depending on the level of integration. On the one hand, there are hybrid systems that are simply a collection of "pure" techniques that are executed sequentially. On the other side, there exist methods for thoroughly integrating and combining several strategies.

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Numerous applications of pattern recognition call for a hybrid approach, including the analysis of electrophoresis gels, document analysis, and comprehension, parameter estimation in multidimensional analysis, multisensor integration, estimation of weights, or probabilities, grammar productions, syntactic translation, grammatical interference, and learning. Image understanding is a typical application that calls for a mixed technique [10].

4. Comparative Study of Biometrics-based Hybrid Neural Networks

In this section, we highlighted the most common approaches that use iris traits recognition based on HNN. As investigated in Table 2, the biometric trait is the iris which is most commonly used to identify subjects. Alwawi and Althabhawee, 2022 [11] present iris recognition system based on Deep learning and convolutional neural networks with a promising accuracy reached to 95.33%. Furthermore, Sun et al. [12] present local circular Gabor filters and multi-scale convolution feature fusion networks and the accuracy achieved was 98.62%. A Local Phase Quantization (LPQ) and the optimal decision model based on Atom Search Optimization (ASO) and Feed Forward Counter propagation Neural Network (FFCNN) presented by Lavania and Kavitha, 2021 [13] achieved an accuracy 99.90%. Shams et al. [14] presents eye localization and detection based on CASIA dataset and the accuracy achieves was 95.00% using deep belief neural networks for classification.

Author	Biometric Trait(s)	Methodology	Accuracy
Alwawi and Althabhawee, 2022 [11]	Iris	Deep Learning Based Convolutional Neural Networks	95.33%
Sun et al., 2022 [12]	Iris	local circular Gabor filters and multi-scale convolution feature fusion network	98.62%
Lavania and Kavitha, 2021 [13]	Iris	Local Phase Quantization (LPQ) and the optimal decision model based on Atom Search Optimization (ASO) and Feed Forward Counter propagation Neural Network (FFCNN)	99.90%
Shams et al., 2022 [14]	Eye	Deep Belief Neural Networks + Speeded up Robust Features and Local Binary Pattern	95.00%
Shams et al. 2011 [15]	Iris	Local Binary Pattern and Combined Learning Vector Quantisation	99.87%

6. Conclusion

In this paper, we introduce the generic biometric system based on hybrid neural network approaches. We briefly stated the different components of generic biometric system and its main parts and the pros and cons of the biometric traits. We further demonstrated the hybrid neural networks approaches with the assistance of pattern recognition and image processing techniques. The comparison between differed HNN and iris traits is performed that stated the current efforts to recognize and match the biometric traits. In the future, we plan to compare different biometrics and linked it with Mobile ad hoc network (MANET) to obtain more secure network with different traits and meta-heuristic optimization.

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