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Survey of Biometric Pattern Recognition via Machine Learning Techniques

Nicolas Ortiz[1], Ruben Dario Hernández[1], Robinson Jimenez[2], Mauricio Mauledeoux[2] and Oscar Avilés[2]

[1] Gi-itec Research Group, Technology in Electronics
and Communications Department
[2] Davinci Research Group, Mechatronics Department
Faculty of Engineering, Universidad Militar Nueva Granada, Carrera 11# 101-80
Bogotá, Colombia

Abstract

Biometrics, as a computer science field, can be understood as the discipline that study how to generate computer models of the physical (e.g. hand geometry, fingerprints, iris and so on) and behavioral (e.g. signature; a kind of behavior pattern) characteristics of the human being for single or several individuals identification. Usually, these characteristics are used to provide authentication information for security systems. However, some of these characteristics are hard to obtain in a properly way and it is necessary to use several algorithms both to process them and to use them on a security systems. In this sense, in this paper it is presented an overview of some Machine Learning approaches for biometric pattern recognition.

Keywords: Biometrics, computer models, pattern recognition, security systems, machine learning

1 Introduction

Biometrics in modern computer science is defined as the automated use of biological properties to identify a person [1]. These properties allows humans identify several individuals depending on their physical and behavioral characteristics as well as their correct use allows computer systems to recognize patterns for security tasks. These certain kind of tasks have turned in a new research

field and, in consequence, its applications have been drastically expanded into many new domains. This was of being expected due the increase demand for security and the advantages of biometric systems; biometric features cannot be stolen, lost or forget [2]. In this sense, any details of the human body which differs from one human to other will be used as unique biometric data to serve as that person's unique identification (ID) [3], it can be said that these systems provide security based on what you own rather than what you know (password/PIN) or what you have (smart-card). In this sense several number of systems have been developed based on various physiological and behavioral traits [4], which include fingerprint [5], face [6], iris [7], retina [8], voice [9], keystroke [10], ear [11], hand geometry [12], signature [13] and gait [14]. Biometric systems relies on the input from a number of fields, starting with various kinds of sensors that are used to sample the biometric data. At its final stage, the system outputs a decision, which links the acquired and processed biometric trait to an identity. In this regard, machine-learning methods are useful in selecting appropriate feature representations that will facilitate the job of the decision function, in dealing with temporal information, and in fusing multi-modal information [15].
In this paper, it is presented a review of some machine learning approaches for biometric features dealing and decision making on different types of biometric systems. Section II gives brief description of biometric measures based on the approaches adopted for feature extraction. Section III describes biometric recognition approaches and performance using different machine learning methods; unsupervised learning, supervised learning and reinforcement learning. Finally, conclusion is given in Section IV.

2 Biometric Measures

Automated methods for verifying and/or recognizing the identity of a living individual can be based mainly on two biometric measure categories: (1) Physiological biometrics (Facial, hand and hand vein infrared thermogram, Odor, Ear, Hand and finger geometry, Fingerprint, Face, Retina, Iris, Palm print, Voice, and DNA) and (2) Behavioral biometrics (Gait, Keystroke, Signature) which measure the human actions [16]. Nevertheless, these biometric measures provide a fool-proof solution with total population coverage and new biometric measures have been proposed like ECG [17], EEG [18], lip-print [19], mouse dynamics [20], dental radiograph [21], tongue print [22] and others.
Thus, biometric measures are expected to possess several characteristics to be practically usable for several applications. Listed below are described the most important characteristics consider for machine learning approaches taken into account those described in [2].

Universality: This is the ability for a specific biometric measure to be applied to a whole population of users. For learning tasks, this can be understood as having consistent data in order to avoid some learning issues as overfitting or bad training [23].

Uniqueness: The ability to successfully discriminate people. This can translate into the ability to classify information. While data is not separable, learning is not possible or learning is not reliable. However, some data collections can be non-linearly separable; in this case, kernel methods can solved this problems taking into account some criteria as k-separability [24].

Cost-efficiency: The whole process should be cost-efficient.

Circumventable: The ability of the system to detect attacks. In this case, this characteristic can be interpreted as a robustness requirement for the learning algorithm. It has to be capable of dealing with inherent data anomalies.

TABLE I: A summary of traditional biometric measures [4].

Biometric Measure	Approaches Adopted
Iris Scan [7], [25] **Advantages** 1. Potential for high Accuracy 2. Resistance to impostors 3. Long term stability 4. Fast processing	I. Complex valued 2-D Gabor Wavelets [19] II. Laplacian of Gaussian filters [20] III. Zero Crossing Wavelet Transform[21] IV. Circular Symmetry 2-D Filters [22] **Disadvantages** 1. Intrusive 2. High Cost
Fingerprint [5] **Advantages** 1. Mature technology 2. Easy to use /nonintrusive 3. High accuracy 4. Long-term stability and ability to enroll multiple fingers 5. Comparatively low cost	I. Minutiae-based methods [26] II. Image based methods **Disadvantages** 1. Inability to enroll some users 2. Affected by skin condition 3. Sensor may get dirty 4. Association with forensic applications
Face [6]	I. Image Based a. Statistical methods i. Eigenfaces [27] ii. Fischer faces [28] II. Feature based [29] i. Geometric ii. Features metric iii. Morphable models

TABLE I: (Continued): A summary of traditional biometric measures [4].

Advantages 1. Non-intrusive 2. Low cost 3. Ability to operate covertly 4. Potential for privacy abuse	**Disadvantages** 1. Affected by appearance/environment 2. High false non-match rates 3. Identical twins attack
Signature [13] **Advantages** 1. Resistance to forgery 2. Widely accepted 3. Non-intrusive 4. No record of the signature	Feature based methods **Disadvantages** 1. Signature inconsistencies 2. Difficult to use 3. Large templates (1K to 3K) 4. Problem with trivial signatures
Hand Geometry [12] **Advantages** 1. Not affected by environment 2. Mature technology 3. Non-intrusive 4. Relatively stable	Feature Based: Finger length, width, thickness curvatures and relative location of features **Disadvantages** 1. Low accuracy 2. High cost 3. Relatively large readers 4. Difficult to use for some users

3 Machine Learning and Biometric Systems

Machine learning is a subject that studies how to use computers to simulate human learning activities [30]. Framed in the context of biometric systems, it can be understood as the subject that studies biometric features in order to simulate individual's identification learning tasks. This can be summarized, according to Kajaree and Behera [31], as the paradigm of learning from past experience (which in this case is previous data; face images, hand geometry databases and so on) to improve future performance (face recognition, fingerprint identification, etc.).

As a field that is in a continuous development, machine learning has been made many advancements in biometric pattern recognition. In this section it is presented some machine learning approaches divided into three types: Unsupervised Learning, Supervised Learning and Reinforcement Learning, on identification, classification, clustering, dimensionality reduction and recognition tasks needed to develop biometric systems.

3.1 Unsupervised Learning

Consider a machine (or living organism) which receives some sequence of inputs $x_1, x_2, x_3, ...$, where x_i is an input (eyes distance, number of fingerprint edges, hand

vein graph representation, color, image on the retina etc.) and the set $X = x_i$ is called the sample set that correpond to a common database or dataset.
In unsupervised learning the machine simply receives inputs $x_1, x_2, x_3, \ldots$, and build representations of the input that can be used for decision making, predicting future inputs, efficiently communicating the inputs to another machine, etc. In a sense, unsupervised learning can be thought of as finding patterns in the data above and beyond what would be considered pure unstructured noise. [32]. In this way, unsupervised learning goal focuses mainly on clustering and dimensionality reduction tasks.
Several algorithms have been developed in order to achieve this goal, but common approaches are based on:

- k-means [33].
- Expectation-maximization algorithm [34].
- Hebbian Learning approaches [35]
- Convolutional Neural Networks [36]
- Gaussian Mixture Models [37]

For biometric applications, unsupervised algorithms are mainly focus on individual data protection by encrypting biometric information [38], [39], feature level fusion [40], biometric data meaning extraction [41], behavioral pattern detection [42] among other. In addition, implemented biometric systems by using unsupervised learning proof exact localization of biometric features ensures better registration and learning policies definition, subsequently allowing better classification. For instance, in the MIT Lincoln Laboratories successful speaker verification system, a universal background model with 2048 diagonal-covariance Gaussian components was employed [43]. Also, in [44] Tardos code for fingerprint recognition was improved with an iterative Expectation-Maximization algorithm for collusion strategy adaptation, and Vlachos and Dermatas [45] propose a novel clustering algorithm named nearest neighbor clustering algorithm (NNCA), which is unsupervised and has been used successfully for retinal vessel segmentation. As it is unsupervised, it can be used for full automatic finger vein
pattern extraction.

Enclosed below are tabulated some recent works based on unsupervised learning applied to biometric systems and the results obtained for each one.
In conclusion, unsupervised learning can be considered a good approach to achieve biometric pattern recognition. However, it only serves normally as a preliminary stage for data analysis, better learning policies definition, features fusion (clustering tasks) etc. It can be considered as a preliminary data issues dealing approach to improve e.g. classification labors.

TABLE II: Unsupervised Learning approaches applied to Biometrics.

Description	Technique	Results
Hassanat et al [46], presented a new way to identify persons, particularly (terrorists) from their victory sign. Their research proposed a computer system that can identify a terrorist from only two fingers (their victory sign).	For hand segmentation three unsupervised learning approaches were used: (1) Otsu's method [47], (2) k-means clustering based on color information, (2) hand segmentation based on color information using Artificial Neural Network (ANN) [48]	For hand segmentation results shows a perfect (100%) segmentation for the hand silhouette using the technique proposed in [48]. For classification, a 93% total identification accuracy was obtained for identifying terrorists.
Hasnat et al [49] proposed to model (deep)-features delivered by the deep neural nets as a mixture of von Mises-Fisher distributions. By Combining von Mises-Fisher Mixture Models with deep neural networks, they derive a novel loss function which enables a discriminative learning.	Von Mises-Fisher Mixture Models combined with deep neural nets based on the methodologies used in [50]–[54]	Results were obtained for 4 face datasets with the above performance: 99.63% accuracy on LFW [55] dataset, 85% accuracy on IJB-A [56] dataset, 96.46% accuracy on YouTube Faces [57] dataset and 99.2% accuracy on CACD [58].
A distributed ultispeaker voice activity detection (DM-VAD) method for wireless acoustic sensor networks (WASNs) was proposed by Bahari et al [59] introducing a distributed energy signal unmixing method to locate the nodes around each source. The VAD problem is transformed into a clustering task, by extracting features from the energy signals and applying a clustering algorithm.	K-Means, K-medians and K-medoids algorithms were used for voice activity source detection	A VAD accuracy of 85% was achieved for a challenging scenario where 20 nodes observe 7 sources in a simulated reverberant rectangular room.

3.2 Supervised Learning

Consider the input and sample set description made in Section 3.1. One can distinguish supervised learning from unsupervised learning, because in supervised learning is also given a sequence of desired outputs $y_1, y_2, y_3, \ldots,$, and the goal of the machine is to learn to produce the correct output given a new input [32].

Unlike unsupervised learning, supervised learning serves mainly in the final stages of a recognition system based on biometrics. While unsupervised techniques are used for discovering clusters, discovering latent factors, discovering graph structure, matrix completion, supervised learning is focused on classification and regression. It has been proofing supervised learning is useful for biometric modalities fusion [60], biometric data classification [61], [62] and regression for reliable, successful and secure multibiometric systems [63], [64].
Interesting results have been obtained from modern techniques. For instance, Taigman et al [54] presented a method of verifying identities with an accuracy up to 97.35% by developing an effective deep neural net (DNN) architecture and learning method that leverage a very large labeled dataset of faces in order to obtain a face representation that generalizes well to other datasets. Outline of learning architecture is shown on Figure 1.

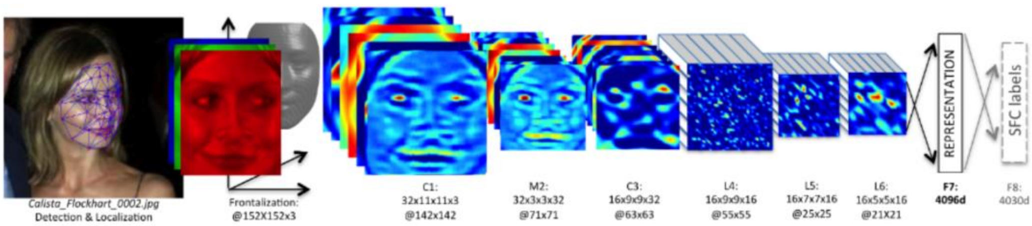

Figure 1 Outline of the depth face architecture proposed by Taigman et al [54]

Enclosed below are tabulated some recent works based on supervised learning applied to biometric systems. Unlike Table II, Table III contains the used algorithm, the biometric application and associated work reference and the performance obtained in each paper.
In conclusion, it could be appreciated supervised learning has been serving for several biometric applications using a large number of algorithms. In contradistinction to unsupervised learning, which only uses mainly K-means algorithm for biometric applications, supervised learning offers a variety of approaches for this kind of tasks: Convolutional Neural Nets (CNN), Kernel Methods (SVM, Kernel Perceptron), Decision Trees, Logistic Regression, etc., all useful for biometric pattern classification principally.

3.3 Reinforcement Learning

In reinforcement learning the machine interacts with its environment by producing actions $a_1, a_2, a_3, \ldots$. These actions affect the state of the environment, which in turn results in the machine receiving some scalar rewards (or punishments) $r_1, r_2, \ldots$ [32]. As a learning problem, it refers to learning to control a system to maximize some numerical value, which represents a long-term objective [78].

TABLE III: Supervised Learning approaches applied to Biometrics.

Algorithm	Biometric Application	Performance
Deep Learning	Face recognition [65], Electromyographic Hand Gesture Signal classification [66], Inferior Myocardial Infarction detection [67], Face Recognition Against Adversarial Attacks [68]	**Metrics scores:** **Accuracy:** 86% [65], 98.31% [66], 84.54% [67], 99.9% [68] **sensitivity:** 85.33% [67] **specificity:** 84.09% [67]
Decision Trees	Face Recognition [62]	**Metrics scores:** **Accuracy:** Results shows a maximum accuracy of 100% on the FERET [69] dataset and 99% on the CAS-PEAL-R1 [70] dataset.
Support Vector Machines (SVM)	Face Alignment [71], text independent speaker verification [72], Gender recognition based [73], Speech Emotion Classification [74]	**Metrics scores:** **Accuracy**: 92.82 % [71], 57.9% [72] using Principal component analysis for dimensionality reduction and Fine-SVM, 96.4% [73] on IITD dataset [75]. The baseline accuracy for speech emotion recognition in [74] was around 50% to 90% depending on the selected technique.
Kernel Perceptron	Facial Emotion Recognition [76]	**Metrics scores:** **Accuracy:** The classifier recognizes the 6 different Emotions with 98.6% efficiency on the JAFFE [77] dataset.

Reinforcement learning is based on the common sense idea that if an action is followed by an improvement in the state of affairs, then the tendency to produce that action is strengthened [79]. Based on this, reinforcement learning approaches for biometrics are focus mainly on classification tasks [80] [81], continuous training

by using a feedback reward or punish signal [82], [83], find out dominant or discriminant features [84] [85] and feature extraction [86].
As it can be seen, reinforcement learning seems to be more versatile than supervised and unsupervised learning. It is useful for both unsupervised labors and supervised labors [87-91]. However, reinforcement learning is limited to fairly lowdimensional problems. But, nevertheless, Deep Reinforcement Learning (DRL) has proven to be useful to solve this problem. In despite the successes of DRL, many problems need to be addressed before these techniques can be applied to a wide range of complex real-world problems [92], [93].

4 Conclusions

As it provides several techniques and many kind of algorithms, machine learning offers several advantages over other approaches for biometric pattern recognition. In this way, this capability satisfies an increasing need for security and smarter applications [15]. Also, it could be appreciated that all the given unsupervised, supervised and reinforcement learning algorithms meet the necessary characteristics proposed in Section 2 for biometric measures dealing and obtained accuracy performances proves they are suitable for real applications. It is expected that the references provided will serve the reader in creating novel machine learning solutions to challenging biometrics problems based on novel approaches as in [62], [76], [86], [94].

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