Pattern Mining Approaches Used in Sensor-Based Biometric Recognition: A Review

Jyotismita Chaki, Nilanjan Dey, Fuqian Shi, *Senior Member, IEEE*, and R. Simon Sherratt, *Fellow, IEEE*

***Abstract*— Sensing technologies place significant interest in the use of biometrics for the recognition and assessment of individuals. Pattern mining techniques have established a critical step in the progress of sensor-based biometric systems that are capable of perceiving, recognizing, and computing sensor data, being a technology that searches for the high-level information about pattern recognition from low-level sensor readings in order to construct an artificial substitute for human recognition. The design of a successful sensor-based biometric recognition system needs to pay attention to the different issues involved in processing variable data being—acquisition of biometric data from a sensor, data pre-processing, feature extraction, recognition, and/or classification, clustering, and validation. A significant number of approaches from image processing, pattern identification, and machine learning have been used to process sensor data. This paper aims to deliver the state-of-the-art summary and present strategies for utilizing the broadly utilized pattern mining methods in order to identify the challenges as well as future research directions of sensor-based biometric systems.**

***Index Terms*— Biometrics, classification, pattern mining, pre-processing, recognition, sensing technology.**

I. INTRODUCTION

DURING the past decade, there has been an unprecedented growth of computer systems and microelectronics that have empowered sensor systems with unique characteristics. Their small size, high computational power, and minimum cost permit individuals to associate with these gadgets as a component of everyday living. Especially, the recognition of biometrics has turned into highly interesting field, particularly for military, medical, and security applications. Unlike the traditional methods of using PIN codes or passwords, biometric data offers some relatively unique, permanent, collectable and universal ways for user authentication.

The multivariate response of sensors with wide-ranging and partly overlapping discrimination can be exploited to characterize an individual by pattern mining techniques. The entire pattern mining procedure can be described as three main consecutive stages or modules: 1) data pre-processing, dimensionality reduction, 2) classification, and 3) clustering and validation. The first module comprises of sensor(s) and a computer for securing the biometric data and required pre-processing including proper alignment of signals, filtering, normalization, etc. A dimensionality reduction module follows to lower the dimensional space with the purpose of avoiding complications related with high-dimensional datasets and aid improved characterization of the data. The resultant feature vector in low-dimensional space is then applied to a specified detection or estimate problem, generally classification and clustering. Classification deals with the issue of recognizing an unfamiliar instance in the form of formerly learned samples and the main goal of clustering is to learn the structural relationships amongst various biometric data. An ultimate step, occasionally ignored, is the choice of parameter settings for a trained model and the assessment of the accurate error rates by means of validation methods.

Although some surveys have been directed in sensors used in biometrics [1] and pattern recognition techniques used in biometrics [2], no specific survey has been conducted on the intersections of these two areas. This is the first article to present recent advancements to the best of our knowledge in sensor-based biometric recognition. The aim of this state-of-the-art survey is to consider various sensing technologies which are required to acquire the biometric data as well as to survey different pre-processing, feature extraction, classification, clustering and validation techniques that are needed for the automatic recognition and analysis of sensor-based biometrics. We truly hope that this survey can deliver a useful overview of prior work and present possible future directions for research.

The rest of this paper is organized as follows. In section II, we briefly introduced sensor-based biometric data acquisition, in section III, IV, V, VI and VII we review techniques in following aspects: data pre-processing, dimensionality reduction, classification, clustering and validation respectively. Finally, in Section VIII conclusions and future directions of sensor-based biometric systems are discussed. Figure 1 shows the building blocks of pattern mining of sensor-based biometric recognition.

II. SENSOR-BASED BIOMETRIC DATA ACQUISITION

The vital task of a biometric system is its ability to become accustomed with the raw data. The capability of biometric systems for data acquisition and delivery of high-quality

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J. Chaki is with the School of Information Technology and Engineering, Vellore Institute of Technology, Vellore 632014, India (e-mail: jyotismita.c@gmail.com).

N. Dey is with the Department of Information Technology, Techno India College of Technology, West Bengal 740000, India (e-mail: neelanjan.dey@gmail.com).

F. Shi is with the College of Information and Engineering, Wenzhou Medical University, Wenzhou 325035, China (e-mail: sfq@wmu.edu.cn).

R. S. Sherratt is with the Department of Biomedical Engineering, University of Reading, Reading RG6 6AY, U.K. (e-mail: r.s.sherratt@reading.ac.uk).

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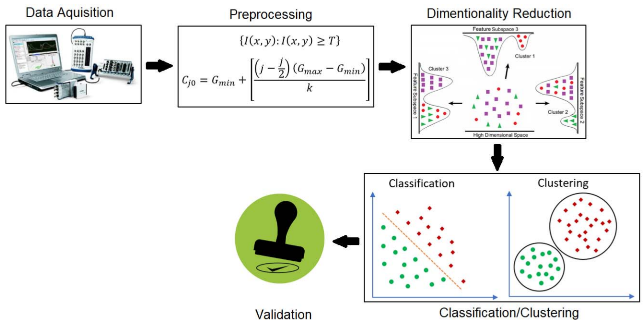

Fig. 1. Building blocks of pattern mining of sensor-based biometric recognition.

information at the beginning of the sensor processing chain, establishes the sensor trenchancy. Biometric data can be obtained from physiological and behavioral characteristics of an individual. Also, bio-signals are typically used as the biometric identification of an individual.

A. Physiological Biometric Data Acquisition

Fingerprint biometric sensors and circuits are combined with entrenched principles and algorithms that are essential for user verification [3]. Fingerprint scanners capture an image of a finger and can be categorized into optical and solid state. There are several types of optical sensors such as the internal reflection sensor that is based on CMOS technology rather than CCD, optical fiber sensor which utilizes a fiber-optic plate instead of prism and lens, electro-optics sensor which uses a photo-electric element, and the in-finger light dispersion sensor which uses an optical imager to capture the fingerprint. Different types of solid state fingerprint sensors (also known as silicon sensors) are used to capture the digitized fingerprint image including capacitive sensors that include a two-dimensional micro-capacitor plate array, thermal sensors that use a silicon die tiled by pixels of delicate pyro-electric material to detect temperature variations, pressure sensors based on the piezoelectric effect, electric field sensors which obtain the image by calculating the differences in the conductive layer under the skin surface; radio frequency sensors which use radio frequency electromagnetic field to generate the fingerprint image, acoustic or ultrasound sensors which use a variation in the acoustic impedance of the skin (ridges) and air (valleys), and micro-electromechanical sensors to obtain clear fingerprint images for different finger surface conditions. An analog-to-digital converter, and a number of small electrodes typically exist in the fingerprint sensor to change the information into a digital form. The creation of a face database can be established by acquiring nodal information from the signals attained from face recognition sensors. To be efficient and precise, the facial image taken is often required to be viewed almost straight at the camera, with slight alteration of light or facial expression from the image in the database. The basic construction of a representative iris imaging system comprises of an optical lens, illuminator and image sensor. The optical lens bears to the lens imaging geometry. The iris image is projected onto the image sensor through a lens. The depth of field, field of view and the focal length are crucial to create an appropriate lens for the iris recognition system. The focal length of the lens governs the magnification of the image. Field illumination is vital factor with most of commercial products using a near-infrared (NIR) LED as the illuminator [4]. The most common image sensors are constructed from CCD or CMOS technology. To image an iris of a suitable size, merging with the optical lens and the working distance, the resolution and sensitivity of the image sensor are vital parameters. The image comprises of its own wellspring of infrared radiation to the eye as the infrared radiation exposes patterns, even for dark eyes.

Nowadays, hand geometry is another biometric attribute which is made in to move to confirm the indistinguishable quality of a person. The existing hand geometry electro-mechanical scanners and solid-state electronic devices utilize an infrared optic sensor and microprocessor for quick capture, effective database formation and template matching [5]. Ear biometrics are also suitable because of their simple acquisition procedure with any digital camera (2D) and laser-triangulation principle (3D) [6]. Vein recognition systems record the radiated vein pattern when veins are exposed to infrared sensors resulting in a black pattern [7] which may be further used to create a digital image. Body odor (olfactory) biometrics is grounded on the principle that almost every human odor or smell is unique and is captured by sensors that are tuned to attain the odor from non-intrusive parts of the body such as the back of the hand [8]. The distinguishing proof of any individual based on retinal scan is developed by acquiring retinal images, an infrared sensor camera is utilized to capture the remarkable pattern of veins positioned at the back of the eye [9].

B. Behavioral Biometric Data Acquisition

Gait based biometric recognition is based on the images captured while the person walks in a plane normal to the camera view which is extremely reliant on the camera viewpoint [10]. Signatures and handwriting are effortlessly captured by using multiple sensor based electronic devices such as Personal Digital Assistants (PDAs), grip pens, pen tablets, smartphones, etc. [11]. Bioacoustics signals can be acquired by using microphone sensors for biometric recognition using various types of analysis such as the amplitude spectrum, localization of spectral peaks correlated to the vocal tract shape or pitch patterns associated to the user's glottal source [12].

C. Bio-Signal Data Acquisition

Bio-signals deliver useful information about an individual which can be used for patient diagnosis as well as for biometrics. Electroencephalogram (EEG) signals are captured by placing electrodes on the scalp [13]. Electroretinogram (ERG) signal is attained by placing electrode on the cornea (at the front of the eye) or by reflected light [14]. Electrocardiogram (ECG) use electrodes to measure heartbeat [15]. Electromyogram (EMG) signal is attained from human muscle using non-invasive electrodes [16]. Electrooculogram (EOG) signals are recorded by placing electrodes onto the skin in the area of the eyes [17]. Galvanic Skin Response (GSR) places the electrodes onto the skin to record the variation in electrical characteristics [18]. Magnetoencephalography (MEG) is used to record brain activity by utilizing very sensitive magnetometers [19]. Magnetocardiography (MCG) measures the magnetic fields produced by electrical activity in the heart using a superconducting quantum interference device [20]. Magnetomyogram (MMG) is used to record the magnetic fields produced when muscles are contracted using sensor arrays [21]. Optical sensors are used to record chemical bio-signal which comprises information about alteration in concentration of different chemical agents in the body including oxygen concentration and to compute levels of lactate, glucose and metabolites. Mercury-based glass thermometer sensors are used to capture thermal bio-signals which describes the body temperature including heat loss and heat absorption in the body, or temperature dispersal over the body surface.

D. Sensor Level Fusion in Data Acquisition

In sensor level fusion, a solitary biometric attribute is imaged utilizing several sensors to extract various data from (spatially) recorded images. Sensor level fusion is pertinent if several sources denote instances of the identical biometric attribute attained either utilizing a single sensor or distinctive sensors for compatibility [22]. For instance, two-dimensional representation of face of a person attained from cameras can be amalgamed to produce a three-dimensional representation of the face. However, the data obtained from sensor level fusion pertaining to a single attribute can improve the recognition accuracy.

E. Sensor Based Data Acquisition Issues

Some of the basic reasons behind biometric signal depiction discrepancies include [23]: 1) varying presentation-the signal taken by the relies on both the basic identifier characteristic along with the way the identifier was offered which obviously is not unique, 2) irreproducible presentation-biometric identifiers offer measurements of different characteristic of individual which are inclined to accidental injury, breakdowns, and pathophysiological development, etc., 3) defective signal acquisition: real-world signal acquisition is not flawless and can causes distinctions in the acquired biometric signals, 4) sensor technology-biometric consistency also differs with change in sensor technologies and manufacturers [24]. Due to distinctiveness, these embedded and precise biometric sensors are controlled from utilizing the information produced by the other unique biometric sensors.

These aforementioned constraints prohibit the user to extend the raw information obtained from numerous biometric sensors with different characteristics to be directly applied to the feature extraction module. Hence, a preprocessing module is needed to convert the raw data generated from different sensors to resourceful information for further processing.

III. PREPROCESSING TECHNIQUES FOR SENSOR-BASED BIOMETRIC DATA

The main goal of a preprocessing module is to select different constraints that are expressive of the sensor data, as this selection can pointedly influence the outcome of the consequent segments in the pattern mining system [25]. Even though preprocessing is bound with the underlying sensor technology, three stages can be acknowledged for physiological biometrics recognition: 1) cropping and resizing, 2) normalization and segmentation, and 3) filtering. Cropping in physiological biometrics recognition is generally termed as content-aware cropping where the salient portion of the sensor response is detected and cropped referred to as the Region Of Interest (ROI). Effective image resizing methods can reserve the ROI and decrease the distortion of the image structure to sustain the synchronization of the image [26]. Normalization is required to convey the image into an assortment of intensity values that is normal, maintaining a statistical normal distribution as far as possible. The mean value will be contingent on the real intensity distribution in the image, but the objective will be to finally state this mean with high confidence level. Instead, global normalization approaches [27] are generally utilized to confirm that sensor magnitudes are analogous, averting consequent pattern-recognition methodologies from getting saturated by sensor data with randomly big values. Two global approaches are typically used in physiological biometric arrangements: 1) autoscaling of sensors, in which the standard deviation and mean of every feature are set to one and zero, individually, and 2) normalization of sensors, where the value range for every feature is set to [0], [1]. Segmentation is used to segment or partition an image into regions that are strongly related to the depicted object or features of interest [28]. Filtering techniques are used for denoising, smoothing and sharpening the sensor response as well as to detect edges from the sensor response [29].

Some of the above discussed pre-processing methods, particularly including resizing, normalization and filtering are also required for behavioral biometric recognition including gait recognition, handwriting recognition and signature recognition [30].

There are numerous sources of bioacoustical distortion that reduce the performance of bioacoustic recognition systems that can collected into two integral classes: additive noise and distortions resulting the convolution of the bioacoustics signal with an unknown linear system. In the bioacoustics enhancement literature, there are two complementary techniques to handle with these problems being spectral normalization and spectral subtraction [31]. In spectral normalization, one approximates the average spectrum when the bioacoustic signal is present and a multiplicative normalization factor is applied with respect to a reference spectrum. In spectral subtraction, one approximates the quantity of background noise existing during non-speech pauses and subtracts the assessed spectral density of the noise from the incoming signal.

The preprocessing of a bio-signal is made for the elimination of noise correlated with the bio-signal due to various types of interference and artifacts, including sensor contact noise, instrumentation noise generated by sensor devices, power line noise, muscle retrenchment, motion artifacts, base line drift, and electrosurgical noise [32]. For the precise and meaningful detection, various filtration techniques are applied to filter out all these noise sources.

TABLE I
REVIEW OF PREPROCESSING APPROACHES IN THE SENSOR-BASED BIOMETRIC RECOGNITION LITERATURE

Biometric Recognition	Technique	References
Physiological & Behavioral (Face, Fingerprint, Hand Geometry, Ear Geometry, Iris, Reina, Vein, body odor, Gait, Signature, Handwriting etc.)	Crop and Resize	[35], [36]
	Normalization	[37], [38]
	Segmentation	[39], [40]
	Filter	[41]
Bioacoustics	Spectral Subtraction	[42], [43]
	Spectral Normalization	[44], [45]
Bio-Signal (EEG, ERG, ECG, EMG, EOG, GSR, MEG, MCG, MMG)	Adaptive filter, spatial filter, median filter	[46], [47], [48]

Preprocessing of olfactory biometric recognition involves two steps being base-line handling and normalization [33]. Baseline handling methods convert the sensor response for the determinations of drift compensation and contrast enhancement [34]. Three baseline handling techniques are generally used being fractional, relative and difference. Fractional handling, deducts and divides by the baseline, producing normalized and answers with the dimensions of 1. Relative handling, instead, divides by the baseline by eliminating multiplicative drift, and generates a response output that is dimensionless. The difference handling method deducts the baseline and is utilized to remove sensor additive drift. Finally, normalization methods formulate the consequent pattern mining segments feature vector on a global or local manner. Local approaches function over the sensor response with the purpose of compensating for instance-to-instance differences because of sensor drift, among others. Global approaches comprise of sensor autoscaling and sensor normalization as discussed before. Table I presents key citations on preprocessing from the sensor-based biometric recognition literature.

IV. DIMENSIONALITY REDUCTION

The preprocessed feature vector is generally not appropriate to be handled by a consequent stage for its redundancy and high-dimensionality. Issues with high-dimensional data is that the amount of training data that exponentially develops with the quantity of features with the purpose to learn a truthful model. With a very high dimensional feature vector the execution of the pattern mining model begins to debase.

A. Feature Extraction

The objective of extracting feature is to discover the mapping of the feature vector in the low-dimensional space $F : p \in \square^M \rightarrow q \in \square^N (N < M)$ that conserves maximum information as the actual feature vector p. It is possible to utilize two fundamental principles to evaluate the projection information content being data representation and data discrimination [49]. Data representation approaches focus on the assembly of the data and should be preferred when the objective is experimental data analysis. Data discrimination approaches, on the other hand, focuses on discrimination abilities (e.g. inter-class distance) and is favored for pattern classification issues, only if the necessary data is available. Principal Component Analysis (PCA) is a data representation approach that produces projections to a new coordinate system such that the maximum variance by some projection of the data will lie on the first coordinate, the second maximum variance on the second coordinate, and so on. [50]. PCA is primarily used to extract the most appropriate information from noisy or redundant data. Linear Discriminant Analysis (LDA) is a data discrimination approach creates projections that maximizes class distinguishability, where the examples of each class generate solid clusters and the dissimilar clusters are distant from each other [51]. Rough Set Attribute Reduction (RSAR) [52] is a data representation approach to reduce the dimensionality of the feature without altering the feature itself, thus it aims to not lose any feature needed for the classification task making it appropriate for biometric feature dimensionality reduction.

Biometric feature extraction techniques are divided into four categories being non-transformed descriptors, transformed descriptors, structural descriptors and graph descriptors [53]. Non-transformed descriptors, also called time-domain descriptors, include moments [54], kurtosis [55], and phase information [56] to determine the statistical characteristics or statistical regularity of the signal.

Transformed or frequency domain descriptors, including the Fourier transform [57], Walsh transform [58] and wavelet transform [59] are used to analyze the signal in the frequency domain for better understanding the dynamic properties of the waveform. The fundamental viewpoint of structural descriptors, such as grammar features [60] and parsing techniques [15] is that the signal features are deterministic, separable and when assembled, define the perception of interest. Therefore, using this descriptor signals can be defined briefly in symbolic form. Graph descriptors, including semantic networks [61] and relational graphs [62] can be supportive to syntactic signal recognition if the training set is very small, or if each signal pattern can be measured as a class sample. A graph is represented as $G = [N, S]$ where N is set of nodes and S is subset of $N \times N$ edges, or arcs, in G.

B. Feature Selection

Feature selection is the procedure of selecting the finest features amongst all the features that are suitable to categorize classes. In case of biometric recognition, feature selection techniques are grouped into three categories based on the objective function [22], being filters, wrappers and embedded. Filter approaches are faster and consume low computational cost but with ineffective consistency in classification as compared to wrapper approaches and better appropriate for high dimensional data sets [63]. Wrappers approaches work well compared to filter approaches because the feature selection procedure is enhanced for the classifier to be used, but are expensive for huge feature spaces with high computational cost as they continuously re-train the pattern recognition methods [64]. Embedded approaches utilize advantages of both wrappers and filters methods.

Feature selection techniques are divided in four main categories based on the strategy: exhaustive search [65], branch and bound algorithm [66], sequential forward and backward selection [67] and bidirectional search [68]. Exhaustive search based on the individual merits of a specified set of features. Given feature set, P_i, $i = 1, \ldots, F$. This search helps to find the best f features from this feature set $\binom{F}{f}$ that reduce the error rate of the classification:

$$\binom{F}{f} = \frac{F!}{(F-f)!f!} \tag{1}$$

The branch and bound algorithm assumes that the feature selection criteria satisfy the monotonicity property, that is: for feature subsets $F_1, F_2, \ldots, F_i$ where $F_1 \subset F_2 \subset F_3 \ldots \subset F_i$, the selection criteria function S fulfills $S(F_1) < S(F_2) < \cdots < S(F_i)$. The Sequential Forward Search (SFS) algorithm initiates from an empty set and successively adds y^+ features to maximize $S(F_i + y^+)$ when joint with the features F_i that have already been selected. The Sequential Backward Search (SBS) algorithm starts from the entire feature set and sequentially eliminates the feature y^- that least reduces the value of the selection function $S(F_i - y^-)$. In bidirectional search, SBS is done for full feature set and SFS is done for empty feature set to assure that SFS and SBS converge to the same solution.

C. Feature Fusion

Feature level fusion denotes to merging various sets of features take out from several biometric sensors [69]. When the feature sets are uniform (e.g. various features of an individual's fingerprint), a solitary resulting feature vector can be premeditated as a weighted average of the distinct feature vectors. If the feature sets are not uniform (e.g. features of various biometric modes such as hand and face geometry), a single feature vector can be formed by concatenating them. Feature selection techniques are used to decrease the dimensionality of the resultant feature vector. When the feature sets are incompatible (e.g., features of EEG signal and fingerprint minutiae) concatenation is not possible.

1) Multi Instance Feature Fusion: Multiple instance features of the identical body attribute are used in this category without using additional sensors [70]. For example, the right and left ring finger features, or the right and left iris features may be used to authenticate an individual's uniqueness. Multiple instance feature fusion is especially advantageous for biometric users whose attributes can't be consistently captured because of inherent complications (e.g., single finger feature of a person having wet skin finger image).

2) Multi Algorithm Feature Fusion: In this category, various feature algorithms (e.g. a minutiae-based feature algorithm and a texture- based feature algorithm on the identical palmprint image) are utilized to handle the same biometric data to obtain a variety of feature sets that can improve the system performance without using of additional sensors, but it involves new feature extractor modules [71].

3) Multimodal Feature Fusion: This category group the features offered by various body characters (e.g. iris and voice) for creating distinctiveness with additional sensors. Physically unrelated features (e.g., iris and fingerprint) are probable to result in improved performance than interrelated features (e.g. iris and eye movement) [72].

Table II presents key citations on feature extraction from the sensor-based biometric recognition literature.

TABLE II

REVIEW OF FEATURE EXTRACTION TECHNIQUES IN THE SENSOR-BASED BIOMETRIC RECOGNITION LITERATURE

Biometric Recognition	Technique	References
Physiological (Face, Fingerprint, Hand Geometry, Ear Geometry, Iris, Reina, Vein, body odor etc.)	Local pattern gradient, Curvature, Wavelet decomposition, Snake model, Multiscale morphology, PCA, Hough transform	[73], [74], [75], [76], [77], [78], [79], [80]
Behavioral (Gait, Signature, Handwriting)	Sparse reconstruction based metric learning, Gradient local binary patterns, longest run feature	[81], [82]
Bioacoustics	Pitch, Zernike moment	[83], [84]
Bio-Signal (EEG, ERG, ECG, EMG, EOG, GSR, MEG, MCG, MMG)	Higher order crossings, Wavelet transform, Moment invariant	[85], [86], [87], [88]

V. CLASSIFICATION

A classifier's objective is to produce a class label for an unidentified feature y on the basis of observed or training labels $x = (x_1, x_2, \ldots, x_n)$. The classification of a sample can be done by assigning the extracted feature (y) of the sample to the class (x_i) with the largest probability $P(x_i|y)$. The most commonly used technique to estimate $P(x_i|y)$ is the Maximum a Posteriori (MAP) method [89] which uses a Bayesian approach. The perception of updating probabilities in the Bayesian method needs a density or probability distribution for the parameters prior to data observation. The MAP method can be expressed as follows:

$$\begin{aligned} y_{MAP} &= \arg\max_{i\in\{1,n\}} P(x_i|y) \\ &= \arg\max_{i\in\{1,n\}} \frac{P(y|x_i)\,P(x_i)}{P(y)} \\ &= \arg\max_{i\in\{1,n\}} P(y|x_i)\,P(x_i) \end{aligned} \tag{2}$$

$P(y)$ can be overlooked for classification determination as it attends as a normalization constant and not a function of x_i. $P(y|x_i)$ is a class conditional density function or likelihood of feature y given x_i.

A. K-Nearest Neighbor

The k-nearest neighbor (KNN) classifier is an influential way which can be utilized to produce extremely nonlinear classifications. The objective of KNN technique is to allocate an unknown sample in the training set amongst to its k nearest neighbors [90]. For biometric classification, these nearest neighbors are generally attained by means of a metric distance. With a suitably high k value and sufficient training instances, KNN can roughly approach to any function which permits it to generate nonlinear boundaries of decision. KNN algorithms are not widespread in the biometric community, possibly for its sensitivity to the curse-of-dimensionality. Though, KNN may prove to be effectual when utilized in low-dimensional feature

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vectors biometric recognition systems. Even though the formulation of KNN classifiers seems exploratory, KNN classifiers are nonparametric approximation of the MAP criterion.

B. Bayesian Classifier

Two non-linear Bayesian classifiers used for biometric recognition are the Hidden Markov Model (HMM) and Bayes quadratic. The objective of Bayes quadratic classification is to create a feature vector of the class having the highest posteriori probability [91]. Using these probabilities and the MAP (Maximum A Posteriori) rule, the feature vector class can be assessed. HMM [92] is a probabilistic automaton that can deliver the probability of detecting a given arrangement of feature vectors. For biometric recognition, these probabilities generally are Gaussian Mixture Models (GMMs).

C. Support Vector Machine

The Support Vector Machine (SVM) is widely used to estimate $P(y|x_i)$ for biometric data. SVM typically gives the best results in numerous non-linear or linear functions from binary or multiclass biometric sample recognition. The first action is data regularization. Actually, biometric features are frequently noisy and probable to comprise with anomalies. Regularization may prevail over this issue and upsurge the classifier's simplification abilities [93]. The second cause may be the ease of the SVM. In the kernel space, the SVM's decision rule is a simple linear function which makes the SVM steady, and thus have a minimum variance. Since biometric features are often unbalanced over time, having a low variance is also crucial for minimum classification error in biometric recognition. Lastly, the SVM's robustness to the curse-of dimensionality has permitted SVM to attain decent outcomes regardless of a small training set and high dimensional feature vectors.

D. Deep Learning for Biometrics

Deep learning methods learn features from the data, and when trained learn indirect features that can differentiate between huge numbers of people [94]. Additionally, if there are adequate numbers of samples characteristic of various factors that affect recognition, deep learning methods can reveal such factors while learning feature representations. This may support in dealing with huge intraclass dissimilarities and noisy biometric data. Enormous efforts are needed to gather data that display progressive variation over time (e.g. voice dataset for detecting gender, face datasets for estimating age etc.) Under such situations, reproductive deep learning methods may be used to blend such variations. With growing privacy and security concerns and the ever-increasing growth of cybercrimes, researchers are investigating behavioral biometrics for verification. The temporal aspects of such behavioral biometrics are captured efficiently using deep learning [95].

Automatic face recognition approaches cam be classified into feature-based methods, that utilize local features, and appearance-based methods, that utilize global representations. Face recognition using a deep-learning framework hierarchically merges both global and local features, while handling

TABLE III
REVIEW OF CLASSIFICATION METHODS IN THE BIOMETRIC RECOGNITION LITERATURE

Classifier	Application	References
KNN	Signature verification, fingerprint recognition, iris recognition	[108], [109], [110]
Bayes quadratic	Facial expression recognition, hand geometry recognition, gait recognition	[111], [65], [112]
SVM	ECG, EEG, EMG biometric authentication	[113], [114], [115]
ANN	Fingerprint recognition, finger vein recognition, bioacoustics recognition	[116], [117], [118]
MLP	Vein identification, fingerprint recognition, gait identification	[119], [120], [121]
RBFNN	Face recognition, ECG biometric authentication, wrist vein recognition	[122], [86], [113]
CNN	EEG biometric authentication, fingerprint recognition, iris recognition	[123], [124], [125]
DBN	Face recognition, multimodal biometrics, audio-video based biometrics	[126], [127], [128]
RNN	Handwriting recognition, EEG, ECG based biometrics	[129], [130], [131]

nuisance factors. Deep learning architectures used in biometrics typically take a Neural Network (NN) approach, typically the Multi-Layer Perceptron (MLP) [96], [97]. An MLP is constructed from layers of neurons with an input layer, one or many hidden layers, and an output layer. To avoid the over-fitting problem of MLP, particularly with non-stationary and noisy biometric data, cautious architecture regularization and selection is required. The output layer of MLP uses SoftMax activation functions, to surmise the posterior $P(y|x_i)$. Other related biometric NN architectures include the Radial Basis Function (RBF) NN [98], [99] and Artificial NN (ANN) [100], [101], Deep Belief Networks (DBN) [102], [103], Convolutional Neural Networks (CNN) [104], [105] and Recurrent Neural Networks (RNN) [106], [107]. Finally, Table III presents some additional approaches mentioned in the pattern classification publications in biometric applications.

VI. CLUSTERING

Clustering, an unsupervised learning, is a procedure to group data depending on spatial similarities or relationships amongst data instances that may be difficult to discriminate the high-dimensional space feature. The clustering procedure includes three major steps [132]: a) specifying a variation in measure amongst samples, generally the Euclidean distance, b) specifying a clustering principle to be enhanced, generally built on between-cluster and within structure, and c) specifying a search algorithm to discover a decent assignment of cluster examples, as thorough listing of the entire probable clustering is undoubtedly impracticable. In most cases, a final domain specialists' validation is essential as, unlike objective supervised measures, clustering outcomes can be subjective.

A. Hierarchical Clustering

These algorithms produce a multi-level taxonomy, or clustering of biometrics data, utilizing the dendrogram tree structure. Dendrograms can be constructed top-down or bottom-up, creating two categories of algorithms [133]: divisive and agglomerative. Divisive clustering algorithms build the dendrogram from the root, where the entire samples enter a single cluster and are successively divided by the worst cluster until every cluster comprises just a single sample. To discover the worst cluster at a specified repetition, the procedure must initially divide the entire clusters and choose the one having two children with maximum variation. This computationally exhaustive task has not received much attention but can generate expressive outcomes than agglomerative approaches for few numbers of clusters. Agglomerative procedures build the dendrogram initiating from the leaves, where every instance procedure an exclusive cluster and continue in the direction of the root by successively combining the two adjacent clusters. A process to measure the similarity of clusters is utilized to decide which two clusters ought to be fused, with minimum-distance also termed as single-linkage producing lengthened clusters and maximum-distance also termed as complete-linkage generating compact clusters.

B. Density Based Clustering

Density based clustering assumes that points that belong to every cluster are drawn from a precise probability distribution [134]. This algorithm can be utilized for only spherical-shaped clusters. The excellence of such clustering is that they have substantial higher density of points than outside the cluster. This technique is efficient in handling noise and thus suitable for biometrics recognition, requiring only one pass of the input dataset. The prerequisite of this algorithm is that the density parameters should be initialized beforehand. It permits the specified cluster to raise continuously as long as the density of neighborhood surpasses a certain threshold.

C. Grid Based Clustering

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A grid-based structure is constructed by quantizing the biometric feature space into limited number of cells [135], i.e. 1) the data space is initially divided into certain number of cells, 2) the cell density for every of the cell is computed, 3) cells are categorized through sorting according to their densities, 4) the center of the cluster is acknowledged, 5) the distance amongst the neighboring cells are computed. The foremost benefit of the grid-based technique is low computational cost regardless of number of data objects. The key feature of this algorithm is that it does not need to calculate distances amongst two data objects. Clustering is achieved only at summarized data points.

D. Partition Based Clustering

Assumed a biometric database of m objects, it constructs k partitions of the data [136]. Every object must belong to just one group and every group comprises of at least one object. The partition method can enhance the iterative relocation method by mining objects from one graph to another with the key objective of splitting the data points into K partitions. Every partition will reproduce one cluster. The limitation of such an algorithm is that when the distance amongst the two points from the center are adjacent to another cluster, the outcome turns out to be poor or misleading due to overlying of the data points. K-means algorithm is an example of partition-based clustering. Finally, Table IV presents some additional representative publications of pattern clustering methods in biometric applications.

TABLE IV
REVIEW OF CLUSTERING TECHNIQUES IN THE BIOMETRIC RECOGNITION LITERATURE

Clustering Approach	Application	References
Hierarchical	Signature recognition, handwriting recognition, hand geometry recognition	[137], [138], [139]
Density based	Signature recognition, EEG recognition, face recognition	[140], [141], [142]
Grid based	Fingerprint recognition, hand vein recognition, EMG recognition	[143], [144], [145]
Partition based	ECG recognition, palm vein recognition, gait recognition	[146], [147], [148]

VII. VALIDATION

This concluding section reports the problems of the choice of a model and performance assessment. When having a new application, not only a proper model amongst such a widespread diversity of processing algorithms must be selected but also the constraint settings for the model to attain ideal outcome. Any realistic performance estimate must be linked to the model's ability to expect new information or expose the basic structure instead of the unplanned correlations in the existing training data. The latter happens when the data is over-adjusted by the model, usually due to an regrettably huge amount of model constraints or excessively high training iterations.

The biometric data are divided into training and validation sets to prevent over-fitting. The training dataset is utilized to learn some models with various learning meta-parameters or structures. A function (approximator) is raised on the training set with the purpose of predicting the output value for the data in the validation set. The subsequent mean test set error is then utilized for assessing the model. The trained model which best performs on the validation data is then referred to as the concluding model. This easy method of validation is recognized as holdout technique [149], [150]. Although the holdout works well, it has two limitations: 1) in the event of inadequate data problems, one can't afford to set a portion of the data set separately for validation and 2) as a single train- and- validate experiment, the holdout performance approximation can be ambiguous if a regrettable split occurs.

The limitation of the holdout approach can be solved with some additional calculation by performing multiple data set dividers and by averaging the model's performance across dividers. K-fold cross-validation [151], [152] attains K data partitions in a way that is ultimately utilized in training and validation for every example. M / K examples are utilized for validation in each K split and the residual M(K-1)/K is utilized for training in which M is the maximum number of instances.

Leave-one-out-Cross-validation (LOOCV) is a special situation of K- fold Cross-validation in which K is selected as the maximum number of instances i.e., $K = M$ [153], [154]. For example, for a dataset with M examples, LOOCV will complete M experiments, each of which utilizes M-1 examples for training purpose and the residual example for validation purpose.

Random subsampling cross-validation utilizes several divisions, the concluding model is then determined by the average K data partitions performance [155, 156]. The performance of this average estimation will undoubtedly based on K. A large K results in a small bias, but large variance. Whereas, a small K results in a small variance, but its bias will be conservative and large as the efficient amount of training samples is minimized. The number of divisions built on mainly on the quantity of data. A small or limited value of (K= 4) is typically satisfactory for large data sets. For very sparse datasets, instead, one may have to utilize LOOCV with the intention of training on as many instances as probable. Computational resource constraints can also be considered by increasing execution time with K.

With computer-intensive techniques [157], [158] like bootstrap, improved performance approximations, as well as their variance and bias, can be achieved, a statistical method that produces several training-test divisions $D*^{(b)}$ by resampling the original dataset with substitution. Examples that are not chosen for training turn out to be the validation set. The basic concept of Bootstrap is that anyone can study the impact of sampling the whole population on the data set D by learning the effect of resampling D on the bootstrap divisions $D*^{(b)}$. The bootstrap can also be utilized to enhance efficiency by training several learning algorithms on various data partitions and merging their outcomes with a weighting or voting system.

When parameter settings and model have been carefully chosen, it is still required to attain an estimation of how well the last model will perform on new data. To attain an entirely independent performance measurement it is required to utilize a third subset comprising data that wasn't beforehand utilized at all, either for choosing the model or training. This argument permits the creation of a data division system with three subgroups: training, validation and test sets [159]. Training set uses the data sample used to adjust the model. Weights and biases are revised to achieve the optimum values. The model sees this information and learns from it. The validation data set provides an unbiased evaluation of a model adapted to the training data set during the tuning of model hyperparameters. The evaluation becomes much more biased because the validation data set is included in the configuration of the model. The gold standard used to evaluate the model is provided in the test data set. It is used only after a model has been fully trained (utilizing the train and validation sets). The test set is utilized in general to evaluate competing models.

VIII. Conclusions

The fast development in technology, mainly the creation of low-priced and improved pervasive sensors permits computer systems to inevitably identify individuals. This ability aids the growing requirement for smarter and secure applications. This paper has surveyed the state-of-art in pattern mining methods for biometric data analysis, including sensor-based biometric data acquisition, data pre-processing, dimensionality reduction classification, clustering and validation. Even though the most suitable method undoubtedly relies on the precise sensor type(s) and application domain. In this paper, we have presented the primary pattern mining methods that make the creation of biometric technology a reality. These methods are vigorously utilized in biometric recognition systems, but there is always the requirement for more exact and faster algorithms. The presented work will help in forming innovative pattern mining solutions to challenge biometrics issues. Biometric recognition systems can offer reliable entree to protected or sensitive areas. Additionally, a digital card offers unlocks innovative prospects for logical access controls (e.g. e-business, e-government, e-banking etc.). Civic requests for such type of applications may be a significant driving force behind more advancement in biometrics research.

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