Data Fusion Applied to Biometric Identification – A Review

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Abstract. There is a growing interest in data fusion oriented to identification and authentication from biometric traits and physiological signals, because of its capacity for combining multiple sources and multimodal analysis allows improving the performance of these systems. Thus, we considered necessary make an analytical review on this domain. This paper summarizes the state of the art of the data fusion oriented to biometric authentication and identification, exploring its techniques, benefits, advantages, disadvantages, and challenges.

Keywords: Biometric · Data fusion · Multimodal systems · Physiological signals · Signal processing

1 Introduction

The biometrics systems are used for access control and identification of human beings, and they are based on different physiological measures such as physical traits (PT), physiological signals, Deoxyribonucleic acid (DNA), among others. This type of identity recognition is very attractive since each person possesses different physical features that cannot be copied easily [5]. Nowadays, it is applied widely to assure computers, smartphones, communication systems, buildings, and confidential information, among others. However, the multiple techniques of individual identification had become vulnerable to falsification such as the identification system based on digital fingerprint [1, 2], which has been used for several years, but it can be falsified with different methods [4], putting at risk the legal and financial integrity of an individual.

Although some physical features are hard to imitate/duplicate, it is not impossible. Therefore, different researchers have proposed the fusion or combination of multiple physiological signals (PS) and traits with the goal of providing major sturdiness to the system [6–34]. However, the biometric is an open research area focused on the type and quantity of the data, algorithms, and functionality modes and they are classified by 3 categories of biometric modalities as follows: *(i)* biological, it is based on the analysis of data obtained from DNA; *(ii)* behavioral, this is based on the analysis of the behavior of the individual; and *(iii)* morphology data, they are based on specific physical features that are permanent and unique to every individual (e.g. face or fingerprints) [1].

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In this paper, we discuss PS and traits applied to biometry authentication together with different combinations among them (i.e. multiple signals and multiple traits) using data fusion techniques. The review was carried out on Scopus and Web of Sciences database based on these search criteria: *(i)* (biometric) and ("physiological signals"); and *(ii)* (("data fusion") or ("information fusion") and (biometric)) or ("physiological signals"). The selected papers were reported between years 2008 and 2017 in journals of quartile 1 and quartile 2 principally.

2 Physiological Signals and Traits Applied in Biometrics Systems

Nowadays, the use of PS has gone from being used only by medical diagnostics, to convert into a very important tool for security demonstrating the capability to provide characteristics that allow identified an individual with high precision.

The PS must comply with a series of criteria that is apt in biometric. The criteria are the following: *(i)* the signal must be able to be recollected in any person; *(ii)* singularity, the signal must able to distinguish different individuals; *(iii)* permanence, the signal must not be abruptly altered in the time; *(iv)* sturdiness against attacks, it must not be imitated easily [35].

Figure 1 shows a summarized taxonomy of the traits and PS reported for biometric authentication and/or identification.

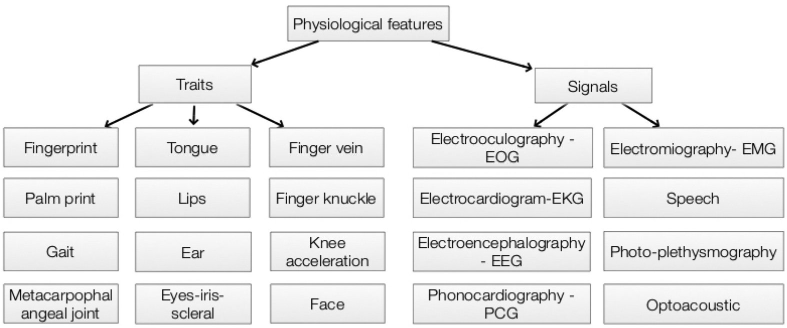

Fig. 1. Taxonomy of physiological signals and physiological traits applied in biometric.

Table 1 presents the results of the review regarding the use of the signals and traits including the type of modality. 56 biometric studies based on unimodal and multimodal modalities (i.e unimodal is the application only one signal or trait and multimodal is the application of two or more signals and PT). Multiple signals and traits have been studied independently (monomodal authentication or identification) such as: Electroencephalogram-EEG, Electrocardiogram-EKG, phonocardiography-PCG, electrooculography-EOG, Electromyogram-EMG, photo-plethysmography-PPG, fingerprint, palmprint, periocular, Laser Doppler Vibrometry-LDV, Speech, Finger Knuckle Print-FKP, finger vein, tongue, Iris, face, ear, lips, eyes, gait, and Knee

Table 1. Monomodal and multimodal biometric studies

Multimodal	References	Monomodal	References
EEG - EOG	[1]	EEG	[2–6]
EKG - EMG	[8]	EKG	[9–16]
EKG - PCG	[17]	FKP	[18, 19]
EKG, face, fingerprint	[20]	Iris	[21–23]
PCG and EKG	[24]	Face	[25–28]
EKG and physical activity	[29]	PCG	[30]
EEG and face	[31]	Palmprint	[32, 33]
Face and palmprint	[34]	Periocular	[35]
Face and iris	[36–39]	Fingerprint	[40–42]
Face and ear	[43]	Tongue	[44]
Face and lips	[45]	Gait	[46]
EKG and LDV	[47]	Scleral	[48]
Fingerprint and palmprint	[49]	KnA	[50]
		Ear	[51]
		Eyes	[52]
		LDV	[53]
		Finger vein	[54]
		Speech	[55]
		PPG	[56]

Acceleration-knA. Other studies are based on combination or fusion of multiples signals together with multiple traits (multimodal authentication or identification) are evidenced.

2.1 Physiological Signals Applied in Biometrics

The EKG and PCG are noninvasive measures and they take heart information, particularly the EKG takes information about heart electrical activity. This signal is acquired situating electrodes in the thoracic zone, with the purpose to collect the signals produced by myocardium, while the PCG signals are based on the analysis of the features of the frequency of the cardiac sounds, these sounds are presented in systole (S1) and diastole (S2) [30, 31]. The condition of the atria, ventricles and heart valves among other, each of these characteristics mentioned are different for each individual when both characteristics are used at the same time we get a lot of information from the heart. In [31] is fused both types of signals obtaining a lower error rate in comparison to the error obtained with the individual signals.

The EEG signals are noninvasive too, and they are usually recorded from the surface of scalp [5]. These signals are split into five frequency bands as follows: Delta (δ) 0.5–4 Hz, Theta (θ) 4–8 Hz, Alpha (α) 8–14 Hz, Beta (β) 14–30 Hz y Gamma (γ) more of 30 Hz [6]. EEG signals can be a great option for biometric identification due to that the brain electrical activity is unique in each individual and besides closely related with the visual, mood, auditory stimuli and in general any stimulus experienced by the person. Therefore is necessary to consider that the cerebral response to any of these stimuli is different for each individual causing that EEG signals are difficult of supplant and get, therefore this signals are practical in biometrics.

Others signals have been less reported in the biometric area such as EOG signals, which consists in the registration of potential difference existing between cornea and retina for ocular movements detecting [55, 56]. Although it is possible to get relevant information about an individual, it is very difficult to implement because it is uncomfortable for the participant since the electrodes located on both sides of the eyes, above and below of these collect the potentials generated from the movement of eyeballs [56]. The EKG, EEG, EOG and PCG have very important characteristics for their use in biometrics since they are not easily accessible and also provide reliable information of the individual.

2.2 Physiological Trait Applied to Biometrics

Figure 2 shows images of the physiological traits reported in the literature, even so, have characteristics quite promising in the recognition of people. These images correspond from left to right to Finger knuckle [17], finger vein [46], lips [44], tongue [47], metacarpophalangeal [57], and gait recognition [48] respectively. The more popular trait nowadays is the fingerprint. It is highly used in personal authentication by the well-known fact that each individual has a unique fingerprint and its acquisition highly easy and cheap [58]. Fingerprint refers to the patterns located on the fingertips. On the other hand, the hands have a lot amount of folds in the knuckles which are used in recognition, this method is named finger knuckle (FKP) and it is based on capture of image around surface of phalangeal joint of the finger [18, 59], whereas, the identification based on patterns in the Metacarpophalangeal joint (MPJs), consists in the obtaining of patterns of the rear surface of the hand, given that this zone presents many lines and folds that allow discriminating a person of other. The MJP recognition offers a promising and robust alternative for authentication of identity [57], although the advantage of these methods is the high quantity of information available, such as lines, forms, and patterns, which are different for each individual, a difficulty in FKP and MJP recognition are the false rejects due to the variation of finger knuckle position on the take of the image [17].

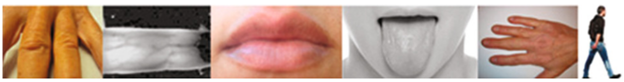

Fig. 2. Physiological traits applied in biometrics

In [46] was proposed a verification system using the finger vein as a biometric feature in response to high vulnerability registered in biometric systems based on the fingerprint. Finger vein recognition consists of locating a beam in the finger, which makes visible the veins in this zone. The patterns of the veins are considered an interesting trait, given that this patterns not easily affordable and different for each person. Blood's temperature and volume, and the incorrect positioning of the surface to analyze affect this feature.

Recently, the gait recognition has been studied in biometric, it is based on gait biomechanics to extract own features of each person. One of its advantages more marked is the possibility of getting hundreds of samples of the cycle of gait in few minutes. This feature is significant given that the success of the design and validation of a pattern recognition system depend to a large degree of the sample size, but also has some challenges such as the clothes of the subject, sensibility to environment variations, angle camera capture and distance between the subject and the camera, which makes the gait recognition systems a difficult task to carry out in the real environment [48–50].

Another biometric trait is the lips, given that is an important feature of the human face. The lips features are geometric simple features based on the contour of these, they are can interpret as multiple spatial thickness and height from of mass center [44]. To be a trait captured by images it presents the same difficulty than previous features, as the incorrect positioning of the area of interest. Also, comes the question of whether it is possible to get a good rate of recognition when the lips are in movement.

The tongue is a trait, which has been very little studied but has features very interesting in biometric identification; it has used dynamic and static features obtained from the tongue. Within of the dynamic features are the texture, geometry, thickness and cracks. All obtained from the image but as is well known all system is exposed to attacks and eventually the system could not be able to differentiate image of a living person and a dead. Therefore, the researchers have raised the need for performing the detection of vitality with the last purpose of securing that the input patterns are not coming from an inanimate object. The dynamic features refer to obtaining of patterns related continuous movement and involuntary of the tongue, is an excellent dynamic firm for biometric. Thanks to all these features, the tongue is used as a physiological trait in biometric [47]. Finally, we had summarized the advantages and disadvantages of PS and traits applied to biometric in Table 2.

Table 2. Traits and physiological signals advantages and disadvantages

Signal/Trait	Advantages	Disadvantages
EKG	Highly reliable source. -It provides too precise features about of electrical activity and physiological of an individual. -The research performed of this signal report high performance. -Difficulty to reproduce EKG signals artificially [9]. -It can easily fuse with others signal [20]	One of the great difficulties encountered in the literature is the lack of acceptance by the user since it is quite uncomfortable its implementation at the physical level [16]. -Few studies on cardiac signals with any medical condition [57]. -Body posture affects cardiac signals [13]

(*continued*)

Table 2. (*continued*)

Signal/Trait	Advantages	Disadvantages
Fingerprint	Ease in acquiring the signal. -High user acceptance. -It is the most widely used biometric trait today [58]	-Susceptible to external factors [41] -Fingerprints can be replaced using fingerprints generated artificially [40, 49]
EEG	It is very difficult to imitate signal. Brain electrical activity varies from one person to another. -The capacity of register the neuron electrical activity since the scalp [2]. EEG shows greater security because they are less likely to be generated artificially [1]	They are complex and irregular signals, which are easily contaminated by external interference [4, 6]. -Difficulty in retrieving the sources of neuronal activity, due to its low spatial resolution [2]. -Published studies on biometrics based on this signal used medical equipment of high cost [59]. -Participants reported discomfort since it is necessary to apply on scalp neck gel to improve conduction between electrodes [59]
PCG	They have individual characteristics that can be considered for use in biometrics [30]	For the acquisition of these signals are susceptible to noise [60]
EOG	This signals are low cost and aren't invasive [61]	The electrodes used for the acquirement of the signals can present instability to eye flicker [62]. -The signals are highly affected by noises on the environment [61]
Finger vein	Low computational complexity. -The pattern of the finger vein it is not exposed to another equipment or people in ordinary situations. -The size of the device that acquires the image is small	It requires a full finger image for getting a template
Lips	Easy acquisition and obtainment of lips characteristics. -It is possible to extract the outline when the person has beard or mustache	The image of lips can not be acquired when the lip is moving
MPJs	Easy acquisition and lots of information from a single image	The trait is very exposed by which can be easily falsified
Tongue	It is an excellent dynamic firm for biometric. Thanks to all these features [44]	The system would not be able to identify the image of a living person and a dead one [44]
FKP	The area of the knuckle has many lines and folds difficult to falsify [63]	The acquisition device is very big and hand must always be in the same position [18, 19]
Gait recognition	The gait is not easily imitable and it is unique to every person [46]	In the recognition, the light affects the results another disadvantage is that the clothing may affect the results [46]

3 Multimodal Systems

The human interaction is considered a natural multimodal process and contains deep physiological and psychological expressions. A multimodal biometric system combines two or more signals or traits [65], during years the authentication has been based on monomodal biometric systems, which compare only one characteristic, however, the performance of these systems vary depending on the presence of external factors, such as noise, computational cost, and the quality devices of signal acquisitions. Therefore, in the ultimate years has been introduced the multimodal biometric system with the purpose to overcome the weaknesses of the monomodal biometric system.

3.1 Architecture of Multimodal Processing Systems

In [66] is presented a description of the architecture of the multimodal system (see Fig. 3) Once has been determined the different biometric sources, the next step to follow is the selection of the architecture of the system. In general, there are two mine type of design of multimodal system, serial and parallel

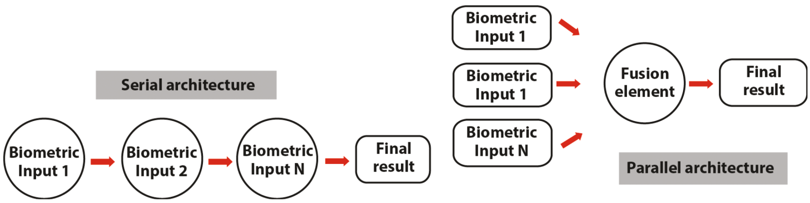

Fig. 3. Multimodal system architecture [66]

(i) serial: Into the serial architecture, also called as cascade architecture, the signal processing is performed in sequence. Therefore the out of first biometric feature influence the transmission second feature; *(ii)* parallel: Into the parallel architecture, the processing of several biometric inputs are independent of one another. Once both signals are processed separately, the results are combined.

4 Data Fusion Systems

Data fusion has notion rather fuzzy that take various interpretations with the applications and specific purposes [67]. However, in this paper the definition adopted in [68] as a set methodologies and technology that possibility the combination synergistic of heterogeneous data of several sources together with new data, content more information than the sum of each source. Through several terms have been reported in the literature such as: decision fusion [69], data combination [70], data aggregation [71] multisensor integration [72], multisensor data fusion [73], and information fusion [74]. In spite that these terms describe the same task, with some variations in terms of application and the type of data that can be difficult to differentiate, which is discussed by [75], Those who used interchangeably term data fusion and information fusion.

Data fusion is considered a very challenging task for several reasons: *(i)* the complexity of data; *(ii)* the processes depend on n variables without being all measurable; *(iii)* in heterogeneous data sets is hard to exploit the advantages of each set and discard the disadvantages [67]. For data fusion are used different techniques such as, the probabilistic, soft-computing, algorithm optimization, among others, whose use (characterization, estimation, aggregation, classification, compression among others) It depends on the type of application and also is necessary consider the advantages and disadvantages of techniques for a proper selection in order to get an effective performance. The Fig. 3, presents the taxonomy of the methodologies of data fusion from which can be categorized data fusion algorithms and are widely discussed in [76].

Particularly in the case of biometrics, the data fusion is highly used a level of signals fusion, level characteristics fusion and level classifiers fusion allowing to improve the performance the identification systems using several PS as reported in [77–79].

Table 3 shows the biometric signals and their respective techniques which got characterization and subsequent classification.

Table 3. Fusion methods used in biometrics

Signals	Data fusion techniques	Ref
EEG-EOG	-Score level fusion: Product, sum, minimum, maximum rules -Bayes decision rule -CCA feature fusion	[1]
EKG-PCG	Feature level fusion	[17]
EKG fingerprint	Weighted sum rule, Computing weights on the equal error rate Computing weights on match scores distributions	[20]
Otoacoustic	MaxScore, SumScore, MulScore, SumRank, MulRank, SumWtRank (classification fusion)	[66]
EKG-physical activity	Feature level fusión, score level fusion	[29]
Palmprint	Feature level fusion: Proposed method (feature fusion)	[32]
Periocular	Score level fusión: Sum rule, weighted sum rule (feature fusion)	[35]
Fingerprint	Transformation-based score fusion: sum rule, mean rule, product rule, max rule, and min rule, Random Subspace of SVM (RSVM), Dempster–Shafer (DS), Dynamic Score Selection (DYN) (feature fusion)	[40]
Face-palmprint	Feature level fusion	[34]
Face	Score level fusion: sum and product rule Decision level fusion - rule OR (logical OR) (classification fusion)	[26]
Face and Iris	Score fusion - product and sum rule Score level fusion - Weighted Sum Rule	[36]
Face and ear	The maximum vote	[43]
Face-iris	Score level fusion: sum rule, Weighted Sum Rule	[37]

(*continued*)

Table 3. (*continued*)

Signals	Data fusion techniques	Ref
Face and Lips	Feature level fusion Score level fusión: based on the likelihood function	[45]
LDV	Data fusion: This method models the intersession variability by the variance (as the log-normal model) Information fusion: train single session based models and separately extract model-dependent informative components. (feature fusion)	[53]
Face	Information fusión: the sum of the scores, AND, OR of the decisions (feature fusion)	[71]
Tongue	Sum rule, product rule, median rule (feature fusion)	[44]
Ear	Score level fusion: weighted sum rule (classification fusion)	[51]
Finger-palmprint	Feature level fusion	[49]
Palm-print	Weighted sum rule, Neyman –Pearson rule, heuristic rule, proposed heuristic rule. (feature fusion)	[33]
EEG-gyroscope	Score level fusion: Mean, product, maximum and minimum rules Decision level fusión: Logical AND method, Logical OR method	[73]
Scleral	Score level fusion - sum rule, min rule, max rule (feature fusion)	[48]
FKP	Sum rule, min rule (feature fusion)	[19]
Face-Iris	Decision level fusion - weighted sum rule, sum rule	[39]
Face-Iris	Feature level fusion Score level fusión: weighted sum rule	[38]
Eyes	Weights mean fusion (Feature fusion)	[52]

5 Conclusion

This review described advantages, disadvantages, and shortcomings of PS and traits oriented to biometric, when they are mixed the identification error rate can be reduced. Until now, an ideal biometric signal that meets criteria of high security, easy acquisition, low computational cost and that the user feels comfortable during the process has been not achieved yet.

In general, the unimodal systems compared to the multimodal systems, these last report less percentage of error. EEG, EOG, PCG, and EKG, among others, they are considered highly promising in the biometric for different authors since they have a fairly small mistake and it ensures the identified subject this alive. Nevertheless, the accessibility to them is very restricted, but in turn involves high-tech equipment due to the complex acquisition, and eventually generating discomfort to the user. In addition, some problems must be solved how analysis of signals with pathologies, noise ratio of the signals, improving the acquisition devices in together with the development of sensors with special characteristics.

Other physiological biometric parameter or of behavior can be fused to do the authentication more dependable [9]. Although the present work shows that there is great potential in the used of PS to the biometric recognition, is important that the future analysis is performed with a grouping largest set of signals. Respect tot he PT, these have the nowadays challenges of the images recognition such as angle of capture of the image. Besides some recognized methods don't detect if the subject is live. Therefore, studies on areas of the body in movement are necessary. Finally, We pose as challenges the study of other biometric techniques such identification bio-inspired and data fusion architectures for PS and traits processing oriented to biometric authentication.

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