Contemporary Engineering Sciences, Vol. 11, 2018, no. 34, 1677 - 1694
HIKARI Ltd, www.m-hikari.com
https://doi.org/10.12988/ces.2018.84166

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 $x_1, x_2, x_3, \ldots$, 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 $y_1, y_2, y_3, ...,$, 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.

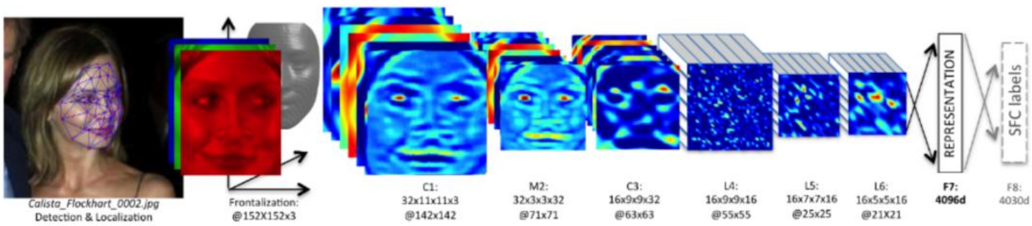

Figure 1 Outline of the depth face architecture proposed by Taigman et al [54]

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].

Acknowledgements. The authors are grateful to the Nueva Granada Military University, which, through its Vice chancellor for research, finances the present project with code IMP-ING-2290 and titled "Prototype of robot assistance for surgery", from which the present work is derived.

References

[1] R. Jiang, S. Al-maadeed, A. Bouridane, D. Crookes, and A. Beghdadi, *Biometric Security and Privacy*, Springer International Publishing AG, 2017. https://doi.org/10.1007/978-3-319-47301-7

[2] I. Buciu and A. Gacsadi, Biometrics systems and technologies: A survey, *International Journal of Computers, Communications and Control*, **11** (2016), no. 3, 315–330. https://doi.org/10.15837/ijccc.2016.3.2556

[3] M. N. Uddin, S. Sharmin, A. Hasnat, S. Ahmed, and E. Hasan, A Survey of Biometrics Security System, *International Journal of Computer Science and Network Security*, **11** (2011), no. 10, 16–23.

[4] S. Chauhan, A. Arora, and A. Kaul, A survey of emerging biometric modalities, *Procedia Computer Science*, **2** (2010), 213–218.

https://doi.org/10.1016/j.procs.2010.11.027

[5] D. Maltoni, D. Maio, A. K. Jain, and S. Prabhakar, *Handbook of fingerprint Recognition*, 2nd ed., ser. Springer Professional Computing. Springer-Verlag London, 2009. https://doi.org/10.1007/978-1-84882-254-2

[6] R. Chellappa, S. Sirohey, and C. L. Wilson, Human and Machine Recognition of Faces: A Survey, *Proceedings of the IEEE*, **83** (1995), no. 5, 705–741. https://doi.org/10.1109/5.381842

[7] K. W. Bowyer, K. Hollingsworth and P. J. Flynn, Image understanding for iris biometrics: A survey, *Computer Vision and Image Understanding*, **110** (2008), no. 2, 281–307. https://doi.org/10.1016/j.cviu.2007.08.005

[8] H. Tabatabaee, A. M. Fard, and H. Jafariani, A novel human identifier system using retina image and fussy clustering, *2nd International Conference on Information & Communication Technologies*, Vol. 1, 2006, 1031–1036. https://doi.org/10.1109/ictta.2006.1684516

[9] T. Kinnunen and H. Li, An overview of text-independent speaker recognition: From features to supervectors, *Speech Communication*, **52** (2010), no. 1, 12–40. https://doi.org/10.1016/j.specom.2009.08.009

[10] F. Monrose and A. Rubin, Authentication via keystroke dynamics, *Proc. of the 4th ACM Conf. on Computer and Communications Security*, (1997), 48–56. https://doi.org/10.1145/266420.266434

[11] M. Choras, Image Feature Extraction Methods for Ear Biometrics–A Survey, *6th International Conference on Computer Information Systems and Industrial Management Applications (CISIM'07)*, 2007. https://doi.org/10.1109/cisim.2007.40

[12] R. Sanchez-Reillo, C. Sanchez-Avila, A. Gonzalez-Marcos, R. SanchezReillo and A. Gonzalez-Marcos, Biometric identification through hand geometry measurements, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **22** (2000), no. 10, 1168–1178. https://doi.org/10.1109/34.879796

[13] M. Faundez-Zanuy, Signature recognition state-of-the-art, *IEEE Aerospace and Electronic Systems Magazine*, **20** (2005), no. 7, 28– 32. https://doi.org/10.1109/maes.2005.1499249

[14] D. Gafurov, A survey of biometric gait recognition: Approaches, security and challenges, *Annual Norwegian Computer Science Conference*, (2007), 19–21.

[15] A. A. Salah, Machine Learning for Biometrics, Chapter in *Handbook of Research on Machine Learning Applications and Trends: Algorithms, Methods, and Techniques*, IGI Global, 2009, ch. 26, 539–560. https://doi.org/10.4018/978-1-60566-766-9.ch026

[16] R. Gad, A. El-Sayed, N. El-fishawy and M. Zorkany, Multi-Biometric Systems : A State of the Art Survey and Research Directions, *International Journal of Advanced Computer Science and Applications (IJACSA)*, **6** (2015), no. 6, 128–138. https://doi.org/10.14569/ijacsa.2015.060618

[17] I. Odinaka, P. H. Lai, A. D. Kaplan, J. A. O'Sullivan, E. J. Sirevaag and J. W. Rohrbaugh, ECG biometric recognition: A comparative analysis, *IEEE Transactions on Information Forensics and Security*, **7** (2012), no. 6, 1812–1824. https://doi.org/10.1109/tifs.2012.2215324

[18] A. Riera, A. Soria-Frisch, M. Caparrini, C. Grau, and G. Ruffini, Unobtrusive biometric system based on electroencephalogram analysis, *EURASIP Journal on Advances in Signal Processing*, **2008** (2007), 143728. https://doi.org/10.1155/2008/143728

[19] J. O. Kim, W. Lee, J. Hwang, K. S. Baik and C. H. Chung, Lip print recognition for security systems by multi-resolution architecture, *Future Generation Computer Systems*, **20** (2004), no. 2, 295–301. https://doi.org/10.1016/s0167-739x(03)00145-6

[20] A. A. E. Ahmed and I. Traore, A New Biometric Technology Based on Mouse Dynamics, *IEEE Transactions on Dependable and Secure Computing*, **4** (2007), no. 3, 165–179. https://doi.org/10.1109/tdsc.2007.70207

[21] H. Chen and A. K. Jain, Dental biometrics: Alignment and matching of dental radiographs, *Proceedings - Seventh IEEE Workshop on Applications of Computer Vision, WACV 2005*, (2007), 316–321. https://doi.org/10.1109/acvmot.2005.41

[22] D. Zhang, Z. Liu and J. qi Yan, Dynamic tongueprint: A novel biometric identifier, *Pattern Recognition*, **43** (2010), no. 3, 1071–1082. https://doi.org/10.1016/j.patcog.2009.09.002

[23] P. Domingos, A few useful things to know about machine learning, *Communications of the ACM*, **55** (2012), no. 10, 78. https://doi.org/10.1145/2347736.2347755

[24] A. Gabriel, B. C. Hiesmayr and M. Huber, Criterion for k-separability in mixed multipartite systems, *Quant. Inf. Comp.*, **10** (2010), no. 9-10, 829-836. http://arxiv.org/abs/1002.2953

[25] R. Yew Fatt Ng, Y. H. Tay and K. Ming Mok, A review of iris recognition algorithms, *2008 International Symposium on Information Technology*, Vol. 2, 2008, 1-7. https://doi.org/10.1109/itsim.2008.4631656

[26] N. Yager and A. Amin, Fingerprint verification based on minutiae features: A review, *Pattern Analysis & Applications*, **7** (2004), 94–113. https://doi.org/10.1007/s10044-003-0201-2

[27] M. Turk and A. Pentland, Eigenfaces for Recognition, *Journal of Cognitive Neuroscience*, **3** (1991), no. 1, 71–86. https://doi.org/10.1162/jocn.1991.3.1.71

[28] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, Eigenfaces vs. fisherfaces: Recognition using class specific linear projection, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **19** (1997), no. 7, 711–720. https://doi.org/10.1109/34.598228

[29] R. Brunelli and T. Poggio, Face Recognition: Features versus Templates, *IEEE Transactions on Pattern Analysis and Machine Intelligence,* **15** (1993), no. 10, 1042–1052. https://doi.org/10.1109/34.254061

[30] H. Wang, C. Ma and L. Zhou, A Brief Review of Machine Learning and Its Application, *2009 International Conference on Information Engineering and Computer Science,* (2009), 1–4. https://doi.org/10.1109/iciecs.2009.5362936

[31] D. Kajaree and R. Behera, A Survey on Machine Learning: Concept, Algorithms and Applications, *International Journal of Innovative Re- search in Computer and Communication Engineering*, **5** (2017), no. 2, 1302–1309.

[32] Z. Ghahramani, Unsupervised Learning, Chapter in *Advanced Lectures on Machine Learning*, Vol. 3176, Chapter 5, Springer, 2004, 72–112. https://doi.org/10.1007/978-3-540-28650-9_5

[33] S. P. Lloyd, Least Squares Quantization in PCM, *IEEE Transactions on Information Theory*, **28** (1982), no. 2, 129–137. https://doi.org/10.1109/tit.1982.1056489

[34] A. P. Dempster, N. M. Laird and D. B. Rubin, Maximum Likelihood from Incomplete Data via the EM Algorithm, *Journal of the Royal Statistical Society. Series B*, **39** (1977), no. 1, pp. 1–38. http://www.jstor.org/stable/2984875

[35] D. O. Hebb, *The Organization of Behavior*, Vol. 911, John Wiley & Sons, Inc., 1949.

[36] Y. LeCun, B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard and L. D. Jackel, Backpropagation Applied to Handwritten Zip Code Recognition, *Neural Computation*, **1 (**1989), no. 4, 541–551. https://doi.org/10.1162/neco.1989.1.4.541

[37] R. M. Gray, Vector quantization, *IEEE ASSP Magazine*, **1** (1984), no. 2, pp. 4–29. https://doi.org/10.1109/massp.1984.1162229

[38] M. Springer, Protection of Fingerprint Data with the Glass Maze Algorithm, *2013 International Conference of the BIOSIG Special Interest Group (BIOSIG)*, (2013), 1–8.

[39] M. Arunachalam and K. Subramanian, Finger Knuckle Print Authentication Using AES and K-Means Algorithm, *The International Arab Journal of Information Technology*, **12** (2015), no. 6A, 642–649.

[40] A. Muthukumar and S. Kannan, K-Means Based Multimodal Biometric Authentication Using Fingerprint And Finger Knuckle Print With Feature Level Fusion, *IJST,Transactions of Electrical Engineering*, **37** (2013), no. 2, 133–145.

[41] B. Chinnavedi, B. Deepikka, R. G. Sowmiya and R. Saranya, Multimodal Biometric Recognition Using Sift And K-Means Algorithm, *International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering*, **2** (2014), no. 3, 1173–1176.

[42] S. Schimke, A. Valsamakis, C. Vielhauer and Y. Stylianou, Biometrics: Different approaches for using gaussian mixture models in handwriting, Chapter in *Communications and Multimedia Security*, Springer, 2005, 261–263. https://doi.org/10.1007/11552055_26

[43] D. A. Reynolds, T. F. Quatieri, and R. B. Dunn, Speaker Verification Using Adapted Gaussian Mixture Models, *Digital Signal Processing*, **10** (2000), no. 1-3, 19–41. https://doi.org/10.1006/dspr.1999.0361

[44] A. Charpentier, F. Xie, C. Fontaine and T. Furon, Expectation maximization decoding of tardos probabilistic fingerprinting code, *Proc. SPIE*, Vol. 7254, SPIE, 2009, 7254-7254. https://doi.org/10.1117/12.806034

[45] M. Vlachos and E. Dermatas, Supervised and unsupervised finger vein segmentation in infrared images using KNN and NNCA clustering algorithms, *XII Mediterranean Conference on Medical and Biological Engineering and Computing 2010*, Vol. 29, Springer, 2010, 741–744. https://doi.org/10.1007/978-3-642-13039-7_187

[46] A. B. Hassanat, E. Btoush, M. A. Abbadi, B. M. Al-Mahadeen, M. AlAwadi, K. I. Mseidein, A. M. Almseden, A. S. Tarawneh, M. B. Alhasanat, V. B. Prasath and F. A. Al-Alem, Victory sign biometrie for terrorists identification: Preliminary results, *2017 8th International Conference on Information and Communication Systems, ICICS 2017*, (2017), 182–187. https://doi.org/10.1109/iacs.2017.7921968

[47] N. Otsu, A Threshold Selection Method from Gray-Level Histograms, *IEEE Transactions on Systems, Man, and Cybernetics,* **9** (1979), no. 1, 62–66. https://doi.org/10.1109/tsmc.1979.4310076

[48] A. Hassanat, M. Alkasassbeh, M. Al-Awadi, and E. Alhasanat, Colour-based lips segmentation method using artificial neural networks, *2015 6th International Conference on Information and Communication Systems, ICICS*, (2015). https://doi.org/10.1109/iacs.2015.7103225

[49] M. A. Hasnat, J. Bohn´e, J. Milgram, S. Gentric, and L. Chen, Von mises-fisher mixture model-based deep learning: Application to face verification, CoRR, vol. abs/1706.04264, 2017.

[50] J. Liu, Targeting Ultimate Accuracy: Face Recognition via Deep Embedding, Cvpr, 4–7, 2015.

[51] O. M. Parkhi, A. Vedaldi and A. Zisserman, Deep Face Recognition, *Procedings of the British Machine Vision Conference 2015*, (2015), 41.1–41.12. https://doi.org/10.5244/c.29.41

[52] F. Schroff, D. Kalenichenko and J. Philbin, FaceNet: A unified embedding for face recognition and clustering, *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition,* (2015), 815–823. https://doi.org/10.1109/cvpr.2015.7298682

[53] Y. Sun, D. Liang, X. Wang and X. Tang, DeepID3: Face Recognition with Very Deep Neural Networks, Cvpr, pp. 2–6, 2015. http://arxiv.org/abs/1502.00873

[54] Y. Taigman, M. Yang, M. Ranzato and L. Wolf, DeepFace: Closing the gap to human-level performance in face verification, *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, (2014), 1701–1708.

[55] G. B. Huang, M. Ramesh, T. Berg, and E. Learned-Miller, *Labeled Faces In The Wild: A Database For Studying Face Recognition In Unconstrained Environments,* University of Massachusetts Amherst Technical Report, Vol. 1, 2007, 07–49.

[56] B. F. Klare, B. Klein, E. Taborsky, A. Blanton, J. Cheney, K. Allen, P. Grother, A. Mah, M. Burge and A. K. Jain, Pushing the frontiers of unconstrained face detection and recognition: IARPA Janus Benchmark A, *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, (2015), 1931–1939. https://doi.org/10.1109/cvpr.2015.7298803

[57] L. Wolf, T. Hassner and I. Maoz, Face recognition in unconstrained videos with matched background similarity, *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, (2011), 529–534. https://doi.org/10.1109/cvpr.2011.5995566

[58] B. C. Chen, C. S. Chen and W. H. Hsu, Face recognition and retrieval using cross-age reference coding with cross-age celebrity dataset, *IEEE on Multimedia*, **17** (2015), no. 6, 804–815. https://doi.org/10.1109/tmm.2015.2420374

[59] M. Hasan Bahari, L. Khadidja Hamaidi, M. Muma, J. Plata-Chaves,M. Moonen, A. M. Zoubir and A. Bertrand, Distributed Multi-Speaker Voice Activity Detection for Wireless Acoustic Sensor Networks, ArXiv e-prints, Mar. 2017.

[60] I. G. Damousis and S. Argyropoulos, Four Machine Learning Algorithms for Biometrics Fusion: A Comparative Study, *Applied Computational Intelligence and Soft Computing*, **2012** (2012), pp. 1–7. https://doi.org/10.1155/2012/242401

[61] A. Bouzerdoum, D. Chai and A. Watson, Naive bayes face/nonface classifier: a study of preprocessing and feature extraction techniques, *2004 International Conference on Image Processing, 2004. ICIP '04*, Vol. 2 2004, 1385–1388. https://doi.org/10.1109/icip.2004.1419760

[62] D. Maturana, D. Mery and ´A. Soto, Face recognition with decision tree-based local binary patterns, in *Asian Conference on Computer Vision*, Vol. 6495, Springer, 2011, 618–629. https://doi.org/10.1007/978-3-642-19282-1_49

[63] Y. Aono, T. Hayashi, L. T. Phong and L. Wang, Fast and Secure Linear Regression and Biometric Authentication with Security Update, IACR Cryptology ePrint Archive, vol. 2015, 692, 2015.

[64] M. M. Monwar and M. L. Gavrilova, Integrating monomodal biometric matchers through logistic regression rank aggregation approach, *Proceedings - Applied Imagery Pattern Recognition Workshop*, (2008). https://doi.org/10.1109/aipr.2008.4906455

[65] M. S. Sarfraz and R. Stiefelhagen, Deep Perceptual Mapping for Cross-Modal Face Recognition, *International Journal of Computer Vision*, **122** (2017), no. 3, 426–438. https://doi.org/10.1007/s11263-016-0933-2

[66] U. Cote-Allard, C. Latyr Fall, A. Drouin, A. Campeau-Lecours, C. Gosselin, K. Glette, F. Laviolette and B. Gosselin, Deep Learning for Electromyographic Hand Gesture Signal Classification by Leveraging Transfer Learning, ArXiv e-prints, Jan. 2018.

[67] T. Reasat and C. Shahnaz, Detection of Inferior Myocardial Infarction using Shallow Convolutional Neural Networks, *2017 IEEE Region 10 Humanitarian Technology Conference (R10-HTC)*, (2017). https://doi.org/10.1109/r10-htc.2017.8289058

[68] G. Goswami, N. Ratha, A. Agarwal, R. Singh and M. Vatsa, Unravelling Robustness of Deep Learning based Face Recognition Against Adversarial Attacks," ArXiv e-prints, Feb. 2018.

[69] P. Jonathon Phillips, H. Moon, S. A. Rizvi and P. J. Rauss, The FERET evaluation methodology for face-recognition algorithms, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **22** (2000), no. 10, 1090–1104. https://doi.org/10.1109/34.879790

[70] W. Gao, B. Cao, S. Shan, X. Chen, D. Zhou, X. Zhang and D. Zhao, The CAS-PEAL large-scale chinese face database and baseline evaluations, *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans*, **38** (2008), no. 1, 149–161. https://doi.org/10.1109/tsmca.2007.909557

[71] L. H. Thai, Face Alignment Using Active Shape Model And Support Vector Machine, *International Journal of Biometrics and Bioinformatics*, **4** (2011), 224–234.

[72] R. Charan, A. Manisha, R. Karthik, M Rajesh Kumar, A text-independent speaker verification model: A comparative analysis, *2017 International Conference on Intelligent Computing and Control (I2C2)*, 2017. https://doi.org/10.1109/i2c2.2017.8321794

[73] M. Afifi, Gender recognition and biometric identification using a large dataset of hand images, ArXiv e-prints, Nov. 2017.

[74] S. Latif, R. Rana, S. Younis, J. Qadir and J. Epps, Cross Corpus Speech Emotion Classification- An Effective Transfer Learning Technique, ArXiv e-prints, Jan. 2018.

[75] A. Morales, A. Kumar and M. A. Ferrer, Incorporating color information for reliable palmprint authentication, *Proceedings – International Conference on Image Processing, ICIP*, (2011), 3193–3196. https://doi.org/10.1109/icip.2011.6116347

[76] R. Bhuvaneswari and K. Tahiyalnayaki, Kernel Collaboration with Perceptron for Facial Emotion Recognition, *International Journal of Computer Applications*, **69** (2013), no. 13, 29–32. https://doi.org/10.5120/11904-7981

[77] M. Lyons, S. Akamatsu, M. Kamachi and J. Gyoba, Coding facial expressions with Gabor wavelets, *Proceedings - 3rd IEEE International Conference on Automatic Face and Gesture Recognition, FG 1998*, (1998), 200–205. https://doi.org/10.1109/afgr.1998.670949

[78] C. Szepesvari, Algorithms for Reinforcement Learning, *Synthesis Lectures on Artificial Intelligence and Machine Learning*, **4** (2010), no. 1, 1–103. https://doi.org/10.2200/s00268ed1v01y201005aim009

[79] R. Sutton, A. Barto and R. Williams, Reinforcement learning is direct adaptive optimal control, *IEEE Control Systems*, **12** (19920, 19–22. https://doi.org/10.1109/37.126844

[80] M. A. Wiering, H. van Hasselt, A.-D. Pietersma and L. Schomaker, Reinforcement learning algorithms for solving classification problems, *2011 IEEE Symposium on Adaptive Dynamic Programming and Reinforcement Learning (ADPRL)*, (2011), 91–96. https://doi.org/10.1109/adprl.2011.5967372

[81] E. Norouzi, M. Nili Ahmadabadi,and B. Nadjar Araabi, Attention control with reinforcement learning for face recognition under partial occlusion, *Machine Vision and Applications*, **22** (2011), no. 2, 337–348. https://doi.org/10.1007/s00138-009-0235-6

[82] K. F. Lee and S. Mahajan, Corrective and reinforcement learning for speaker-independent continuous speech recognition, *Computer Speech and Language*, **4** (1990), no. 3, 231–245. https://doi.org/10.1016/0885-2308(90)90006-r

[83] T. Kato and T. Shinozaki, Reinforcement Learning of Speech Recognition System Based on Policy Gradient and Hypothesis Selection, in arXiv, 2017.

[84] M. T. Harandi, M. Nili Ahmadabadi and B. N. Araabi, Optimal local basis: A reinforcement learning approach for face recognition, *International Journal of Computer Vision*, **81** (2009), no. 2, 191–204. https://doi.org/10.1007/s11263-008-0161-5

[85] M. Harandi, M. Ahmadabadi and B. Araabi, Face recognition using reinforcement learning, *2004 International Conference on Image Processing, 2004. ICIP '04*, Vol. 4, 2004, 2709–2712. https://doi.org/10.1109/icip.2004.1421663

[86] S. Tiwari and N. Sharma, Q-Learning Approach for Minutiae Extraction from Fingerprint Image, *Procedia Technology*, **6** (2012), 82–89. https://doi.org/10.1016/j.protcy.2012.10.011

[87] N. Kohl and P. Stone, Policy gradient reinforcement learning for fast quadrupedal locomotion, *IEEE International Conference on Robotics and Automation, 2004. Proceedings. ICRA '04*, 2004, Vol.3, 2004, 2619–2624. https://doi.org/10.1109/robot.2004.1307456

[88] A. Y. Ng, A. Coates, M. Diel, V. Ganapathi, J. Schulte, B. Tse, E. Berger and E. Liang, Autonomous inverted helicopter flight via reinforcement learning, *Experimental Robotics IX*, Springer, Vol. 21, 363 372, 2006. https://doi.org/10.1007/11552246_35

[89] S. Singh, D. L. Man, M. Kearns and M. Walker, Optimizing dialogue management with reinforcement learning: Experiments with the NJFun system, *Journal of Artificial Intelligence Research*, **16** (2002), 105–133.

[90] G. Tesauro, Temporal difference learning and TD-Gammon, *Communications of the ACM*, **38** (1995), no. 3, 58–68. https://doi.org/10.1145/203330.203343

[91] C. Fyfe and W. Barbakh, Immediate reward reinforcement learning for clustering and topology preserving mappings, *Similarity-Based Clustering*, Vol. 5400, Springer, 2009, 35–51. https://doi.org/10.1007/978-3-642-01805-3_3

[92] B. M. Lake, T. D. Ullman, J. B. Tenenbaum and S. J. Gershman, Building Machines That Learn and Think Like People, *Behavioral and Brain Sciences*, (2016), 1–101.

[93] K. Arulkumaran, M. P. Deisenroth, M. Brundage and A. A. Bharath, A Brief Survey of Deep Reinforcement Learning, *IEEE Signal Processing Magazine Special Issue on Deep Learning for Image Understanding*, (2017), 1–14.

[94] Y. Rao, J. Lu and J. Zhou, Attention-aware Deep Reinforcement Learning for Video Face Recognition, *Int. Conf. on Computer Vision (ICCV)*, (2017), 3931–3940. https://doi.org/10.1109/iccv.2017.424

Received: April 24, 2018; Published: May 23, 2018