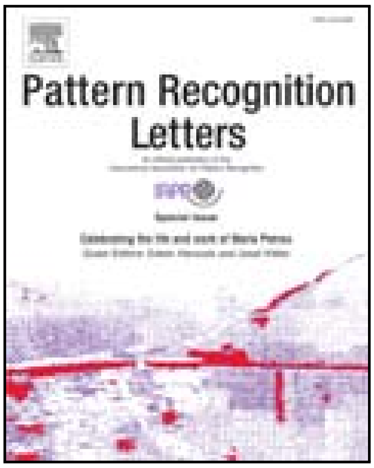

Iris Recognition through Machine Learning Techniques: a Survey

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Highlights

We provide a review of iris biometrics with Machine Learning techniques.

We propose a taxonomy of Machine Learning techniques for iris recognition.

We mention approaches ranging from neural networks to deep learning.

We discuss some aspects related to the mentioned methods.

Iris Recognition through Machine Learning Techniques: a Survey

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ABSTRACT

Iris recognition is one of the most promising fields in biometrics. Notwithstanding this, there are not so many research works addressing it by Machine Learning techniques. In this survey, we especially focus on recognition, and leave the detection and feature extraction problems in the background. However, the kind of features used to code the iris pattern may significantly influence the complexity of the methods and their performance. In other words, complexity affects learning, and iris patterns require relatively complex feature vectors, even if their size can be optimized. A cross-comparison of these two parameters, feature complexity vs. learning effectiveness, in the context of different learning algorithms, would require an unbiased common benchmark. Moreover, at present it is still very difficult to reproduce techniques and experiments due to the lack of either sufficient implementation details or reliable shared code.

Keywords: biometrics; iris recognition; periocular recognition, machine learning

1. Introduction

In the last 50 years, research related to computer science has attempted to replicate the (human) basic ability of recognition. This ability was specialized across the human evolution according to the different kinds of objects/situations requiring understanding (gesture, language, written symbols, concrete objects, peer friendly or adverse intent, etc.), or, generally speaking, problems of pattern recognition (PR). Robust recognition deals with distilling the wide appearance variety displayed by the objects surrounding us, in order to abstract the basic discriminative as well as characterizing features, allowing to generalize recognition results. Only meaningful information is retained, despite uncontrolled and changing settings, to avoid over-fitting and therefore lower the prediction risk. In this context, a fascinating possibility is not only that of reproducing the human capability of recognition, but even that of learning, especially related to the recognition itself. Machine learning (ML) evolved from the joint study of pattern recognition and computational learning theory, and is especially concerned with the implementation of computer applications that can learn and also make predictions on new data in a (possibly completely) autonomous way. In particular, in supervised learning the computer is trained with (positive and/or negative) example inputs and their correct outputs, given by a human supervisor. The goal is to learn an adequately general rule that maps new inputs onto outputs. On the contrary, unsupervised learning requires that no labels are provided at all to the learning algorithm, that the aim is to find a meaningful structure, as well as a possibly hidden pattern (knowledge discovery), in the data fed as input. When there is no enough availability of labeled data, the combination of labeled data and a huge pool of unlabeled data can provide abundant resources for the learning paradigm that is referred to as semi-supervised learning. Nearby (e.g., similar) points (e.g., object parts) are likely to share the same label (local constraints) and points on the same structure (cluster or manifold) are likely to share the same label (global constraints). It is worth noticing that supervised learning incorporates only local constraints, e.g., using k-NN. In this case, predictions/classifications are derived assuming that the data are generated independently by the same unknown probability distribution. In other words, it is supposed to deal with independent and identically distributed (i.i.d.) random variables, even if this assumption may be relaxed in some conditions (Vovk *et al.*, 2005) or it is possible to directly infer the values of the classification function only at the points of interest using observations only (e.g., context-aware) (Vapnik, 2000).

Biometrics reserves a peculiar role in PR: the recognition of human subjects by their physical (appearance) and/or behavioral (activity) traits is one of the most attractive but also useful task in many scenarios. In particular, appearance, mostly from still imagery but moving now to video, is one of the elements on which PR approaches have focused mostly. Appearance (e.g., physical biometrics) varies, while identity remains constant. Reliable recognition must allow to both specializing and generalizing, while maintaining a separation margin to distinguish between classes and identities. The margin must be robust enough to withstand input variability. Towards that end, the “only solution … is to incorporate learning capabilities within the vision system that allow it to both learn to see, as well as, learn by seeing.” Learning balances internal representations and external regularities (Nayar and Poggio, 1996). In biometrics, the constant challenge is to handle the continuous changes in human traits, due to internal (e.g., aging or expression) or external (e.g., illumination or capture resolution) factors. As for iris, the latter play the main role. As a matter of fact, iris is time invariant and extremely distinguishing. Moreover, it is visible yet well protected, and its image can be acquired without contact. The reverse of the medal is that iris surface is very limited (only about 3.64 cm^2), so that acquisition for a reliable processing requires a distance of less than one meter to guarantee a sufficient resolution. In other words, an accurate recognition is only possible by ensuring subject cooperation and quality of the captured image. Therefore, present research trend is towards trying to significantly relax the constraints. The goal is a matching system with a sufficient robustness to different kinds of distortion, such as blurring, off-axis, reflections and occlusions by eyelids or eyelashes, to allow processing of noisy iris images, which are often partially compromised.

One of the factors hindering the adoption of machine learning approaches for biometrics is the huge number of classes (individuals) that have to be discriminated. As a matter of fact, in this case one seldom needs to distinguish among few classes, as in the case of age or gender. Each individual requires an ad-hoc training with positive and negative samples, but the former are typically not available in a sufficient number. Moreover a stable distribution of features across time is expected. Therefore, in massive real world applications classical machine learning approaches seem to have limited appeal. Nevertheless, the potential of such techniques attracts researchers since the first studies concerning artificial neural networks (ANN), i.e. the intriguing possibility to provide brain-like learning abilities to computers. In the case of biometrics, the ability for an automatic application to learn the features, rules, and strategies exploited by the human cognitive system to recognize human companions. As for iris, this implies doing something difficult for a human too, given the complex and high-resolution visual structure to process.

Iris recognition is a relatively young field (the first significant results are from early ’90, see Daugman, 1993) but advances have been very fast and effective (see for example ICE and NICE contests). The approaches to exploit machine-learning techniques are even more recent. As a matter of fact, the majority of the works considered in this paper has been published in the last five years, showing a young but constantly increasing interest of scientific community. We will review here the most interesting of such methods in literature.

Two main classes of methods can be identified as those relying on ANNs and those relying on Support Vector Machine (SVM) or more generally Kernel Machines.

The ANNs are layers of neurons, each computing an activation function according to weights attached to the links among neurons. With one single output neuron, the class of binary classification problems is addressed, whilst in the case of multiple classes, more outputs are used till to be equal to the number of classes. The ANN architecture includes a family of functions (the activation functions), and the network training allows choosing one such decision function. In particular, this family is defined by the complexity of the neural network: number of hidden layers, number of neurons in these layers, and topology of the network. The decision function is determined by choosing appropriate weights for the neural network connections. Optimal weights usually minimize an error function for the particular network architecture.

SVM classifiers are basically generated by a two-step procedure. First, the sample data vectors are projected onto a very high-dimensional space. The dimension of this space is significantly larger than the original data space. Second, the algorithm finds a hyperplane in this new space with the largest margin (linearly) separating classes of data. Classification accuracy usually requires a sufficiently high dimensional target space. If it is not possible to find the separating hyperplane, a tradeoff must be accepted between the size of the separating margin and penalties for every vector that is within the margin. Explicit mapping to a new space can be avoided if it is possible to calculate the scalar product in this high dimensional space for every two vectors. This scalar product can be defined by introducing a kernel function $(x \bullet x') = K(x, x')$, where x and x’ are a pair of vectors in the low-dimensional space for which the kernel function K corresponds to a scalar product in a high dimensional space. Various kernels may be applied, and this characterizes the different kinds of SMs approaches.

In addition, also techniques considering the periocular region are taken into account. This emerging research line aims at addressing the problems of low resolution, distance and blur that affect iris in uncontrolled conditions, using the periocular region instead, either as an alternative trait or as a complement.

The rest of the paper proceeds as follows. Section 2 presents a description of ML methods applied to iris recognition, distinguishing mainstream ones from those using the fuzzy variation of neural networks and form those using different improvements to the basic techniques; periocular recognition by

ML is also presented. Section 3 deals with some discussion about the presented methods and Section 4 draws some conclusions.

2. Main machine learning approaches to iris and periocular recognition

In this section we describe the main contributions available so far to the field of iris/periocular recognition through machine learning techniques. Most of the works considered pertain to the last decade and two thirds of them have been presented in the last five years, showing an increasing interest of scientific community for this topic. It is worth remarking that the present paper is specifically focused on the machine learning methods applied to the recognition problem and, consequently, it does not cover in detail any feature extraction methods unless this step is a characterizing part of the ML approach. In the same way, as we wanted to provide a coherent and uniform view of the state of the art, almost the totality of the papers cited in this survey concern iris/periocular recognition instead of their detection. On the contrary, some missing works especially tackle these two problems, leaving less space to the investigation of original ML techniques. For these further papers the interested reader can refer to (Sharma *et al.*, 2014). The same holds for papers presenting very similar techniques.

Notwithstanding the relatively small corpus of existing works, a wide range of different machine learning methods have been proposed. These mainly rely on (yet are not limited to) Artificial Neural Networks (ANN) in general, and in particular, Multi Layer Perceptrons (MLP), Self Organizing Map (SOM) neural networks, Radial Basis Function Neural Network (RBFNN), Fuzzy Neural Networks, Probabilistic Neural Networks (PNN), Gabor Wavelet Neural Networks (GWNN), and Restricted Boltzmann Machines (RBM), and include Support Vector Machines (SVM). This variety of techniques, together with the uneven distribution of iris vs. periocular papers (at the best of our knowledge, only three of the latter exploit ML) suggested us the structure of the survey. We organized the contributions in four groups, covered in subsections 2.1 to 2.4, according to the kind of ML technique applied. In this case, the usual classification of machine learning methods in “supervised” and “unsupervised” (or possibly semi-supervised) is not well suited to provide a meaningful characterization of the state of the art. Three out of these four groups strictly concern iris recognition, while the fourth one deals with periocular recognition and also with the application of ML to iris and eye detection. The periocular region can be considered as a trade-off between two well-established biometrics, face and iris. It represents a valid alternative to constrained environments requiring active cooperation by users, allowing a more “relaxed” capture of subjects to be authenticated. The size of the periocular region, indeed, simplifies its acquisition with respect to the much smaller iris surface and its moving profile. Periocular recognition may be useful in applications where, due to occlusions, it is difficult to obtain a clear picture of an iris or a complete picture of a face. Periocular biometrics can be used together with iris recognition, by fusing the corresponding scores, or also alone. To the best of our knowledge, there are only a few works exploiting ML methods for periocular recognition so far, and they are briefly described in the following paragraphs.

At the end of this section, Table 1 summarizes all the methods covered herein, providing a quick comparison of the main features and performance with regard to the specific datasets used.

2.1. Mainstream methods

The first group of considered methods, that is also the largest one, comprises works in which the feature matching/recognition stage is based on the most diffused machine learning architectures and procedures, such as SOM, Feedforward Back Propagation Neural Network (FBPNN), Multilayer Feedforward Neural Network (MFNN), MLP and kernel/SVM methods.

In order to better reflect the research trends, we chose to list the relevant works in chronological order, but the main distinction between methods exploiting Neural Networks and those based on SVM will underlie the presentation.

One of the first proposals concerning the use of machine learning techniques for iris recognition has been presented by Liam *et al.* in 2002 (Liam *et al.*, 2002) and exploits a Self-Organizing Neural Network for matching iris patterns. The authors describe a simple network architecture based on a single layer of Euclidean weight functions, where Manhattan distance is the metric adopted for computing the distance between a couple of neurons; a competitive transfer function without bias is exploited to upgrade the weight. The network is composed of a grid of 25 neurons; it is trained with a subset of a proprietary iris database containing 150 samples, some of which presenting a relevant distortion. The system is tested with 30 sets of five samples, achieving an overall accuracy of 83%.

In (Moinuddin *et al.*, 2004), two different types of neural networks are experimented and compared to each other to improve the recognition accuracy: the MFNN and the RBFNN. The former is implemented using a single hidden layer featuring 30 neurons, an output layer with 10 neurons and backpropagation to update the weights. The proposed RBFNN network is simpler than the MFNN, having only one layer and 10 neurons and therefore requiring a much lower computational load. The experiments are conducted on a subset of the Daugman’s iris database (Daugman 1993), with Gaussian noise added with different signal-to-noise-ratios (SNRs) to 70% of the training set, and iris contours extracted as a 1D feature vector. Results show a similar recognition performance between MFNN and RBFNN, with a slight advantage in terms of accuracy for MFNN and a much lower computing time for RBFNN (less than a half of MFNN).

In 2005, Gu *et al.* (Gu *et al.*, 2005) first propose to exploit the classification performance of SVM for the iris recognition problem. A fractal-based procedure extracts iris features (see Gu *et al*., 2004). The main concern in this approach is the reduction of the computational load typical of kernel-based methods by combining different optimization techniques. To this aim they use active learning to remove most non-support vectors rapidly, thus greatly reducing the computing time required by sequential optimization. In addition, a polynomial kernel function is preferred over RBF and sigmoid function, and a strategy for negative samples reuse is also implemented (negative samples are reused when they support vectors). Finally, other optimizations in feature representation and in storing of training results allow further improvement of the SVM’s efficiency for this particular task. Experiments on the CASIA-IrisV1 database achieve a recognition rate of 98.4% for the standard SVM implementation, and slightly less for the optimized version; however, the latter is more than five times faster than the non-optimized one.

Similarly, Roy and Bhattacharya (Roy and Bhattacharya, 2005) test SVM performance with various kernel types on the CASIA-IrisV1 database. Iris feature vectors are extracted via Gabor wavelets. According to the reported findings, RBF kernel provides the best recognition accuracy with a recognition rate of

97.34%. A False Acceptance Rate (FAR) of 2.06% and a False Rejection Rate (FRR) of 0.6% confirm the suitability of the proposed architecture for both authentication and recognition applications.

In 2008 also Ali and Salami (Ali and Salami, 2008) experiment on a subset of CASIA-IrisV1 database (42 grayscale eye images) with a SVM architecture and different kernel types. Even in this case the proposed procedure exploits Gabor wavelets for extracting the deterministic features in the segmented iris. SVM–based authentication gives very good results for FAR in both closed set and open set conditions (in the close set, an authorized person uses other authorized person identity. In the open an impostor uses authorized person's identity). This implies that the proposed system is well protected from attacking by impostors. In contrast, the FRR values are very high with an average value of about 19.80%. Hence, the system seems to have poor usability. Experimental results show that the best FRR reachs about 33%, with an average value of 19.80%.

The aim of devising an adaptive learning strategy for a NN-based iris classification method, is central in the work of Abiyev and Altunkaya (Abiyev and Altunkaya, 2008). The NN architecture consists of two hidden layers, respectively including 120 and 81 neurons. It is enhanced by a gradient-based learning algorithm, featuring an adaptive learning rate in order to increase learning speed and also for guaranteeing convergence. The experiments conducted on the CASIA-IrisV1 database report up to 99.25% of recognition accuracy.

Kocer and Novruz (Kocer and Novruz, 2008) compare two particular implementations of a Modular Neural Network and of conventional MLP to investigate whether one of the aforementioned architectures might result more suited than the other to the task of iris recognition. More in detail, a feed-forward multilayer perceptron is compared to a MNN featuring several subcomponents (miniaturized MLPs) that can dynamically vary in structure and number to perform a specific subtask. Feature vectors are extracted through the Average Absolute Deviation (AAD) algorithm. The training session is performed on subsets of CASIA-IrisV1 and UBIRIS.V1 database (490 iris images captured from 70 people, 7 images per person from CASIA database, and 300 iris images captured from 60 people, 5 images per person from UBIRIS). The results achieved show an advantage of more than 3% in recognition accuracy for the MNN that reaches a 97.14% rate on the CASIA images, while at the same time it results much faster than standard MLP.

Also Shin *et al.* (Shin *et al.*, 2009) exploit a MLP architecture, but with a different purpose. They propose to use multiple MLPs to implement a super-resolution approach aimed at enhancing the spatial resolution of iris images, which are typically affected by camera-subject distance, camera lens and sensor resolution, and often result not suitable for accurate recognition. The proposed restoring pipeline takes as input the low-resolution iris image, estimates pixel values of the super-res image by means of three MLPs, without the reduction of middle or high frequency components, and finally the procedure fills up the remaining dark pixels by using bilinear interpolation. In order to test the saliency of the features extracted through Gabor wavelet from the resulting images, the authors train the MLPs iteratively on a randomly selected subset of the CASIA-IrisV3 database, by means of a back propagation algorithm. Experiments confirm the improvement in recognition accuracy provided by the method when the input images are of low resolution.

In 2009, Sarhan (Sarhan, 2009) proposes another MLP-based approach characterized by a three-layer network. The architecture exploits back-propagation for the learning algorithm and log-sigmoid transfer function for the output layer; this layer is composed by 30 neurons, one for each of the individuals to be classified according to feature vectors based on a Discrete Cosine Transform (DCT). The method achieves a 96% of recognition accuracy on the CASIA-IrisV2 database.

Gaxiola et al. (Gaxiola *et al.,* 2010) present a modular neural network for iris recognition. It is made up of three simple neural networks and each module input handles 33 individuals (264 images for training - 198 images for testing). To integrate all results of the three modules, a Gating Network is used. Iris patterns are extracted by the software by Makek and Kovesi (Masek and Kovesi, 2003). The authors perform experiments with 3 types of learning algorithms: gradient descent with adaptive learning (GDA), gradient descent with adaptive learning and momentum (GDX) and scaled conjugate gradient (SCG). The best learning algorithms are the scaled conjugate gradient (SCG) and gradient descent with adaptive learning (GDA) with images of size of 21x21. The best reported identification rate adding the Gating Network is 96.80% when the approach is applied to CASIA-IrisV1 database. In 2011 the same research group (Gaxiola *et al.*, 2011) proposes a similar approach but uses type-2 fuzzy integration at the level of submodules, and Gating Network at the level of the modules, achieving a recognition rate of 97.98% of recognition rate on the same CASIA-IrisV1 set.

In 2010, Lu *et al.* Wang (Lu *et al.*, 2010) propose a new approach based on Kohonen network (SOM) that recalls the one from (Liam *et al.*, 2002) mentioned above, but exploits Independent Component Analysis (ICA) for feature extraction. The method is trained on a subset of 180 iris specimens out of a proprietary iris database of 400 images, and reaches up to 98.81% of recognition accuracy.

Along a similar line of research, Wagdarikar and Subbaraman (Wagdarikar and Subbaraman, 2010) compare the recognition accuracy of a FBPNN whose input vectors are obtained by extracting iris pattern features through either ICA or Single Value Decomposition (SVD). Their findings suggest that, at the cost of a greater training time, the simple NN used performs better with SVD than ICA for feature vectors up to 10 dimensions (recognition rate of 96.29%), while performance drops rapidly for 20+ dimensions. The experiments exploit the CASIA-IrisV1 database.

Dias *et al.* (Dias *et al.*, 2010) compare the efficacy and efficiency of several back propagation algorithms (Fletcher-Reeves conjugate gradient, Polak-Ribiére conjugate gradient, Powell-Beale conjugate gradient, Scaled conjugate gradient and One-step secant method) for the same ANN architecture on the same subset of CASIA-IrisV1 database. The experiments conducted on a network trained for 99 people on 990 training images, highlight the good accuracy achievable by means of conjugate gradient algorithm whose Powell-Beale's version reaches 94.24% of recognition accuracy.

An interesting comparison of performance achieved by varying the number of hidden layers of an ANN, the number of neurons in each hidden layer, the input format (analog vs. binary), the noise level in the input image and the training/testing-data ratio is available in the work by Sibai *et al.* (Sibai *et al.*, 2011). A NN architecture that can be configured in different ways and three different data partitioning techniques (horizontal strip, vertical strip and block) are exploited to investigate how these parameters possibly affect the recognition accuracy. Experimental results on the CHEK image database (CHEK ref.) show that the best accuracy of 93.33% is obtained with 10-block partitioning, featuring 10 neurons in the input layer and 50 neurons in the hidden layer and 1 hidden layer only, while by reducing the number of neurons in the input layer, the recognition rate drops to 86.66%. Performance is negatively affected also by increasing the number of hidden layers, by using binary (instead that analog) input and by greater noise levels.

According to the work of Baqar *et al.* (Baqar *et al.*. 2011) it is possible to improve the recognition accuracy of a MFNN, a type of neural network already explored by other authors, by providing as input a more salient feature vector obtained by concatenating the contour points of the Pupil-Iris boundary and the Sclera-Iris boundary. The back-propagation MFNN used for the experiments features the common three-layers architecture with a 720 neurons input layer, a 90 neurons hidden layer and a 10 neurons output layer. The experiments use the MMU Iris Database. Noisy iris samples, generated by adding Gaussian noise at various intensity levels, are used for the training stage. According to the results provided the proposed dual-boundary based approach outperforms the conventional single-boundary method (on the same NN architecture) with recognition accuracy up to 99.3% (dual) vs. 93.4% (single).

Khedkar and Ladhake (Khedkar and Ladhake, 2013) extract features from iris images in the CASIA-IrisV1 database via the 2D Walsh Hadamard Transform (WHT). They then compare MLP, RBF and SVM by varying a set of parameters including momentum, step size in hidden and output layers, learning rules and number of neurons in the hidden layer, to the purpose of selecting the NN configuration best suited to classification of irises. Different variants of BP like momentum, conjugate-gradient, quick propagation, delta-bar-delta, Levenberg-Marquardt and step are also experimented. The experiments show an advantage of the single-hidden-layer MLP with momentum BP over other architectures considered (accuracy of 95%) and this advantage is confirmed also on iris patterns modified by injecting Gaussian and uniform noise at the cost of small drop of recognition accuracy (90.5%).

AL-Allaf *et al.* (AL-Allaf *et al.*, 2013) propose an ANN based on the PatternNet model and characterized by a multilayer architecture with one input layer, five 15-neurons hidden layers and one output layer. They compare this configuration trained by ten different algorithms (e.g., Levenberg-Marquardt, Bayesian regularization, Gradient descent, Gradient descent with momentum and adaptive learning rate, etc.) to other four types of NN including FBPNN, Cascade ANN, FitNet and LVQNet. Previously segmented iris images are partitioned into ten sub blocks 10x10 pixels in size. The experiments are carried out on a subset of the CASIA-IrisV1 database. The results in terms of Mean Square Error (MSE), Peak Signal/Noise Ratio (PSNR) and Recognition Rate (RR) show that the best accuracy (RR of 98.9%) is achieved with the proposed PatterNet model of ANN trained by means of Levenberg-Marquardt algorithm. Interestingly, the addition of a second hidden layer reveals to be counterproductive for the system's performance.

In 2014, Rai and Yadav (Rai and Yadav, 2014) propose to combine SVM with Hamming distance to improve both accuracy and robustness of iris recognition. In their approach the authors hypothesize an advantage in using the SVM as the main classifier and the Hamming distance as a secondary classifier in case SVM-based classification of iris features fails. They also propose to use two different feature extraction techniques (Haar wavelet decomposition and 1D Log Gabor wavelet) for the two classifiers instead than using the same features for both of them. The reason for this is in the known accuracy of SVM in correctly classifying impostors (very low FAR) and, at the same time, the tendency to incorrectly classify genuine subjects (FRR is not that low). The idea is to use the SVM on Haar wavelet features first, then, for the probably small percentage of patterns not correctly classified (a fraction usually below 10% of the total, containing patterns either falsely rejected or belonging to imposters) a second feature extraction is performed with 1D Gabor wavelets, and Hamming distance is used to match again this subset of feature vectors. This approach cope with the typical "unsatisfying" performance of SVM with regard to non-false acceptance rate. Experiments on both the CASIA-IrisV1 (RR=99.91%) and the CHEK database (RR=99.88%) confirm the efficacy of this technique and a clear improvement over using the same features extraction techniques for both the matching stages.

Srivastava *et al.* (Srivastava *et al.*, 2014) propose in 2014 a synergic approach to iris recognition which entails evolutionary, fuzzy and neural techniques. In practice, they combine evolutionary fuzzy clustering and functional modular neural networks (FMNN). The former exploits Minkowski distance (EFC-MD) to carry out a pre-classification task which allocates training patterns into an optimal number of clusters. In comparison with Euclidean distance, Minkowski distance matrices allow flexibility in handling any cluster shape. Clusters are used to devise the parameter for the functional modular network. The functional modular neural network is trained according to the fuzzy distribution of patterns in a cluster identified by EFC-MD. It has a single hidden layer. The experimental results on CASIA prove that the novel approach is more flexible than the Local Phase Quantization (LPQ) techniques and provides a recognition rate of 98.12%.

More recently, Saminathan *et al.* (Saminathan *et al.*, 2015) present a new multi-class SVM based approach to both iris authentication and recognition. Three types of kernel (linear, polynomial and quadratic) are combined with three methods (sequential minimal optimization, quadratic polynomial and least square) and compared to other three classification methods: Hamming distance, Local Binary Pattern and FFNN. Feature extraction and representation produces row vectors of 2400 intensity values. The results of the experiments based on the CASIA-IrisV3-Interval database, highlight that the best performance is achieved by using the least square method and quadratic kernel SVM, accounting for a recognition rate of 98.5% with zero percentage of False Acceptance Rate (FAR) in the best case.

The work by Fasca *et al.* (Fasca et, al., 2012) is the first example of a periocular recognition system that exploits Local Binary Pattern (LBP) and Histogram of Oriented Gradients (HOG) for feature extraction and a ML technique for an effective classification and recognition of authorized individuals. In their approach, indeed, the authors use a classical FFBPNN with a single hidden layer for training and classification. Gradient descent method and sigmoid function are used for training while the hidden layer contains 70 neurons. A proprietary database consisting in left/right periocular images from twenty subjects is built for the purpose of testing the efficacy of the proposed method. The results of the experiments report a recognition rate of 91% for L/R periocular regions and of 88-90% for single periocular region, with a clear advantage when using the BPNN.

Since face recognition is generally performed under visible wavelengths and iris recognition performs best in Near Infra-Red (NIR) wavelengths, a cross-spectral matching problem might arise when combining two differently captured biometrics in the context of periocular recognition. To address this issue, Sharma *et al.* (Sharma *et al.*, 2014) are the first to propose an algorithm based on NN for learning the class of image variations caused by different spectral ranges. According to the architecture described in their paper, three learning stages with corresponding NN are introduced for the first spectrum, the second spectrum and for cross-spectral matching respectively. The first two networks (i.e. for spectrum 1 and spectrum 2) are trained using back-propagation with regularization, where the fitness function is the verification accuracy at 1% of FAR. The third cross-spectral-variability network combines the other two previously trained NN which receive as input a cross-spectral feature vector while their outputs are connected to a sigmoid threshold unit through specific weights. Once trained, this combined network is used for cross-spectral periocular classification. To the aim of addressing the lack of cross-spectral periocular databases, the authors have built the IIITD Multispectral Periocular (IMP) database, featuring near-infrared, visible and night-vision periocular samples. On this database, the proposed approach produces superior accuracy compared to other four methods like LBP, HOG, PHOG and FPLBP and with a recognition rate ranging from 76.97% (visible spectrum) to 92.5% (NIR) for same-spectrum recognition and from 48.21% (night vision – NIR) to 71.93% (visible - night vision) for cross-spectral recognition. In most experiments, combined L+R periocular provides a better recognition accuracy than single L/R periocular.

2.2. Methods based on Fuzzy neural networks

Neural networks and fuzzy systems have some things in common. They can be used for solving problems for which no mathematical model of the given problem exists. They also involve certain disadvantages and advantages that can possibly disappear by combining both concepts. Neuro-fuzzy systems, also known as Fuzzy Neural Networks (FNNs) are hybrid fuzzy systems characterized by a learning algorithm derived by neural network theory to determine its parameters (fuzzy sets and fuzzy rules) by processing data samples (Caianiello and Petrosino, 1994; Baraldi *et al.*, 1997). The learning procedure operates on local information, and causes only local modifications in the underlying fuzzy system. The following papers apply the idea of combining fuzzy reasoning to neural networks in the effort of improving robustness and/or accuracy of iris recognition systems, even in case of non-optimal iris images.

In 2011, Chowhan *et al.* (Chowan *et al.*, 2011) start from the Fuzzy HyperSphere Neural Network (FHSNN) originally developed by Kulkarni *et al.* (Kulkarni *et al.*, 2001) to propose an extension of this concept, the Modified Fuzzy HyperSphere Neural Network (MFHSNN). The latter features the ability to rapidly learn patterns by creating /expanding hypersheres. The MFHSNN architecture is based on four layers. Iris feature vectors extracted via Singular Value Decomposition (SVD). The input layer consists of n processing node where n is the dimension of the input pattern. The subsequent layer includes q nodes (resulting from the training stage) each representing hypersphere fuzzy sets characterized by hypersphere membership function. The third delivers fuzzy decision so that the output of its k_{th} node represents the degree to which the input pattern belongs to the class n_k, while each connection between the second and the third layer represents binary values. Finally the fourth layer delivers a de-fuzzyfied output. Experiments conducted on the CASIA-IrisV1 database confirm the feasibility of MFHSNN for iris recognition achieving a recognition rate of 94%.

Chowan and Shinde (Chowan and Shinde, 2011) propose a different neuro-fuzzy approach based on the work by Simpson (Simpson, 1992) on Fuzzy Min-Max Neural Networks (FMNN). The approach is characterized by hyperbox (instead of hypershpere) fuzzy sets to build the neural networks. Even in this case the procedure extracts iris features by SVD. The three-steps algorithm performing hyperbox expansion, overlap testing and (in case the overlap exists) hyperbox contraction, applied to the CASIA-IrisV1 database delivers a recognition rate of up to 95.68% with a training time of about six seconds and a recall time of slightly more than two minutes.

In Raghavi *et al.* (Raghavi *et al.*, 2011) the proposed FNN is based on a two-layers feed-forward back-propagation neural network with a number of input nodes that is double of the number of (continuous-valued) input parameters. The number of output nodes is the same as the number of classes in the data. This configuration is used to match feature vectors previously extracted from a small (20 samples) proprietary iris dataset through Harr wavelet and embedded zero tree wavelet coding. The results of experiments reach 99.25% of recognition rate after training.

2.3. Others (PSO, GA, PNN, etc.)

In the following we report about approaches that try to explore new ways of applying machine learning to iris recognition. They follow other research lines like genetic algorithms, particle swarm optimization techniques, probabilistic neural networks, etc. Some works also focus on aspects not sufficiently covered in literature, as the impact of sensors on the recognition. In particular, GAs finds application in supporting efficient and effective search, in our case for the synthesis of neural network architecture, and better selection of feature subsets based on different feature selection methods to obtain the best classifier. Also PSO mainly addresses feature selection. As anticipated, we will not cover the latter aspect if not strictly related with the rest of the approach. Related papers can be found in the survey by Sharma *et al.* (Sharma *et al.*, 2014).

In 2005, Chu and Chen (Chu and Chen, 2005) are the first to exploit a PNN trained through a Particle Swarm Optimization algorithm (PSO) to classify 1D iris features extracted by means of LPC-derived cepstrum (LPCC) and Linear Discriminant Analysis (LDA). Particle Swarm Optimization (PSO) is a kind of algorithm originally conceived to model complex natural behavior like that of a flock of birds or a school of fish. In this case the authors aim at optimizing the PNN by finding the best smooth parameters during the training stage. According to the experimental results on the CASIA-IrisV1 database, the PSO algorithm is beneficial to the average recognition rate that reaches 99.14% compared to 98.38 without PSO.

In the same year Chen and Chu (Chen and Chu, 2005) propose a network to classify the pattern of iris features by a technique called wavelet probabilistic neural (WPNN). WPNN combines Wavelet Neural Network and Probabilistic Neural Network. Sobel Transform and vertical projection extract the features and adjust the weights of WPNN. The method exploits PSO again to train the WPNN. This system is applied to CASIA-IrisV1 dataset. Experimental results show that recognition time per image is less than 1ms and Equal error rate (EER) 3.32%.

Working on improving the PSO algorithm, Zhang *et al.* (Zhang *et al.*, 2007) describe a hybrid PSO-BP approach. It is inspired by Adaptive Particle Swarm Optimization Algorithm (APSOA) that is combined with the BP algorithm to perform global search in the starting stage; then it exploits the BP algorithm to performing local search in the surrounding of global optimum. This approach is used to train the weights of a FFNN to the aim of achieving increased convergence speed and generalization capability. To prove the advantages brought by the proposed solution, the authors compare PSO-BP to APSO and BP alone using the iris classification problem as a challenging benchmark. Their findings show that PSO-BP, though not superior to PSO in the peak recognition rate (99.33%), has better mean recognition rate than both PSO and BP; this is obtained thanks to the local gradient descending method used to search around global optimum, which improves the searching efficiency.

An attempt to combine genetic algorithms and SVM in the context of iris recognition is due to Roy and Bhattacharya (Roy and Bhattacharya, 2007). The authors exploit Multi Objective Genetic Algorithm (MOGA) to select optimal features for tuning the SVM and therefore maximizing recognition accuracy. More precisely, the goal of feature subset selection is to use fewer features to improve performance. The fitness evaluation is based on the accuracy from the validation data and on the number of features considered, while the performance of SVM classifier is used to guide the genetic algorithm. Trying to address the known not-so-good FRR of standard SVM architecture, an asymmetrical architecture is applied to satisfy different types and levels of security applications and to handle unbalanced data by reducing the FAR; the latter goal is achieved through an asymmetrical parameter used to adjust the decision hyperplane. Two different iris datasets are used for the experiments: the ICE (Iris Challenge Evaluation) and the WVU (West Virginia University). Iris features are extracted by means of 2D Gabor wavelets. RBF kernel is adopted for iris pattern classification according to a comparison with other kernel types. The results achieved highlight a measurable (though slight) advantage in the MOGA enhanced system with recognition rate of 97.70% on ICE dataset and of 95.6% on WVU dataset. The asymmetrical SVM architecture affects positively the Equal Error Rate (EER) that drops from 0.72% to 0.43% on ICE and from 1.6% to 0.9% on WVU.

Zhou *et al.* (Zhou *et al.*, 2008) present a Gabor Wavelet Neural Network (GWNN) that can be represented as a perceptron characterized by a Gabor-node as a preprocess unit for feature extraction exploiting the improved steepest descent algorithm. The extraction algorithm layer of GWNN is used for determining the optimal parameters of wavelet basal function. To this aim, Gabor parameters are adaptively adjusted through Gabor wavelet atomic transform function. When optimal values are found, Gabor filtering and wavelet methods are used to extract iris features whose dimensionality is reduced by means of 2D Principal Component Analysis (2DPCA). Features matching and classification is therefore performed through another layer of the GWNN architecture. The experiments conducted on a proprietary iris dataset including fifteen subjects and ten iris images for each eye report a maximum recognition rate of 99.3% that compares favorably to more classical architecture like FBPNN and SOM which score 98.2% and 98.25% respectively.

The idea of exploiting the concept of Probabilistic Neural Network (PNN) is proposed by Sundaram and Dhara (Sundaram and Dhara, 2011). A PNN is an artificial neural network specialized for nonlinear computing which approaches the Bayes optimal decision boundaries by estimating the probability density function of the training dataset. This particular architecture features an input layer, a pattern layer, a summation layer and an output layer and it results much faster than FFNN as it requires only one training step. The procedure extracts iris features through Gray Level Co-occurrence Matrix (GLCM) based Haralick features (Haralick *et al*., 1973). The approach is tested on the UBIRIS.V1 database, and achieves 97% of recognition accuracy with FAR=2.74% and FRR=3.15% at a threshold Th=0.6.

An example of combining Modular Neural Network genetic algorithms (GA) and fuzzy integration is provided by Melin *et al.* (Melin *et al.*, 2012). The authors propose a MNN composed by three perceptrons (modules) each consisting in a MFNN using a matrix to represent the neural network and suited to not linearly separable problems. Each module is specifically shaped for one third of the subjects belonging to a subset of 77 people from the CASIA-IrisV3 database, as in (Gaxiola et al., 2010), resulting in a not uniform architecture. The feature vectors are extracted by compressing the iris images via wavelet transform. The GA is introduced to optimize the basic architecture, by finding the appropriate type of training and the optimal number of neurons and hidden layers. Various information integration methods are experimented, including gating network, type-1 fuzzy integration and even fuzzy integration through GA. Experimental results show that the best recognition accuracy of 99,76% is achieved when both the MNN structure and fuzzy integration are optimized by means of GA.

The use of genetic algorithms for optimizing multilayer NN is also explored in (Raja and Rajapaln, 2013). In this work GA is executed ten times to find the average and standard deviation values for neurons number, methods and number of layers. The results achieved show a clear improvement of recognition accuracy and learning time for the GA optimized NN (RR=98.48%, 20 s) compared to the not optimized NN (RR=93.3%, 10.8 s).

The efficacy of iris biometrics is known to be affected whenever different sensors are used for subject enrolment and for subject recognition in a given application scenario. This is very likely, as iris biometrics is becoming more and more accepted and diffused for a wide range of applications that may require enrollment and testing to be performed under different conditions. To address the problem of cross-sensor iris recognition, Pillai *et al.* (Pillai *et al.*, 2014) present a novel machine learning-based approach aimed at reducing the recognition performance degradation by adapting iris samples from one sensor to another. A specifically designed optimization framework is used for learning the transformations of iris biometrics having the desired properties (which are represented by kernel functions) and is therefore exploited for sensor adaptation by enforcing the distances between iris samples belonging to the same class to be small (while interclass distance stays large) regardless of the sensor used for their acquisition. Matching is therefore performed using the transformed iris samples. The authors also propose an efficient solution to this convex optimization problem by means of an objective function using Bregman projections, thus avoiding to perform the optimization every time a test sample is acquired. Experiments have been conducted on the Notre Dame (ND) dataset also adopted for the Cross-sensor Iris Competition. The experimental protocol randomly selects three iris samples of both eyes from thirty subjects as the training data for the learning framework, while the remaining subjects are considered for cross-sensor recognition. The recognition rate for the adapted samples is always higher (87.82%) than the result achieved on non-adapted samples (84.34%) and it reaches a peak value of 95.73% on a subset of the ND dataset that is free from segmentation errors. A further advantage of the proposed methodology is that it has a low computational impact on the iris recognition pipeline and it can be easily integrated into existing architectures.

Deep learning is the last frontier of ML. At the best of our knowledge, at present the only work addressing iris recognition through deep learning (DL) is that by Liu *et al.* (Liu *et al.*, to appear in this same Special Issue). In particular, this work tackles the even harder problem of cross-sensor iris recognition. As a matter of fact, large-scale identity management system often require matching heterogeneous iris images captured at different resolutions or by different iris devices. However, it is very difficult to manually design a robust encoding filter to address the intra-class variations of heterogeneous iris images. This paper proposes DeepIris, a DL-based method devised to this aim. It exploits convolutional neural networks to learn the relational features which measure the similarity between pairs of iris images. The system is able to directly learn a nonlinear mapping function between pairs of iris images and the identity supervision, instead of carrying out two separate steps of iris feature extraction and feature matching. In practice, DeepIris learns a pairwise filter bank to establish the relationship between heterogeneous iris images. Pairs of filters are learned for two heterogenous sources, respectively. While traditional methods depend on handcrafted features, DeepIris can automatically learn a pairwise filter bank (PFB). The model is composed by nine layers of different kinds: one Pairwise Filter Layer (PFL), one convolutional layer, two pooling layers, two normalization layers, two local layers and one full connection layer. The PFL takes as input a pair of heterogeneous images. After being filtered by the learned pairwise filters, the two feature maps are summarized into the similarity map. The convolutional layer includes 64 pairs of filters of the size of 5×5. The normalization layers carry out a cross-map normalization in each unit and experimental results show that two normalization layers in the network can increase performance. The aim of local layers seem is to capture more local information. Convolutional layers, local layers and the full connection layers all rely on the same Rectified Linear Unit (Krizhevsky et al., 2012) as activation function. Two datasets are used for experiments. Q-FIRE dataset (Johnson et al., 2010) includes iris images captured at different distances (5, 7, and 11 feet) by the same sensor, producing different resolutions of iris rings. The first 160 subjects are selected to construct the cross-resolution dataset. The second dataset is CASIA cross sensor dataset. The cross-sensor dataset is collected by means of a close-up sensor (IrisGuard H100 - IR) and a long-range iris recognition system (LRI) able to capture iris images at a distance of 3 to 5 meters. Both subsets contain 350 subjects, each with 10 images per eye. This dataset has not been published yet. The obtained results for cross resolution iris verification show an EER of 0.15% with a genuine accept rate (GAR) as high as 95% when the false accept rate (FAR) is about 10^{-4}. Cross sensor verification achieves 0.31% EER.

Convolutional Restricted Boltzmann Machine (CRBM), a variant of RBM designed to deal with large resolution image data, represents an example of unsupervised ML methods that has not been explored in the context of iris/periocular biometrics before the work by Nie *et al.* (Nie *et al.*, 2014). The authors propose an approach for completely automated periocular recognition using a unsupervised feature learning; a few trained genuine pairs are used as constraint and the Mahalanobis distance is learned. While the unsupervised CRBM is used during the training process, the supervised metric learning is used for the verification. Finally, a binary SVM is trained to classify the genuine pairs. During the evaluation of unseen test images, the CRBM features are generated by means of the pre-trained CRBM model. For the combination with the handcrafted features, two SVM scores are employed. The final scores are generated by fusing two scores via non-linear transformation. Experimental results on the UBIPr database suggest that the supervised Manhalanobis distance outperforms in comparison with traditional metric space. According to the Receiver Operating Characteristics (ROC) curves provided (recognition rates are not reported in this paper) the best Equal Error Rate (EER) achieved is 6.4%., The experimental results also suggest that the nonlinear score level combination can better separate the genuine pairs than the traditional weighted sum and linear SVM fusion approaches.

3. Discussion

The choice between the two main classes of approaches, ANN vs. SVM, depends on their achievements in solving specific problems. For instance, in the work by Byvatov *et al.* (Byvatov *et al.*, 2003) SVM and ANN systems are applied to an example of binary decision problems, namely a drug/nondrug classification problem in early-phase virtual compound filtering and screening. The results of that work indicate that solutions entailing SVM training appear to be more robust and to produce a smaller standard error than those relying on ANN training.

In the mentioned work, the SVM classifiers yield slightly higher prediction accuracy than ANN, irrespective of the features extracted to encode object characteristics, the size of the training data sets, and the algorithms employed to train the two network architectures considered. However, a previous comparison of SVM to several machine learning methods (Burbidge *et al.*, 2001) had shown that an SVM classifier outperformed other standard methods, but a specially designed and structurally optimized neural network was again superior to the SVM model in a benchmark test.

Tab.1. Comparison of main approaches to Iris and Periocular recognition through Machine Learning techniques.

#	Authors, Year	Dataset	Peri ocular	Features	Rec. %	ML Approach
1	Abiyev and Altunkaya, 2008	CASIA-IrisV1	N	Intensity image	99.25	Neural network featuring gradient based learning algorithm with adaptive learning rate
2	AL-Allaf et al, 2013	CASIA-IrisV1	N	Partitioned intensity image	98.9	Feedforward Back Propagation Neural Network (FBPNN)
3	Ali and Salami, 2008	CASIA-IrisV1	N	Gabor wavelet	100 ?	Support Vector Machine (SVM)
4	Baqar et al. 2011	MMU Iris Database	N	Dual boundary contour vector	99	Dual boundary detection via robust variable learning rate Multilayer Feedforward Neural Network(MFNN)
5	Chen and Chu, 2005	CASIA	N	Sobel and vertical projections	EER =3,32 %	Wavelet Neural Network and Probabilistic Neural Network
6	Chowan et al, 2011	CASIA-IrisV1	N	Singular Value Decomposition (SVD)	94	Modified Fuzzy HyperSphere Neural Network with different distance measures (MFHSNN)
7	Chowan and Shinde, 2011	CASIA-IrisV1	N	SVD	95.68	Fuzzy Min-Max Neural Network
8	Chu and Chen, 2005	CASIA-IrisV1	N	LPCC / Linear Discriminant Analysis (LDA)	99.14	Particle Swarm Optimization (PSO) + Probabilistic Neural Network (PNN)
9	Dias et al, 2010	CASIA-IrisV1	N	Intensity image	94.24	Back Propagation Neural Network (BPNN), various back propagation algorithms
10	Fasca et al, 2012	Proprietary	Y	LBP and Histogram of Oriented Gradients (HOGs)	91	Local Binary Pattern (LBP), Histogram of Oriented Gradients (HOGs), Backpropagation Neural Network (BPNN)
11	Gaxiola et al., 2010	CASIA-IrisV1	N	Masek and Kovasi	96.80	Modular Neural Network (a module for each subset of subjects to recognize) with different learning algorithms and integration carried out by Gating Network
12	Gaxiola et al., 2011	CASIA-IrisV1	N	Masek and Kovasi	97.98	Modular Neural Network with type-2 fuzzy integration at submodule level and Gating Network integration at module level
13	Gu et al, 2005	CASIA-IrisV1	N	Variation fractal dimensions	98.4	Polynomial kernel Support Vector Machine (SVM)
14	Khedkar and Ladhake, 2013	CASIA-IrisV1	N	2D Walsh-Hadamard Transform (WHT)	95	Radial Basis Function (RBF), Multi Layer Perceptron (MLP), Support Vector Machine (SVM)
15	Kocer and Novruz, 2008	CASIA-IrisV1 UBIRIS.V1	N	Average Absolute Deviation (AAD)	97.14 100	Modular Neural Network (MNN)
16	Liam et al, 2002	Proprietary	N	Intensity image	83	Self-Organizing Map (SOM) Neural Network
17	Liu et al, to appear	Q-FIRE CASIA	N	-		Deep Learning with Convolutional Neural Network
18	Lu and Wang, 2010	Proprietary	N	Independent Component Analysis (ICA)	98.81	SOM Neural Network
19	Melin et al, 2012	CASIA-IrisV3	N	Wavelet transform	99.76	ANN + Fuzzy Integrator + Genetic Algorithm
20	Moinuddin et al, 2004	Daugman's iris dataset	N	1D iris contour	97	Multilayer Feedforward Neural Network (MFNN) and Radial Basis Function Neural Network (RBFNN)
21	Nie et al, 2014	UBIPr	Y		50.1	Unsupervised Convolutional Restricted Boltzmann Machine (RBM) Feature Learning
22	X Pillai et al, 2013	Notre Dame (ND)	N	Daugman's iris code	87.82	Kernel-learning framework for cross-sensor adaptation
23	Raghavi et al, 2011	Proprietary	N	Haar wavelet	99.25	Fuzzy Neural Network (FNN) algorithm
24	Rai and Yadav, 2014	CASIA-IrisV1 CHECK	N	Haar wavelet decomposition / 1D Log Gabor wavelet	99.91 99.88	Support Vector Machines (SVM) and Hamming distance
25	Raja and Rajagopalan, 2013	N/A	N	?	98.48	Artificial Neural Network (ANN) + Genetic algorithm (GA)
26	Roy et Bhattacharya , 2005	CASIA_IrisV1	N	Gabor wavelet	97.34	Support vector Machine (SVM) with different kernel types
27	Roy et Bhattacharya , 2007	ICE WVU	N	2D Gabor wavelets	97.7 95.6	Multi-Objective Genetic Algorithm (MOGA) and asymmetrical Support Vector Machine (SVM)
28	Saminathan et al, 2015	CASIA-IrisV3-Interval	N	Intensity image	98.5	Least square method of quadratic kernel Support Vector machine (SVM)
29	Sarhan, 2009	CASIA-IrisV2	N	2D Discrete Cosine Transform (DCT)	96	Artificial Neural Networks (ANN)
30	Sharma et al, 2014	IMP	Y	DSIFT, LBP and HOG	92.5* 71.93 **	Cross spectral periocular matching via combined Neural Networks
31	Shin et al, 2009	CASIA-IrisV3	N	Gabor wavelet	99.4 ?	Super-Resolution method based on Multiple Multi-Layer Perceptrons (MMLP)
32	Sibai et al, 2011	CHEK	N	RGB image	93.3	Feedforward Neural Network (FNN)
33	Srivastava et al., 2014	CASIA	N	Evolutionary fyzzy clustering	98.12	Evolutionary fuzzy clustering and functional modular neural network
34	Sundaram and Dhara, 2011	UBIRIS.V1	N	Haralick features	97	Haralick features + Probabilistic Neural Network (PNN)
35	Wagdarikar and Subbaraman, 2010	CASIA-IrisV1	N	ICA / SVD	96.29	Feedforward Back-Propagation Neural Network (FBPNN)
36	Zhang et al	N/A	N	N/A	99.33	Adaptive Particle Swarm Optimization Algorithm (APSOA)
37	Zhou et al, 2008	Proprietary	N	Gabor wavelet + 2D DPCA	99.3	Gabor Wavelet Neural Network (GWNN)

The only work among the ones mentioned in this survey that reports an extensive comparison among MLP, RBF and SVM by varying, e.g., momentum, step size in hidden and output layers, learning rules and number of neurons in the hidden layer, in the case of iris recognition is (Khedkar and Ladhake, 2013). Contrarily to (Byvatov *et al.*, 2003), the experiments show an advantage of the single-hidden-layer MLP (with momentum BP) over other architectures considered, achieving an accuracy of 95% that is, however, slightly lower that results achieved by other surveyed methods. To this regards, it is to consider the wide variety of features used for classification, and of architectures. A direct comparison is very difficult if not carried out in the single works, since experiments are very often hardly repeatable, due to the lack of a common benchmark. As a matter of fact, a further difficulty for a thorough discussion is that in many cases, only part of the datasets are used, and that part is randomly chosen or not clearly identified, so that even reproducing the experiments exactly is quite unfeasible. A particular advantage of an SVM classifier is that the classifier function is not influenced by the whole data set and the results depend only on the support vectors. Differently from ANN, whose complexity rapidly grows with data dimensionality, another characteristic of SVM is the possibility to exploit kernel functions to efficiently deal with a very large number of features, which makes it attractive when the problem at hand requires dealing with high-dimensional features. In both cases, the combination with a suitable strategy for relevant feature selection might achieve higher efficiency and better results.

Among different types of ANNs, the difference in performance can be due to a number of architectural choices that range from the kind of features used for training, and therefore for classification, to the network structure. The work by Godara and Gupta (Godara and Gupta, 2012) provides an interesting description of a number of ANN architectures that can be used for iris recognition. Unfortunately, no experimental result is presented to support the selection of the best one.

Regarding ANNs, we can observe that in general the number of nodes in input layer is equal to the dimension in feature vector and the number of nodes in the output is equal to number of subjects in the dataset (classes). An interesting approach to solve the problem of the high number of classes might be the modularization of the network according to subsets of individuals, instead of designing modules with different functions (Gaxiola et al., 2010; Melin *et al.*, 2012). However, the integration of results must be accurately designed, and experiments should be carried out to verify is different subdivisions may lead to different results, As a matter of fact, the average inter-class differences might differ from one module to the other, and it would be interesting to check if this might affect the final result. The problem of the choice of images in clusters has been recently addressed by fuzzy clustering techniques (Srivastava et al., 2014).

While modularization can help solving the problem of a huge output, GA and PSO are possible approaches to reduce the input complexity by selecting the most relevant features. In addition, the same techniques can also allow optimizing the structure (layers and connections) of the network. Given this, the learning algorithm also depends on the kind of extracted features. Wavelets seem to be especially suited to capture the iris pattern at different resolutions. However, there is room for further research and we expect that new results in this direction will come by going deeper for learning more discriminative and different type of features. Deep neural architectures like Convolutional Neural Networks (CNN) seem a viable solution along this direction.

Also, it would be worth investigating the specific relation between features, network structure and learning algorithm. This requires first of all to working on a common benchmark, to avoid the influence of a specific dataset on the overall system performance or to introduce bias in the comparison of different approaches. Unfortunately, this is not the case yet with ML for iris recognition, therefore, notwithstanding the very high performance reported, it is difficult to evaluate the true robustness of the different systems. We can notice that the declared performance is comparable if not better that state-of-the-art. However, the fact that it is often not clear how many subjects/classes are involved makes such results difficult to appreciate when not questionable at all. It is also to notice that most works use CASIA as dataset. Given the images in the papers, that seldom specify the version of the dataset used, it seems that many works use version 1 or some version where the pupil is very well identifiable. The union of controlled conditions and of near-infrared illumination makes up a different problem than using more challenging datasets, e.g., UBIRIS (1 or 2). A more extensive experimentation with the latter datasets would allow a more reliable evaluation of the suitability of ML approaches for iris recognition.

4. Conclusions

Though iris recognition is a relatively young field in biometrics and in pattern recognition in general, it is interesting to observe that ML techniques have not been fully investigated and exploited for this problem. As a matter of fact, most available works in literature developing this research line come from the last few years. A possible explanation can be identified in the complex input structure, and in the high number of classes to discriminate.

Different types of neural networks have been investigated as feature classifiers in this context, e.g., WPNN, BPNN and RBFNN. Each technique has its peculiar advantages. For instance, RBFNN does not require any mathematical description of how input and output features are connected. Neural networks have high training time so researchers test methods to hybridize them with the PSO and GA to reduce their complexity.

SVM allows the use of various kernel functions to avoid the explicit mapping of feature vectors onto a higher dimensional space. The aim of the latter operation is to find a linear boundary among classes, that however might not be possible to establish.

Deep learning is the new frontier of Machine Learning, and this approach has the potential to solve all the above problems. It will be interesting in the future to compare its performance and computational demand with those of more traditional algorithms.

References

Abiyev, R.H., Altunkaya, K., 2008. Personal Iris Recognition Using Neural Network, International Journal of Security and its Applications Vol. 2, No. 2, April, 2008

AL-Allaf, O. N. A., AbdAlKader, S. A., Tamimi, A. A., 2013. Pattern Recognition Neural Network for Improving the Performance of Iris Recognition System. Int'l Journal of Scientific & Engineering Research, 4(6), 661-667.

Ali, H., and Salami, M., 2008. Iris Recognition System Using Support Vector Machines, in Biometric Systems, Design and Applications, Edited by Mr Zahid Riaz, In Tech, 2011, pp169-182

Baqar, M., Azhar, S., Iqbal, Z., Shakeel, I., Ahmed, L., & Moinuddin, M., 2011. Efficient iris recognition system based on dual boundary detection using robust variable learning rate Multilayer Feed Forward neural network. In Information Assurance and Security (IAS), 2011 7th International Conference on (pp. 326-330). IEEE.

Baraldi, A., Blonda, P., Petrosino, A., 1997. Fuzzy Neural Networks for Pattern Recognition, Neural Nets '97, pp. 35-83, Springer Verlag.

Byvatov, E., Fechner, U., Sadowski, J., Schneider, G., 2003. Comparison of support vector machine and artificial neural network systems for drug/nondrug classification. Journal of Chemical Information and Computer Sciences, 43(6), 1882-1889.

Burbidge, R., Trotter, M., Buxton, B., Holden, S., 2001. Drug design by machine learning: support vector machines for pharmaceutical data analysis. Computers & chemistry. 26, 5-14.

Caianiello, E.-R., Petrosino, A., 1994. Neural Networks, Fuzziness and Image Processing, Human and Machine Vision: Analogies and Divergences, pp. 355-370, Plenum Press, USA.

Chen, C.-H., Chu, C.-T., 2005. Low Complexity Iris Recognition Based on Wavelet Probabilistic Neural Networks. In 2005 IEEE International Joint conference on Neural Networks, IJCNN'05,. Vol. 3, pp. 1930-1935.

Chowhan, S.S., Kulkarni, U. V., and Shinde, G. N., 2011. Iris recognition using modified fuzzy hypersphere neural network with different distance measures. International Journal of Advanced Computer Science & Applications, vol. 2, no. 6, pp. 122–129.

Chowhan, S. S., and Shinde, G. N., 2011. Iris Recognition Using Fuzzy Min-Max Neural Network. J. Computer and Electrical Engineering, vol. 3, pp. 743-749.

Chu, C. T., & Chen, C. H., 2005. High performance iris recognition based on LDA and LPCC. In Tools with Artificial Intelligence, 2005. ICTAI 05. 17-th IEEE International Conference on (pp. 5-pp). IEEE

Daugman, J., 1993. High Confidence Visual Recognition of Persons by a Test of Statistical Independence, IEEE PAMI, vol. 15, no. 11, pp. 1148-1161.

Dias, U., Frietas, V., Sandeep, P.S and Fernandes, A., 2010. A Neural Network Based Iris Recognition System for Personal Identification. ICTACT Journal On Soft Computing, Vol. 1, No. 2, pp. 78-84.

Mary, P. F. G., Paul, P. S. K., & Dheeba, J. (2013). Human Identification Using Periocular Biometrics. International Journal of Science, Engineering and Technology Research (IJSETR) Volume, 2.

P. Fasca Gilgy Mary, P. Sunitha Kency Paul, Dheeba., J., 2013. Human Identification Using Periocular Biometrics, International Journal of Science, Engineering and Technology Research (IJSETR) Volume 2, Issue 5.

Gaxiola, F., Melin, P., Lopez, M., 2010. Modular neural networks for person recognition using segmentation and the iris biometric measurement with image pre-processing. In 2010 International Joint Conference on Neural Networks (IJCNN), pp. 1-7.

Gaxiola, F., Melin, P., Valdez, F., & Castillo, O., 2011. Modular neural networks with type-2 fuzzy integration for pattern recognition of iris biometric measure. In Advances in Soft Computing (pp. 363-373). Springer Berlin Heidelberg.

Godara, S., Gupta, R., 2012. Comparison of Different Neural Networks for Iris Recognition: A Review. Network and Complex Systems, Vol.2, N0.4, pp. 8-14.

Gu, H., Pan, H., Wu, F., Zhuang, Y., Pan, Y., 2004. The research of iris recognition based on self-similarity. Journal of Computer-Aided Design and Computer Graphics, 16(2004) 973-977

Gu, H., Zhuang, Y., Pan, Y., Chen, B. A New Iris Recognition Approach for Embedded System. In: Wu, Z., Chen, C., Guo, M., Bu, J. eds. (2005) Embedded Software and Systems. Springer, Heidelberg, pp. 103-109

Haralick, R. M., Shanmugam, K., Dinstein, I., 1973. Textural features for Image classification. IEEE Transactions on Systems, Man, and Cybernetic, vol- 3, pp. 610–621.

Johnson, P., Lopez-Meyer, P., Sazonova, N., Hua, F., Schuckers, S., 2010. Quality in face and iris research ensemble (q-fire), in: International Conference on Biometrics: Theory Applications and Systems, IEEE.

Khedkar, M. M., & Ladhake, S. A., 2013. Robust human iris pattern recognition system using neural network approach. In Information Communication and Embedded Systems (ICICES), 2013 International Conference on (pp. 78-83). IEEE.

Kocer, H.E. and Novruz, A., 2008. An efficient iris recognition system based on modular neural networks. In Proceedings of the 9th WSEAS International Conference on Neural Networks. 2008: Sofia, Bulgaria.

Krizhevsky, A., Sutskever, I., Hinton, G.E., 2012. Imagenet classification with deep convolutional neural networks, in: Advances in neural information processing systems.

Kulkarni, U.V., Sontakke, T.R. , 2001. Fuzzy Hypersphere Neural Network Classifier. Proceedings of 10th International IEEE Conference on Fuzzy Systems, University of Melbourne, Australia.

Liam, L. W., Chekima, A., Fan, L. C., & Dargham, J. A. (2002). Iris recognition using self-organizing neural network. In *Research and Development, 2002. SCOReD 2002. Student Conference on* (pp. 169-172). IEEE.

Liu, N., Zhang, M. Li, H., Sun, Z., Tan, T., to appear. DeepIris: Learning Pairwise Filter Bank for Heterogeneous Iris Verification. Pattern Recognition Letters, Special Issue on "Insight on Eye Biometrics". Available online 31 October 201. DOI:10.1016/j.patrec.2015.09.016

Lu, B., Wu, J., Wang, Y., 2010. An iris recognition algorithm based on ICA and SOM neural network. In Image and Signal Processing (CISP), 2010 3rd International Congress on (Vol. 5, pp. 2445-2448). IEEE.

L. Masek, L., P. Kovesi, P., 2003. MATLAB Source Code for a Biometric Identification System Based on Iris Patterns. The School of Computer Science and Software Engineering,, University of Western Australia.

Melin, P., Herrera, V., Romero, D., Valdez, F., & Castillo, O., 2012. Genetic optimization of neural networks for person recognition based on the Iris. TELKOMNIKA (Telecommunication Computing Electronics and Control), 10(2), 309-320.

Moinuddin, M., Deriche, M., Ali, S.S.A, 2004. A New Iris Recognition Method based on Neural Networks. In: WSEAS Transaction on information science and applications, Issue 6, Vol 1, Dec. 2004.

Nayar, S. K., & Poggio, T. (Eds.), 1996. Early Visual Learning (Vol. 11). New York, NY: Oxford University Press.

Nie, L., Kumar, A., & Zhan, S., 2014. Periocular Recognition Using Unsupervised Convolutional RBM Feature Learning. In *Pattern Recognition (ICPR), 2014 22nd International Conference on* (pp. 399-404). IEEE.

Pillai, J. K., Puertas, M., Chellappa, R., 2013. Cross-sensor Iris Recognition through Kernel Learning. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. PP, pp. 1-1.

Raghavi, K. A., Paiva, G. P. M., Priya, M. V., & Mohan, S., 2011. Human Iris Recognition Using Fuzzy Neural Concepts. In The 2011 International Conference on Bioscience, Biochemistry and Bioinformatics (IPCBEE) (Vol. 5, pp. 256-260).

Rai, H, Yadav, A., 2014. Iris recognition using combined support vector machine and Hamming distance approach. ScienceDirect, Expert Systems with Applications 41: pp. 588-593

Raja, V. S., Rajagopalan, S. P., 2013. IRIS Recognition System using Neural Network and Genetic Algorithm. International Journal of Computer Applications 68(20):49-53.

Roy, K., Bhattacharya, P. (2005). Iris recognition with support vector machines. In Advances in Biometrics (pp. 486-492). Springer Berlin Heidelberg.

Roy, K., Bhattacharya, P., 2007. Application of multi-objective genetic algorithm and asymmetrical SVM to improve the reliability of an iris recognition system. IEEE conference on Systems, Man, and Cybernetics (SMC'2007).

Saminathan, K., Chakravarthy, T., and M. Chithra Devi, M.C., 2015. Iris Recognition Based On Kernels Of Support Vector Machine, Ictact Journal on Soft Computing: 2015, Volume: 05, Issue: 02

Sarhan, A. M., 2009. Iris Recognition Using the Discrete Cosine Transform and Artificial Neural Networks. Journal of Computer Science (JCS), 5(4): 369-373.

Sharma, A., Verma, S., Vatsa, M., Singh, R., 2014, On Cross Spectral Periocular Recognition, Proceedings of ICIP 2014, IEEE, 2014

Sharma, S., Agrawal, S., & Silakari, S., 2014. Computational Intelligence Techniques Used In Iris Recognition: A Survey. International Journal of Computer Science and Information Security, 12(3), 38-49.

Shin , K. Y. , Park , K. R. , Kang B. J. , and Park, S. J., 2009. Super-resolution method based on multiple multi-layer perceptrons for iris recognition. In Proc. Int. Conf. Ubiquitous Information Technologies Applications (ICUT\'09), pp.1 -5 2009

Sibai, F.N., Hosani, H. J., Naqbi, R.M., Dhanhani, S., Shehhi, S., 2011. Iris Recognition Using Artificial Neural Networks. Expert Systems With Applications 38,5940-5946.

Simpson, P. K., 1992. Fuzzy min-max neural networks. I. Classification. Neural Networks. IEEE Transactions on, 3(5), 776-786.

Srivastava, V., Tripathi, B. K., & Pathak, V. K., 2014. Biometric recognition by hybridization of evolutionary fuzzy clustering with functional neural networks. Journal of Ambient Intelligence and Humanized Computing, 5(4), 525-537.

Sundaram R, Dhara B, 2011. Neural network based Iris recognition system using Haralick features. In 3rd International Conference on Electronics Computer Technology (ICECT) 2011, vol. 3, (IEEE Piscataway, 2011), pp. 19–23

Vapnik, V., 2000. The Nature of Statistical Learning Theory (2nd. ed.), NY: Springer.

Vovk, V., Gammerman, A.,, & Shafer, G., 2005. Algorithmic Learning in a Random World, NY: Springer.

Wagdarikar, A. M. U., Patil, B. G., & Subbaraman, S., 2010. Performance evaluation of IRIS recognition algorithms using neural network classifier. In Computer Science and Information Technology (ICCSIT), 2010 3rd IEEE International Conference on (Vol. 1, pp. 146-149). IEEE.

Zhang, J. R., Zhang, J., Lok, T. M., & Lyu, M. R., 2007. A hybrid particle swarm optimization–back-propagation algorithm for feedforward neural network training. Applied Mathematics and Computation, 185(2), 1026-1037.

Zhou, Z., Wu, H., Lv, Q., 2008. A new iris recognition method based on Gabor wavelet neural network. In *Intelligent Information Hiding and Multimedia Signal Processing, 2008. IIHMSP'08 International Conference on* (pp. 1101-1104). IEEE.

CASIA IrisV1 dataset, http://biometrics.idealtest.org/findTotalDbByMode.do?mode=Iris

UBIRIS Iris dataset, http://iris.di.ubi.pt

UBIPr Periocular dataset, http://socia-lab.di.ubi.pt/~ubipr/

MMU Multimedia Iris database, http://www1.mmu.edu.my/~ccteo/

BTAS 2012 Cross-sensor Iris dataset, http://www3.nd.edu/~cvrl/CVRL/Data_Sets.html

IIITD Multispectral Periocular database, https://research.iiitd.edu.in/groups/iab/impdatabase.html

CHEK Image Database. Iris images retrieved from http://www.phoenix.inf.upol.cz/iris/download/

ICE (Iris Evaluation Challenge) http://iris.nist.gov/ICE/.

WVU dataset from West Virginia University http://www.wvu.edu/.