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Iris recognition with 4 or 5 fuzzy sets

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Abstract

In current literature, the degrading performances of iris recognition systems is put in user's responsibility (Biometric Menagerie-BM), or explained through a vague mix of time-related changes in biometric pattern, its presentation and the acquisition sensor (Template Ageing-TA). Actually, BM and TA are annoying symptoms illustrating intrinsic limitations of the statistical model of iris recognition. In order to avoid such limitations, a decisional model with 4/5 fuzzy sets is defined and tested here. The novelty is that among these fuzzy sets, two (the imposter and genuine score sets) are mutually exclusive and therefore, the confusion between imposter and genuine scores is no longer statistical.

Keywords: Iris recognition, biometrics, fuzzy biometric menagerie, template ageing, cointension, Turing test in iris recognition.

1. Introduction

For a long time before [28], one very common belief regarding the fuzzy membership and the probability of membership was that they are not or they cannot be clearly related to each other. However, it is illustrated in [28] that they came in pairs each time when the so called possibility/probability consistency principle introduced by Zadeh in [34] is instantiated as σ−additivity axiom within the definition of probability. This is because accepting σ−additivity axiom is a way of achieving a logically consistent (and computational) translation between possibility, probability and fuzzy membership. What bounds us to this view is the need to describe the reality of iris recognition by a unitary and non-self-contradictory model: an imposter comparison pair should never qualify as a genuine one (i.e. impersonation should be impossible), a genuine comparison pair could have a corresponding degraded recognition score from a cause (i.e. non-self-matching is possible from a cause), an impossible recognition event is 0-probable while a 1-probable event is certain and at last but not the least probability distributions of (imposter and genuine) recognition scores can be translated easily [28] to fuzzy membership functions illustrating the degree of membership of each comparison pair to the fuzzy sets of genuine and imposter pairs. Hence, debating if fuzzy logic is needed or not in iris recognition is far less important than realizing that fuzziness is intrinsic in this problem at least for the fact that, so far, iris recognition used only partial knowledge about matched irides and this is the main cause for which the imposter and genuine scores are sometimes ambiguously confused. Increasing and refining the knowledge stored in the system is the right solution for avoiding recognition errors in fact and in principle.

On the contrary, in the majority of the current literature on iris recognition, when someone puts the degrading performances of an iris recognition system in the responsibility of some users, we are dealing with Biometric Menagerie ([5], [32], [33]), whereas when recognition failures are explained through a vague mix of time-related changes in the biometric pattern, its presentation and the acquisition sensor, we are dealing with Template Ageing ([2]).

The truth is that the users have no fault when an iris recognition system is not enough adapted to face the variability of probe acquisition. On the other hand, the fact that a biometric system acquires instances of a given biometric source with a certain degree of variability does not allow us to talk about ageing. Variability occurs, in general, even in the absence of a considerable time-lapse, hence in the absence of any ageing process that would hypothetically exist.

When a biometric recognition system is not enough adapted to face the variability of probe acquisition during exploitation, its design is to blame. Regardless what name we choose for the increase in recognition error rates (BM or TA or both), this increase is a symptom showing that a certain biometric system came close to its design limitations, a symptom that points out to the necessity of improving iris recognition theory and practice – a process that makes more sense than inventing excuses (outside logic and common sense), preserving design limitations and reenrolling the users over and over again along the time.

Actually, the fact is both BM and TA ([2], [6]-[9], [13], [14], [32], [33]) are two annoying symptoms illustrating intrinsic limitations of the statistical model of iris recognition [4], [5]. When it happens, the increase in the recognition error rates does not need new names like BM or TA nor naive justifications (some users are somehow special – in case of BM; or biometric templates are "ageing"– in case of TA). Only the actions undertaken in response are important. Nothing else. Is the system improvable? Are the users well enrolled indeed? Is the false reject (FR) so unnatural when the variability that a system can handle is certainly limited? Isn't the increase of the recognition error rates the right reason for answering these questions? We think it is, indeed.

Another wrong assumption in the current literature of the domain is that iris recognition (IR) will progress in the absence of the Turing test [31], i.e. without meaningful corrections brought to the iris recognition theories and practice by qualified human agents after experiencing iris recognition with their own eyes and minds, after analyzing the differences between how iris recognition is achieved by humans and by nowadays artificial agents, respectively.

On the contrary, here in this paper, as a consequence of analyzing a huge amount of experimental data gathered during a seven years period (2008-2014) of working on iris recognition ([3], [12], [15]-[27]), the Turing test is considered of critical importance because it draws a realistic expectation regarding the level of performances maximally achievable by artificial agents when performing iris recognition. We saw a direct connection between what the logical positivist A.J. Ayer [1] defined as being verifiable in principle and empirically verifiable [1], respectively, and the fact that Turing [31] qualified the intelligence (of artificial agents) as being both verifiable in principle (through the procedure that we now refer as the Turing test) and also empirically verifiable (when and if the artificial agent passes the Turing test successfully). In short, the artificial intelligence is verifiable and so should be the intelligence incorporated in any state of the art biometric iris recognition system. The main coordinates used for making here an objective comparative analysis on the performance of different artificial agents in achieving a given goal in relation to the performance of a qualified human agent in achieving the same goal are the following ones: logic, intelligence (both incorporated in Turing Test), relevance maximization and error minimization by cointension.

2. Comparison to the related works

There are 4 necessary prerequisite lectures to the present paper, each of them related up to a certain level to the new approach proposed here: [25] and [26] describe the formal logic underlying the current development, [23] introduced the concepts of evolutionary iris recognition systems and evolutionary digital identities and illustrated their use toward improving iris recognition performances, whereas [28] clarified the relation between possibility, probability and fuzzy membership. Fig.3-5 from [23] present our previous performances in training an Intelligent Iris Verifier System. The key points there are the artificial network (ANN) structure used in the process and the ANN Based Evolutionary Intelligent Iris Verifier (Section 3.8 in [23]). The same basic design is used here with the only difference that, in what follows here, the goal is to achieve a partitioning of the comparisons in four classes. Three of them are illustrated from left to right in Fig.1.a through recognition score histograms, as follows:

- Strong (and True) Imposter Pairs and Scores, abbreviated SIP/SIS (illustrated as the leftmost histogram in Fig.1.a) are those generated by honest users when they post a true claim in the system, regardless if it is a positive (or negative) positive claim - I'm (or I'm not) X.
- Weak (Degenerated) Imposter pairs and scores, denoted WIP/WIS (and illustrated by the histogram marked with gray disks in Fig.1.a) are those generated by dishonest users when they post false positive claims on each of the other identities within the system. Due to their source these pairs and scores are also Fake Genuine ones.
- Strong Genuine pairs and scores (see the rightmost histogram in Fg.1.a) are those corresponding to all honest positive claims made by the users enrolled in the system.

These three classes of comparison pairs and matching scores described above are defined and taken in consideration during the training stage of the IIV (Intelligent Iris Verifier system, [23]) while the fourth one – which is that identifying Weak Genuine Pairs/Scores and further denoted WGP/WGS (see the left tail of the rightmost histogram in Fig.1.b) – comes into existence and into view only during the testing phase, as a confirmation of the fact that the learning converged to a memory configuration which is able to have an accurate artificial perception for the distinction between the similarity produced by chance (this is the matching inside the category of Fake Genuine Pairs) and the dissimilarity produced by a cause (this is the matching corresponding to genuine comparisons when they are affected by recognition noises such as the changes in posture, orientation, illumination, occlusion and pupil extent). WGS is witnessing that non-matching between the members of pair that otherwise is a genuine one is always happening for a specific cause and is weaker than the non-matching between the members of fake genuine pairs corresponding to (dishonest and) actively assumed impersonation attempts.

As an objective point of view on the matter of TA, the authors of IREX VI [10] said that, accordingly to the correct definition of ageing, while using two large operational datasets, they found "no evidence of a widespread iris ageing effect. Specifically, the population statistics (mean and variance) are constant over periods of up to nine years". A lot of factors, other than some hypothetical big enough and irreversible anatomical changes in the iris texture, are known to be causal for the increase in recognition error rates during the exploitation of an iris recognition system. Therefore, the attempt to define "ageing" as the "increase in recognition error rate with increased time since enrollment" [9] is not appropriate. We subscribe in support of this opinion which is consistent with our experience. Moreover, we point out to the fact that for an iris recognition theory (and practice), the moment when Template Ageing or Biometric Menagerie phenomenon is valid and consistently supported by experimental data is the moment from which that theory is certified as being self-contradictory.

3. Formal fuzzy logic framework for fuzzy modeling of iris recognition

The vocabulary of the formal fuzzy logic framework that underlies this paper consists in:

a) the set of fuzzy values of truth (i.e. scores),

$$S = 0:1/255:1 = \{k/255 \mid k \in \overline{0,255}\}, \quad (1)$$

used to quantify the degree of truth associated to an identity claim posted by the users in the biometric system;

b) the set of 50 users (each unique eye within the database [35] is considered an unique user of an iris recognition system),

$$U = \{u_k \mid k \in \overline{1,50}\}, \quad (2)$$

c) the set of 1000 images available in [35] for each user (20 per user, where an unique user means an unique eye),

$$IMG = \{img_k \mid k \in \overline{1,1000}\}, \quad (3)$$

d) the set of 512x32 unwrapped normalized uint8 iris segments extracted through segmentation procedure for the users in (2),

$$UI = \{ui_k \mid k \in \overline{1,1000}\}, \quad (4)$$

e) the set of occlusion masks computed for all normalized iris segments from (4):

$$OM = \{om_k \mid k \in \overline{1,1000}\}, \quad (5)$$

f) the set of 512x32 binary iris codes extracted for the users in (2) using a Log-Gabor encoder,

$$IC = \{ic_k \in M_{512\times 32}(\{0,1\})\,;\, k \in \overline{1,1000}\}, \quad (6)$$

g) the comparison pairs, i.e. the pairs of iris codes corresponding to the comparisons that can be made using all 1000 images within the database [35],

$$CP = \{cp_p = (ic_k, ic_j) \mid k, j \in \overline{1,1000}\}, \quad (7)$$

h) the partitioning of CP in genuine and imposter comparison pairs:

$$CP = GCP \cup ICP, \quad (8)$$

i) the set of digital identities corresponding to and trained for the enrolled users mentioned in (2),

$$DI = \{di_k \mid di_k \in M_{512\times 32}(R);\, k \in \overline{1,50}\}, \quad (9)$$

j) the iris codes used to train the digital identities (for each user, the first five iris codes extracted for its first five images within the database [35] are used for training the digital identities) i.e. the learning (data)set of iris codes, further denoted

$$LDS = \{ic_{20(k-1)+p} \mid p \in \overline{1,5};\, k \in \overline{1,50}\}, \quad (10)$$

k) the test (data)set of iris codes used to deliver experimental evidence for the quality of trained digital identities, further denoted

$$TDS = \{ic_{20(k-1)+p} \mid p \in \overline{6,20};\, k \in \overline{1,50}\}, \quad (11)$$

l) the set of recognition function candidates (RFC) and the set of processing methods candidates (PMC), the possible recognition functions and a processing methods being all considered legal finite assemblies of strings found within a given dictionary of functions D, i.e. elements of the free monoid on D (further referred to as D*):

$$RFC \subset D^*,\ PMC \subset D^*, \quad (12)$$

m) a dictionary of functions denoted D, from which all processing procedures involved in the system can pick their (sub-)components during their adaptation toward better performing their tasks;

n) the CCBL theory – a sound, complete, Computational and Cognitive formalization of Binary Logic introduced in [25] as a way of reasoning with binary valued propositional variables describing the process of iris recognition;

o) the Cognitive Dialect – an extension of CCBL introduced in [26], which supports translating optimization criteria common in iris recognition back and forth to SQL and natural language, on the one hand, and endows iris recognition system with the sound conversational capacities of a cognitive intelligent agent (CIA, [26]) Building a formal model of iris recognition as an extension of a CIA ensures that the system will inherit two critical properties of CIA model: firstly, it will be able to accept all well-formed recognition queries and secondly, it will be able to deliver only true assertions in response. If the second condition would not be satisfied, the system could fail very often during a Turing test and consequently its degree of (artificial) intelligence would be proven as being very limited, indeed. By design, such a system cannot formulate false assertions and specifically, affirmations that contradicts the mass of experimental data.

p) a set of well-defined state attributes of the system (WDSA). It contains, for example, the definition of the “consistency” (ability to deliver only true answers) and “responsiveness” (capability of receiving, parsing and understanding queries and formulating answers) attributes of the system.

Def. 1: The system is recognizing its users consistently if and only if, it can prove on its data a consistent understanding of iris recognition, i.e. among the data stored in the system there is no counterexample to correct recognition (there is no example of impersonation), i.e. if and only if:

$$\max(Score(ICP)) < \min(Score(GCP)), \quad (13)$$

Usually, it is believed that the membership to GCP of a given comparison pair is guaranteed when the pair is formed with codes generated for the same eye. This is far for being true: extended occlusions, different illumination and different pupil dilation are regular causes for disqualifying a pair that, otherwise, should be expected to belong in GCP. As a source of FR this mechanism is totally distinct from accidental matching of two iris templates expected to belong in ICP.

If consistency is a required attribute of the system, it follows that the entire comparison space is partitioned into two distinct sub-parts: assertion set (AS, that part of CP allowing the system to formulate only true assertions) and query set (QS, that part of CP allowing the system to be responsive).

Def. 2: A strong theory of iris recognition is a consistent one that also admits a large safety band [t_{imp}, t_{gen}] between the fuzzy sets of imposter and genuine similarity scores, i.e.:

$$\max(S(ICP)) < t_{imp} < t_{gen} < \min(S(GCP)), \quad (14)$$

In such cases (14), the two distributions of imposter and genuine scores are situated at a comfortable distance from each other.

On the one hand, the consistency of the system can be proved only on the AS, and, on the other, the consistent enrolment is the only guarantee for system consistency. Therefore, the assertion set AS is the sub-part of CP formed with data provided by correctly enrolled users. Hence, the formulae (13) and (14) should be considered on the assertion set only.

Def. 3: The system is logically inconsistent if and only if, there are similarity scores for the data stored in the system that supports (that can be used in giving examples of) impersonation:

$$\max(Score(ICP)) \geq \min(Score(GCP)), \quad (15)$$

In such a case, the two distributions of imposter and genuine scores are overlapped and so are the fuzzy sets D and I (corresponding to the fuzzy linguistic labels “f-Different” and “f-Identical”) that have their membership functions defined by these two distributions, respectively (the fact that probability distribution functions came in pairs with fuzzy membership functions is illustrated in [28]).

This vocabulary defined above, in the previous section, from (a) to (p), allows us to express a given functionality of the system computationally, i.e. with formal correctness, in a manner that a computer could parse and understand. For example, a prototype recognition function that illustrates the statistical paradigm of iris recognition (proposed by Daugman, [4]) is the following:

$$R(ic_k, ic_p) = Decision(Score(ic_k, ic_p), t), \quad (16)$$

where R is the recognition function expressed as a biometric decision taken accordingly to the relative position of the Hamming score (or other type of score) computed for the two binary iris codes ic_k and ic_p in relation with a recognition threshold t.

A surprising aspect is that the formula (16) is not quite an explicit one. In fact, it contains a priori knowledge encoded as values (t, for example) and argument position (in the case of the two iris codes). Knowing / choosing the threshold t, iris codes dimension and their encoding procedure is a matter of analyzing what happens with the scores for a given dataset of images for which iris codes of different dimensions are extracted and compared.

$$t = InferThreshold(LDS, CRF, CMP), \quad (17)$$

where LDS, CRF and CPM are the learning dataset, the set of candidate recognition functions and the set of candidate processing methods - possibly those specified in (10) and (12), or other ones, if required.

Hence, a learning dataset and a training stage is needed even in the statistical paradigm of iris recognition in order to design and calibrate the system, only that it is a human agent who train himself in order to establish that a priori knowledge which is implicitly present in the formula (16). Therefore, it is logical to assume that an artificial agent whose goal is to recognize irides has the right to be trained or to train itself.

As said above, another piece of a priori knowledge present in (16) is the fact that the position of binary iris codes as arguments of score function really matters, i.e. the arguments of score function do not commute. One of them, let us say the first one, is there as a candidate iris code extracted for a current user that interacts with the system at a given time,

$$\begin{aligned} ic_k = EncodeIcFrom(& \\ & ExtractIrisSegmentFrom(\\ & \quad AcquireImage(CurrentUser))), \end{aligned} \quad (18)$$

whereas the other one is an enrolled iris code:

$$\begin{aligned} ic_p = EncodeIcFrom(& \\ & ExtractIrisSegmentFrom(\\ & \quad GetEnrolledImageFrom(\\ & \quad\quad WellEnrolled(User)))), \end{aligned} \quad (19)$$

In the worst case scenario, the two iris codes correspond to eye images taken in very different conditions (position, distance, focus, illumination, sensor, pupil dilation, iris scale, occlusions, etc.) and segmented using different segmentation tools. Of course that a good strategy is to have good quality images stored at enrollment, not otherwise (it is easier and more accurate for matching to produce altered images starting from good quality source images and it is harder and often inefficient trying to reconstruct a good quality image from an altered one). In our experience, when each user is enrolled with a single eye image, a pupil dilation of around 25%-30%, good lightening, focus, distance and posture conditions, as well as the lack of occlusions are all advisable in order to ensure that the users are well enrolled, or else, adverse effects should be expected in terms of rapidly increasing error rates during exploitation. For example, enrolling users with images having hardly occluded irides and dilated pupils could lead at least to subsequent radial and angular alignment errors, which are known to affect recognition performance dramatically.

The enrolled iris codes ic_p from (16) and (19) cannot "age" simply because they are constants. The iris texture itself is documented to be (enough) stable in time (at least for periods of 9 years, [10]), hence an increase in recognition error rates could not originate elsewhere than in the difference between the data springs (18) and (19) that throw iris codes (data) in the recognition function (16). Among these differences, the occlusions (hair, lights, eyelids, eyelashes) could play an important role if their extent onto the iris is notable, of course, case in which the recognition function should take them into account:

$$R(ic_k, ic_p) = D(S(ic_k, om_k, ic_p, om_p), t), \qquad (20)$$

Still, masking the iris segments will not avoid the variations induced on the unoccluded part of iris by the differences between the data springs (18) and (19). Hence, the inherent variability of probe acquisition is not solved by default, regardless the fact that the irides could be occluded or not.

Since the variability of probe acquisition proved to be inherent during exploitation, the logical thing to do is an attempt to include some degree of variability in the enrollment data, case in which some iris codes are extracted for different enrolled images of the same iris and stored in the system as a part of an enrolled digital identity [17], which follows to be taken into account by the recognition function:

$$R(ic_k, ic_p) = Decision(Score(ic_k, di_p), t), \qquad (21)$$

The matching score in this case could be the mean-deviation similarity score [17] or a different and suitable one, where a suitable matching score function is one that makes iris recognition possible either in a statistical [4] or in a logically consistent approach of iris recognition [20], [21].

4. Organizing the experimental dataset

All the images within the database [35] are segmented using the second variant of Circular Fuzzy Iris Segmentation (CFIS2) previously introduced in [19] and encoded as 512×32 binary iris codes using the single-scale, 1D (angular) Log-Gabor iris texture binary encoder that may be downloaded from [18] - if the replication in Matlab-32 is intended. Generic algorithms "RLE-FKMQ Based Pupil Finder" - [15], "Circular Fuzzy Iris Segmentation" - [15], "Fast Limbic Boundary Detector" - [19], and the classical formula (1) from [19] may be used for implementing the two utilities in other programming languages.

The data collection (1000 eye images for 50 eyes, 20 images for each eye) is split into two parts: from each set of 20 images representing an eye, 5 are reserved for and included in the training dataset, whereas the other 15 are assigned to the test dataset. Hence, there are 250 eye images and the corresponding 250 iris codes in the learning dataset and 750 in the test dataset.

5. Experimental results

The comparison between the binary iris codes is made by using trained digital identities [23] evolved for ensuring simultaneously ternary classification of all comparison pairs. In this scenario (see Fig. 1), during the training stage, a comparison pair could not pass (could not be accepted by the system) as a truly genuine one if:

- it is not scored in the interval [0.9, 1];
- the attempts of impersonating all the other identities enrolled in the system are not simulated or the similarity scores corresponding to these simulated attempts are found outside the interval [0.1, 0.45].
- the honest denials (I'm not X) of all the other identities enrolled in the system are not simulated or the corresponding similarity scores are found outside the interval [0.02, 0.14].

The same restrictions are imposed during testing with the exception of the genuine scores, which are allowed to slightly decay in quality (toward 0.5, - see Fig.1.b).

The experimental results synthetized in Fig.1 illustrate a mature stage of an iris recognition theory and practice that by its quality is situated very far beyond and ahead from whatever is considered these days to be a state of the art (statistical) iris recognition approach simply because in our result there is no statistically expressed confusion (overlap / battle) between the true imposter scores (the leftmost histogram in Fig.1.a-c) and true genuine scores (the rightmost histogram in Fig.1.a-c). Training and hosting digital identities within the recognition system ensure a critical increase in the knowledge that the system has and therefore it becomes able to perceive better the distinction between the genuine and imposter comparison pairs (and scores).

Due to this improved artificial perception of the separation between the two main classes of comparison pairs and scores, the system is able to support 2-valued, 3-valued and 4-valued models of iris recognition (see Fig.1.b).

A 5-valued model of iris recognition can be easily derived and proposed by naming the comparison pairs and the corresponding claims illustrated in Fig.1.b, from left to right, as follows:

- Strong/true imposters (Fig.1.b, square markers),

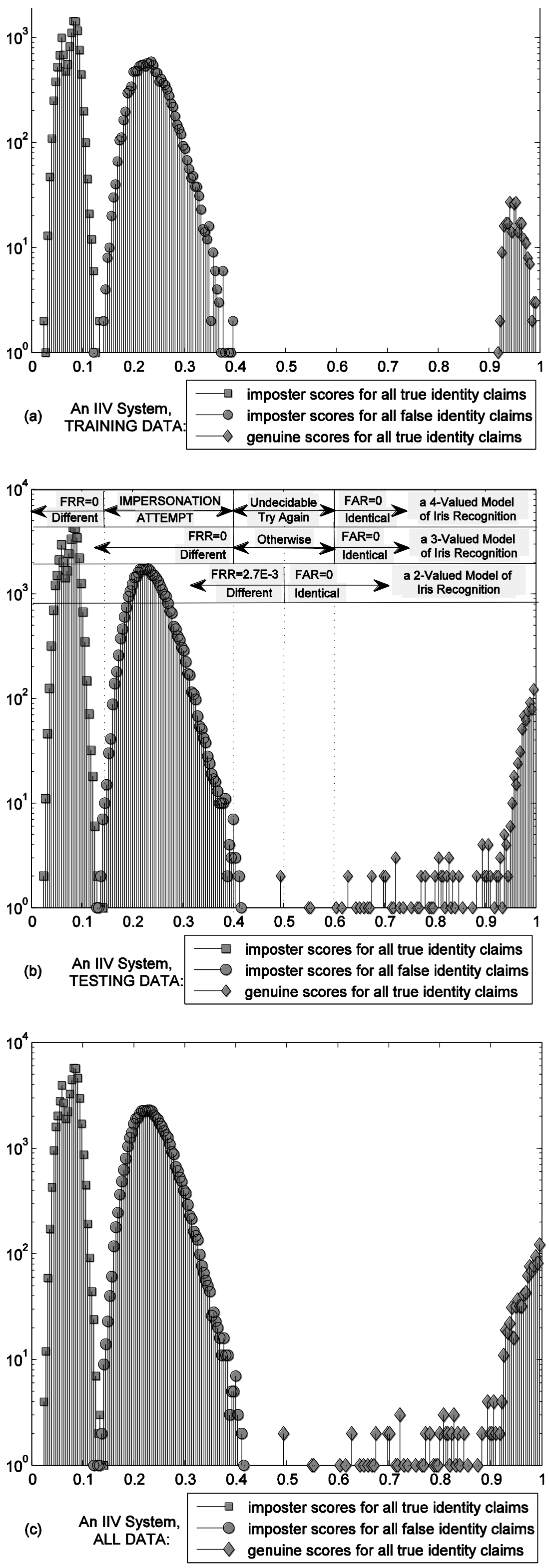

Fig. 1 Testing the trained IIV system: (a) on learning dataset; (b) on test dataset; (c) on the entire dataset

- Offenders (weak imposters that actively post dishonest identity claims in the system - Fig.1.b, the round markers situated in the left-side of 0.4),
- Undecided / uncertain cases (Fig.1.b, round and diamond markers situated inside (0.4 , 0.6) interval),
- Weak / degenerated genuine comparison pairs and scores (Fig.1.b, diamond markers situated inside [0.6 – 0.88] interval),
- Strong genuine comparison pairs and scores (Fig.1.b, diamond markers situated on the right side of 0.88

The explicit expressions of recognition function and the detailed numerical procedure for training the digital identities used to generate the results illustrated in Fig.1.a cannot be published prior to their exploitation in industry. Still, the existence of such objects possessing such good properties can be easily exemplified starting with one of the most basic and simple neural model, namely that of the Perceptron - initially proposed by Rosenblatt ([29], [30]) and slightly adapted by us for enabling it to achieve not just binary crisp classification but multiclass fuzzy classification. On this matter the main question for us was why the perceptron is able to encode the separation in (only) two classes? The answer was proven to be surprisingly simple, namely because it has only two output values, hence it is able to support only the artificial perception of the separation between two half-hyperspaces in which the space is divided by the hyperplane corresponding to the augmented Perceptron memory (the ensemble formed with the synaptic weights and the threshold). Endowing the Perceptron to have multiple output values allows it to encode the fuzzy membership to more than two classes (as illustrated below for a 3-D example) with the only restriction that the chunks of space between which the Perceptron is able to discern are defined by hyperplanes parallel to that defined by its augmented memory. The number of classes that can be perceived by a Perceptron equals the number of possible distinct output values configured by the programmer. Artificial perception of the fuzzy membership to n disjoint classes is done by mapping the classes into a 2^n-valued Boolean algebra generated by the corresponding disjoint activation intervals found on the direction of the normal to the hyperplane defined by its augmented memory.

In order to illustrate that, the first step was to take distance from those classical neural models in which a neuron is unable to have a nuanced fire function (such as the model proposed in [11]). For example, if for the Perceptron basic neuron it is assumed that the output values are integer values obtained by rounding its internal activation, then the perceptron is able to count and encode the membership to as many classes as desired. In order to keep the graphical representations as simple as possible, the following model can be considered:

- The space of examples X is $R^{3;}$
- Synaptic memory is $W = (1, 0, 0)^T$;
- The threshold θ is zero;
- The fire function is:

$$F(X) = round(W^T X), \tag{22}$$

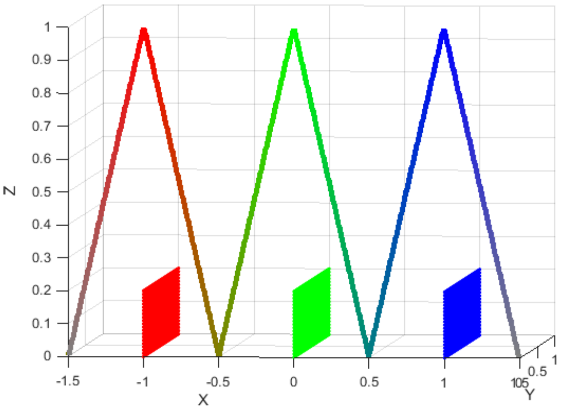

Fig. 2 A perceptron with a nuanced 3-valued firing function able to recognize three slices of R^3 space and to fire with the class label (-1, 0 or 1) and also with the membership degree indicated by the triangular membership functions plotted in gradient color.

In these conditions the neuron encodes the separation between slices of R^3 delimited by planes having the abscise as normal direction and sectioning the abscise at points k+0.5, with k in Z;

For simplicity, the space of example points is further restricted to the space slice delimited between the planes intersecting abscissa axis at -1.5 and 1.5, respectively, whereas the fire function is no longer a scalar function but a vector-valued function:

$$F_2(X) = (F(X), T(F(X), W^T X)), \qquad (23)$$

where T is the triangular fuzzy membership function of the fuzzy interval of unitary length centered in F(X) and situated on the abscissa axis, as illustrated in Fig.2. Such a Perceptron model is not only able to encode the separation between the slices of spaces corresponding to 3 fuzzy intervals within R^3 but it is also able to express the degree of fuzzy membership of examples X to the three classes (see Fig.2). The color gradient applied when drawing the triangular membership functions shows the transition of the degree of membership between two neighbor classes. Therefore, closer the activation value of an example vector to the activation values corresponding to the classes labeled numerically as (-1, 0, 1) and visually (Red, Green Blue), stronger the degree of membership to those classes is.

The mechanism described in this example is the same by which the digital identities are able to recognize multiclass fuzzy classification with the only important difference that the membership functions that are mapping comparison pairs to the classes of strong imposters, weak imposters, undecided, weak genuine and strong genuine are imposed by experimental data, not otherwise.

6. Conclusion

Proposed fuzzy 5-valued decisional model of iris recognition (Fig. 1. b) illustrates that exceptional unprecedented recognition results can be obtained when using carefully and properly acquired eye image databases such as [35], the quality being a requirement for consistent enrolment. As it is expected, the variability is present at the genuine comparisons with iris codes obtained from iris images that are different enough than those stored in system for each enrolled eye / identity.

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