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Multiple Neural Networks System for Dynamic Environments

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***Abstract*—We propose a "Multiple Neural Networks" system for dynamic environments, where one or more neural nets may no longer be able to properly operate, due to sensible partial changes in the characteristics of the individuals. We assume that each expert network has a reliability factor that can be dynamically re-evaluated on the ground of the global recognition operated by the overall group. Since the net's "degree of reliability" is defined as "the probability that the net is giving the desired output", in case of conflicts between the outputs of the various nets the re-evaluation of their "degrees of reliability" can be simply performed on the basis of the Bayes Rule. The new vector of reliability will be used for making the final choice, by applying the "Inclusion based" algorithm over all the maximally consistent subsets of the global outcome. Finally, the nets recognized as responsible for the conflicts will be automatically forced to learn about the changes in the individuals' characteristics and avoid to make the same error in the immediate future.**

***Keywords*-Multiple Neural Networks; Face recognition; Belief revision; Bayes rule; Inclusion based;**

I. Introduction

Several researches in the field of Artificial Neural Networks indicated that there are problems which cannot be effectively solved by a single neural network [1]. This led to the concept of "Multiple Neural Networks" systems for tackling complex tasks improving performances w.r.t. single network systems [2]. The idea is to decompose a large problem into a number of subproblems and then to combine the individual solutions to the subproblems into a solution to the original one [1]. This modular approach can lead to systems in which the integration of expert modules can result in solving problems which otherwise would not have been possible using a single neural network [3]. The modules are domain specific and have specialized computational architectures to recognize and respond to certain subsets of the overall task [4]. Each module is typically independent of other modules in its functioning and does not influence or become influenced by other modules. The modules generally have a simpler architecture as compared to the system as a whole, thus a module can respond to given input faster than a complex single system. The responses of the individual modules are simple and have to be combined by some integrating mechanism in order to generate the complex overall system response [4]. The combination of expert modules can be competitive, cooperative or totally decoupled among the individual expert neural networks in a given modular neural network. Generally, in a decoupled approach, individual specialist modules have no information about other modules in the network and the output of the best performing special neural net (according to some criteria) is picked to be the overall output of the modular neural network [1]. The combination of individual responses is particularly critical when there are incompatibilities between them. Such situations may arise for example when the system operates in dynamic environments, where it can happen that one or more modules of the system are no longer able to properly operate [5]. In this context it is necessary to use mechanisms to deal with sets of contradictory information. In this work we analyze the problem of face recognition and its aim is to propose a model for detecting and solving contradictions into the global outcome. The proposed model consists of a "Multiple Neural Networks" system, where each neural network is trained to recognize a significant region of the face and to each one is assigned an arbitrary a-priori reliability (that may depend on the region of the face that must be recognized). All the networks have a reliability factor that can be dynamically re-evaluated on the ground of the global recognition operated by the overall group. In case of conflicts between the outputs of the various nets the re-evaluation of their "degrees of reliability" can be simply performed on the basis of the Bayes Rule. The conflicts depend on the fact that the subject has not been univocally recognized by all networks belonging to the system, because some features of the face are changed. The new vector of reliability obtained through the Bayes Rule will be used for making the final choice, by applying the "Inclusion based" algorithm [6] over all the maximally consistent subsets of the global outputs of the neural networks. The nets recognized as responsible for the conflicts will be automatically forced to learn about the changes in the individuals characteristics. In this way the modular system is in a continuous phase of training.

II. Theoretical Background

In this section we introduce some theoretical background taken from the "Belief Revision" (BR) field. A Belief Revision occours when a new piece of information that is

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inconsistent with the present belief (or database) is added to that system in such a way that the result is a new consistent belief system [7].

In Figure 1, we can see a Knowledge Base (KB) which contains two pieces of information: the information α, which come from source V, and the information being a rule ("If α, then not β"), which comes from source T. Now there is another piece of information β, produced by the source U.

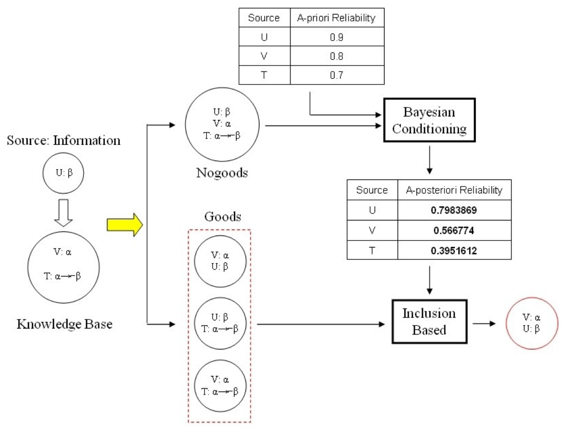

Figure 1. A "Belief Revision" mechanism

This new coming information deals conflicts in the KB. To solve the conflicts we have to found all the maximally consistent subsets (*Goods*) inside the inconsistent KB, and choose one of them as the most believable one. For instance in the figure 1 there are three *Goods*: $\{\alpha, \beta\}$; $\{\beta, \alpha \rightarrow \neg\beta\}$; $\{\alpha, \alpha \rightarrow \neg\beta\}$. Maximally consistent subsets (*Goods*) and minimally inconsistent subsets (*Nogoods*) are dual notions. Given an inconsistent KB finding all the *Goods* and finding all the *Nogoods* are dual processes. Each source of information has an a-priori "degree of reliability", which is intended as an a-priori probability that source provides correct information. In case of conflicts the "degree of reliability" of sources should decrease, this means that after the evidence of the conflicts we will have new conditioned a posteriori "degree of reliability". Bayesian conditioning is obtained as follows. Let $S = \{s_1, ..., s_n\}$ be the set of the sources, each source s_i is associated with an a-priori reliability $R(s_i)$. Let Φ be an element of 2^S. If the sources are independent, the probability that only the sources belonging to the subset $\Phi \subseteq S$ are reliable is:

$$R(\phi) = \prod_{s \in \phi} R(s) * \prod_{s \notin \phi} (1 - R(s)) \tag{1}$$

This combined reliability can be calculated for any ϕ providing that:

$$\sum_{\phi \in 2^S} R(\phi) = 1 \tag{2}$$

Of course, if the sources belonging to a certain ϕ give incompatible information then $R(\phi)$ must be zero. Having already found all the *Nogoods*, what we have to do is:

- Summing up into $R_{Contradictory}$ the a-priori reliability
- Putting at zero the reliabilities of all the contradictory sets, which are the *Nogoods* and their supersets;
- Dividing the reliability of all the other (no-contradictory set) set of sources by $1 - R_{Contradictory}$.

The last step assures that the constrain (2) is still satisfied and it is well known as Bayesian conditioning.
The revised reliability $NR(s_i)$ of a source s_i is the sum of the reliabilities of the elements of 2^S that contain s_i. If a source has been involved in some contradictions, then $NR(s_i) \leq R(s_i)$, otherwise $NR(s_i) = R(s_i)$.
For instance, the application of this Bayesian conditioning to the case of figure 1 is showed in table I and II.

Table I
THE CONFLICTS TABLE

ϕ	R(U)	R(V)	R(T)	R(ϕ)	NR(ϕ)
	0.1	0.2	0.3	0.006	0.0120967
T	0.1	0.2	0.7	0.014	0.0282258
V	0.1	0.8	0.3	0.024	0.048387
VT	0.1	0.8	0.7	0.056	0.1129032
U	0.9	0.2	0.3	0.054	0.1088709
UT	0.9	0.2	0.7	0.126	0.2540322
UV	0.9	0.8	0.3	0.216	0.4354838
UVT	0.9	0.8	0.7	0.504	0
				$\sum_{\phi \in 2^S} R(\phi) = 1$	$\sum_{\phi \in 2^S} NR(\phi) = 1$

Table II
THE NEW RELIABILITY

ϕ	NR(ϕ)	NR($U \in S$)	NR($V \in S$)	NR($T \in S$)
	0.0120967	0	0	0
T	0.0282258	0	0	0.0282258
V	0.048387	0	0.048387	0
VT	0.1129032	0	0.1129032	0.1129032
U	0.1088709	0.1088709	0	0
UT	0.2540322	0.2540322	0	0.2540322
UV	0.4354838	0.4354838	0.4354838	0
UVT	0	0	0	0
		NR(U)=0.7983869	NR(V)=0.566774	NR(T)=0.3951612

where $NR(U) = \sum NR(U \in S)$, $NR(V) = \sum NR(V \in S)$ and finally, $NR(T) = \sum NR(T \in S)$.
These new "degrees of reliability" will be used for choosing the most credible *Good* as the one suggested by "the most reliable sources". One of the algorithms to perform this job is called "Inclusion based". This algorithm works as follows:

1) select all the *Good* which contains information provided by the most reliable source
2) if the selection returns only one *Good*, *STOP*, that is the searched most credible *Good*
3) else if there are more than one *Good* then pop the most reliable source from the list and goto step 1
4) if there are no more *Goods* in the selection, the ones that were selected at the previous iteration will be returned as the most credible ones with the same degree of credibility.

III. Face Recognition System: an Example

In this section we will apply the theoretical background to the problem of recognizing faces by means a "Multiple Neural Networks" system. The sources will be neural nets and the pieces of information will be the outputs. The conflict will be a simple disagreement. Face recognition is a biometric approach that employs automated methods to verify or recognize the identity of a living person based on his physiological characteristics [8]. Many methods of face recognition have been proposed during the past 30 years. Face recognition problem has attracted several fields of research: psychology, pattern recognition, neural networks, computer vision, and computer graphics [9]. These methods are broadly classified in three categories, according to the types of features used by various methods: *Holistic methods*, *Local methods* and *Hybrid methods* [10]. In the *Holistic methods* each face image is represented as a single high-dimensional vector by concatenating the grey values of all the pixels in the face; *Local methods* use the local facial features for recognition, and finally *Hybrid methods* use both local and holistic features to recognize a face. We focus the attention on the *Local methods* that provide flexibility to recognize a face based on its parts. *Local methods* are classified into two main categories: local features-based method and local appearance-based method. The first method is based on the geometrical measures, while the second method divides the face image in different regions. The simplest and the most widely-used region shape is rectangular blocks [11]. In this work we also consider a recognition technique based on the use of whole image grey-level templates. So each person is represented by a database of a set of four rectangular masks representing eyes, nose, mouth and hair [12]. In the simplest version of multiple template matching, each template of the face to recognize is compared using a suitable metric (typically the Euclidean distance) with the corresponding template of each image belonging to the database.

Instead, in the present work a number of independent recognition modules, such as neural networks, are specialized to respond to individual template of the face. In order to solve the problem to recognize the face even if partially changes occurred it is necessary to introduce a system in which expert modules can be adapted to the new situation. Unlike the Euclidean distance neural networks are better able to upgrade themselves in presence of changes in the input pattern. We propose a modular system consisting of four neural networks, for example four Self Organizing Maps of Kohonen [13], in a way that each network is specialized to perform a specific task: eyes recognition (E network), nose recognition (N network), mouth recognition (M network) and, finally, hair recognition (H network). Considering a simple theoretical example, we suppose that during the testing phase, the system has to recognize the face of four persons: Andrea, Franco, Lucia and Paolo. So, we suppose that each network has the following possible codified outputs: A output of each network is the subject Andrea, F output of each network is the subject Franco, L output of each network is the subject Lucia and finally, P output of each network is the subject Paolo. According to the value of the weights of each trained network, each net will provide in output a list of names of subjects by considering the nearest one in terms of Euclidean distance. For the purpose of this example, we considered to take into account only the first two outputs as threshold. We suppose that after the testing phase the the outputs of the networks are as follows:

Table III
THE FIRST TWO OUTPUTS OF EACH NETWORK

E	**N**	**M**	**H**
A	A	L	L
F	P	P	A

so, the 4 networks do not agree in the choice of the subject since there is no individuals in the intersection of the four outputs (intersection is void). Now the problem is to establish the most credible individual corresponding to the contradictory outputs. To solve this problem we adopt the method described in section 2. First of all we need to give an a-priori reliability factor of degree of each network. Then we have to find *Goods* and *Nogoods*. Considering the table III we can detect three *Goods*, that are the largest subsets of {E,N,M,H} which agree in the choice of at least one subject; these *Goods* are: {E,N,H} corresponding to Andrea, {N,M} corresponding to Paolo and, finally {M,H} corresponding to Lucia. Besides, we identify two *Nogoods*, that are the smallest subsets of {E,N,M,H} which have no subject in common; these *Nogoods* are: {N,M,H} and {E,M}.

Now we have to choose which the most credible *Good*; that will be the one provided by the most reliable networks. However the reliability of the networks are changed due to the fact they felt in conflict. Starting of an undifferentiated a-priori reliability factor of 0.9, and applying the method described in the previous we get the new-reliability described in table IV.

Table IV
A POSTERIORI RELIABILITY

Network	**New Reliability**
E	0.7684
N	0.8375
M	0.1459
H	0.8375

The networks N and H have the (same) highest reliability, and by applying the "Inclusion based" algorithm it turns out that the most credible *Goods* is {E,N,H}, which corresponds to Andrea. So Andrea results the collective image processing.

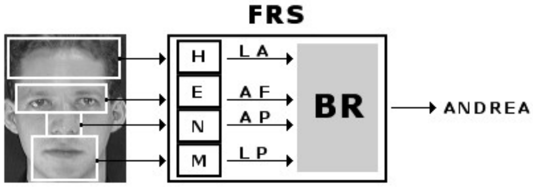

Figure 2. Schematic representation of the Face Recognition System (FRS)

Figure 2 shows a schematic representation of the system (named Face Recognition System, FRS). In conclusion of this paragraph we remark that the proposed system is able to recognize the most probable individual even in presence of serious conflict among the outputs of the various nets.

A. *Face Recognition System in a Dynamical Environment*

Following the previous example, we note that the network M which is not able to recognize Andrea from is mouth could be forced to re-train itself on the basis of the outputs provided by its colleagues networks. There can be two reasons for the fault of M: the task of recognizing the mouth is objectively harder, or Andrea could have changed the shape of the mouth (perhaps because the moustaches are grown). The second case is very interesting because it shows how our FRS could be useful for implementing "Multiple Neural Networks" systems able to follow dynamical changes in the features of the subjects (dynamical environment). In a dynamical environment, when the input pattern partially changes some neural networks could be no longer able to recognize them. However, if the changes are minimal, we can hope that most of the networks will still correctly recognize the face. So, we force each faulting network to re-train itself on the basis of the recognition made by the overall group. This is an evolutionary system. On the basis of the a-posteriori reliability and of the *Goods*, our idea is to re-train the networks that did not agree with the others. The network is subjected to a new process of training forced to recognize the face, because it has partially changed, according to the opinion of the group. Each iteration of the cycle applies Bayesian conditioning to the a-priori "degrees of reliability" producing an a-posteriori vector of reliability. To take into account the history of the responses that came from each network, we maintain a vector of the average "degrees of reliability" produced by Bayesian conditioning at each cycle. This vector of average "degrees of reliability" will then be given as input to the "Inclusion based" algorithm in order to choose the most credible *Good*, i.e. to perform the final recognition. The difference with respect to the BR mechanism described in section 2 is that we do not give the a-posteriori vector of reliability to the "Inclusion based" algorithm, but the average a-posteriori vector of reliability calculated from the beginning of the iteration.
At each cycle, Bayesian conditioning is applied to the same vector of a-priori reliability. This because Bayesian conditioning never increases the a-posteriori reliabilities; starting each cycle from the a-posteriori reliability produced at the previous cycle could produce a global flattening towards zero of the reliability of each network involved in contradictions. This feedback allows a continuous learning by the system that adapts to partial continuous changes of the environment.

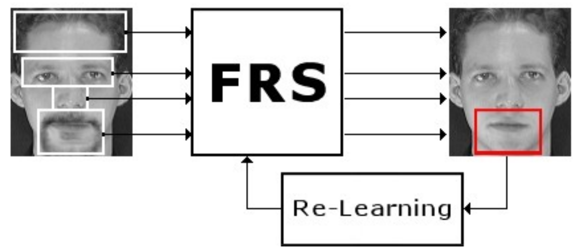

Figure 3. Schematic representation of re-learning of the system when the input is partially changed

Figure 3 shows the behaviour of the system when the testing image partially changes. Now the subject wears the moustaches. So $\mathrm{O_M}$ network (specialized to recognize the mouth) is no longer able to correctly indicate the tested subject. Since all the other still recognize Andrea $\mathrm{O_M}$ will be retrained with the mouth of Andrea of new input pattern.

IV. Conclusion

In this work we presented a new theoretical approach to face recognition when the face partially changes in the time. One possible way to deal with this problem is to train several specific feature detectors corresponding to each facial part (e.g., eyes, nose, mouth, and hair) so as to detect the facial parts and use them for recognition purpose. The idea is to build a modular system of neural networks in which each network is specialized to recognize a region of the face. The number of output units of each neural network is equal to the number of persons to be recognized. Every output unit is associated with one person. After training highest output of each neural network indicates recognized person for test image. We consider a constrained environment in which the image of the face is always frontal, lighting conditions, scaling and rotation of the face remain constant. We hope that the changes of the face are partial, for example the mouth and hair do not simultaneously change, but one at a time. A system of modular neural networks in which each network is specialized to perform a specific task ensures greater robustness to the recognition system, especially when there are localized changes. You have not to adjust the whole system, but you need only adapt the units of neural network specialized to the recognition of the region changed. In this regard, the system assigns a reliability factor to each neural network, which is recalculated on the basis of conflicts that occur in the choice of the subject. The new "degrees of reliability" are obtained through the conflicts table and Bayesian conditioning. These new "degrees of reliability" could be used by the "Inclusion based" algorithm to select the most likely subject. Certainly, when the subject partially changes its appearance, the network responsible for the recognition of the region amended comes into conflict with other networks and its reliability will suffer a sharp decrease. That network will be forced to re-train itself on the basis of the output that comes from the others. So, the overall system is engaged in never ending loop of testing and re-training that makes it able to coop with dynamical changes in the features of the subject. Our work is now purely theoretical, but our aim is to test the system by introducing experimental results that demonstrate the robustness and efficiency of the proposed theory.

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