A Continuous Learning in a Changing Environment

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Abstract. We propose a Hybrid System for dynamic environments, where a "Multiple Neural Networks" system works with Bayes Rule to solve a face recognition problem. One or more neural nets may no longer be able to properly operate, due to partial changes in some of the characteristics of the individuals. For this purpose, 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 to establish who is the conflict winner, making the final choice (the name of subject). Moreover the network disagreed with the group and specialized to recognize the changed characteristic of the subject will be retrained and then forced to correctly recognize the subject. Then the system is subjected to continuous learning.

Keywords: Belief revision, face recognition, neural networks, unsupervised learning, hybrid system.

1 Introduction

A single neural network cannot effectively solve some complex problems as several researches in the field of Artificial Neural Networks show[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 [2]. 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 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 individual responses is particularly critical when there are incompatibilities between them. Such situations may arise for example when the system operates

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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, we propose a "Multiple Neural Networks" system to solve a face recognition problem. Each part of the system consisted of a single neural network is trained to recognize a specific region of the face and to each one is assigned an arbitrary a-priori reliability. Each network has an a-priori reliability factor that is the likelihood that the source is considered credible. This factor will be dynamically re-evaluated on the ground of the global recognition operated by the overall group. In other words, 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 there may be no global agreement about the recognized subject, may be for she/he changed some features of her/his face. The new vector of reliability obtained through the Bayes Rule will be used for making the final choice, by applying the "Inclusion based" algorithm [3] or another "Weighted" algorithm over all the maximally consistent subsets of the global output 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 through a continuous learning process.

2 Theoretical Background

In this section we introduce some theoretical background taken from the Belief Revision (BR) field. Belief Revision occurs when a new piece of information inconsistent with the present belief set (or database) is added in order to produce a new consistent belief system [6].

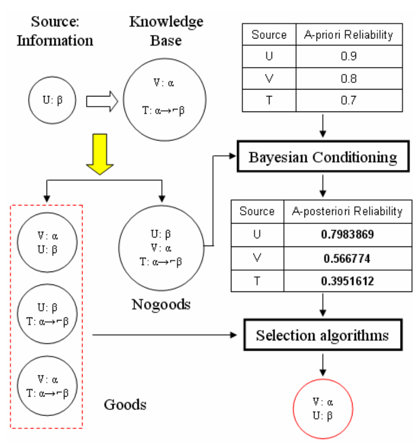

Fig. 1. "Belief Revision" mechanism

In figure 1, we see a Knowledge Base (KB) which contains two pieces of information: the α information , which come from V source, and the rule "If α, then not β" that comes from T source. Unfortunately, another piece of β information produced by the U source , is coming, causing a conflicts in the KB. To solve the conflicts we have to found all the "maximally consistent subsets", called Goods, inside the inconsistent KB, and we choose one of them as the most believable one. In our case (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 is associated with an a-priori "degree of reliability", which is intended as the a-priori probability that the source provides correct information. In case of conflicts the "degree of reliability" of the involved sources should decrease after "Bayesian Conditioning" which 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:

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

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 inconsistent 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 of Nogoods;
- 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 of sources by $1 - R_{Contradictory}$ we obtain the new reliability (NR).

The last step assures that the equation 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 the following table 1 and table 2.

2.1 Selection Algorithms

These new or revised "degrees of reliability" will be used for choosing the most credible Good as the one suggested by "the most reliable sources". One of the

Table 1. Conflict table

ϕ	R(U)	R(V)	R(T)	$R(\phi)$	$NR(\phi)$
	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	
				$\sum_{\phi \in 2^S} R(\phi) = 1$	$\sum_{\phi \in 2^S} NR(\phi) = 1$

Table 2. Revised reliability

ϕ	$NR(\phi)$	$NR(U \in S)$	$NR(V \in S)$	$NR(T \in S)$
	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

algorithms to perform this job is called "Inclusion based" (IB) [7]. This algorithm works as follows:

1. Select all the Goods which contains information provided by the most reliable source;
2. if the selection returns only one Good, STOP, that's the searched most credible Good;
3. else, if there are more than one Good then pop the most reliable source from the list and go to 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.

The other algorithm is "Inclusion based weighted" (IBW) a variation of Inclusion based: each Good is associated with a weight derived from the sum of Euclidean distances between the neurons of the networks (i.e. the inverse of the credibility of the recognition operated by each net). If IB selects more than one Good, then IBW selects as winner the Good with a lower weight.

The third and also the last algorithm is "Weighted algorithm" (WA) that combines the aposteriori reliability of each network with the order of the answers provided. Each answer has a weight $1/n$ where $n \in [1; N]$ represents its position among the N responses. Every Good is given a weight obtained by joining together the reliability of each network that supports it with the weight of the answer given by the network itself, as shown in the following equation 3:

$$W_{Good_j} = \sum_{i=1}^{M_j} \left(\frac{1}{n_i * Rel_i}\right) \tag{3}$$

where W_{Good_j} is the Weight of $Good_j$; Rel_i is the reliability of the network i; n_i is the position in the list of answers provided by the network i and finally M_j is the number of network that compose $Good_j$. If there are more than one Good with the same reliability then the winner is the Good with the highest weight.

3 Face Recognition System: An Example

In the present work, to solve the face recognition problem [8], we use a "Multiple Neural Networks" system consisted of a number of independent modules, such as neural networks, specialized to recognize individual template of the face. We use 4 neural networks specialized to perform a specific task: eyes (E), nose (N), mouth (M) and, finally, hair (H) recognition. Their outputs are the recognized subjects, and conflicts are simple disagreements regarding the subject recognized. As an example, lets suppose that during the testing phase, the system has to recognize the face of four persons: Andrea (A), Franco (F), Lucia (L) and Paolo (P), and that, after the testing phase, the outputs of the networks are as follows: E gives as output "A or F", N gives "A or P", M gives "L or P" and H gives "L or A"', so the 4 networks do not globally agree. Starting from an undifferentiated a-priori reliability factor of 0.9, and applying the Belief revision method, for each expert network we get the following new degree of reliability: NR(E) = 0.7684, NR(N) = 0.8375, NR(M) = 0.1459 and NR(H)=0.8375. The networks N and H have the same reliability, and by applying a selection algorithm it turns out that the most credible Good is {E,N,H}, which corresponds to Andrea. So Andrea is the response of the system.

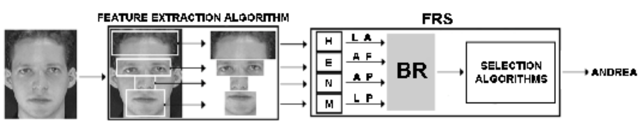

Fig. 2. Face Recognition System (FRS) representation

Figure 2 shows a schematic representation of the Face Recognition System (FRS), which is able to recognize the most probable individual even if there are serious conflicts among their outputs.

4 Face Recognition System in a Dynamical Environment

As seen in the previous section, one or more networks may fail to recognize the subject, there can be two reasons for the fault of the net: either the task of recognizing is objectively harder, or the subject could have recently changed something in the appearance of his face (perhaps because of the grown of a goatee or moustaches). The second case is very interesting because it shows how our FRS could be useful for implementing Multiple Neural Networks able to follow dynamic changes in the features of the subjects. In a such dynamic environment, where the input pattern partially changes, some neural networks could no longer be able to recognize the input. However, if the changes are minimal, we guess that most of the networks will still correctly recognize the face. So, we force the faulting network to re-train itself on the basis of the recognition made by the overall group. Considering the a-posteriori reliability and the Goods, our idea is to automatically re-train the networks that did not agree with the others. The network that do not support the most credible Good is forced to re-train themself in order to "correctly" (according to the opinion of the group) recognize the face. 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 an "average vectors of reliability" produced at each recognition, always starting from the a-priori degrees of reliability. This average vector will be given as input to the two algorithms, IBW and WA, instead of the a-posteriori vector of reliability produced in the current recognition. In other words, the difference with respect to the BR mechanism is that we do not give an a-posteriori vector of reliability to the two algorithms (IBW and WA), but the average vector of reliability calculated since the FRS started to work with that set of subjects to recognize. Now the subject has moustaches and goatee, while, when the system is trained, the subject did not have them. So O_M network (specialized to recognize the mouth) is no longer able to correctly indicate the tested subject. Since all the others still recognize Andrea, O_M will be retrained with the mouth of Andrea as new input pattern.

The re-learning procedure occurs when the changing is longer than the previously fixed temporal window (windowlength equals to 10) associated to each neural network. So we avoid the re-learning for a subject with a very variable feature. We define imm_i the portion of the image containing the feature

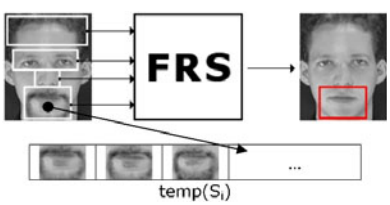

Fig. 3. Functioning of the temporal window

analyzed by the network r_i; S the subject identified by the synthesis function of the FRS; s_{ik} is the subject i in the k-th position of the list ordered on the base of the distance of the LVQ output. So the re-learning procedure consists of the following steps:

1. For each network r_i the system compares S and s_{ik} used to find the Good. If $S \neq s_{ik} \forall k$ then in the temporary directory $temp(S_i)$ (that is the temporal window) of the subject S related to the network i is saved the imm_i portion, as showed in Figure 3. On the contrary if $S = s_{ik}$ for one k the temporary directory temp(S_i) is empitied;
2. If in temp(S_i) there are windowlength samples, the $temp(S_i)$ images are transferred in riadd(S_i) removing its old images, then the retraining of the r_i network begins using the riadd(S_i) images for S and the most recent images for all other subjects.

We have to highlight that the windowlength chosen strongly depends on the variability of subjects, and so on the database used for the testing. It is important also to note that there will always be a limit to the size of the windowlength beyond which for any dataset the system will be able to filter all the changes, to a value beyond this limit the system behaves as a system without re-learning. If not recognized by the networks, the introduction of re-learning in the facial recognition system allows, that the networks maintain higher reliability values than in the case without re-learning, as shown in Figures 4a and 4b. This because, the network now can recognizes a feature that could not recognize with the original knowledge acquired during the first training of all networks. If a network is no longer able to recognize one feature can not contribute to the final choice. Moreover if other networks do not recognize the subject, but indicate the same wrong subject, the whole system fails. In this case there would be a wrong Good that could be the most likely for the system but associated to the incorrect subject.

Figure 4 shows the a-posteriori reliability trend related to five expert neural networks concerning a particular subject. Observing the two graphs, we can see that until the networks are agree, the reliability maintains high values. While, if one of the networks (eg mouth) comes into conflict with the others giving in output another subject (since perhaps he changed his appearance) then the

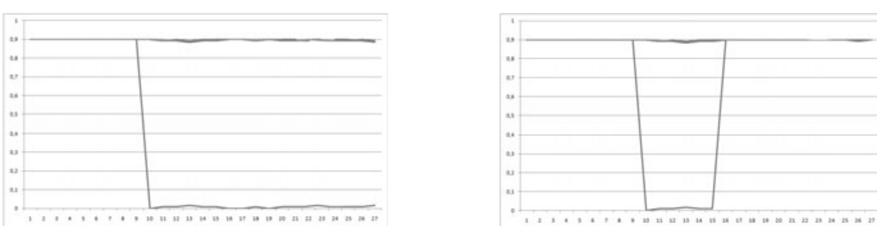

Fig. 4. Performance of the a-priori reliability (a) without and (b) with re-learning

reliability goes down. In Figure 4a, we can see how this conflict will bring the net loser to have a low reliability. Conversely, in Figure 4b, we can see that if the network does not recognize the subject for a consecutive number of times corresponding to the windowlength samples the re-learning begins, after which the a-posteriori reliability again increases.

5 Experimental Results

This section shows only partial results: those obtained without the feedback, discussed in the previous section. In this work we compared two groups of neural networks: the first consisting of four networks and the second of five networks (the additional network is obtained by separating the eyes in two distinctive networks). All the networks are LVQ 2.1, a variation of Kohonens LVQ [9], each one specialized to respond to individual template of the face. The training set is composed of 20 subjects (taken from FERET database [10]), for each one 4 pictures were taken for a total of 80. Networks were trained, during the learning phase, with three different epochs: 3000, 4000 and 5000. To find Goods and Nogoods, from the networks responses we use two methods:

1. Static method: the cardinality of the response provided by each net is fixed a priori. We choose values from 1 to 5, 1 meaning the most probable individual, while 5 meaning the most five probable subjects.
2. Dynamic method: the cardinality of the response provided by each net changes dynamically according to the minimum number of "desired" Goods to be searched among. In other words, we set the number of desired Goods and reduce the cardinality of the response (from 5 down to 1) till we eventually reach that number (of course, if all the nets agree in their first name there will be only one Goods).

In the next step we applied the Bayesian conditioning depending from Goods obtained with these two techniques. In this way we obtain the new reliability for each network. These new "degrees of reliability" will be used for choosing the most credible Good (then the name of subject). We use two selection algorithms to perform this task: Inclusion based weighted (IBW), Weighted algorithm (WA). To test our work, we have taken 488 different images from 20 subjects and with these images we have created the Test set. As shown in figure 5 using the system without re-learning the results show how the union of the Dynamic method with the selection algorithm WA and five neural networks gives the best solution to reach a 79.39% correct recognition rate of the subjects. Moreover using only one LVQ network for the entire face, we obtain the worst result. In other words, if we consider a single neural network to recognize the face, rather one for the nose, one for the mouth and so on, we have the lowest rate of recognition equals to 66%. This is because a single change in one part of the face makes the whole image not recognizable to a single network, unlike a hybrid system.

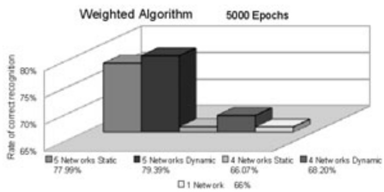

Fig. 5. Average rate of correct recognition with either Test Set and the results obtained using only one network for the entire face

In Figure 6, we can see the comparison between the average rate of correct recognition in the following cases:

- Hybrid system with re-learning (Static method, WA selection algorithm), 89.25%
- Hybrid system without re-learning (Static method, WA selection algorithm), 79.39%
- Only one neural network for the entire face, 66%.

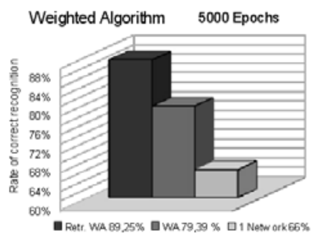

Fig. 6. Average recognition with re-learning

So the re-learning is a procedure very useful not only to increase the reliability factor of the misleading network, but also to improve the recognition itself.

6 Conclusion

Our hybrid method integrates multiple neural networks with a symbolic approach to Belief Revision to deal with pattern recognition problems that require the cooperation of multiple neural networks specialized to recognize subjects that dynamically change some their characteristics for that some nets occasionally fail. We tested this hybrid method referring to a face recognition problem, training each network to recognize a specific region of the face: eyes, nose, mouth, and hair. Every output unit is associated with one of the persons to be recognized. Each net gives the same number of outputs. We consider a constrained environment in which the image of the face is always frontal, lighting conditions, scaling and rotation of the face being the same, as in all biometric recognition systems for access to restricted areas. We accommodated the test so that changes of the faces are partial, for example the mouth and hair do not change simultaneously, but one at a time. Under this assumption of limited changes, our hybrid system ensures great robustness to the recognition. Will never happen that an authorized person tries to access a restricted area controlled by a biometric recognition systems with his face distorted. In case of permanent injury of face all the networks will be retrained to the new face by the system operator. 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" can be used to select the most likely subject. When the subject partially changes its appearance, the network responsible for the recognition of the modified region comes into conflict with other networks and its degree of reliability will suffer a sharp decrease. So, the overall system is engaged in a never ending loop of testing and re-training that makes it able to cope with dynamic partial changes in the features of the subjects. To maintain high values of the reliability for all the networks is very important since the choice of the right subject strongly depends on the credibility of all the experts.

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