Image Representation Based Hybrid Intelligent Diagnosis Approach for Computer Aided Diagnosis (CAD) Systems

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Abstract: *Computer Aided Diagnosis (CAD) is one of the most interesting and most difficult dilemma dealing in one hand with expert (human) knowledge consideration. On the other hand, fault diagnosis is a complex and fuzzy cognitive process and soft computing approaches as modular neural networks and fuzzy logic, have shown great potential in the development of decision support systems. In this paper, a brief survey on fault diagnosis systems, knowledge representations, and modular neural networks is given. From the classification and decision-making problem analysis, a hybrid intelligent diagnosis approach is suggested from signal to image conversion (image representation). In this approach, each image is divided in several sub-images (local indicators) which are classified by global approximators MultiLayer feedforward Perceptron networks (MLP) and by local approximators Radial Basis Function networks (RBF). Then, the suggested approach is developed in biomedicine for a CAD, from Auditory Brainstem Response (ABR) test, and the prototype design and experimental results are presented. Finally, a discussion is given with regard to the reliability and large application field of the suggested approach.*

Ke_words: Decision support, knowledge representation, classification and decision-making, soft computing, fuzzy logic, modular neural networks.

I. INTRODUCTION

Computer Aided Diagnosis (CAD) is one of the most interesting and most difficult dilemma dealing in one hand with expert (human) knowledge consideration. On the other hand fault diagnosis is a complex and fuzzy cognitive process and soft computing approaches as modular neural networks and fuzzy logic, have shown great potential in the development of decision support systems. Among difficulties contributing to challenging nature of this problem, one can mention the need of fine classification and decision-making.

Recently, several intelligent systems for diagnosis applications have been developed [1], [2]. Such systems have been used in a variety of domains: plant disease diagnosis, medical diagnosis, fault detection in nuclear power systems, ... The use of neural networks [3] to built such intelligent systems appears to be interesting and necessary to achieve an efficient and intelligent diagnosis help of system faults. Such neural systems for classification can ensure a satisfactory reliability to computer aided diagnosis from signal to image conversion.

Several approaches have been developed in order to analyze biomedical signals: electrocardiogram signals [4] and particularly Brainstem Auditory Evoked Potentials (BAEP) [5], [6], [7]. The approach developed by [5] is based on fuzzy sets for identification and particularly in BAEP analysis. A cross-correlation with a priori information have been used in a pattern recognition approach [6], whereas wavelet transform has been used in [7]. Over past decades, neural networks and related techniques show many attractive features in solution of wide class of problems: classification, decision-making, expert knowledge modeling [8], [9].

This paper deals with pattern recognition (classification) and decision-making based on Artificial Intelligence using soft computing implying modular neural networks and fuzzy logic applied to a biomedicine problem, and particularly from BAEP signals. Three chief difficulties make the computer aided diagnosis of such signals challenging: the first one is due to the high similarity of BAEP signals corresponding to different pathologies; the second one is related to expert's (physician's) subjective way or reasoning to point out the appropriated diagnosis. Finally, the last one is related to the relative rareness of available examples. In fact, one of physician's difficulties in cancer diagnosis (based on BAEP) is related to the weak number of certain diagnosis. The aim of this paper is absolutely not to replace specialized human but to suggest a decision support tool with a satisfactory reliability degree for Computer Aided Diagnosis (CAD) systems. In Section II, an overview is given on fault diagnosis systems, knowledge representations, and modular neural networks. Then, the hybrid intelligent diagnosis approach is suggested for computer aided auditory diagnosis (biomedicine application) in Section III. Afterwards, the prototype design and experimental results are presented in Section IV. Finally, a discussion is given with regard to the reliability and large application field of the suggested approach.

II. FAULT DIAGNOSIS SYSTEMS, KNOWLEDGE REPRESENTATIONS, AND MODULAR NEURAL NETWORKS

Globally, the main goals of fault diagnosis systems for Computer Aided Diagnosis (CAD) are: to detect if a fault is in progress as soon as possible, to classify the fault in progress, to be able to suggest suitable remedies (systems able of advising) or to give a reliability rate of the identified fault through a Confidence Index (CI).

A. Fault diagnosis systems

CAD is an attractive area leading to future promising fault diagnosis applications. However, dealing with expert (human) knowledge consideration, the computer aided diagnosis dilemma is one of most interesting, but also one of the most difficult problems. The fault diagnosis help is often related to the classification of several information sources implying different representations.

Fault diagnosis can be obtained from the classification of only one kind of information (knowledge) representation. However, experts use several information to emit their diagnosis. Then, an interesting way to built efficient fault diagnosis system can be deduced from this concept in order to take advantage from several information. More, experts can use several information sources, in various forms; qualitative or quantitative data, signals, images, to emit their diagnosis. Thus, these information could be issued from different information sources and/or from different representations of a same test. For instance, in case of diagnosis of the same fault classes set, one can consider that these information are independently, in parallel, classified and after the decision-making of their results gives then final results. Such final results gives the fault classes set and suitable remedies or a reliability rate of the possible identified fault class.

B. Knowledge representations (signal and image representations)

Signal to image conversion is an interesting transformation leading to a richer data representation. For example, biomedical signals are, traditionally, processed using signal processing approaches, mainly based on peak and wave identification approaches and pattern recognition approaches, such as in [4], [5], [6]. The main problem is then to identify pertinent parameters. This task is not trivial, because the time (or frequency) is not always the variable that points up the studied phenomena's features (behavior, etc...). Contrary to a time or frequency (signal) based representation, the image representation, taking benefit from its 2-D nature, offers advantage a richer representation taking into account more complex features (shapes, objects, ...).

C. Modular neural networks

Designing pattern recognition systems for the classification of not easily separable patterns and especially with satisfactory classification rates (or the best possible classification rate) is a difficult problem which has been developed in many research works [10], [11]. One usual solution consists of the use of multiple classification schemes (multiple models) and then the choice of the best scheme. However, it has been observed that although one design may outperform the others, the patterns that are misclassified by the different schemes are not necessarily the same. This observation suggests that the use of multiple classifiers can complement the decision about the patterns under classification, hence, improves the reliability of the overall classification process.

Over the past decades, new approaches based on artificial neural networks have been developed aiming to solve problems related to optimization, modeling, decision-making, classification, data mining, and nonlinear functions (behavior) approximation. Inspired from biological nervous systems and brain structure, artificial neural networks could be seen as information processing systems, which allow elaboration of many original techniques covering a large field of applications. Among their most appealing properties, one can quote their learning and generalization capabilities [3], [8], [12].

Elsewhere, one can take advantage from different capabilities of different models of artificial neural networks, such as those related to global and local approximations. In fact, MultiLayer feedforward Perceptron networks (MLP) are neural *global* approximators, whereas Radial Basis Function networks (RBF) are neural *local* approximators [3].

III. HYBRID INTELLIGENT DIAGNOSIS APPROACH FOR COMPUTER AIDED AUDITORY DIAGNOSIS (BIOMEDICINE APPLICATION)

The ABR test involves attaching electrodes to the head to record electrical activity from the auditory nerve (the hearing nerve) and other parts of the brain. This recorded electrical activity is known as brainstem auditory evoked potentials (BAEP) [13].

A. Brainstem Auditory Evoked Potential (BAEP)

BAEP based clinical tests provide an effective measure of the whole the auditory pathway up to the upper brainstem level. It is based on analysis of BAEP which are electrical response caused by the brief stimulation of a sense system. BAEP are generated as follows, see Fig. 1 (a), the patient hears clicking noise or tone bursts through earphones. In fact, the stimulus triggers a number of neurophysiologic responses along the auditory pathway. An action potential is conducted along the eight nerve, the brainstem and finally to the brain. A few times after the initial stimulation, the signal evokes a response in the area of brain where sounds are interpreted. Fig. 1 (b) represents two critical cases of such BAEP: first one corresponds to a healthy patient and second to an auditory disorder pathology. In fact, usually the experts diagnose the pathology using a surface of 50 estimations called Temporal Dynamic of the Cerebral (TDC) trunk, more details are given in [5], [6], [7], [13], [14].

B. Signal and image representations (extraction)

Before presenting how BAEP signals are converted in an image representation, it is pertinent to notice that a large number of signal issued representations could be converted in image-like illustration (representative). A large number of examples (but not limited to) could illustrate that. The first class of signal to image conversion issued representation concerns those obtatined from a direct conversion of a signal as infra-red thermography or ultrasonor (echographical) images. Another class of such representations concerns those obtained from some mathematical transformation of the original signal as a thresholding of wavelet transform issued time-frequency representation of a vibratory signal.

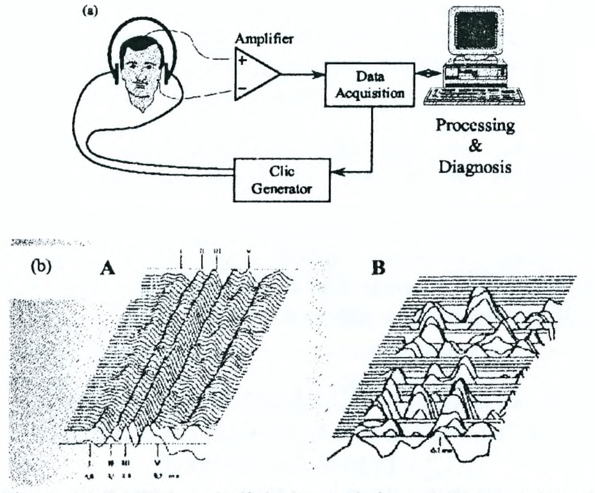


Fig. 1. (a) BAEP based clinical test chain and (b) examples of obtained TDC Surfaces showing a healthy A and an auditory disorder B cases respectively.

In this work, the BAEP signals are transformed in images to be processed and analyzed, as shown in Fig. 2. Indeed, each image is built of 50 BAEP signals where each BAEP signal is sampled and represented by 80 points. The conversion of BAEP signals to representative issued images is performed thanks to conventional thresholding interpolation techniques [15]. Consequently, each resulting image is represented in a matrix of 50 lines by 80 columns. In fact, the observation of these data leads us to consider only a matrix of 40 lines by 70 columns, since some last lines and some first columns have many zero values and/or very high values as shown in Fig. 3 (black parts left and down). This figure shows an example of obtained image (using signal to image conversion) of a patient belonging to Retro-cochlear Class (RC), Endo-cochlear Class (EC), and Normal Class (NC), respectively.

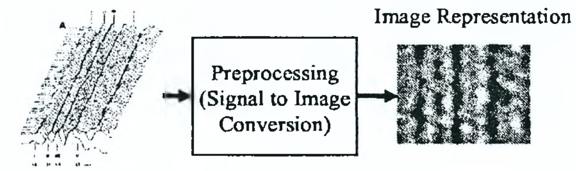


Fig. 2. Signal to image conversion (image representation).

C. Suggested hybrid intelligent diagnosis system

The hybrid intelligent diagnosis system suggested in Fig. 4 (c). is built of data processing stage, classification stage, primary fuzzy decision-making stage leading to a primary diagnosis, and final fuzzy decision-making stage leading to the final diagnosis.

Fig. 3. Image representations of a patient belonging to a Retro-cochlear Class (RC), Endo-cochlear Class (EC), and Normal Class (NC), respectively.

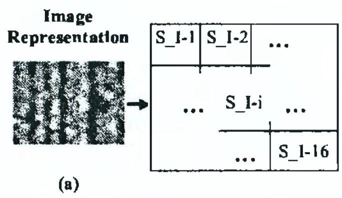
The data processing stage consists of extracting signal representation, from data source (signals: TDC surface), converted in image representation.

The classification stage consists of the signal classification which is based on RBF networks while the image classification is based on MLP networks.

The primary and final fuzzy decision-making stages consists of the Fuzzy System 1 (FS_1) and Fuzzy System 2 (FS_2), respectively. These fuzzy decision-making systems are used to capture the decision-making behavior of a human expert while giving the appropriate diagnosis [9], [16], i.e., it must mimic the input/output mapping of this human expert. Note that the two fuzzy inferences of FS_1 and FS_2, based on Mamdani's fuzzy inference, are developed as detailed in the diagnosis approach described in [14] with the simplification detailed in [17]. From this simplification, the fuzzy rule base of FS_1 which is built of $3^6 = 729$ rules will make in use only $2^6 = 64$ rules in each inference, while the fuzzy rule base of FS_2 which is built of $3^4 = 81$ rules will make in use only $2^4 = 16$ rules in each inference.

Thus, the double classification, from image representation, is exploited in FS_1 to ensure a satisfactory reliability for a computer aided auditory. Input parameters, from statistical processing, of FS_1 are RC_MLP, EC_MLP, NC_MLP, RC_RBF, EC_RBF, and NC_RBF. Thus, for each input, FS_1 is able to decide of appropriate diagnosis among Primary Outputs PO_{RC}, PO_{EC}, and PO_{NC}.

The diagnosis reliability obtained from the FS_1 is reinforced (enhanced) using the obtained diagnosis result with an Auditory Threshold (AT) parameter of patients, used as a confidence parameter, exploited in FS_2 in order to generate the final diagnosis result. Input parameters, issued from FS_1, of FS_2 are AT, PO_{RC}, PO_{EC}, and PO_{NC}. Thus, for each input, FS_2 is able to decide of the appropriate diagnosis among Final Outputs: FO_{RC}, FO_{EC}, and FO_{NC} with their Confidence Index (CI).



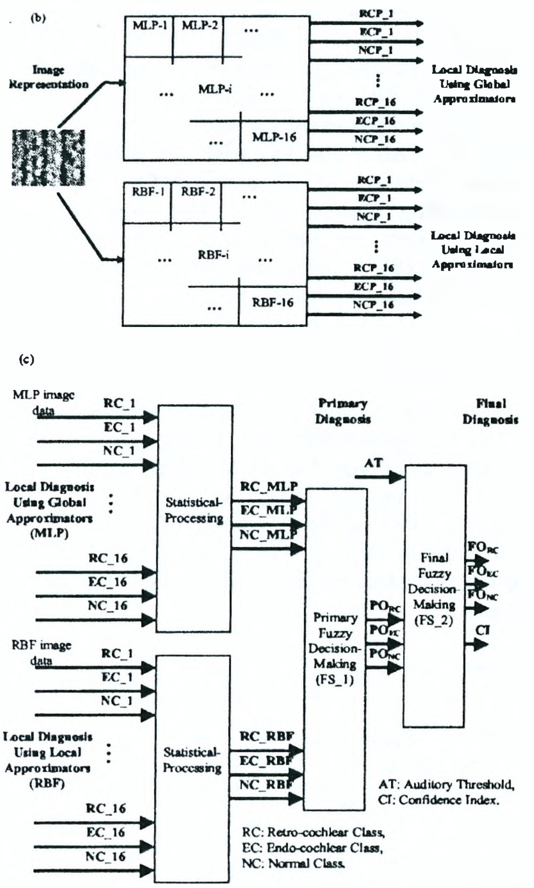


Fig. 4. (a) Image splitting principle, (b) modular neural network architecture, and (c) hybrid intelligent diagnosis synopsis.

IV. IMPLEMENTATION AND RESULTS

The used image database, issued from a specialized center in functional explorations in oto-neurology CEFON (Centre d'Explorations Fonctionnelles Oto-Neurologiques, Paris, France) [6], is built of 206 images such as: 38 images represent Retro-Cochlear-Patients, 77 images represent Endo-Cochlear-Patients, and 91 images represent Normal-Cochlear-Patients. From this database, 104 images (around 50 % of the database) are used as learning base (19 Retro-Cochlear-Patients, 39 Endo-Cochlear-Patients, 46 Normal-Cochlear-Patients) while 102 (around 50 % of the database) are used as generalization test base (19 Retro-Cochlear-Patients, 38 Endo-Cochlear-Patients, 45 Normal-Cochlear-Patients).

A. Design

The suggested approach is mainly based on a subdivision of the image in several sub-images as illustrated in Fig. 4 (a), in order to process each pixel in each sub-image [18], avoiding thus some approximations such as mean of a set of pixels. The idea here is to process the original information (pixels), without any kind of approximation, in local sub-images (local indicators). The implemented classification strategy takes advantage from a multiple neural networks based structure. It includes two kind of neural classifiers operating in an independent way: MLP and RBF, as shown in Fig. 4 (b). The obtained images from BAEP's signal to image conversion leaded to divide each image into 16 sub-images (12 areas of 10x20 pixels and 4 areas of 10x10 pixels). So, 16 local diagnosis (aiming to obtain 16 local indicators) are done on the 16 sub-images (S_I-1, ..., S_I-i, ..., S_I-16) using 16 global approximators (MLP-1, ..., MLP-i, ..., MLP-16), while 16 others local diagnosis (16 others local indicators) are done in the same way using 16 local approximators (RBF-1, ..., RBF-i, ..., RBF-16). Indeed, MLP and RBF classifiers operate on the basis of a local pattern recognition using local indicators in image, leading to a first diagnosis (local diagnosis).

A. 1. MLP issued results (local indicators). The MLP-1 to MLP-16 classifiers are trained using BP learning paradigm from the training set (learning base). The weights are adjusted from a random weight initialization between [-1, +1] with the learning rate η = 0.1. These classifiers yields convergence to the tolerance E_T = 0.01 in well under different Cycle Numbers (CN) around CN = 2500. The learning and generalization results are given in Fig. 5 for each class RC, EC, and NC. Globally, learning rates of the three classes are almost 100 % of the learning base, while generalization rates are between 10 % and 65 % of the generalization base.

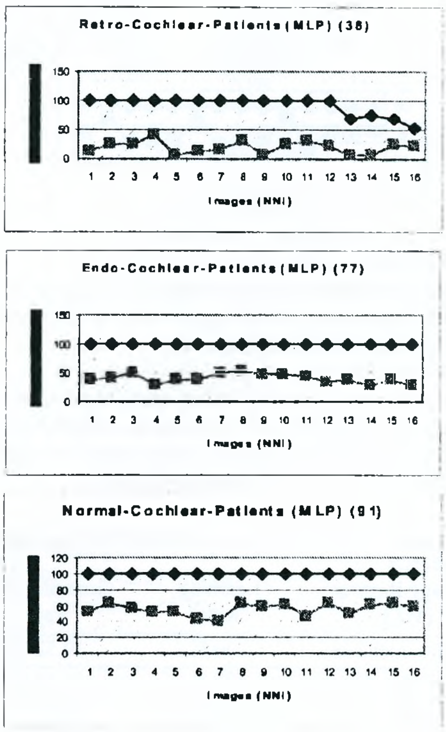


Fig. 5. MLP classification results (local indicators) of each sub-image: black and gray curves represent learning base and generalization base results, respectively.

A. 2. RBF issued results (local indicators). The RBF-1, ..., RBF-i, ..., RBF-16 classifiers are trained using the BP paradigm from the training set (learning base) using a random weight initialization between [-1, +1] with the learning rate $\eta = 0.1$. Convergence tolerance has been set to $E_T = 0.01$ and has been well under different Cycle Number around CN = 5000. Concerning the RBF model's "Region of Influence", it has been set to the fixed value of 0.1. The learning and generalization results are given in Fig. 6 for each class RC, EC, and NC. Globally, learning rates of the three classes are almost 100 % of the learning base, while generalization rates are between 10 % and 90 % of the generalization base.

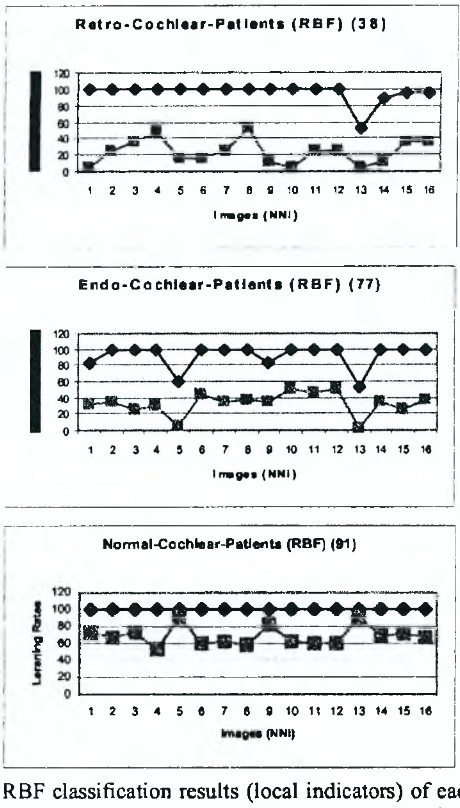


Fig. 6. RBF classification results (local indicators) of each sub-image: black and gray curves represent learning base and generalization base results, respectively.

The learning and generalization test results after the statistical processing of MLP networks and RBF networks gives the two global indicators: MLP global indicator see Table 1 and RBF global indicator see Table 2.

Table 1. Image neural classification results (MLP) giving MLP global indicator

Image Results (MLP)	Learning Rate	Generalization Rate
Retro-cochlear	100 %	10.52 %
Endo-cochlear	100 %	31.57 %
Normal	100 %	66.66 %

Table 2. Image neural classification results (RBF) giving RBF global indicator

Image Results (RBF)	Learning Rate	Generalization Rate
Retro-cochlear	100 %	21.05 %
Endo-cochlear	100 %	13.15 %
Normal	100 %	88.88 %

The results of the two neural classifications, from MLP networks MLP-1 (RC_1, EC_1, NC_1), ..., MLP-16 (RC_16, EC_16, NC_16) and RBF networks RBF-1 (RC_1, EC_1, NC_1), ..., RBF-16 (RC_16, EC_16, NC_16), are then processed statistically to give RC_MLP, EC_MLP, NC_MLP and RC_RBF, EC_RBF, NC_RBF normalized between [0, 1] and exploited in a fuzzy decision-making system FS_1. The suggested fuzzy system is based on Mamdani's fuzzy inference as developed in [9]. It must be able to decide of the appropriate diagnosis among the fuzzy system Outputs: RC, EC, and NC. Thus, the input vector of FS_1, see Fig. 4 (c), is then the vector **I** = [RC_MLP, EC_MLP, NC_MLP, RC_RBF, EC_RBF, NC_RBF]. For each input, this *Fuzzy Decision-Making System* must be able to select the appropriate diagnosis among Primary Outputs PO_{RC}, PO_{EC}, and PO_{NC}. The membership functions of RC, EC, and NC are the same for RC_MLP, EC_MLP, NC_MLP as well as for RC_RBF, EC_RBF, NC_RBF have been defined in Fig. 7 (a), Fig. 7 (b), and Fig. 7 (c), where Far (F), Medium (M), and Near (N) are the fuzzy variables.

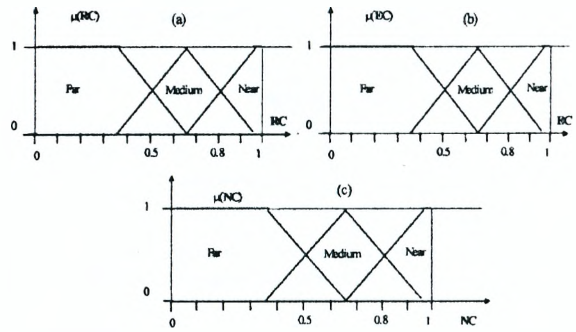


Fig. 7. Membership functions of: (a) RC. (b) EC. (c) NC.

For FS_2, the membership functions of Auditory Threshold (AT), PO_{RC}, PO_{EC}, and PO_{NC} have been defined in Fig. 8 (a), Fig. 8 (b), Fig. 8 (c), and Fig. 8 (d), where Good (G), Medium (M), Bad (B), and Low (L), Medium (M), and High (H) are the fuzzy variables.

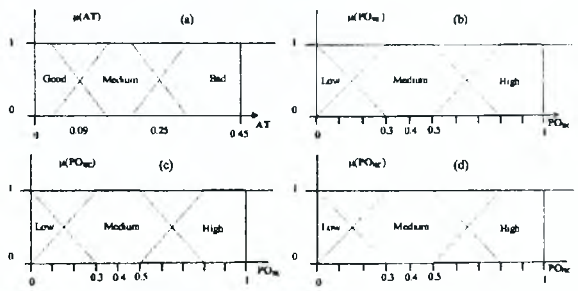


Fig. 8. Membership functions of: (a) Auditory Threshold (AT). (b) PO_{RC}. (c) PO_{EC}. (d) PO_{NC}.

B. Auditory diagnosis results

The results of the primary fuzzy system FS_1 are given in Table 3, while the results of the final fuzzy system FS_2 are given in Table 4.

Table 3. Primary fuzzy decision-making results

Primary Fuzzy System	Learning Rate	Generalization Rate
Retro-cochlear	100 %	10.52 %
Endo-cochlear	100 %	13.15 %
Normal	100 %	77.77 %

Table 4. Final fuzzy decision-making results

Final Fuzzy System	Learning Rate	Generalization Rate
Retro-cochlear	100 %	10.52 %
Endo-cochlear	94.87 %	63.15 %
Normal	100 %	86.66 %

Note that the particularity of the suggested fuzzy decision system is to give for each patient the final diagnosis FO_{RC}, FO_{EC}, FO_{NC} and a Confidence Index (CI) on its decision, e.g., the fuzzy output result $\mathbf{O} = \{FO_{RC}, FO_{EC}, FO_{NC}, CI\}$. Then, the final result is given by: $\mathbf{O} = (\mathrm{Max}\{FO_{RC}, FO_{EC}, FO_{NC}\}, CI)$.

V. DISCUSSION AND CONCLUSION

In .his paper, a hybrid intelligent diagnosis approach based on image representation for computer aided auditory diagnosis, based on neural classifications (modular neural networks) and fuzzy decision-making systems has been suggested. It is pertinent to notice that a large number of signal issued representations could be converted in image representations. In fact, such approach take advantage from features which are unreachable from unidimentional signal (time dependent waveform). More, it allows to use image-like representation and processing, which offers benefit of a richer information representation (than the signal related one), i.e., features which are unreachable from unidimensional signal.

In fact, the double classification suggested in this work is exploited in FS_1, for a primary diagnosis, to ensure a satisfactory reliability. Second, this reliability is reinforced using a confidence parameter Auditory Threshold (AT) with the primary diagnosis result, exploited in FS_2, in order to generate the final diagnosis giving the appropriate diagnosis with a Confidence Index (CI). In fact, the aim is then to achieve an efficient and reliable CAD system for three classes: two auditory pathologies RC and EC and normal auditory NC. Note that the redundancy inherent in this scheme acts to the benefit of the overall system. Another important point concerns the number of classes in the suggested approach, i.e., only three output classes (fault classes set). In fact, this approach could be generalized to many output classes exploiting the concept of modular neural networks [11]. Such concept allows to avoid to deal with a huge number of f.uzzy rules in case of a great number of output classes.

Another aspect of increasing importance, and strongly linked to data processing and the amount of data available concerning processes or devices (due to the high level of sensors and monitoring), is the extraction of knowledge from data to discover the information structure hidden in it. Traditionally, biomedicine signals are processed using signal processing approaches, mainly based on peak and wave identification from pattern recognition approaches, such as in [4], [5], [6], [7], [13]. The main problem is then to identify pertinent parameters. This task is not trivial, because the time (or frequency) is not always the variable that points up the studied phenomena's features leading then to a necessity of multiple knowledge representations (signal, image, ...).

With regard to other approaches [4], [5], [6], [7], [13] the suggested BAEP signal analysis and interpretation approach for a reliable computer aided medical diagnosis exploits the three main advantages from its signal to image conversion (image representation rather than signal representation) and multiple model approach [19], and the CI parameter given on the final diagnosis. An interesting alternative for future works could be, on the one hand, the investigation in aspects related to different ways to fuse neural classifiers issued information., such as fuzzy neural networks or fuzzy artmap neural networks [9], and on the other hand the generalization of suggested approach to a larger field of applications such as fault detection and diagnosis in industrial plants [1], [2], e.g., mechatronic system as illustrated in Fig. 9.

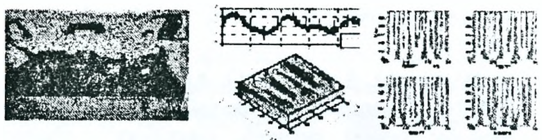


Fig. 9. Example of industrial diagnosis system and signal to image conversion (image representation).

However, before that, a number of current system's aspects could be enhanced. For this purpose, at first a fine tuning of fuzzy rules is necessary as well as a more detailed presentation of the results (the results presented are those only with a high CI). Second, one of those aspects is related to the statistical processing stage. In fact, finer statistical features could be investigated (higher order statistical features).

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