HYBRID VISUAL-DRIVEN DECISION SUPPORT SYSTEM IN VIDEO MONITOR MANUFACTURING

F.M. Kawaoku[1] , J.E. Araujo[2] , K.H. Kienitz[1] , L. Mesquita[3]

[1] *Instituto Tecnológico de Aeronáutica (ITA), Electronics Engineering Division, Brazil*
[2] *Instituto Nacional de Pesquisas Espaciais (INPE), Integration and Testing Laboratory (LIT), Brazil*
[3] *Universidade Estadual Paulista (UNESP), Electrical Engineering Department, Brazil*

Abstract: An intelligent system that emulates human decision behaviour based on visual data acquisition is proposed. The approach is useful in applications where images are used to supply information to specialists who will choose suitable actions. An artificial neural classifier aids a fuzzy decision support system to deal with uncertainty and imprecision present in available information. Advantages of both techniques are exploited complementarily. As an example, this method was applied in automatic focus checking and adjustment in video monitor manufacturing.

Keywords: Decision support systems, Visual pattern recognition, Neural networks, Fuzzy inference, Classification.

1. INTRODUCTION

In many engineering problems computers have been used to provide more efficiency and precision in tasks usually carried out by humans. Nevertheless, there are problems whose computational solution is still impractical. Human beings, for instance, are able to recognize regularities when they extract information from environment; to establish cerebral patterns by using mechanisms of sensorial perception; and, afterwards, to manipulate them directly and automatically to make decisions.

Deciding from visual perception and classifying the resulting patterns is a complex task that computers should be able to perform in order to emulate human behavior. In so doing, the automation of decision-making process from image manipulation becomes an important alternative to improve precision and to increase productivity of industrial processes. In order to choose the best action in a production process, decision support systems may help operators to act appropriately meanwhile, in this case, information is obtained by image processing.

Nevertheless, information used during a decision-making process may suffer influences that introduce imprecision and uncertainty in the final choice. In visual perception tasks, humans recognize patterns that are detected and identified through the input data by biological neural network even under noise (Yegnanarayana, 1994). Regarding visual patterns, for instance, images may present deformation, e.g., due to noise, translation, rotation, and scale changes. Despite these difficulties, human reasoning is able to process that information and accomplishes consistent and conclusive decisions.

Pattern recognition and decision-support research have driven the search for algorithms that emulate the working of the human brain and of human reasoning. Artificial Neural Networks (NN) is an efficient approach largely applied to pattern recognition and classification (Basheer *et al.*, 2000, Schalkoff, 1991, Yegnanarayana, 1994). Fuzzy Logic (FL) is another tool from artificial intelligence used in process control and decision-making systems in environments affected by uncertainty, imprecision or vagueness (Araujo *et al*., 2003, Bellman *et al*., 1970). In the literature, different approaches are found that merge NN and FL (Du *et al*., 1995, Li, 2000, Lin *et al*., 1996). Some of these approaches are: FL system as the core component and NN as a tool to optimize membership functions; FL system and a NN implemented sequentially; NN to learn or process fuzzy data; NN for pattern learning and FL for decision support; FL to modify the learning rate of a NN.

The approach proposed in this paper merges NN and FL in a neuro-fuzzy decision system for visual perception and pattern recognition, i.e. an *intelligent hybrid system* for *visual-driven decision making*. This approach may be applied to industrial processes to automate image classification and decision-making based on visual pattern detection. This approach may be particularly important in video monitor manufacturing that incorporates on-line focus checking and adjustment.

2. RECOGNITION AND DECISION IN SOFT COMPUTING

The schematic diagram that depicts the hybrid system merging NN and FL is shown in Fig. 1. A digital camera captures images from the process, which is processed by a NN to identify patterns and to classify them in different levels. The purpose of the neural network is to extract information from image through a mapping between visual input and output datum that, by its turn, will be furnished as input data for the fuzzy decision support system. After the NN approach filters the visual information the decision-making system is ready to operate. The fuzzy system is employed to determine the best alternative for decision, according to a knowledge base previously established and the difference that emerge from the comparative analyses between the resulting pattern produced by the NN and a reference pattern formerly settled. In applications that there is no reference to be compared, the pattern classified by the NN is directly provided as an input to the fuzzy system. The advantage of employing the fuzzy system for making decisions is its desirable attribute to cope with uncertainties. Thus, the hybrid system is able to deal with imprecision or noise in the information generated within image processing, by a non-distinct and non-appropriate training set used by the neural network.

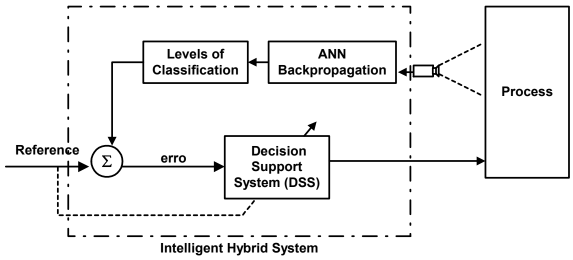

Fig. 1 Hybrid system applied for perception and decision-making.

2.1 Pattern recognition by using neural network

The neural network employed during the process of image pattern recognition is of the *feedforward architecture* while the adjustment of training assignment enforced by the learning rules is the *back-propagation algorithm* (Schalkoff, 1991, Zurada, 1992). The advantage of this approach is to process non-linear information characteristics; to perform tasks with parallel behavior; to be tolerant to fault and noise; and to demonstrate abilities of learning and generalizing.

These characteristics permit the NN to recognize patterns not exactly identical to those used during the training phase; to represent relationships between input and output when they are not clearly established or trained; and to map these relationships when there is a large amount of variables or a substantial diversity of data. A typical image classification process by using the neural network approach is depicted in Fig. 2. Each pixel (matrix element) of an acquired image corresponding to an object is assigned to the input of a neural network. Another point that deserves attention is the output of the NN, since it is crisp and does not stands for uncertainty or vagueness, even if some times it is hard to (Fig. 3) or it is not possible to discern an input data from another easily (see section 3).

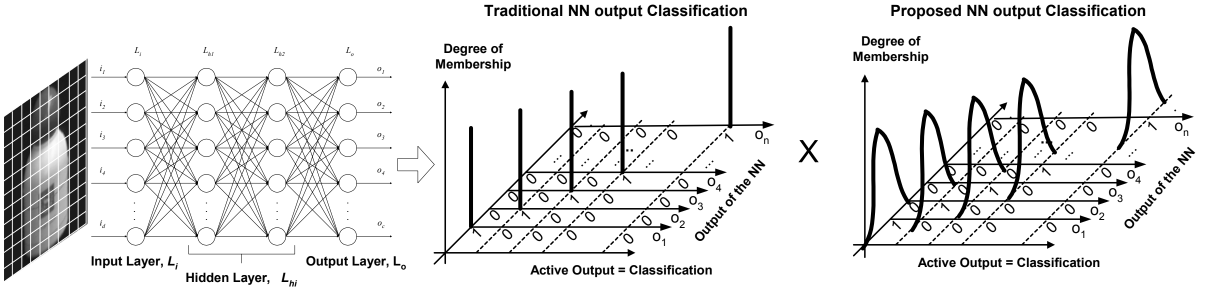

Fig. 2 Traditional NN applied to image classification and the proposed approach.

2.2 Decision-making in a fuzzy environment

Fuzzy logic is a technique based on set theory and represents the uncertainties inherent in human descriptions of nature phenomena. However, different from classical sets, where an element belongs to a set or not, fuzzy sets employ membership functions to determine the degree which an element belongs to a set. Extended to decision problems in fuzzy environments goals and constraints are represented by fuzzy sets, as presented in the seminal paper by Bellman and Zadeh (1970). According to this approach, the decision is also a fuzzy set, since it must simultaneously satisfy both goal and constraint. If the decision, *D*, is defined in the same space of alternatives, *X*, it is fulfilled by the conjunction between goal, *G*, and the constraint, *C*. The decision, *D*, in a fuzzy environment is usually defined by the intersection operation, $\cap$, used to manipulate the fuzzy set denoting a goal (or objective), *G*, and the fuzzy set standing for a constraint, *C*, as given by:

$$D = G \cap C \, . \tag{1}$$

Moreover, if there are *n* goals, G_1 ... G_n, and *m* constraints, C_1 ... C_m, instead of presenting a single goal and a single constraint as shown in equation (1) then the decision is rewritten as the interaction among all elements that belongs to the decision-making process:

$$D = G_1 \cap G_2 \cap \cdots \cap G_n \cap C_m \cap \cdots \cap C_2 \cap C_1 \tag{2}$$

The calculus of fuzzy constraints plays an important role, since it can be defined as an elastic restriction on the values that may be assigned to a variable related to a measurement or perception (Zadeh, 1975). Moreover, fuzzy restrictions are related to human cognition; particularly, in situations involving concept formation, patterns recognition, or making decisions. The cognitive process is characterized by the mental activity by which the knowledge is acquired through the perception, intuition and reasoning mechanisms.

3. NEURO-FUZZY SYSTEM FOR DECISION AND APPROXIMATE REASONING

3.1 Neuro-fuzzy recognition: imprecise cognition

The purpose of the NN in this hybrid system is to emulate the process of visual perception achieved by by human beings as well as to use its learning capability for being applied during the pattern recognition. Likewise to the restriction caused by the intrinsic, operational limitation of a system, the output of the neural network also limit the decision space in fuzzy environment by giving a new constraint representing the existing behavior of the process, which one is interested to interfere in. Thus, the output may be associated to the measurement (or perception) of the state that describes the dynamic of the process and equation **(2)** becomes:

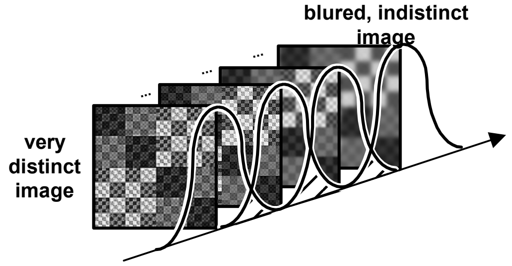

Fig. 3 Degree of precision (uncertainty) for image classification.

$$D = G \cap C \cap M \tag{3}$$

where *M* is the additional constraint imposed by the cognitive process.

Despite the advantages of the neural network when applied for pattern recognition even under noise, this approach suffers from the major drawbacks to distinguish patterns remarkably similar. The efficiency of this technique depends on its structural geometry, the adjustment of its internal parameters, and its learning and validation process (Basheer *et al*., 2000, Maier *et al*., 1998). Design a suitable structure for neural networks, however, is still controversial. If the geometry is sub-dimensioned, for instance, having few hidden nodes, the NN is not able to generalize (does not learn). It means that the net is unable to create adequately complex boundaries and the output error does not decrease. On the other hand, if the geometry is super-dimensioned, for instance, having too many hidden nodes, the learning speed becomes very slow (Caloba, 1992). Another problem comes up when the NN has a large number of elements in the hidden layer because the net can model the noise during the training stage, since it presents a large number of degrees-of-freedom (Nascimento Jr. and Yoneyama, 2000). In this case the net also lost its ability to generalize. The loss of generalization is also connected to the choice of an adequate training set and the number of samples used during this phase. If the training set is small, the NN is not able to recognize or classify the input data; if large, the net becomes specialized to work only with that training set. Hence, the NN can fail in discriminating the digitalized images, even if they are not identical. Due to this, during the decision process, it is necessary to consider this uncertainty generated by inadequate training and validation set as well as a possible inappropriate geometry.

An alternative to deal with aforementioned imprecise information is to assign fuzzy values represented by possibility distribution functions for the output of the neural network (Fig. 5), instead of crisp values as usually adopted (Fig. 2). Although the outputs are usually discrete (singleton), setting them apart as fuzzy sets can be especially useful when there is a large variety of patterns which are not essentially distinct; or when it is necessary to extract characteristics not sufficiently explicit from the input data. In a glimpse, it is possible to notice in Fig. 5 not only how the output of a classification process can be associated to possibility distribution functions but also that the resulting output is, actually, an additional constraint, *M*. Thus it is an example of decision-making process with multiples constraints within a fuzzy environment.

3.2 Neuro-fuzzy decision: Intelligent hybrid system

Another important role attributed to the calculus of fuzzy constraints is the ability to provide a conceptual base for fuzzy logic to build a sort of reasoning that is neither exact nor inexact. Known as *approximate reasoning*, this technique assumes an important role when attempting to emulate the human decision process, mainly if it is considered that the human reasoning is naturally approximate. This approach is able to represent not only the reasoning, but also the knowledge and experience of human beings by using the inference principle that links the rules given in the knowledge base with the facts provided in the database.

Approximate reasoning theory comprises the *compositional rule of inference* (*CRI*), *fuzzy relations*, and *probability distribution function* (Zadeh, 1979) and represents the human knowledge through a set of fuzzy rules of the kind IF <*input is A*> THEN <*output is B*>. Input and output refer to linguistic variables while *A* and *B* are fuzzy sets in the universes of discourse *X* and *Y*, respectively. Statements in this rule form can be defined through a fuzzy relation, *R*, with the membership grade, $R(x,y)$ on *X* and *Y*, and *f* is $f:[0,1]^2 \rightarrow [0,1]$ in such a way that the relational equation is:

$$R(x,y) = f[A(x), B(y)], \quad \forall (x,y) \in X \times Y \qquad (4)$$

Two important operations in fuzzy relations are

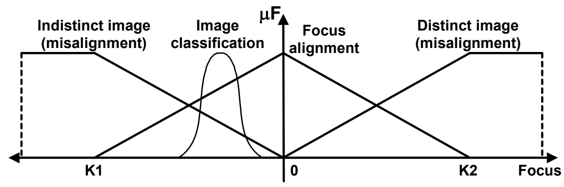

Fig. 4 Output NN classification set as input for if then rules

projection and conjunction that (together) make up the compositional rule of inference. This mechanism is a cornerstone in many applications of fuzzy systems, chiefly because it is regarded within a general category for fuzzy reasoning. One of its key elements is the extension principle that is used to transform fuzzy sets via functions into their fuzzy-set counterparts and, thus, permits to compute induced constraints within different universe of discourse. When it is used the conclusion, $B(y)$, is derived as follows:

$$\begin{aligned} B(y) &= proj(conj(R(x,y), cyl(A(x)))) \\ &= \sup_{x \in X} [A(x) \wedge R(x,y)] \end{aligned} \qquad (5)$$

where *proj* corresponds to the projection operation, *conj* corresponds to the conjunction operation; *cyl* corresponds to the cylindrical extension, and $R(x,y)$ is defined as equation **(4)**. This mapping, *f*, of $X = \{x\}$ in $Y = \{y\}$ is obtained by using $y = f(x)$, where *x* represents the input (cause) and *y* the output (consequence).

This mapping is important to solve decision-making problems whose goals, *G*, and constraints, *C*, are in different spaces of alternatives, since it allows reducing the problem to the simpler form with goals and constraints defined in the same space. Given *n* goals, G_1, ..., G_n, in the space of alternatives *X*, and *m* constraints, C_1, ..., C_m in the space of alternatives *Y*, a goal, G_i, in *X* is mapped in *Y* as a new goal, $\widetilde{G}_i$, by updating the membership function, $\mu_{\widetilde{G}i}(x) = \mu_{Gi}[f(x)]$. The resulting decision becomes an intersection of $\widetilde{G}_1, \ldots, \widetilde{G}_n$ and $C_1, \ldots, C_m$, that is:

$$\mu_{\widetilde{G}i}[f(x)] \wedge \cdots \wedge \mu_{\widetilde{G}n}[f(x)] \wedge \mu_{C1}(x) \cdots \wedge \mu_{Cm}(x) \quad (5)$$

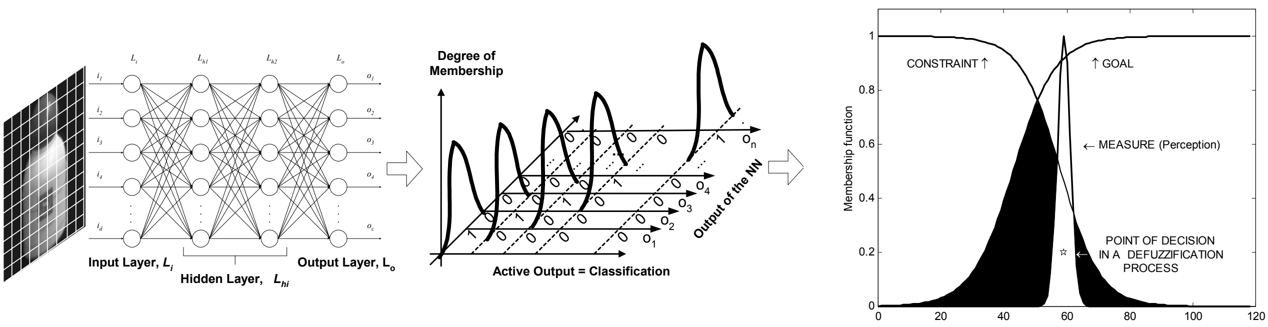

Fig. 5 Decision in fuzzy environment with constraint imposed by cognitive process of visual perception.

4. VIDEO MONITOR ADJUSTMENT BASED ON VISUAL-DRIVEN DECISION SYSTEM

4.1 Industrial Application

Consider the industrial process of video monitor manufacturing that needs to check and adjust focus on-line. Standard images in front of screen are different only by minor modification in focus when compared with a reference. This is a typical example of images that are alike but not identical. Although the task of discriminating them is particularly difficult to detect, operators identify this sort of misalignment and, afterwards, use their experience to decide about what action should be carried out to adjust the monitor (Araujo *et al*., 2000). Illustrated in Fig. 6 this procedure is fairly equivalent to that described in Fig. 1 and signalizes that the hybrid visual-driven decision support system proposed in this paper is an alternative to cope with this problem, although there are different possible solutions to this problem (Nathaniel *et al*., 2001). This application illustrates, thus, the possibility of emulating the human behavior for imitating a real industrial production line, where monitors are usually manually adjusted.

In order to deal with those strikingly similar images used during the NN training, a degree of uncertainty is assigned to their classification through the use of fuzzy sets (Fig. 3). When images are fundamentally distinct, that is, they have high membership degrees in distinct classes, discrimination among them is well defined and they are properly classified. However, there will be images that might generate misclassification, since they can activate more than one membership function (Fig. 4) as observed in the hachured area in Fig. 3.

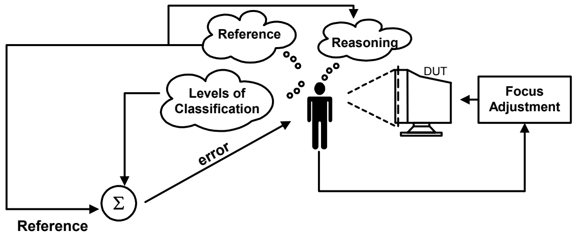

Fig. 6 Manual focus adjustment.

The fuzzy set representing the degree of certainty settled during the image classification is inserted as an input to the fuzzy decision support system. The use of CRI allows treating the decision-making process and the control approach alike (Araujo and Kienitz, 2003) since the decision, *D*, and the control signal, *U*:

$$U = M \circ R\,, \tag{6}$$

are closely related to each other:

$$M \circ R \leftrightarrow G \bigcap C\,. \tag{7}$$

Thus the measure, M, supplied by the NN classification may be considered as the input statement in the IF-THEN rule, as shown in Fig. 7a and Fig. 7b. Combined with the inference engine, these rules compose the knowledge base used to represent the expertise of a specialist as well as intrinsic constraints within the system and goals to be accomplished. Working as an extra constraint to the decision-making process, this measure suffers a cylindrical extension through the knowledge base (Fig. 7c). After the conjunction principle is applied, the resultant set is projected (Fig. 7d) in decision area to obtain the final decision (Fig. 7e) through the output statement (consequent). The resulting decision requires a transformation to a crisp value that can be obtained, for example, by computing the maximum

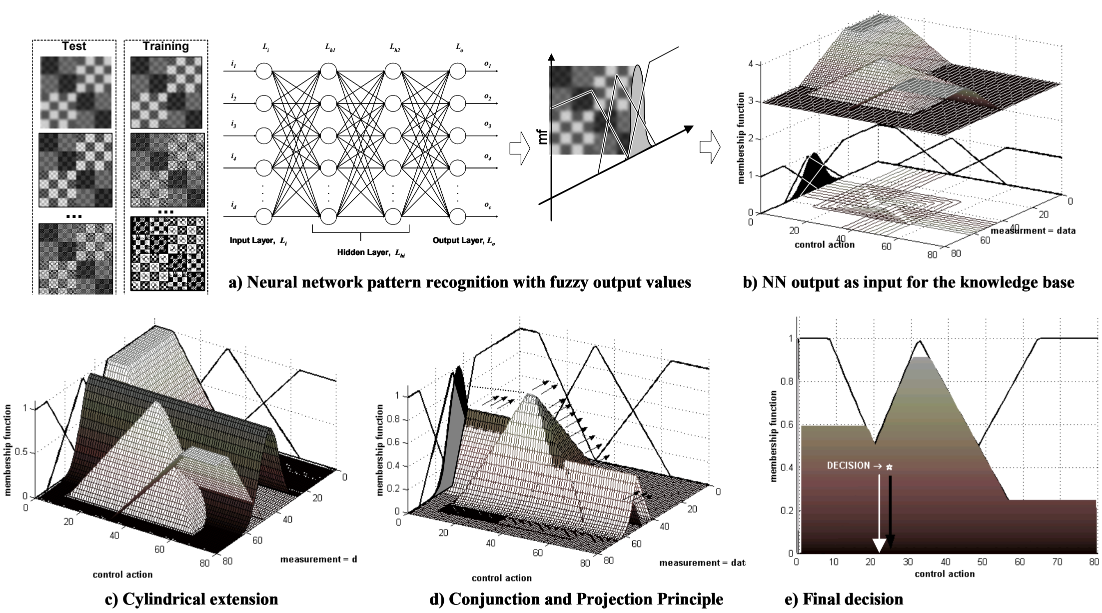

Fig. 7 Fuzzy reasoning through the compositional rule of inference after uncertain visual classification.

value or even the center of area of the final membership function.

4.2. Improvement proposal

It should be noticed, however, that the reference is not only employed in the comparing process in order to check if the standard image in front of screen is adjusted or not. The reference may also affect the human decision when, for instance, there are modifications in the characteristics of the video monitor or new goals determined by the rigorousness of focus checking are introduced. Since this additional information influences the decision-making process making the operator to adapt its decision according to the new goals, consequently it should be incorporated into the decision support system. An alternative to deal with this problem is the fuzzy reference gain-scheduling (FRGS) agent that is able to mimic the paradigms and mechanisms related to adaptive human decisions (Araujo *et al*, 2004). This approach adapts the membership functions of the fuzzy decision support system in order to accommodate small changes introduced by external input information and, thus, permits adaptive behavior according to goals, intentions, desires, or beliefs. This adaptive goal-driven agent may be employed to when there are changes in the objective (reference) to be achieved.

5. CONCLUSION

In the proposed approach, the fuzzy system is able to determine the adequate action based on a visual data acquisition and fuzzy image classification carried out by a neural network. While traditional neural network presumably assumes precise value in its output, in this paper possibility distribution functions are used to model the uncertainties in the image processing. The fuzzy system attempts to emulate the human approximate reasoning and the neural network is used to pattern recognition with uncertainty. The fuzzy output supplied by the NN serves as input to the decision support system in a complementary way rather than competitive manner. This association yields intelligent hybrid systems that overcome their individual limitations This hybrid system presented here suggests an alternative to deal with imprecision in visual classification almost in the same way humans do.

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