Genetic Tuning of a Laser Pointer Environment Control Device System for Handicapped People

Francisco Chávez, Francisco Fernández, Jesús Alcalá-Fdez, Rafael Alcalá and Francisco Herrera

Abstract— **In this paper we present a new approach for laser-based environment device control systems by laser pointer for handicapped people. The paper proposes the design of a Fuzzy Rule Base System for laser pointer detection. The idea is to improve the success rate of the previous approaches decreasing as much as possible the false offs, i.e., the detection of a false laser spot (since this could lead to dangerous situations).**

To this end, Genetic Fuzzy Systems have also been employed for improving the laser spot system detection thus reducing the system false offs, that is the main objective in this problem. The system presented in this paper, using a Fuzzy Rule Base System adjusted by a Genetic Algorithm, shows a better success rate, and the most important thing, the not desired false offs are completely avoided.

I. Introduction

Nowadays, people with handicap or chronic illness have less problems to control their home devices than some years ago. Thanks to the research effort in smart homes [1], [2], [3], [4], [5], systems designed for disabled people have been successfully developed. These kinds of systems are adapted to the needs of elderly or disabled people thanks to a computer system which controls the appliances of their homes, by means of which, they can have a normal life. Further, such automatic systems are also able to send information about the behavior of the people in a home in order to avoid dangerous situations. An extensive review on smart homes can be found in [1], showing the great evolution of these kinds of systems in the last years.

We can find different kinds of smart home systems in the specialized literature. Park et al. [2] presented a robotic smart house, by means of which disabled people can be assisted by a robot sending orders with body movements. Other researchers have used non-invasive brain-computer interfaces [3], where a brain computer interface is used to control different devices. On the other hand, the work presented in [4] makes use of a robot for helping disabled people to pick up different objects. In this work, the authors also proposed an interesting way to point out the desired objects by means of a laser pointer. The robot should then be able to detect the laser spot on an object in order to pick up this object. Since they represent cheap and easy to handle devices, laser pointers have been used as an indicator element for controling large displays [6], [7], [8], [9] and now they have been also used to help to disabled people in home device environment control.

To this end, an environment device control system for handicapped people has been recently presented in [5]. By means of this system, a handicapped person can use a laser pointer in order to indicate which home device he wants to use. A video camera takes an environment image and sends it to the computer. This image is analyzed with different algorithms for detecting a laser spot. Finally, if the laser spot is on a home device, a KNX/EIB domotic system [10] sends an order for controlling it. Thanks to this kind of systems, people with handicap will be able to control their home devices easily by a laser pointer.

The main goal in these types of systems is to detect the laser spot effectively. In [4], the authors deal with this problem by using especial physical filters in the video camera while it is taking the environment photos, with the aim of only capturing the laser spot. However, this is still an open problem that can be addressed by using laser spot detection algorithms based on the original non-filtered images.

As we have mention, we also presented in [5] a set of algorithms, that can detect the laser spot effectively on the image obtained by the video camera. Nevertheless, this algorithms have false offs, when a laser spot is detected by the algorithm but the image does not have any laser spot. In this event, a wrong order is sent to the domotic system which could provoke undesirable, dangerous or at least unexpected, situations.

In this paper, we present a new approach to detect the laser spot in the environment device control system presented in [5]. It consists of a Fuzzy Rule Based System (FRBS) [14], [15] for trying to improve the success rate in images without laser spot, and to completely avoid the false offs of the previous systems. Since it is a very particular problem, in which only a few training examples are available, the rules comprising this FRBS will be initially obtained by an expert. Even though that this initial system improves the success rate of the previous techniques in [5], it still presents false offs. In any event, we will benefit from the expert knowledge to obtain the initial definition of the FRBS, in order to later improve the FRBS performance by applying a genetic tuning of the Membership Functions (MFs) [11], [12], [13]. The results obtained by the tuned FBRS show a better success rate, and the most important thing, the not desired false offs are completely avoided.

This contribution is arranged as follows. In section II, the environment device system for handicapped people by

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using a laser pointer is described together with the previous work. The initial FRBS designed by an expert is described in section III. Section IV introduces the genetic tuning of MFs and describes the Genetic Algorithm (GA) used in this work. The results obtained by the initial and the tuned FRBS are shown and analyzed by comparing them to the previous technique in section V. Finally, section VI points out some conclusions.

II. System Description and Previous Work

As we mentioned, the laser pointer systems enable handicapped people to control different home devices. These systems analyze different environment images sent by a video camera, detect the laser spot on these images and automatically recognizes the device which the user has selected with the laser pointer, sending the necessary orders to control the home device by means of a domotic system.

In our case, this system consists of three sections (see figure 1):

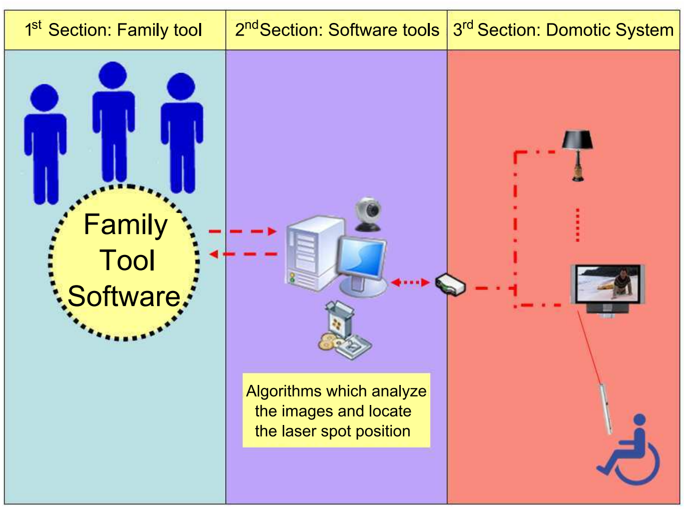

Fig. 1. Environment control system

- 1^{st} *Section*: The family tool let family members or teachers select the home devices that will be controlled by the system. In this tool, they will able to mark the active zone for each home device using the images sent by the video camera.
- 2^{nd} *Section*: In this section the system uses different techniques in order to analyze the image sent by the video camera and to locate the position of the laser spot.
- 3^{rd} *Section*: KNX/EIB architecture [10] let the system to control the different home devices. Once the laser spot is found and it is in an active zone, the system sends to the domotic system the necessary orders to turn on/off the device selected.

This contribution is focused on the 2^{nd} *Section*, in order to improve the laser spot detection ability, which becomes one of the most important tasks in these kinds of systems. The home environment control system based on laser pointer presented in [5] used three different algorithms, Dynamic Umbralization, Template Matching and Template Matching + Dynamic Umbralization to detect the laser spot. In the following subsections, we will briefly introduce the methods that we have presented in this previous work to detect the laser spot on an image (more information on the 1^{st} and the 3^{rd} *Sections*, and a deeper description of these algorithms can be found in [5]).

A. Dynamic Umbralization

Dynamic Umbralization (DU) was the first algorithm used in this system. This algorithm calculates a threshold value, by means of which, the pixels under this value are eliminated. The threshold value is calculated by means of the following expression:

$$V_{umb} = ((Sv\_I_{min}) - (Sv\_I_{max})) * \frac{X}{20} + (Sv\_I_{min}), \quad (1)$$

where Sv_I_{min} and Sv_I_{max} are the minimum and maximum sub intervals balance, and X is the sum of the balance parameters obtained from the pixel numerical information (see [5] for more information on how this values are calculated). As a consequence of this umbralization, the resultant image has the candidate pixels of the laser spot searched.

B. Template Matching

In order to improve the system performance, we have also used a second technique, namely Template Matching (TM). The algorithm that uses TM is based on convolution techniques. By means of this algorithm, an image named template is searched on the image sent by the video camera. A template is a laser spot image previously stored. Figure 2 shows a template image example.

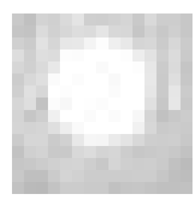

Fig. 2. Laser spot template

Each image sent by the video camera may have a section similar to the used template. The TM algorithm searches for such template on the obtained environment image. This algorithm obtains the probability of coincidence between the analyzed image sections and the template image. This probability ranges between -1 and 1, by using the following expression:

$$\Phi(I_r, I_l) = \frac{\sum_{i,j\in[-w,w]} AB}{\sqrt{\sum_{i,j\in[-w,w]} A^2 \sum_{i,j\in[-w,w]} B^2}},$$

$$A = I_r(x+i, y+j) - \overline{I_r(x,y)},$$

$$B = I_l(x'+i, y'+j) - \overline{I_l(x',y')}, \quad (2)$$

where the expression part known as A contains the set of pixels which are in the principal image section, and the section known as B contains the set of laser template pixels (see [5] for more information on how this formula can be applied). The TM algorithm proposes the image section with the highest correlation since, the laser spot should be found in the position of the obtained image section with the highest correlation.

C. Template Matching + Dynamic Umbralization

The algorithm described above has the same problem that the DU algorithm, the false offs. Trying to improve the algorithms and to eliminate the false offs, we proposed a new approach in [5] by joining both techniques in a new algorithm. The first step is to calculate the image section with highest correlation, by using the TM algorithm. The second step is to check if the section calculated is a laser spot image by using the DU algorithm. In this step, if the image calculated has pixels with high energy, these pixels will not be eliminated, and it is possible to say that the image calculated is a laser spot image.

III. Initial Fuzzy Rule Based-System Design from Expert's Experience

The previous algorithms have good success rate in images with laser spot, but still they have some false offs. In order to improve the results presented in [5], we propose the design of a FRBS for determining whether an image section is detected as a laser spot or not. This way working allows to have a system based on labels [14], [15], with a near human language, making easy the derivation of rules [16] that can provide a positive or negative response for each analyzed image section.

The first step is to determine a set of interesting system variables by analyzing some example images, with and without laser spots. From images with a laser spot we can determine the set of parameters/variables which can better characterize an image as a laser spot. In Figure 3, an example of images with and without laser spot is presented.

An interesting characteristic is that the laser spot pixels should present high energy in any image. The pixels values of a laser spot in an RGB system are approximately [255,255,255]. Moreover, we can observe that a laser spot is similar to a circle. These two properties should be present at any part of the analyzed image in order to detect that the laser spot is present in such image. In order to consider these two properties for obtaining a correct laser spot detection, we are going to consider five input variables. They are described in the next.

Figure 4 shows a typical laser spot image histogram. If the laser spot image histogram is analyzed, we can observe that there is a set of pixels which indicate us that the image has a section with high energy pixels. The algorithm has to eliminate every no laser pixel of the image. To do this, the percentile 80 of the histogram distribution is calculated. Once it has been calculated, every pixel under this value is eliminated. The remaining pixels in the imagen may be the laser spot pixels. The percentile 80 together with the number of laser spot pixels (not eliminated pixels), will be two of the FRBS input variables.

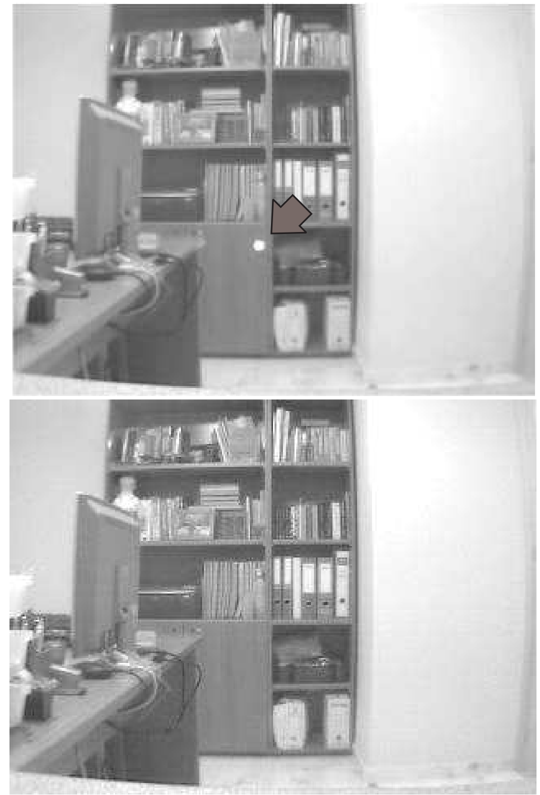

Fig. 3. Image with laser spot (top), Image without laser spot (bottom)

Once the pixels under percentile 80 have been eliminated, the image has only a set of candidate laser pixels. This set of pixels should be similar to a circle. In order to take this fact into account, the values for the next two input variables, long and cross standard deviation, are calculated. Figure 5 shows as the laser spot standard deviations are obtained. For obtaining the standard deviation values, the diameters shown in Figure 5 have to be obtained. Once, the diameters are obtained, the standard deviations calculated.

Finally, the similarity to a perfect circle is calculated. For this, an image with a perfect circle is generated. Using the TM technique (see expresion 2), the main image and the image generated are compared. The correlation between these images is the similarity to a perfect circle, which also represents an input variable.

To sum up, the six variables determined by the expert (five inputs and one output) represent the following information:

- X1: Long standard deviation.
- X2: Cross standard deviation.
- X3: Similarity to perfect circle value.
- X4: Laser spot number of pixels.
- X5: Percentile 80 value.
- Y: Laser spot probability (laser spot is detected if this

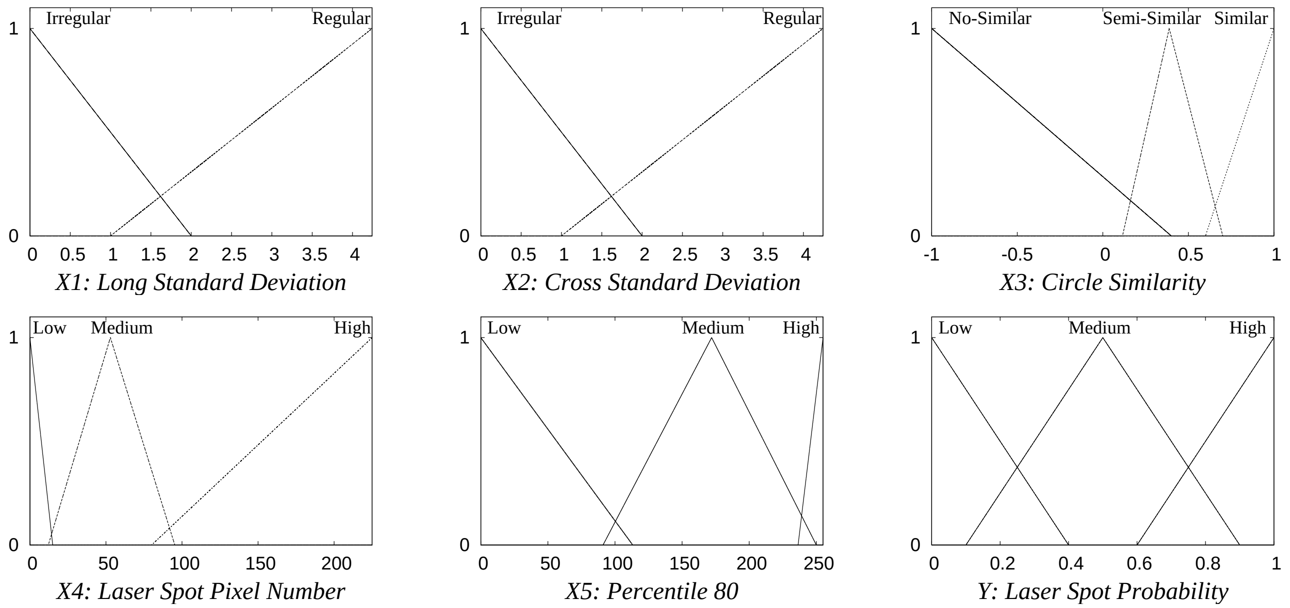

Fig. 6. MFs

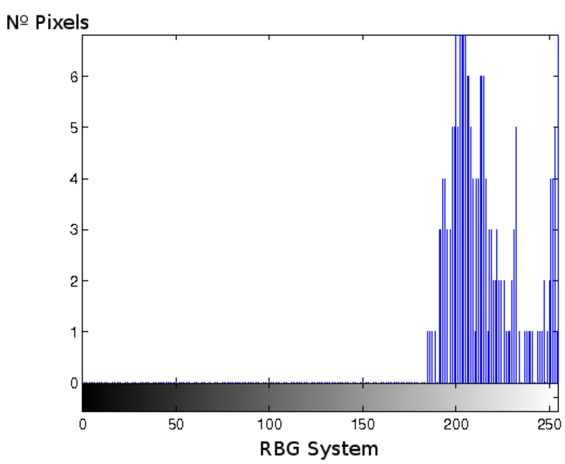

Fig. 4. Laser spot image histogram

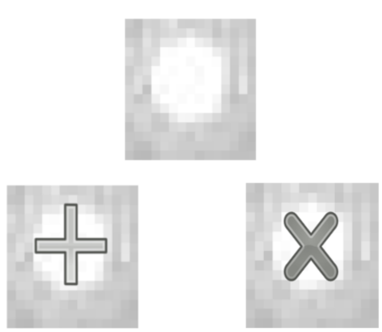

Fig. 5. Laser spot (top). High and long standard deviation (bottom left). Cross circle standard deviation (bottom right).

value is over a threshold).

Figure 6 shows the associated intervals and the MF definitions obtained from the expert experience. These MFs have been tuned by hand by an expert in order to obtain useful definitions. Once the input variables and their domains have been defined, the expert can define useful rules for the detection task. Table I shows the set of rules determined by the expert by using the linguistic concepts defined for each variable.

TABLE I
FUZZY RULES

Rule	X1	X2	X3	X4	X5	Y
1	regular	regular	no-similar		medium	Low
2	regular	regular	Similar		medium	High
3	regular	regular	semi-similar		medium	High
4	irregular	irregular	no-similar		medium	Low
5	irregular	irregular	semi-similar		medium	Low
6	irregular	irregular	similar		medium	Medium
7			no-similar		medium	Low
8			semi-similar		medium	Low
9	irregular	regular			medium	Low
10	regular	irregular			medium	Low
11				high	medium	Low
12	regular	regular	semi-similar	medium	medium	Medium
13					low	Low
14					high	High

In order to apply the obtained FRBS in the laser spot recognition task, it is combined with TM, giving way to a new hybrid technique, TM + FRBS. The first algorithm, TM, analizes the image sent by the video camera together with a template image. This obtains the image section with the highest correlation. The obtained image section is then analyzed by using the FRBS described. This new combination of algorithms directly presents a better performance than the algorithms described in sections II-A and II-B. The corresponding results will be shown in the experimental section.

IV. Genetic Tuning of the Proposed Fuzzy Rule-Based System

Even though that the new approach, TM + FRBS, has better results than the previous techniques, it can be further refined by performing a genetic tuning of the MFs, i.e., by means of a GA [17], [18], the MFs of the FRBS are adjusted. This kind of hybridization between fuzzy logic [14], [15] and GAs is well-known as Genetic Fuzzy Systems (GFSs) [11], [12], [13].

This section briefly introduces the genetic tuning technique and the GA used to optimize the MF parameters of the initial FRBS presented in the previous section.

A. Genetic Tuning of Membership Functions

With the aim of making a FRBS performs better, some approaches try to improve the preliminary Data Base (DB) definition, i.e., the definitions of the MFs, or the inference engine parameters once the Rule Base (RB) has been derived [11], [12], [13]. In order to do so, a tuning process considering the whole KB obtained (the preliminary DB and the derived RB) is used a posteriori to adjust the MFs or the inference engine parameters. A graphical representation of the tuning process is shown in figure 7.

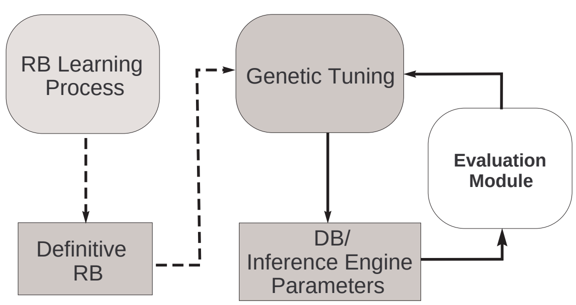

Fig. 7. Genetic tuning process.

Among the different possibilities to perform tuning, one of the most widely-used approaches to enhance the performance of FRBSs is the one focused on the DB definition, usually named *tuning of MFs*, or *DB tuning* [19], [20], [21], [22], [23], [24], [25], [26]. In [22], we can find a first and classic proposal on the tuning of MFs. In this case, the tuning methods refine the parameters that identify the MFs associated to the labels comprising the DB. Classically, due the wide use of the triangular-shaped MFs, the tuning methods [11], [22], [23], [24], [26] refine the three definition parameters that identify these kinds of MFs (see Figure 8).

In this paper, we perform a DB tuning to refine the three definition parameters that identify the triangular-shaped MFs in order to improve the FRBS performance in the laser pointer environment control problem. In the next subsection, the evolutionary algorithm used to perform the genetic tuning is described.

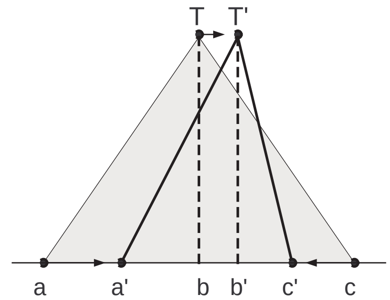

Fig. 8. Tuning by changing the basic MF parameters.

B. Evolutionary Algorithm

To perform the genetic tuning we consider a GA that presents a real coding scheme and uses the stochastic universal sampling as selection procedure together with an elitist scheme. The operators employed for performing the individual recombination and mutation are uniform mutation and the max-min-arithmetical crossover [23]. In the following, the components needed to design this process are explained.

1) Chromosome Evaluation: For each input example, the FRBS generates a output value into interval [0, 1]. If this value is higher than a threshold value (L) the example will be classificated as a laser spot image, in otherwise, it will be classificated as image without a laser spot. Thus, a input example can be considered as:

- False Negative (FN): If the example is classificated as a image without laser spot and it is a laser spot image.
- False Positive (FP): If the example is classificated as a laser spot image and it is a image without laser spot.
- Hit: If the example is correctly classificated.

The objective of this algorithm is to minimize the number of FNs and FPs obtained by the FRBS. To evaluate a determined chromosome C_j we use the following function:

$$Fitness(C_j) = \frac{|FN|}{|D|} + 3 \cdot \frac{|FP|}{|D|} \tag{3}$$

where $|FN|$ is the number of FNs obtained, $|FP|$ is the number of FPs obtained and $|D|$ is the dataset size. Notice that the number of FPs is penalized in order to eliminate the wrong orders send to the domotic system.

The fuzzy inference system uses the center of gravity weighted by the matching strategy as a defuzzification operator and the minimum t-norm as implication and conjunctive operators.

2) Coding Scheme and Initial Gene Pool: A real coding scheme is considered. Each chromosome is a vector of real numbers with size $3{\cdot}F{+}1$ (F being the number of MFs in the given DB) in which the three parameters that identify each MFs and the threshold value are coded. Then, a chromosome

TABLE II

TECHNIQUES USED IN THE EXPERIMENTS.

Method	Ref.	Year	Description
TM+UD	[5]	2008	Template Matching plus Dynamic Umbralization (described in Section II-C)
TM+FRBS	proposed here	-	Template Matching plus FRBS from expert experience as explained in Section III
TM+FRBS (tuned)	proposed here	-	Template Matching plus tuned FRBS by using GAs as explained in Section IV

C_j has the following form, being m^i the number of MFs of each of the n variables in the DB:

$$C_j = C_{j1}\ C_{j2}\ \cdots\ C_{jn}\ L_j\ ,$$
$$C_{ji} = (a^i_{j1}, b^i_{j1}, c^i_{j1}, \ldots, a^i_{jm^i}, b^i_{jm^i}, c^i_{jm^i}),\ i = 1, \cdots, n$$

The initial gene pool is created making use of the initial DB definition. This initial DB with 0.5 as threshold value is encoded directly into a chromosome, denoted as C_1. The remaining individuals are generated at random in the variation intervals associated to each MF and to the threshold value. For each $MF_j = (a_j, b_j, c_j)$ where $j = (1, ..., F)$, the variation intervals are calculated in the following way (See Figure 9):

$$\begin{array}{l} [I^l_{a_j}, I^r_{a_j}] = [a_j - (b_j - a_j)/2, a_j + (b_j - a_j)/2] \\ [I^l_{b_j}, I^r_{b_j}] = [b_j - (b_j - a_j)/2, b_j + (c_j - b_j)/2] \\ [I^l_{c_j}, I^r_{c_j}] = [c_j - (c_j - b_j)/2, c_j + (c_j - b_j)/2] \end{array} \tag{4}$$

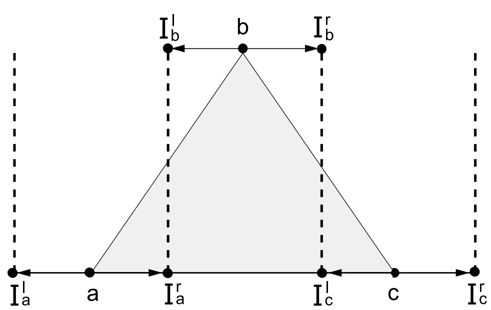

Fig. 9. The variation intervals.

The variation interval for the threshold value is [0, 1]. Therefore, we create a population of chromosomes containing C_1 as its first individual and the remaining ones initiated randomly, with each gene being in its respective variation interval.

3) Max-min-arithmetical crossover: If $C_v = (a^1_{v1}, \ldots, e_{vk}, \ldots, L_v)$ and $C_w = (a^1_{w1}, \ldots, e_{wk}, \ldots, L_w)$ are to be crossed, the following four offspring are generated

$$\begin{array}{l} C_1 = aC_w + (1-a)C_v \\ C_2 = aC_v + (1-a)C_w \\ C_3 \text{ with } e_{3k} = \min\{e_{vk}, e_{wk}\} \\ C_4 \text{ with } e_{4k} = \max\{e_{vk}, e_{wk}\} \end{array} \tag{5}$$

This operator can use a parameter a which is either a constant, or a variable whose value depends on the age of the population. The resulting descendents are the two best of the four aforesaid offspring.

4) Uniform mutation: If $C_j = (a^1_{j1}, \ldots, e_{jk}, \ldots, L_j)$ is a chromosome and the element e_{jk} was selected for this mutation (the domain of e_{jk} is $[e^l_{jk}, e^r_{jk}]$), the result is a vector $C'_j = (a^1_{j1}, \ldots, e'_{jk}, \ldots, L_j)$ and

$$e'_{jk} = e_{jk} + (e^r_{jk} - e_{jk}) \cdot r, \tag{6}$$

where r is a random number into the interval $[-1.0, 1.0]$.

V. EXPERIMENTAL RESULTS

To evaluate the usefulness of the approaches proposed in the previous sections, we have considered the previous environment control system presented in [5]. In order to have a performance measure and to perform the automatic tuning, we were provided with a little set of data containing 105 images, of which 65 are an image with laser spot and 40 are an image without laser spot. No more examples are available at this moment since each image have to be obtained by hand by the system experts, which consists on a tedious task in order to represent adequately the different situations.

Within this framework, the experts intention was to try to completely avoid false offs, if possible, while the detection rate is maintained or even improved. The methods considered in this study are shown in Table II. The previous technique have been applied as it was done in [5]. In the case of the genetic tuning-based approach, the input parameters for the GA are:

- Evaluations = 50000
- Population size = 61
- Parameters a and b, 0.35 and 5 respectively.
- Crossover probability = 0.6
- Mutation probability = 0.1
- Umbral initial value (L) = 0.5

The results obtained by the different techniques are shown in Table III. The following terms are used in this table:

- G.S.R.: General Success Rate of the system.
- S.R. with L.S.: Success Rate in Images with Laser Spot.
- S.R. without L.S.: Success Rate in Images without Laser Spot.

From the results in Table III, we can point out that the use of a FRBS obtained from the expert experience is able to reach good performance levels, increasing the detection rate

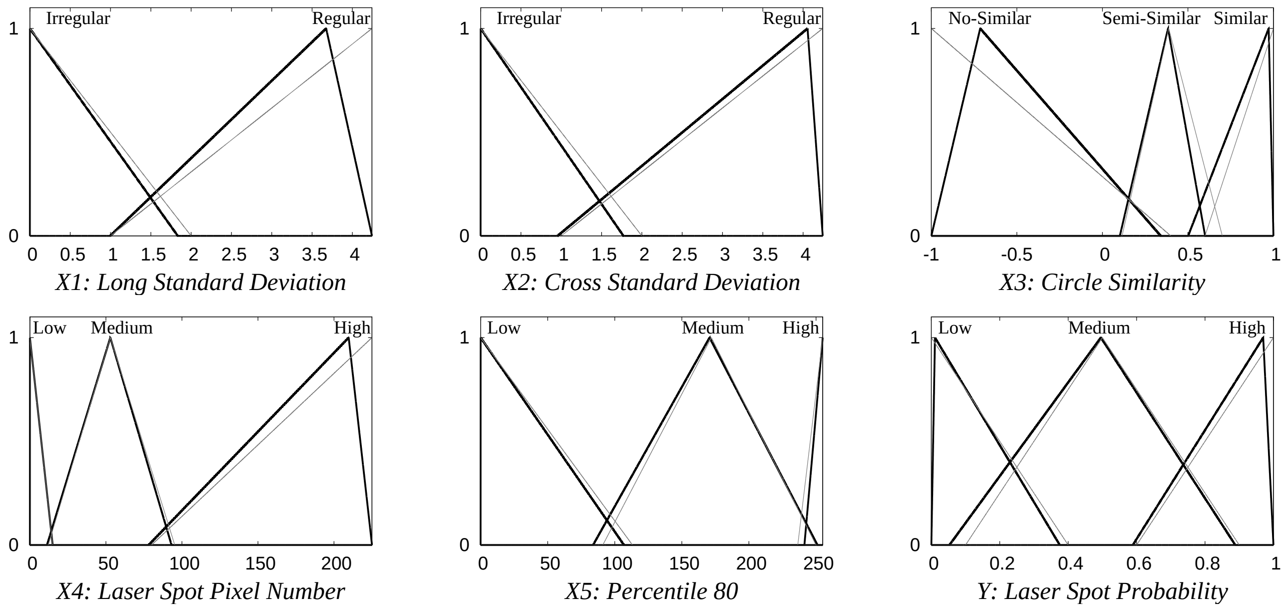

Fig. 10. Initial (grey) and Tuned MFs (black).

TABLE III
EXPERIMENTAL RESULTS WITH THE DIFFERENT TECHNIQUES.

Method	G.S.R	S.R. with L.S.	S.R. without L.S.
TM+UD	76.19 %	63.08 %	97.50 %
TM+FRBS	80.00 %	69.23 %	97.50 %
TM+FRBS (tuned)	83.81 %	73.85 %	100.00 %

with respect to the previous technique but still presenting some false offs. As can be seen, this last problem can be solved by using an appropriate post-processing technique that is still able to improve even more the detection rate. Thus, GFSs can benefit from the expert knowledge to obtain the set of rules in a problem with a few number of data, later improving the system performance to much higher performance levels and solving the main problem, the false offs.

Once the initial FRBS is adjusted by the genetic tuning process, a new set of MFs are generated. Figure 10 shows the initial (by hand) and tuned MFs (by GA). As it can be seen, only little changes are needed to completely avoid false offs. It is particularly interesting the effects in circle similarity, in which 'Similar' is applied to a wider range (increasing the laser spot detection ability with respect to this variable). On the contrary, in the standard deviation variables, in the percentile 80 and even in the output variable, it becomes a little bit more difficult to activate the labels that represent the higher values (just for avoiding false offs).

VI. CONCLUDING REMARKS

In this paper we have presented a new approach for laser-based environment device control system by laser pointer for handicapped people. The paper analyses the application of GFSs for laser pointer detection in images. In this way, we make use of an initial FRBS developed by an expert in order to asses laser spot detection together with a genetic tuning process in order to reach high performance levels. This genetic tuning process allows us to obtain a new set of MFs increasing the success rate up to 73.85% in images with laser spot, and a 100.00% (no false offs) in images without a laser spot. The main achievement is that the false offs have been eliminated while it is obtaining higher detection rates. This represent a promising contribution to the problem, since thanks to it we can avoid sending any wrong orders to the domotic system, preventing from possibly dangerous situations.

Thanks to the kinds of systems presented in this work, handicapped people can have a normal live, independently from their disability. These kinds of systems allow handicapped people to integrate both socially and professionally giving them the right to enjoy a life as normal and complete as possible; as the Rights of Disabled Persons says [27].

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