2011 IEEE International Conference on Fuzzy Systems
June 27-30, 2011, Taipei, Taiwan

Evolutionary Learning of a Laser Pointer Detection Fuzzy System for an Environment Control System

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***Abstract*—Recent studies in smart homes have proposed methods to use a laser pointer for interacting with home devices, which represents a more user-friendly and less expensive home device control environment. However, detecting the laser spot on the original non-filtered images, using standard and non expensive cameras, and considering real home environments with varying conditions, is currently an open problem.**

In this paper we propose a hybrid technique, combining a classic technique used in image detection processes, such as Template Matching, with an evolutionary learning of a Fuzzy Rule Based Systems for the laser spot detection system in real home environments. This proposal improves the success rate in images without laser spot of the previous classical and non-classical algorithms used for detecting the laser spot in previous works, decreasing the detection of the false offs which could lead to dangerous situations. Experimental results on a real home environment show the effectiveness of the proposed approach.

***Index Terms*—Interaction Systems, Domotic Control Systems, Laser Pointer Detection, Fuzzy rule-based systems, Genetic Learning.**

I. Introduction

Nowadays, a home can be controlled by different devices like special indoors control devices; or by means of mobile phones, personal computer, etc. using Internet if the users are outdoors. Recent research in intelligent homes provide great solutions for controlling home devices [1]–[6].

We can find different kinds of smart homes 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 [7] 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 controlling large displays [8]–[11] and now they have been also used in the environment control system.

The main goal in these types of systems is to detect the laser spot effectively. In [7], 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 avoiding the expenses of using special cameras and filters.

An alternative making use of standard and therefore cheaper cameras can be found in [12] where a set of algorithms, were proposed to detect the laser spot effectively on the image obtained by a standard video camera. Nevertheless, this algorithms present some 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. For this reason, in [13] we presented a new approach hybridizing a classic technique with the use of a Fuzzy Rule Based System (FRBS) designed from expert's knowledge [14], [15] for trying to improve the success rate in images without laser spot. Further, this initial FRBS was tuned in [16] by means of a Genetic Algorithm (GA), in order to improve the success rate in images without laser spot.

In this paper, we present a new approach to detect the laser spot in the environment device control system presented in [13], [16] by means of an evolutionary learning of the FRBS for the laser spot detection system. It consists on an embedded evolutionary learning of the Data Base (DB) as the way to effectively obtain a complete Knowledge Base (KB) and it is based on using the linguistic 2-tuples representation [17], which allows the lateral displacement of the labels considering an unique parameter per label, decreasing the complex search space that learning together the Rule Base (RB) and the Data Base (DB) represents. Using this particular representation, the search space is reduced with respect to the classic triangular Membership Functions (MFs) representation in order to easily obtain optimal models. The embedded learning scheme consists of an evolutionary process that learns the DB and wraps a simple method to derive a set of rules for each DB definition. This allows learning the most adequate context for each fuzzy partition (i.e., granularities and MFs displacements) together with the associated RB which will help to significantly improve the performance of the obtained FRBS for the laser spot detection problem. The results obtained by using the proposed approach on a big set of image samples (990 images in total) and following a cross-fold validation model show a better general success rate with respect to the previous techniques, and the most important advantage, the not desired false offs are virtually avoided.

This contribution is arranged as follows. In section II, the environment device system for environment control by using a laser pointer is described together with the previous approaches applied to solve this problem. Section III presents the evolutionary learning of a FRBS for the laser spot detection system used in this work. The results obtained using the classic technique, and the hybrid approaches based on the derivation of a FRBS from expert's knowledge, automatic tuning or automatic learning (respectively) are shown and analyzed by comparing them in section IV. Finally, section V points out some conclusions.

II. System Description and Previous Work

As we mentioned, the laser pointer systems allows 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):

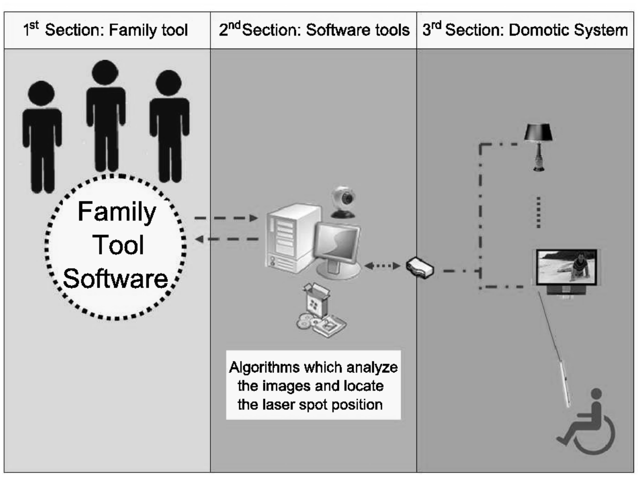

Fig. 1. Environment control system

- 1^{st} *Section*: The configuration tool allows to the users 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 [18] 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. In Figure 2, an example of images with and without laser spot is presented.

Fig. 2. Image with laser spot (top), Image without laser spot (bottom)

The algorithms previously used to detect the laser spot on an image have been the following:

1) Dynamic Umbralization (DU)
2) Template Matching (TM)
3) Template Matching + Dynamic Umbralization (TM + DU)
4) Template Matching + FRBS design from Expert's Experience and automatic evolutionary tuning (TM + FRBS).

The home environment control system based on laser pointer presented in [12] used three different classic algorithms, DU, TM and TM + DU. In [13] an initial hybrid model is proposed combining TM with a FRBS obtained from expert's experience, which is after improved by applying a genetic tuning of the FRBS membership functions in [16]. 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 [12], [13], [16]).

A. Dynamic Umbralization

Dynamic Umbralization 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 [12], [13] 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. 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 3 shows a template image example.

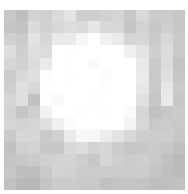

Fig. 3. Laser spot template

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 A contains the set of pixels which are in the principal image section, and B contains the set of laser template pixels (see [12], [13] 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 [12], [13] 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.

D. Template Matching + Fuzzy Rule Based Systems

In order to improve the results presented in [12], an hybrid approach between TM and FRBSs has been proposed for determining whether an image section provided by TM 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 [19] that can provide a positive or negative response for each analyzed image section.

A set of interesting system variables where proposed in [13] by analyzing some example images, with and without laser spots. These 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 value is over a threshold).

Once the input variables and their domains were defined, the expert defined useful rules and manually adjusted the membership function definitions for the detection task. The process to determine these variables as well as the finally proposed FRBS from the expert's experience can be found in [13].

The complete recognition task is therefore comprised of two main parts (algorithms). The first algorithm, TM, analyzes 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 proposed. This new combination of algorithms [13], namely $TM + FRBS_{expert}$, directly presented a better performance than the algorithms described in sections II-A and II-B as we can see in [13].

On the other hand, though that the new approach, $TM + FRBS_{expert}$, presented better results than the previous techniques, it can be further refined by performing a genetic tuning of the MFs [20], i.e., by means of a Genetic Algorithm (GA) [21], [22], 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) [23]–[25].

In this way a new approach, namely $TM + FRBS_{tuned-GA}$, was proposed in [16] to perform an automatic evolutionary tuning of the initial FRBS based on the existence of 105 image samples that were used for training the model. To perform the genetic tuning it was considered 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 were uniform mutation and the max-min-arithmetical crossover.

Once the GA optimizes the MF parameters of the initial FRBS ($FRBS_{expert}$), the new FRBS obtained ($FRBS_{tuned-GA}$) presented better results than the previous techniques used to detect the laser spot, as we can see in [16].

III. Template Matching and Evolutionary Learning of a FRBS for the Laser Spot Detection

In this section, we present a new approach considering the problem to detect the laser spot on an image. This is based on the use of a more advanced technique for a complete learning of the FRBS used to detect the laser spot in the image sections obtained by TM. Therefore, in this work we propose the TM technique in combination with the learning of the complete KB. Learning together the rules and the parameters of the MFs let us consider the interaction between both parts and therefore obtaining more accurate models. Nevertheless, this proposal represents a more complicated search space for the use of a initial RB obtained by an expert and further tuning technique [16].

In order to effectively apply this new approach to our concrete problem, we consider eight input variables: the variables used in the FRBSs presented in subsection II-D, plus 3 input variables which represent the laser spot color (Red, Green and Blue) and one output variable. Using this new approach we obtain a new FRBS named $FRBS_{learning-GA}$ which in combination with the TM technique gives way to a new hybrid approach, namely $TM + FRBS_{learning-GA}$.

In this way, this section presents a learning algorithm of the KB which can efficiently manage the search space. To do that, the learning scheme is presented in the next. Then, a model of representation of the BD is introduced, which decreases the search space with respect to the classical MFs triangular representations. Finally, a specific evolutionary algorithm is proposed, which is applied for machine learning of FRBSs from data.

A. FRBS learning scheme

In addition to the classical approaches, some new directions to apply genetic (evolutionary) techniques to FRBSs can be found in [25]: selection of fuzzy rules, feature selection, learning of KBs via genetic derivation of the DB, interpretability maintenance via multi-objective genetic processes, learning approaches considering different model structures, etc. These kinds of techniques try to find a better trade off between the efficiency of the learning/post-processing process and the dimensionality of the search space.

This is the case of the *learning of KBs via genetic derivation of DBs*, a recent approach involving a simpler search space than the classical learning of KBs. It consists of obtaining the DB and the RB separately, based on the embedded learning of the DB [26]–[29] (see Figure 4). This way to work allows us to learn the most adequate context for each fuzzy partition, which is necessary in different application contexts and different fuzzy rule extraction models.

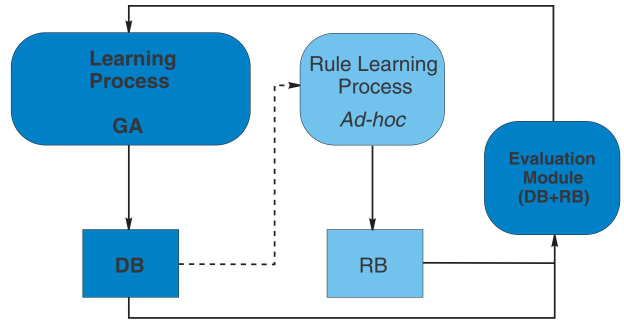

Fig. 4. Learning scheme of the KB

The learning scheme considered in this work belongs to this last group and is comprised of two main components:

- A process to learn the DB, which allows to define:
  - The number of labels for each linguistic variable.
  - The lateral displacements of such labels.

  Triangular membership functions are considered for their simplicity.
- A quick *Ad-hoc data-driven method* to derive the RB [30] considering the DB previously obtained. This method is run from each DB definition generated by a Genetic Algorithm (GA), thus, allowing the proposed hybrid learning process to finally obtain the whole definition of the KB (DB and RB) by means of the cooperative action of both methods.

B. The Linguistic 2-Tuples Representation

In [31], a new model of tuning of FRBSs was proposed considering the linguistic 2-tuples representation scheme introduced in [17], which allows the lateral displacement of the support of a label and maintains the interpretability associated to the obtained linguistic FRBSs. This proposal also introduces a new model for rule representation based on the symbolic translation concept that is a number within the interval [-0.5, 0.5) expressing the domain of a label when it is moving between its two lateral labels. Formally, we have the pair,

$$(s_i, \alpha_i), \;\; s_i \in S, \;\; \alpha_i \in [0.5, -0.5).$$

Figure 5 shows the lateral displacement of the label M. The new label "y_2" is located between B and M, being enough smaller than M but closer to M.

C. Evolutionary Algorithm

In this work, we will consider the use of CHC [32] to design the proposed learning algorithm. CHC is a GA that presents

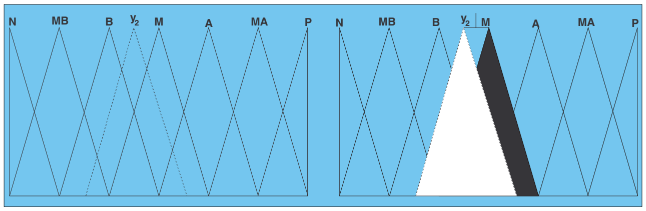

Fig. 5. Lateral Displacement of the Linguistic Label M

a good trade-off between exploration and exploitation, being a good choice in problems with complex search spaces. This genetic model makes use of a mechanism of "Selection of Populations". N parents and their corresponding offspring are combined to select the best N individual to take part of the next population.

Considering this approach, the learning process of the DB have to define both, the granularity of the linguistic partitions and the lateral displacements of the involved labels. For this reason, a double coding scheme is considered (granularity + displacements).

In the following, the components needed to design our FRBS are explained. They are: DB codification, chromosome evaluation, initial gene pool, crossover operator and restarting approach.

1) DB Codification: A double coding scheme ($C = C_1 + C_2$) to represent both parts, *granularity* and *translation parameters*, is considered:

- Number of labels (C_1): This part is a vector of integer numbers with size N (being N the number of system variables). The possible numbers of labels considered are the set $\{3, \ldots, 9\}$:

$$C_1 = (L^1, \ldots, L^N) \ .$$

- Lateral displacements (C_2): This part is a vector of real numbers with size $N*9$ (N variables with a maximum of 9 linguistic labels per variable) in which the displacements of the different labels are coded for each variable. Of course, if a chromosome does not have the maximum number of labels in one of the variables, the space reserved for the values of these labels is ignored in the evaluation process. In this way, the C_2 part has the following structure (where each gene is associated to the tuning value of the corresponding label):

$$C_2 = (\alpha_1^1, \ldots, \alpha_{L^1}^1, \ldots, \alpha_1^N, \ldots, \alpha_{L^N}^N)$$

2) Chromosome Evaluation: To evaluate a determined chromosome we will apply the well-known rule generation method of Wang and Mendel [30] on the DB coded by such chromosome. Once the whole KB is obtained, the following function is minimized:

$$F_C = w_1 \cdot FF + w_2 \cdot NR,$$

where:

- NR is the number of rules of the obtained KB (in order to penalize an excessive number of rules).
- $w_1 = 1$.
- w_2 is computed from the Mean Square Error (MSE) and the number of rules of the KB generated from a DB considering the maximum number of labels (9 labels) and without considering the displacement parameters,

$$w_2 = \alpha \cdot \frac{MSE_{max-lab}}{NR_{max-lab}} \ ,$$

with α being a weighting percentage given by the system expert that determines the trade-off between accuracy and complexity. Values higher than 1.0 search for linguistic models with few rules, and values lower than 1.0 search for linguistic models with high accuracy. A good neutral choice is for example 1.0 (good accuracy and not too many rules), but in this particular problem we use $\alpha = 1.15$.
- FF is the Fitness Function used to analyze the number of False Negative (FN) and False Positive (FP) obtained with the KB generated,

$$FF = \frac{|FN|}{|D|} + 10 \cdot \frac{|FP|}{|D|}$$

where $|FN|$ is the number of False Negatives obtained, $|FP|$ is the number of False Positives obtained and $|D|$ is the dataset size. Notice that the number of FPs is penalized in order to avoid the wrong orders to be sent to the domotic system.
For each input example, the FRBS must generate an output value into interval [0, 1]. If this value is higher than 0.5, the example will be classificated as a laser spot image, in otherwise, it will be classificated as image without a laser spot. Thus, an input example can be considered as:
  - FN: If the example is classified as an image without laser spot and it is a laser spot image.
  - FP: If the example is classified as a laser spot image and it is an image without laser spot.
  - Hit: If the example is correctly classified.

For the fuzzy inference, we have selected the *minimum t-norm* playing the role of the implication and conjunctive operators, and the *center of gravity weighted by the matching* strategy acting as defuzzification operator.

3) Initial Gene Pool: The initial population will be comprised of two different parts (with the same number of chromosomes):

- In the first part, each chromosome has the same number of labels for all the problem variables and considers strong fuzzy partitions with translation parameters initialized to zero.
- In the second part, the only change is that each variable could have a different number of labels.

Since CHC has no mutation operator, the translation parameters remain unchanged and the most promising number of labels is obtained for each linguistic variable. The algorithm operates in this way until the first restarting is reached.

4) Crossover Operator: Two different crossover operators are considered depending on the two parent's scope to obtain two offspring:

- *When the parents encode different granularity levels in any variable*, a crossover point is randomly generated in C_1 and the classical crossover operator is applied on this point in both parts, C_1 and C_2 (exploration).
- *When both parents have the same granularity level per variable*, an operator based on the concept of environments (the offspring are generated around one parent) is applied only on the C_2 part (exploitation). These kinds of operators present a good cooperation when they are introduced within evolutionary models forcing the convergence by pressure on the offspring (as the case of CHC). Particularly, we consider the Parent Centric BLX (PCBLX) operator [33], which is based on the BLX-α.
  The PCBLX is described as follows. Let us assume that $X = (x_1 \cdots x_n)$ and $Y = (y_1 \cdots y_n)$, $(x_i, y_i \in [a_i, b_i] \subset \Re, i = 1 \cdots n)$, are two real-coded chromosomes that are going to be crossed. PCBLX generates the offspring $Z = (z_1 \cdots z_n)$, where z_i is a randomly (uniformly) chosen number from the interval $[l_i, u_i]$, with $l_i = max\{a_i, x_i - I\}$, $u_i = min\{b_i, x_i + I\}$, and $I = \mid x_i - y_i \mid$. The parents X and Y will be named differently: X will be called *female parent*, and Y will be called *male parent*. In this way, by taking X as female parent (Y as male), and then by taking Y as female parent (X as male) our algorithm generates two offspring.
  On the other hand, CHC makes use of an incest prevention mechanism, i.e., two parents are only crossed if their hamming distance divided by 2 is over a predetermined threshold, L. It will be only considered in order to apply the PCBLX operator. Since, we consider a real coding scheme (the C_2 part is going to be crossed), we have to transform each gene considering a Gray Code with a fixed number of bits per gene ($BITSGENE$) determined by the system expert. In this way, the threshold value is initialized as:

$$L = (\#GenesC_2 * BITSGENE)/4.0.$$

Following the original CHC scheme, L is decremented by one when no cross is performed in one generation. In order to avoid very slow convergence, in our case, L will be also decremented by one when no improvement is achieved respect to best chromosome of the previous generation.

5) Restarting approach: To get away from local optima, a restarting mechanism is considered [32] when the threshold value L is lower than cero. In this case, all the chromosomes set up their C_1 parts to that of the best global solution, being the parameters of their C_2 parts generated at random within the interval [-0.5, 0.5). Moreover, if the best global solution had any change from the last restarting point, this is included in the population (the exploitation continues while there is convergence). This operation mode was initially proposed by the CHC authors as a possibility to improve the algorithm performance when it is applied to solve some kinds of problems [32].

IV. Experimental Results

To evaluate the usefulness of the approaches proposed in the previous sections, we have considered the previous environment control system presented in [12]. In order to have a performance measure and to perform the automatic tuning [16] and learning, we extend the 105 example images used in [16] with a big set of data containing 990 images. This set of images has been randomly divided in 5 subsets with the 20 % of the images for each. Applying 5-fold cross-validation method we obtained 5 different sets of images with 792 images for training and 198 images for test.

Table I presents a brief description of the studied methods.

The parameters for the methods $TM + FRBS_{expert}$ and $TM + FRBS_{tuned-GA}$ were selected according to the recommendation of the authors in [13] and [16]. Notice that in the $TM + FRBS_{tuned-GA}$ algorithm, the number of evaluation used by the GA in the tuning process was 50000. The values of the input parameters considered by our proposal are shown in the next:

- Evaluations = 50000
- Population size = 50
- Bits per gene = 30.
- α factor = 1.15

Table II presents the results of $TM + UD$ algorithm using the new set of 990 images divided in 5 subsets and with similar configuration that the algorithm presented in [12].

Tables III and IV show the $TM + FRBS_{expert}$ and $TM + FRBS_{tuned-GA}$ results using the new set of 990 images, with similar input parameters which were presented in [13] and [16] respectively. We can see that classic techniques $TM + UD$ are better than $TM + FRBS_{expert}$ and $TM + FRBS_{tuned-GA}$ using a big set of images. This is due to that the classic technique works with heterogeneous data like brightness and luminosity, otherwise, the FRBS developed by the expert and tuned by GA works with data of the appearance of the image like similarity of circle, etc. This kind of data is useful when we work with learning algorithms, where they are used in corporate form. For this reason, we have combined the classic technique TM with the learning algorithm, obtaining the new hybrid algorithm named $TM + FRBS_{learning-GA}$, the results are the best (see Table V).

We can see that the percentage of success rate in images with laser spot is 70.50 % and in images without laser spot is 98.76 %, very close to 100 %, the optimal success rate.

V. Conclusion

In this paper a new hybrid technique combining Template Matching and an evolutionary learning of the FRBS to detect a laser spot in a home environment is presented. Thanks to the system developed in conjunction with a standard domotic system, we provide a more user-friendly and less expensive home device control environment.

TABLE I
TECHNIQUES USED IN THE EXPERIMENTS

Ref	Method	Year	Description
[12]	$TM + DU$	2008	Template Matching plus Dinamic Umbralization (described in Section II-C)
[13]	$TM + FRBS_{expert}$	2010	Template Matching plus FRBS design from Expert's Experience (described in Section II-D)
[16]	$TM + FRBS_{tuned-GA}$	2010	Template Matching plus FRBS design from Expert's Experience and tuned by GA (described in II-D)
Our proposal	$TM + FRBS_{learning-GA}$		Template Matching plus learning FRBS as explained in Section III.

TABLE II
RESULTS OF $TM + UD$

	Training		Test	
	Average	Standard Deviation	Average	Standard Deviation
General Success Rate	83.48 %	0.01206	83.54 %	0.04705
Success Rate with Laser Sopt	67.86 %	0.01575	68.13 %	0.05705
Success Rate without Laser Spot	98.32 %	0.00481	98.36 %	0.01647

TABLE III
RESULTS OF $TM + FRBS_{expert}$

	Training		Test	
	Average	Standard Deviation	Average	Standard Deviation
General Success Rate	78.59 %	0.01229	78.59 %	0.04917
Success Rate with Laser Sopt	66.21 %	0.01845	66.52 %	0.06770
Success Rate without Laser Spot	90.35 %	0.00821	90.30 %	0.03226

TABLE IV
RESULTS OF $TM + FRBS_{tuned-GA}$

	Training		Test	
	Average	Standard Deviation	Average	Standard Deviation
General Success Rate	75.80 %	1.81965	74.97 %	5.03560
Success Rate with Laser Sopt	51.44 %	3.59527	50.51 %	6.84627
Success Rate without Laser Spot	98.91 %	0.33398	98.35 %	1.34530

An experimental study on a big set of image samples (990 images in total) of the previous algorithms used to detect a laser spot on an image versus the new approach using the evolutionary learning of the FRBS is presented in this paper. We can see how the proposal method has better results than other approaches. However, the most important result is that the new approach has a 98.76 % of success rate in images without laser spot, very close to 100 %, where the false offs will be completely eliminated.

The new approach presented in this paper is particularly useful for remote acting on home devices, the user can reach any device in sight. Moreover, we think the results show the usefulness for any environment where devices are not easily reachable by the user, industrial operation, for instance.

ACKNOWLEDGMENT

This work has been supported by the Spanish Ministry of Education and Science under project TIN2008-06681-C06-01 and National Nohnes project TIN2007-68083-C02-01, and by the University of Extremadura, regional government Junta de Extremadura, Consejería de Economía-Comercio e Innovación and FEDER, under project GRU09105.

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TABLE V
RESULTS OF $TM + FRBS_{learning-GA}$

	Training		Test	
	Average	Standard Deviation	Average	Standard Deviation
General Success Rate	87.27 %	0.78990	84.92 %	2.90425
Success Rate with Laser Sopt	73.87 %	1.28823	70.50 %	4.48146
Success Rate without Laser Spot	100 %	0.00000	98.76 %	1.14364

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