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Hybrid laser pointer detection algorithm based on template matching and fuzzy rule-based systems for domotic control in real home environments

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Abstract A fundamental problem for disabled or elderly people is to manage their homes while carrying out an almost normal life, which implies using and interacting with a number of home devices. 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.

This paper proposes a hybrid technique, where a classic technique used in image detection processes, such as Template Matching, has been combined with a Fuzzy Rule Based System for detecting a laser spot in real home environments. The idea is to use this new approach to improve the success rate of the previous algorithms used for detecting the laser spot, decreasing as much as possible the false offs of the system, because, the detection of a false laser spot could lead to dangerous situations.

Using this new hybrid technique a better success rate has been obtained, eliminating almost completely the possibility of dangerous situations that may occur due to incorrect detection of the laser spot in real home environments.

Keywords Fuzzy rule based systems · Template matching · Laser pointer detection · Disabled people · Domotic control systems

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1 Introduction

Around 500 million people, which represents about 10% of the world's population, suffer some kind of disability. Two thirds of this group live in under-developed countries. Moreover, due to the increase in life expectancy, a steady growth of the elderly population is expected, and developed countries are also facing the problem: 20% of their citizens today suffer from some kind of physical handicap [23]. According to the World Health Organization, there are around 600 million people aged 60 years and over, and this total will double in 2025 and will reach virtually two thousand million in 2050—the vast majority of them in the developing world [24]. Important challenges are thus arising for the coming decades: to meet the higher demand for healthcare while improving life conditions.

A fundamental problem for disabled or elderly people is to manage their homes while carrying out a normal life, which implies using and interacting with a number of home devices. Developing accessible homes is thus of paramount importance for this group. Recent research on smart homes [7, 14–16, 26, 28, 35, 40–42, 45] show the convenience of developing systems that integrate domotic systems for helping disabled and elderly people at home. Disabled people can thus control their home appliances and other home devices. Furthermore, they can be monitored by their family when using this kind of system: information about their behavior or dangerous situations that might arise can be sent to family members.

A complete review of Smart Homes is presented in [7, 26, 35] showing the great evolution of this technology in the last few years. Smart homes integrate sets of sensors, cameras, computer based technologies, vision systems, IR sensors and robots, which are at this moment too expensive for the end users. In [14], a robotic smart home is presented: a disabled person is helped by a robot which picks up different objects previously indicated by the user by means of a laser pointer.

The idea of using laser pointers for interaction purposes is not new. They have been used for some time now as an indicator element for interacting with large displays [29, 37, 39, 53]. In these works, the algorithms detect the laser spot in a controlled environment, with optimum light conditions, without reflections and inclinations with the cameras focused on the large displays, but these situations are not applicable in a real home environment.

In [14], the authors deal with this problem by using optical filters in special video cameras in charge of collecting environmental images, with the aim of easing detection of the laser spot. However, this is an on-going problem that can be addressed by using laser spot detection algorithms based on the original non-filtered images, i.e. by using standard and non expensive cameras, without the necessary optical filters. Furthermore, improving basic detection algorithms will also improve results regardless of the optical system employed. This is the main contribution of this paper, to provide a new laser spot detection system, which, in conjunction with a standard domotic system, will enable a more friendly home environment.

We addressed a similar problem when trying to improve domotic systems for disabled people. Some of our previous work [15] has analyzed a number of algorithms aimed at detecting the laser spot effectively on the image obtained by a standard video camera. Nevertheless, the false offs detected are crucial problems to be fixed when interacting with home devices: when a false laser spot is detected by the algorithm an incorrect order is sent through the domotic system which could produce undesirable, dangerous or at least unexpected, situations.

In this paper, we present a new approach to detect the laser spot in the environmental device control system. It consists of the combination of Template Matching (TM) [20] with Fuzzy Rule Based Systems (FRBSs) [19, 33, 34, 51, 52] for trying to improve the success rate of images with a laser spot, while also trying to completely avoid the false offs of the previous systems. This kind of system allows easy adaptability to the problem at hand. With classic techniques the system only works with exact values, but this kind of systems works with labels which allow the use of values similar to human language. With FRBS it is possible to quantify values as low, medium, high, similar, etc., this being the main advantage of this kind of systems. This main characteristic allows the derivation of a system from human experience, representing an alternative when a good set of training data is not available (which is our case).

With this new hybrid technique TM + FRBS, TM will be applied on complete images to extract a candidate image section and the FRBS will determine whether the proposed section is a laser spot image or not.

The FRBS presented in this paper has been designed by an expert, due to the particularly problematic conditions. There is not enough information about the system to automatically learn the fuzzy rule set and the Membership Functions (MFs) needed to correctly detect the laser spot. Consequently, it was developed thanks to expert knowledge of the problem. Results show the benefits of this technique, with noticeable improvements in the success rate compared to the previous systems.

This new system allows disabled people to have at their disposal a system with reduced cost because it will detect the laser spot by software, without the need for special hardware equipment or optical filters.

The system presented in this work can be used by disabled or elderly people, but we must to differentiate what kind of people will adapt better to the system. Disabled people can be divided in 6 big groups, people with physical, sensory, cognitive or intellectual disability, people with mental or psychosocial illness and people with chronic illness. On the other hand, older people may have a degenerative disease, Alzheimer, sensory diseases, etc. It should be noted that any person cited previously can have a limit or basic intellectual function, or intellectual function zero. Thanks to the simplicity of using the system, any disabled or elderly people with limited or basic intellectual function can use it. On the other hand, physically disabled people could have some limit to use the system, but nowadays, there are a lot of devices adapted to physical disabled people as mouses, keyboards, screens even bikes, cars, etc. The system needs a laser pointer to indicate the device which could be easily adapted for physically disabled people. Finally, although this work is focused for people with disabilities, it can also be used as general purpose.

This contribution is arranged as follows. In Sect. 2 the problem of using a laser pointer as a pointer device is described. The home environment control system and the previous algorithms applied to this problem are described in

Sect. 3. The definition of the FRBS developed, as well as its combination with TM, are presented in Sect. 4. The results obtained by the proposed technique are analyzed and compared to the previous proposal in Sect. 5. Section 6 makes some conclusions. Finally, Appendix shows the list of acronyms used in this paper.

2 Laser pointer as a pointer device

In this section a short review of the previous systems is presented. Usually, these works present different uses of a laser pointer on a large display and on systems to help disabled people.

The papers presented in [3, 10–12, 18, 29, 30, 36, 37, 39, 46, 50, 53] use a laser pointer as a pointing device on large displays. The aim of these works is to be able to control the different objects presented on a large display. The laser pointer was used in the same way as the mouse cursor. Thanks to the laser pointer, users can interact directly with objects projected on the screen.

Different techniques have been used for solving the problem and detecting the laser spot, such as threshold value, pattern recognition, color analysis, etc. Kirstein and Müller used an algorithm divided into three phases for detecting the laser spot. The algorithm phases were, Motion Detection, Pattern Recognition and Histograms Comparison [30]. By means of these techniques, the laser spot is detected only on a 50% of the frames.

The works presented in [3, 11, 12, 18, 32, 37, 39, 53] used an algorithm only based on threshold value. These algorithms can classify the brightest pixels using a threshold value calculated previously. This set of classified pixels could be the laser spot pixels. But these algorithms have similar results to the algorithm referred to above.

A different technique for detecting the laser spot is presented in [29]. This algorithm uses different color systems, such as Red, Green and Blue (RGB) and Hue, Saturation and Intensity (HSI) systems, for detecting the laser spot on an image. A video-camera takes a color image in the RGB system. The algorithm changes the color system to the HSI system. By means of a segmented function, the laser spot is detected.

The main problem in these previous works is that light conditions, inclinations and textures are controlled and fixed. For example, the laser spot can not be detected correctly with high brightness light on the displays.

On the other hand, since the previous approaches typically present many false offs, special cams including optical filters have also been used. In [18] the authors used wavelength bandpass filters together with several video-cameras for detecting the laser spot. In [12] and [53] a red filter is applied to the video-camera to try to solve the false off. With the Homography technique, several video-cameras and several computers are used in [3] to try to detect the correct laser spot position. In [29] a laser filter is used to improve the efficiency of the algorithm. Finally, in [11] and [39] a set of images is analyzed and compared to try to eliminate the false offs. We can observe that the laser spot is located not only by software, the Authors use special filter cameras, several computers, and other intrusive techniques for detecting the laser spot. Furthermore, in the most of the cases the algorithms work in controlled light environment conditions. In this setting, it is easier to locate the laser spot than in a real home environment, where the brightness of light conditions are almost impossible to control, and the algorithms have to solve incontrollable situations.

Recent research has attempted to integrate a domotic system in the home to help disabled and elderly people. These are known as smart homes [7, 14–16, 26, 28, 35, 40–42]. The most relevant work is found in [14], where a robot will pick up the object indicated by the user with a laser pointer. This is a similar technique to the technique presented in this paper, but the robot uses especial physical filters in the video camera for filtering the images and detecting the laser spot.

Our main contribution in this paper is a new robust algorithm for effectively detecting a laser spot on an image, together with a system to control the home devices selected by the user. The system presented removes the need for the special equipments employed in the works referred to above, such as camera filters, several video-cameras or other invasive techniques. Thanks to the new system presented in this paper, disabled and elderly people have at their disposal a system with which they will be able to control the different home devices easily with a laser pointer cheaper than those previously presented.

3 Preliminaries: system description and starting point

The environment device control system by a laser pointer for disabled and elderly people is described in-depth in this section. Furthermore, the previous techniques applied to this particular system [15] are also described as the starting point on which we should improve. These techniques are:

- Dynamic Umbralization (DU).
- TM.
- TM plus DU.

3.1 System description

The system is divided in three sections, Family Tool Section, Algorithms Analyzer and Domotic Control System. Figure 1 shows the different system sections. In the following subsections we describe in detail each system section.

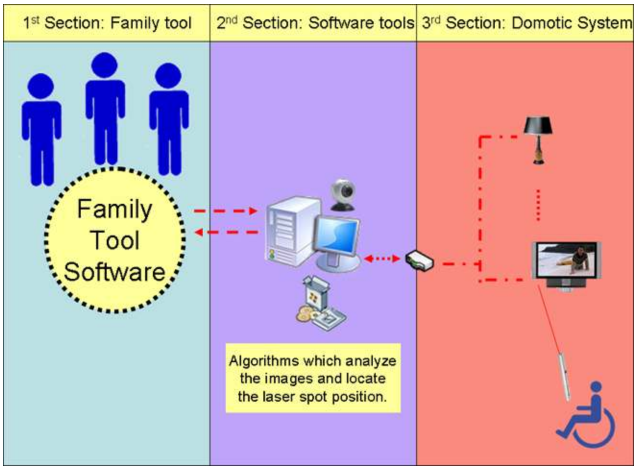


Fig. 1 Environment control system

3.1.1 Family tool

The first action to use the system must be carried out by Family members or Teachers. They have to indicate where the devices are, which will be handled by the domotic system. For this, there is an especial software tool for the family members. By means of this tool, a fixed video camera in an home environment takes an image and sends to the computer. This image is shown in a tool and the user (family member or teacher) marks, by using a simple click method, the devices that will be handled by the domotic system. The subsequent marked image is known as an "active zone". Therefore, an active zone is a set of pixels which contains information on the positioning of the devices. Previously, the domotic system must be configurated by an expert, whom will indicate how many home devices will be handled and the type of each device. When the active zone has been marked, the user must select a device of the list of devices previously defined by domotic system expert. Whit this action, the active zone will be matched with the home device and the system has information on the positioning of this device.

Once the actives zones have been marked, a disabled or elderly person can indicate what device he/she wants to use by a laser pointer. The system will analyze the actives zones previously indicated, and if on an active zone the laser spot is found, the domotic system will handle the home device associated.

Finally, if a home device or camera is changed within a given environment then the active zones must be recreated so that they are updated by the system.

3.1.2 Algorithms analyzer

The second section of the system is the algorithm which will analyze the images sent by the fixed video camera and locate the position of the laser spot. By means of the laser pointer the user selects the device he wants to use. The laser pointer makes a red or green spot on the device. The video camera sends the environmental image with the laser spot information and the computer analyzes this image and locates the laser spot. If the laser spot is on an active zone, the user wants to use the device marked in this zone, and finally, the computer sends the necessary orders to turn on/off this device using the domotic system.

The video camera used by the system is an Axis 207W video camera. This camera has 1.3 Megapixels with an image sensor of $1/3''$ Micron progressive RGB CMOS, lens dimensions of 3.6 mm/F1.8 and 2–10000 (Lux). The laser pointer used is a green laser pointer *class III* with maximum power < 5 mW and wave length of 532 nm.

In some of our previous works, a number of algorithms aiming at detecting the laser spot on the images sent by the camera were employed and analyzed [15]. These algorithms are presented in the following section.

3.1.3 Domotic control system

The third section of the system deals with the devices controlled by the domotic system using KNX/EIB architecture [22]. Once the laser spot is found and it is in an active zone, the system sends different orders to turn on/off the device associated with this active zone, to the domotic system. But the system can be configurated to do more complex actions. Depending of the final user, the complex functions of the home devices can be encoded differently. For instance, if the final user is a person with physical disability, a panel close to the device to handle will be put. This panel could have four sections, Volume, Channel, $+$ and $-$, indicating the user the complex action for the TV on the panel. Other possibility could be including different active areas on a single device, thus allowing largest set of actions. However, if the final user has best skill, the system could analyze gestures users, tracking the laser pointer.

3.2 Algorithms and methods based on dynamic umbralization and template matching

The algorithm DU is the first algorithm used. This algorithm is based on umbralization [44], and tries to find high energy pixels generated by a laser spot within the image. The second algorithm used was TM [13]. This algorithm is used to find a laser template—previously calculated—on the image. Finally, we use a new joint process algorithm which joins both previous algorithms, TM and DU. Using this new algorithm we have achieved a more stable environment control system for disabled people by using a laser pointer [15]. In the following section, these techniques are presented.

3.2.1 Dynamic umbralization

DU algorithm is based on umbralization [44], which is a technique frequently used to locate information on an image using a threshold value.

This technique calculates a value known as a threshold value. This value is used to eliminate the image information over or under it. With this technique, the relevant information of an image can be separated, that is, the laser spot information.

The steps we took in the procedure are the following. We analyzed a set of images with and without laser spot pixels, and discovered that the laser spot pixels have their own characteristic information. These pixels, as we discovered, have lower numerical information, due to high energy. We used a static threshold value which could eliminate all pixels without laser spot information. The results were positive; the algorithm could locate the laser spot on the image. The next step was to change the light conditions. Depending on different light conditions the threshold value calculated was not the ideal. Therefore, we calculated a dynamic threshold value using four parameters extracted from the image. The parameters taken from the histogram included the largest value, a percentage of the largest value and the average and the sum of the pixel numerical information, thereby giving us a more dynamic umbralization. With these parameters we could calculate a different threshold for each image sent by the video camera.

For a more precise evaluation we divided the parameter values from the smallest and largest values in six intervals represented in [15].

The first step is to calculate the histogram. This histogram is calculated using a color environmental image sent by the video camera. For each pixel, the algorithm takes the integer value of the pixel and this value is divided by 256. The histogram is represented by a vector with 256 positions. The vector position corresponding to the remainder calculated in the previous division is incremented by one, so it generates the histogram of the image.

The next step is to calculate the percentage of the largest value histogram intervals [15] by using the following expression:

$$percentage = \frac{largest\ value * 100}{weight_{image} * height_{image}} \tag{1}$$

Once the intervals where the different parameters are were calculated, we divided the intervals into three different sub intervals and checked where each parameter value was within these three sub intervals. In order to find where the parameter value was within the sub intervals, we established Table 1.

The parameter values are of varying importance within the dynamic umbralization calculation. The importance of this is shown in Table 2.

Table 1 Sub intervals balance

Level	Balance
Low (0%–33%)	0
Middle (33%–66%)	1
High (66%–100%)	2

Table 2 Parameters balance

Parameter	Balance
% largest value of the histogram	$4 *$ *sub interval balance*[a]
Largest value of the histogram	$3 *$ *sub interval balance*[a]
Average	$2 *$ *sub interval balance*[a]
Sum	$1 *$ *sub interval balance*[a]

[a]The sub interval balance is obtained by applying the criteria in Table 1 for each parameter

Once the interval parameters have been obtained, we must take the smallest interval (I_{min}) and the largest interval (I_{max}) previously calculated. With these two numbers we can obtain the rate of umbralization as we can see in Table 3.

The final threshold value is calculated by applying the following expression.

$$V_{umb} = \left(((Sv\_I_{max}) - (Sv\_I_{min})) * \frac{X}{20} \right) + (Sv\_I_{min}) \tag{2}$$

Where X is the sum of the balance parameters obtained when applying Table 2, Sv_I_{min} is the lowest value of I_{min} interval corresponding to Table 3 and Sv_I_{max} is the highest value of I_{min} interval corresponding to the same table.

The threshold value is calculated for each image sent by the video camera. With this operation the threshold value changes in real time, depending on the light conditions.

The DU algorithm eliminates all pixels under the V_{umb} calculated. The pixels which have not been eliminated are the laser spot pixels.

To measure the effectiveness of the algorithm used in DU we performed several experiments using the algorithms [15]. We used two kinds of laboratory controlled environments, one with optimum light conditions using normal-low light, and another with non-optimum light conditions using intense light. In the second condition, there are many reflections which the system interprets as pixels with high energy, as if they were laser spot references. Figure 2 shows the optimum and non-optimum light conditions.

In non-optimum light conditions and in images with reflections, the DU algorithm had false offs. Figure 3 shows an example of a laser spot and a false off located.

Trying to eliminate the false off we used the TM technique. Instead of analyzing the pixel information, this technique tries to find a template laser, previously calculated, on the image sent by the video camera.

Table 3 Umbralization intervals

Interval 0	Interval 1	Interval 2	Interval 3	Interval 4	Interval 5
0	$2 * 10^6$	$4 * 10^6$	$6 * 10^6$	$8 * 10^6$	$10 * 10^6$
$2 * 10^6$	$4 * 10^6$	$6 * 10^6$	$8 * 10^6$	$10 * 10^6$	$12 * 10^6$

Fig. 2 Light conditions

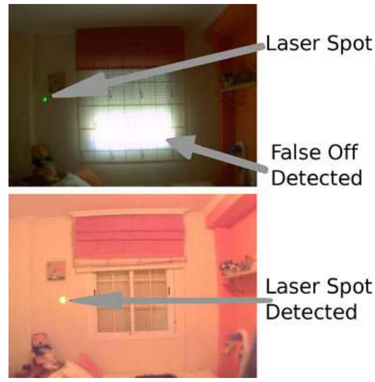
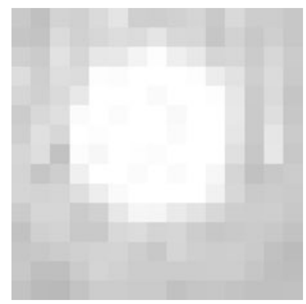


Fig. 3 Success and false off using the DU algorithm

Fig. 4 Template laser spot



3.2.2 *Template matching*

This technique is based on locating a template which is on an image. This algorithm analyzes small image sections that are compared with the template which it wants to find. In this operation the correlation between the image section and the template is calculated. Using the pattern search technique [44] the algorithm can find a template for the whole image. Figure 4 shows a template laser used by the algorithm.

The kind of measure used to calculate the correlation values between the template and the image is known as Zero Mean Normalized Cross Correlation (ZMNCC). The value obtained with this kind of correlation is normalized between −1 and 1 [20] and [38]. The expression is as follows:

$$\Phi(I_r, I_l) = \frac{\sum_{i,j\in[-w,w]} AB}{\sqrt{\sum_{i,j\in[-w,w]} A^2 \sum_{i,j\in[-w,w]} B^2}}$$
$$A = I_r(x+i, y+j) - \overline{I_r(x,y)}$$
$$B = I_l(x'+i, y'+j) - \overline{I_l(x',y')} \tag{3}$$

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.

In order to use this technique, a set of templates must be previously calculated. The algorithm to calculate the set of templates is divided in two sections:

1. Section 1: The algorithm takes 30 images of a laser spot on a white surface.
2. Section 2: The algorithm calculates an average image with the images previously taken.

To calculate the set of templates it is necessary a video camera fixed in a specific location and focused on a white surface. A laser spot is then drawn on this surface with a laser pointer. A snapshot image is then taken every 0.5 seconds, ending with a total of 30 images. With these 30 images the system calculates an average image in the second step. With the average image we eliminate the CCD noise of the video camera. This average image is the resulting template. This process is carried out between 2 and 5 meters from the video camera to the surface and with different light conditions. Once the process has finished, we obtain the set of templates used by TM algorithm to search the laser spot in the images sent by the video camera.

The TM algorithm consists on a process to calculate the correlation value between a section of the image sent by the video camera with a similar size to the templates used. The system uses different templates depending on the environmental conditions. There are two parameters to chose the correct template, the distance and the light condition. The distance between the video camera and the home devices is known by the system, because for each zone, the user has to indicate the distance between the camera and the home devices. On the other hand, the lights conditions depend on the system operating hours and the a luminance image analysis.

Using the expression (3) the TM algorithm obtains the correlation between an image section and the template used. 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. With both sets of pixels the correlation value is calculated and saved in a vector together with the coordinates which appear in the center of the main image section. Using a convolution technique the algorithm can analyze the whole image sent by the video camera. Finally, all correlation values are saved in a vector together with the analyzed image coordinates, thereafter it extracts the highest value. Generally, the template which is searched for can be found in the coordinates which have the highest values.

With this new improvement we eliminate DU false offs, thereafter obtaining better results than when using the previous algorithm.

TM obtains better results than DU, however the new algorithm now has new false offs [15]. This is due to the fact that it may interpret small component devices like buttons, LEDs, circular reflections on devices, etc., as laser spots. An example of a false off obtained with TM algorithm can seen in Fig. 5.

To eliminate false offs in both algorithms we developed a new algorithm to join the two techniques.

3.2.3 Combining template matching & dynamic umbralization techniques

This method combines the advantages of TM and DU. This algorithm analyzes only the active zones. For each active zone it searches a template and obtains a maximum correlation value. A section of the active zone of 15 × 15 pixels is taken where the highest correlation value was found. This section has a similar size to the template used. In this new image the laser spot could be found, being necessary that it has high energy output. In the following step we use DU to check these pixels. If they have high energy, we can say that the laser spot can be found here, because this section is very similar to a template. The process is shown in Fig. 6.

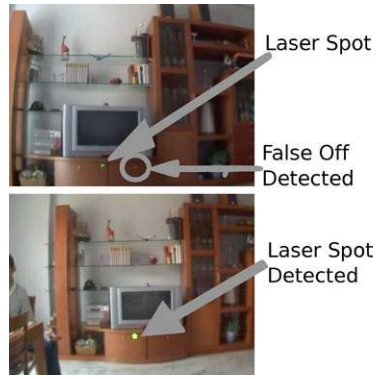


Fig. 5 Success and false off using the TM technique

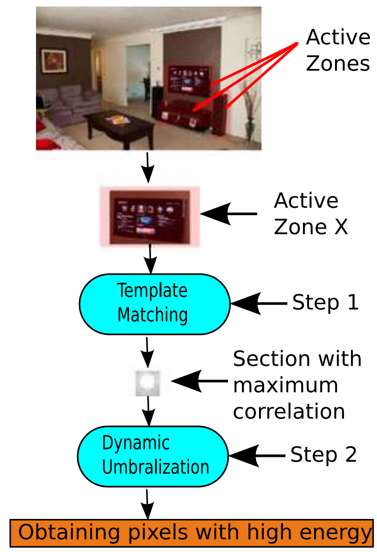


Fig. 6 Description of TM + DU

The results of this new approximation are presented in Sect. 5.

4 Fuzzy rule based system for the domotic system

In Sect. 3 the previous algorithms used classic techniques to detect the laser spot. The false offs of this system indicate to us that these algorithms have to improve. If the algorithm has several false offs, a dangerous and uncontrollable situa-

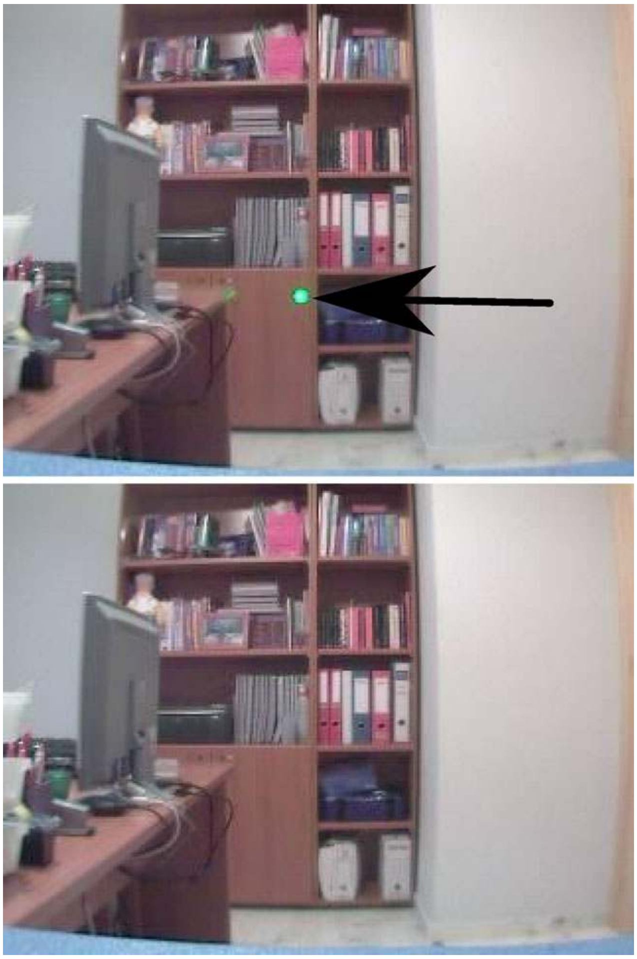


Fig. 7 Image with laser spot (top), Image without laser spot (bottom)

tion may arise, because an incorrect order will be sent to the domotic control system.

The main aim of this work is to design and develop a system which will try to avoid the false offs of the previous systems and to increase the general success rate. The problem in detecting a laser spot on an image is that we do not have enough data to learn it automatically. For this reason, we have considered an FRBS [19, 33, 34, 51, 52]. The proposed FRBS rules will be designed by an expert since in this case the expert knowledge will be beneficial to the system.

4.1 Methodology based on FBRSs

The first step is to obtain a set of variables, which will be extracted by analyzing a set of images, with and without laser spots. Thanks to an expert experience and a complete study of the histograms of laser spots and non laser spots images, the expert can determinate the correct set of characteristics which can differentiate images with laser spot and images without laser spot. In Fig. 7, an example of images with and without a laser spot is presented.

The most interesting characteristic is that the laser spot pixels should present high energy in any image. The pixel 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 have been considered by the expert as the most important properties of a laser spot image. Taking these characteristics as the starting point, we have to obtain a number of variables which can describe the characteristics of the laser spot on an image for detecting it correctly.

In the next section, we describe the definition of these variables as a part of the evolution of the FRBS developed by the expert, from the initial FRBS to the final FRBS proposed in this paper.

1. $FRBS_{init}$: Initial FRBS which uses 6 variables to detect the laser spot (five inputs and one output).
2. $FRBS_{tuned}$: Final FRBS which uses 6 variables to detect the laser spot where the MFs have been tuned to improve the results (five inputs and one output).

The fuzzy rule set for each of these two systems comprised of the following type of rules:

if X_1 is A_1 and ... and X_n is A_n THEN Y is B

where $X_i(Y)$ are the input (output) linguistic variables, $A_i(B)$ are the linguistic labels used in the input (output) variables.

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 [17].

More complete information on the inference process of FRBSs can be found in [8, 19] and [47], where FBRSs are explained in detail. The FRBS presented in this paper uses Mamdani-type rules and as it can be seen from the previous description the defuzzification method is based in mode B: Defuzzification First, Aggregation After. An example of this kind of fuzzy inference system is shown in [4–6] and [21] for the control of a Heating, Ventilating and Air Conditioning System. FRBSs are used in processes such as, industrial control [49], robotics control [2] or control in communications [9].

4.1.1 An initial FRBS ($FRBS_{init}$)

$FRBS_{init}$ uses the following 6 variables to try to detect the correct laser spot,

- X_1: bell amplitude near the 255 value in the image histogram.
- X_2: bell height previously calculated.
- X_3: Long standard deviation.
- X_4: Cross standard deviation.

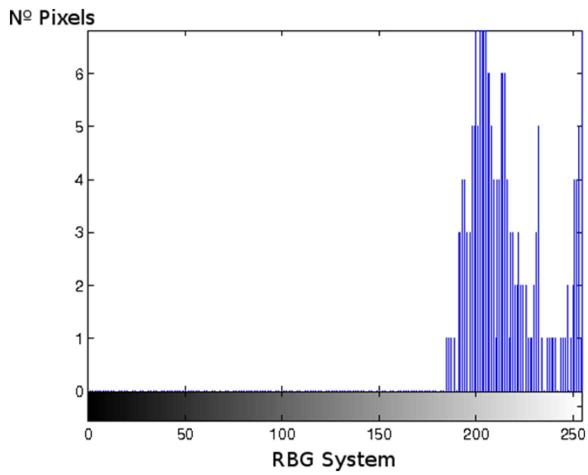


Fig. 8 Laser spot image histogram

- X_5: Similarity to perfect circle value.
- Y: Laser spot probability.

Figure 8 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 indicates that the image has a section with high energy pixels, the pixels close to the 255 value.

Every FRBS referred to above uses a previous algorithm to extract the variable's values. The algorithm calculates the amplitude of the bell corresponding with the pixel near to the 255 value of the histogram, and its height (variables X_1 and X_2). With X_1 variable can be determined if there are some pixels in 255 value in the histogram. With X_2 variable can be determinated how many pixels there are close to the 255 value in the histogram. These variables are very important to determinate if there are pixels with high energy.

In the next step, the algorithm tries to eliminate all non-laser pixels in the image. Once the non-laser pixels have been eliminated, the image only has 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 (variables X_3 and X_4). Figure 9 shows the laser spot standard deviations obtained. To obtain the standard deviation values, the diameters shown in Fig. 9 have to be obtained. Once, the diameters are obtained, the standard deviations are 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 expression (3)), the main image and the image generated are compared. The correlation between these images is the similarity to a perfect circle (variable X_5), which also represents an input variable.

The variables X_3, X_4 and X_5 indicate if the candidates laser pixel are similar to a circle, the second characteristic of a laser spot image.

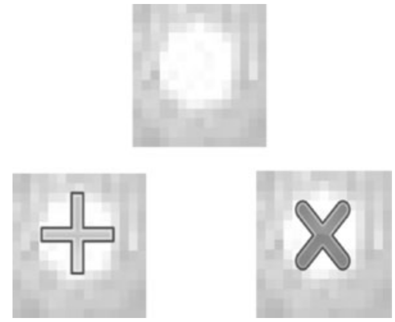


Fig. 9 Laser spot (*top*). High and long standard deviation (*bottom left*). *Cross circle* standard deviation (*bottom right*)

The algorithm explained previously extracts 5 variables which represent the characteristics of a laser spot image. With these 5 variables, the FRBS will try to determinate if the images analyzed are laser spot images or not.

4.1.2 *Final FRBS ($FRBS_{tuned}$)*

Once the $FRBS_{init}$ was developed the results indicated that the system could be improved. In the next approximation, the algorithm to eliminate non-laser pixels was adjusted and improved. A new variable was added, laser spot number of pixels. This variable stores the number of candidate laser pixels. Finally, the bell amplitude near the 255 value in the image histogram and the previously calculated bell height variables are eliminated from the system.

A new adjustment to the algorithm to eliminate non-laser pixels was made. In this new adjustment we used the percentile 80 of the histogram distribution. With this value, the algorithm can eliminate all pixels of the histogram distribution with low energy, and only pixels with high energy will not be eliminated, independently of whether this set of pixels is close to the 255 value in the histogram. We observed that the value of percentile 80 is an important variable for the FRBS; for this reason, in the next approximation it is added as a new variable.

Finally, in the final FRBS ($FRBS_{tuned}$) designed by the expert, the MFs corresponding with the variables X_3 and X_5 are changed to triangular MFs and are newly adjusted by the expert. The results show that with the percentile 80 variable, together with this new adjustment in the triangular MFs, we have developed a robust FRBS to detect a laser spot on an image.

The set of variables in $FRBS_{tuned}$ are:

- X_1: Long standard deviation.
- X_2: Cross standard deviation.
- X_3: Similarity to perfect circle value.
- X_4: Laser spot number of pixels.
- X_5: Percentile 80 value.
- Y: Laser spot probability.

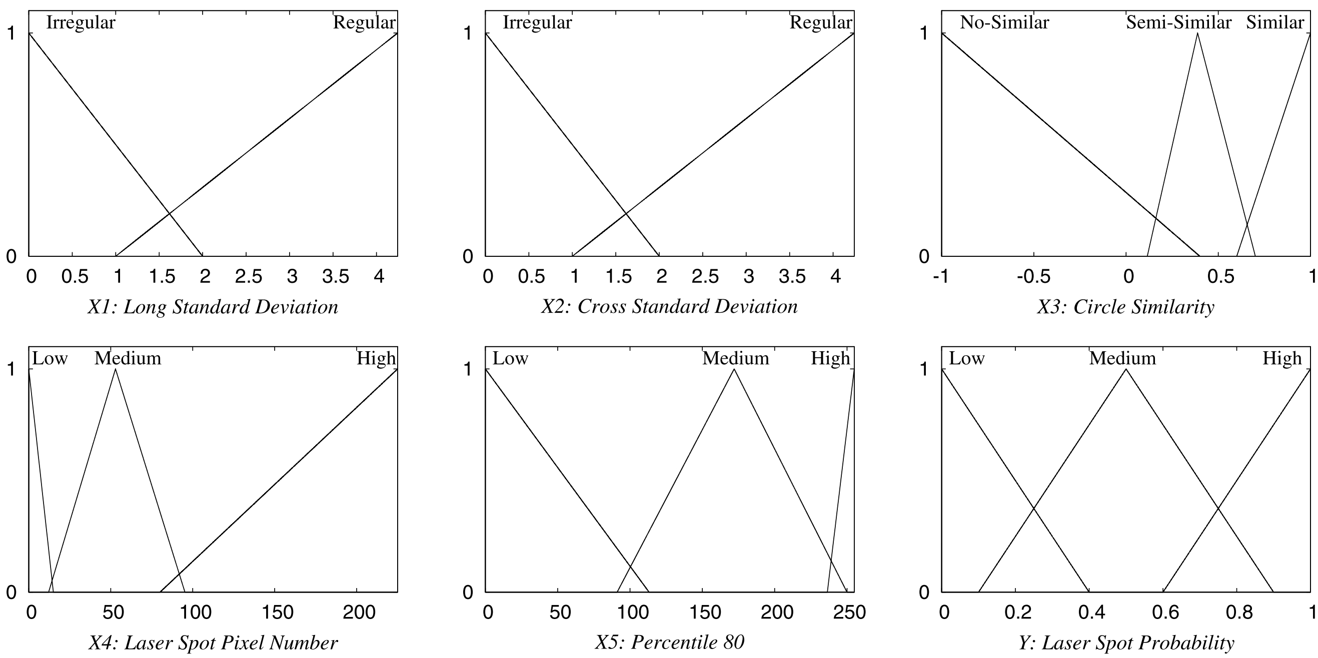


Fig. 10 Definition of the $FRBS_{tuned}$ MFs

Where the variables X_1, X_2 and X_3 indicate us if the pixels no eliminated are similar to a circle. The variable X_5 indicates us where pixels will be considered as pixel with high energy, independently if these pixels are close to 255 value. We observed that depending on light conditions, the pixels with high energy could be close to 255 or not. Finally, the variable X_4 indicates us how many pixels have not been eliminated. With this information it is possible to determinate if the image analyzed is a false offs when there are few pixels no eliminated.

4.2 Final membership functions and rule base

Once the $FRBS_{tuned}$ input variables have been determined, the next step is to design the $FRBS_{tuned}$ MFs. The $FRBS_{tuned}$ MFs have been designed by an expert thanks to his system knowledge and experience. Once the MFs were designed, they were tuned by hand by an expert in order to obtain useful definitions. Figure 10 shows the associated intervals and the MF definitions.

Once the input variables and their domains have been defined, the expert can define useful rules for the detection task.

Table 4 shows the set of rules determined by the expert using the linguistic concepts defined for each variable.

In this work, the membership and rules have been obtained from human experience. Once the initial FRBS was developed, this system was improved to obtain a new FRBS, applying again the human experience. The membership functions and rules were initially tuned by hand by the expert.

Fig. 11 Images with laser spot

4.3 Application of the FRBS in the domotic system

In order to apply the obtained FRBSs (init and tuned) in the laser spot recognition task, it is combined with TM, giving way to a new hybrid technique, TM + FRBS. 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. To do this, this technique makes use of a precision coefficient. If the ZMNCC value between the image section that is being analyzed and the template image used is equal to or higher than this precision value, this section image will be stored in the correlation vector. Once the main image has been completely analyzed, the algorithm takes the image section with the highest correlation saved in the vector. Thus, the image section with the highest probability of being a laser spot is obtained.

In Figs. 11 and 12 we can see an example of images' sections extracted by the TM technique.

This image section is analyzed using $FRBS_{init}$ or $FRBS_{tuned}$. The output FRBS value will indicate whether the image analyzed is a laser spot image. This decision is taken by a threshold value known as umbral (U). If the inferred

Table 4 Fuzzy set of rules

Rule	X_1: Long standard deviation	X_2: Cross standard deviation	X_3: Similarity to perfect circle	X_4: Laser spot number of pixels	X_5: Percentile 80	Y: Laser spot probability
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

Fig. 12 Images without laser spot

value is higher than this U value, the system considers that the image analyzed is a laser spot image. By contrast, the system will consider that the image analyzed is a non laser spot image, if the inferred value is under U. This new combination of algorithms directly presents a better performance than the algorithms described in Sect. 3.2. The corresponding results will be shown in the next section.

5 Framework and experimental study

This section is divided into three different parts. The first part shows the framework where the different models are used on a domotic control system. Then, the results obtained by the proposed technique are shown in two subsections where TM + DU [15], TM + $FRBS_{init}$ and TM + $FRBS_{tuned}$ are analyzed and compared.

To evaluate the different systems and for assessing the quality of them, we were provided with a large set of images, with 210 real home environment images (see an example in Fig. 7). This set of images has been divided in a training set of 105 images used during the learning process and a set of 105 images used to test the quality of the system. The images that make up the database were taken trying to simulate the final user actions different conditions:

– Light conditions: normal light, bright light and artificial light.
– Distance: distance between the laser pointer and the area where the device is placed. This distance is between 2 and 5 meters.

Every system presented in this paper uses a TM algorithm to obtain an image section candidate which could have the laser spot looked for. An image template previously calculated, using the technique shown in Sect. 3.2.2, is used to compare the image sent by the video camera with this template image, and thus, to extract the image section with the highest correlation using the TM algorithm. To extract this section, TM uses the most appropriate template, indicated by the expert, to look for the laser spot on an image. This process is used for both training and test set of images.

TM uses a precision coefficient to select as a candidate the image section that is being analyzed by the main image. We have considered the following two values for our study: 0.3 and 0.5.

On the other hand, the performance of the TM + FRBS system has been calculated. The system can analyze 8 images per second. It must be aware that the system is sequential and it is in the development phase using MatLab software tools. Once the system will be parallelized, it will analyze a enough set of image for working in real-time.

In the following, we describe the framework where the hybrid laser pointer detection algorithm is integrated in the domotic control system for real home environments. Then,

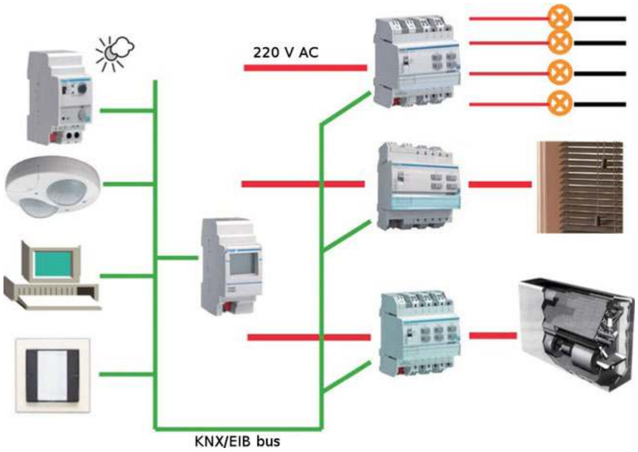


Fig. 13 KNX/EIB bus

we show the experimental results and an analysis of the studied techniques.

5.1 Framework: domotic control used by the environment control system

In this section we describe the framework of the domotic control system where the TM + FRBS system is integrated to detect the laser spot on an image and to control the home device selected by the user. This system is endowed with KNX/EIB architecture [22] by means of the laser pointer. Our software tool has been easily combined with KNX/EIB control software, such as ETS software [31].

KNX technology is an open standard for all applications in home and building control. KNX technology is composed of BATIBUS, EIB y EHS, the base of KNX is EIB (European Installation Bus). KNX/EIB is the first European standard (EN50090 and EN 13321-1) [43] international standard (ISO/IEC 14543-3) [25] and Chinese Standard (GB/Z 20965). This technology is used to control security systems, heating, ventilation, air conditioning, monitoring, alarming, water control, energy management, metering as well as household appliances, audio [27].

KNX/EIB is a multimedia protocol with which it is possible to send signals by a cable (BUS). The signals can be Power Line, RF, IR, Bluetooth, and this protocol accepts the Ethernet protocol. This signal can be sent by a PC, domotic devices or home devices such as switches. A configuration of a system is presented in Fig. 13.

The TM + FRBS algorithm, which allows us to know the position of the laser spot and the device that the user wants to use, combined with a Linux based KNX/EIB domotic system developed by Werntges [48] has enabled us to obtain a whole system allowing us to send orders to devices selected by users by means of the laser pointer.

We have used a KNX/EIB domotic system for experiments. It is composed of a power supply, a switch device, a USB interface and the KNX/EIB bus. The power supply is used to feed the various domotic components. The power supplies are essential for a specific, robust and efficient communication bus. The switch device allows us to connect the different home devices which will be turned on/off by it. Finally, the USB interface enables communication between the PC and the KNX/EIB installation. The USB interface is simply connected to the KNX/EIB bus and then connected to the PC. The USB interface is automatically detected by the PC operating system and installed. Figure 14 shows the domotic panel that we use to simulate a real home environment. The system sends the information by a USB cable which allows us to turn on/off the devices selected by the handicapped person, using the laser pointer.

Fig. 14 Domotic panel

The whole system allows the users to indicate the active zones and the home devices to control, by means of the family tool. In the second step, by using a laser pointer, a disabled or elderly person can indicate the environment device which he wants to use. Thanks to the KNX/EIB domotic system, the computer can send the necessary orders to turn on/off the device selected by the user to the domotic panel.

Finally, with the aid of this kind of system, many disabled people could lead an almost normal life, in spite of their

Table 5 TM and DU system results

System	Precision of ZMNCC in TM algorithm	Success rate in general		Success rate in image with laser spot		Success rate in image without laser spot	
		Training	Test	Training	Test	Training	Test
TM + UD	0.3	76.19%	77.14%	63.08%	60.38%	97.50%	94.23%
TM + UD	0.5	75.24%	77.14%	61.54%	60.38%	97.50%	94.23%

Table 6 TM + $FRBS_{init}$ using images sections obtained with a ZMNCC coefficient value of 0.3

System	Precision of ZMNCC in TM algorithm	U	Success rate in general		Success rate in images with laser spot		Success rate in images without laser spot	
			Training	Test	Training	Test	Training	Test
TM + UD	0.3		76.19%	77.14%	63.08%	60.38%	97.50%	94.23%
TM + $FRBS_{init}$	0.3	0.3	68.57%	53.33%	100.00%	94.34%	17.50%	11.54%
TM + $FRBS_{init}$	0.3	0.4	69.52%	58.10%	96.92%	94.34%	25.00%	21.15%
TM + $FRBS_{init}$	0.3	0.5	67.62%	71.43%	80.00%	86.79%	47.50%	55.77%
TM + $FRBS_{init}$	0.3	0.6	69.52%	73.33%	70.77%	75.47%	67.50%	71.15%
TM + $FRBS_{init}$	0.3	0.7	73.33%	73.33%	66.15%	58.49%	85.00%	88.46%

disability. These kinds of systems allow disabled people to integrate both socially and professionally, giving them the ability to enjoy a life as normal and complete as possible; as the international law on the Rights of Disabled Persons states is their right [1].

5.2 Results obtained by TM + $FRBS_{init}$

In this section the results of TM + $FRBS_{init}$ are presented. To compare the initial FRBS developed by the expert versus the previous TM + DU system designed [15], this system applies the DU algorithm for each image of the set of image sections obtained using the ZMNCC coefficient value with 0.3 and 0.5 respectively. The success rates of the TM + DU system are shown in Table 5.

The results shown in Tables 6 and 7 use $FRBS_{init}$ with umbral U between 0.3 and 0.7. This results have been obtained using the training and test set of images.

We can see that the TM + $FRBS_{init}$ system has a general success rate of 73.33% and a success rate in images without laser spots of 85.00%, using the training set of image sections obtained with a ZMNCC coefficient value of 0.3. If the system uses the test set of images, we can see that the system has similar results, a general success rate of 73.33% and a success rate in images without laser spots of 88.46%. These results have been obtained with a defuzzification value over the U value of 0.7 in training and test. On the other hand, if the $FRBS_{init}$ uses the image sections obtained with a ZMNCC coefficient value of 0.5, the system has the best success rate of 73.33% and a success rate in images without laser spots of 90.00%, using the training set of images. We can see that the system has been well designed because the results using the test set of images is similar. Obtaining a success rate in general of 73.33% and in images without laser spots of 88.46%, with a defuzzification value over the U value of 0.7 in both test.

The TM + $FRBS_{init}$ has better results using training set of images and these results are very similar if the system uses the test set of images. But the TM + DU has better results than TM + $FRBS_{init}$. We can see that the TM + $FRBS_{init}$ system has worse results in images without laser spot, however, the system has better results in images with laser spot. For this, $FRBS_{init}$ must be tuned to obtain the best results.

5.3 Results obtained by TM + $FRBS_{tuned}$

In this section the results of TM + $FRBS_{tuned}$ are presented to compare the final FRBS developed by the expert versus the previous TM + DU system designed.

The results are shown in Tables 8 and 9 with ZMNCC coefficients of 0.3 and 0.5, respectively, and using $FRBS_{init}$ with an Umbral (U) between 0.3 and 0.7. These results have been obtained using the training and test set of images.

Once the FRBS is adjusted and the percentile 80 as a new variable is introduced, we can observe in Tables 8 and 9 that the system has a good success rate using the training and test set of images. If the $FRBS_{tuned}$ uses ZMNCC precision to 0.3, the system has its best success rate if the defuzzification value is over a U value of 0.6. With this FRBS adjusted by the expert, the general success rate of the system is 80.00%, the success rate in images without laser spots is 97.50%, and the success rate in images with a laser spot is

Table 7 TM + $FRBS_{init}$ using images sections obtained with a ZMNCC coefficient value of 0.5

System	Precision of ZMNCC in TM algorithm	U	Success rate in general		Success rate in images with laser spot		Success rate in images without laser spot	
			Training	Test	Training	Test	Training	Test
TM + UD	0.5		75.24%	77.14%	61.54%	60.38%	97.50%	94.23%
TM + $FRBS_{init}$	0.5	0.3	74.29%	58.10%	92.31%	90.57%	45.00%	25.00%
TM + $FRBS_{init}$	0.5	0.4	75.24%	62.86%	90.77%	90.57%	50.00%	34.62%
TM + $FRBS_{init}$	0.5	0.5	73.33%	73.33%	76.92%	83.02%	67.50%	63.46%
TM + $FRBS_{init}$	0.5	0.6	73.33%	73.33%	67.69%	75.47%	82.50%	71.15%
TM + $FRBS_{init}$	0.5	0.7	73.33%	73.33%	63.08%	58.49%	90.00%	88.46%

Table 8 TM + $FRBS_{tuned}$ using images sections obtained with a ZMNCC coefficient value of 0.3

System	Precision of ZMNCC in TM algorithm	U	Success rate in general		Success rate in images with laser spot		Success rate in images without laser spot	
			Training	Test	Training	Test	Training	Test
TM + UD	0.3		76.19%	77.14%	63.08%	60.38%	97.50%	94.23%
TM + $FRBS_{tuned}$	0.3	0.3	73.33%	74.29%	78.46%	90.57%	65.00%	57.69%
TM + $FRBS_{tuned}$	0.3	0.4	75.24%	73.33%	78.46%	88.68%	70.00%	57.69%
TM + $FRBS_{tuned}$	0.3	0.5	77.14%	75.24%	76.92%	77.36%	77.50%	73.08%
TM + $FRBS_{tuned}$	0.3	0.6	80.00%	79.05%	69.23%	64.15%	97.50%	94.23%
TM + $FRBS_{tuned}$	0.3	0.7	80.00%	79.05%	69.23%	64.15%	97.50%	94.23%

Table 9 TM + $FRBS_{tuned}$ using images sections obtained with a ZMNCC coefficient value of 0.5

System	Precision of ZMNCC in TM algorithm	U	Success rate in general		Success rate in images with laser spot		Success rate in images without laser spot	
			Training	Test	Training	Test	Training	Test
TM + UD	0.5		75.24%	77.14%	61.54%	60.38%	97.50%	94.23%
TM + $FRBS_{tuned}$	0.5	0.3	75.24%	76.19%	76.92%	88.68%	72.50%	63.46%
TM + $FRBS_{tuned}$	0.5	0.4	77.14%	75.24%	76.92%	86.79%	77.50%	63.46%
TM + $FRBS_{tuned}$	0.5	0.5	79.05%	77.14%	75.38%	75.47%	85.00%	78.85%
TM + $FRBS_{tuned}$	0.5	0.6	79.05%	80.00%	67.69%	64.15%	97.50%	96.15%
TM + $FRBS_{tuned}$	0.5	0.7	79.05%	80.00%	67.69%	64.15%	97.50%	96.15%

69.23%. We can observe that there is a good success rate in images with laser spot and in images without laser spots. Furthermore, both have better results than the previous TM + DU and TM + $FRBS_{init}$ systems, even with a ZMNCC coefficient value of 0.3, because the $FRBS_{tuned}$ has been adjusted correctly. On the other hand, if we observe the results using the test set of images, we can say that the system is well designed, and that using a set of different images as test, the system obtains similar results. As conclusion, we can say that the new approach—TM + $FRBS_{tuned}$ system—improves the success rate of the TM + UD system. And the system presented in this paper has been well designed as the results show us.

The TM + DU system has great problems in non-optimum light conditions. With this kind of light condition the system is not able to detect the laser spot on an image. However, the TM + $FRBS_{tuned}$ system helps to solve this problem, and the system is able to manage uncertainty and unknown conditions, making it able to operate in different conditions.

6 Concluding remarks

In this paper a new hybrid technique between TM and Fuzzy Logic to detect a laser spot in a home environment together with a domotic KNX/EIB system is presented. As far as we know, these kinds of hybrid techniques have not been used to detect a laser spot on an image and to control home devices using a domotic KNX/EIB system. 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, by means of which disabled people will be able to control their home devices easily.

This system has been tested in real home environments with varying conditions, in contrast to the rest of the previous systems which were tested in controlled conditions. Furthermore, this system works without expensive video cameras with filters and complex laser pointers.

We have presented an FRBS improved algorithm in combination with a laser pointer as candidate for helping disabled people to control home devices. It 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.

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Appendix: Acronyms

1. TM: Template Matching
2. FRBSs: Fuzzy Rule based Systems
3. MFs: Membership Functions
4. RGB: Red Green Blue color system
5. HSI: Hue Saturation Intensity color system
6. DU: Dynamic Umbralization
7. ZMNCC: Zero Mean Normalized Cross Correlation
8. $FRBS_{init}$: Fuzzy Rule Based System initial
9. $FRBS_{tuned}$: Fuzzy Rule Based System tuned
10. U: Umbral
11. KB: Knowledge Base
12. DB: Data Base
13. RB: Rule Base

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