DISTRIBUTED IR SENSOR ARRAY FOR OBJECT CLASSIFICATION

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Abstract – This paper addresses the problem of recognition and identification of objects with an IR diode array, working on a reflection light scanner principle. Essentially two arrays comprising of 3 emitter-receiver pairs are mounted on two sides of the area of inspection, enabling the estimation of the size of the object in different dimensions and reducing the requirements with regard to the detection range. The sensors are driven successively in time, hence no signal overlapping and cross-talk occur. For the recognition, a neural network approach based on the Backpropagation algorithm has chosen. The array data are preprocessed via a Principal Components approach. As a result various objects can be recognised and classified easily and are well separable from other echoes. This work is preliminary for a practical system determining the number of people and identifying people getting into or out of a room and other applications supporting important home appliances like occupation-driven HVAC control or determining behaviour patterns.

Keywords: IR multi-sensor array, object classification, neural network approach

1. INTRODUCTION

Object differentiation and localization are important for intelligent systems that need to interact with and autonomously operate in their environment. Systems for the detection, localisation and identification of persons are very helpful for many tasks in home environments: (1) economical and environmental issues (occupancy-driven lighting, heating and ventilation), (2) security issues (e.g. intruder detection), (3) comfort issues (e.g. user-dependent settings, prediction of user behaviour and presence patterns for automated pre-settings) [1,2]. For all these applications, to know the *correct cumulative number of occupants per room* and possibly *their identity* is essential for an optimal performance. Hence, the monitoring of every entrance of a room with a reliable cheap device is desired. For presence detection and counting systems, numerous technical solutions based on a large variety of physical phenomena are available and still refined [3]. However, simple systems like mechanical counters, light barriers or passive infrared (PIR) detectors as well as vision based systems, are largely dependent on the kind of reflector and highly influenced by changes of the environment (object reflectivity, light, shadows,

etc.). Moreover, often it is difficult to recognize objects, which move or partly cover. In this paper, we will focus on a versatile data processing approach to improve the reliability and flexibility of object recognition with a simple and low-cost detector array.

2. SYSTEM DESCRIPTION

For proximity sensing, position control and the recognition of target primitives, low-cost active infrared (IR) sensors can be used [4,5]. However, simple range estimates obtained with infrared sensors are not reliable, because the return signal intensity depends on both the geometry and the surface properties of the target.

2.1 Choice of sensors

Most important for an array-based object classification is the ability to measure the distance to the reflecting surface with high resolution. Therefore, high angle resolution and a response being largely independent of the reflectivity of the surface are needed. An essential drawback of simple IR sensors is their strong dependence of the reflected signal amplitude from the properties (roughness, material, color) of the reflecting surface. Furthermore, the classical time-of-flight method for distance measurement cannot be used here due to very small time intervals (below 1ns) for typical distances. Therefore, in our application sensors based on a triangulation principle are used. Another approach would be the combination of IR and ultrasonic sensors gaining a combination of high axial resolution of ultrasonic gauges and the high angular resolution of the IR array [6].

For the experimental installation, Sharp GP2D12 IR distance sensors have been chosen, working on the triangulation principle. The IR beam emitted from the transmitter is spread from the reflecting surface and reaches the receiver under a certain angle being dependent on the distance of the surface from the sensor, Fig. 1. On a position sensitive device (PSD), a light point is illuminated. The sensor works largely independently of the properties of the reflecting surface (color, roughness, tilt etc.).
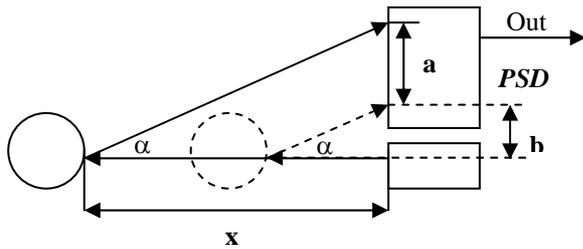
Fig. 1. Triangulation principle

2.2. *Sensor arrangement*

When a high angular resolution is required, mechanical scanning devices can be used [5]. However, for many applications scan systems are costly devices with inconvenient dimensions. Here, a IR array without any moving parts is proposed. In order to improve the performance of object detection and recognition, it is proposed to mount two arrays, each comprising of 3 IR distance sensors arranged in a row, on two sides of the area of inspection, see Fig. 2. (For recognition and counting of people, e.g. this is a doorway). This simplifies the estimation of the size of the object in different dimensions and helps to reduce the requirements with regard to the detection range.

The emitters are driven successively in time, hence no signal overlapping and cross-talk occur. To control of the IR arrays a PL device is used.
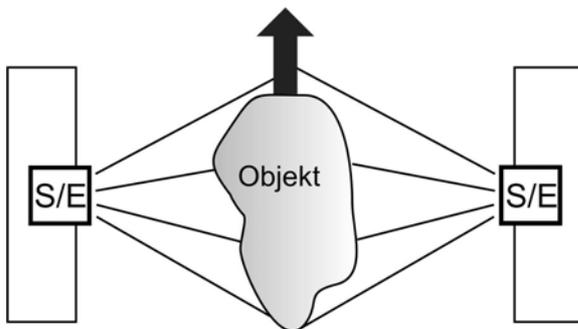

Fig. 2. Detection principle: IR diode arrays on both sides of possible objects (top view)

From the distance measurements from each sensor, the form of the object can be roughly derived, Fig. 3, which is then used to identify the object. Motion of the object leads to changes in amplitudes resp. distance information of the channels, delivering – from combinations of amplitudes – potentially more information about the object's form and the orientation of the reflecting surfaces towards the array. Comparing the received data with pre-stored knowledge about possible objects, the ability to recognise different objects is further improved.

Modelling different sensor arrangements and configurations, the optimum parameters of the detector system, like the distance between sensors and their quantity and orientation towards each other, have been found.

For the setup described in the following, objects with basic forms (square, circle and triangle) have been used. The side dimensions varied from 5 to 25 cm. Therefore, the distance between the two rows of sensors was set to 80 cm with 5 cm between two sensors on one side.
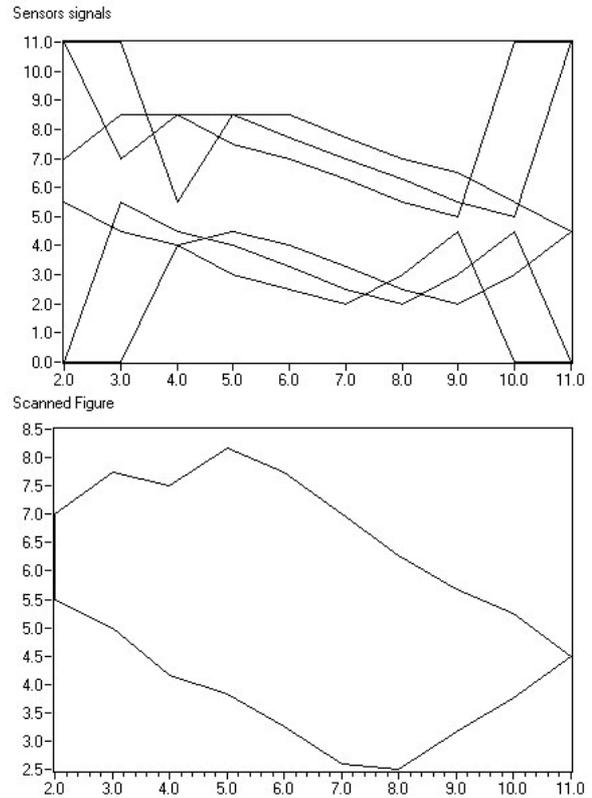

Fig. 3. Results of modelling: signals from sensors (top) the restored form of object (bottom)

3. NN APPROACH

For the object recognition, a neural network approach based on the Backpropagation algorithm (BPG) has been applied. After extensive testing of different modifications of the BPG algorithm, 3 methods have been considered: Backpropagation with Learning Rate and Impulse (BPG-M), Backpropagation with Learning Rate (BPG-L) and Backpropagation with Adaptive Learning Rate (BPG-AM).

For the net construction, a constructive method is chosen. Hence, already with a small number by neurons the effect on the result of the net can be studied. Furthermore, certain weight connections can be abolished or added during the net developing.

To feed data blocks into the net, they have to be pre-processed in order to reduce the number of effective variables. Often used attempts are (1) the generation of geometrical parameters of the object and (2) the Principal Components Analysis (PCA).
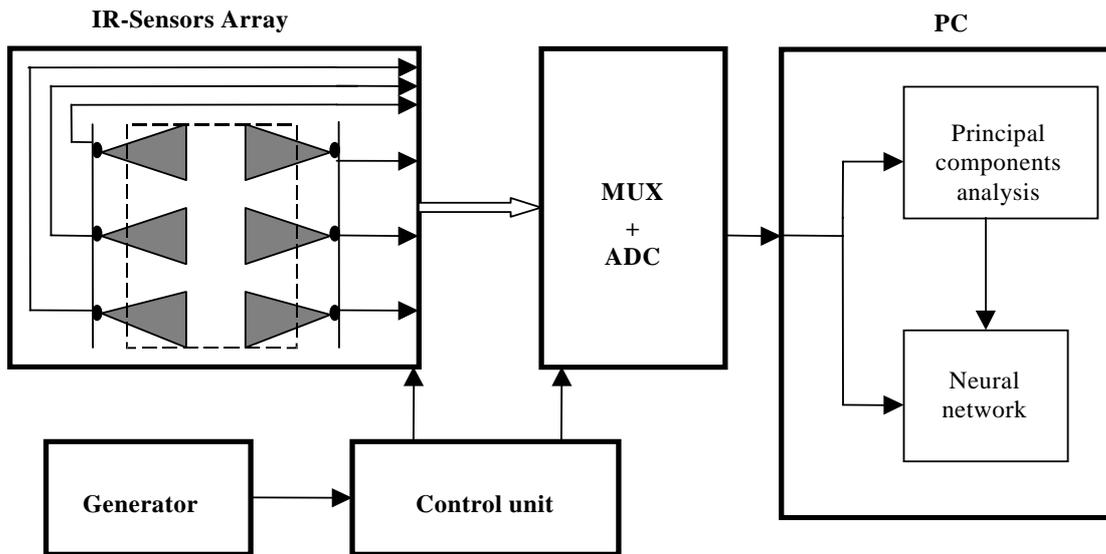
Fig. 4. Experimental setup

As has been found, relying on geometrical parameters like width and length, circumference and surface, give quite unreliable results, since many parameters were nearly equal for different measuring situations.

The Principal Component Analysis shows clear advantages and is used in the pre-processing phase with all examined algorithms. PCA is a common method to reduce the number of effective variables.

In answering the question, how large is the loss of information as a function of the number and kind of the main components, the concept of the complete variation is used. The complete variation is calculated after the following formula:

$$ V = \left(\frac{\sum_{i=1}^{p} \lambda_i}{\sum_{j=1}^{m} \lambda_j} \right) \qquad (1) $$

where λ_i are the eigenvalues of the principal components and p and are the number of processed and overall principal components, resp.

Generally, the first principal components are responsible for the largest variations in the original data, Fig. 5. It is assumed here, that a right decision is met only if at least 90% of the complete variation survives. According to (1), with 6 main components, 92% of the complete variation is reached, Fig. 6. The first 10 principle components comprise 98% of the complete variation.

Using these 10 principal components, the net would need 10 neurons in the input layer. With the number of neurons increases also the number of net weights between input layer and hidden layer and hence the overall complexity of the net.

In our case, only the first 6 principal components have been used. The input vectors are therefore reduced from 30 to 6 components (see next Section), leading of course to a certain loss of information.

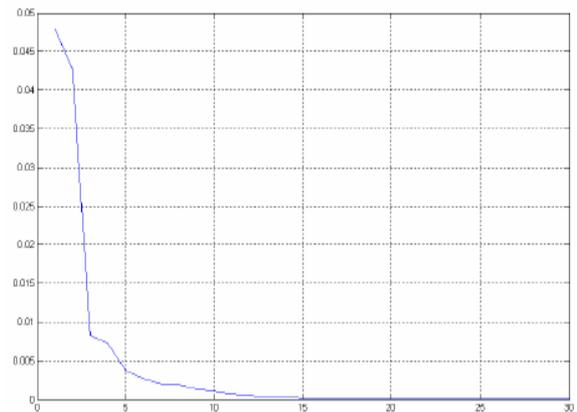The overall experimental setup is shown in Fig. 4.

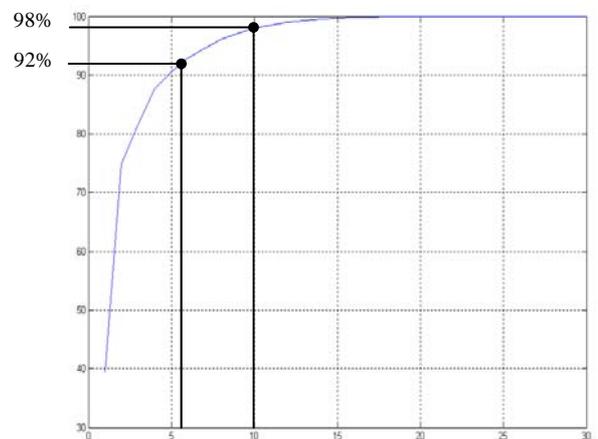Fig. 5. Eigenvalues of the principal components

Fig. 6. Complete variation of the principal components

486

4. EXPERIMENTAL RESULTS

The data vector has been analysed for three objects: square, circle and triangle. For every object, 100 measurements were carried out. The objects were measured in 5 different positions towards the sensor array. In every position, a 6-element-vector comprising the amplitudes of the 6 IR sensors is formed. The vectors from all positions are then summarized to vectors $\mathbf{X} = \begin{bmatrix} X_1, \dots X_N \end{bmatrix}$ of $N = 30$ elements.
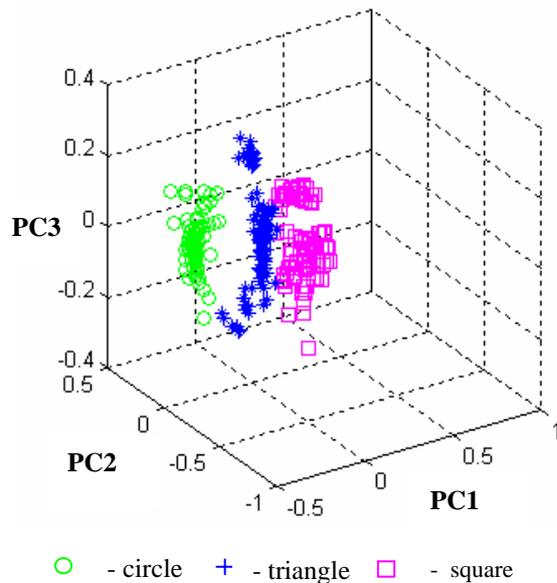

Fig. 8. 3D representation of the measuring data with PCA.

As stated previously, with the BPG algorithm alone, the classification is not reliable, see Fig. 7. From the 30 recorded variables of each object, 3 variables X_1, X_7, X_{13}. Obviously, not of three objects is really classifiable.

In Fig. 8, the same situation is shown using PCA before NN analysis. Already using only the first 3 principal components PC1, PC2, PC3 (from 6 calculated, as motivated earlier), a clear grouping is obtained. It is immediately recognisable how the measuring data are distributed into three clusters. Using all 6 main components the tolerance to misclassification will be improved.

In the next step, different net types and different modifications of the back propagation algorithm (see Section 3) have been investigated. With every net type different parameters were changed and from the quality of recognition, the optimum net types were selected.

To obtain the optimum net configuration, the learning rate and the number of the neurons were varied in the hidden layers. For the activation of neurons in the hidden layers and the output layer, the hyperbolic tangent and logical sine function were selected, resp. The total net error was calculated as the middle square error (MSE). For the net development termination, a
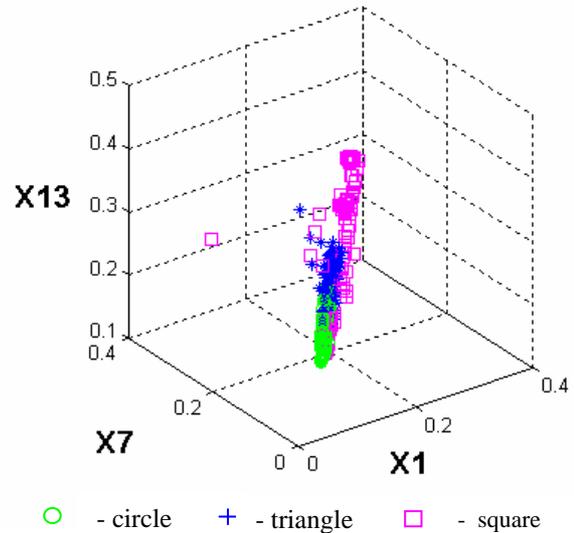

Fig. 7. 3D representation of the measuring data without PCA.

maximum MSE of 0.005 was given for all nets. For the calculations, 15,000 iterations were fixed.

Altogether, 72 different net configurations were examined. For every net configuration five experiments were carried out. At the end of every training phase the respective net was tested with a test amount comprising of 30 test vectors. The first 10 test vectors corresponded to the measuring data of the square, the second 10 to the measuring data of the circle and the third 10 to the measuring data of the triangle. Exemplary results are shown in Table 1. It has been found that generally with the BPG-AM algorithm the best results have been reached.

From the example shown in Fig. 9 it can be seen, that from the 30 different vectors submitted to the network, only one has been misinterpreted. This is probably due to an insufficiently large training sample.

5. CONCLUSIONS

In the paper, an approach to recognize and classify objects with an infrared array has been described. The array comprises of 2 rows of range sensors on two opposite sides of the area of inspection enabling the estimation of the object's size in 2 dimensions with high distance and angle resolution. In this preliminary stage, Sharp GP2D12 range sensors with readings being largely independent of the properties of the reflecting surface have been used. Later, using ordinary IR diodes which are tiny and low-cost, the proposed array arrangement together with reasonable assumptions about the object's properties (either the rough size or its material) will allow to differ between contributions to the received amplitude due to the object range and due to the reflectance. For the processing of the array data, a neural network approach preceded by a Principal Components Analysis to reduce to dimension of the input vector have been used.

Table 1 Results for selected net configurations and algorithms

Algorithm	Parameters			Circle (C)	Square (S)	Triangle (T)	Σ
	Layers	Learning rate	Impulse				
BPG-L	(3,3)	0,6	-	7 2T, 1S	7 2T, 1C	6 3S, 1C	20 - true. 10 - false
	(5,3)	0,6	-	10 0	9 1C	8 2S	27 - true 3 - false
	(5,3)	0,3	-	10 0	9 1T	9 1S	28 - true 2 - false
	(7,5,3)	0,6	-	9 1S	10 0	9 1C	28 - true 2 - false
BPG-M	(3,3)	0,6	0,5	10 0	7 3T	10 0	27- true 3 - false
	(5,3)	0,3	0,5	10 0	9 1T	9 1S	28 - true 2 - false
	(7,5,3)	0,6	0,5	10 0	9 1T	10 0	29 - true 1 - false
BPG-AM	(3,3)	0,08	-	10 0	9 1T	9 1S	28 - true 2 - false
	(5,3)	0,08	-	10 0	10 0	9 1S	29 - true 1 - false
	(7,5,3)	0,1	-	10 0	10 0	9 1S	29 - true 1 - false

- O - *circle*
- + - *triangle*
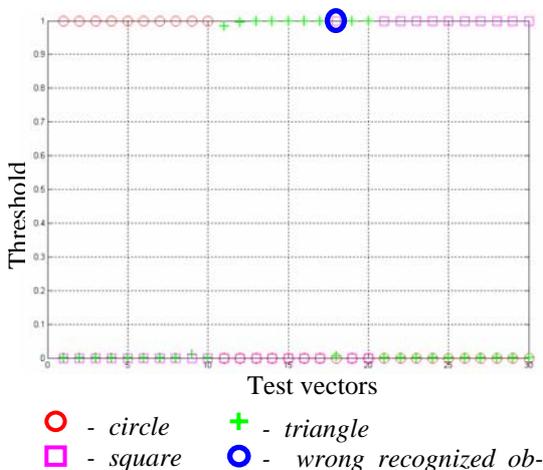- □ - *square*
- O - *wrong recognized ob-*

Fig. 9. Test results for BPG-AM

The results show the good applicability of different backpropagation algorithms. The next step will be to expand the presented approach to the detection and recognition of more complex objects like human bodies, moving e.g. through a doorway. Recognising and classifying different parts of the body (corpus, hands, legs) from a known population (e.g. the users of a room, residents of a home) will lead to a simple and reliable personalised people-counting system.

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