Neural Network-Based Geometric References Recognition Applied to Ultrasound Echo Signals

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Abstract- **Ultrasonic sensing systems are often used in robotics for navigation purposes, such as obstacle avoidance and distance measurements. However, a very desirable but difficult task is the detection and recognition of geometric references. This is a tough task due to the hard interference caused to the ultrasonic sensing system by the environment, such as temperature variations and air convection or wind. Furthermore, the echo signal variation due to the various detected references is non linear. The use of neural networks is strongly recommended when the process involved is non linear or has a very complex mathematical model, witch is exactly the present case. The application of neural networks to the recognition of geometric references via ultrasound obtained very good results.**

I. INTRODUCTION

Ultrasound transducers, given their good cost-benefit ratio, are heavily employed in robotics [1] in tasks such as distance measurement, obstacle avoidance, map construction of the robot's environment, and robot self-localization in previously mapped environments [2].

Ultrasound-based map building and robot's self-localization usually are based on large and plane objects, or geometric references, such as walls and their relative positions and orientations. However, a substantial improvement would be attained if smaller structures such as table and chair legs, encountered at the height of the transducers from the floor, were included in the set of geometric references. This paper deals with the recognition of such references using neural networks applied to ultrasound echo signals, to be employed in the robots being developed in our facilities, such as the robot Brutus [3] (fig. 1). It is related to the work of [4], which employed fuzzy logic for the same objective, and [5], which trained a neural network to discriminate between sonar signals bounced off a metal cylinder and those bounced off a roughly cylindrical rock.

The paper is organized as follows: in section 2 we present Brutus, a robot being developed in our labs and on which we intend to test the results in its navigation strategy, and the basics of ultrasound waves. Section 3 describes the employed neural net paradigm. Sections 4 and 5 present the geometric references as classes of structures to be recognized, echo signal acquisition, and the selected features to be extracted from. Section 6 describes the neural training and presents the obtained results. Finally, the conclusions in section 7 followed by the bibliographic references.

II. ULTRASOUND IN ROBOTICS

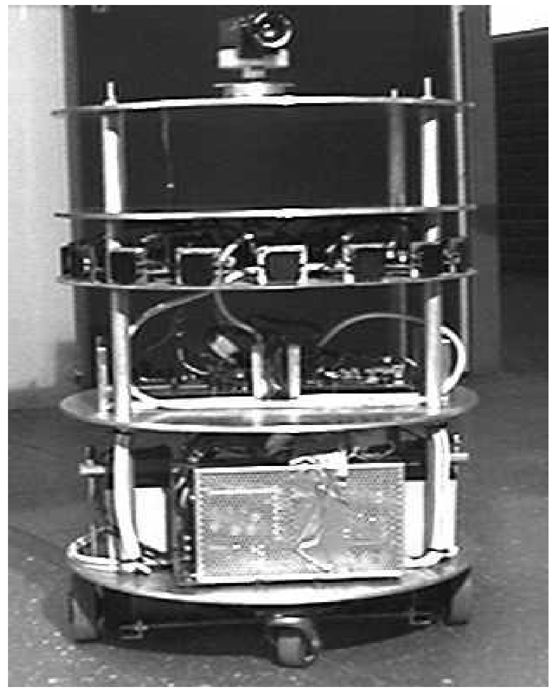

Fig. 1. Mobile robot Brutus

The sensory system of a robot encompasses the internal odometry (usually based on optical encoders attached to the wheels) and one or more type of external sensing such as sonar, radar, laser and vision. Brutus uses, besides odometry, a ring of sixteen 50KHz electrostatic transducers from Polaroid® and a vision system. It employs a hierarchical, behavior-driven control architecture, in which the odometry and ultrasound systems are responsible for the safe robot navigation while the vision system supplies information needed by the higher level control tasks. This work seeks to make better use of the existing ultrasound system, giving it a higher level of recognition. The use of ultrasound for external sensing in mobile robots is due to the low cost of the transducers and associated electronics together with the benefits of their applications. An array of such transducers enables a robot to navigate safely in partially structured environments.

Ultrasound waves are acoustical (mechanical) waves with frequencies above the human hearing threshold, i.e., above approximately 20KHz [1].

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For the task of distance measurement, the most widely used technique is the determination of time of fly (TOF), which consists in emitting a short ultrasound pulse burst and then timing the corresponding echo arrival. The distance (d) from se transducer to the reflecting surface or obstacle is determined by the physical relation:

$$d = \frac{ct}{2} \quad (1)$$

Where *c* is the sound velocity in air (approximately 345 m/s at 22^o C), and t is the round trip time of fly, from emission to echo detection [6].

However, distance measurement for obstacle avoidance alone is not sufficient for safe robot maneuvering . It is often required the recognition of some landmarks strategically located, or already encountered, in the robot's environment in order to allow its self-localization with reasonable precision within the robot world's model (map), which also permits such things as the identification of a recharging point and the reset of the cumulative errors of its internal sensory system (odometry).

Unlike distance measurement, landmark recognition is not a simple task. Both tasks share ambiguities related to drifts in sound velocity and spurious reflections due to temperature variation and air convection and also to wave scattering, but the later is not dependent on the simple time-of-fly: it can only be tried from characteristics extracted from the temporal sequence of the echo signal, involving a highly nonlinear and mathematically unknown mapping function. For those reasons, neural nets are one of the best candidates for the task, endorsed by the excellent results presented later.

III. NEURAL NETWORKS

Neural networks have been studied extensively in the last two decades and used in many areas. Abundant literature is available on the theory and applications, and we refer to [7]. for a good study. For the sake of clarity, we will make a very superficial introduction, focusing on the type of network used in this work.

They consist of a network of highly interconnected simple nonlinear processing elements called *neurons* (Fig.5). The parallelism, nonlinearity, and high degree of interconnection enable them to perform any mapping, if it exists. Their most important characteristics are (1) to learn a mapping from examples, without any human expert knowledge other than the proper choice of the data, and (2) to be able to *generalize* during operation (after training), i.e., to respond correctly to unknown data belonging to the input domain for which it was trained. The most widely used *paradigm*, for its suitability to all neural network applications, is the *multilayer perceptron*, or the *feedforward neural network*, made up of neuron *layers* connecting the input(s) to the output(s), where interconnections are allowed only from neurons of one layer to neurons of the next one. The neuron has the following mathematical model:

$$y = f\left(\sum_{k=1}^{n} w_k \times x_k - b\right) = f\left(\sum_{k=0}^{n} w_k \times x_k\right) \qquad (2)$$

where y is the neuron output, x_k (k=1,2,..,n) is the n-dimensional neuron input vector, b is a *bias* term (transformed to the weight w_0 corresponding to a fictitious input x_0 = -1 in the rightmost term of (5)), w_k are *weights* and f is a nonlinear function called the *activation function*.

The network stores the desired knowledge for the application in a distributed way as the weight values. This is

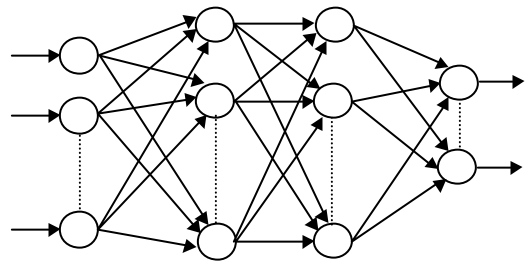

Fig. 2. Feedforward Neural Network

done by a *training* process called *supervised learning*, in which a statistically significant number of exemplar input-output pairs (the *learning* or *training set*) is presented to the network in an iterative manner. The most popular learning algorithm associated with the feedforward neural network is the *error back-propagation* with the *gradient descent* minimization technique.

The most common activation functions belong to the class of the sigmoids, because they are continuous monotonic, have the needed nonlinearity for universal mapping, and have the effect of automatic gain control.

The network is trained several times, with various combinations of network parameters such as number of layers, number of neurons in each hidden layer, and type of activation function, usually in a trial-and-error fashion. An insufficiently large network is not able to learn satisfactorily (the learning algorithm does not converge to a specified minimum), while a very large network simply memorizes the examples of the learning set, loosing generalization. One popular way to verify generalization (prevent overtraining) is to set aside another set of input-output pairs, called the *validation set*. While the network is being trained with the training set it is constantly tested with the validation set and the process stops when the validation error begins to increase, meaning that going further generalization will degrade. Once a training trial has been accepted the weights are fixed, proper for network operation, where it responds to unknown input vectors. It is also good practice to use a third set, the *test set*, for final evaluation.

We employed two variations of the *backpropagation* algorithm: *Resilient Back-Propagation (Rprop)* [8], for its very fast convergence, and the Levenberg-Marquardt [9] optimization associated with Bayesian Regularizarion, which provides robust convergence and very good generalization, even for oversized networks, and also gives a hint on the effective number of neurons necessary for the learning process.

IV. GEOMETRIC REFERENCES

The choice of geometric references was based upon the kind of indoor navigation environment of the robot Brutus, such as an office or home. The most frequently identified objects are:

1. Wall (planes);
2. Square table-leg;
3. Round table-leg;
4. Chair leg;
5. Corner (wall corners).

V. DATA ACQUISITION

A previous work based on fuzzy logic [4] was accomplished for the same objective. In that work, the filtered ultrasound echo passed through and analog envelope detector and then acquired by a PC via analog to digital conversion. The selected features were (figs. 3 and 4):

$\mathbf{T_v}$	Echo duration
$\mathbf{T_a}$	Envelope rise time
$\mathbf{T_d}$	Envelope fall time
$\mathbf{T_0}$	Echo delay (initial peak time)
$\mathbf{T_p}$	Peak time
$\mathbf{T_f}$	Final peak time
Área	Total envelope area
Área1	Envelope area between T_0 and T_f
Área2	Envelope area between T_p and T_f
Peak	Peak amplitude

For comparison reasons, we followed the same set of features for the neural classification, and repeated the acquisition, collecting 1110 echoes for each class (reference) with obstacle distances spanning from 50 to 100 cm.

VI. NEURAL NETWORK RECOGNITION OF GEOMETRIC REFERENCES – OBTAINED RESULTS

The development of this work was done in MATLAB® for the PC platform, for subsequent implementation of the trained network in an onboard embedded microcontroller, if results proved satisfactory.

Before neural training, we performed a Principal Components Analysis (PCA) pre-processing phase on the dataset, in order to detect redundant features and thus reduce the input dimensionality, since it was clear that some features employed by [4] were highly correlated. Retaining 99% of the total information content (in the context of the PCA), resulted in only three input components obtained from the PCA matrix transformation (coordinate system rotation) on the original 10-dimensional dataset.

As for the neural network, the topology that gave satisfactory results was: input layer of dimension 3 (reduced dimension from the PCA), one hidden layer with 16 neurons and the output layer with 5 winner-takes-all [7] neurons, one for each class. The activation function was the hyperbolic tangent.

The training set had 487 exemplars, and also validation and test sets each with 300 exemplars, were employed. All sets were mutually exclusive, and contained exemplars spanning the considered distance range.

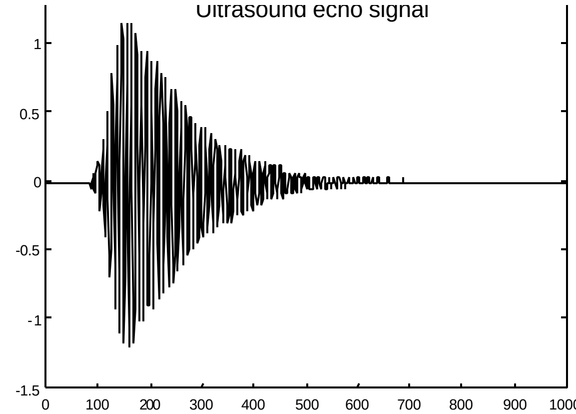

Fig. 3. Ultrasound echo signal

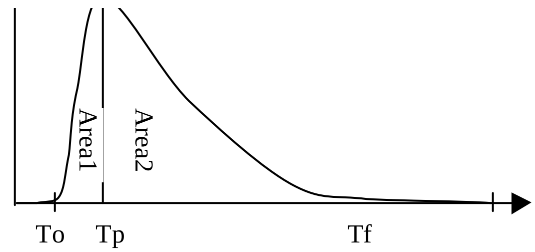

Fig. 4. Echo signal envelope and some of the employed features.

The following table summarizes the results, were the values refer only to the test set, unknown to the network during training:

TABLE I
RESULTS

Type of Geometric Reference	RPROP	Levenberg-Marquardt
Wall corner	94,3%	97,7%
Chair leg	100,0%	100,0%
Square table-leg	100,0%	100,0%
Round table-leg	100,0%	100,0%
Wall	93,4%	96,7%
Overall	97,5%	98,7%

VII. CONCLUSIONS AND SUGGESTIONS FOR FUTURE WORK

The recognition of geometric references by ultrasound, although attractive in sensor cost and electronics and in echo processing, have been regarded as difficult for many reasons such as ultrasound sensibility to temperature and air convection, noise and spurious echoes. The use of neural networks proved to be very promising for this accomplishment. Improvements will have to be done, however, to approach more realistic situations encountered by the robot during navigation.

One means of improvement is the use of multiple, neighbor receivers from the ultrasound ring, in order to bust robustness and attain reasonable reference rotation invariance.

The feature set was suitable for the linguistic variables in the fuzzy system of the original work [4]. For the present case, better results might be achieved also if we try other feature sets, or employ the raw sequence preprocessed by a suitable digital processing algorithm before neural training, at the price of higher computational demand on the onboard microcontrollers and higher cost.

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