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LEARNING BASIC HUMAN GUIDING STYLES FOR MOBILE ROBOT

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Abstract: The real-time control of mobile robots in uncertain, dynamic environments is one of the major fields of the current research. The main objective of this paper is to find a suitable method to model different styles of guiding. Motivated by the chosen algorithm's (potential based guiding) limitations an extended method is presented. A common type neuro-fuzzy algorithm is developed which can approximate the proposed model. The extended model improves the modeling properties and eliminates some disadvantages of the PBG model.
Keywords: guiding model, PAL optic, autonom robots, neuro-fuzzy systems

1 INTRODUCTION

The objective of the mobile robots is to reach their destination, while avoiding any obstacles that appear. In the present paper the development of an autonomous robot transportation system to be used on the corridors of a building is discussed. The obstacles on corridors can be mostly walking people and other robots running on the hallways. This implies that it is inevitable to set various traffic rules for the robots. They may have different priority in the traffic depending on how dangerous material they are carrying. The robot having the more dangerous material onboard (high priority), must move more safely. The others with lower priority should move next to the walls on the left or right side (depending on which way they are running) in order to minimize "traffic jam" situations. Consequently, the robots have to imitate various guiding styles just like humans, for example staying close to walls or keeping as far as possible from obstacles that may appear. They also have to be reactive which is implied by the dynamically changing environment.

In order to achieve various guiding styles, a widely adopted guiding model was chosen from the literature: the potential based guiding (PBG) model [1]. Despite the advantages of the artificial potential field model, its use is restricted by the fact that its guiding strongly alternates in some cases [2]. This problem arises, for example, when the robot has to run parallel with a wall. This is the most frequent situation in corridors. Another constraint is that the modeling property is somewhat limited. The potential based model is only capable to generate rules such as: "If obstacle is in a direction, then move in the opposite of that direction". In most cases it would be necessary if the model could give the direction of avoiding the obstacle, for example: "If obstacle in a direction, then avoid it from the left side".

Motivated by these facts, this paper proposes an extension of the potential field based model to a vector field based model (VFB), that eliminates the mentioned disadvantages. In order to form the proposed model to be an engineering tool this paper also proposes a vector consequent based fuzzy logic algorithm, which uses vectors instead of fuzzy sets as the consequent terms. The fuzzy algorithm generates the approximation of the desired arbitrary VFB model. Having fuzzy approximation offers a chance to define a simple numerical training algorithm. Applying these tunable algorithms the robots are able to learn guiding styles even from human being via experiences, and to imitate the learned styles in a new environment occupied by dynamic obstacles. A least mean square method based algorithm is proposed in this paper for realizing the learning purpose.

A method for detecting obstacles all around the robot is needed. A special optical device, the PAL optic with a CCD camera, what the robot is equipped with, generates a 360 degree view around the robot directly without any additional hardware and movements. Finding reference points the position of the obstacles can be defined, this advantage is offered by the feature of PAL optic.

The paper is organized as follows. The robot's environment is described in the next section, then the principle of PAL optic is introduced (section 3). Basic guiding styles are defined in section 4. In section 5 the concept of artificial potential field methods is briefly presented. Then the PGB model is extended to a vector-field-based guiding strategy (section 6), and an approximation technique is shown in section 7. Then a simple tuning algorithm is given (section 8), and the last section presents some examples to show the effectiveness of the proposed algorithms.

2 ROBOT'S CONNECTION TO ITS ENVIRONMENT

Robots need to gather information of the surrounding area in order to define proper guiding strategy [11]. In this application a special optic is used which can provide the distances of objects if a reference point's position is known (section 3). The corridors have lights assembled on the ceiling, and a well recognizable line is painted on all the walls (Fig. 1). (The height of both the lights and the markers are known.) The feature of PAL optic with these fixed objects guarantee that 3D information can be regained from the 2D pictures generated by the onboard camera. The corridor should be colored in such a way that objects can be easily recognized (black line on the wall, red robots, etc).

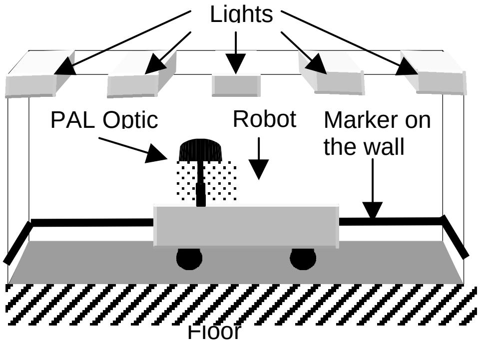

Figure 1. Mobile robot in a corridor

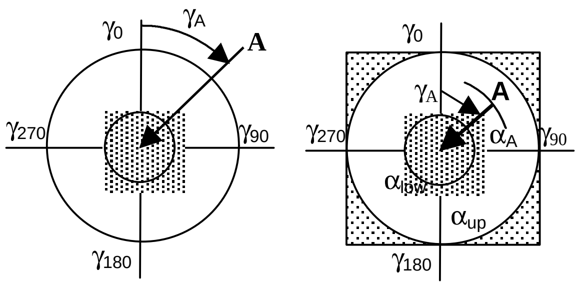

Figure 2. Creating the ring shaped picture

3 THE CONCEPT OF THE PAL OPTIC

In order to gather information from the environment, a special panoramic optical device (PAL optic) can be used. The main concept of this device (CMI, FCP) is described briefly in this section.

Centric Minded Imaging (CMI) is a unique method in the image mapping theory which gives a different projection of 3D space from the Cartesian coordinate system. CMI results a ring shaped picture which forms the 2D shell of the 3D environment [3]. However, this is more than a simple projection because the depth information – which is lost in traditional mappings – is preserved. The reason for it is that CMI considers its field to be cylindrical (rather than spherical), so the image volume is projected to a cylindrical wall then transformed to a plane perpendicularly to the optical axis of the CMI system. These operations produce a ring shaped image. In this technique the width of the ring is proportional to the field of view of centric minded imager in the direction of its optical axis. The radial distance of an object point measured form the center of the imager is proportional to the acceptance angle of its picture in the image plane. This type of technique is also known as Flat Cylinder Perspective (FCP). The FCP method – which is basically the mapping principle of CMI – results a real virtual image of the object field inside the centric minded imager which can be taken out with the help of an auxiliary lens that focuses the picture to a focal plane of an imaging device.

Figure 2 shows how FCP image plane is created and outlines the acceptance angle of the object point 'A' (α_A) and the field of view (FOV) of the image bordered by α_{up} and α_{low} angles. Both of the angles are measured from the optical axis: FOV = $\alpha_{low} - \alpha_{up}$

The 360° panoramic view is available in the FOV around the optical axis. To define the orientation of an object point it is necessary to know the γ rotation angle measured from a reference direction beside the α acceptance angle. Knowing the parameters of the imager and measuring the rotation- and acceptance angles the object position in space can be calculated. The imager parameters are the upper acceptance angle (α_{up}), its corresponding radial distance (r_{up}), the radial distance of the object point on the image (r_A), and the image constant (k). With these factors the acceptance angle of the object point can be calculated as:

$$a_A = \arctan\left[\frac{k \cdot (r_A - r_{up}) \cdot tg(a_{up})}{k \cdot (r_A + r_{up}) - 2 \cdot (r_A - r_{up}) \cdot tg(a_{up})}\right]$$

The realization of CMI is available as a Hungarian patent: Panoramic Annular Lens (PAL optic). This optical system has the feature to provide a full 360° angle of panoramic view information, thus the whole surrounding space can be mapped with no moving. FCP images can be used as range detectors because of the correspondence between the radial distance and the acceptance angle [5]. The space mapping ability without any movements results in less chance to failure and makes it suitable for roaming explorer robots.

4 ROBOT GUIDING BASICS

This section explains some guiding styles. The robot can detect objects in the scanned area (Fig. 3a).

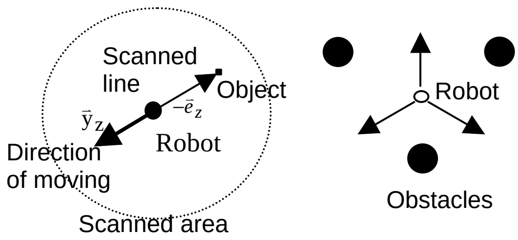

Figure 3. Rule of PBG model b. Stuck position

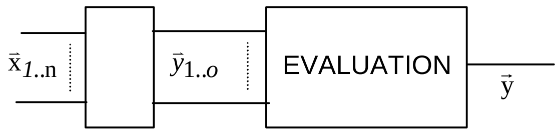

Figure 4. Guiding control

The scanned area is divided into scanned lines that are pointed into directions of $-\vec{e}_z$ (unique vectors). The scanned lines have an important advantage that they density is growing with the decreasing distance to the robot. The sensor system provides the distance between the robot and the object on the scanned lines. These lines are virtual processed from the ring shaped pictures generated by the PAL optics set on the robot. This information can be gathered by real sensors (e.g. sonars) as well [4]. The robot is able to turn 0-360 degrees.

The main task of guiding control is to define the moving direction according to the required style and to the scanned area. Let us consider two extreme styles. The main guiding rule of an aircraft carrying dangerous material is to ”keep as far from the mountains as possible”. Remaining in secret while seeking a mouse leads to the opposite behavior for a cat, namely, “get as close to the object as possible”. A combination of these can characterize the rule of a traffic system: “keep close to right side”. However, the basic guiding control has no intelligent task for problem solving. For example finding a path in a labirynth needs additional intelligence.

5 POTENTIAL BASED GUIDING MODEL (PBG)

The main rule of PBG is to repulse the robot from the objects [6,7]. The guiding process is divided into two blocks (Fig. 4). One defines the possible moving directions the second evaluates them.

This means that the first block defines a moving vector $\vec{y}_z = y_z \vec{e}_z$, $z = 1..o = n$ (*n* is the number of scanned line, and *o* is the number of evaluated directions) from the measured distances x_i to each scanned line. These vectors are pointed into the opposite of the scanned direction (key idea of PBG), and their absolute values depending on the detected distances are:

$$\vec{y}_z = \vec{e}_z w_z(x_z) \qquad (1)$$

This means that the potential function of the robot is sliced in the scanned directions (Fig. 5). Usually the evaluation is based on the sum operator that results in [8]:

$$\vec{y} = \sum_{z=1}^{n=o} \vec{e}_z \cdot w_z(x_z) \qquad (2)$$

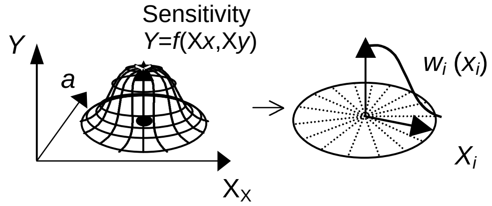

Figure 5. Structure of the potential function

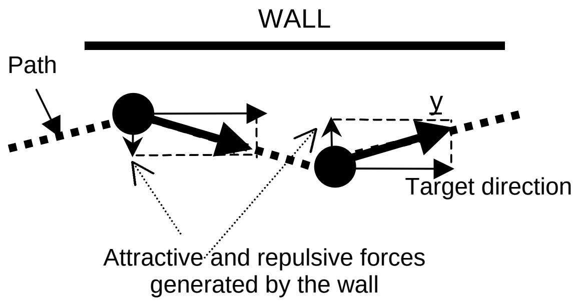

Figure 6. Guiding fluctuation of the PGB model

Obviously in many cases this kind of evaluation is not effective like in following example. Let set the same potential function on each scanned line. Applying (2) to a symmetrically located obstacles, will result in a zero vector (Fig. 5b). Choosing one of the $\bar{y}_z$ in the evaluation would lead to a solution.

6 FUZZY TECHNIQUE FOR MODELING THE PGB

This section specializes the product-sum-gravity (PSG) [10] based fuzzy technique regarding to its computational complexity in order to approximate the potential based guiding model. The proposed fuzzy rule base is specialized in the sense that the number of rules in the rule base does not grow exponentially by the number of inputs. This specialization is offered by the fact that the potential surface is three dimensional independently on the number of scanned lines, hence, the number of inputs.

According to figure 4 the inputs of the fuzzy rule base are distances, the number of inputs is *n*. The algorithm results in values $\vec{y}_z$ that are pointed to the opposite of the scanned directions.

Algorithm 1: Vector based product-sum-gravity

Characterization of observation, antecedents and consequents:

<u>Antecedents</u>: The antecedent fuzzy sets $A_{i,j} : m_{A_{i,j}}(x_i)$, $i = 1..n$, $j = 1..m$, $x_i \in X_i$ are defined on each input universe X_i in *Ruspini*-partition .

<u>Consequents:</u> Let us define consequents fuzzy sets as vectors: $\vec{B}_j = \vec{e}_j \cdot b_j = \vec{b}_j$, where B_j is *j*-th output.

<u>Observation:</u> Let the input value x_i be fuzzificated into a singleton observation fuzzy set A^*_i such as: $m_{A^*_i}(x_i) = d(x_i)$.

Characterization of the rules

The potential function is a 3 dimensional surface, which implies that, the co-relation of the inputs can be omitted. Therefore let us define the rules such as: IF $A_{i,j}$ THEN $\vec{B}_{i,j}$

Characterization of the inference

We use fuzzy inference based upon product-sum-gravity [10].

This step follows the center of gravity defuzzification technique. All consequent set are weighted by their corresponding contribution and summed to produce the output vector $\vec{y}_i$:

$$\vec{y}_i = \frac{\sum_j m_{A_{i,j}} \vec{b}_{i,j}}{\sum_j m_{A_{i,j}}} = \sum_j m_{A_{i,j}} \vec{b}_{i,j} \qquad (3)$$

Examples for the proposed method is given in section 9.

7 VECTOR FIELD BASED GUIDING MODEL (VFB)

In spite of the advantages the applicability of potential based guiding model is restricted by the fact, which has been noticed that its result strongly alternates incapable of guiding smoothly [2]. The key idea of potential based model is that the scanned object points repulse or attract the robot on the scanned line depending on the potential function. For instance, if the robot has to run parallel with a long wall the required vectors or et least their sum must be parallel with the wall. The PBG model is not able to generate such vectors (Fig. 6).

This section extends the potential based guiding model to a vector field model, which defines a direction at every point of the potential surface (Fig. 7).

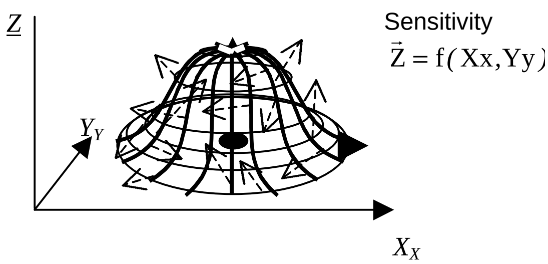

Figure 7. Extended potential function

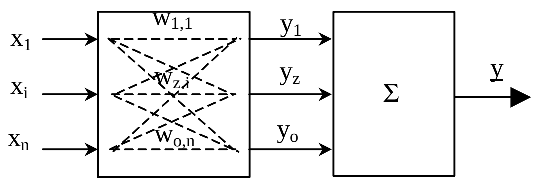

Figure 8. Modeling the VFB

The proposed model is able to define arbitrary directions at each value of the measured distance on a scanned line. Therefore this model is able to generate output vectors $\bar{y}_z$ that are parallel with a long wall located next to the robot. The key difference from PBG is that all inputs of the first block in fig. 4 have contribution to all outputs connected to the evaluation unit (Fig. 8). The potential field based model is a special case of the VFB.

8 GENERAL FEED FORWARD NEURAL NETWORK AS A VFB MODEL

VFB model can be approximated by a generalized forward neural network that is general in the sense that it has various weighting functions set on the connections among the neurons.

$$\bar{y}_z = \bar{e}_z \sum_{i=1}^{n} w_{z,i}(x_i) \tag{5}$$

In order to approximate the proper non-linear weighting functions $w_{z,i}(x_i)$ in the weighting units let us apply the proposed specialised fuzzy approach obtaining a neuro-fuzzy algorithm.

Algorithm 2: Neuro-fuzzy based on the specialised fuzzy algorithm.

Let connections $w_{z,i}(x_i)$ be approximated by (3) as: $w_{z,i}(x_i) = \sum_{j=1}^{m} \mu_{A_{i,j}}(x_i)\vec{b}_{z,i,j}$ From (5):

$$\bar{y}_z = \sum_{i=1}^{n} \sum_{j=1}^{m} \mu_{A_{i,j}}(x_i)\vec{b}_{z,i,j} \tag{6}$$

9 LEARNING ALGORITHMS FOR THE PROPOSED TECHNIQUES

This section proposes a practical simplification, namely the widely adopted sum operator based evaluation unit is applied (2). A training method is proposed for both the PGB and the VFB models.

The training algorithm does not tune all sets, but the absolute value of the consequent vectors, namely values $b_{i,j}$. The *k*-th training pattern contains input values $x_i(k)$ and the desired output direction $\vec{d}(k)$. Based on the LMS [9] let the error criteria of the algorithm is the square instantaneous error as:

$$\bar{\varepsilon}(k) = \vec{d}(k) - \bar{y}(k) = \vec{d}(k) - \sum_i \sum_j \mu_{A_{i,j}} \vec{b}_{i,j}(k)\,.$$

Therefore instantaneous gradient:

$$\hat{\nabla}(k) = \frac{\partial \bar{\varepsilon}(k)^2}{\partial b_{i,j}} = -2\bar{\varepsilon}(k)\mu_{A_{i,j}}(x_i(k))\bar{e}_i$$

In order to tune values $b_{i,j}$ the gradient descent method is applied as:

$$\Delta b_{i,j}(k+1) = -p'\hat{\nabla}(k) = p\mu_{A_{i,j}}(x_i(k))\bar{\varepsilon}(k)\bar{e}_i$$

where J is the angle of the error vector $\bar{e}(k)$ and the unique vector $\bar{e}_i$, and *p*.is the learning parameter.

This training method can easily be extended to VFB, where the evaluation unit is also based on the sum operation. So, the output from (6) is:

$$\bar{y}_z = \sum_{z=1}^{o} \sum_{i=1}^{n} \sum_{j=1}^{m} \mu_{A_{i,j}}(x_i) b_{z,i,j} \bar{e}_z\,.$$

Based on the key ideas of LMS [9] method the training iteration steps are:

$$\Delta b_{z,i,j}(k+1) = p\mu_{A_{i,j}}(x_i(k))\cos\vartheta\,.$$

10 EXAMPLES

In order to show the effectiveness of the specialized fuzzy logic technique proposed for PBG we implemented various PBG based techniques chosen from the literature and used it as a “teacher” robot. We concluded that the trained “student” robot showed the same style and the path had small difference to the “teacher” robot even in case of a new set of obstacles.

As an other example, we controlled the “teacher” robot manually. Let us present only three extremes of the results. Figure 9 shows three cases. The basic guiding styles of the manual control were: 1) keep on left side. 2) keep on right side. 3) get as far from the objects as necessary. Figure 9 shows the guiding of the three trained "student" robots among the new set of objects.

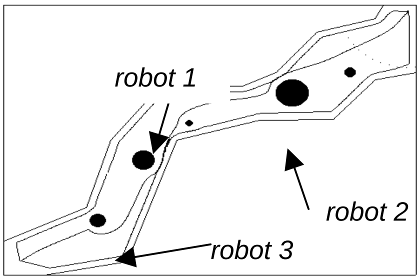

Figure 9. Guiding styles learned from humans.

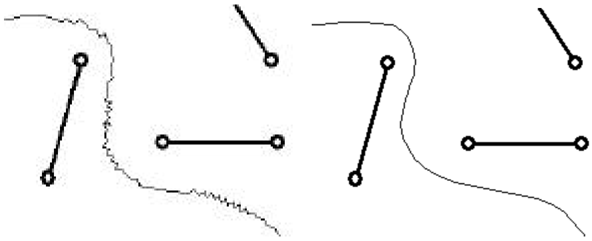

Figure 10. Path by PGB, b: VFB model

We concluded that the robot was able to pick up the main human guiding styles.

The third example shows the effectiveness of the VFB in contrast to PBG. Figure 10a is a result by PGB when its motion oscillates as discussed previously. The guiding of the VFB technique results in a rather smooth path depicted in figure 10b.

11 CONCLUSION

An extension of the potential based guiding model was proposed, which eliminates its strongly alternating behavior. A simplified neuro-fuzzy algorithm is also presented to approximate both the PGB and the extended model. Learning algorithms are also given for the proposed models. Some examples were shown to demonstrate the effectiveness of the algorithms.

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