2003 International Symposium on Advanced Intelligent Systems
September 25-28, 2003, Jeju, Korea

Estimation of Walking Habit in iSpace

Peter T. Szemes, Hideki Hashimoto
Institute of Industrial Science, The University of Tokyo
4-6-1 Komaba, Meguro Ku, Tokyo, Japan
email: szemes@hlab.iis.u-tokyo.ac.jp, hashimoto@iis.u-tokyo.ac.jp

Abstract – **In this paper, the Intelligent Space (iSpace) concept is applied for helping disabled or blind persons in crowded environments such as train stations, or airports. The main contribution of this paper is a general mathematical (fuzzy-neuro) description of obstacle avoidance method (walking habit) of moving objects (human beings) in a limited area scanned by the iSpace. A mobile robot with extended functions is introduced as a Mobile Assistant Robot, which is assisted by the iSpace. The Mobile Assistant Robot (MAR) can guide and protect a blind person in a crowded environment with the help of the Intelligent Space. The prototype of the Mobile Assistant Robot and simulations of some basic types of obstacle avoidance method (walking habit) are presented.**

I. INTRODUCTION

The definition of Intellugent Space (iSpace) from robotics point of view is a space (room, corridor or street), which has distributed sensory intelligence (various sensors, such as cameras and microphones with intelligence, haptic devices to manipulate in the space) and it is equipped with actuators and mobile agents [1].

The sensory intelligence is a distributed camera system in our current configuration. Pan-Tilt-Zoom CCD cameras are mounted on the walls to cover the all space. The processing of CCD's data is done by intelligent devices, called DIND. The DIND stands for Distributed Intelligent Network Devices. These devices form the intelligence of the iSpace [2].

The mobile robots in iSpace are equipped with sensory only for minimal safety reasons. They survive in the space by sharing the information with DINDs. The mobile robots receive information about they current and other object locations in the space (see Fig. 1.).

Mobile robots are mainly used to provide information and physical support to the inhabitants. The sensory intelligence of DINDs and mobile robots cooperate with each other autonomously, and as a result, the whole space has high intelligence, [3], [4].

The intelligent agent has to operate even if the inside environment changes, so it needs to switch its roles and behaviors autonomously. iSpace recomposes the whole space from each agent's sensory information, and returns intuitive and intelligible reactions to man. In this way, iSpace is the space where man and agents can act mutually.

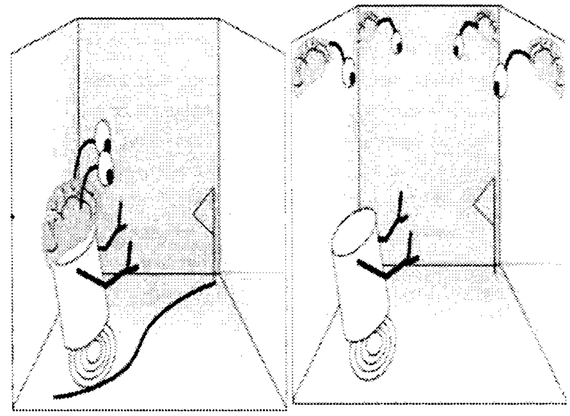

Fig.1 The concept of iSpace as a distributed sensor system

The iSpace tries to identify the behavior of moving objects (human beings) and tries to predict their movement in the near future. Using this knowledge, the intelligent space can help avoiding the fixed objects and moving ones (human beings) in the Intelligent Space.

The aim of this paper is twofold. One goal is to define a suitable mathematical model for general description of obstacle avoidance behavior of moving objects (human beings). The second is to introduce the adaptibility of this method.

Adaptibility is very important for successful operation. It is necessary both for the guided person, and for the unsteady environment. The vector field based method is suitable for handling both types of adaptibility.

The section II. introduces the basic theory for guiding styles. Scalar field based and vector field based methods are introduced. Learning and tuning of the potential and vector field based methods is also introduced in section II. The section III, show some example potential field and guiding styles.

II. BASIC OBSTACLE AVOIDANCE METHOD

A simple example illustrates the importance of knowledge of obstacle avoidance. Let's assume that a Japanese and an American person are walking towards each other. Recognizing this situation, they try to avoid each other. Using their general rule, the Japanese person keeps left and the American keeps right and they are again in front of each other. In the end they may even collide (Fig. 2.).

If the Intelligent Space can learn the walking habit of a human being, it can send a proper command to the robot in such situation.

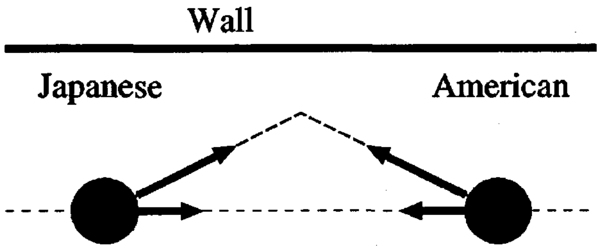

Fig. 2. Human Collision Avoidance

One of the most popular methods of description of the walking habit is the potential field based (PFB) model [6]. The robot can detect objects in the scanned area (Fig. 3.).

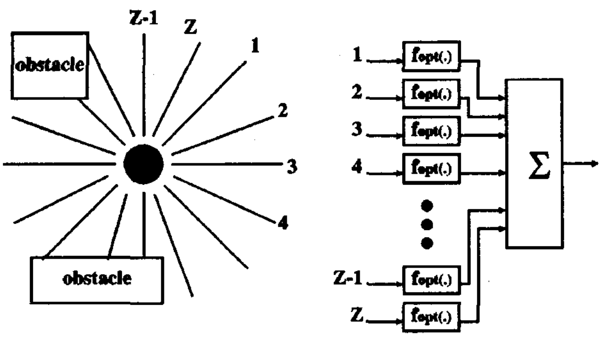

Fig. 3. Sensor Area of the Robot (left), and the block diagram of the PBG (right)

The scanned area is divided into n scanned lines that are pointed into directions of $-\vec{e}_z$ (unique vectors, where $z = 1 \ldots Z$). The main idea of the potential based model is to repulse (or attract) the robot from/to the obstacles. The objects and the target generate imaginary forces acting on the robot. The walking path is defined by the sum of repulsive forces. The magnitude of repulsive forces, F, in the different directions can be described by a potential field (Fig. 4.), which are usually inversely proportional to the distance between the obstacles and the robot but they can be described by any non-linear functions. This potential field includes information of the walking habits (obstacle avoidance methods). In many applications the same formula is used for all directions, resulting a symmetrical potential field (see in Fig. 4.(left)), which achieves "keep as far as possible" walking style. In the case of a "keep close to left side" style (see in Fig. 4.(right)), the repulsive force must be bigger at the right side of the moving object than that of the left side.

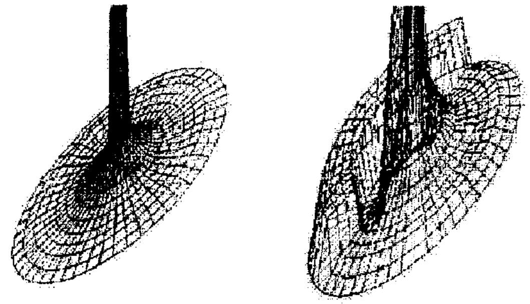

Fig. 4. "keep as far as possible" (left) stay on right side (right)

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 [7]. 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 at least their sum must be parallel with the wall. The PBG model is not able to generate such vectors (Fig. 7).

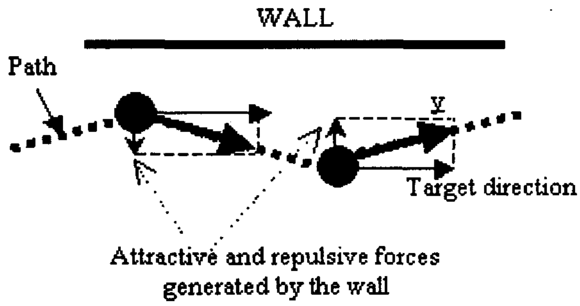

Fig.5. Guiding fluctuation of the PGB model

The PFB model can be extended to a vector field based (VFB) model [6]. The VFB model is able to define arbitrary directions at each value of the measured distance on a scanned line (see in Fig. 6.). Therefore this model is able to generate output vectors that are parallel with a long wall located next to the robot. To explain the difference let's assume that the robot detects an obstacle in a certain direction. In case of PFB model a repulsive/attractive force is generated only in this direction. In case of VFB model, the repulsive/attractive can be generated in any other direction. That is why the robot can move around an obstacle if the target is behind of it.

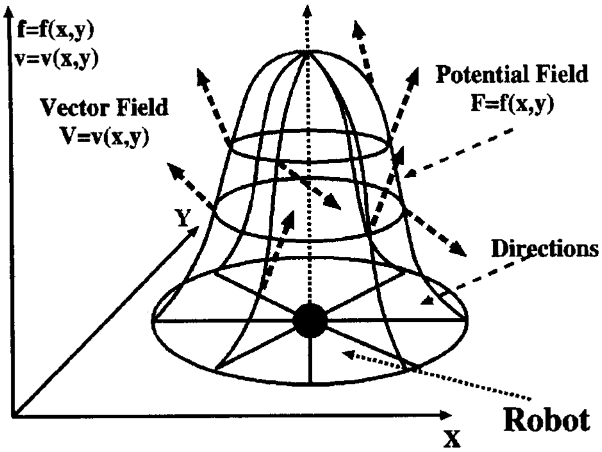

Fig. 6. Vector Field Based Model

VFB model can be approximated by a generalized forward fuzzy-neural network that is general in the sense that it has various weighting functions set on the connections among the neurons [7]. The force, $\bar{y}_i$, generated in the direction of $\bar{e}_i$ is calculated as follows:

$$\bar{y}_z = \bar{e}_z \sum_{i=1}^{I=Z} w_{z,i}(x_i) \qquad (1)$$

In order to approximate the proper non-linear weighting functions in the weighting units let us apply the proposed specialized fuzzy approach obtaining a neuro-fuzzy algorithm.

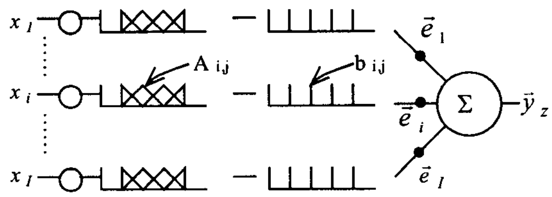

Fig.7. Fuzzy-Neuro Structure

Fig. 7. shows the applied structure to approximate the vector field based method.

Let weighting functions $w_{z,i}(x_i)$ be approximated as:

$$w_{z,i}(x_i) = \sum_{j=1}^{J} \mu_{A_{i,j}}(x_i) b_{z,i,j} \qquad (2)$$

From (1 and 2):

$$\bar{y}_z = \bar{e}_z \sum_{i=1}^{I} \sum_{j=1}^{J} \mu_{A_{i,j}}(x_i) b_{z,i,j} \qquad (3)$$

A practical simplification, namely the widely adopted sum operator based evaluation unit is applied (1). A training method is proposed for the VFB model. 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 $\bar{d}(k)$. Based on the LMS [8] the error criteria is the instantaneous error as:

$$\bar{\varepsilon}(k) = \bar{d}(k) - \bar{y}(k) = \bar{d}(k) - \sum_i \sum_j \mu_{A_{i,j}} \bar{b}_{i,j}(k) \qquad (4)$$

The instantaneous gradient:

$$\hat{\nabla}(k) = \frac{\partial \bar{\varepsilon}(k)^2}{\partial b_{i,j}} = -2\bar{\varepsilon}(k)\mu_{A_{i,j}}(x_i(k))\bar{e}_i \qquad (5)$$

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

$$\Delta b_{i,j}(k+1) = -p'\hat{\nabla}(k) = 2p'\bar{\varepsilon}(k)\mu_{A_{i,j}}(x_i(k))\bar{e}_i =$$
$$= p\mu_{A_{i,j}}(x_i(k))\bar{\varepsilon}(k)\bar{e}_i \qquad (6)$$

where p is the learning parameter. Consequently

$$\Delta b_{i,j}(k+1) = p\mu_{A_{i,j}}(x_i(k))\cos\vartheta \qquad (7)$$

where ϑ is the angle of the error vector $\bar{\varepsilon}(k)$ and the unique vector $\bar{e}_i$.

This training method can easily be extended to VFB, where the evaluation unit is based on the sum operation. So, the output from (5) is:

$$\bar{y} = \sum_{z=1}^{O} \sum_{i=1}^{I} \sum_{j=1}^{J} \mu_{A_{i,j}}(x_i) b_{z,i,j} \bar{e}_z. \qquad (8)$$

In order to save the computational complexity, simplified triangular fuzzy sets defined in Ruspini-partition are used.

III. EXAMPLE SIMULATIONS

There are 7 sets at each input direction that implies rough approximation, however, the guiding style of the operator and the "student" robot has no remarkable difference. Mobile robots are controlled by operator manually in different way, namely in regarding to the mentioned different walking styles. As the result of training, potential fields of "student" robots are asymmetrical in accordance with their guiding stiles, although before theirs were symmetrical. Let us present only three extremes of the results.

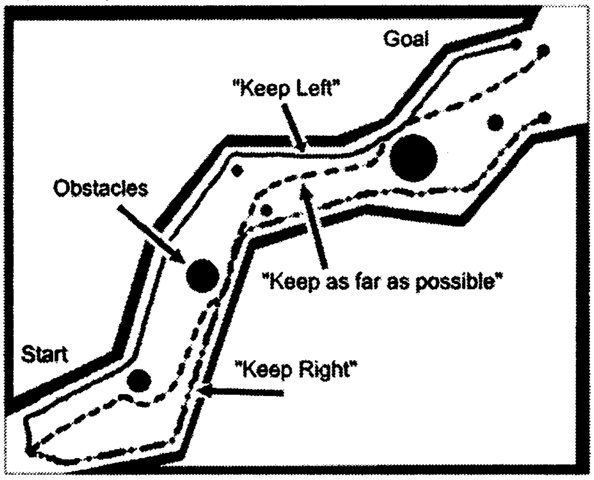

Fig. 8 Guiding Styles Learned from Humans

Fig. 8. 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. Fig. 8. shows the guiding of the three trained "student" robots among the new set of objects. We concluded that the robot is able to pick up the main human walking styles.

The following example shows the effectiveness of the VFB in contrast to PBG. Fig. 9.a) 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 Fig. 9.b).

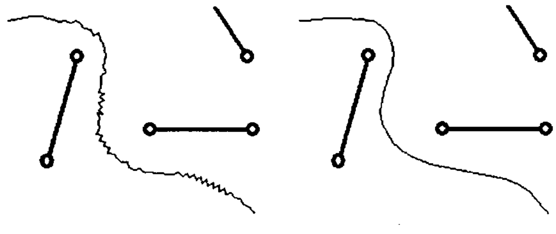

Fig 9. a) Path by PGB, b) VFB model

IV. Conclusions

In this paper, the Intelligent Space concept is applied for helping disabled or blind persons in crowded environments such as train stations, or airports. The main contribution of this paper is a general mathematical (fuzzy-neuro) description of obstacle avoidance method (walking habit) of moving objects (human beings) in a limited area scanned by the Intelligent Space. 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 extended PGB model (VFB). Learning algorithm is also given for the proposed model. Some examples were shown to demonstrate the effectiveness of the algorithm. As well as this VFB based General Neural Network Guiding Style Model applied for the common structure of the adaptive system to be trained, gives a very flexible and easy to train background to many application areas. The authors suppose, that based on the common format of guiding style description, the guiding styles and recognizing walking habits, introduced in this paper, can serves as a suitable background for collision avoidance.

V. References

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