분산형 센서로 구현된 지능화 공간을 위한 계층적 행위기반의 이동에이젼트 제어

Human Hierarchical Behavior Based Mobile Agent Control in Intelligent Space with Distributed Sensors

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Abstract : The aim of this paper is to investigate a control framework for mobile robots, operating in shared environment with humans. The Intelligent Space (iSpace) can sense the whole space and evaluate the situations in the space by distributing sensors. The mobile agents serve the inhabitants in the space utilizes the evaluated information by iSpace. The iSpace evaluates the situations in the space and learns the walking behavior of the inhabitants. The human intelligence manifests in the space as a behavior, as a response to the situation in the space. The iSpace learns the behavior and applies to mobile agent motion planning and control. This paper introduces the application of fuzzy-neural network to describe the obstacle avoidance behavior learned from humans. Simulation results are introduced to demonstrate the efficiency of this method.

Keywords : human behavior, mobile agent, obstacle avoidance, fuzzy-neural network, intelligent space

I. Introduction

The Intelligent Space (iSpace) is a space (room, corridor or street), which has ubiquitous distributed sensory intelligence (various sensors, such as cameras and microphones with intelligence) actuators (TV projectors, speakers, and mobile agent) to manipulate the space [1-3]. The iSpace propagates mobile robots in the space, which act in the space in order to change the state of the space. These mobile robots are called mobile agents. Mobile Agents cooperating with each other and core of the iSpace to realize intelligent services to inhabitants. The intelligence in iSpace has capability of evaluation of situations inside the space [2]. The evaluated situations are applied for learning the behavior of inhabitants. The evaluated behaviors are given to the control system of mobile agent. There are many definitions of the intelligence. The intelligence can be considered as a reaction against a given action.Behavior is a generalized mapping between situations (state of the space) and actions. But the intelligence is also means capability of learning. The iSpace integrates both types of definitions. Inhabitants in the iSpace are producing intelligent reactions against instantaneous situation.

The iSpace evaluates situations (actions-reactions) from sensed information [4]. The evaluated situations are given to the learning system, where behaviors are concluded from situations. The mobile agents serve the inhabitants in the space utilizes the evaluated information by iSpace [5]. The mobile agents have sensors and/or actuators with computational devices and computer network communication capabilities. The iSpace senses the space and acting in the space. The sensing is done through distributed sensory network, and the acting is done by global actuators like projectors or speaker systems, or by local actuators like mobile agents. The mobile agents can sense the space and can act in the space locally.

The personal communication between the iSpace and a certain individual is an example for local sensing and acting. iSpace intelligence of the motion planning and control are based on learned human behaviors. The human behaviors are extracted from the space by sensor system of iSpace. The pedestrian walking behavior includes many parts like planning activity, obstacle avoidance and walking pattern. This paper focuses on obstacle avoidance behavior of pedestrians. The mobile agent control is derived from pedestrian hierarchical behavior model.

The rest of this paper is organized as follows. The following section summarizes the pedestrian behavior models and proposes a mobile agent control framework. Section III explains the obstacle avoidance behavior and introduces a mathematical model to describe the particular behavior. Obstacle avoidance behavior is modeled by artificial potential fields. Fuzzy-Neural Non-linear Function Approximation is applied to describe the artificial potential functions. Section IV introduces the evaluation and learning capability of Fuzzy Neural Network. The evaluation is done by walking path extraction from spatially distributed camera sensors. Section V introduces some simulation examples to demonstrate the effectiveness of this method.

II. Mobile control framework

The task of the mobile agent is to provide certain set of services to inhabitants, cooperation with distributed sensory intelligence. This section focuses on the human behavior that describes walking from one place to other place.

Understanding pedestrian behavior is essential in a shared environment, where the mobile robots should operate without disturbing humans. The robot has to realize the human walking intentions, and avoid any collision with humans and other obstacles. Human walking behavior in defined by the features of the environment, the physical conditions, and the goals [11,12].

A vertical layered model is composed from walking sub-behaviors [11] and applied in this paper as a theoretical foundation of mobile robot control. The layered control framework is adapted to the distributed feature of the iSpace. As a result of analysis of walking subtasks, we concluded a tree-layer control structure comparison of human behaviors with mobile agent control tasks (table I.). Long term

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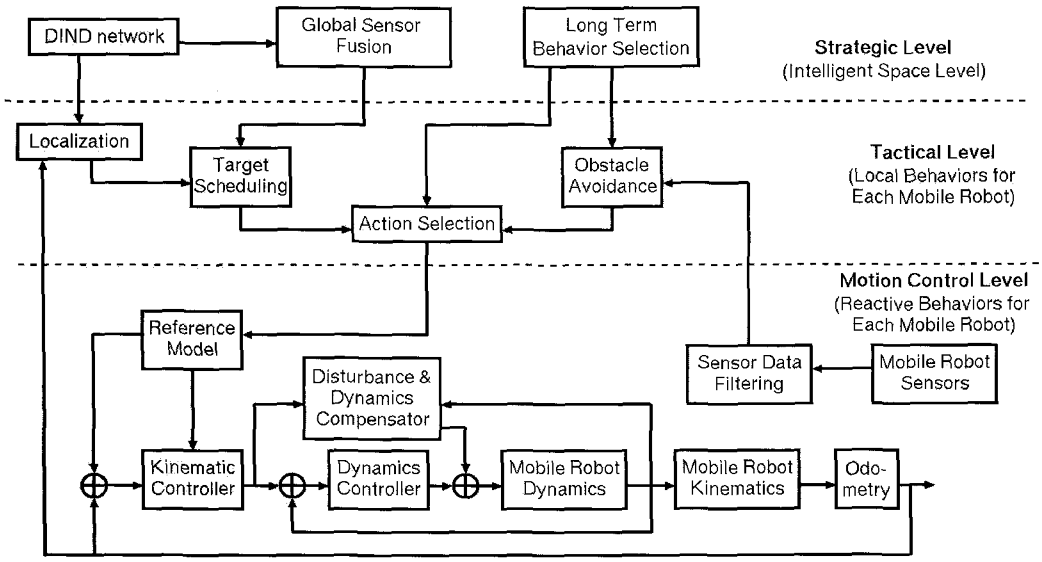


Fig. 1. Control framework of mobile robot.

decisions are made in Strategic Level. The strategically decisions are often made by groups of person in real life. Therefore, strategic decisions are made globally for mobile agents in iSpace. Corresponding human sub-behaviors are Activity Listing and Long Term Perception. Activity listing is a series of actions to fulfill some requirements of Social Behaviors while realizes a specified goal. The long-term perception is intention free but action oriented model of the sensed space. Long Term Behavior Selection and Global Sensor Fusion models the Social Behavior on the mobile robot side. The social behavior of the inhabitants is recognized by long term behavior selection as global behavior of the humans and creates cooperative or counteractive behavior for mobile robots. The Global Sensor Fusion function is the fusion of various sensor data into an integrated data structure which is describes the various aspects of the space. Global sensor fusion involves cooperation with DINDs, the distributed sensory network.

The short term decisions are made in Tactical Level. Activity Scheduling is the decision mechanism to realize the listed activity in order to maximize the effectiveness of each activity. The Activity Area and Route Choice behavior modifies of the scheduling according to the local and instantaneous features of the space. Tactical level controls the mobile robot local behaviors. Local Behavior Arbitration takes care of the action-reaction between the robot and its local environment. Tasks of Obstacle Avoidance and Target Scheduling model activity area and route choice behavior of pedestrian. Motion Control Level involves reflexive behaviors both for human and mobile robots. Walking Pattern behavior is depends on physical condition and personal characteristics.

Many small reflexive behaviors, like balancing, stepping, and walking, are combined together for fast and accurate movement control. Attention filtering behavior implements fast and accurate selection of sensed local information to drive motion behaviors. Dynamical Motion Control belongs to this layer at the robot side. The task of dynamical control is external and internal disturbance rejection to keep the motion of mobile robot in stable and controllable states. The robot should adapt also dynamically to its local environment, even if the robot parameters or the environmental parameters have changed. Local sensors and sensor filtering functions are needed for

Table 1. Sub-behaviors of pedestrian behavior, comparison of walking subtasks between humans and mobile agents.

	Pedestrian	Mobile Robot
Strategic Level (Social Behaviors)	-Activity Listing -Long Term Perception	-Behavior Selection -Global Sensor Fusion
Tactical Level (Local Behaviors)	-Activity Scheduling -Activity Area and Route Choice	-Local Behavior Arbitration -Obstacle Avoidance -Target Scheduling
Motion Control Level (Reactive Behaviors)	-Walking Pattern -Attention Filtering	-Dynamics Control -Sensor Data Filtering

fast reflexive behaviors. Sensor Data Filtering models the attention selection and filtering behaviors of pedestrian.

Fig. 1 shows proposed mobile control framework in iSpace. The Strategic Level belongs to the iSpace, which has connection with the DIND network. The DINDs could filter specific information from the space like human location or human gesture with attention filtering. The Tactical Level and Motion Control Level are belonging to a specified mobile robot.

The Global Sensor Fusion module receives information from DINDs and issues target for Target Scheduling module of a specified mobile robot. Global behavior of pedestrians is considered in Long Term Behavior Selection module, and corresponding behavior is sent to Obstacle Avoidance module. Each mobile robot has Tactical Level control unit. The tactical control unit receives strategic behavior commands, and also local information around the specific robot from DIND network. For example, location of the robot and the object around the robot is necessary for obstacle avoidance. The tactical control unit sends dynamical parameters, such as velocity and speed of angle to the operation level. Motion Control Level handles the robot dynamics. The aim of motion control level is a dynamical motion control against the parameter uncertainties of the robot's body and external disturbances.

III. Modeling obstacle avoidance behavior

Let us consider two typical styles (Fig. 2). One, main navigation behavior of an aircraft carrying dangerous material is to keep "as far from the mountains as possible" Two, remaining in secret while seeking a mouse leads to the opposite behavior for a cat, namely, "get as close to the object as possible"

If the iSpace can observe and learn the behavior of a human being, then it can send a proper command to the Mobile Agent in such situation and the Mobile Agent avoids the collision. The Mobile Agents can change its obstacle avoidance behavior according to the local situation around the agent.

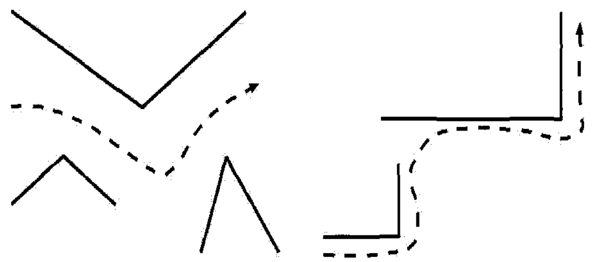


Fig. 2. Basic obstacle avoidance strategies: "as far as possible" (left) and "as close as possible" (right).

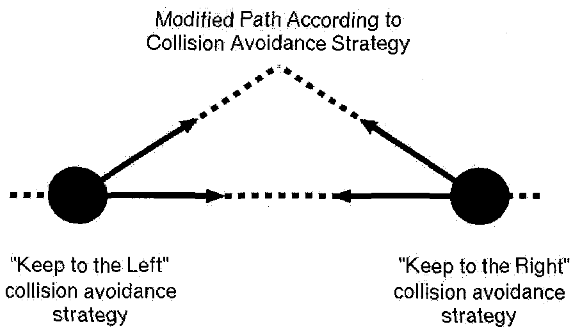


Fig. 3. Two different obstacle avoidance strategy may result dangerous situation.

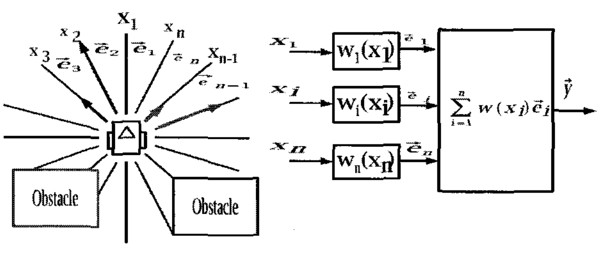


Fig. 4. Scanning area of the robot (left), direct evaluation of sensor information (right).

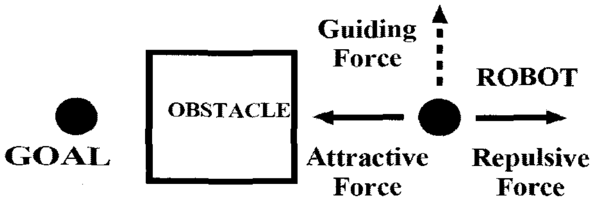


Fig. 5. Local minimum point of the potential based guiding.

A simple combination of these basic behavior styles can characterize the main rule of a traffic system: "keep close to the right or the left side". Let's consider a simple example to illustrate the importance of this knowledge. Let's assume that Japanese and American persons are walking towards each other. Recognizing this situation, they try to avoid each other. Using their national traffic rule, the Japanese person keeps left and the American keeps right and they are again in front of each other. It might be ended in a collision. (see Fig. 3).

1. Direct evaluation of sensor information

Artificial potential based guiding approach is applied to handle the dynamic and uncertain environment around the robot ([6,7]). The robot can detect objects in the scanned area (Fig. 4).

The scanned area is divided into n scanned lines that are pointed into directions of $\vec{e}_i$ (unique vectors, where $i = 1 \ldots n$). The radial scanned lines structure has an important advantage that spatial density of the scanning is growing with the decreasing distance between the obstacle and the robot. The sensor system provides the distance between the robot and the object on the scanned lines [10]. The main idea of the potential based guiding is to repulse (or attract) the robot from/to the obstacles [8]. The objects and the target generate imaginary forces (y_i, $i=1 \ldots n$) acting on the robot. Summing the effect of these virtual forces, the desired moving direction can be obtained. The virtual vectors must be calculated for each location as quickly as possible to achieve a smooth and reactive guiding. The magnitudes of the repulsive forces are usually inversely proportional to the distance between the obstacles and the robot but they can be described by any non-linear functions.

The virtual force along the scanned line:

$$\vec{y}_i = w_i(x_i)\vec{e}_i \tag{1}$$

where $i = 1 \ldots n$ (n is the number of scanned lines) from the measured distances (x_i) to each scanned lines. The $w_i(x_i)$ is the weight function of the scanned line. The virtual force vectors are pointed into the opposite of the scanned direction (key idea of potential based guiding), and their absolute values depending on the detected distances are: $|\vec{y}_i| = w_i(x_i)$. The overall force is the summation of the virtual forces along the directions of the scanned lines:

$$\vec{y} = \sum_{i=1}^{n} w_i(x_i)\vec{e}_i \ . \tag{2}$$

In many cases this kind of evaluation is not effective. For example let the weight function on each scanned line the same. Applying (2) to symmetrically located obstacles, will result attractive and repulsive force, and the sum results zero vector (see Fig. 5).

The attractive force represents the goal reaching behavior, while the repulsive force represents the obstacle avoidance behavior. Choosing one of the $\vec{y}_i$, what is perpendicular to the attractive and repulsive force, in the evaluation would lead to escape from the local minimum.

2. Indirect evaluation of sensor information

To avoid the local minimum problem (Fig. 5) an extension of the above mentioned method is introduced. All sensor information is propagated to all outputs (Fig. 6). Weight function is introduced between scanned inputs i and the output nodes j ($j=1... m$):

$$\vec{y} = \sum_{i=1}^{n} w_{j,i}(x_i)\vec{e}_i \tag{3}$$

The summarized vector output is calculated as in (2), but with extended weight functions as in (3):

$$\vec{y} = \sum_{j=1}^{m}\sum_{i=1}^{n} w_{j,i}(x_i)\vec{e}_i \tag{4}$$

3. Fuzzy-neural approximation

The weight functions are approximated by fuzzy sets. The fuzzy approximation gives piece-wise linear approximation in case of triangular antecedent fuzzy set. The number of antecedent fuzzy sets are denoted with k, where $k=1... l$. Fuzzy approximation of direct sensor evaluation is shown first. The weight function of direct evaluation of sensor input [9]:

$$w_i(x_i) = \sum_{k=1}^{l} \mu_{A_{i,k}}(x_i) b_{i,k} \tag{5}$$

The $\mu_{A_{i,k}}(x_i)$ is the membership values of the sensor value, x_i case of antecedent set k, and direction of scanned line i. The $b_{i,k}$ is the consequent set for antecedent set k, and direction of scanned line i. In this model the consequent set is only one value set. The virtual vector along the scanned line i is generated by:

$$\vec{y}_i = \sum_{k=1}^{l} \mu_{A_{i,k}}(x_i) b_{i,k}\vec{e}_i \tag{6}$$

Where $\vec{e}_i$ is a unique vector pointed into the direction of scanned line as in (2). Summarized vector output (2) approximated by fuzzy sets:

$$\vec{y} = \sum_{i=1}^{n}\sum_{k=1}^{l} \mu_{A_{i,k}}(x_i) b_{i,k}\vec{e}_i \tag{7}$$

The indirect evaluation of sensor information 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 [10].

One weight function which connects the sensor input i and the output node j:

$$w_{i,j}(x_i) = \sum_{k=1}^{l} \mu_{A_{i,k}}(x_i) b_{j,i,k} \tag{8}$$

In equation (8) the antecedent sets ($A_{i,k}$) are depend only the scanned lines i, but independents from the output nodes j. The consequent sets are depend both on the scanned lines i, and the output nodes j. Vector output along one output node j:

$$\vec{y}_i = \sum_{i=1}^{n}\sum_{k=1}^{l} \mu_{A_{i,k}}(x_i) b_{j,i,k}\vec{e}_i \tag{9}$$

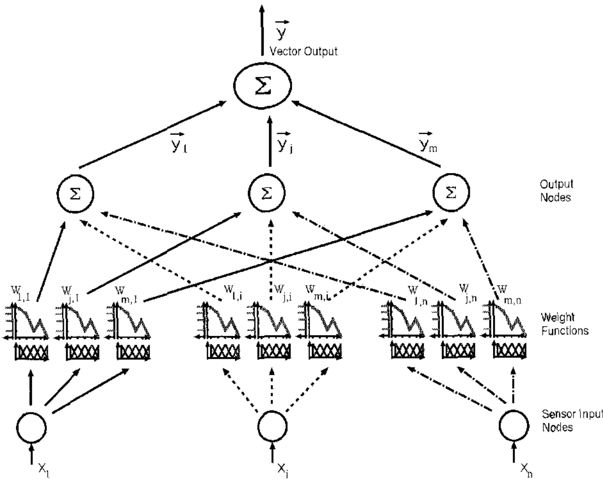


Fig. 6. Fuzzy approximation of indirect evaluation of sensor information.

Summarized vector output of the fuzzy-neural network:

$$\vec{y}_i = \sum_{j}^{m}\sum_{i=1}^{n}\sum_{k=1}^{l} \mu_{A_{i,k}}(x_i) b_{j,i,k}\vec{e}_i \tag{10}$$

Fig. 6 illustrates the applied fuzzy neural network architecture. Each sensor data ($X_i, i = 1...n$) is distributed to each sensor node ($\vec{y}_i$) via the weight function, $W_{j,i}(X_i)$. Weight functions are piece-linear approximated by fuzzy sets. The input fuzzy set is Ruspini partitions in our case. The consequent fuzzy sets are one valued fuzzy sets. This simple architecture enables fast computation, and simple implementation algorithm.

IV. Evaluation and learning of pedestrian behaviors

This section illustrates the learning capability of the obstacle avoidance behavior of mobile robot. The learning capability enables by the fuzzy-neural network which is applied for approximation of direct and indirect sensor evaluation.

1. Evaluation and learning framework

Fig. 7 shows the actual configuration of learning. The picture of the human walking is taken by the DIND and sent to the Human Localization Module. The module calculates the human position and sends to the Learning module. The result of the leaning is a potential function, what is given to the robot control module.

2. Learning method of fuzzy neural network

Learning method is introduced for indirect sensor evaluated control (Section III-B). The human walking path ($p[t]$) calculated by Human Localization module. The walking path is a discrete series of position, along time series $t:=\{t=t(k)|k=1... z\}$. The path is scaled to the obstacle avoidance control:

$$\vec{d}[t] = |\vec{y}[t]| \frac{\vec{p}[t]}{|\vec{p}[t]|}, \tag{11}$$

where $\bullet[t]$ denotes vector value at $t=t(k)$ time instance. $|\vec{y}[t]|$ is the absolute value of obstacle avoidance initial rule base. The training algorithm does not tune all sets, but the absolute value of the consequent vectors, namely values $b_{j,i,k}[t]$. The t-th training pattern

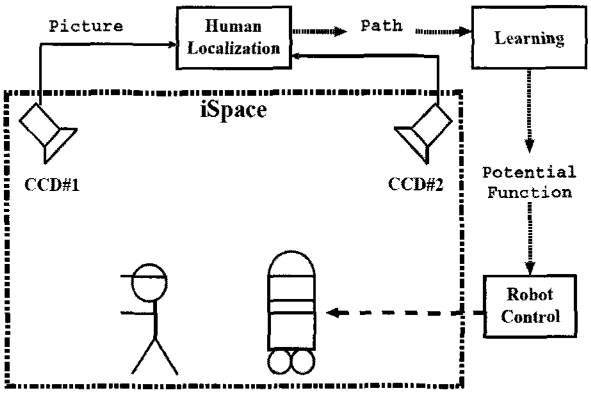


Fig. 7. Learning and evaluation framework in Space.

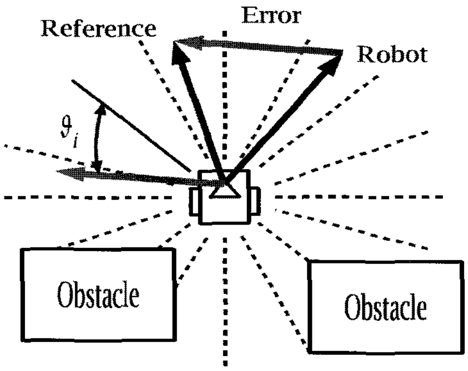


Fig. 8. Evaluation of error vector, difference between the reference vector and the robot vector.

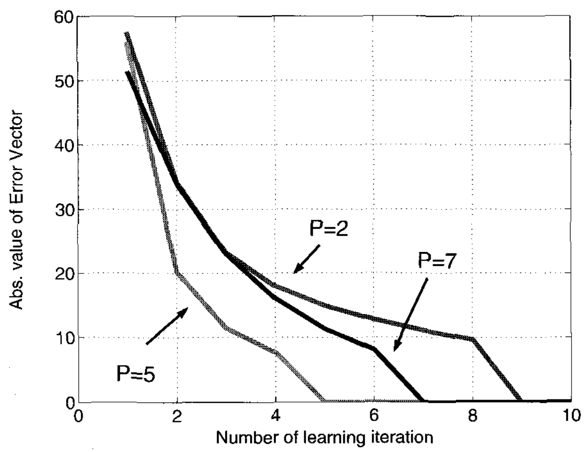


Fig. 9. Speed of learning: fall of error vector absolute value at different learning parameters (P).

contains input values $x_i[t]$ and the desired output direction $\vec{d}[k]$. The error criteria is the instantaneous error between the reference vector and the robot (Fig. 8):

$$\vec{\varepsilon}[t]=\vec{d}[t]-\vec{y}[t]=\vec{d}[t]-\sum_{j=1}^{m}\sum_{i=1}^{n}\sum_{k=1}^{l}\mu_{A_{i,k}}(x_i[t])b_{j,i,k}\vec{e}_i \quad (12)$$

The instantaneous gradient:

$$\hat{\vec{\nabla}}_{i,k}[t]=\frac{\partial(\vec{\varepsilon}[t])}{\partial b_{j,i,k}}=-2\vec{\varepsilon}[t]\mu_{A_{i,k}}(x_i[t])\vec{e}_i \quad (13)$$

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

$$\begin{aligned}\Delta b_{j,i,k}[k]&=-p'\hat{\vec{\nabla}}_{j,k}[t]=-2p'\vec{\varepsilon}[t]\mu_{A_{i,k}}(x_i[t])\vec{e}_i=\\&=p\mu_{A_{i,k}}(x_i[t])\vec{\varepsilon}[t]\vec{e}_i\end{aligned} \quad (14)$$

where $p=2p'$ is the learning parameter. In (14) the vector product can be calculated as:

$$\vec{\varepsilon}[t]\vec{e}_i=|\vec{\varepsilon}[t]|\cos(\vartheta_i[t]) \quad (15)$$

Consequently, the tuned consequent sets:

$$b_{j,i,k}[t+1]=b_{j,i,k}[t]+p\mu_{A_{i,k}}(x_i[t])\,|\vec{\varepsilon}[t]|\cos(\vartheta_i[t]) \quad (16)$$

where $\vartheta_i[i]$ is the angle of the error vector $\vec{\varepsilon}[t]$ and the unique vector $\vec{e}_i$.

Fig. 8 shows the obstacle avoidance behavior learning method. The error defines as the difference between, the reference moving direction (Reference vector) (walking habit from the observed path) and the Robot's moving direction (Robot vector). This error vector is evaluated back to the direction of the sensors, and tunes the weight constants, $b_{j,i,k}[t]$.

Fig. 9 shows the convergence of the training procedure with different values of learning parameters, *P*. When *P=2* almost 10 learning iterations is necessary with the same training data for small error. Increasing learning parameter, *P* may not means faster learning. In this training session, *P=5* gives faster learning, than *P=7*. The learning parameter should be tuned for each training session, as a conclusion of training process.

V. Examples

Tactical Level Control of Mobile Agent is considered in this section. The control framework for tactical control is shown in Fig. 10. The output of this layer is Moving Vector that points toward the moving direction, and its absolute value represents the desired instantaneous traveling speed.

The Moving Vector ($\vec{M}$) is weighted summary of the Obstacle Vector ($\vec{y}$) and the Target Vector ($\vec{T}$):

$$\vec{M}(t)=a\vec{y}(t)+b\vec{T}(t) \quad (17)$$

To approach the target and avoid objects behavior can be tuned by the weight parameter *a* and *b*. If *b* is positive, then the mobile agent approaches the target even there is no obstacles $\vec{y}=0$. If *b* is negative, than the mobile agent is pushed by the target.

Fig. 11 shows a basic example of obstacle avoidance. The robot moves from start position to goal position. The robot cannot move directly form start to goal position because of corner. Fig. 11(a) shows the resulted path according to (17). The resulted path and the resulted behavior can be changed by parameter *a* and *b*.

Fig. 12 shows three cases of trained obstacle avoidance behavior. The basic obstacle avoidance behavior of manual control were: 1) keep

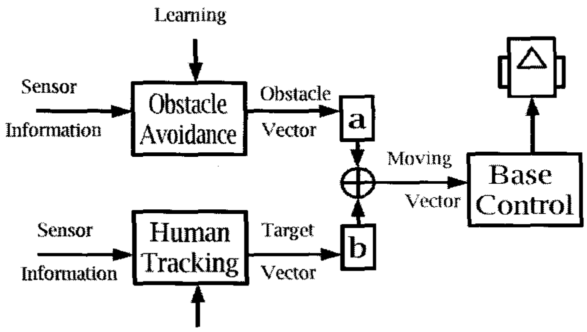
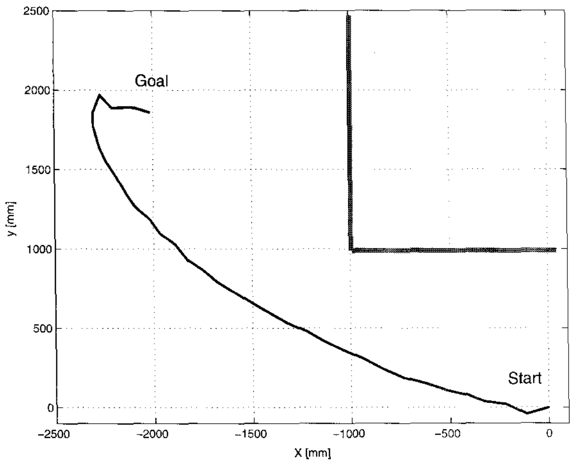
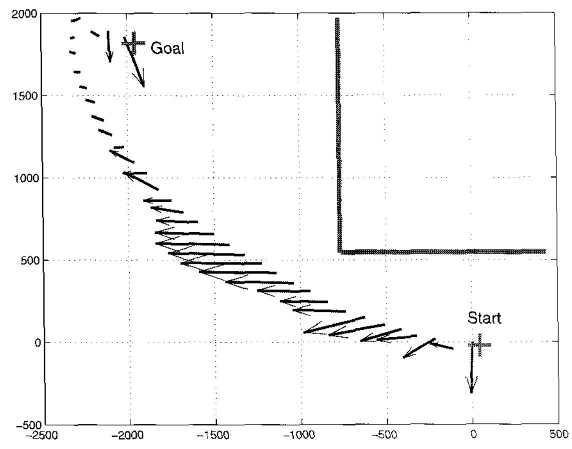


Fig. 10. Tactical level control of mobile agent.



(a)



(b)

Fig. 11. Path of the mobile robot (a) and the obstacle vectors along the path (b).

on left side. 2) keep on right side. 3) get as far from the objects as necessary. Fig. 12 shows the obstacle avoidance behavior of the three trained mobile agent among the new set of objects. We concluded that the robot is able to pick up the main human obstacle avoidance behaviors.

The next demonstration illustrates the limitation of the presented method to describe the obstacle avoidance behavior. The thick lines represent wall-type objects. In Fig. 13, the mobile agent try to reach the goal position on the right side, using three different guiding styles.

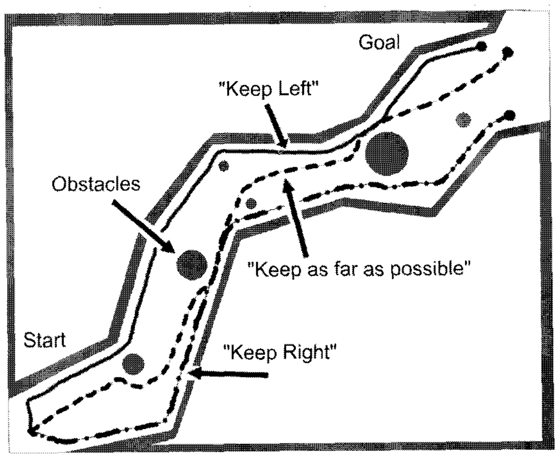


Fig. 12. Path of the mobile robot (left) and the obstacle vectors along the path (right).

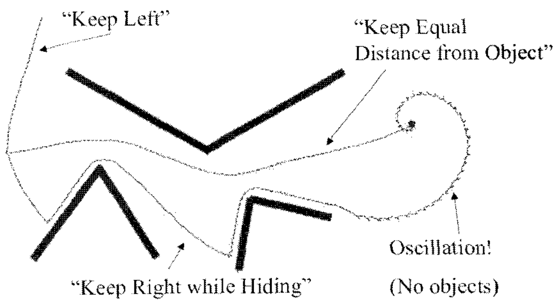


Fig. 13. Demonstration of basic obstacle avoidance Behaviors; application of behaviors in different environment, where the learning has been done.

The "keep on the left side" style in not successful in this environment, because the mobile agent does not approach the goal position. Robot with "keep on the right side" style approaches the wall, and moving along the wall. Circular vibration is observed in the robot's path, when the robot lefts the walls. This caused by the decision mechanism between the obstacle avoidance and the goal reaching when the robot left the walls. The "get far from the objects" guiding style is optimal for this environment.

VI. Conclusion

The aim of this paper is to investigate a control framework for mobile robots, operating shared environment with humans. The principle of control framework is derived from pedestrian behavior model. The obstacle avoidance behavior is a characteristic feature of the proposed framework. Virtual potential based obstacle avoidance method is applied to describe the obstacle avoidance behavior. The virtual potential method is approximated by fuzzy-neural network. The learning capability of fuzzy-neural network, and learning methods is also presented. The learning methods, and the learning configuration in the iSpace will be revised as a future work.

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