A NOVEL APPROACH TO HUMAN MOTION ESTIMATION WITH APPLICATIONS IN HUMAN-ROBOT SAFETY

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ABSTRACT

Assistive robotics has brought convenience especially to disabled and handicapped including the blinds. Mobile housekeeping robots such as floor cleaners are capable of local obstacle avoidance. However there is always a risk of hitting moving obstacles or blind human when they walk through the environment. In this article, a new decision mechanism is introduced for modelling path planning strategies adopted by blind travellers including wall-following, and taking shortcuts in indoor spaces e.g.; home, and office. A statistical path prediction method is used together with Fuzzy Cognitive Map FCM for prediction of entire paths from partial trajectories. Supplying knowledge from the presented model of spatial cognition and path planning to mobile robots can enhance their motion algorithms for better obstacle avoidance as well as safer service to users with visual impairment and blindness.

Keywords: *Assistive Robotics, Fuzzy Cognitive Map, Human Motion Estimation.*

INTRODUCTION

Understanding the needs of the blinds and visually handicapped is of utmost importance in every society [1-2], including Malaysia [3-5], where a single state (Kelantan) is estimated to have 50,000 people who are either blind or sight impaired [6]. Study in this field has signified especial care for this population, and therefore led to development of facilities, services, and assistive technology. Various studies focused on comfort, and safety issues in house, office, transit terminals, and etc.

In the context of assistive technology, housekeeping robots such as floor cleaners are becoming more popular. Considering the aging society and therefore upcoming problems for care systems, housekeeping robots might even not be only tempting but becoming really useful and even necessary [7]. However, safety is naturally a critical issue for all robots which operate in vicinity of humans. Therefore, it is important to have a clear safety philosophy and implementation which prevents the robot from injuring anyone under all circumstances [8]. This is by providing more information about safety into current robot navigation algorithms in addition to the knowledge related to map building, localizations, goal, and task to be accomplished by them.

In this research, a new systematic decision model is introduced for real time estimation of blind trajectories in unknown environments. The system's data-base is a collection of all facts and rules i.e.; if-then expert assertions on blind way-finding which help to create predictive models of blind path planning decisions. The decisions are made at time instances called productions, and generating a series of these productions using expert models result in prediction of an entire path. While factor concepts such as behavioral and environmental are discovered and defined according to observation and empirical test, a decision model is required to justify the relationship between those factor concepts and the choices made i.e.; decision concepts.

The objective is to provide safety for blind humans in vicinity of mobile robot by making the robot aware of their process of spatial cognition, and therefore path planning behavior. In way-finding, the goal is to understand how blind people conceive their environments [9], and therefore how assistive device must be designed to be more useful with higher safety. A real time path prediction method enables the robot to estimate future motion of the person and reduce the risk of any collision.

RELATED THEORIES

The basic theories of deficiency, inefficiency, and difference were introduced about the role of vision in way-finding [10]. However, the difference theory was further supported by other scientists [11-12]. Unlike the theory of deficiency i.e.; lack of visual experience results in a total lack of spatial understanding, the difference theory suggests that blind people can compensate the lack of vision by using different senses i.e.; haptic, and hearing, as well as different path planning strategies. Blinds have abilities which are qualitatively different from, but functionally equivalent to those of sighted people. Therefore, blinds' way-finding and mobility is not necessarily inferior to that of sighted people as suggested by the inefficiency theory.

Spatial information is available to the blinds through senses other than vision which form the basis of spatial coding. However, the lack of vision changes the way in which information is coded [12]. Vision provides reliable information about objects in further distances as well as boundaries enabling for external referencing or map-like cognition. On the other hand, the most reliable forms of spatial coding through touch and haptic are based on movement of body and limbs which can detect objects in nearer distances. This generally gives rise to egocentric referencing in way-finding without vision. Therefore, blinds explore and gain knowledge mostly through procedural routes in their environment i.e.; sequential representations. From local exploration of declarative subspaces, landmarks are transformed into routes and even to maps from which a global understanding of the whole space is obtained.

EXPERT MODEL OF PATH PLANNING

In this article, in line with previous experts' conclusions [12-13], it is hypothesized that the fundamental assertions constitute as basis of one's decision making process including; spatial inference, spatial reasoning, and productions. Figure 1 illustrates the idea of an action selection system (AI production) developed on the basis of blind psychological concepts i.e.; referencing, and behavioral strategies, as well as physiological, and environmental factors in way-finding. As an analysis tool, the model is applicable to modify current navigation algorithms used for mobile assistive robots by supplying information about way-finding patterns of blind travelers.

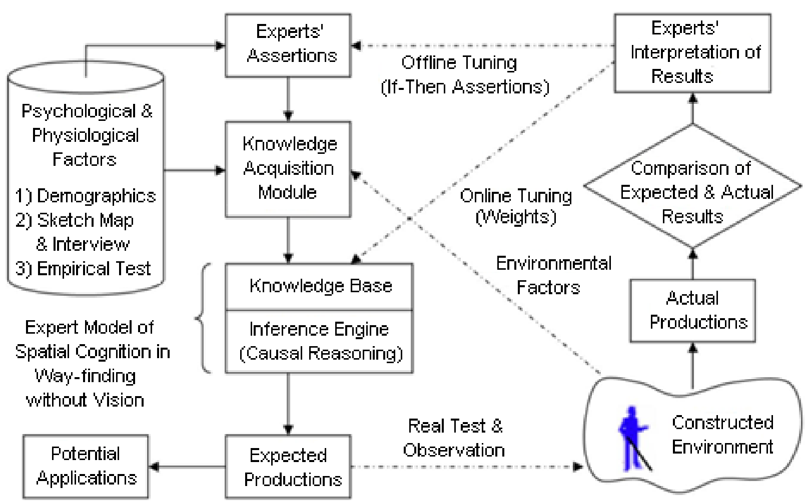

Figure 1: Action selection for predicting blind motion productions.

FCM Decision Mechanism

The supply of factor concepts as well as decision concepts to the expert model of Figure 1 is from previous research findings [11-13]. As the main part namely causal knowledge acquisition and inference, fuzzy cognitive map FCM is used to generate new weights of concepts from their initial values. Fuzzy models are advantageous in inclusion of uncertainties since no precise initial weight is needed for concepts and their causal interactions. Besides, FCM is applicable to group decision support mechanism by aggregating multiple decision makers' views on a specific problem [14]. This ability is also useful for validating the model through more experiments with blind subjects i.e.; by aggregating, and averaging of the weights.

The initial weights of environmental factors i.e.; current position, and direction of motion are set from real-time tracking of the subjects which will be explained in ‘Actual Experiments’. While for physiological and psychological factors, the weights are defined once, and with reference to subjects’ clinical and empirical records. The weights are defined qualitatively, and later tuned through more experimental work until more realistic results obtained.

As depicted in Figure 1, during the downward process, at any time instance the next production is predicted according to current production information as well as expert assertions about interrelation of contributing factors. The correctness of anticipations is then verified during the reverse process (upward) which is in fact based on actual observation of the traveler’s motion. From comparison of anticipated and actual results, two tuning strategies are available.

During Online tuning, the concepts i.e.; FCM nodes, get series of GA-based optimized values until more comparable productions are anticipated. While in Offline tuning, the causal interactions are redefined. It must be noted there are two sources of knowledge for defining causality and intensity of the interactions namely direction, and weights of the FCM edges.

The causalities are defined from previous studies [12-13], and are considered to be unchangeable throughout the work. Although in some cases there are new assertions proposed by the authors and therefore are subjected to changes until strongly validated by experimental evidences. From intensity perspective, the interaction weights can be realistically optimized. Figure 2 shows a simple inference structure consisting of some of the concepts engaged in motion productions.

The FCM model showed good results by anticipating trajectories along walls, and shortcuts which will be explained in ‘Results’. But there are shortcomings such as system inability in predicting critical points of the path, i.e.; the points where shortcutting starts or ends. Another disadvantage is that the system is strongly dependant on the experts’ views on defining the weights which sometimes result in poor anticipation of an entire path.

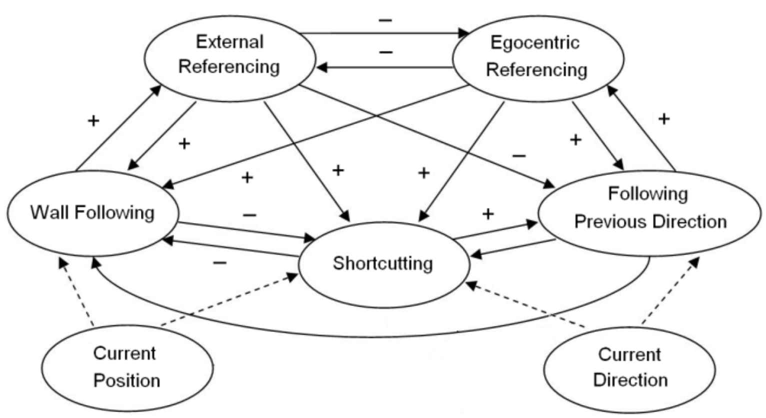

Figure 2: Causal inference of contributing factors based on FCM implementation.

Statistical Case Based Reasoning CBR

The FCM model provides a reliable framework for prediction of trajectories as well as the overall paths. However, due to inherent variability of biological systems, prediction of behaviors can not be fully achieved. Therefore, based on ideas in dynamical systems and quantum theory, the more viable aspect is to look at models of the statistical properties of the system, i.e.; probability density function.

As suggested by the difference theory [10], the differences in perception channels, knowledge acquisition and knowledge structures, provide more or less information to blind individuals that are different in nature but qualitatively equal to those of sighted individuals.

According to this, and based on the fact that blind motions fall into certain categories as addressed by [13], motion patterns can be used to estimate one's trajectories in both known and unknown environments. Therefore, integration of a case based reasoning CBR structure into the existing FCM can be a solution to the stated problem. Here, CBR-augmented FCM decision support system is particularly suitable as it is capable of making decision for a new case with respect to the most similar one. The cases are various motion patterns obtained statistically from empirical tests, and the new case to be examined is partial trajectories of an individual blind traveler for which the path is being estimated.

Figure 3 shows the proposed CBR-FCM method to be applied to the problem of path prediction. The actual performance of a traveler is frequently compared against memorized motion patterns through the CBR module. The pattern with highest level of likelihood which is the one with similar characteristics of normal distribution function is then anticipated to be followed by the traveler.

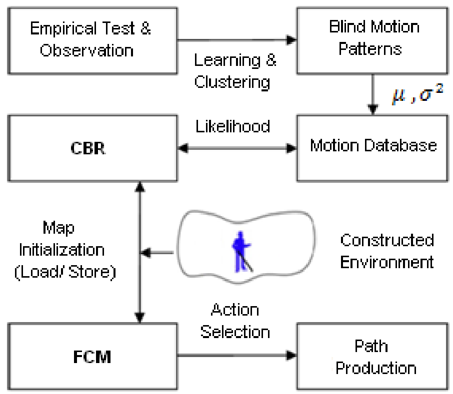

Figure 3: The proposed CBR-FCM decision support system.

The CBR is responsible for updating the FCM initial weights every time before FCM runs. This is by reading the map concepts' weights after every map convergence, and readjusting them with respect to an anticipated path from the CBR motion database. Therefore, every time the map runs with more accurate initial weights which result into more realistic productions respectively. Here, the emphasis is given on adjusting the weights of wall following and shortcutting behaviors, as well as external and egocentric referencing as the main factor concepts of the FCM.

The combination of CBR and FCM models gave more accurate predictions of entire paths including the critical points where the shortcuts start and end. The ultimate path productions take place in the FCM. With every map convergence, either wall following or shortcutting gets the higher weight, and therefore constitutes for the selected action. Upon the selected action, a path production is anticipated which is either 1) to keep following the walls, 2) to start a shortcut, 3) to keep shortcutting, or 4) to end a shortcut.

Way-finding Patterns and Path Estimation

In order to obtain the way-finding patterns, empirical test was conducted with contribution of 35 eye-masked sighted students aged 19 to 23. The path functions $\{L_1(t), \ldots, L_n(t)\}$, $n = 35$, are modeled mathematically in form of combination of line segments on the XY surface of the test environment, where $t \in \{0, \ldots, T_i\}$, and T_i, $i = \{1, \ldots, n\}$ are durations of the n trajectories. The dissimilarity model of [15] was adopted to examine each of the path functions against the others via pairwise distance measurement. By measuring the total RMS value of the distances between two paths at time instances, a numeric value (δ) is obtained which accounts for the dissimilarity of the two path shapes (Eq. 1).

$$\delta_{ij} = \left(\frac{1}{\max(T_i, T_j)} \sum_{t=0}^{\max(T_i, T_j)} \left(L_i(t) - L_j(t) \right)^2 \right)^{\frac{1}{2}} \quad (1)$$

Empirical paths can be clustered according to dissimilarity measures and by using any clustering algorithm. In this work, clustering is done by comparing one path once against the others in order to find the most similar ones, and therefore k clusters, each with $n_k = n/k$ members have been generated. The clustering concept is exemplified in Eq. 2, where the number of clusters is chosen to be $n/2$. The paths i, j shall therefore belong to the cluster C_i since the latter has the minimum dissimilarity with the former.

$$\delta_{ij} = \min(\delta_{i1}, \delta_{i2}, \dots, \delta_{in}),\ j \in \{1, \dots, n\},\ i \neq j \tag{2}$$

By using an averaging strategy, the path patterns can be obtained from the clusters. The mean value path of a bunch of n_k paths which belong to a cluster C_i represents the path pattern corresponding to that cluster (Eq. 3).

In this research, an estimation technique is introduced for prediction of blind motions i.e.; anticipation of entire trajectory from partial trajectories made by a blind traveler. While comparing a new trajectory against the known path patterns can be a cue to path prediction by itself, in this method, normal distribution function is used to estimate which path pattern is the most probable future of a new partial trajectory. In order to define normal distribution of each pattern, its standard deviation must be obtained with respect to the mean value path, and all members of the cluster. Eq. 4 shows variance calculation for cluster C_i.

$$L_{\mu_i}(t) = \frac{1}{n_k}\sum_{m=1}^{n_k} L_m(t)\ ,\ L_m(t) \in C_i \tag{3}$$

$$\sigma_i^2 = \frac{1}{n_k}\sum_{m=1}^{n_k} \delta\left(L_m(t), L_{\mu_i}(t)\right)^2 \tag{4}$$

From (3), and (4) each cluster C_i can be represented by the two values of mean path $L_\mu(t)$, and variance σ^2. The normal distribution is the most widely used family of distributions in statistics and many statistical tests are based on the assumption of normality. Probability density function PDF of the normal distribution is used to assess the likelihood of a partial path with the reference patterns (Eq. 5).

When a blind traveler performs new trajectories, at each production through the path e.g.; production $L(t_p)$ at time t_p, its location is given to a series of PDFs of memorized path patterns; $\{L_{\mu_1}(t_p), \sigma_1^2\}$, $\{L_{\mu_2}(t_p), \sigma_2^2\}$, … from which the most probable pattern will be chosen. The future of the current production $L(t_{p+1})$ is therefore anticipated from the estimated path pattern.

$$P\left(L(t_p) \in C_i\right) = \frac{1}{\sigma_i\sqrt{2\pi}} e^{-\left(L(t_p) - L_{\mu_i}(t_p)\right)^2 / 2\sigma_i^2}\ ,\ 0 < t_p < T_i \tag{5}$$

$$\begin{aligned} \textit{where} &\ ;\ L(t_p) : X(t_p), Y(t_p) \\ \textit{and} &\ ;\ L_{\mu_i}(t_p) : X_{\mu_i}(t_p), Y_{\mu_i}(t_p) \end{aligned}$$

From partial trajectories it can be found that which pattern a traveler is following, so that the entire path can be estimated. However, since the goal is to discover the process of the person's spatial cognition, the estimated path must be transformed into a series of spatial actions which correspond to their spatial cognition. This is what the FCM module is responsible for, and the actions will include wall following, and shortcutting, as the main concepts, as well as the changes between them i.e.; wall flowing to shortcutting, and vise versa. In order to model the actions with the FCM module, all to do is to update the map according to the results from the CBR module.

Suppose the last map convergence has resulted in having the highest weight for the wall-following concept, and therefore it is anticipated that the person follows the wall for the next motion production. Now, if the map is run again for generation of the next production, and without considering the CBR output for the current production, again wall-following will be anticipated as the next action to be taken by the traveler. This will continue for ever since there is no condition for selection of another action resulting in poor trajectory predictions.

By considering the CBR outputs at time instances, the FCM nodes can be readjusted every time for realistic action selection. This automatically will result in generating conditions for switching between the actions, so that the entire series of actions along the path can be predicted.

ACTUAL EXPERIMENTS

The conception of blindness has different interpretations. However, in this research the term blind is referred to as total blindness which is the complete lack of any form and light perception (NLP). Form another perspective blind people fall into categories based on the period of time they had any kind of visual experience. Late-blinded are more like blind-folded sighted, while early and congenitally blinds are different in the sense that they have very little or no visual experience at all. In this research, the focus has been on late-blinded subjects. And in order to avoid excessive work for our blind subjects, the research began with blind-folded experiments up to the current stage.

The experimental work was from January to May 2008. The environment was constructed in a large conference room; $11.5_m \times 6.2_m$, with a large oval shape table; $7.6_m \times 2.1_m$, placed at its centre representing the environment of [16]. 35 blind-folded subjects contributed for motion patterns extraction. Upon completion of this stage, new subjects who were 16 blind-folded undergraduate students (aged 19 to 22) were chosen for path prediction experiments. For all experiments, the eye-masks were completely dark and the room luminance would not give any cue of light perception. Exploration of environment was without use of cane, and detection of path patterns were the initial concerns throughout the work.
For tracking the subject movements, a number of colored stickers were used to stick on the test floor, and the time between intervals i.e.; each sticker placement, was recorded with accuracy of 1 sec. The method of Part 3.3 was used for path clustering. Figure 4 (a), (b), and (c) show the environment with soft-padded walls and the table at its centre. An eye-masked subject is trying to reach the target in a space she has no previous knowledge of it.

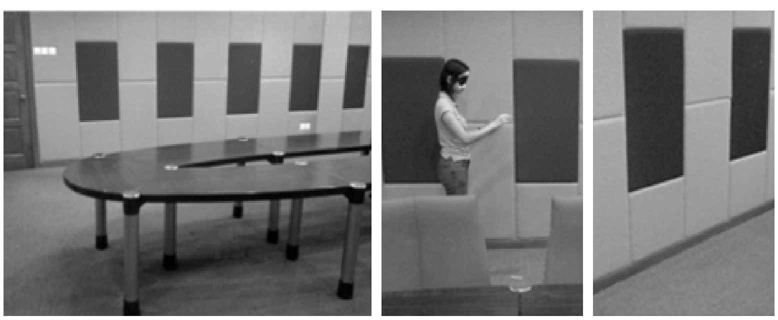
(a) (b) (c)

Figure 4: (a) Test environment with a large oval table, (b) A blind-folded performance, (c) Soft-padded walls.

Simulation Environment

The FCM was implemented by developing a software with capability of interrelating a maximum of 30 concepts. The GUI was designed using VC++ for convenient text and graphic representations. The uncertainties in referencing strategy adopted by the blind-folded subjects was included into the FCM by assigning partial weights to both concepts of egocentric and external referencing.

Among environmental factors, information about blind productions i.e.; position, and direction of motion were the most important. Another important factor was level of familiarity with the space. However it was tried to minimize the effect of this factor on the system. This was done by choosing the subjects from those who had never been to the test environment before, and therefore had no previous perception of it. As for the statistical CBR module, MatLab toolboxes including the statistical toolbox were used. The motion patterns were used to define relative weights for updating the FCM module. Integration of the two modules was done by merging the two algorithms from C and MatLab into one programme for one-time generation of results. However, graphical representation of ultimate path estimations is still in progress.

RESULTS

Experimental work revealed that mostly subjects showed shortcutting behavior while exploring the space. The sketch maps and interviews also revealed the same facts. Based on the pure FCM analysis, only the two behaviors of wall following and shortcutting were anticipated. Initially the module was run using expert definitions of crisp weights. Later, the initial event (cause) and concept weights were optimized using genetic algorithm. However, up to this part of experiments, yet no CBR module was added to the FCM and therefore the results were merely according to expert definitions of the system.

The FCM formulation (Eq. 6) was according to the definition method of Kosko [17], where each concept weight is completely defined anew during each forward step (cycle). During each cycle, first a summation of all concept-cause multiplications must be calculated for each of the affected concepts. Then this summation is squashed into the standard range of 0-1 by means of a logistic function with a certain Gain. The finalized concept weights are then decided upon convergence or oscillation of the map.

$$Weight\ of\ Concept_j = \frac{1}{1 + e^{-(Summation_j \times Gain)}} \tag{6}$$

$$Summation_j = \sum_{i=1}^{n} Concept_i \times Cause_{i,j} \quad , \quad i \neq j$$

Figure 5 shows simplified walking locus i.e.; demonstrating only 3 paths for each of the 4 types of experiments, with arbitrary start and goal locations. However, before doing the experiments, the subjects were guided from the room's entrance at top-left to each of the start locations in order to help them with mental rotation ability.

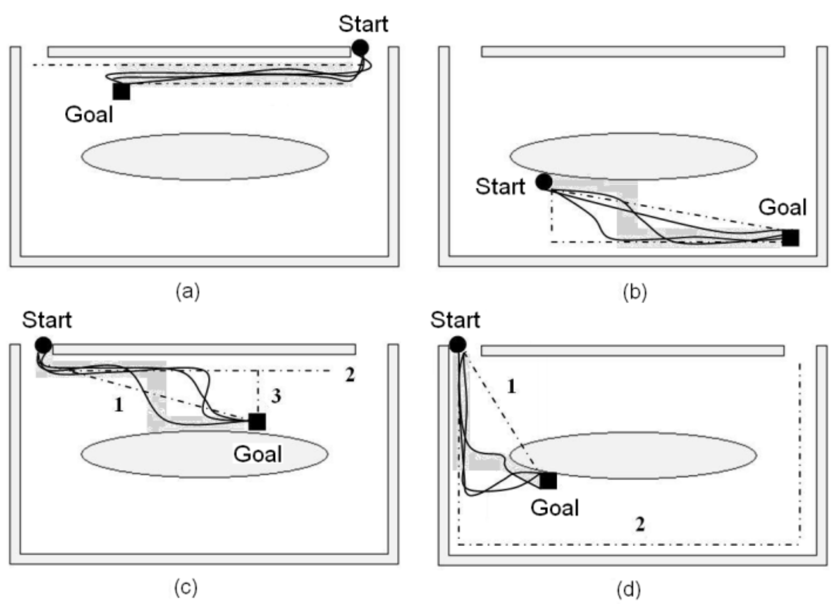

Figure 5: Examples of blind-folded motion patterns; Expected paths based on FCM model (dotted), and CBR-FCM model (gray highlights) are compared against actual (solid) results.

The pure FCM model showed good results by anticipating trajectories along walls, and shortcuts (Figure 5 (a), and (b)). However, it was only capable of predicting path productions of one type either wall following or shortcutting. In other words, it was not possible to anticipate when and how travelers change their way-finding strategies from one to another, and therefore prediction of entire path was not possible.

For example in Figure 5 (c), by assuming the subject to take a shortcut from the beginning (path 1), the path can be anticipated though not exactly. But if wall following is assumed as the initial behavior (path 2), the result will be completely wrong as the model is not capable of defining a point of start for the shortcut (path 3). This was more discovered in complicated situations such as in Figure 5 (d). The target was set to be behind the table where path 1 was no longer suggested and only path 2 would be expected for the productions which caused incomparable results.

CBR module was added to resolve this problem in addition to other modifications such as inclusion of more concepts as offline modifications to the existing FCM model. Having added the CBR module to the system, the critical points where a shortcut starts or ends i.e.; wall-following to shortcutting or vice versa, were predictable. In other words, based on CBR-FCM, another two actions of switching from wall-following to shortcutting, and vice versa were added to the two previous actions of wall following and shortcutting. This ability enabled the system for predicting the entire paths (the gray highlights) as shown in Figure 5 (a, b, c, and d).

CONCLUSION

It is suggested that way-finding assistive technology can be improved if added with AI action selection systems for prediction of blind motions. This requires a tracking strategy which is capable of anticipating consecutive productions as well as the entire path. This article discussed a new decision model for anticipating blind motion productions in indoor environments. In general such modifications to current navigation algorithms of indoor mobile robots can bring about more comfort and safety by considering decision models of blind path planning.

As the future direction of research, it is aimed to apply the findings of this work to develop a new navigation algorithm for mobile robot platforms. The robot will be capable of self positioning while a fuzzy-logic algorithm will govern the basic behaviors of obstacle avoidance and target seeking. Environmental data about current position and direction of motion i.e.; partial trajectories of blind person will be supplied from a vision system. And the algorithm itself will be capable of predicting the entire traveler motions using the method of this article. The robot then reacts in a proper way in order to avoid any collision with the person or the object placed in the environment.

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