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Distance Estimation Method with Snapshot Landmark Images in the Robotic Homing Navigation

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***Abstract*— Animals and insects use their own navigating system to return home in various ways. One of the most widely used senses is vision. They use visual information to remember the home snapshot image which is useful in returning home from an arbitrary location. Inspired by behaviours of insects and other animals, there have been many homing algorithms applied to mobile robots. These methods use visual information to choose the moving direction by comparing the current landmark view with the snapshot taken at the nest. In this paper, we suggest a new image-based navigation method which is called landmark navigation with distance estimation. This method computes the distance to each landmark by using only the visual information of an omnidirectional camea. Estimated distance is then used to locate the robot in an environmental map. As a result, this new method shows better performance in returning home from an arbitrary location than other methods. The corresponding robotic experiments will be demonstrated.**

I. INTRODUCTION

Many insects and other animals return home accurately after leaving their home area for foraging or hunting. Their methods are based on various senses [1], [2], [3]. They use visual, olfactory, auditory, magnetic, or two or more combined senses. Insects and other animals show better performance in homing navigation than any other mobile robot in real life. Therefore, biologically inspired homing algorithms would lead to more efficient systems if applied to mobile robots. Insects and animals use path integration to return home; for examples, desert ants, fiddler crabs, and honeybees. Path integration is also called dead reckoning, and they use this method to calculate their current position with respect to the nest by tracking the angle and distance every time they move [1], [4]. As they integrate their own movement path, they can calculate the direct route to their nest when they decide to return home after exploration. Insects can return home with a little error, with path integration. At the end, they use visual information as an additional sensory information to perform more accurate homing navigation.

Many researches have focused on SLAM algorithm for the vision-based navigation. Simultaneous localization and mapping (SLAM) algorithm performs localization and mapping simultaneously by identifying the viewed region to the previous one. They detect features in the image and create a map in which the mobile robot explores. This algorithm shows good performance in mapping the environment and locating itself. However, since it needs to update the feature map and the location information continuously the method requires large memory and computation.

Insects navigate and return home with a method that can be interpreted in a simple neuronal architecture. Therefore, we focus on the simpler navigation method that uses reduced visual information to locate itself and return home. The mobile robot does not need to continuously update the map and remember the complex environment but only recognizes several landmarks.

The vision-based navigation method to detect the homing path by remembering landmarks surrounding the nest is commonly used. The agent can remember the location of the nest by the specific landmark around, or the arrangement of several landmarks viewed from the nest. Many different robotic navigations have been suggested to model the vision-based biological navigation system. The robot generates its own environmental map called 'vision map' by collecting visual information on landmarks [5], [6]. The vision-based navigation method can be classified based on whether the mobile robots keep the map information or not and how they use this informtaion. Landmark navigation is a navigation method without any environmental map [7]. In landmark navigation, the mobile robot recognizes landmarks surrounding the agent and uses the position or size of the landmark to find its path toward the goal point. The landmark navigation system usually operates based on information obtained from a set of snapshots taken by robots at the target location [8]. In this paper, we suggest a new navigation method choosing the moving direction each time the moving agent takes a new snapshot image.

Several interesting approaches of landmark navigation methods have been suggested and applied to a mobile robot returning home. "Pixel-based image matching method" by Franz et al. [9] is the navigation method using information of landmarks obtained from captured image. This navigation method determines the moving direction through the estimation procedure of predicting new images and comparing these to the nest image. When the mobile robot is in a task of returning home, the agent takes snapshot image at the current location and the landmarks in captured image is recognized. Using the captured image, the agent predicts a new image that would be obtained when it moves in a given direction. Comparing the new image for every possible direction to the home snapshot image, the agent chooses the best matching image and the corresponding direction will be selected for the next movement. To generate predictive images, the mobile robot assumes all landmarks are in the same distance from the mobile robot. In spite of the equidistance assumption, this

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method has been proved to guide the agent to the home area. The pixel-based navigation method shows good performance when the nest is surrounded by landmarks, but this method is sensitive to noise in the snapshot images. When there are only few landmarks available in its view, or there are large landmarks that could affect the decision, the agent may misjudge the moving direction with high probability.

In this paper, we propose a new navigation method using landmark distance estimation and demonstrate it with mobile robot experiments. First, the landmark distance estimation method will be introduced in details with some mathematical descriptions, and the results of the mobile robot experiments will be shown.

II. METHOD DESCRIPTION

Several previously suggested image-based navigation algorithms only consider the distribution of landmarks from the view of the agent, but have not handled landmark properties in details, for instance, size or distance of landmarks. The pixel-based image matching method explained in the previous section assumes that every landmarks is in the same distance to generate the predictive images. However, for the new navigation method we propose that the distance of each landmark is estimated and the resulting information is used to determine its own position.

To efficiently recognize landmarks in view and estimate the distance to each object from the agent, we use a self-designed omnidirectional camera. An ordinary camera has a limited view to take the front side of the agent, and to obtain the entire view of the environment, the robot needs to rotate itself. In contrast, the omnidirectional camera has $360°$ view which is advantageous in detecting landmarks surrounding the mobile robot [10].

In landmark navigation, the agent takes a snapshot over the environment including landmarks, and it compares the image with the stored home snapshot image to determine the next moving direction. In the navigation method we suggest that the agent does not simply compare a pair of images, one at the nest and the other at the current position, but uses the estimated distance information for each landmark. When the agent starts exploration in an unknown environment, the mobile robot estimates and remembers the distance of every landmark from the agent at the nest. After exploration or foraging activity, when the agent decides to return to the nest, the moving agent starts estimating the distance of each landmark surrounding the current position. Using two sequential snapshot images of landmarks in the environment, the robot can estimate the landmark distances. These two captured images being processed are taken one at the current position and the other after moving one step forward. Although the two captured images differ slightly in size and angular position of the landmarks, the amount of angular deviation for each landmark location can lead to the distance of a landmark with the known distance of the agent's one step movement. Calculating the distances of landmarks available in its view, the mobile robot can reversely estimate its own location using the environmental

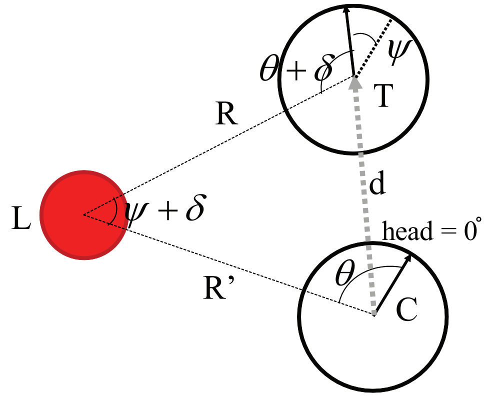


Fig. 1. Mathematical description of the procedure taking two snapshots for distance estimation by angles(θ, ψ, and δ) and distances(d, R).

map it has produced earlier when exploration starts from the nest. The detailed mathematical explanation will be given in the next subsection.

A. Mathematical computation

As mentioned in the previous section, we use an omnidirectional camera to take snapshots, which are recorded in the form of omnidirectional ring. Each landmark appears as an arc image in the ring.

The mathematical explanation of the distance estimation starts by setting some important definitions. The angular position of a landmark in the omnidirectional ring is θ, when the midpoint of the arc image is deviated θ counter-clockwise from the heading direction. We determined the position to be in the range of $-180 < \theta \leq 180$. After the robotic movement, the image shifts from one point to another, from θ_1 to θ_2 in the omnidirectional ring. In other words, if the agent moves with distance d from the current position C to the next actual target point T, the recorded image of landmark L is shifted from the position θ to $\theta + \delta$ while the ψ in the Fig.1 denotes the amount of rotation before moving one step forward. The angular deviation δ is the key element in estimating distance to each landmark.

The distance between the landmark L and current point C is denoted as *R'*, while the distance between the landmark and the target point T is R. Applying the trigonometric equation, we obtain the relationship among one step moving distance d, angular position of landmark in the omnidirectional ring θ, angle between the initial heading direction and the moving direction ψ, angular deviation δ, and the distance of landmark from the target point R.

$$R = \frac{d \sin(\theta - \psi)}{\sin(\delta + \psi)} \tag{1}$$

Under the assumption that the moving agent does not change its heading direction while it moves from C to T, the equation shown above yields distance to the landmark on the basis of angular deviation and the initial position θ on the omnidirectional ring. Therefore, by using two captured snapshot images before and after moving one step of distance

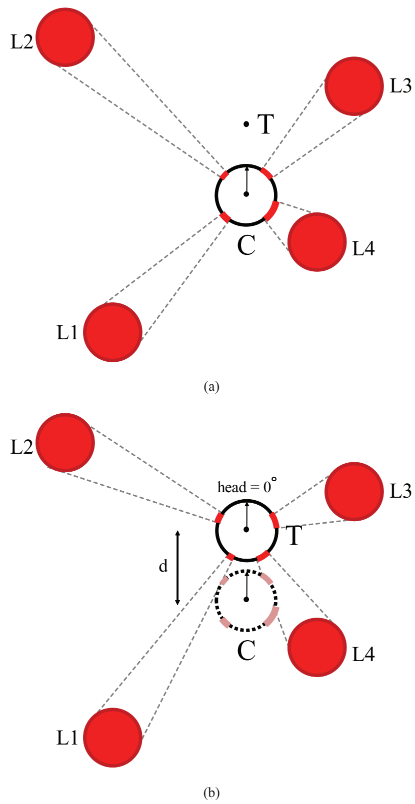


Fig. 2. Changes in the projected images of four landmarks as seen by the omni-directional camera when the mobile robot moves one step forward. The robot will move straightforward without any rotation.

d, the distance to the landmark can be computed with simple equation as eq.1.

B. Position estimation on the environmental map

For the mobile robot, the ultimate goal of distance estimation process is to locate itself in the environmental map it has developed earlier. As the moving agent knows the angle of the landmark with respect to its heading direction and the distance to each landmark, the robot can draw the egocentric map of landmarks. Therefore, the landmark map in the view point of the mobile robot can be created at every arbitrary location where the robot is positioned through two snapshot images and simple computation.

The egocentric landmark map includes relative positions of landmarks with respect to the current direction of heading of the mobile robot. Since the map is generated from the point of view of the agent, the heading direction or the upper side of the map does not always match with the reference compass. In other words, the landmark on the left of the agent in its egocentric map at an arbitrary position may not match the landmark in the same side at the nest. Therefore, the matching procedure of each landmark at the current position to that in the snapshot image at the nest which has been stored earlier should be determined. Landmark matching is easier when the reference compass is given. Otherwise, we need a sophisticated algorithm to solve the correspondence problem.

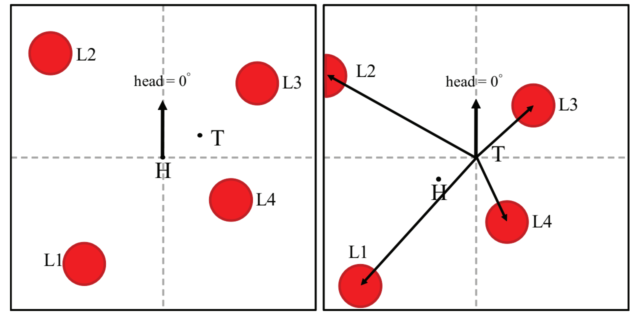


Fig. 3. Drawing the environmental map based on the estimated distance and angle of each landmark.

For new distance estimation method we suggest using the arrangement order of landmarks for matching procedure. The agent does not know which landmark in its view is a match for the other one in its environmental map, since it has been changing its direction of heading during the exploration phase. Even though the agent estimated the distance to landmarks accurately, it cannot pinpoint its own location in the environmental map directly. Therefore, we assume that every arrangment of landmarks is possible and compute the current location for every possible landmark arrangment. If the arrangement is different from that of the initially taken image at the nest, the current location of the moving agent would not converge into one point. On the other hand, if the agent computes the current location based on the same arrangment order of landmarks of the environmental map generated earlier, the resulting location is most likely to pinpoint the specific position.

After the successful landmark matching procedure, the mobile robot returning to the nest obtains the coordination of its current position relative to the reference frame at the nest. Comparing the coordination of the nest and the current point, the moving agent can determine the angle and distance to the nest. After determining the homing direction, the agent can move one step forward and obtain the next snapshot image in order to compute the appropriate next moving direction. This procedure is repeated.

III. EXPERIMENTS

We performed robotic experiments using our suggested method of distance estimation in an environment with several landmarks. The agent starts exploration at the nest as insects and other animals in nature leave their home for foraging. After exploration, the robot decides to return home by using the visual information about the landmark environment. We chose four red cylinders as landmarks in the environment. These four landmarks have the same size of 10.75 centimeters radius and 38.5 centimeters of height. We used an arena, a square of 240 centimeters for each side.

When a mobile robot is at an arbitrary position, it attempts to return home by deciding the moving direction through the process of landmark information. In our distance estimation method, the robot estimates distance to each landmark by moving one step forward and localizes itself in the environ-

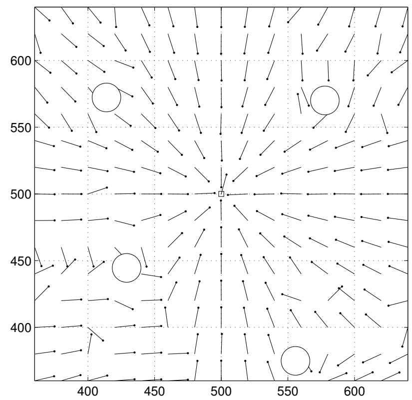


Fig. 4. Vector map created with the distance estimation method in a simulation experiment. The dot indicates the heading direction at eacp point.

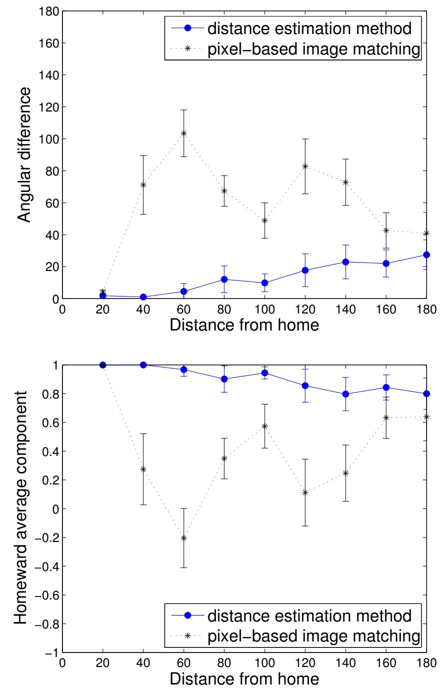


Fig. 5. Error curves for distance estimation method and the pixel-based image matching method over distance from home(centimeters). (a)Angular difference(degrees) and (b) average homeward componone without a reference compass

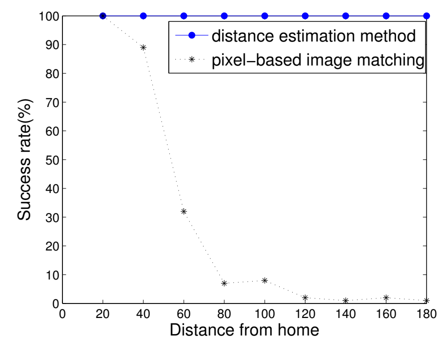


Fig. 6. Success rate of the two methods obtained from 100 trials measured with respect to the distance(centimeters) from home without reference compass

mental map it has generated earlier. Following the moving direction at an arbitrary position, the agent can successfully reach the goal point from its current position.

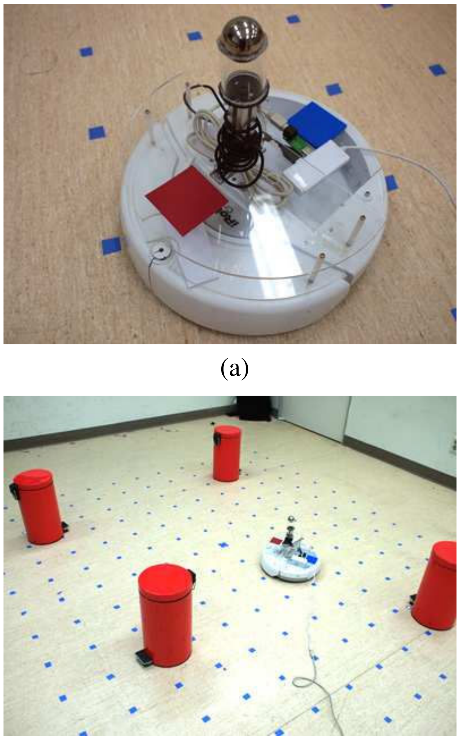
Initially we tested simulation experiments for a given environment with landmarks. Fig.4 is the vector map showing the moving direction at a specific point, using the distance estimation of landmarks. In the experiments, the position and size of landmarks are the same as those in real robotic experiments. The arrow at each point in the vector map represents the moving direction of the mobile robot to return to the nest. As we can see from Fig.4, the direction of arrows head almost directly to the location of the nest.

We can assess the performance of navigation methods based on the vector map intuitionally. We offer three different perspectives of performance evaluation, that is, the angular deviation, the homeward component of the angular deviation and the success rate. As we draw vector map using the navigation method, the error between decided angle and the desired angle can be measured, where the desired angle is computed by drawing a straight line from the current position to the goal point. The homeward component of the angular deviation is the result of applying cosine to the angular deviation and therefore, the value will be in the range from -1 to 1. Both the anguar deviation and the homeward component of the angular deviation are plotted with error bars, including mean errors and the t-distribution deviations with 95 percent confidence level. The success rate is computed by counting the number of successes out of 100 trials. For each returning trial, the mobile robot is positioned at an arbitrary position with random direction of heading.

Error curves in Fig.5 show a comparison of angular errors obtained with the two methods. Both the pixel-based image matching method by Franz et al. as well as the distance estimation method have been applied to the landmark environment. In Fig.5, the distance estimation method shows much better performance in the angular error and the cosine of the angular error than the other method. The success rate performance also shows that the distance estimation method is more suitable for homing mobile robots.

The success rate with the pixel-based image matching method in Fig. 6 declines rapidly as the mobile agent gets farther from the nest. This means that the navigation method by Franz et al. is significantly affected by the distance from the nest. However, the success rate with the distance estimation method shows constantly high probability of returning to the nest. Therefore, we can conclude that in most of the cases the mobile robot can successfully return to the nest using the distance estimation method, regardless of the distance.

To validate our simulation experiments with the distance estimation method, robotic experiments have been carried out in the same situation. We used a Roomba robot mounted with a self-made omnidirectional camera consisting of a Logitech webcam and a single ball bearning. (see Fig.7(a)). This mobile robot has a radius of 16 centimeters and a height



(a)

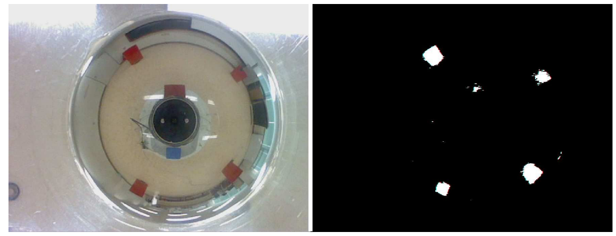
(b)

Fig. 7. Mobile robot and the experimental environment. (a) Mobile robot and omnidirectional camera and (b) landmark environment test space

of 20 centimeters for the camera structure. The mobile robot was positioned in a test area size of about 3 meters in each side. As shown in Fig. 7 (b), four cylinders were placed as landmarks. Since the complicated landmark recognition system is not the focus of our paper, landmarks are set as red cylinders to optimize the environment for the segmentation, and it allows us to focus on the navigation algorithm.

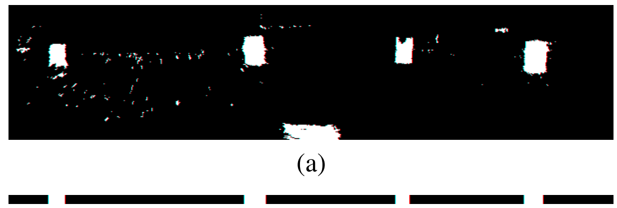
In the environment shown in Fig.7(b), the mobile robot is initially positioned at the nest (500,500) and the robot draws an environmental map by estimating the distance of each landmark. Then, the robot is positioned at each test point by assuming the robot arrives at the point after exploration, and then estimates its location in the map by applying the distance estimation method.

Unlike the simulation experiments, the experiments using the mobile robot in real test space need additional image processing. First, the snapshot image is taken using the omnidirectional camera. The omnidirectional camera, unlike the standard camera, has a view of 360° and can capture every landmark whether it is in the front or in the back of the agent. We searched every pixels in the image and select the pixel if its value is closer to red which is regarded as the landmark. Fig.8 shows the original snapshot image and the converted image of landmarks distinguished. The next step is to convert the panoramic image into polar coordinates of an easier assessment of the angular positions of the landmarks(see Fig.9(a)). Since the camera is fixed to the robot, the center point and the radius of the captured image do not change through the experiment phase, where



(a) (b)

Fig. 8. Image conversion. (a)Image captured by the omni-directional camera and (b)the converted image with the red objects detected



(a)

(b)

Fig. 9. Panoramic image (a) converted from the polar image of detected landmarks and (b) the 1-dimensional ring obtained from the panoramic image

the center point was positioned at (353,245) and the radius was 160pixels while the acquired image size was 640x480 pixels. Based on these information, we can unwrap the acquired image into the panoramic view. Finally, we create 1-dimensional ring image by slicing the image of 10px height and averaging vertically. The slicing height is appropriately predetermined.

Finally, Fig.9(b) shows the one-dimensional image including landmarks. From this, we can express the angular positions of the landmarks as well as their angular widths in terms of deviation from the direction of heading of the robot (θ), and the relative size of landmarks. Using the information on landmarks, the mobile robot can compute the distance to each landmark and therefore decide the moving direction.

Fig.10 and Fig.11 shows the experimental result with the mobile robot in the test space. The vector map is generated by placing the mobile robot at each grid point and computing the moving direction after driving one step movement forward. If the robot is close to an obstacle, it cannot determine the moving direction by taking one step forward. The position is represented as a dot with no arrow.

Similar to the simulation experiments, the angular error and the homeward component based on the vector map with a real mobile robot are shown in Fig.11. The errors are a little higher than in the simulation experiments, but the performance is still much better than for the pixel-based image matching method by Franz et al. (see Fig.5). The algorithm applied to the mobile robot in the real environment offers similar performance rate as it was shown in simulation experiments. A slight increase in error performance with the distance estimation method is found in Fig.11 when compared with the simulation result in Fig.5. It may be due to noisy vision signals in real environment and the error in

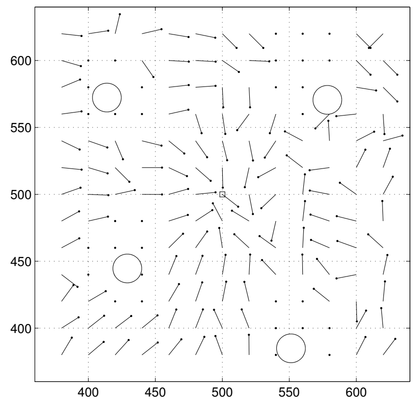


Fig. 10. Vector map obtained in the mobile robot experiments with the distance estimation method. The dots indicate the heading directions

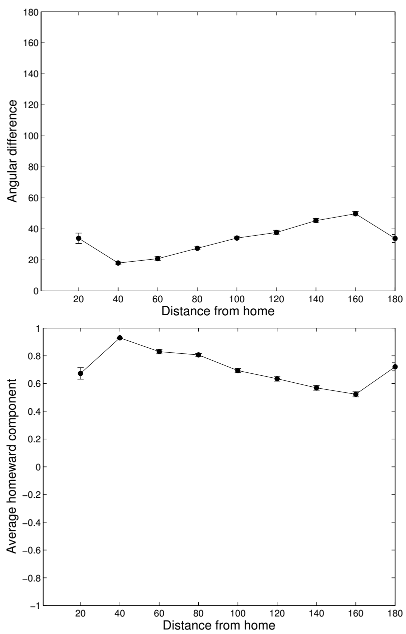


Fig. 11. Error curves for distance estimation method (a) angular difference and (b) average homeward component computed based on the vector map generated by mobile robot experiment

distance estimation.

IV. CONCLUSION

In this paper, we develop a new landmark navigation method using the distance estimation to each landmark. We assess the performance of the method and show an excellent success rate in finding home and a smaller angular deviation from the direct route home to the nest. In this method, the mobile robot first creates the environmental map when the robot starts exploration from the nest. When the robot starts returning to the nest after exploration, the robot estimates the distance of each landmark by observing the image shift of the landmark and localizes itself in the environmental map.

By obtaining the distances of landmarks, the suggested method yields the position of the mobile robot in the egocentric map, and by coupling the information with the map it has created at the nest, the agent can pinpoint its position in the egocentric map. This type of coupling information in different point of view is also shown in the navigation method in some insects. The desert ants (genus *Cataglyphis*) obtain their positional information within a larger environmental framework using the landmark information they captured during the exploration [11].

We compared the performance of this method with the pixe-based image matching navigation method suggested by Franz et al. [9]. The distance estimation method shows better performance in both angular error and the success rate. The smaller angular error and higher probability in success rate is shown in both simulation experiments and real robotic experiments. All the experiments have been done without any reference compass, but only with visual information. Even if the reference compass exists, the performance of the distance estimation method is still superior than the pixel-based image matching approach.

Many approaches in the indoor navigation use the laser scanner for localization experiments. In contrast, we used a simple equipment with a webcam camera for the omni-directional vision. We showed the localization experiments specialized for homing navigation can be run successfully with a cheap-cost vision camera.

V. ACKNOWLEDGMENTS

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REFERENCES

[1] M. Collett and T. Collett, "How do insects use path integration for their navigation?" *Biological Cybernetics*, vol. 83, no. 3, pp. 245–259, 2000.

[2] J. Mather, "Navigation by spatial memory and use of visual landmarks in octopuses," *Journal of Comparative Physiology A: Neuroethology, Sensory, Neural, and Behavioral Physiology*, vol. 168, no. 4, pp. 491–497, 1991.

[3] P. Luschi, F. Papi, H. Liew, E. Chan, and F. Bonadonna, "Long-distance migration and homing after displacement in the green turtle (Chelonia mydas): a satellite tracking study," *Journal of Comparative Physiology A: Neuroethology, Sensory, Neural, and Behavioral Physiology*, vol. 178, no. 4, pp. 447–452, 1996.

[4] J. Zeil and J. Hemmi, "The visual ecology of fiddler crabs," *Journal of Comparative Physiology A: Neuroethology, Sensory, Neural, and Behavioral Physiology*, vol. 192, no. 1, pp. 1–25, 2006.

[5] B. Cartwright and T. Collett, "Landmark learning in bees," *Journal of Comparative Physiology A: Neuroethology, Sensory, Neural, and Behavioral Physiology*, vol. 151, no. 4, pp. 521–543, 1983.

[6] ——, "Landmark maps for honeybees," *Biological Cybernetics*, vol. 57, no. 1, pp. 85–93, 1987.

[7] T. Collett, "Insect navigation en route to the goal: multiple strategies for the use of landmarks," *Journal of Experimental Biology*, vol. 199, no. 1, p. 227, 1996.

[8] D. Lambrinos, R. Moller, T. Labhart, R. Pfeifer, and R. Wehner, "A mobile robot employing insect strategies for navigation," *Robotics and Autonomous Systems*, vol. 30, no. 1-2, pp. 39–64, 2000.

[9] M. Franz, B. Schölkopf, H. Mallot, and H. Bülthoff, "Where did I take that snapshot? Scene-based homing by image matching," *Biological Cybernetics*, vol. 79, no. 3, pp. 191–202, 1998.

[10] Y. Sun, Q. Cao, and W. Chen, "An object tracking and global localization method using omnidirectional vision system," in *Proceedings of the 5th World Congress on Intelligent Control and Automation WCICA*, vol. 6, 2004, pp. 4730–4735.

[11] R. Wehner, B. Michel, and P. Antonsen, "Visual navigation in insects: coupling of egocentric and geocentric information," *Journal of Experimental Biology*, vol. 199, no. 1, p. 129, 1996.