A Sector-based Image Matching Approach to Visual Navigation

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Abstract

It is known that many insects and animals including mammals use peculiar navigation algorithms in order to return home safely and effectively. The process as to how the insects and animals find a target point has been an highlighted issue, and the vision-based navigation is one of the methods which are known as the inherent navigation algorithms for the insects and animals. Especially, honeybees (*Apis melli fica*), returns to their nest accurately using a landmark navigation method. The bees recognize the surroundings like a bush, a flower and a tree as a landmark. After exploring for the food, the bees determine in which direction their nest was and fly back to it.

The bees are expected to move with a simple mechanism owing to the fact that they have relatively small number of neurons and memories. Consequently, it can be thought that such a simple mechanism is enough for a highly efficient navigation system to return home. From this point of view, many researchers have investigated on how the bees recognize the visual environment and use the landmarks to remember a position. Various models which is tried to implement the bees' homing behavior have been proposed.

The behavioral mechanism of the honeybees can be applied to the robotic vision and navigation algorithm. The previous mechanical models based on visional information processing contain a complex calculation and great amounts of memories, along with a complicated image processing. On the contrary, the models for the insects and animals are much simpler, and yet provide more effective results.

Inspired by these behavior, the various models of visual landmark navigation have studied. In this research, a new model of which performance is improved is suggested, and the performance is confirmed by computer simulation and robot experiments comparing the other methods.

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Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

(*Jiwon Lee*)

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Chapter 1

Introduction

Recently, several researches have been conducted to overcome the problem of redundancy in the conventional navigation algorithms in robotics which are implemented with mathematical formula including trigonometric components, transcendental functions, and probability estimations, containing much information and complex calculations. Along the courses of development, the navigation systems of the insects and animals have received great attentions for their ability in accurately returning to their nests by using their own navigation algorithms, which made it possible for the lower level organisms to successfully find their way back home after their exploration to search food. The biological navigation systems of the insects and animals are simpler than the existing navigation methods, and they let the insects or animals respond instantly and directly to a change of position.

A navigation model inspired from the behavioral mechanism found in real nature has many advantages when applied to operate a robot. Such models allow an efficient method of establishing a resourceful home navigating system even with the use of devices having low resolution CPUs. This establishment contributes to the scaling down of the sizes of the robots. The implementation of a bio-inspired algorithm is expected to bring back a robot home as effectively as an animal or an insect does in nature. Bio-inspired algorithms require a robot to not know of its destination from the beginning, but rather make it possible to decide which direction it should move to from the set of information received on every movement it makes. The previous decisions or memories used to determine the homing direction are not stored, but replaced with new updates that the robot receives on its journey home. Hence, not much of a memory is required in the bio-inspired algorithm, and a robot can find its way back home by a simpler method that does not require a specific learning process.

1.1 Vision-based robot navigation

For the robot navigation systems, various strategies that use the visual information obtained from the environment have been suggested. In such vision-based navigation methods, a robot generates a kind of map to record the information, which is called ‘vision map’. It could navigate using the vision map. The type of vision map is various, and the vision-based navigation methods could be classified according to the types of vision map. They are map-based navigation, map-building-based navigation, and a map-less navigation.

Looking at these different types of navigation methods, the map-based navigation system uses a geometric or topological map which is already created by a user, not a robot. The map-building-based navigation method is that a robot recognizes the environment through the sensors attached to itself and produces the vision map using the sensor values. The map-less navigation method is different from the others, and it does not create and use a vision map. A robot also gets a visual information, however, it does not collect all information continuously in order to produce an entire map of environment. An example of this method can be that the robot recognizes some landmarks in the environment and navigates by tracking them or remembering the configuration of them.

The use of the vision map requires the probabilistic calculations and estimations from the images. It also needs a lot of memories to store data which is obtained from the captured images and the high resolution imaging devices. It is the same as not only the vision-based method but also the general navigation method as like SLAM. If a robot uses the highly efficient devices and the complex processes, it could approach the goal point much accurately. Though, the question remains unsolved as to whether the robot could find its location relative to the goal point and find it without the need of those calculations or high-tech devices.

1.2 Why bio-inspired model is applied for robotics?

Many robots are modeled after the appearances or the behavioral mechanism of the animals and insects. For example, there is a robot that is based on the behavior principles of a cricket: it tracks down a male cricket by its song (Webb, 1996). A ‘robolobster is designed to follow an underwater chemical plume to its source of generation (Hood, 2004). Such examples of robots are interesting in that they were not designed to represent a simple, mechanical system and they imitated the systems from the animals and insects in the real nature. Due to the many advantages that can be obtained by mimicking the behaviors of the animals and insects, the researches in the bio-inspired robots that resemble the systems in nature have increased in numbers recently.

One of the advantages of a bio-inspired system is its ability to respond to an external stimulation immediately. The bio-inspired systems are much simpler and adaptive than the mechanical devices as they intend to operate in the same manner as the animals and insects that don’t have a complex mechanism of speculation and making judgments. Rather, the animals and insects are known for their power to adapt to changing environments in the nature for a long period of history, and such trait became inherent and trainable. Similar to the animals and insects, if a robot makes its own decision on its movements without any external control to perform its task, it can be said that the robot has an intelligent system on which it can operate upon by itself.

The solution to the problems found in the robotics is closely related with how the real animals and insects have solved theirs. Robots can be regarded as models of specific systems of nature . Hence, studying the behavioral mechanism of the animals and knowing the basis on the purpose of their actions can be associated with implementing a compact and intelligent system in the robotics. In this respect, the bio-inspired researches are worth studying, and it can be expected that the bio-inspired system becomes another branch of intelligence system.

1.3 Motivation

Navigation systems that allows a robot to use the visionary information obtained on its surrounding environment has been suggested by many researches. The navigation system operates based on the set of snapshots taken by the robot at target locations on its surroundings. In this system, a vision-based homing algorithm is implemented so that the robot navigates between neighboring target locations. There are several interesting approaches to realize this system, and such experiments with the mobile robots have demonstrated that similar mechanisms also work under the real-world conditions.

Two previously suggested algorithms, the pixel-based image matching model and the distribution model, are the theories that are founded as the basic methods in this investigation. The pixel-based image matching method is an attempt to apply the mechanism of the honeybees to a robot, suggested by Franz (Franz et al., 1998). In the pixel-based image matching method, the robot compares the matched part between snapshot taken at home (starting position of the navigation) and a subsequent snapshot taken at the changed position pixel by pixel, and decides the homing direction based on the computations. Although the suggested algorithm was much simpler than any conventional methods, the robot failed to return home from every point. Namely, the scope of the region that a robot can return home successfully was limited due to the calculation of the matching rate by dot product.

Based on the distribution model, a novel bio-inspired navigation system based on information received through visionary senses is presented in this paper, which is motivated by biological navigation algorithm of the honeybees. A concept of a sector is implemented, where the visual environment is divided into some number of sectors, and this new method of visual navigation is called “sector-based image matching”.

The performance between the pixel-based image matching method and the new algorithm proposed is compared through a computer simulation. The sector-based image matching method improved the performance of the conventional pixel-based image matching method, covering almost all the region as a scope of returnable point. Lastly, this research may help robotic researches that try to implement the behavioral mechanism of insects.

1.4 Objectives

The main purpose of this research is to design a novel, simple yet proficient home navigation system for a robot which is motivated from the landmark navigation mechanism of the insects. The navigation system proposed in this paper should be adequate even for the robots having a poor visual recognition system of the environment. The detailed objectives are as follows:

- Modeling of a navigation system using a new sector-based matching method, based on the conventional pixel-based matching method and distribution model.

- Compare the performances of a robot using the suggested sector-based matching method and pixel-based matching method when a reference compass is not used.

- Compare the performances of a robot using the suggested sector-based matching method, pixel-based matching method and average landmark vector method when a reference compass is used.

- Distinguish the most efficient method from the aforementioned four separate methods based on analytic and semi-quantitative examination.

- Prove the performance of sector-based matching method by robot experiment.

1.5 Structure of the dissertation

To realize the given objectives in establishing a bio-inspired navigation system, the appropriate measures were taken and experimented which could be summarized in the following outline:

Firstly, in this section, an explanation of existing navigation systems of the insects that allow them to effectively return to their home, which has been the basis motive for this research is given with the emphasis on the landmark navigation method. Specifically, a vivid example of three different navigation methodologies, including path integration algorithm, landmark navigation algorithm, and image matching algorithm are given to provide a comprehensive understanding of how insects navigate their way back home.

In Chapter 2, the algorithm used throughout this research are thoroughly reviewed. Based on comparing and complementing the pixel-based image matching method and the distribution model, a sector-based image matching method is suggested. The ideas of a "sector" and an "estimation process" which are the principal concepts of the sector-based matching method are explained.

Chapter 3 presents the results as to whether a robot is capable of returning home using the two image matching methods (pixel-based and sector-based) depending on only its visionary sensor without using a reference compass. Under an equivalent condition, the robot finds its homing direction based on the two different methods, and the result of which and how the robot makes its decisions is compared. The performances of the experiments are evaluated based on the accuracy on the angular difference between the desired homing direction and the calculated direction, average homeward component and success rate.

Chapter 4 compares the outcomes of the image matching methods and average landmark vector method with using a reference compass by the same criterions in Chapter 3. How the methods are vulnerable to noise is tested in a noisy environment, and the performance of sector-based image matching method is proved by a robot experiment.

Finally, in Chapter 5 the performances from the different experiments, varying the algorithms and the use of a reference compass are discussed. With all the factors considered, the advantages of the sector-based matching method are thoroughly explained, and the paper ends by mentioning the future directions by extension of this research.

1.6 Literature Review

1.6.1 Navigation of animals and insects

The insects and animals use various senses to retrieve the necessary information to determine the homeward direction. *Cataglyphis fortis*, or a desert ant is the representative animal known for using the path integration method (Mittelstaedt, 1983; Müller and Wehner, 1988; Wehner and Wehner, 1990). The desert ants have their own internal odometers that allow a self-calculation of their specific belonging position with respect to their nests. To be more specific, the desert ants measure an angular position of their current location relative to the sunlight, and continuously integrate all of the angular values. The integrated value, finally, points toward the homeward direction. The desert ants use the path integration method to return to their nests, and demonstrate an accurate result of returning even from regions far away without the aim of any landmark near the nest or other environmental information given (Wehner, 2003). The application of path integration for a mobile robot has approved in a previous paper (Lee and Kim, 2008).

Fiddler crabs, having the scientific name of *Uca lactea*, are another type of animals that use the path integration method to find their way back home (Layne et al., 2003a,b;

Zeil and Hemmi, 2006). The fiddler crabs always keep their major axis of the body towards the direction of their burrow, meaning that they are ready to return to their nest at any moment of their travel, calculating their own path continuously and repeatedly. It is known that the fiddler crabs draw a certain type of path map, calculating the total distance between their current locations and the nest by counting the total number of footsteps taken (Layne et al., 2003a). For the path integration method, the spatial information is the dominant component to the process of evaluation and making decisions.

Another notable navigation method used by the insects and animals is the landmark navigation algorithm, which is based on the visual information such as the surrounding environments. Animals that use the landmark navigation algorithm receive a visual input and remember according information and upon their return, they compare the newly received images with the previously stored images. The fiddler crabs are also known to use the vision-based navigation system along with the path integration method: at the entrance of a burrow, the crabs build a semi-domelike shaped structure (Kim et al., 2004), and it is an assumption that the crabs use their structure as a landmark.

Apart from the mentioned species, there are many other animals and insects that are known to return home by using a vision-based navigation system. To briefly mention some of them, rodents such as gerbils, hamsters, rats, and birds, for example pigeons, use landmarks to find the original location of their home (Collett et al., 1986).

Sea animals, including octopuses and various types of fishes are able to notice a change when the location of a landmark is changed during their exploration for food and their way back home (Cain and Malwal, 2002; Mather and O'Dor, 1991). Insects like wasps, ants, and honeybees, also have the ability to navigate by using the retrieved visual information (Cheng et al., 1987; Collett and Land, 1975).

Studies show that a rat can remember the spot it has been to by using a visionary sense. A rat has two distinct types of memories; a reference memory and a working memory. The former allows a rat to remember the location where food exists, and the latter is used to store the memory of where it has already visited. An octopus also has a similar memory system for spatial recognition which is based on its visions. It remembers a landmark array at home and where the food was located, and is able to find the target zone in spite of changing the location of the landmarks (Mather and O'Dor, 1991).

In the case of a pigeon, it can correctly find its way back home even when its home is located far away from its visual field because it can tell whether the landscape is familiar or not (Braithwaite and Guilford, 1991). In addition, a pigeon has a good depth vision, meaning it can discriminate the distance between the landmarks. The vision ability of a pigeon is expected to help it fly towards the location of which the image is similar to that of its home (Cheng, 1989).

Furthermore, there have been many researches that show the evidence of insects using the landmark navigation algorithm, and one interesting example to look at is the case of the honeybee's (Srinivasan et al., 2000). Various models are suggested to explain the navigation system of the honeybees, including "pixel-based image matching algorithm" and "average landmark vector algorithm". Here, both algorithms are built upon the concept a "snapshot", which is the remembered visional information generated from home (Cartwright and Collett, 1983).

In average landmark vector algorithm (ALV), the insects recognize a landmark as a vector (Möller, 2000; Lambrinos et al., 1998; Lambrinos, 1999). The average landmark vector (AL vector) is directed towards a specific landmark, and each AL vector is composed of two contributing vectors of a radial component and a tangential component. The radial vector indicates the direction in which the difference of the size of the landmarks becomes minimal, and the tangential vector indicates the same for the bearings of the landmarks. A "snapshot" is processed from the summation of the AL vectors, each pointing a different landmark from home. During the course of the homing process, the insects compare the resulting vector at the current position and the vector of the snapshot.

On the other hand, in pixel-based image matching algorithm, an image is recognized as a type of a circular array, which indicates a series of all directions. The insects determine 0 and 1 from whether a landmark exists or not: if a landmark cannot be detected, the according binary code is 0, and 1 for the opposite case. The size and the position of an individual landmark can be known according to the location and the amount of 1s filled in the binary array. A distinguishable characteristic of the image matching method that makes it special from other algorithms is an estimation process, in which an agent estimates how the position and size of a landmark will change prior to moving some distance. For this estimation process, the direction of the agent's movement plays an important role in achieving accurate calculations.

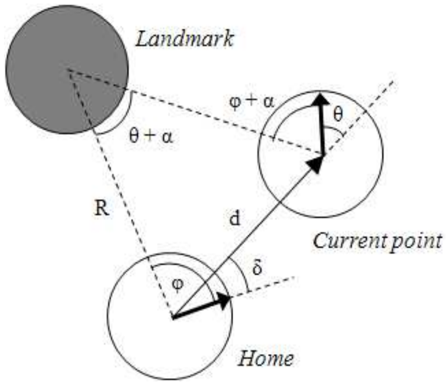


Figure 1.1: Pixel-based image matching algorithm(Franz et al., 1998)

From the aforementioned methods that the honeybees use for their navigation system, it can be concluded that "the bees are not measuring the position of each individual landmark but the overall landmark configuration" (Collett and Land, 1975; Anderson, 1977; Möller, 2000). This is in good agreement with the "Gestalt" hypothesis proposed by van Beusekom (Van Beusekom, 1948), and from this point of view it can be inferred that the image matching method is more analogous to the actual way in which the insects find their ways compared to that described in the ALV algorithm.

Another prominent method is Anderson's "distribution model", which is based on the findings from the experiments with real honeybees. The distribution model contains a new concept of a "sector", which correspond to a spacious and cognitive region of an environment that the honeybees can recognize.

On the following paragraphs, the previously proposed algorithms are reviewed in detail.

1.6.2 Pixel-based image matching algorithm

"Pixel-based image matching method" by Franz (Franz et al., 1998) is amongst the most famous methods where the performance of the navigation system is tested with a mobile robot. The estimation process can be categorized into three major methods according to the direction in which a robot moves. A robot could consider two kinds of movement, which are a rotational movement and a translational movement(see Fig. 1.1). The first method can be explained as a robot considering only the distance it travels with respect to a certain landmark. During this estimation process, the angle of the robots head is virtually fixed and the position of the robot changes, meaning that the dominant factor playing in this process is the difference in the size of the landmarks due to the movement that the robot makes.

In the second method, the robot solely takes into account the rotational angle of its head. Maintaining its position, the robot only rotates around to the designated head angle. Lastly, the third method simultaneously considers both the change in the head angle and position of the robot. However, if the two factors are to be operated on every movement that the robot makes, it would take too much time for the estimation process. For example, for a change in the resolution of the angle to 1 degree, the total number of iterations is 129,600 times. Consequently, the routine would become too much complex and the amount of data that the robot has to handle also becomes too large. Hence, a hair-trigger and a simpler estimation process are required to suggest a modified methodology for the estimation process.

Considering a case for which a robot moves some distance while maintaining its head direction, the ratio of the distance from a landmark to the moving distance in the estimation process becomes the decisive factor (hereinafter referred as "ratio"). In the pixel-based image matching method, it is assumed that the landmarks have identical distances from "home", which was called as "equal distance assumption" by Franz (Franz et al., 1998). By this assumption, the robot will always regard all the distances to its surrounding landmarks from its belonging position after moving to any positions surrounded by any landmarks. This is an egocentric model of the visual-based navigation system, where the robot recognizes the change in the distances to the landmarks as a change in the size of the landmarks, and this model is in good accordance with the real method that the insects and animals use to recognize the environment.

The pixel-based image matching algorithm (Franz and Mallot, 2000) is extremely sensitive to the captured image of the surroundings, how many landmarks are included in the image and the visual resolution of it. For the captured images having a few landmarks, there is a high probability that the robot will misjudge its direction during the homing process. The original criterion on which the robot makes its decisions to choose a direction to move is based upon the value of the dot product between the binary arrays of the initial and random positions, and the robot heads towards the direction that maximizes the value of the dot product. In order to maximize this value, the robot tends to choose one specific landmark as a reference and match the images. However the robot cannot distinguish and recognize the individual landmarks. For example, consider an environment where there exists three different landmarks surrounding “home”. After moving to a random position, the robot captures an image at the according position and compares it with the stored image taken at home. Because what the robot tries to calculate is a value that maximizes the result from the dot product, if the robot stands facing one of the landmarks, there is a possibility that it would try getting close to that landmark located in front. In most cases the robot would move towards home, but nevertheless sometimes it loses its way back home, no matter how close are the stored images and the newly taken images are due to the fact that the robot will face towards the direction that maximizes the value of the dot product.

To overcome this issue of misleading the robot to a wrong direction, an ‘exclusive nor’ logic is included to the criterion set for the robot to choose its direction. Whereas the previous method calculates only a portion of the matched images of the landmarks, the modified method calculates all of the matched parts from the extracted environment, covering not only the images of the landmark but also the space between each landmark. Consequently, the robot will have a less probability of pointing and moving to a wrong direction as compared to the conventional method.

According to the new method including the ‘exclusive nor’ logic, the homing angle is decided as shown in Table 1 to 8. The desired angle is shown to be as follows: 0 degree from the west, 270 degrees from the north, 180 degrees from the east, and 90 degrees from the south. If a robot is placed at 70 cm away from home, the ratio that best matches is approximately 0.5, which means that the image taken at the next position would match well to the snapshot after moving 50 cm from the current position. The experimental data proved this assumption to be a right one.

The region that a robot can enter and find its way back home depends on the location of the landmarks. In order for the robot to find the accurate homing direction, it has to be located within the boundary of the landmarks. Accordingly, fewer amounts of landmarks will lead the robot to make more misjudgments as the regions surrounded by the landmarks would also decrease. Generally, for a robot placed inside a region enclosed by three landmarks of an equilateral triangular shape, it is highly probable that the robot will confuse one landmark with another. The image matching method does not consider the features that each landmark has, which makes it impossible for the robot to differentiate the various landmarks. Hence, in addition to the ‘exclusive nor’ logic, a supplementary modification is highly necessary. It is verified through some computer simulation (Lee et al., 2008).

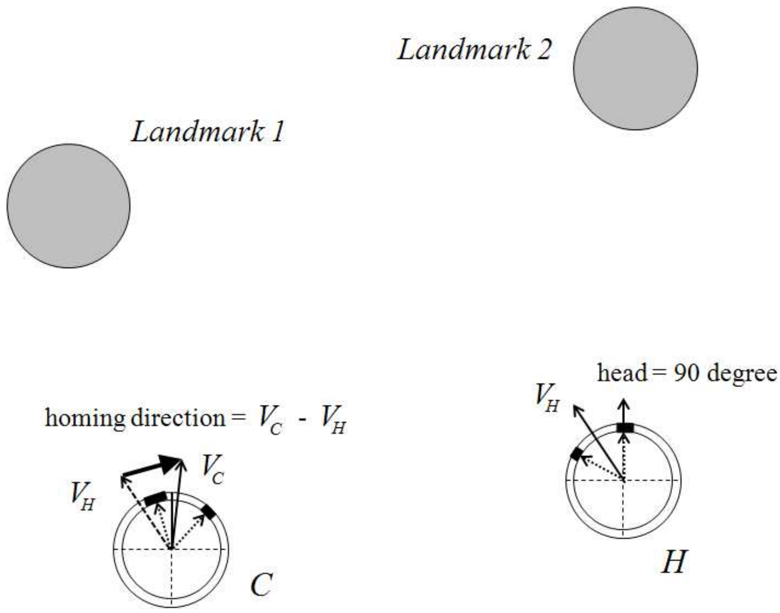


Figure 1.2: Average landmark vector method with compass

1.6.3 Average landmark vector method

Lambrinos invented the “Average landmark vector (ALV)” model which has its basis on the techniques that actual animals use for their navigation (Lambrinos, 1999; Lambrinos et al., 2000; Möller, 2000). In this method, the navigation robot stores an average landmark vector instead of a snapshot image. The robot is programmed to recognize simple features like an object, a structure with considerable volumes, or edges as landmarks. The recognized landmarks are converted into vector representations, and the summation of the vectors simply leads to the information of where its current location is. Fig. 1.2 illustrates the examples of the average landmark vectors. The direction to the destination is determined by the difference of the landmark vector calculated at home with that obtained at the local position. It can be identified that the ultimate vector points toward home. The advantages of this model are that it does not require any complex computations and that the robot can determine its future directions simply from the retrieved information of the landmarks. Although the process seems much uncomplicated, the implementation of the ALV method have proven to yield good performances.

1.6.4 Distribution model

In a more recent research of the honeybee's landmark navigation system (Anderson, 1977), it is suggested that the behaviors of the honeybees resemble that of the desert ants' landmark navigation method. The bees remember the circumstances of the surrounding environment from home visually, and compare the scenes at their placed positions when returning home. Here, it is important how the bees recognize the surrounding and how they match the image of from the starting point to that of the current position. Anderson suggests a new model based on the "Gestalt" hypothesis (by Beusekom), which implies that the bees consider the "degree of closure" when deciding which is the best matched direction towards the goal from their current position (Van Beusekom, 1948). This means that the honeybees regard their surrounding environment as a complex of landmarks, not as individual, separate landmarks. Thus, it can be inferred that the crucial factor in the visual recognition is an overall perception of the entire configuration corresponding to an arrangement of a group of landmarks, and not the precise shape of the landmarks. This conjecture that the insects do not consider the features of an individual landmark, for example the number of landmarks or a distinct shape of each landmarks is further evidenced by reports on wasps (Tinbergen and Kruyt, 1932). From this aspect, Anderson's hypothesis is constructed by two concepts: "surroundedness" and the "average distance".

The concept of surroundedness is decided on the pattern of the surroundings: the surrounded scene is divided into sectors, and the bees judge whether each sector is occupied or not. Since the scene is divided into smaller pieces corresponding to sectors, the bees are able to recognize the visual environment much more simply and rapidly. It is suitable to explain that insects and animals has the ability of finding out own goal readily. By partly changing or eliminating the arrangement of the surroundings, an adjacent result to a desired designation can be revealed.

The second concept, the average distance, means the distance from an occupied section in each sector to the insect, since it is thought that the bees judge the distance by comparing the current distance to a previously conceived value instead of measuring the exact distance.

The effect of Anderson's distribution model on the decision of direction is confirmed in Fig. 1.3. Anderson calculated the average matching score for all estimated directions to obtain a result which is similar to a real data in the experiment of honeybee. The dis-

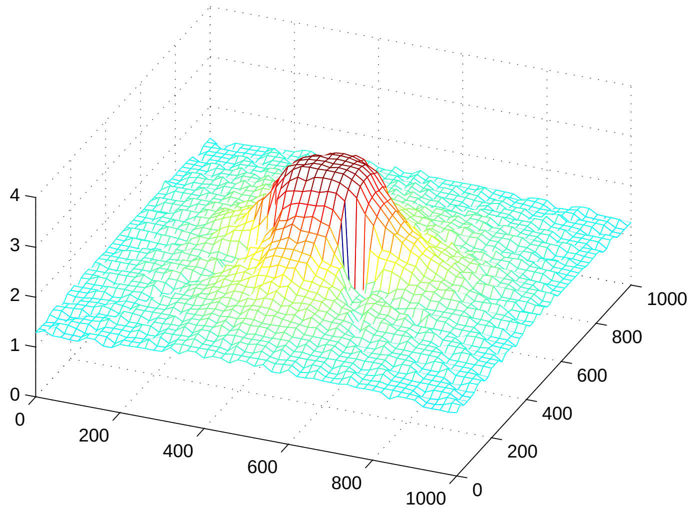


Figure 1.3: Distribution of matching score by Anderson's model

tribution map which is based on these average values corresponds with the distribution of how many times the honeybees visit an arbitrary point.

Fig. 1.3 illustrates an example of the distribution map using Anderson's model. The graph is shown to be a shape of a parabola, and the peak value for the score is retrieved at the desired point, which is the starting point (home) in this experiment. It is modeled to make honeybees find the maximum value by searching and moving onto the highest value, which eventually becomes maximized at the end. However, this model is valid for the point of which the score is maximum, not for the direction to move next in order to get a higher score. The purpose of Anderson's research was to find on which location the bees target at given different environmental circumstances compared to the original state. Even when the environment is changed to the bees, they are capable of finding their way back home or moving to their goals. In spite of the fact the Anderson's method provide an improved version of the conventional navigating systems, there are some drawbacks that require further modifications.

Hence, in the sector-based image matching method, the robot goes towards the direction of which score is highest among that of estimated directions to compensate such a problem. The process of satisfying two components which are suggested by Anderson leads the robot to safely return home. In Anderson's model, the consideration of pointing towards an instant direction at a specific position is not included: in some perspective, the distribution of scores in this model leads to the right information of ultimate goal, the bees are not capable of deciding to which direction they should go along their path of travel, knowing only the scores of the current and past positions. Here, “score” refers to the dot product of difference in the distance and the occupancy value of the designated sector. If the bees were to measure the overall score of the map at once, they would head for the goal straightly no matter where their positions are. However, no animals and insects including the honeybees can perform such task, and therefore the concept of estimation needs to be added to Anderson’s model.

Chapter 2

Method

In this chapter, a new algorithm for home navigation, which is called "sector-based image matching method" is suggested (Lee and Kim, 2009c, 2010). Based on the previous analysis, it is a vision-based homing model with special emphasis on the visual cues as a landmark in the surrounding environment. The important concept and computational structure of the new model will be discussed.

2.1 Concept of sectors

A sector can be regarded as an index that determines how a visual environment should be recognized. The visual environment must be recognized not only by each pixel, but also by each sector. The environment is divided into sectors of equal sizes, and for this experiment, it is designed in such a way that a single sector did not overlap with any other sectors. For instance, if a robot recognizes the visual environment as five different divided sectors, the range of each sector is 72 degree with the robot as the center.

Several similarities can be found in between the concept of an image array in the image matching algorithm and the concept of a sector in Anderson's model. In the image matching algorithm, the visual world of the honeybees is represented as a binary array for the whole bearings. Likewise, in Anderson's model, the concept of a sector can be regarded to be a binary array in which the resolution is much poorer than that of the image matching method.

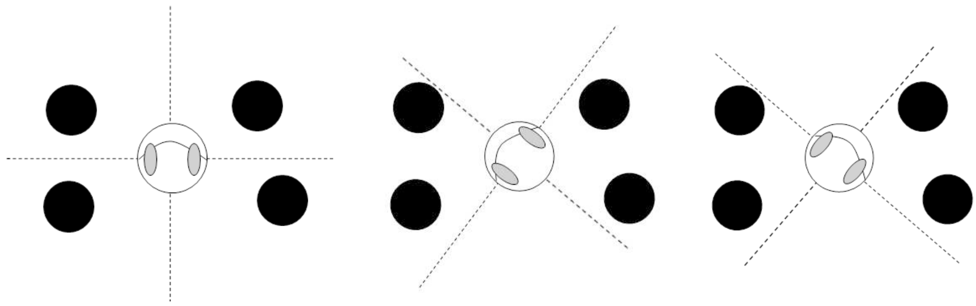


Figure 2.1: Visual environment which is surrounded by four landmarks of a bee divided into four non-overlapping sectors (a) The bee heads for the front side, and thus the sector boundaries lie on between two far-away spaced landmarks (b) The orientation of the bee leans to the left (c) to the right

If there are one or more landmarks inside a sector, the bees recognize that sector as an occupied one, and the occupancy is represented as a binary code of 1. For a sector that does not contain any landmarks, 0 is assigned to the sector. Although, in Anderson's experiments, the scenes are divided equally into four sectors by 90 degrees, without any overlaps, there are other possible options for dividing the scenes into different sectors. For instance, the divided sectors can overlap or either finely divided, and the number of sectors does not always have to be four. Applying this methodology, for the environment surrounding the robot with four landmarks, located in such a way described in Fig. 2.1, the total occupancy is 1 1 1 1 (Fig. 2.1(a)). By changing the orientation of the bee, or the robot in real experiment, the occupancy is measured as 1 0 1 0 (Fig. 2.1(b)) and 0 1 0 1 (Fig. 2.1(c)).

	(a)	(b)	(c)
Occupancy	1 1 1 1	1 0 1 0	0 1 0 1
Distance	a b b a	a x c x	x a x c

2.2 Components of comparison: Occupancy and Average size difference

When comparing the images at home and an arbitrary point, two components are used. They are the "occupancy" and the "average size difference".

Occupancy is a component that determines whether a landmark exists in each sector or not. If a landmark is in a sector, the occupancy of the sector is “1”. On the contrary, if a sector does not contain any landmarks, the occupancy would read “0”. The average size difference refers to how the sizes of the landmarks change at arbitrary positions with respect to its original memory stored from home. A robot is programmed to not count how many landmarks there are in each sector, but rather it only checks for the existence of the landmarks. The robot does not need to know the accurate sizes of the individual landmarks as long as it knows how much portion of a sector is filled with the landmarks.

The premise of the equidistance in the landmarks is also applied in this research, and it can be said that the concept of the distance is the same as how the robot perceives the size of the landmarks. The equidistance assumption implies that the robot will regard a size of a landmark as it actually appears without considering how far or near it is. Hence, for a snapshot taken at an arbitrary position, if the size of the landmark is bigger than that taken at home, the robot will know that it is closer to that specific landmark. In this respect, it is not important to know the actual size of the landmark and the distance away from the landmark as the robot will be able to tell in which direction it has traveled and has to travel by the concept of size. Unlike the methods used in the distribution model where the actual distances were compared, the amount of size difference is regarded in this research, and the question as to whether such simplified information will guide a robot back home successfully will be tested in this paper.

Upon the verification of the average size in landmarks within a sector at an arbitrary point, the difference between the image at an arbitrary point and home can be calculated from the initial point.

2.3 Estimation process

The decision on which direction the robot should head to cannot be determined by calculating the matching rate of a single point. Much more information on diverse points is needed for the correct computation. Therefore, the estimation of how the visual environment changes have to be processed when a robot moves toward any direction in any distance. For this process, we used the estimation method which is systemized in Franz’s image matching method (Franz et al., 1998).

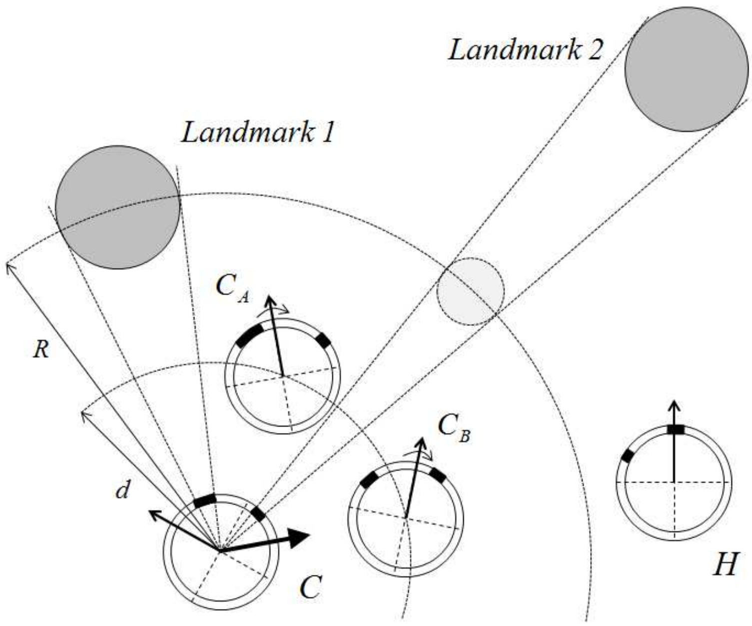


Figure 2.2: Sector-based image matching method without compass

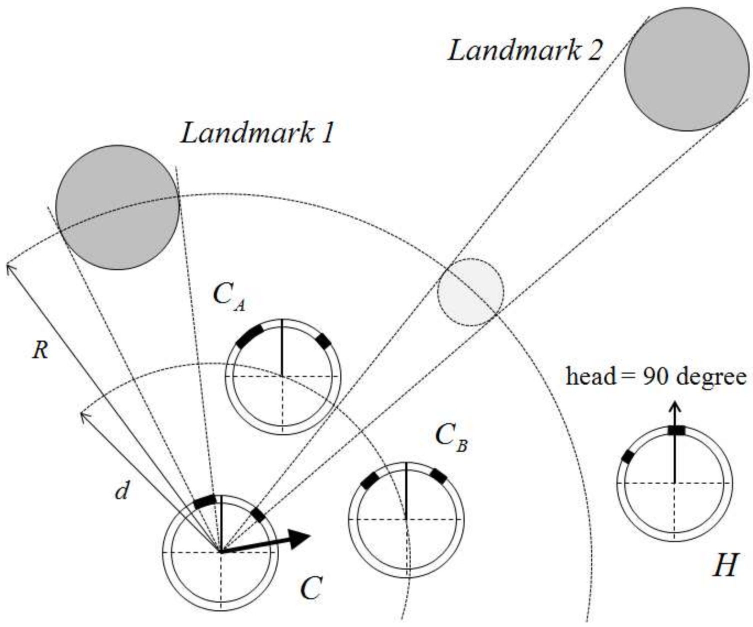


Figure 2.3: Sector-based image matching method with compass (reprinted from Lee and Kim (2009a))

The robot takes an image at the current point, and generates a virtual image by estimating the changes of location of landmark for a certain moving direction. An example of virtual images by estimation is illustrated in Table 2.1. By using this virtual image for each direction, it calculates the matching scores. Finally, the robot chooses the

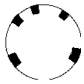
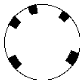
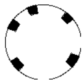
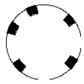
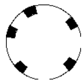
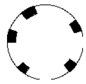
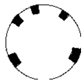
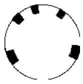
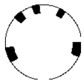
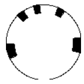
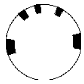
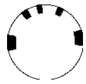
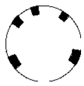
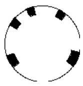
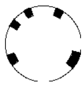
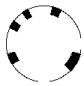
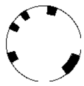
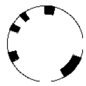
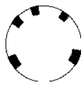
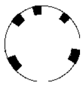
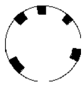
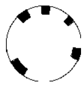
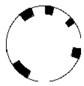
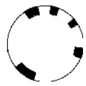
		Ratio				
Direction	current image	0.1	0.2	0.3	0.4	0.5
North						
South						
East						
West						

Table 2.1: Predictive images for possible movements (four directions, north, south, east, west); robot's current position at an arbitrary point (reprinted from Lee and Kim (2009b))

direction of which score is maximized.

At this stage, both the direction for the next movement and for the head to rotate should be considered (see Fig. 2.2). Owing to the fact that the standard line vary according to the direction of head, the measures of occupancy and distance difference might vary. Image matching method based on the concept of sector and estimation process is much similar to the simple mechanism in daily life. For example, suppose that two objects lay in front of you. When you move forward, the distance gap between two objects gets smaller and the sizes of objects seems to be larger. On contrary, moving backward makes the gap larger and the sizes of the objects seem smaller. On the basis of these fundamentals, the fact that a robot can continuously make movements to obtain a desired image and finally reach the destination has been proved based on experimental observations. If a robot has a reference compass which gives the information of angular position, the estimation process could be simplified. The robot knows the direction of own head at a current point as well as home, and has only to consider the movement while keeping the head direction, not the rotational movement. Fig. 2.3 demonstrates the estimation process in the case of using a compass.

2.4 Calculation of matching score

The score at the current location of a robot is calculated from a summation of two different components, the occupancy value of a sector and the average distance difference. Knowing the scores, the robot compares the score of the current position to that of the previous location and moves towards the direction having a higher score. In order to navigate with great accuracy using Anderson's model, an additional process that enables an instant pointing towards the homing direction is required. Therefore, we suggest a novel model of navigation system for the robot based on the concept of sectors with the addition of the estimation process in the image matching method.

in each sector :
Matching score = Sector occupancy $\times$ Average size difference

For each estimated position, the robot measures the matching score from the occupancy of a sector and difference in the average distance. After all the estimations are finished, the robot compares the scores and heads toward the place that has the highest calculated score. Even though the robot is not aware of the precise features and sizes of each landmarks and the distance between a certain landmark and the robot itself, the robot is able to judge and determine the most effective path that will lead it to home based on what has been observed. In the visual world, the robot realigns the landmarks on the assumption that all the landmarks are at the same distance from its according position.

Through these processes, the robot determines the homing direction at a current point, and the entire decision-making procedure of sector-based image matching method is demonstrated in Table 2.2. In a real environment, the image processing is additionally needed to extract the factors (occupancy and average size difference) from a captured image (see Fig. 2.4).

Step 1	capture an image at a current point
Step 2	estimate the change of the current image as the direction of translation and rotation
Step 3	extract the 'occupancy' component and 'average size' component in each sector from the estimated image
Step 4	compare with the initial component from home image and calculate the matching score
Step 5	Choose the homing direction which has the maximum score

Table 2.2: Procedure of sector-based image matching method

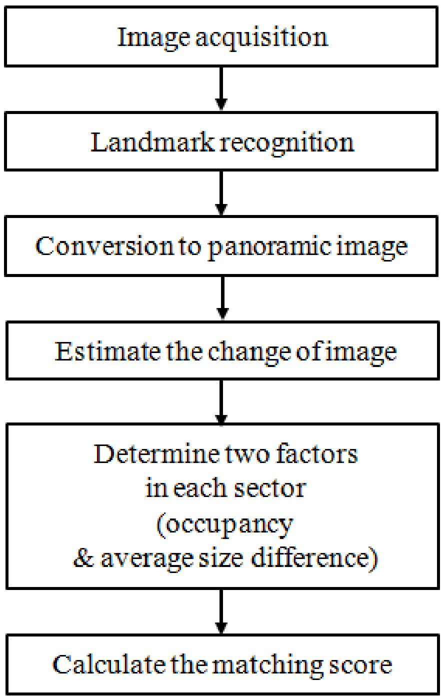


Figure 2.4: Flow chart of the sector-based matching method with real image processing

Chapter 3

Image matching method without compass

In this chapter, a test was conducted to see whether the robot can be find a homeward direction from any point using the sector-based image matching which has been suggested in Chapter 2. For a comparative study, the performance result is compared to that of using the pixel-based image matching method. For both cases, it is assumed that a robot does not use any other sensor except the visionary sensor, which is a web camera for this experiment. In order to calculate the relative angular position of home with respect to the information about where the robot stands currently, the robot needs a reference compass that indicates a standard point of location. Nevertheless, the use of a reference compass was prohibited for this specific experiment to test the assumption that the robot can return home even without the use of a reference compass by using the suggested image matching. The analysis of the results obtained from the experiment can be expressed in two different forms: through a vector map and a trajectory map. The vector map illustrates with a unit vector all the directions selected by the robot at an arbitrary point in overall regions. In other words, the vector map is a collection of unit vectors pointing the direction towards home within a range of region. The second form, trajectory map, expresses a set of trajectories from each arbitrary point to home. Many of the concepts used in this chapter are based on the previous researches (Lee and Kim, 2009c,b).

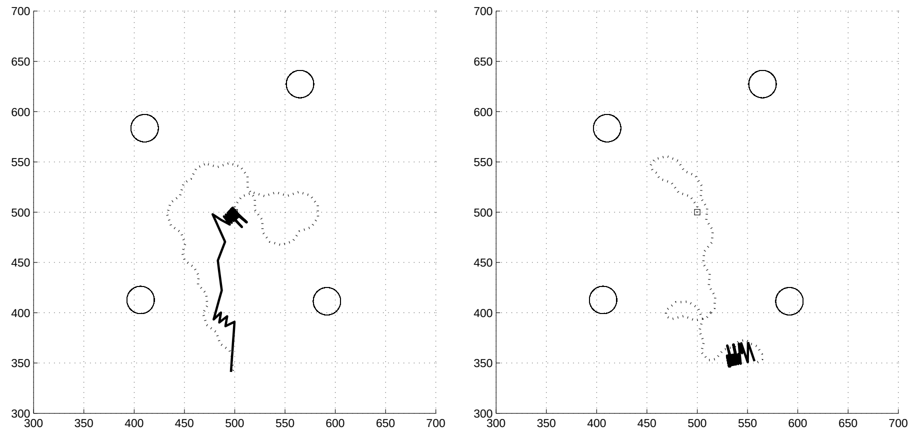
3.1 Experimental environment and assumption

A robot is placed in a virtual space consisting a home and some landmarks, and the robot is programmed to return home using a specific algorithm after some exploration of the region. At any point within the region, the robot is able to recognize the landmarks unless they are overlapped, and it is assumed that the robot uses an omnidirectional camera.

For the experiment, four landmarks of the same shape and size were used. On every movement that the robot makes, it takes an image and figures out the direction towards home by comparing the binary array converted from the newly taken image to the array from the original snapshot in all directions. This process is defined as an estimation process, and two factors must be taken into consideration for the estimation process (Franz et al., 1998), the value of the rotational angle and the length of the moving distance. The landmarks used in this experiment are placed approximately 100 cm away from home, which is an adequate assumption when compared to the actual distance that the honeybees travel before coming back to their nests.

3.2 Pixel-based image matching method without compass

On previous reports, the performance of the image matching method was already revealed through a computer simulation. The trajectory map for a robot moving according to the image matching method is shown in Fig. 3.1(a) and Fig. 3.1(b). In these figures, the dotted line indicates a trajectory of exploration, and the solid line indicates that of the returning path. The robot, when placed fully inside the boundaries of the landmarks, performs its duty of finding its way back home, but it fails to do so if it goes outside of the boundaries of the landmark, even in a single direction. When the robot gets outside of the landmark, it misinterprets the environment by considering the landmarks as an overlap and confuses in which direction it should move to. The robot spins about its location near the outside of a landmark, unable to come back inside the designated target region and find the way back home. This error is due to the fact that the image matching ratio is an overall outcome which is evaluated by the dot product, and for the points outside the landmark the values of the dot product are mistaken. The



(a) (b)

Figure 3.1: Home navigation system using the pixel-based image matching method when the ratio is 0.3 (dotted line : travel path, solid line : return path (a) successful trial (b) failed trial

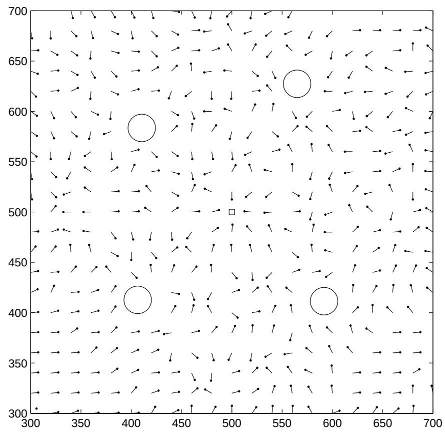
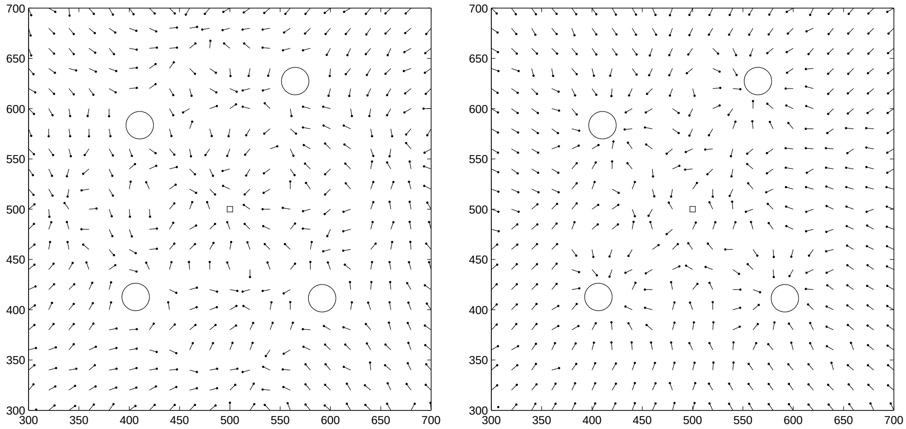


Figure 3.2: Vector map through the pixel-based image matching method without compass (ratio = 0.1)

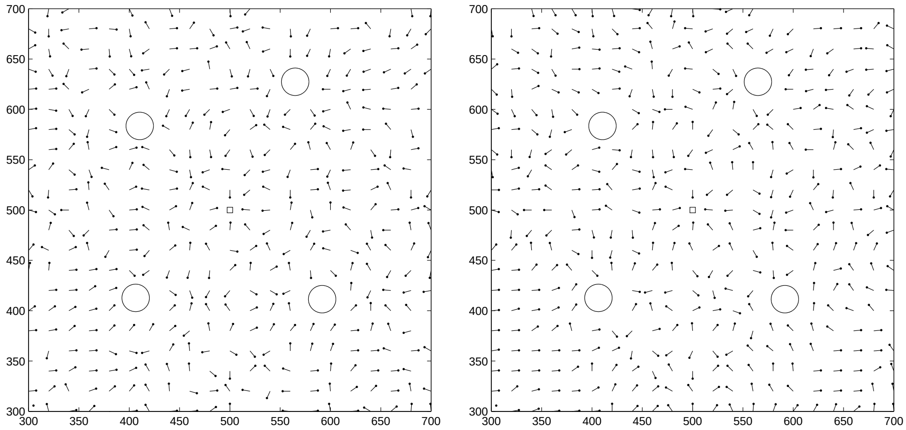
pixel-based image matching method is much simple and effective in some aspects, but it is fragile to the change in the visual environment. Judging from the results of the simulation, the pixel-based image matching method is insufficient to lead a robot back to its home if the robot is placed outside of the landmark surroundings.

As shown in Fig. 3.2, the unit vectors corresponding to the direction that the robot chooses to move to from a certain location have the tendency to radially point towards home in most of the cases. The vector map reveals the possible outcomes for the case without the use of a reference compass, meaning that a standard coordinate system is



(a) (b)

Figure 3.3: Vector map by pixel-based image matching algorithm : R = 100, resolution of estimation = 72 (a) estimated distance = 30 (ratio = 0.3)(b) estimated distance = 80 (ratio = 0.8)

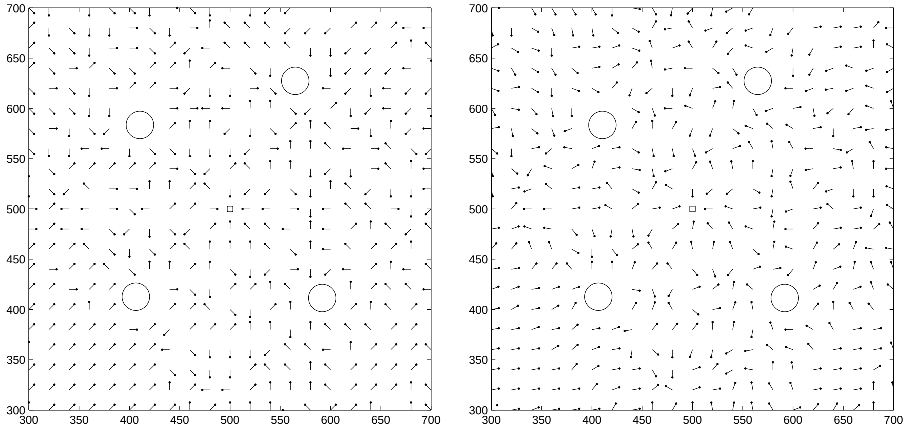


(a) (b)

Figure 3.4: Vector map by pixel-based image matching algorithm : resolution of estimation = 72, R = 100, estimated distance = 10 (ratio = 0.1) (a) number of view point = 8 (b) number of view point = 36

not established prior to the experiment. A unit vector at a point indicates the selected angle among 72 different angular directions in the pixel-based image matching method.

In Fig. 3.2, at the boundaries of the region, the unit vectors are dispersed in all directions. The directions that some vectors indicate point towards other places which are not the final destination. For a successful journey home, the robot is to travel in a series of movements indicated by the unit vectors following their heads that ultimately lead to



(a) (b)

Figure 3.5: Vector map by pixel-based image matching algorithm : R = 100, estimated distance = 10 (ratio = 0.1), number of view point = 72 (a) resolution of estimation = 6 (b) resolution of estimation = 36

the original place when connected from the heads to tails. The problem here is that at outside the boundaries, the vectors pointing outwards do not lead to the vectors pointing inwards, thus making the robot to sit stationary. Although the robot approaches near the region surrounded by the landmarks from a far point, it cannot advance into the region. This tendency can be confirmed from the earlier figure of Fig. 3.1. Hence, in order for the robot to approach home, some additional concepts are needed to surmount these barriers outside of the boundaries generated by the landmarks.

In the pixel-based image matching method, the equidistance assumption is the dominant determining factor in choosing the direction, and the decision that the robot make is revised along the path that it takes. Another important element in this method is the amount that the robot travels upon choosing the direction to move to. The estimation of how the environment will change after the robot travels certain amount of distance may differ from the amount of actual travel distance. Considering these two factors, the decision that the robot makes can alter according to the ratio of the assumed distance of the surrounding landmarks to an estimated step size of the robots movement (hereinafter referred as 'ratio').

In Fig. 3.3(a) and 3.3(b) the resulting vector map for choosing two different ratio is represented. In comparison to Fig. 3.2 and Fig. 3.3(b), the result shown in Fig. 3.3(a) shows to be the most ideal case: if the ratio is too low, the robot has the tendency to wonder about certain points, and if the ratio is too hard, the robot cannot accurately locate its home. Such errors can be attributed to the discrepancy between the real distance of the landmark and the assumed value.

An additional problem in the pixel-based image matching method is that the unit vectors near and outside region of the landmark boundaries concentrate on the nearest landmark. When the robot approaches to a certain landmark, the number of 1s marked in the image array increases. The robot, by means to increase the rate of matching degree between the current array and the initial array, concentrates on the nearest landmark at the sacrifice of the other landmarks. A simple avoidance algorithm utilizing an infrared-ray detecting sensor is implemented to prevent the robot from colliding with the landmarks. Nevertheless, the robot still has difficulties in getting inside the region surrounded by the landmark when placed outside the boundaries. Only when the ratio of the assumed distance to the landmark to the estimated distance for the robot to travel in one step becomes large the robot is able to find its way in successfully.

Besides the value of the ratio, the resolution of two angular components in the estimation process can affect the performance of the algorithm. Fig. 3.4 shows the resulting vector map for the robot with different number of view points. It can be inferred that for the robot that generates the estimated images with more view points, meaning more directions it can choose, there is a higher probability that it finds the desired direction for returning home more accurately by computing the highest value of the dot product.

To better understand the effect of the resolution of the direction, which corresponds to the number of possible directions that the robot can choose to move to, the resulting vector map is presented in Fig. 3.5. As confirmed in the figure, if the robot is able to specify the angle of its moving direction more precisely, the path it takes becomes in a straighter manner (Fig. 3.5(b)). Here, the robot being able to decide from more directions to go means the probability that such directions contain the desired homeward direction is higher, and thus more accurate result can be obtained when the angular resolution is higher.

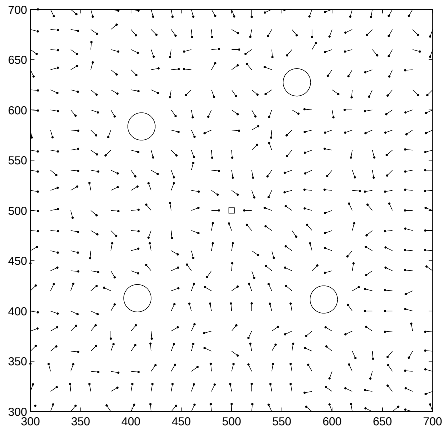


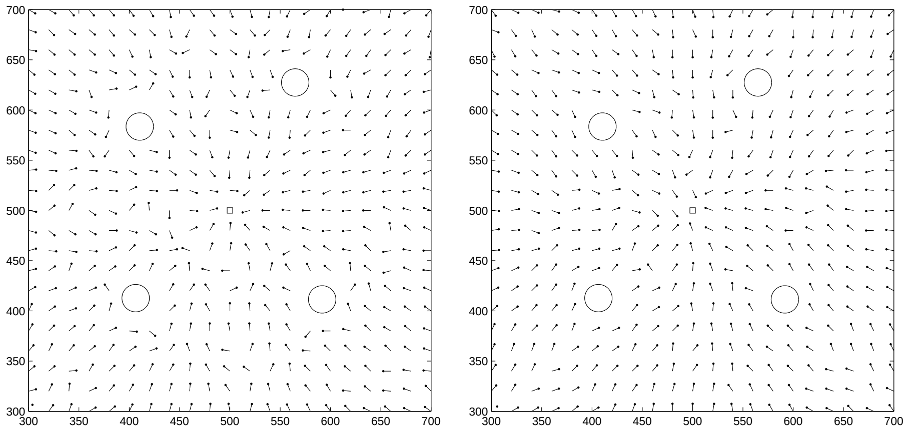
Figure 3.6: Vector map through the sector-based matching method without use of compass (ratio = 0.1)

3.3 Sector-based image matching method without compass

When a reference compass is absent, the robot does not have any information of the initial head direction it chose at home. Thus, especially in the environment with symmetrical arrangement of landmarks, it is more probable that the robot makes a wrong decision. When the visual environment is divided into sectors with respect to different angles in the same direction of home, a single landmark may be recognized as an overlap in two sectors, and thus recognized as two different landmarks, leading to a fatal misjudgment. The distribution model is used with the assumption that there is no use of the compass as to solve such problem mentioned above.

The vector map of the sector-based image matching method without the use of a reference compass shows that not only at the point inside of the landmarks but also at the outside the angular direction of the vectors point towards the starting point (Fig. 3.6). Comparing this result to that of Fig. 3.2, it shows a good performance even at the boundaries of the region surrounded by the landmarks. The robot is capable of entering the region fluently and arriving home through the sector-based matching method. The vectors do not go directly through the landmarks, but instead they go around them as if the vectors are avoiding them. It can be expected that the robot can find and travel back home through the result of the sequential moving.

Hence, it can be concluded that the performances of the case using the sector-based

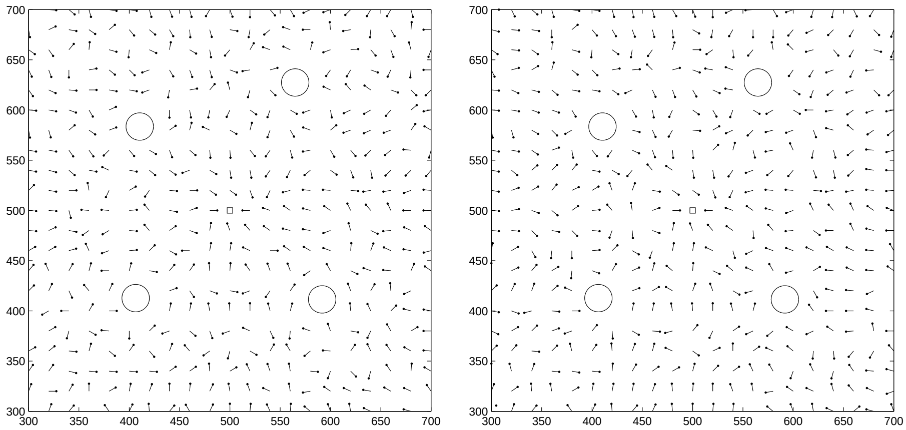


(a) (b)

Figure 3.7: Vector map by sector-based algorithm : resolution of estimation = 72, number of view point = 72, R = 100 (a) estimated distance = 30 (ratio = 0.3) (b) estimated distance = 80 (ratio = 0.8)

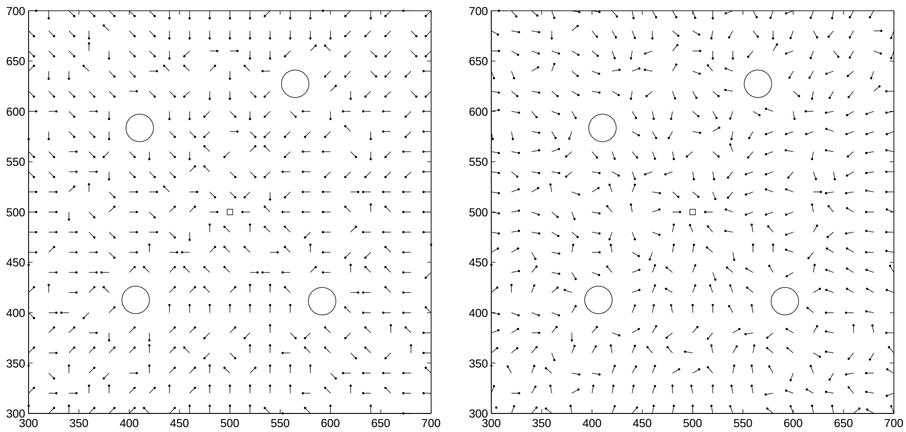
age matching method is better than that of case using the pixel-based image matching method. The sector-based matching algorithm is built on the concept of the surroundedness and the difference in the average distance from the distribution model, and it provides a solution to errors found in the pixel-based image matching method. Two factors can be manipulated as to increase the matching ratio of the algorithm based on the sector method: making the location of the robot surrounded by the landmarks closer to home and making the average distance between the robot and a landmark of each sector closer. In other words, the robot tries to enter the region in order to increase the amount of surroundedness, and it maintains the distance from a landmark in order to decrease the difference of the average distance. Considering the degree of two components, the matching score for a specific direction of the robot's head is evaluated.

The effect of increasing the number of view points and the angular resolution is seen in Fig. 3.8 and Fig. 3.9, respectively. It is obvious that the selected angle gets more accurate when the resolution of the angle becomes higher. Fig. 3.8 shows that the density of the vectors becomes more concentrated as the robot is able to select from more possible head directions. The similar effect was found when the robot makes estimation of the next movement in more angular directions. As proven in Fig. 3.9, the vectors point at the goal point much precisely and correctly in the case that the resolution of estimation is higher. It means that the robot's head is turned to more



(a) (b)

Figure 3.8: Vector map by sector-based algorithm : resolution of estimation = 72, R = 100, estimated distance = 10 (ratio = 0.1) (a) number of view point = 8 (b) number of view point = 36



(a) (b)

Figure 3.9: Vector map by sector-based algorithm : number of view point = 36, R = 100, estimated distance = 10 (ratio = 0.1) (a) resolution of estimation = 6 (b) resolution of estimation = 36

diverse range of directions, and the decision is made upon from the average value achieved from those trials. By doing so, the robot can make an optimized decision as to which direction it must head to without knowing the exact direction of its head. Even if the robot is far from home, it is able to return home accurately, and the path forms almost in straight line.

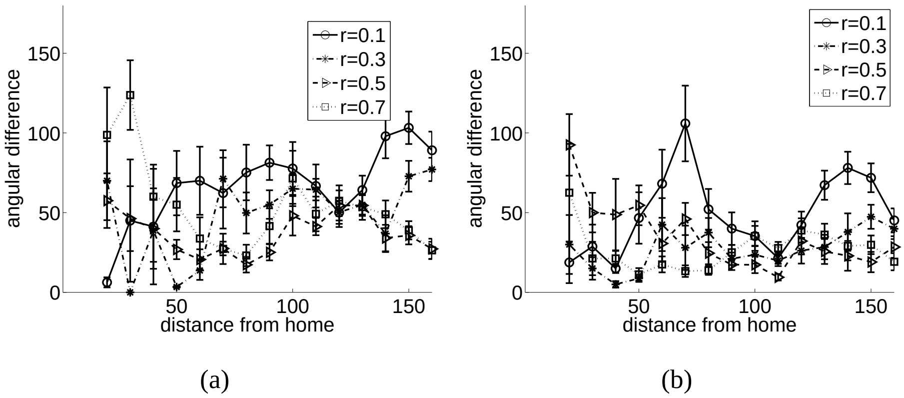


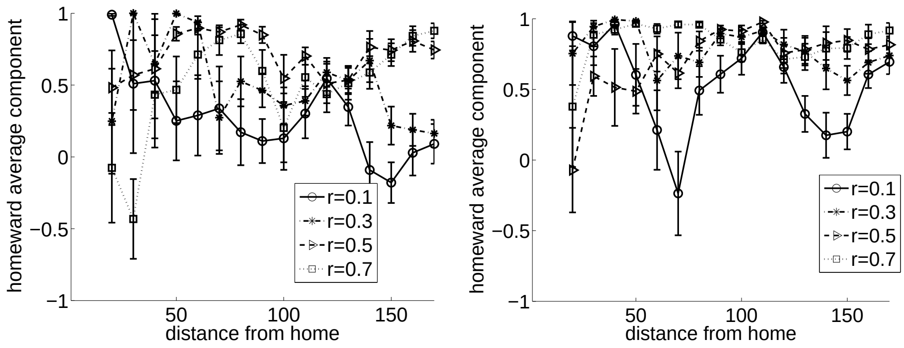
Figure 3.10: Error curves in distance measured with respect to home without compass ($0 < \text{ratio} < 1$) (a) pixel-based image matching (b) sector-based image matching

3.4 Performance of pixel-based and sector-based matching method

3.4.1 Angular difference

The performance of the image matching methods can be measured directly by calculating the amount of error, which indicates the difference between the selected angular direction and the desired direction at an arbitrary position. The error bars indicate the mean values and the t-distribution deviations which corresponds to the 95 percent confidence level (The t-distribution is often used as an alternative to the normal distribution as a model for data.). An emphasis should be made on the fact that the highest level of performance can be achieved only on specific range of values for the ratio, which is highly dependent on the equidistance assumption. Here again, the ratio to be measured between the distance through the equidistance assumption and the estimated value of distance on the next movement.

Therefore, it can be inferred that a good performance is achieved only when the actual distance between the robot and the landmark is similar to the assumed distance. A higher ratio corresponds to a higher probability to jump and miss the final destination, home, due to estimating to travel too far on the next step.



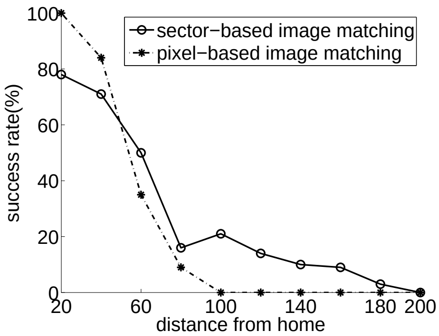
(a) (b)

Figure 3.11: Average homeward component measured with respect to home without compass (Mean values and T-distribution deviations which corresponds to the 95 percent confidence level) (a) pixel-based image matching (b) sector-based image matching

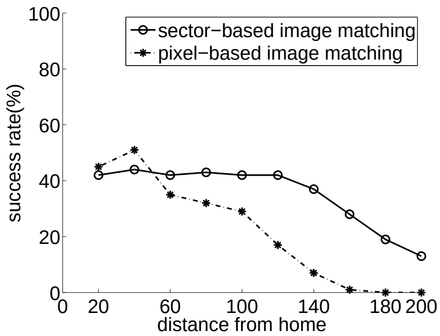
3.4.2 Average homeward component

In addition to the angular difference, the performance of homing direction through each method was evaluated from the average homeward component. It is a measure of accuracy, and the average homeward component has been used generally in many researches. The cosine of an angular difference indicates the accuracy in deciding the homing direction. This value characterizes both the accuracy and the angular dispersion of the decided homing direction. All values are normalized between -1 and 1, and the value which is closer to 1 means that the direction of vector points to home more correctly. In other words, as long as the homeward component stays significantly above 0, the robot moves nearer to the goal.

Fig. 3.11 reveals how the direction of the vector is different from the desired direction to point at home according to the distance from home. When the sector-based image matching method is used, the data of average homeward component is close value to 1, and thus the accuracy is higher than the pixel-based image matching method in the aggregate. As seen by the result of angular difference, the pixel-based method is much influenced by the ratio between the distance from landmark by the equidistance assumption and the next moving distance. On the other hands, the sector-based method relies less on the ratio, and the difference between the curves which is driven by changing the ratio is smaller. The sector-based image matching method is effective to find homeward direction in aspects of not only accuracy but also stationary performance.



(a)

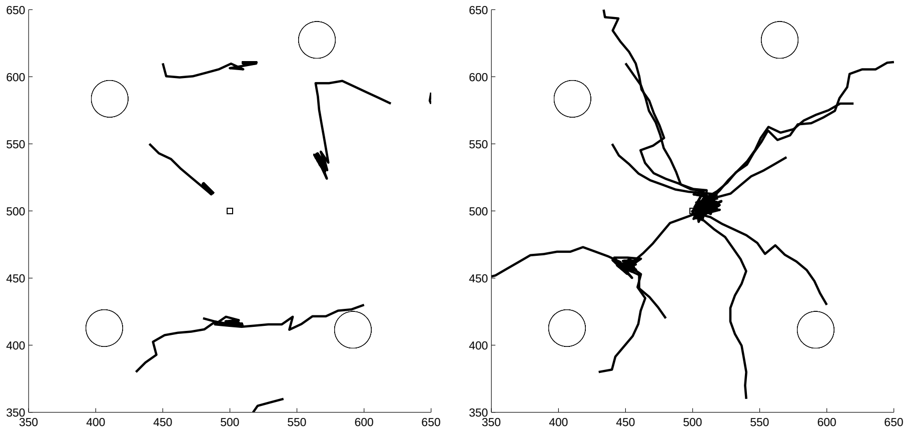


(b)

Figure 3.12: Success rate among 100 trial times measured with respect to distance from home without compass (a) ratio = 0.1 (b) ratio = 0.3

3.4.3 Success rate

Through the concepts of the angular difference and the average homeward component, it was proven that a robot can properly find the direction towards its home from an arbitrary assigned position. The vector maps reveal the decisions that the robot makes on the direction at each individual positions, and if the vectors are connected in heads to tails to generate a sequence of movements, the line would be the path that the robot takes to return home from an arbitrary starting position. To test whether a robot can return home by making such sequential movements from a random position other than home within 50 movements, the number of successes were counted for varying the starting position to 100 different places and the result is plotted in Fig. 3.12. In Fig. 3.12(a), the success rate for the case when the robot predicts it needs to make 10 movements before reaching home is shown after making 10 movements. In Fig. 3.12(b), the number of movements that the robot made was fixed at 10 but the prediction number on its movement was increased to 30. Success rates over 50 percent signify that the robot accurately returned home for more than five times. For the pixel-based image matching method, the success rate shows a sharp decrease when the robot is placed farther away from its home. This result is in good agreement with the previous finding where the pixel-based method showed poor results when starting from the outer region of the boundaries. The result of sector-based image matching method shows a slower decrease in the success rate for increasing the distance, and thus a slight chance of the robot's return can be expected for distances larger than 100. When the ratio was increased to 0.3 (Fig. 3.12(b)), the success rate showed a decrease for closer distances but the scope of the distance for a success return increased, leading



(a) (b)

Figure 3.13: Trajectory with use of compass when a robot moves 10 per step (total 50 steps) (a) pixel-based image matching (ratio = 0.3) (b) sector-based image matching (ratio = 0.3)

to the increase in the success rate.

The success rate could be improved by setting the robot to move forward greater distances than the calculated distance from the estimation. In Fig. 3.12(b), the performance of the two different methods is shown for increasing the ratio to 0.3. As compared to when the ratio was 0.1, the success rate has significantly increased even when the starting location for returning home increased. This is attributed to the fact that the further distance the robot predicts than it actually moves, the larger change of the images are estimated. This helps to decide the homeward direction more accurately.

Fig. 3.13 shows the trajectory of the returning path from an arbitrary position for different image matching methods when the ratio was set to 0.3 and the amount of travel distance per movement to 10. Sector-based image matching method yielded much higher performances from the same starting positions, while the results of pixel-based matching method showed its limits overcoming the boundaries, and the robot remained near its home after the finish on its movements.

3.4.4 Summary of Chapter 3

In this chapter, the pixel-based and the sector-based image matching methods were tested and compared, and the performance of the robot, that is, whether it has successfully arrived home is evaluated in three different aspects. It was assumed that the robot has no other sensor except for a vision sensor, and the robot had to find the location of home only by comparing the image it took. The vector maps represent the decision of homing direction at a point through each method, and a large number of points which is outside the surroundings head towards home when the sector-based method is used. The homing direction is less correct within the short distance from home than that of the pixel-based method.

The first evaluation was on the angular difference between the chosen direction and the accurate direction towards home. The obtained results show that the difference was not greater than 90 degrees for almost all the homing directions chosen and better performances were achieved for starting points located nearer to home, as seen by the vector map. The performance of the pixel-based method depends on the ratio of the equidistance assumption and the movement. It was confirmed that the error curve varies much according to the ratio. In contrast, the sector-based image matching method is more stable because the robot could return home after long-distance traveling and is less affected by other parameters as like the ratio.

For the second evaluation, the cosine values were taken on the angular differences, which correspond to the average homeward difference. The data obtained in the first evaluation process were normalized between -1 and 1, and values closer to 1 means the direction that matches well with the actual homeward direction. The sector-based image matching method showed good stability in the sense of success rate and trajectory map. There is a high probability that the robot arrives home using the sector-based method, especially from outside the region surrounded by the landmarks.

The third evaluation was on the success rate, which was driven from the vector maps by connecting the sequential vectors to see if the resulting line led its way home. The number of successful returns was counted for the starting points within the same distance to home, and the success rate showed the measure of possibility of the robot to return home safely.

Based on the three evaluations, it can be concluded that although for the lower values of ratio and regions closer to home the sector-based image matching method showed poor performances, the performances were much better when the starting location was further away from home independent of increasing the values of the ratio compared to the pixel-based image matching method. Thus, it was proved in this chapter that a robot can successfully return home by processing the information received from only a visual sensor, and that the sector-based method is more efficient with respect to variable parameters like the ratio and the location of the returning start positions.

Chapter 4

Image matching method with compass

Chapter 3 analyzes the results of the pixel-based and sector-based image matching method in finding the accurate way back home based on the information received from the visual sensor solely, without any help of any other types of sensors. It should be noted that a reference compass is used during the experiments carried out throughout this chapter, and the performances of each algorithm are compared to the results from the previous cases in chapter 3. Generally, it was found that the use of a reference compass leads to a higher performance. The use of compass in the navigation algorithm was already dealt in previous papers (Lee and Kim, 2009c,a).

The use of a compass is meaningful in the sense that the robot can modify the information retrieved from the visual sensor, and it is practical as in the real nature the animals and insects too have a similar standard for determining their movements. A desert ant can distinguish left from right based on the position of a landmark, and it remembers the angle at which a specific landmark existed relative to its position (Collett et al., 1992). A bee has the sense of absolute position with respect to a reference point as well as the sense of relative direction, which is thought to be related to the magnetic field of the Earth. Backing this theory up are the studies showing that if there are distinguishable landmarks near home, bees approach home from the same direction continuously over and over (Collett and Baron, 1994). Hence it can be considered that bees have a sort of magnetic compass that enables them to remember the direction traveled away from home, and uses that information to match its path when returning home.

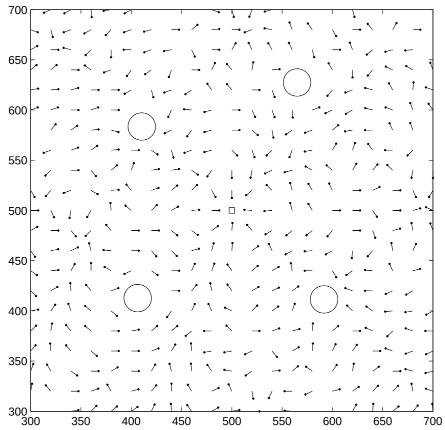


Figure 4.1: Vector map through the pixel-based image matching method with use of compass (ratio = 0.1)

4.1 Computer experiment

In the case of using a compass, owing to the fact that the robot can recognize its direction of head precisely, the results are expected to become more accurate. Furthermore, the calculation process can be simplified because the only estimation process needed is on the amount of movement whereas for the case without the use of a reference compass, the robot has to estimate the angle of rotation for the next movement as well. For this experiment, the robot remembers the initial head direction chosen at home, and converts an image at an arbitrary point during returning based on its initial head direction. Even when the landmarks are placed in a symmetrical formation, the use of a reference compass is advantageous in that the robot can distinguish and compare each landmark according to a standard coordinate, resulting in the reduction of errors.

Fig. 4.1 illustrates a vector map when the ratio (defined in Chapter 3) is 0.1 and a compass is used. Compared to Fig. 3.2, the vectors, especially which are within the region surrounded by landmarks concentrate towards home with greater precision. Furthermore, the cases of choosing random directions are reduced which can be attributed to the robot remembering its initial head direction chosen at home. The robot can match each sector more accurately, based on the same angular direction of its head from any arbitrary point.

A higher performance was also achieved through the sector-based matching method using a reference compass. A clear comparison can be found in between Fig. 3.6 and Fig. 4.2, where the vectors show a lot more clever paths for the case that a reference

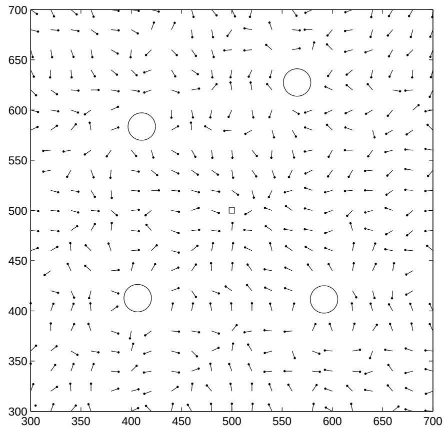
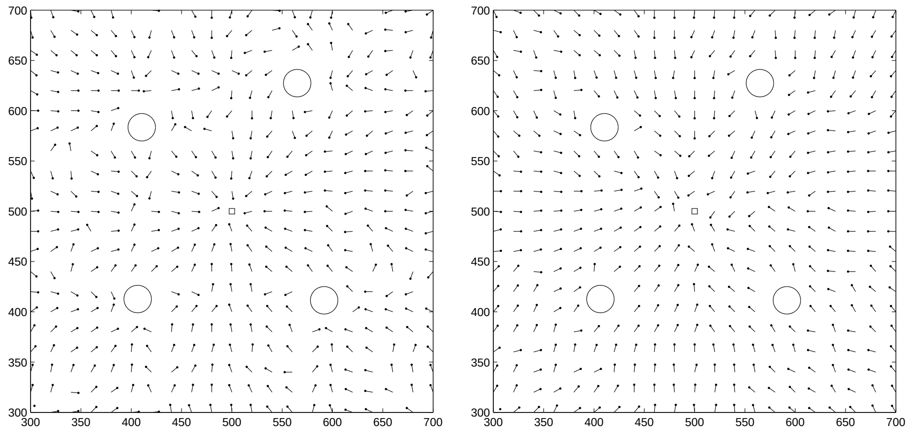


Figure 4.2: Vector map through the sector-based image matching method with use of compass (ratio = 0.1)



(a) (b)

Figure 4.3: Vector map by sector-based image matching algorithm : R = 100, resolution of estimation = 72 (a) estimated distance = 30 (ratio = 0.3)(b) estimated distance = 80 (ratio = 0.8)

compass has been used. The use of a reference compass affects the decision that the robot makes in a way that redirects its head of direction when a misjudgment is made.

However, there exist other types of errors that cannot be corrected with the use of a reference compass. Within the region surrounded by the landmarks, almost all the unit vectors point towards home with some approximations. On the contrary, in the outside regions, some vectors point at an entirely different direction that is not relevant to homeward direction. Such errors are found when a single landmark is included in two or more sectors that the robot divides when traveling back home. In this experiment,

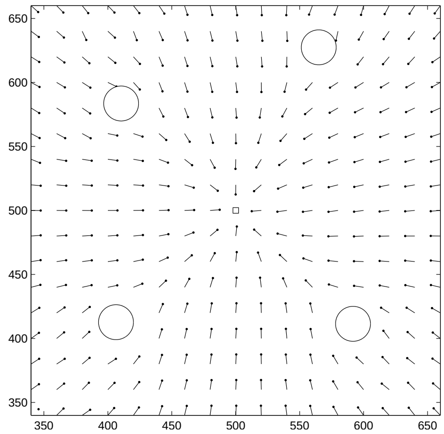
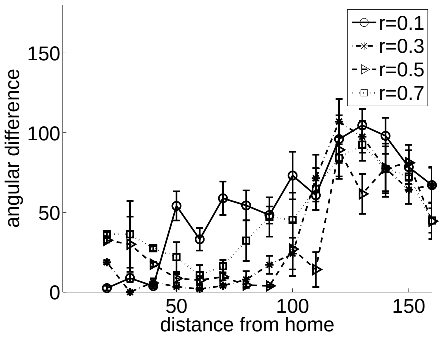


Figure 4.4: Vector map through the ALV method with use of compass

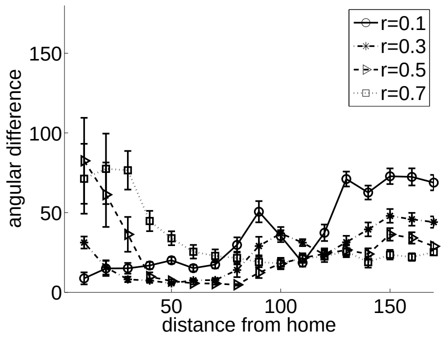
the occupancy and the distance difference can be measured when a specific landmark is included in only one of the sectors, not divided into two or more sectors. When the robot is located near or parallel to a specific landmark, that landmark is occupied by more than two sectors, and therefore a miscalculation error occurs. These errors can be fixed by slightly increasing the value of ratio. If the robot estimates the distance it will travel on the next movement largely, the change in the estimated image would become larger. Consequently, the cases that the landmarks are contained to two or more sectors are reduced.

If a use of a reference compass is permitted for the robot, an alternative model for the navigation system based on the visual information can be taken into consideration. The ALV method mentioned earlier in chapter 1 corresponds to such model as the recognition process of a landmark as a vector requires the accurate information on its angular position, which in turn requires the use of a compass. Therefore, the results obtained by navigating on the ALV method is taken into analysis along with the pixel-based image matching method and the sector-based image matching method.

Fig. 4.4 is the vector map which shows the choices of direction to return home through the ALV method, and the vectors on all points head towards home precisely. All angular position of landmarks are converted to a vector, and then the robot has much accurate information of own location. When the ALV method is used, all vectors point at home, and the vectors spread out like the spokes of a wheel, with home as the hub. Therefore, it could be said that the ALV method is the most correct method in the case that the robot uses a compass. However, if the noise occurs, the performance would be changed.



(a)



(b)

Figure 4.5: Error curves in distance measured with respect to home with compass (Mean values and T-distribution deviations which corresponds to the 95 percent confidence level) (a) pixel-based image matching (b) sector-based image matching

4.2 Performance of pixel-based, ALV and sector-based matching method

4.2.1 Angular difference

The variation of error in distance measured with respect to the starting point is shown in Fig. 4.5 when Franz's image matching method and sector-based image matching are used with a compass.

The two graphs shown in of Fig. 3.10(a) and Fig. 4.5(a) present two different cases, with and without the use of a reference compass: the latter graph shows the case with the use of a compass, and the angle of its head are measured. Compared to the pixel-based image matching method, the sector-based method shows an average of 20 percent lower error at most of the points which are within 130 cm from home (Fig. 4.5). The reason why the amounts of error at very close range (lower than 50 cm) seem exceptionally high is due to the estimated position of the final movement. In other words, a high error occurs for the case where the estimated point goes beyond the final destination, thus making the value incorrect as if the estimation was made from the opposite side. It is evident from by comparison that among the four models, the sector-based matching method with the use of a reference compass is the most stable and efficient method for returning home regardless of the value of the ratio or the starting return position of the robot.

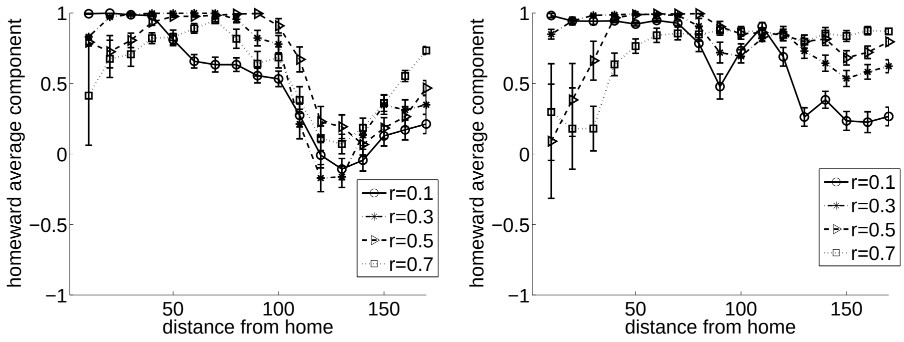


Figure 4.6: Average homeward component measured with respect to home with compass (Mean values and T-distribution deviations which corresponds to the 95 percent confidence level) (a) pixel-based image matching (b) sector-based image matching

4.2.2 Average homeward component

Fig. 4.6 plots the variations of accuracy with respect to the increasing distance of the starting location and home for different values of the ratio in the case of using a compass. The characteristic curves shown in this figure have an exact opposite tendency to that obtained in the previous section 4.2.1. In the curve of the angular difference (Fig. 4.5), a smaller difference indicates a vector pointing home with more accuracy. On the contrary, the average homeward component increases as the direction of a vector is rightfully placed toward the homeward direction. Thus, the reverse relationship reveals an opposite graph as shown in Fig. 4.6 to that of Fig. 4.5.

A decrease in the accuracy in some range of the calculated distance for the sector-based image matching method is revealed. When the ratio is set at 0.1, the accuracy obtained shows a close value to one at points near home. However, for increasing the values of the ratio to above 0.5, the accuracy becomes poor in the same distance range, and the curve decreases to a lower value. This is ascribed to the setting of the estimated moving distance too large compared with the assumed distance between the each landmarks and the robot. The homeward component in a higher ratio is much close to 1 at the almost all points, and thus the performance level can be brought up by selecting which value as a ratio.

The comparison with other methods of pixel-based matching and ALV is depicted in Fig. 4.7 for experimenting with the value of the ratio of 0.3. The performance of the ALV method is considered for the first time as the use of the reference compass is

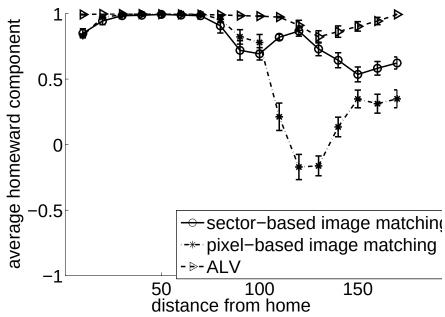
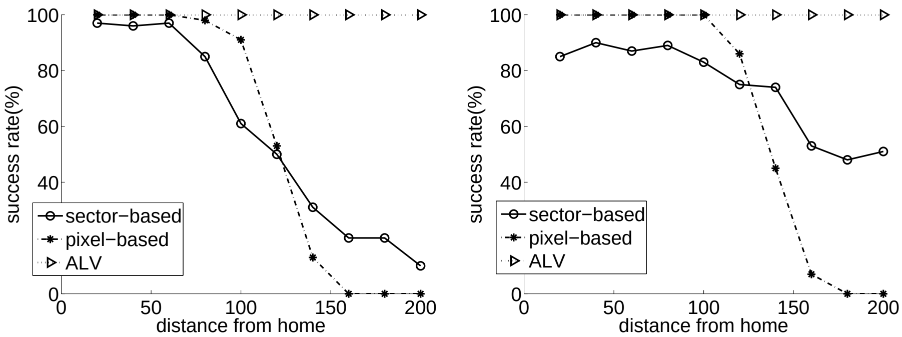


Figure 4.7: Average homeward component measured with respect to distance from home



(a) (b)

Figure 4.8: Success rate among 100 trial times measured with respect to distance from home with compass (a) ratio = 0.1 (b) ratio = 0.3

included in this chapter. Until the distance is 100, the measured values of homeward component are approximately similar for all three methods compared in the graph. However, when the starting position of the homewarding process becomes farther away from home, a sharp drop in the curve of pixel-based method appears. The dramatic decrease for the pixel-based method suggest that the accuracy becomes extremely poor under the according circumstances, and for the achieved homeward components values lower than 0, the robot completely loses its direction and the navigation algorithm does not work at all.

4.2.3 Success Rate

Fig. 4.8 reports the success rates of different navigation algorithms for counting the successful records among 100 trials for increasing the difference in distance of the

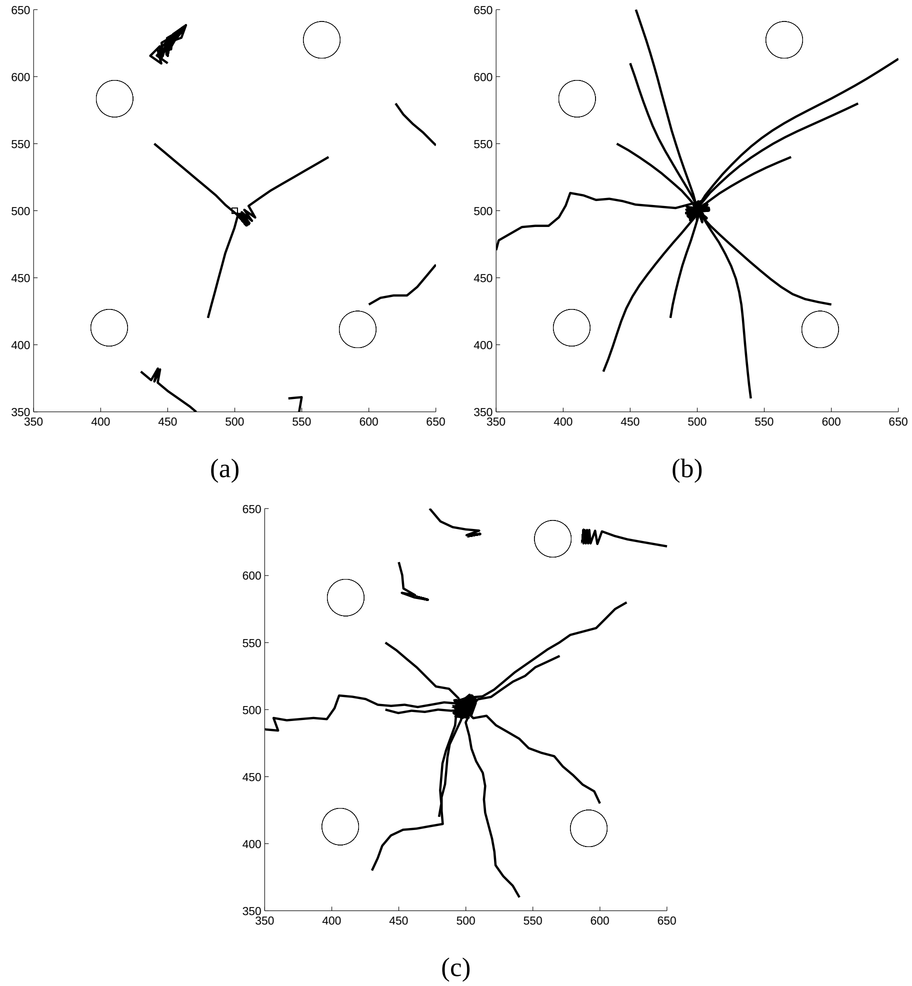


Figure 4.9: Trajectory with use of compass when a robot moves 10 per step (total 50 steps) (a) pixel-based image matching method (ratio = 0.3) (b) ALV method (c) sector-based image matching method (ratio = 0.3)

starting location and home for different values of the ratio in the case of using a compass. Comparing the results to that obtained in Fig. 3.12, it can be said that a wider range of distance which is possible for the robot to return home exists for the case of using a reference compass. For the sector-based method, the possible range of distance where the probability of arrival is higher than 50 percent is 120 when the ratio is 0.1, and all the ranges are covered when the ratio is increased to 0.3. When a compass is used, the robot knows its initial heading direction taken from home, and it only has to estimate the images while maintaining its head direction, minimizing the rotational movements. Hence, finding the matching degree by comparing the images has been simplified in great amounts during the homing process, and the probability of successfully returning home becomes higher. The ALV method shows the perfect rate of success at any return starting point in the area as it is expected in the vector map. On the occasion of using the pixel-based image matching method, the success rate drastically decreases, and the successful return is available to the extent of short distance.

Fig. 4.9 illustrates the trajectories of the path taken by the robot when returning home by varying the starting points for the different navigation methods with the use of a compass. The robot was programmed to move 10 units before making the decision for in which direction it should head to on its subsequent movement and the maximum number of movements that it can make was set to 50. When the robot calculates the homing direction through the ALV method, it can always return home correctly drawing a smooth path. The result of the sector-based image matching method shows better performance than that of the pixel-based method. From some positions, the sector-based matching method failed to lead the robot back to its home, but in any cases, a good possibility was shown in both the journeys of long distances as well as short distance.

4.2.4 Noise Test

For the navigation methods based on the recognition of landmarks and the comparison of images, a problem with noise could occur. The vulnerability to noise is an important factor to be considered in the robot application, mainly related to stability issues. To test how the homing direction is changed due to the presence of a noise in each method, an artificially created noise was introduced to the navigation environment. When taking the initial snapshot at home, a robot is not able to recognize the noises introduced to the environment; the noise is only noticeable when the robot is on its way back home. The interruption by a noise is possible in all angular directions, and a size of a noise was set to be at least 1 pixel in size.

In the first noise test, the angular deviation during the measurement of the homing direction corresponding to the error is tested for the introduction of a noise with size of 1 pixel at different angular positions. Fig. 4.10(a) shows the representation of the visual environment recognized by the robot as an array when a noise is added to the environment. The position of the robot when the snapshot was taken is (550,550). By varying the angular position where the noise is effectively introduced, the number of landmarks that a robot recognizes can increase by regarding the noise as an additional

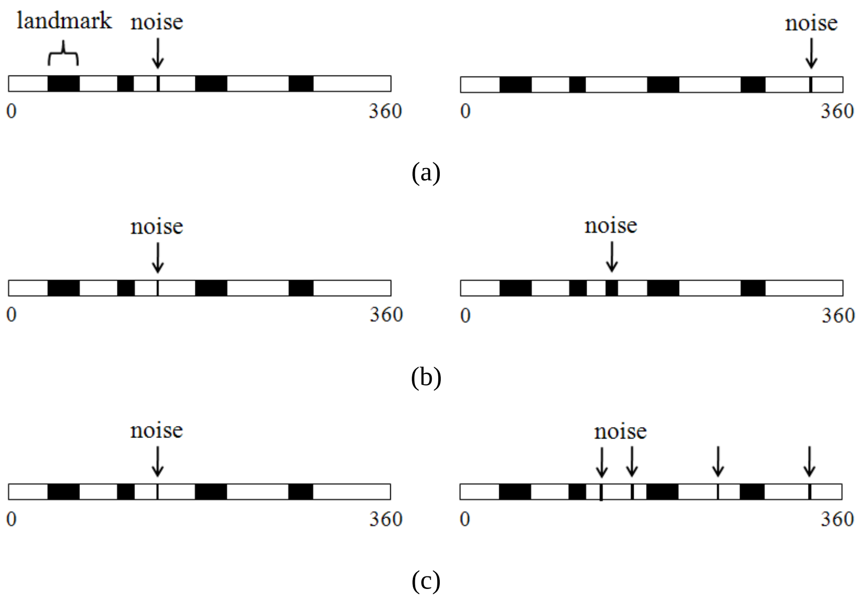


Figure 4.10: Binary arrays in three noise tests (a) when the angular location of a noise is varied (b) when the pixel size of a noise is varied (c) when the number of noise is varied

landmark. In the case like Fig. 4.10(a), five landmarks are recognized. The effect of noise is showed in Fig. 4.11. Fig. 4.11 illustrates the decision of homing direction in each case of use the pixel-based image matching, ALV or sector-based image matching method. The decision is changed due to a noise, and the angular differential becomes larger or smaller. In spite of such noise, it can be concluded that the robot decides the possible direction to return home because the difference between the decided direction and the desired direction is always smaller than 90 degree. Namely, the robot does not head in the opposite direction of home. One pixel might seem small as compared with

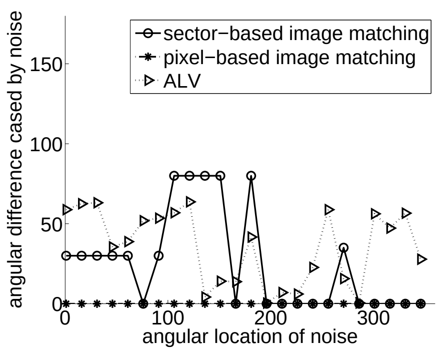


Figure 4.11: Error curves in distance measured with respect to home when the angular location of noise is varied at a point (550,550)

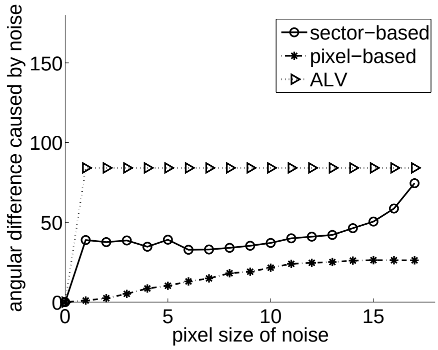
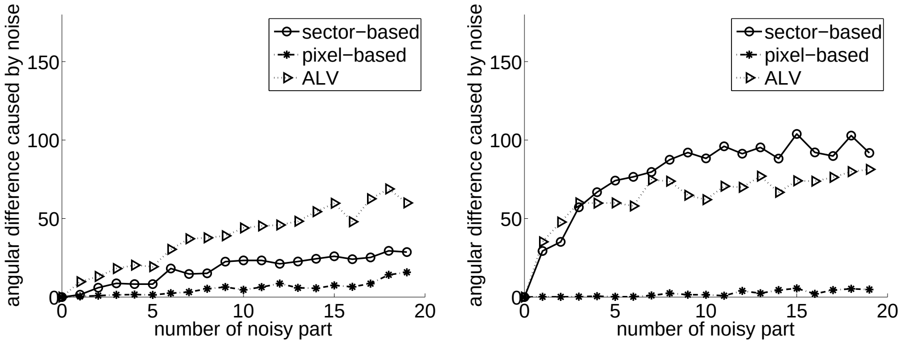


Figure 4.12: Error curves in distance measured with respect to home when the pixel size of a noisy part is varied at a point (550,550)

the size of landmark, so its effect is negligible. In other words, in this case, the error of homing direction is permissible for an insignificant portion of an overall array.

The second noise test intended to verify the effect of a larger size noise on the decision made by the robot in choosing the correct direction of the different navigation algorithms. The image array corresponding to the introduction of a larger pixel size noise can be found in Fig. 4.10 (b) and the corresponding error test is shown in Fig. 4.10(b). Here, the angular difference caused by noise refers to the amount of angle measured without the case of the noise introduction minus the values obtained from the results with the noise introduction. It is reasonable that the sector-based image matching method is more susceptible to the size of noise than the ALV method. In ALV method, the robot receives only the directional information unaffected by the size of a landmark because landmarks are represented as a unit vector. The angular position that the noise is placed is important, though, the number of pixels of noise does not be measured. For such a reason, the result from the ALV method does not change whether a pixel size of noise is small or large with no increase in error.

When the image matching method is used, the error goes up with increasing the size of the noise owing to the algorithm that counts the number of pixels which corresponds to a landmark and recognizing the position or size of each landmark from the counted value. Such process can be confirmed from Fig. 4.10(b), and the angular difference is mostly smaller than 90 degrees even though the sector-based method is used. This implies that the robot never move its head in the opposite direction of home under even an extreme situation where the size of the introduced noise is equal to that of the landmark.



(a) (b)

Figure 4.13: Error curves in distance measured with respect to home when the number of noisy part is varied (a) current point (320,480) which is located inside the region surrounded by the landmarks (b) current point (550,550) which is at the boundary of the region

The next experiment evaluated the performance of the different navigation models when the number of introduced noises is increased to more than one, placed at random positions in the navigation environment. In Fig. 4.10(c), the left array is the image array when a single noise is introduced with the size of one pixel, and at the right is the array when more than one noise input is given at many angular positions. The resulting performance using different navigation methods are as follows and the detailed analysis is given in Fig. 4.13.

Angular deviation due to interference by noises :

ALV $>$ Sector-based image matching $>$Pixel-based image matching

Fig. 4.13 represents the angular deviation corresponding to the amount of error in respect to increasing the number of noise introductions measured at two distinct positions inside of the navigating region and at the boundary position. Here again, the magnitude of the error was calculated by subtracting the angle measured from the error ambient to that of error-free ambient. It can be concluded that the effect of a noise introduction when the number of noises increases is the most pronounced for the ALV method, and the least sensitivity was obtained for the pixel-based matching method. In the pixel-based method, the number of noise introductions did not have much impact due to the uniform distribution of the noises regardless of their random locations.

4.3 Sector-based image matching method with total size difference

It has been revealed that the sector-based image matching method requires an alternative technique to compensate for the poor output given the interference by a noise when compared to the other vision-based navigation methods. To improve the performance of the sector-based image matching method, the concept of size difference recognition is used instead of an average distance difference. By this it means that a robot can compare the overall size of the landmarks per sector between the image taken at home and the image taken for the estimation process. The modification of recognizing the size of the landmarks rather than calculating the average distance can lead to a more stable system in the case of noise interference. In the case of the sector-based image matching method by calculating the average distance difference, the robot counts the number of landmarks in each sector to obtain the 'average' difference in the distance. Therefore, the existence of a noise can shift the angle that the robot chooses to head towards during the returning process. To put this in a simpler way, suppose that the total number of landmark that a robot recognizes is n; then the total pixel of according landmarks can be defined as P_n, where P is the number of pixels occupied by the landmarks. For an interference with a noise of unity pixel size, n and P_n is increased to n + 1 and $P_n + 1$, respectively.

in a sector which is included a noise,

average size of bearing : $\frac{P_n+1}{n+1}$

Then, as can be derived from the aforementioned equation, increasing the number of the landmarks has a higher effect than increasing the number of pixels when calculating the average size of the landmarks. As a result, the measured value for the bearing size of the landmarks is confused, which in turn leads to a wrong matching score to be obtained.

The performance of the sector-based image matching method can be significantly improved by implementing the concept of the 'total size difference'. Here, the 'total size' refers to the summation of all the number of pixels occupied by the landmarks in a sector, and the difference between the total pixel number obtained from an image processed at arbitrary position to that of initial image taken at home image is the 'total size difference'.

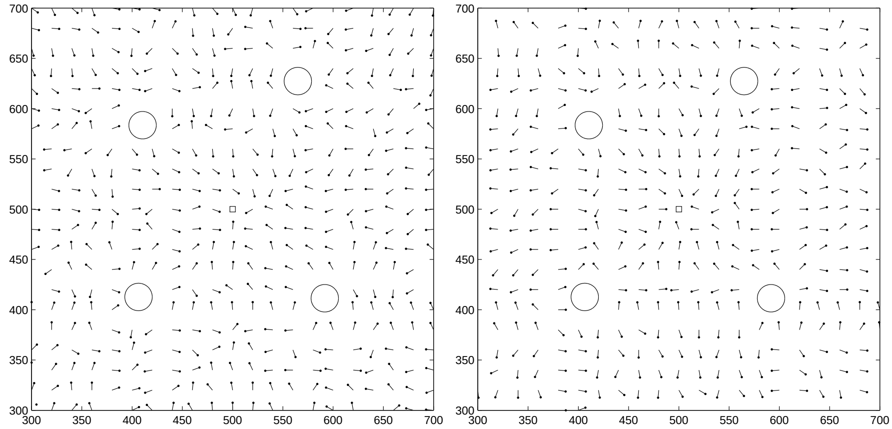
in a sector which is included a noisy part,

size of bearing : $P_n + 1$

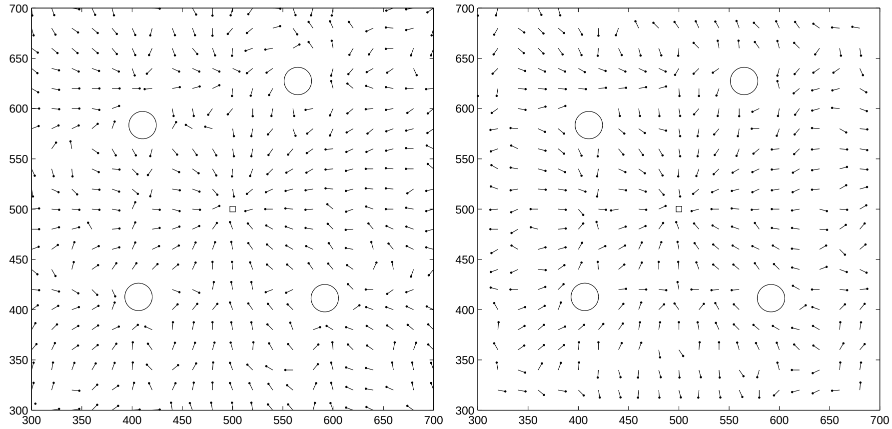
In other words, the sector-based matching method with the total size difference concept is to sum all the sizes of the pixels occupied by the landmarks and calculate the matching score considering the occupancy and the size difference, which are not average values. If such calculation with total pixel size per sector is used, the effect of noise can be significantly suppressed. The probability that the robot makes a wrong decision in determining its direction gets much lower if the number of pixels that a noise occupies is relatively small compared to that occupied by the landmarks. For the sector-base image matching method without the concept of an 'average distance', the navigation process becomes somewhat similar to that of pixel-based image matching method. In the pixel-based image matching method, the part which is marked as the landmarks is compared pixel by pixel in all directions. In the sector-based method with total size difference concept, the marked part is compared sector by sector which is basically the same as the pixel-based image matching method with much lower resolution. For example, if the environment is divided into four sectors, the total number of pixels occupied by the landmarks among 90 pixels in each sector is compared to what has been previously found at the beginning of the journey at home. Accordingly, this method is closer to the pixel-based image matching method than the previous sector-based image matching method, but still the advantages of the original sector-based image matching method are present.

in each sector :
Matching score = Sector occupancy $\times$ Total size difference per sector

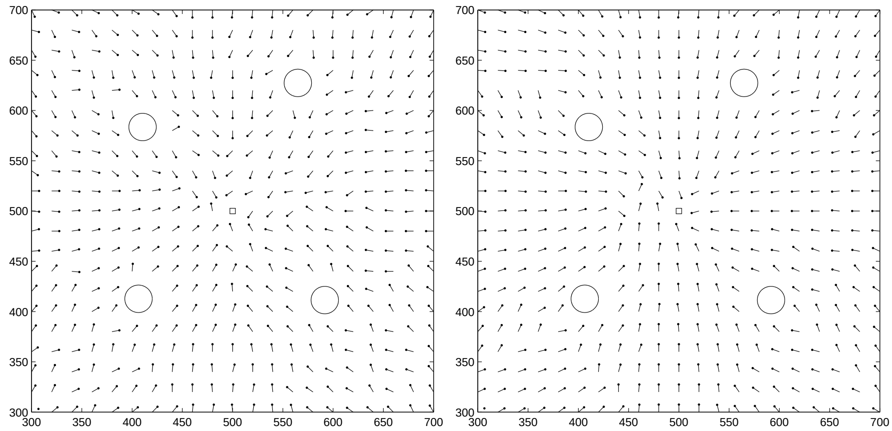
For the convenience, the previous sector-based image matching method without the concept of the total size difference shall be referred as "sectorA" and the new sector-based image matching method as "sectorB" hereinafter. Fig. 4.14 illustrates the resulting vector map using sectorA and sectorB methods while increasing the ratio from 0.1 to 0.8. The use of a reference compass was allowed to make a comparison with the performances of pixel-based image matching method and ALV method. The vectors maps presented at the left sides are the results of using sectorA method, and it shows that by changing to sectorB method, the accuracy improves for the regions surrounded by the landmarks. On the contrary, on the outer regions of the landmarks, the vectors point towards the opposite direction to the homeward direction, and this can be ascribed to



(a)

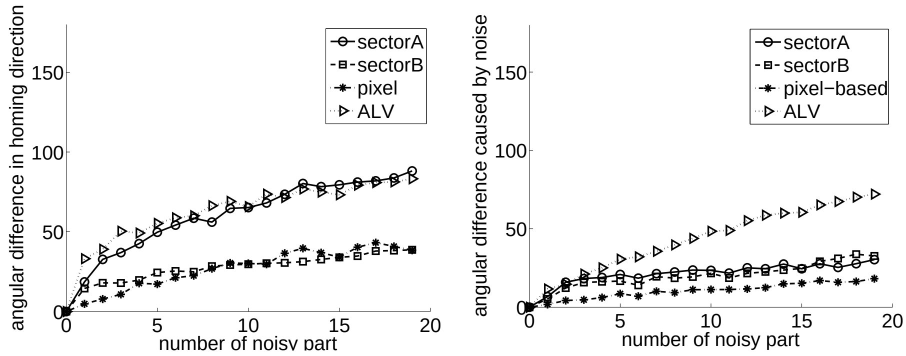


(b)



(c)

Figure 4.14: Vector map by sector-based image matching algorithm with compass : R = 100, resolution of estimation = 72 (left : sectorA, right : sectorB) (a) estimated distance = 10 (ratio = 0.1) (b) estimated distance = 30 (ratio = 0.3) (c) estimated distance = 80 (ratio = 0.8)



(a) (b)

Figure 4.15: Change of angular difference between an original homing direction in the case without any noise and a homing direction in the case with noise based upon varying a number of noisy part (a) inside the region surrounded by the landmarks (b) outside the region

the fact that for the outer regions the method becomes similar to that of the pixel-based image matching method under low resolutions. Assuming the following experimental conditions where the position of home is at (500,500) and the position of the robot at (460,360), then the occupancy and the total size can be represent as follows:

	Home	Current point
Occupancy	1 1 1 1	1 0 0 1
total size	14 13 13 12	28 0 0 19

The desired angle for choosing the correct direction towards home is approximately 74 degree, but the calculation shows that the decision made by using sectorB method is 270 degree. To minimize the difference in the total size, the robot tries to reduce the number of pixels which are occupied by the landmarks, leading it to choose an opposite direction where the number of pixels occupied by the landmarks is smaller. The occupancy on the outer region of the landmarks is not uniform, and for testing with lower values of ratio, the occupancy in the calculated estimation process is still unchanged. However, as shown in Fig. 4.14(b) and Fig. 4.14(c), such error of choosing the opposite direction can be compensated.

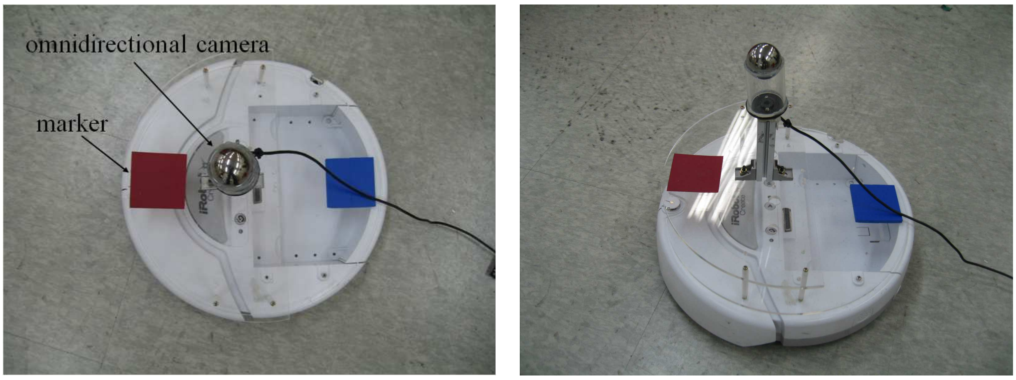
To evaluate the vulnerability to noise, the same measures that were taken in Fig. 4.13 were tested with the two different sector-based image matching methods along with the different navigation systems, and the result is shown in Fig. 4.15. To set a reference point, the positions with distance less than 135 units away from home were regarded as inner regions, and regions farther away were regarded as outer regions. The number 135 was chosen because the average distance between each landmark was 135. As shown in the figure, the effect of noise becomes less important in inner as well as outer region.

Angular deviation due to interference by noises :
ALV $>$ SectorA (average size difference) $>$ SectorB (total size difference) $>$ Pixel-based image matching

The ALV method shows the worst performance with the noise test. Thus, the suggested sector-bassed methods can be valid in the real noisy environment.

4.4 Robot Experiment

4.4.1 Experimental environment



(a) (b)

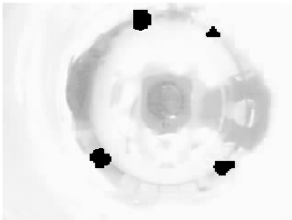
Figure 4.16: ROOMBA and omnidirectional camera (the square markers are for notifying a direction of robot's head)

The robot experiment was conducted in the same environment with the computer simulation by using the sector-based image matching method(Lee and Kim, 2009a). In this experiment, a laptop computer and Roomba are used to test the new sector-based image matching method. Roomba is a typical mobile robot with two wheels (Fig. 4.16), and its movement can be controlled with simple commands. The robot is programmed to find its way back home with sequences of movements. A movement corresponding to a single segment is composed of a rotational movement without changing its position and a consequent movement in a straight line once the proper direction has been determined.

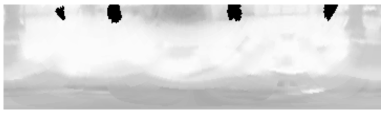
As an image sensing device, a widely used web camera was chosen. On top of the camera, an acrylic cylinder is set and a metallic sphere is placed on it so that the camera is omnidirectional. The existing omnidirectional cameras are almost parabolic, but in this work the visual field was covered with a spherical omnidirectional camera. This image pick-up structure is located at the center of Roomba, and the visual information on the environment is retrieved continuously as an image, which is analyzed in real time through the sector-based matching method using a laptop. All experimental procedures were carried out in Linux environment.

The experimental environment for the navigation of Roomba is an open space, and there are four identical landmarks with the shape of a cylinder. The radiuses of the landmark were 21.5 centimeters and its color was red. The landmarks were placed without any symmetry, and home was surrounded by the landmarks with about 150 centimeters of average distance. Each landmark was placed with different distance variations from the home's location. The shape of the testing space was a square of a side with 240 centimeters in length and for all points at intervals of 15 centimeters within the space, the decision of homing direction is recorded by the change in the position of the robot. The robot distinguishes the landmarks from the other parts of visual environment through color. The images that include a landmark was converted into panoramic images for convenient purposes, and the image processing flow is described in Fig. 2.4. For the experiment, it was assumed that a robot had a reference compass to get the information on its head direction, and thus the robot's head directions at every point are the same each time it produces an image.

The use of an omnidirectional camera refers to the robot's ability to receive visual information for all directions as a whole image from an arbitrary point. The image taken from an omnidirectional camera is a circular image, and to compensate for the distortion in the image and to allow a more convenient processing, the omnidirectional images are converted into panoramic images (Franz and Mallot, 2000; Scaramuzza and Siegwart, 2008), which is a simple and general method to process an omnidirectional image (Fig. 4.17(a)). As the robot moves, the marked points which correspond to the landmark in the panoramic image are changed as shown in Fig. 4.18 and Fig. 4.19, pro-



(a)



(b)

Figure 4.17: Images at home (a) omnidirectional image (b) panoramic image

duced from the images taken by the omnidirectional camera. The converted panoramic images presented in Fig. 4.17(b) have angular resolutions of 1 pixel per degree. From the panoramic images, the landmarks are depicted as 1s when transformed into a binary code and the rest are converted as 0s. Hence, every image is converted into a form of binary array, which is the simplest form to find the best match between the initial snapshot and a new one from the robot's traveled position. By this conversion into a simplified array, the necessary sections for comparisons can be extracted from the entire visual environment, and the remaining parts can be disregarded.

On all moments, a new array is created and compared to the first generated array from the memorized image from the starting position. The binary value of an array signifies whether a landmark is located in the direction or not. The relationship between a new array and the first array is computed by their dot product(Franz et al., 1998). When the array is shifted, the robot evaluates the value of the dot product, and checks how well the current image is in match with the original image. When the value of the dot product is the maximum, the direction of that specific time that the robot heads indicates the homeward direction.

4.4.2 Results

The purpose of the robot experiment is to find whether the same homing performance that is proven from the computer simulation is properly obtained with use of a real robot and an imaging device. As previously stated, when the ratio is too small, the decision of homing direction is scattered at the boundaries of region surrounded by landmarks. When the ratio is too large, the direction of vector near the boundaries

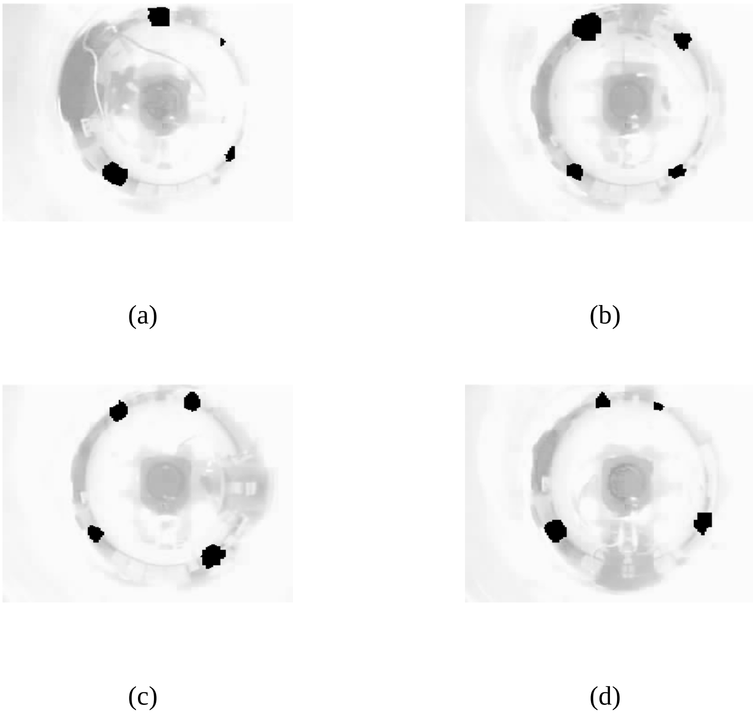


Figure 4.18: Circular images (distance from home = 35cm)(a) at west (b) at north (c) at east (d) at south

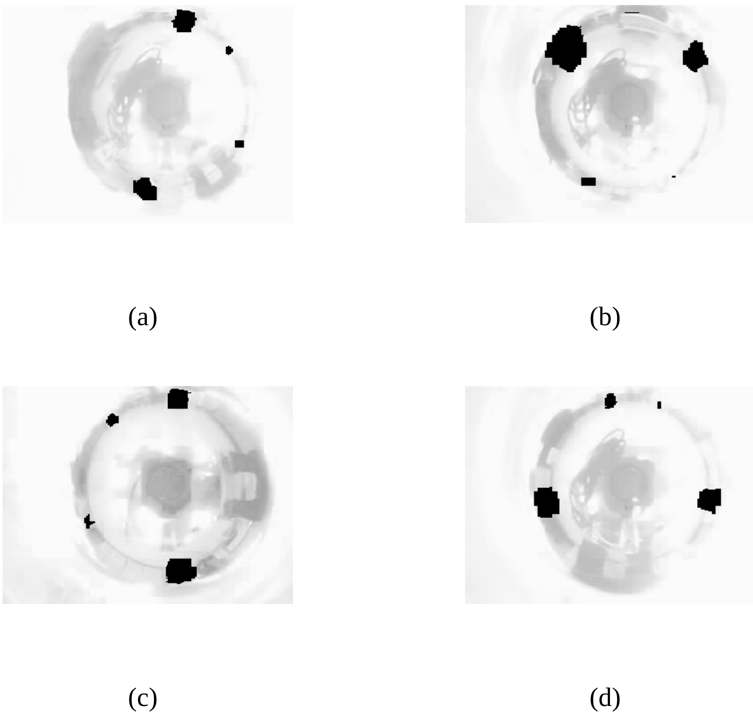


Figure 4.19: Circular images (distance from home = 70cm)(a) at west (b) at north (c) at east (d) at south

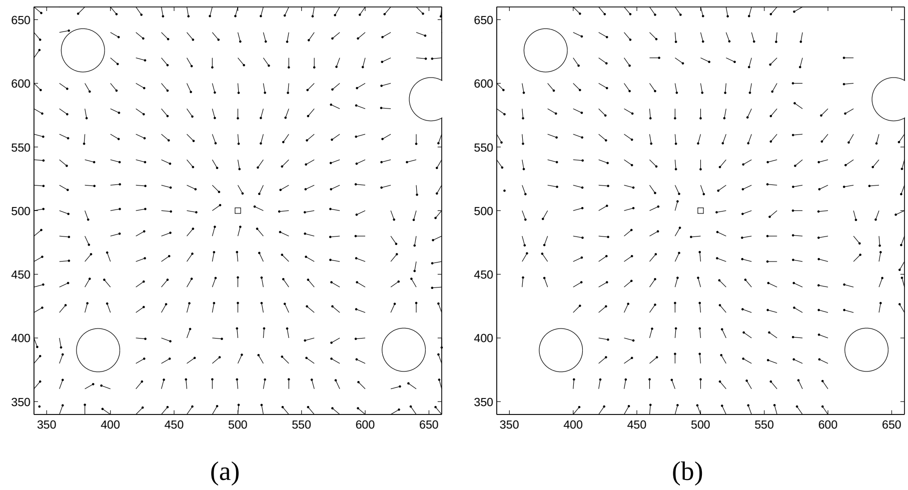
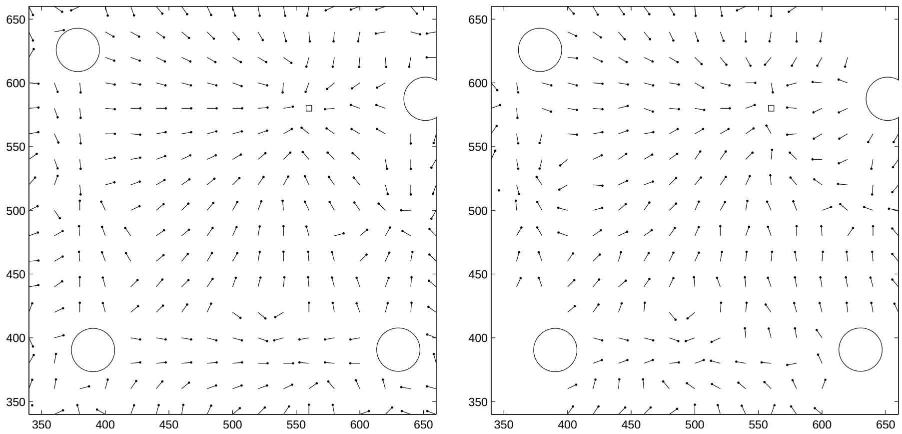


Figure 4.20: Vector map by sector-based image matching algorithm : R = 100, resolution of estimation = 72, estimated distance = 30, home (500,500) (a) simulation (b) robot experiment

is adjusted to the desired homeward direction, at the expense of lower accuracy near home. To guarantee the accuracy level starting at overall more points, the ratio was adjusted to the value of 0.3.

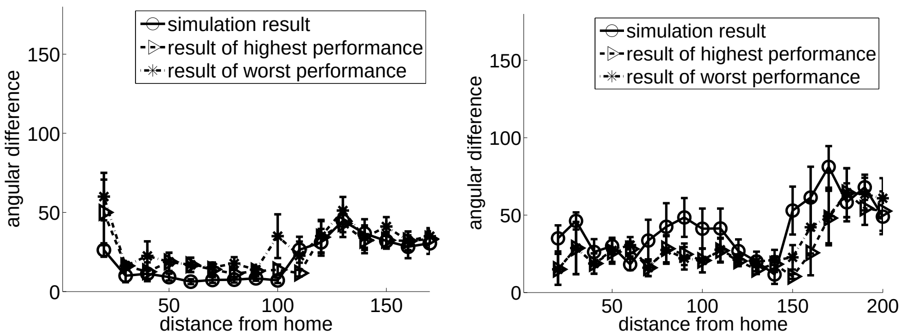
Fig. 4.20(b) reveals the results of robot experiment with Roomba and a web camera in the form of a vector map. The ratio is set as 0.3, and the experimental environment which is showed in a vector map is equivalent to the environment in simulation. The distance 100 means in the real experiment a length of 75 centimeters.

Comparing the vector map of Fig. 4.20(b) to that of the simulation result shown in Fig. 4.20(a), it can be seen that almost exact results is obtained for the two different cases in overall points of the environment. For the regions inside of the surroundings of the landmarks, the direction vectors point towards home with great accuracy, implying that the robot can return home correctly. The error curves of two cases shown in Fig. 4.22(a) also confirm that the result of practical experiment coincides with that of the simulation. Their tendencies in the variation are an almost exact match which implies that the homing performance verified from the simulation also applies the same in real conditions. In the robot experiment, there are some points in which the robot's choice change depending on the specific occasion that it meets. If an instantaneous image changes at an arbitrary point due to a delicate change of light, a robot would have one or more choices for the homing direction at such point.



(a) (b)

Figure 4.21: Vector map by sector-based image matching algorithm : R = 100, resolution of estimation = 72, estimated distance = 30, home (560,580) (a) simulation (b) robot experiment



(a) (b)

Figure 4.22: Error curves in distance measured with respect to home through the sector-based image matching method with compass ($0 < \text{ratio} < 1$) (a) home (500,500) (b) home (560,580)

The performance of the sector-based image matching method is evaluated based on different choices made by the robot in the respect of which angular direction it will choose to move on its following movements (Fig. 4.22). Even when the robot chooses the worst direction (the direction that leads the robot to farthest away from home), the performance level is not much different from that shown in the case for optimized decisions. The performances of robot experiment in the best case and worst case show a similar tendency, and it also follows the same curve as the performance in the case of computer simulation. Every angular difference between the homing direction of robot and the desired homeward direction is smaller than 90 degrees. Therefore, it can be concluded that the robot always heads towards home in the range that is possible to return home. The result is a clear indication that the robot is highly capable of returning home by using the sector-based image matching method.

4.5 Summary of Chapter 4

In Chapter 4, it can be proved that the use of a reference compass is effective in finding the homing direction, and both the pixel-based and the sector-based image matching methods show better performances when the robot obtains an additional information with the use of a compass. The accuracy of the ALV method is the highest; however, this method is also highly sensitive to interference by noise owing to the algorithm that represents a landmark as a vector. The result from the sector-based image matching method is also affected by the noises, and a new concept of sector-based method was needed to compensate for the loss in the efficiency of the suggested algorithm. To enhance the performance in a noisy environment, the modified sector-based image matching method with the concept of 'total size difference' (sectorB) was suggested in this chapter. The sum of all the sizes of the landmarks in each sector is calculated and compared with that previously extracted from the image taken at home. This method is similar to the pixel-based image matching method with a low resolution, and it has an advantage of the pixel-based method, which is invulnerable to the introduction of a noisy factor. Therefore, the sector-based image matching method with the concept of total size difference delivers positive results in a noisy environment. However, the new method suggested has its drawback in that when the values of the ratio are small, the accuracy is dramatically reduced due to the consideration of the environment as a low resolution. Despite such weaknesses, the modified sector-based image matching method can be another choice for a successful home navigation system under the environment containing only a few sectors.

Based on the computer simulation test, the robot experiment using the sector-based image matching method (sectorA) was carried out. The result from the experiment with a mobile robot is almost the same to that obtained from the simulation. Hence, it verifies that the sector-based image matching method is available to find the homing direction under real environmental conditions.

Chapter 5

Conclusion

5.1 Summary of Methods

In this paper, an algorithm with a motive inspired from the real nature is used to illustrate that a navigation system with highly desirable results can be obtained through a simple logic. The image matching method, suggested by Franz, was used to compare and analyze the results of four different models of vision navigation algorithms.

The image matching method was further subdivided into an algorithm that utilizes a reference compass and the other for not using the compass, and the results showed that the outcome for the case with the use of compass produced a better performance. The compass allows the robot to compare all the images it recognizes to a standard reference angle, giving an accurate matching, whereas in the case without the compass the robot makes an error of calculating the matching degree by comparing the images in irrelevant directions. However, nonetheless of the use of the compass, the pixel-based image matching method has its limitations in its accuracy due to the fact that the method only provides reliable outcomes within the area surrounded by the landmarks.

The robot showed excellent performance as to finding its way back home when placed inside the surrounding landmarks, but for the cases when the robot went out of the landmarks for even a small distance or when the robot reached near other landmarks, the results were different. In such cases, the robot did figure its way back to approach to the area surrounded by the original landmark, but failed to get inside the surrounded region.

Despite the limitations shown in the method suggested by Franz, the image-matching method provided much more efficient process of returning home with reduced and simpler calculations for the equidistance assumption as compared to the conventional robot navigation algorithms. A new algorithm that implemented Anderson's method based on the actual experiment of the honeybee, is introduced to overcome the aforementioned limitations of pixel-based image matching method, while at the same time taking its advantages as well.

The distribution model suggested by Anderson is based on the important concept that the honeybees recognize the visual environment as several divided sectors. Applying this concept of sector division recognition, the matching process can be further simplified as compared to the conventional method of comparing each single pixel. In addition, comparing and analyzing the visual environment by dividing it into different sectors means that an effective navigation under a low resolution can also be achieved.

The new sector-based matching method averages the calculation of the matching degree in the occupancy and distance difference of each sector for all directions based from the robot's predicted position of movement, and a higher performance is given for the case when a reference compass is used. This is due to the fact that the estimation for the distance is evaluated with the consideration for all the directions, directing the robot to the point with the highest matching degree, and the sequential movements of such action leads the robot back home with great accuracy. An important contrast to the pixel-based image matching method here is that in sector-based image matching method the distance difference is also taken into the consideration for the calculation in addition to the occupancy, and the average of the results to all the directions is set as the representative value for the next movement. Although there have been previous studies that suggested such calculation of the tangential component and radial component for the vision algorithm, the introduction of sector concept provided much higher efficiency by reducing the amount of calculation in great numbers.

5.2 Summary of Results

In this paper, a much simpler and efficient algorithm for a robot's vision system is realized through designing a model based on the visual mechanism of actual animals and insects, as compared to the customary algorithms consisted of complex geometric and complicated calculations. The pixel-based image matching method showed high accuracy within the perimeter near home and the original landmark, but requires a fundamental goniometer to set as a basis, and without it the method requires large amounts of calculations. The new algorithm delivered in this paper has the advantage of reducing the amount of calculations required, and is capable of efficiently finding the way back home from long distances and under low resolutions. The use of a reference compass leads to a higher performance of the implemented algorithm, but the difference in the amount of error produced is almost unconsiderable, which leads to the conclusion that even for the robot that does not have a compass, or that uses any types of compass the new method provides a reliable homing process with minimal error in calculating the environment.

5.3 Future directions

The sector-based image matching method contains various variables that affect the performance of the robot, such as the number of sectors. Further studies are needed to solve the problem of recognition of the robot, since the landmark may be extended in more than one sector, and for such case the robot will not regard the parts together as a whole but instead recognize as different landmarks in each sector. Strengthening the algorithm when a landmark is missed in the visual environment is another important issue to be achieved in further experiment.

An important issue when using the landmark navigation method is how a robot will differentiate the landmarks from the rest surrounding environment. Biologically inspired homing methods, such as the sector-based image matching method, are an interesting solution for local navigation due to its simplicity. However, a modification of the environment by placing artificial landmarks is usually required in order to for the sector-based image matching method to work with reliability. For a simple indoor environment, it is not difficult to recognize the landmarks because an indoor scene is more monotonous than an outdoor scene. It also facilitates to distinguish clearly the surrounding environment by using the artificial landmarks. On the contrary, in a complex indoor or outdoor environment, a recognition error can occur where the robot has a hard time defining a landmark prior to the processing of the matching rate between the images. In this research, a robot detected the landmark by its color; however, in real world such method for recognizing a landmark is not recommendable. The color is easy to be confused by the external factors like the illumination or the existence of similar-colored objects.

The method where two images are compared in each pixel for all directions could be suggested as a solution to the previously stated problem, as proven by the research of Zeil (Zeil et al., 2003; Stürzl and Zeil, 2007). Zeil carried out experiments about whether it is possible to know the direction toward a goal point through vision-based navigation algorithm by calculating the difference of all the pixels in two images. The method used by Zeil is in part similar to the image matching method, and it uses the concept of comparison between an arbitrary image and an original snapshot for each pixel. In Zeil's research, it is mentioned that the most parsimonious model for the vision-based home navigation is the ALV method, proposed by Lambrinos and Moller as it requires only one vector to be generated for the final output at an arbitrary point, rather than an image array of its derivatives.

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