Visual Features Based Motion Controller for Mobile Robot Navigation

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Abstract— **This paper describes a new approach to vision-based control in robotics. The problem of controlling the pose of a mobile robot with respect to a target position by means of visual feedback is investigated mainly. The proposed method enables a mobile robot to identify its own position using visual features of environment. At the same time, the robot performs an orientation recognition using the same recognition method of position identification in order to follow a path in environment. One of the advantages of the proposed method is that both position and orientation recognition uses the same task where this situation will help for lowering the cost of the robot system development. Furthermore, the calculation method is simple, no precise and accurate measurement is used in the proposed navigation method. Experimental results demonstrate the effectiveness of our proposed method.**

Keywords-Orientation Recognition, Position Recognition, Vision, Mobile Robot

I. INTRODUCTION

The study of indoor navigation robot has been tackled for a very long time, hence the number of the proposed methods is also considerable large. The major problem to be solved of indoor navigation robot is the perception and learning of the indoor environment, target location identification, as well as obstacle avoidance. The actions above are all based on the understanding of the environment received by the robot. A relatively simple way to achieve indoor robot navigation is using odometry and sonar sensing [1]. However, slipping problem always cause a cumulative error in odometry.

Autonomous navigation is related to the capability of capturing environment information through external sensors, such as vision, distance or proximity sensors. In various indoor mobile robot navigation developed in recent years, the localization techniques are proposed based on techniques including RFID [2], Zig-Bee [3], and wireless networks, etc. [4], based on signal strength. These methods, however, suffer from inaccurate measurements because the signal strength is generally deteriorated by various noises. Meanwhile, some work has been done for indoor robot localization [5-6], using magnetic fields. However, this kind of information has not been exploited in the design of an indoor navigation system for humans.

Ultrasonic sensors are widely used for the indoor navigations to recognize the position of the mobile robot and to avoid obstacles around the mobile robot. Yi and Jin [7] in their research work have introduced ultrasonic sensor to measure the position and orientation of the mobile robot. Although distance sensors (e.g., ultrasound and laser types), which allow to detect obstacles and to measure distance to walls near the robot are the most usual sensors, at present the tendency is towards vision sensors which supply better and a larger amount of information from images.

In many recent research works of vision based robot navigation, the similarity between newly captured image and the images stored in the database can be based on features such as global descriptors, like the whole image [8] or image gradient [9], or local descriptors such as SIFT points [10] or photometric invariant [11].

The objective of this paper is to implement a new vision-based navigation system for a mobile robot operating in indoor environment where the robot is able to navigate successfully towards the target destination without obtaining accurate position or orientation estimation. No distance information will be provided as the robot will move on the expected path and only stop when a neural network (NN) output is achieved higher than a set threshold, which is supposedly in a near range of the targeted position. Furthermore, no orientation information is given as well, and the robot will identify its own orientation based on the proposed method and moves along the expected path.

For that, we need qualitative information regarding the robot posture during the task that is sufficient to trigger further actions. As it is not necessary for the robot to know the exact and absolute position, a topological navigation will be the most appropriate solution. We developed a visual perception navigation algorithm where the robot is able to

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recognize its own position and orientation through robust distinguishing operation using a single vision sensor.

The paper is organized as follows. In section 2, we briefly review the indoor navigation. Section 3 will detail the explanation about the proposed navigation method. Our experiment results are presented in section 4. Finally, with a summary, we conclude this paper.

II. RELATED WORKS

Navigating using a topological map, as the case in this paper, will let the robot to repeatedly moves between nodes before finally stops at the desired position. During the journey between the nodes, a large error in robot displacement and orientation after travelling for a certain distance might be occurred due to the inconsistency of the floor surface flatness level of the indoor environment where the robot is navigating.

To execute topological navigation, we need to solve two important problems which are reliable detection of nodes for topological mapping and safe obstacle avoidance navigation. However, this paper does not put focus on the second issues. We should let the robot to reliably detect nodes which have different qualitative properties from edges arcs). Beeson *et al.* [12] categorizes space into places (i.e. nodes) and the others (i.e. edges). Using notions of gateways and path fragments, he defined qualitatively different and reliably detectable places. This definition about places, however, is useful only when there are accumulated sensor output data.

A major limitation of the topological approach comes from its combination of localization and action behavior. Mobile robot in topological navigation must be able to travel on the arcs connecting a pair of places (nodes), and must stop when reaching the arc endpoint. This issue is generally able to be accomplished through the careful design of control loops, or behaviors, that exhibit these properties robustly [13]-[15]. For example, Brooks creates an executable *Hall-Follow* program that exhibits the behavior of traveling reactively down a hall and terminating at the next intersection [14]. Research in the principled design of behaviors has been conducted, employing analytical techniques to attempt a robust set of motion behaviors. Nourbahksh *et al.* [16] uses a control loop that follows the lines of a Voronoi diagram in their research work. Nagatani *et al.* [17] defines distinct features in terms of primitive sensor readings, and then defines control loops that move the robot to positions where these sensor readings are attained.

When advanced autonomous robots navigate within indoor environments, they have to be endowed the ability to move through corridors, to follow walls, to turn corners and to enter open areas of the rooms. This is important in order to let the robot moves smoothly and reach the target destination without crashing on the walls.

With regards to this issue, many researchers have proposed control algorithms to solve the problem. Most current techniques are based on complex mathematical equations and models of the working environment [13].

Some control algorithms based on artificial vision have been introduced, where the robot is allowed to move by following the wall in the corridor like the one introduced by Durrant-Whyte *et al.* [18]. In this case, the planning must include the availability of walls in the route description, which require for the position of the wall to be known accurately. But what happen if the robot enters open areas such as rooms or hall area at the end of the corridor. In this kind of situations, the robot might lose the wall and thus lost its direction.

Saitoh *et al.* [19] introduced a method for mobile robot navigation by following the center of the corridor. In this research work, the robot is assigned to detect the corridor boundary in order to capture the center line of the corridor. The left and right boundary lines of the corridor are assumed to be a straight line and detected through Hough transform which require a lot of calculation costs and time. Moreover, this method is difficult to be use in a wide indoor area such as hall at the end of some corridors.

In other research work, Zhou *et al.* [20] let the robot in their work to identify the heading direction through a vanishing point of lines extracted from the corridor structure. The lines look like they are scattering from one point in the image of the corridor. This 'one point' is the vanishing point. Although it looks easy to extract the lines, but capturing the vanishing point require a complex mathematical calculation.

Many researchers presented methods of controlling robot pose by combining the problem with navigation towards the goal in indoor environment, where visual servoing is most popular. This method again requires a tedious calculation process as it focus on precise and accurate posture identification.

In certain cases where the robot is not necessarily to move in a straight line at the center of the corridor or in a hall area, a robust navigation method will be enough as long as the robot is able to reach the target destination safely. For example, in elementary missions such as giving a guide in indoor environment, the main objective of the robot's task is to give a guide. Therefore, accurate and precise navigation is not a must.

III. NAVIGATION METHOD

A topological map represents the robot environment by a graph. Paths are defined as sets of two distinct points, or "places" which must be detected and recognized by the robot using sensors data. These points provide the nodes of the map. Only little relevant information about the places is required to locate and identify them. These navigation operations take the robot from one node to another.

Although topological navigation has some advantages, there are two important properties that need to be guaranteed: first, the nodes have to be detected and identified with certainty, and secondly, the navigation operations must lead the robot from one node to another.

In our research work, first the robot is brought to the environment to perform a recording run. In this recording run, the robot will only have to capture representative images which are associated with the corresponding nodes. At the end of the recording run, a topological map of the environment will be built by the robot. The nodes are set at a distance from walls or objects in the environment, but not recorded in the map. Furthermore, no distance information between each node is recorded.

When the robot performs autonomous run, it will moves step by step between two nodes. The robot will capture 1 image at each step. Visual features data from the image will be extracted and fed through the NN for position identification first. The robot is considered near to the targeted node if the output of the NN for the captured image is higher than the setting threshold 0.7. Otherwise the orientation identification process will be executed. Visual features data from the same captured image will be fed into NN data of 5 different angles of the target node. The 5 NN data are prepared during the recording run, separately from the preparation of NN data for position identification.

One advantage of separating the NN data between position and orientation identification is that the width of the domain area for position identification can be organized (the domain area cannot be too wide in order to avoid from robot identify node too early and also to avoid from false identification) without giving influence to the orientation identification. Through this, it is believed that extensively orientation recognition can be achieved.

From the results produced by the 5 NN data, the robot will be able to determine its current progress direction through a computation of the median point of the results (Fig. 1). The robot will then correct its direction towards 0°, which supposedly is the true direction towards the target node, depending on the result of its current progress direction. The overview of this orientation identification process can be seen in Fig. 2.

The robot then will moves another step and the same procedure is repeated, starting by the position identification first and follow by the orientation identification if the robot is not reaching the target destination yet. These processes are shown in Fig. 3.

If the output of the position identification is higher than 0.7, than the robot will recognized that it has reached the respective target node, and there will be no orientation identification done. The robot will determine whether the node it has reached near is the target destination or not. If the robot is still not reaching the target destination, it will then captures information from the map about the next target node in the planned path and continue the navigation towards the next target node.

The same procedure is repeated until the robot able to recognize that it has reach within the domain of the target destination and stop. This exercise will help keeping the robot on the true expected path. Through this, the robot will be able to navigate on the path to the target destination.

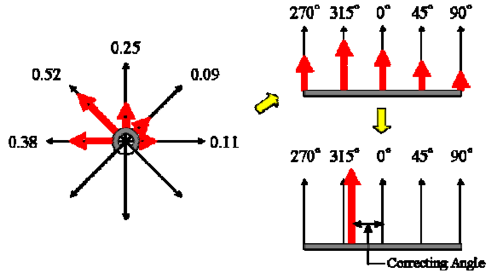

Figure 1. Evaluation method for progress direction.

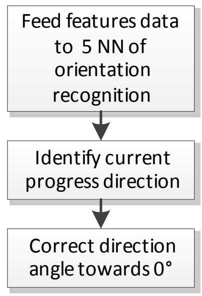

Figure 2. Orientation recognition algorithm.

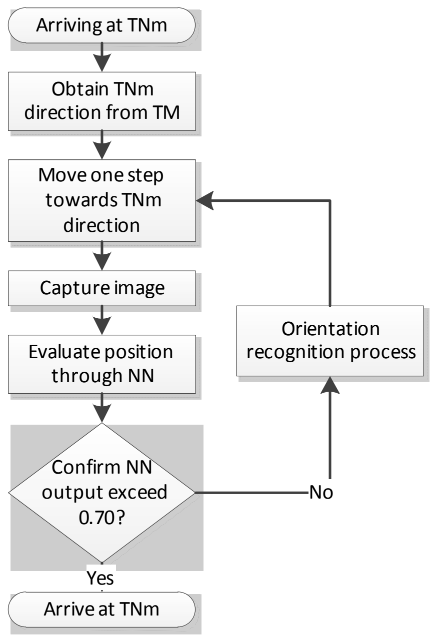

Figure 3. Navigation algorithm between two nodes.

This kind of motion in topological navigation is feasible because the path between two nodes does not have to be traced exactly; it is sufficient if the robot can traverse a general path (not exactly defined) between two nodes.

However, navigating in indoor environment will not guarantee the robot that it will move only in a straight path. Especially, in hall area, the robot might need to turn to the left or right at certain designated node (point). This require for the robot to be able to determine whether it need to turn to the left or right, or moving backward, or just move forward in order to move to the next target node. This information can be obtained from the data of each respective node in the topological map. This is another advantage of topological map as the storage capacities required are small, since only information about the nodes are stored.

An earlier contribution in the area of mobile robot navigation using image features and NN is the work of Pomerleau [21]. It was then followed by many other research works where they have successfully let the robot navigate in the human working environments [22].

One very similar research work with our proposed method is the one introduced by Meng *et al.* [23]. The robot navigates in a hallway environment through two modules; landmark detector module and hallway follower module; which composed with collections of NNs. The landmark detector module consists of a NN that is capable to detect junctions and dead ends. The robot in this work able to move straight down the hallway based on the prospective projection in a camera image of either the left or the right hallway edge within a certain angular range. There are too many NNs required in this method.

One of the advantages of our approach compared to the previous research works is that our system doesn't need to capture images between two nodes during the recording run phase. The robot needs to capture image only around the specified nodes. There is no image required to be capture along the path between two nodes. This will help to reduce the data storage capacity.

A. Visual Features

Visual features used in the proposed navigation method are color and shape. The reason why color and shape were chosen is that both features are easily extracted from the environment. Especially for color feature where color appearance is always used to distinguish many places, which make us believe that color in images provide sufficient information for place recognition. Furthermore, shape feature provides a compact and discriminative representation of images as well as the place where the image is captured.

We employ 11 colors which are determined through a separation of CIE chromaticity diagram (Fig. 4). The chromaticity diagram is separated into 8 colors with non-coloring space at the center as we regard those colors which are located in the same partition as the identical color. The non-coloring space is separated into three colors white, black, and grey based on luminosity factor. We also used the luminosity to classify between black and the primary color of each partition in the separated chromaticity diagram.

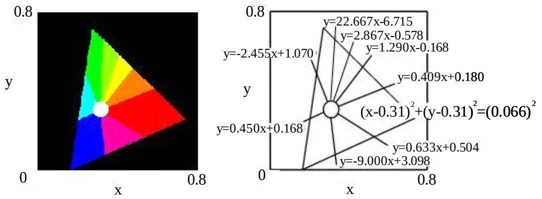

Figure 4. Separating chromaticity diagram into 8 color partitions.

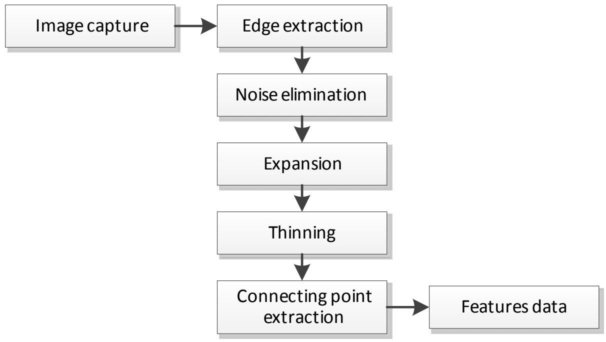

Figure 5. Flow of the shape features extraction processes.

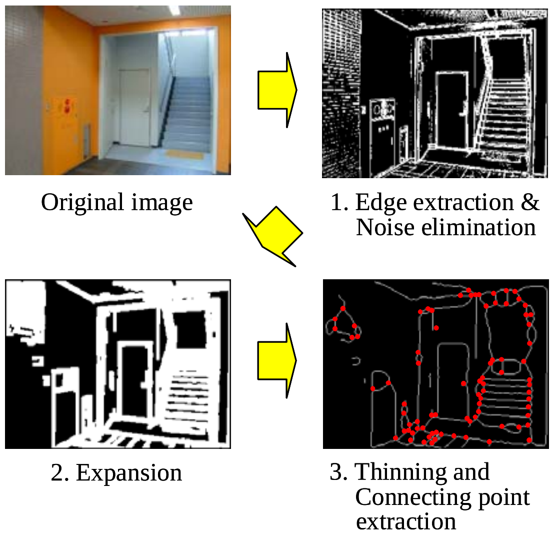

Figure 6. Extracting edges and connecting points

We extracted edges form the images using Robert operator. Through a further image processing done on the edges, we can also obtain points which are connected through the edges and we used these points together with the extracted edges as the visual features. The processing pipeline of the shape feature extraction process is shown in Fig. 5. From the extracted connecting points and edges as shown in Fig. 6, it is able to acquire 2 data of visual features, which are the ratio of the lines in the entire image and the ratio of the connecting points in the entire image.

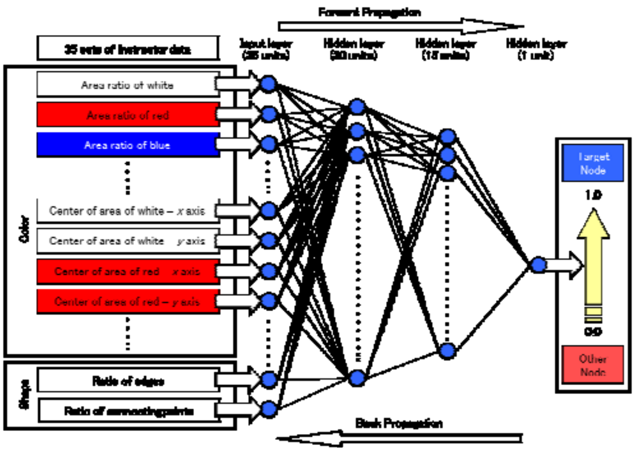

Figure 7. Multilayer perceptron neural network.

B. Evaluation System - Neural Network

Neural networks (NN) are about *associative memory* or *content-addressable* memory. If content is given to the network, then an address or identification will be return back. Images of object could be storage in the network. When image of an object is shown to the network, it will return the name of the object, or some other identification, e.g. the shape of the object.

A stratum type of multilayer perceptron neural network (NN) method is used in our approach as the computation tool. 4 layers NN (Fig. 7) is used where the number of input layer depends on the number of combination data between colour features and shape features, and the unit number of each middle layer is depends on the number of input data.

In order to let the robot in the proposed approach achieve a sufficiently cursory and stable recognition during the navigation, if the robot arrives in the proximity around the centre of the memorized node, the robot must be able to identify that it has reached the node. In other word, it is important to provide each node with a domain of area which can be identified by the robot.

For that, a set of instructor data for the neural network (visual features data from the captured images during recording run) is needed to be provided with consideration that the robot will be able to localize and recognize its own direction within a certain area around each place, rather than the exact centre of the place.

The backpropagation learning rules in the NN are used to adjust the weights and biases of networks so that the sum of squared error for the network is minimized. The network is adjusted based on a comparison of the output and the target, where in our case we set the target as 1 for respective place and 0 for other places, until the network output matches the target.

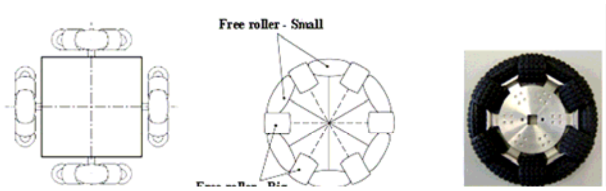

Figure 8. Robot Wheel.

IV. EXPERIMENTS

We have conducted three experiments in order to verify the effectiveness of the proposed navigation method. The first experiment, which is to determine the capability of the orientation recognition performance, was conducted in a long corridor of an indoor environment. The total length of the corridor is about 52.2m and the width of the corridor is about 1.74m. The second experiment is the navigation experiment where we tested the robot's navigation performance in a hall environment, located at the end of a corridor. In the third experiment, we tried to evaluate the performance of the mobile robot navigation in a long distance without any turning movement required. This experiment has been conducted in the same environment is the same long corridor where the first experiment was conducted.

A. Experimental Platform

The autonomous mobile robot system in this study is based on the Zen360 omni-directional mobile robot which was developed by RIKEN Research Centre [24]. The robot consists of a computer and a CCD colour camera. Each image acquired by the system has a resolution of 320 x 240.

The robot has 4 wheels where the wheel diameter is 360mm on the circumference of circle with the rotating shaft is pointing towards the centre. The robot mechanism possesses 2 translatory DOF and 1 rotating DOF, which in total of 3 DOF (Degree of Freedom).

During the actual movement, the opposing 2 wheels are rotating on the same translation direction derived through the activation of the 2 wheels bearing, therefore a stabilize translation motion towards *x* axis or *y* axis is feasible. Furthermore, a turning motion is also feasible due to the same direction driven of the 4 wheels.

Under ordinary circumstances, the arranged wheels become resistance to the travelling direction and the vertical direction. However, there are free rollers fixed on the wheel periphery of all the wheels as shown in Fig. 8, where it reduced the resistance on the wheel rotating direction and allowed for a smooth movement. Each wheel is built up from 6 big free rollers and 6 small free rollers. The two type of free rollers are arranged 30[deg] in angle alternately, and the free roller outer envelope form the outer shape of the wheel. With this condition, the robot is able to perform feasible omni-directional locomotion where it can move in all directions without affecting its posture.

B. Orientation Recognition Experiment

To conduct this experiment, first we have to prepare the instructor data. The robot is arranged to capture 5 images as shown in Fig. 9. The instructor data images are captured on 5 different directions (as shown in Fig. 1), which produced 5 sets of NN data after being trained by the NN.

In order to obtain the finest distance for the 4 images on the *x* and *y* axis, we prepared the NN data under various distance of the 4 images. However, in this paper we fixed the distance of images taken on *y* axis at 80mm. This is due to the result of preliminary tests conducted, which has shown that when instructor data (images) taken at the distance of 80mm on the *y* axis, the recognition will produce the best results compared to other distances. As for the *x* axis, the 2 images are taken at 10mm interval between the distances of 10mm to 30mm (30mm is the farthest position we can take image, limited by the corridor width). After the NN data preparation, a set of test images have been captured at every 15mm from a starting point which is about 4650cm far from the center point of where the instructor data images taken.

The output results are shown in Fig. 10. The results show that the test against NN data which consists of 2 instructor data images captured at 30mm from the center of the point on the *x* axis produced the finest recognition result. The test images output is mostly constant above 0.70 from a distance of about 4000cm (from the point), with few failure recognitions were recorded.

C. Navigation Experiment in Hall Environment

The first navigation experiment took place at a hall environment, where 5 nodes have been arranged. Distance between each node is vary, where the longest distance is between node 2 and node 3 which is about 4 meter as shown in Fig. 11.

The robot is scheduled to follow a path generated off-line on a topological map of the hall. The robot will have to navigate from Node 1 to Node 5 following the sequences of the node, and is expected to perform a turning task at Node 2, 3 and 4. The robot was first brought to the hall area and a recording run has been executed. The robot is organized to capture images around each node in order to supply the visual features of the respective node for both position and orientation identification. After completed the recording run, the robot will generate a topological map consists the 5 nodes, and visual features of the images taken were used for training NNs. 1 set of NN for position recognition and 5 sets of NN for orientation recognition are prepared for each node.

Then, we brought the robot once again to the starting point (first node) and let the robot perform a number of autonomous runs. Before start moving, the robot will identify its current position and based on the input of target destination, it will then plan the path to move on.

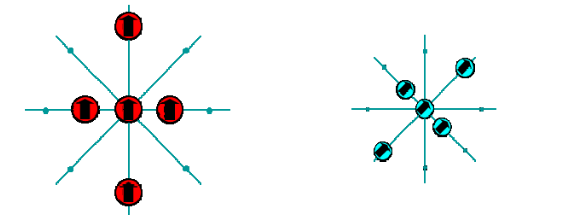

Figure 9. Positions of instructor data images.

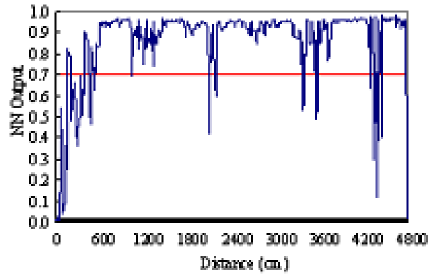

Figure 10. Recognition result against NN data of orientation recognition.

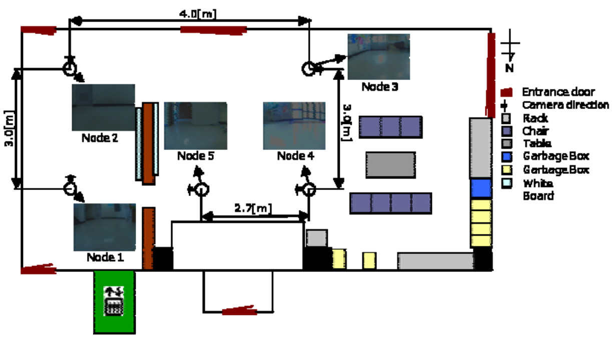

Figure 11. The hall layout.

In the experiment, the robot navigates from Node 1 to Node 2 and corrects its own orientation at each step of movement based on the result of a comparison between visual features of the captured image against the 5 directions NN of Node 2. We also let the robot to localize itself at each step in order for the robot to determine whether it's already near the targeted node or not. This is important as the robot need to perform a turning task once it reaches the node. These actions are repeated by the robot for a movement towards the rest node before stop at Node 5. The results of the experiments are shown in Fig. 12.

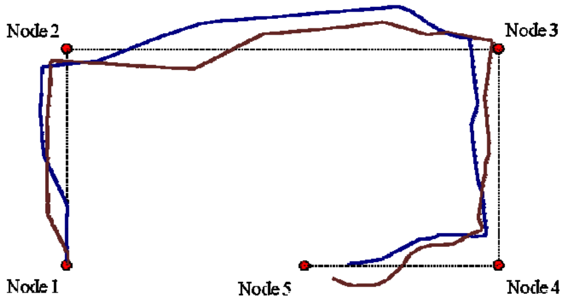

Figure 12. Experimental result; brown path – first run, blue path – second run.

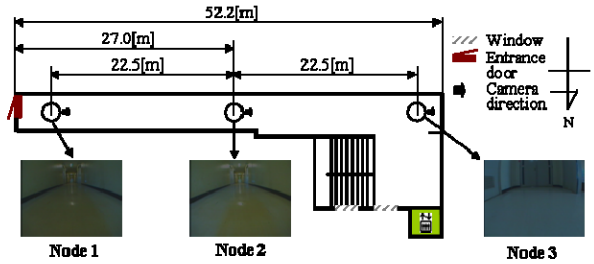

Figure 13. Corridor layout with representative images.

The experiments are producing successful results as the robot able to navigate along the expected path, identified Node 2, 3 and 4 and turned safely towards the next node. Incidentally, after navigating half of the journey between Node 2 and 3 in the second run, the robot movement fell out from the path (to the left) but managed to return back to the path before recognizing Node 3. This proved that the robot is able to determine its own moving direction and correct it towards the target.

The localized positions at each node were pretty much near to the centre of the node except for Node 4 where the robot identified the node a bit earlier. The environmental factor surrounding (sunlight through doors etc.) might give influence to the localization performance that caused the robot to localize the node slightly far before reaching near the node. Although the discussed factors may give influences to the robot localization performance, the robot is still able to turn to the right successfully and moves towards before safely and successfully stopped at Node 5.

D. Navigation Experiment in Long Corridor Environment

The layout and representative images of the corridor where the second navigation experiment took place can be seen in Fig. 13.

In this navigation experiment, the robot was to follow a path generated off-line on a topological map containing a total of 3 nodes separated from each other about 22.5m. Again, the robot was first brought to the corridor and a recording run has been executed. We let the robot capture images to supply environmental visual features for both position and orientation identification at around the specified 3 nodes. Then, the robot generated a topological map and the visual features were used for training NNs.

After the recording run, a number of autonomous runs were conducted to see the performance of the proposed navigation method. In the experiments, the robot navigated in the corridor from a starting point which is about 1.5m from node 1. While moving towards node 1, the robot corrects its own orientation at each step of movement based on the result of a comparison between visual features of the captured image against the 5 directions NN data of node 1 as explained in section 3.1. The same procedure is used for a movement towards node 2 and node 3.

Based on the result shown in Fig. 14, the robot successfully moved on the expected path towards Node 3 in each run. Even though at some points, especially during the first run test, the robot moved slightly away from the expected path on the centre of the corridor (to the right and left), it still able to come back to the path. The results demonstrated the proposed method to be asymptotically dexterous as the robot displacement in x axis along the expected path during the navigation is small.

V. CONCLUSION

This paper was concerned with the problem of vision-based mobile robot navigation. It built upon the topological environmental representation. A method for the autonomous mobile robot to navigate in a corridor environment, taking the advantages of the visual features in the environment has been described. The visual features are evaluated by the neural network. The robot is able to achieve efficient orientation recognition since the NN for the orientation recognition is prepared separately with the NN for localization.

The result of the first experiment proved that the robot is able to determine the direction (orientation) of the targeted goal even from a place which is quite far from where the robot is moving. This shows that the robot is able to identify, hence correct its own direction to move towards and converging towards the targeted destination.

In the first navigation experiment, the robot is able to navigate safely without colliding with any furniture in the hall area as it always moves near to the expected path along the journey. The similar results were achieved in the second navigation experiment where the robot is able to move mostly at the center of the corridor although at some points, the robot is 'slip' a little bit from the center position of the corridor. The results proved that the proposed navigation method is asymptotically dexterous, allowing the robot to navigate while successfully recognize its own position and the directions towards the target destination.

As an overall conclusion, the navigation results proved that the proposed navigation components have successfully operating properly under experimental conditions, allowing the robot to navigate in the environments. The robot is able to control its own posture while navigating and moved along the expected path without losing the direction to the target destination.

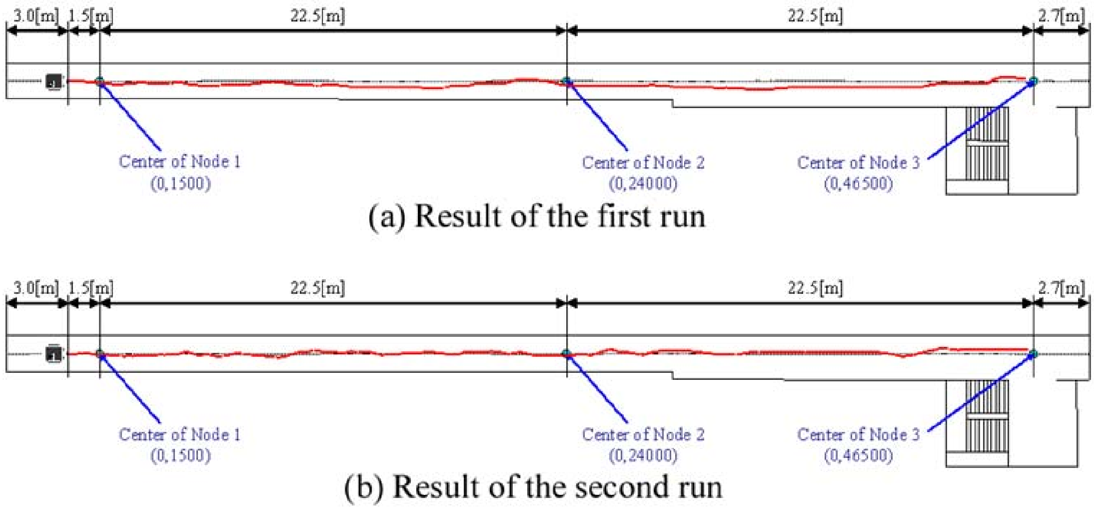

Fig. 14 Results of navigation experiment in long corridor environment.

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