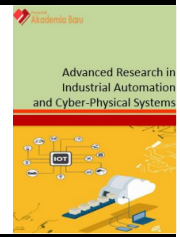




Journal of Advanced Research in Industrial Automation and Cyber-Physical System

Journal homepage: www.akademiabaru.com/ard.html
ISSN: 2637-0263



Topological Localization Based on Visual Features in Manufacturing Environment

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ARTICLE INFO

Article history:

Received 15 August 2018
Received in revised form 16 August 2018
Accepted 17 August 2018
Available online 23 August 2018

Keywords:

Topological localization, visual features,
manufacturing environment

ABSTRACT

Many research studies on the localization for mobile robot introduced precise and accurate robot self-localization methods. But in some situation, we believe that it is not crucial for a robot to precisely identify its own position through accurate measurement. We believe that with a robust yet no complicated measurement of self-localization method, robot will still able to identify the position of where it is located. This paper presents a mobile robot localizer that detects topological transactions using a visual features based recognition method. In this method, the robot does not have to measure its own position precisely but through the visual features which could be extracted from the environment, and with Neural Network as the computational tool, the robot is able to identify its targeted position. Experimental results demonstrate the effectiveness of our proposed method. This method is especially designed for AGV localization in manufacturing environment.

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1. Introduction

Nowadays, mobile robot has been developing very fast and become one of the importance things in manufacturing, AGV is one of the mobile robot applications that have in industry and generally for material handling. AGV has played an important role in moving material or product for more than 50 years. Thus, AGV play important role in manufacturing according to task performed.

Information regarding current position and where an AGV should go, as well as guidance on how to go to the designated position are important information that need to be acquire by an AGV in order to move safely in manufacturing environment. In other words, AGV should be able to perform localization and navigation when they are given with task assignments [1-2]. In this paper, we are focusing on the problem of robot self-localization in the typical indoor environment, or in more exact word, a manufacturing environment.

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Localization is a fundamental problem that needs to be tackled first before an AGV is allowed to move independently in any manufacturing environment. Most AGVs must be able to locate themselves in their working environment so that they are able to accomplish their tasks, for example to move from one place to another place. Since AGV is one type of mobile robot and mobile robot localization is a prerequisite for most applications, research has been done actively in this field [3].

Approaches to mobile robot (AGV) localization can be divided into two major classes; which are Geometric Localization and Topological Localization. In *Geometric Localization* the AGV will depends on a metric internal representation, or map of the environment. Meanwhile, in *Topological Localization*, AGV uses a graph representation that acquires the connectivity of a set of features in the environment [4-5]. The issue of topological localization will be explained in the next section.

2. Topological Localization

Topological localization has attracted much attention of researchers around the world in the last few years, especially the localization methods that used vision sensors. Recently a special type of camera, which is omnidirectional camera, has become more popular. The omnidirectional camera with its capability of viewing 360° field has various advantages over a normal camera. The robot can view the whole surrounding environment by just one snapshot without consideration of its heading. Designated places can be recognized through fewer images and landmarks can also be tracked from long distances.

The proposed topological localization approach in this research work does not require a 3D model of the environment. The research work of this paper presents the advantage of AGV to work directly in the sensor space. In this case, the environment is described by a topological graph. Topological map is simple, effective, and compatible with human knowledge. Each node (points) reflects to a description of a place in the environment that can be obtained using sensor data, and can be associated with an action, such as turning, crossing a door, stopping, or going straight ahead. A link between two nodes representing the possibility for the robot to move autonomously between two associated places [6-7].

The problem of direct topological based indoor navigation has been analysed by many researchers. Their approaches differ from how to define and identify nodes. Many researchers employed features; either local or global features, but both of them have same objective which is to identifying the similarity on solving localization problem. Feature is a very unique data that needed to be extracted in order get the desire output, many researchers come out with different techniques and methods to analyse the features and make it as an input for localization system.

In a vision-based topological localization system, a location in an environment can be represented by different kinds of image features. Global features can be defined as looking the whole image where the overall information may gain, while local feature means focusing on something which is more relevant information that can be gained. Global features can be extracted from histogram, integral invariant, and image gradient. Matsutomo *et al.*, [8] stated that using global features for robot localization need memorizing the whole image and required large space of data stored in robot system.

In recent years, many local feature detectors are proposed to conquer partial occlusion and viewpoint change problems. Jafar *et al.*, [9-10] stated that localization of mobile robot can be achieved through a computation of the similarity of images that obtain by the robot at the designated places in an environment. Tamimi and Zell [11] stated that areas of high relevant in the image under consideration such as wavelet-based features and Scale Invariant Features Transform (SIFT) were computed under local features. Harris-Laplace interest point detector, which is another scale

invariant feature detector, was used by Wang *et al.*, [12] to determine the location of a camera system. Although it seems that affine or perspective invariant features are better choices for a localization system, they have not been used in localization because the computations of those features usually are very expensive.

3. Overall System

3.1 Localization Method

Fig. 1 shows the localization method that is proposed in our approach. In this localization method, first we will bring the AGV to the designated places in the topological environment and let the AGV to capture few images at each place. Those places are the nodes that we want the AGV to identify in the environment later. Data of visual features is extracted from all images captured at each place and trained in the NN during the Learning Phase to obtain NN data for each place, which is to be used later for the AGV to recognize the designated places in the environment.

In the localization phase that is conducted right after that, the same method of capturing images during the learning phase is conducted by the AGV, visual data features are extracted from those images and evaluated through the NN. If output of the NN evaluation for the image is higher than a certain threshold, where in our method we set the threshold to 0.7, then the image is considered from the respective place or near to the place. In other word, localization is done by matching the current visual features from images taken at the designated places against the sets of features of the places that are stored in a database.

The AGV does not conduct any precise distance measurement in our approach in order to know distance between one place with another place. Moreover, we do not control the AGV's posture so that the AGV is freely to capture image. The AGV is recognizing places only based on the visual features. Due to this condition, we believe that it is important to allow every respective place to possess a region area in which if the AGV capture image within the region area, the AGV will be able to realize that it has come near to the place or in other words, the AGV would identify that it has arrives in the proximity around the centre of the memorized place.

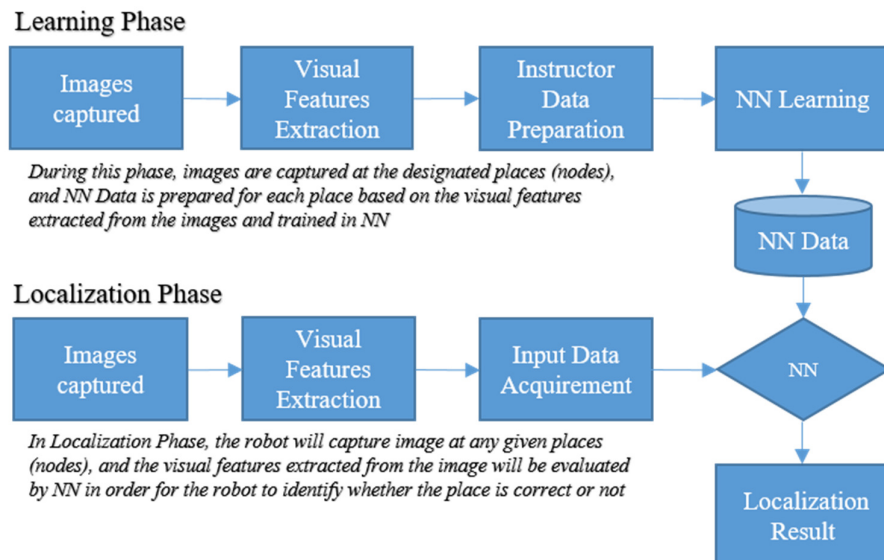


Fig. 1. The proposed localization method

In order to produce the region area for the AGV localization, we let the AGV to capture 5 images at each designated place during the learning phase, with 1 image at the centre and another 4 images at about 15cm from the centre to the front, back, right and left, as shown in Fig. 2.

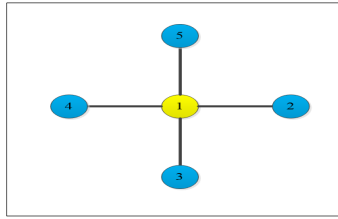


Fig. 2. Positions of acquiring images during the learning phase to initiate the region area for localization

3.2 Visual Features

Swain and Ballard [13] had pioneered the idea of using colour histogram to match two images. Since then, few researchers also employ colour histogram in their method for robot localization [14-15]. These research works had previously successfully proved that colour can be used as the features in mobile robot localization. However, our approach is different to those studies, in which we evaluate all the colours in an image, and use their ratio in the image as features, rather than histograms.

Colour information in an image captured by camera is affected by the photographing condition such as illumination etc. The data could be very large and computation cost is expected to become high if we are going to calculate every single pixel of an image.

Thus, we consider formulating a simple and easy way using the details of colour information, by separating the colours roughly into 11 classifications through a separation of CIE chromaticity diagram as shown in Fig. 3 as well as consideration on luminosity factor. In the chromaticity diagram, those colours which are located in the same partition is viewed as the identical colour, and through that we separated the chromaticity diagram into 8 colours. The non-colouring space at the centre of the chromaticity diagram is later separated into three colours which are white, black, and grey based on luminosity factor. We also used the luminosity to classify between black and the primary colour of each partition in the separated chromaticity diagram. We examine all the colours which are exist in an image before convert them into numerical data. And those pixels whose colours fall into one colour territory are considered to have the same colour. Through this, a total of 33 data of visual features is acquired from colour features, and a robust system for robot self-localization that required just a simple algorithm and established fast processing capability is developed.

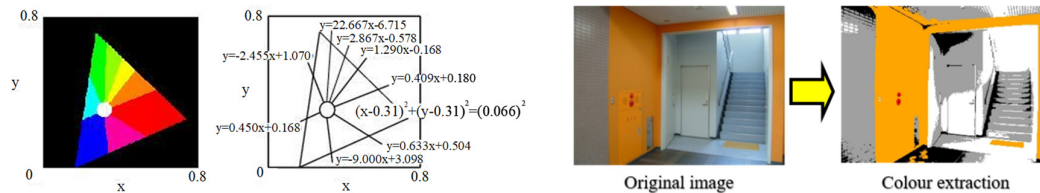


Fig. 3. Left image: Separating chromaticity diagram; Right Image: Colour extraction

In addition to colour features, we also extracted edges from an image using Robert operator. We are able to obtain points which are connected through the edges through a further image processing done on the edges. And we used these points together with the extracted edges as the visual features. The edges and connecting points are able to be extracted through the process shown in Fig. 4.

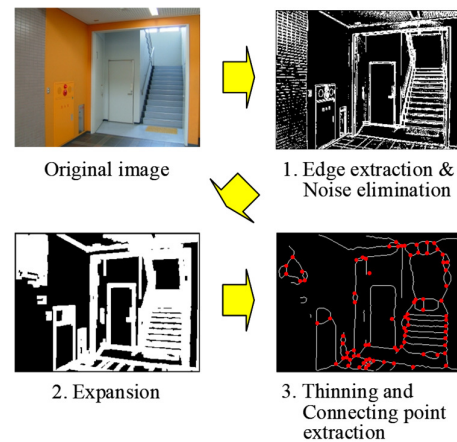


Fig. 4. Extracting edges and connecting points

From the shape features extraction process where we are able to obtain edges and connecting points, 2 data of visual features can be acquired, which consist of;

- Ratio of the edges.
- Ratio of the connecting points.

4. Experiment

In order to verify the performance of the proposed localization method, we have conducted a series of experiments. The experiments of this project were conducted in the environment of a manufacturing factory located at the Faculty of Manufacturing Engineering in our university. For the position of the AGV localization, eight positions have been considered and designed as Node 1 ~ 8, as shown in Fig. 5. The experimental platform of these experiments, which is an AGV, is mounted with a CCD color video camera to capture the images. The images acquired in this experiment have a resolution of 320 x 240.

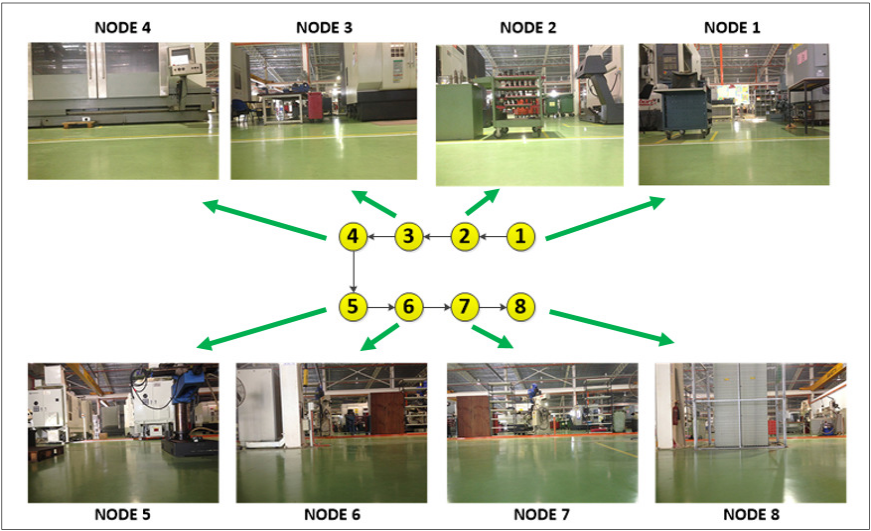
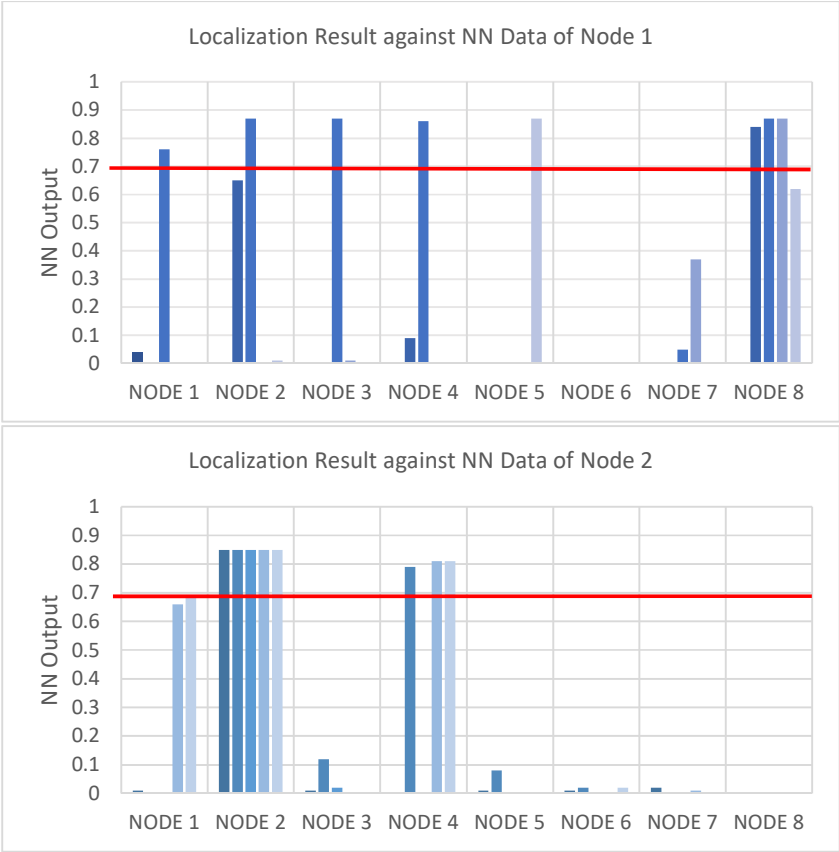


Fig. 5. Topological layout with representative image for each place



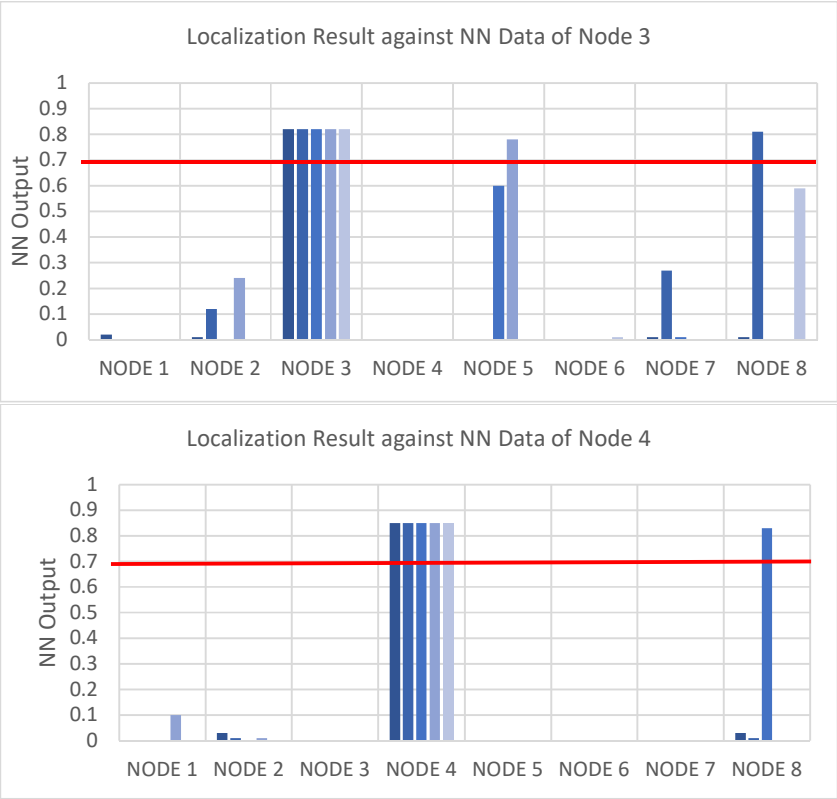
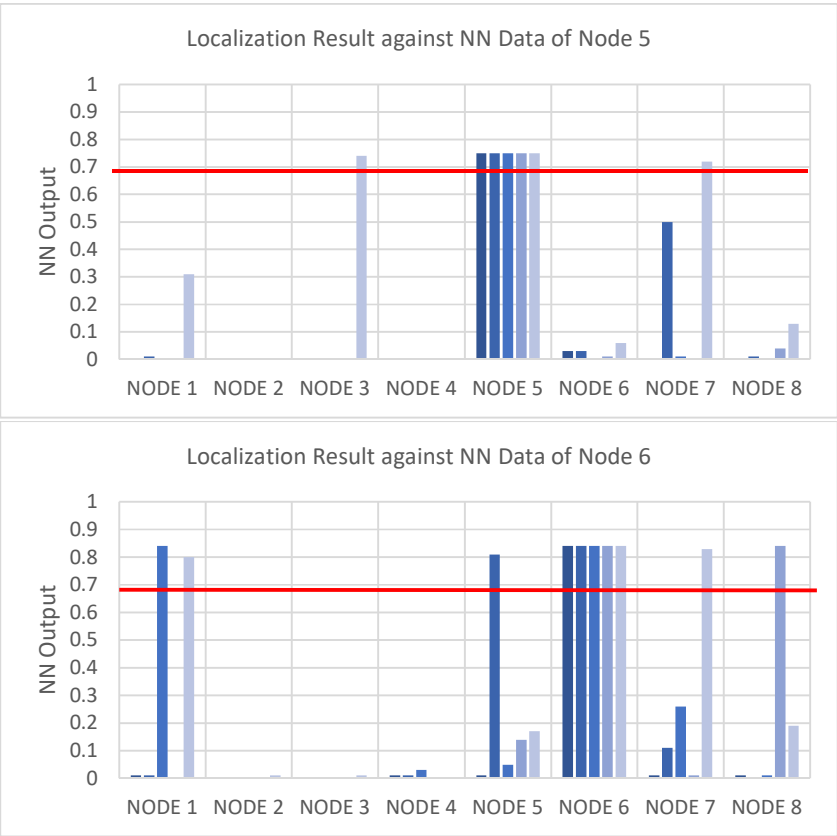


Fig. 6. Localization result tested against Node 1~4



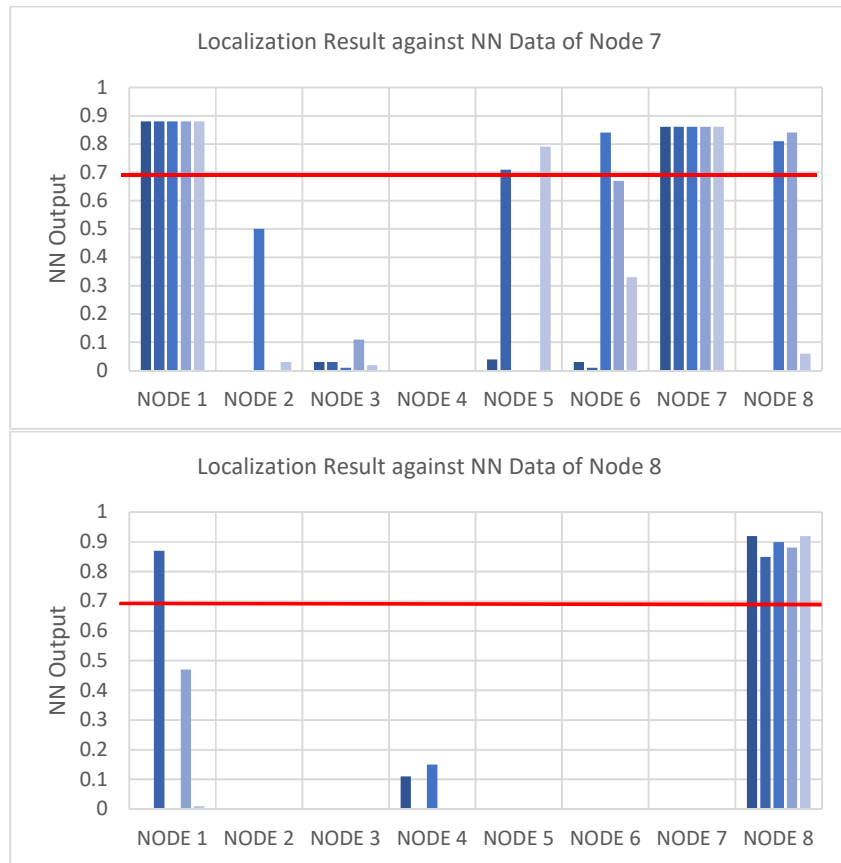


Fig. 7. Localization result tested against Node 5~8

Images captured at each node are tested on the NN Data of Node 1~8 in order to analyze the robustness of the proposed method. 5 images were taken at each node during the localization phase, in which a total of 40 images were taken from all the 8 nodes. The features data of all these 40 images were extracted and run through the NN Data of Node 1~8. Overall 320 tests were conducted for this experiment. Results of the experiments are shown in Fig. 5~7.

Images captured at the respective node are expected to obtain the set threshold 0.7 or more against the NN Data of the respective node, while those images taken at other nodes are not supposed to respond to the NN Data of the node. We classified those errors of when any image from certain node is not able to obtain 0.7 or more after run through the NN Data of the node itself, as *false negative*. In other word, image that is captured from certain node supposed to respond to the NN Data of that node but failed to do so. Meanwhile, we classified *false positive* for error that occurred when image taken from other nodes but unexpectedly responded (achieved 0.7 and above of the NN result) to NN Data of other nodes, other than the NN Data of the node where the image is taken.

With the classification of false negative and false positive, we found out that overall there are 4 false negative errors, mainly occur on images from Node 1, and 31 false positive errors occurred where majority are from images against the NN Data of Node 1 (7 errors) and Node 7 (10 errors). Out of the 7 false positive errors occurred against NN Data of Node 1, 3 errors are from the images taken at Node 8, while 1 error each occurred on image from Node 2, 3, 4 and 5 respectively. Meanwhile, all 5 images captured at Node 1 were mistakenly responded against NN Data of Node 7 and 1 error each occurred on image from Node 4, 5 and 6, and 2 errors occurred on images from Node 8.

Further analysis need to be done to identify the main reason of the false positive errors especially those that occurred against NN Data of Node 7. Basically, a quick thoughtful reason of these errors is

might due to the flickering condition of lighting condition in the environment, but further experiment or analysis need to be carried out to confirm this prediction. In fact, as all images from Node 1 were responded to the NN Data of Node 7, detail analysis on the features data value of images from Node 1 need to be identified of why images taken at Node 1 mistakenly responded against NN Data of Node 7. Furthermore, the reason why 4 images of Node 1 were not able to obtain 0.7 or more against the NN Data of the respective Node 1 also need to be clarified in order to carry out improvements during the next stage of this research work, to ensure for the robustness of the proposed localization system.

Anyway, the proposed localization system is still considered as successful, significant and possesses high potential to be applied on AGV in manufacturing system as the overall success rate of the localization performance is 89.06%. However some improvements need to be done in order to reduce both false negative and false positive errors.

5. Conclusions

The problem of vision based AGV localization is evaluated. A method for AGV to navigate in a manufacturing environment, taking the advantages of the visual features in the environment has been described. It built upon the topological environmental representation. The visual features are evaluated by neural network. The proposed localization system is able to achieve efficient place recognition. However, some issues arose that required to be tackled in a proper way in order to make sure that the proposed localization system is robust enough and ready to be used in whatever manufacturing environment. For that, the future work of this research study is to look into the visual features value, the method to extract the features especially for colour features, as well as the method of capturing image. Perhaps, the method of providing region area for localization (5 images captured at the designated place for localization) need to be re-considered. Moreover, the angle of camera direction also needs to be considered and study.

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