Room Recognition For Mobile Robot Using Appearance-Based Method

Eileen L. M. Su[1], Shamsudin H.M. Amin[2], Rosbi Mamat[3], Yeong Che Fai[4]
Center for Artificial Intelligence and Robotics (CAIRO)
Universiti Teknologi Malaysia
City Campus, Jalan Semarak
54100 Kuala Lumpur
MALAYSIA
eileensu@yahoo.com[1], sham@fke.utm.my[2], rosbi@fke.utm.my[3], cfyeong@fke.utm.my[4]

Abstract

One popular approach for vision based mobile robot localization is the appearance based method, where the image can be used for recognition in its basic form without extracting local features. The general aim of this work is to develop a room recognition system using appearance-based method for mobile robot localization. The room recognition is achieved by matching color histogram of image using the Artificial Neural Network. A hardware module and a software module have been developed for this project. The hardware module consists of a catadioptric sensor system implemented on a mobile robot platform. The software module encompasses several sub modules namely image acquisition; image pre-processing; histogram plotting; histogram filtering, sampling and normalization; neural network for offline training and testing, and finally real time room recognition. A few experiments have been conducted to evaluate the performance of the system and the results have been favorable. Testing for suitable network setting was also carried out and a recommendable setting was proposed.

1. Introduction

Designing a mobile robot that can navigate and operate in a real world environment is a challenging task. The most fundamental competence it should have is the localization capability [1][2][3][4]. To localize, a robot needs to have external sensor information and be able to give an estimate of its location. Localization is made complicated due to a few factors such dynamism of environment, noise and errors, limitations in computational resources and the ease of use of the system. Various techniques and sensors have been introduced to tackle these issues. In this work, an appearance-based room recognition system is developed and investigated for global localization of a mobile robot in an unmodified, indoor environment. Engelson called the problem of global localization the 'kidnapped robot problem', suggesting that a robot should be able to localize itself even if some external force carried it to an unknown location [3]. When using an appearance-based model, the image can be used without extracting local features, as visual information gets interpreted in its basic form [5].

2. System Design

Generally, room recognition for the purpose of localization applies the same concept as pattern recognition. The development process can be separated into four major stages – the software development, the hardware design, integration of hardware and software, and finally the performance analysis for the overall system. In the context of hardware design, a few parts that are needed have been identified, such as the laptop as the main system controller, the mobile robot as the implementation platform and a vision sensor capable of capturing omnidirectional view of a room. The software architecture includes a main program that integrates the room recognition module with screen display, robot control and performance analysis.

2.1 The Software

The target operating system for the software module is the Windows 98 or Windows 2000. The software is written in Microsoft Visual Basic 6.0 platform. The software includes functionalities for image acquisition, image conversion, plotting of color histogram, filtering, sampling and normalization of histogram and finally a neural network for training and testing.

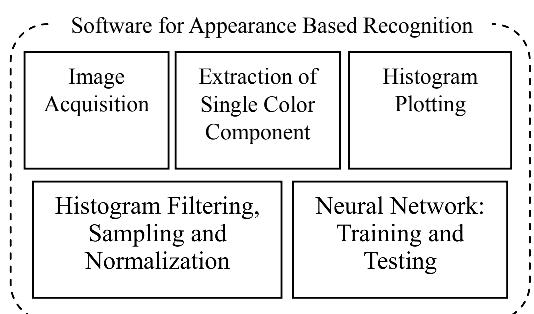


Fig 1: Sub modules in the appearance based recognition software

2.2 The Hardware

The mobile robot selected for this project is the Bluetooth Enabled Mobile Robot (BeMR) from the UTM Robotic Research Laboratory designed by Yeong [6]. This robot has been equipped with multiple Human Robot Interaction methods and has the capability to perform domestic tasks under human control. Implementing the ability to self-localize onto the mobile robot will give this robot an added functionality, which is to globally localize itself by recognizing the room it is currently in. The catadioptric sensor is constructed using a reflector ball, a shade and a webcam on an aluminium rod, then mounted onto the robot.

Fig. 2: BeMR with the catadioptric sensor

3. The Recognition Process

To recognize a room image, the initial step is to acquire a set of color images of the different rooms. These images are pre-processed to reduce their memory requirement. Pre-processing includes extraction of single color component, plotting histogram, filtering, sampling, normalization and finally recognition using Multi Layer Perceptron (MLP) neural network before the system could recognize the room.

3.1 Image Acquisition

For image acquisition, the catadioptric sensor is used. The catadioptric image of Room A is shown in Figure 3. The image captures a 360° view of the room and in fact, one image is sufficient to represent a room.

Fig 3: Catadioptric Image of Room A

3.2 Extraction of Single Color Component

Once the original images are captured and saved, they go through a process to extract the single color component from the image. Each pixel in the original color images contain 24-bit RGB color values with Red occupying the lowest order byte, Green in the middle byte and Blue in the highest byte. To isolate the R, G and B color values from each image, each color value is segregated into 3 bytes, and saved accordingly as Red, Green or Blue values to be used for histogram plotting. The Graphical User Interface (GUI) in Figure 4 shows images of only Red, Green or Blue color component constructed from the original color image.

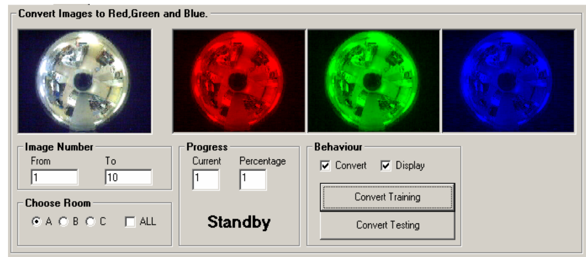


Fig 4 : Original image displayed in its Red, Green and Blue components

3.3 Plotting Histogram

After the extraction stage, histograms of single color component are plotted to show color intensity distribution in the image. Darker pixel carries lower intensity value while brighter pixel carries higher intensity value. Figure 5 shows the histograms for Red, Green and Blue component for an image of Room B. Recognition performance using the three different color components can thus be made.

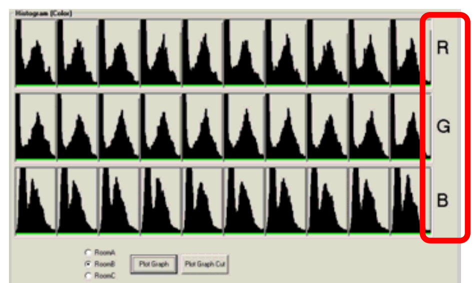


Fig 5: Histogram of different color components for a room

Histograms are also plotted for different rooms using a particular color component Ten red color histograms for the three different rooms, A, B and C are as shown in Figure 6. With histogram of same color component for different rooms, we can compare the performance of that particular color component in different environments.

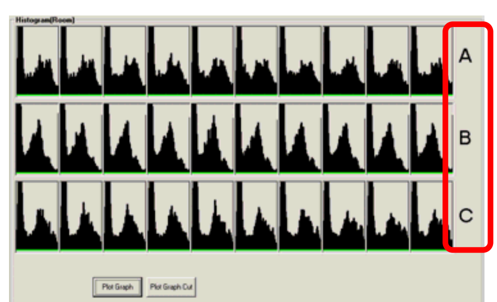
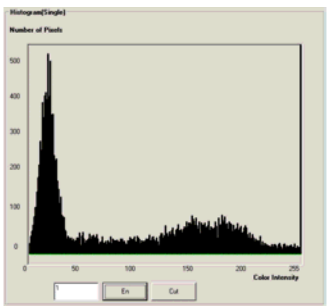


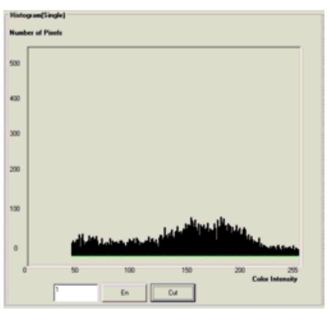
Fig 6: Red Color Histograms plotted for different rooms

3.4 Filtering

The next step is to filter the plotted histograms. Figure 7 (a) shows a histogram before filtering and a filtered histogram in (b). The histograms are filtered of dark colored pixel at a threshold value of 40. Pixels with color intensity below 40 are cut off as the dark pixels are mostly caused by the black shade of the vision system (Figure 8) and do not contribute towards room recognition. Figure 9 shows the different patterns for three different rooms after filtering. Figure 10 presents ten histogram patterns red color component for the rooms A, B and C after filtering. It can be seen that the histogram pattern for each room is distinctively different and thus could be used for room recognition.



(a)



(b)

Fig 7: A histogram (a) before filtering and (b) after filtering

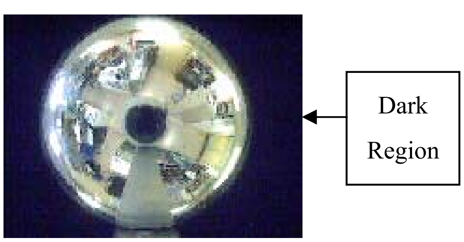


Fig 8: Dark region contains no room information

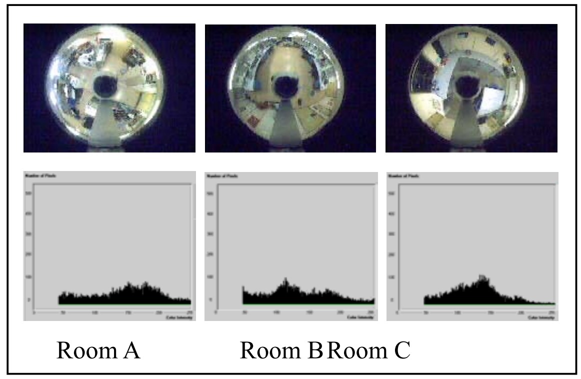


Fig 9: Histogram for three different room images

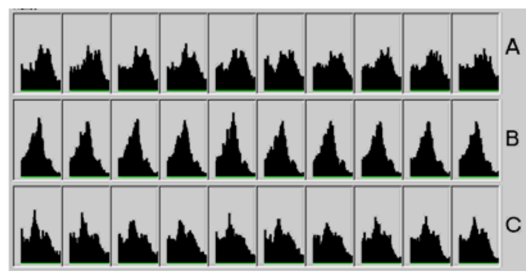


Fig 10: Histogram patterns that represent different rooms after filtering

3.5 Sampling

After filtering, each histogram contains 216 bins, representing intensity level from 40 to 255. However, to train a neural network with 216 input nodes require an excessive memory capacity and computational time. Therefore, data sampling is carried out to reduce the bins to 50 bins per image. This is done simply by taking vertical values at interval of 4 bins until 50 bins are obtained. Remaining bins are ignored. Sampling at 50 has given the most favourable results compared to some other values such as 200, 100 and 25 which we have tested with.

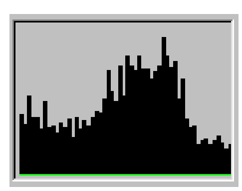


Fig 11: The histogram pattern after being sampled to 50 bins per image.

3.6 Normalization

After the sampling stage, the vertical values of the bins are normalized between the range of 0 and 1 to speed up the training process. For normalization, all vertical values are divided by a denominator which is 100. The value 100 is selected due to it being the average maximum vertical values across all sample sets.

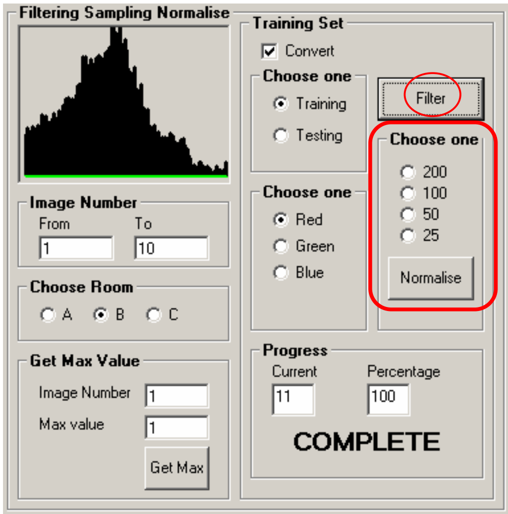


Fig 12: GUI for filtering, sampling and normalization

3.5 Recognition Using Artificial Neural Network

One popular recognition engine is the Artificial Neural Network (ANN). In this work, the Multi Layer Perceptron (MLP) is used as recognition engine and trained using backpropagation (BP) method. Three different MLP network structures are constructed using different number of hidden neurons to check their influence in this recognition:

a) Method A where the number of hidden neurons is the same as the number of input neurons.

b) Method B where the number of hidden neurons is double the number of input neurons.

c) Method C number of hidden neurons is half the number of input neurons.

The normalized histogram is fed into the neural network for offline training, and then for real time room recognition. The vertical values of the histogram are fed as input to the input nodes, while the number of bins in the histogram determines the number of input nodes used. The system is tested for recognition offline and online.

3.5.1 Offline Recognition

Offline room recognition experiments were conducted using image database stored in the computer. A total number of 100 Test Images are saved for testing purpose. The recognition result is displayed individually for each room, and also collectively for all the three rooms. This can be seen in Figure 13.

Comparisons of the system's performance using various settings were made through the offline room recognition experiments. The offline experiments checked the performance of the system when firstly, input data was of different color components and secondly using different neural network structures. Based on the results, the setting combination that generates the best performance was selected and used for the third experiment - real time room recognition.

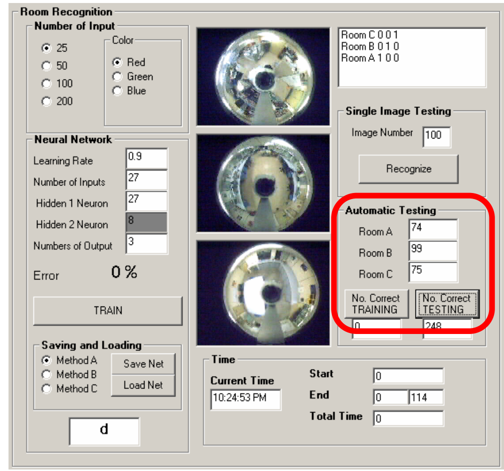


Fig 13: GUI with automatic testing to recognize Training and Test Set images

3.5.2 Real Time Recognition

Real time room recognition experiments utilized real time images taken during robot navigation. Real time testing is separated into two types – the random real time testing, and the continuous real time testing.

In random real time testing, the robot was placed randomly at various locations and tested for its recognition performance. This was to generate the 'kidnapped' robot scenario where a robot is moved from one place to another without the robot knowing it. The robot had to identify its current location without knowledge of its previous position to fulfill the objective of global localization. In this experiment, the robot was randomly placed at 50 different locations in each room. Hence, a total of 150 locations were tested for real time recognition.

In continuous real time testing, the robot was let to navigate from Room A to Room C continuously while capturing and recognizing the rooms. This was to mimic a robot that is trying to localize itself while navigating. During the navigation, the robot was made to recognize its environment, making a stop for recognition at a periodic interval of 5.0s.

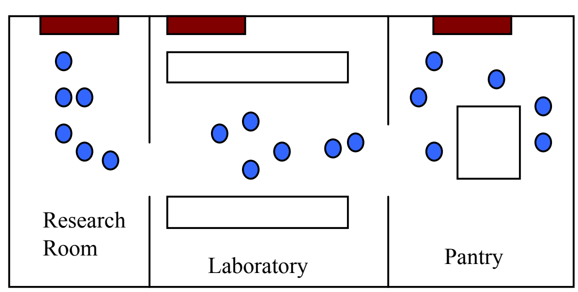


Fig 14: Illustration of the random locations for real time recognition

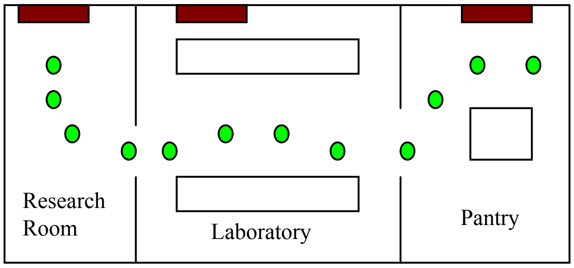


Fig 15: Illustration of the locations for robot continuous real time recognition

A GUI is created for real time room recognition function. There is manual recognition button and another automatic recognition button. For manual recognition, the user can go to a specific location in the room and try to make the system recognize a particular view by pressing the 'Manual' button. For automatic recognition, the system is in a continuous manner, where image acquisition is running periodically with adjustable interval time. The recognition will be done automatically every time the system captures an image. When the either 'Manual' or 'Automatic' button is pressed, the system captures an image, saves it into a folder, plots the histogram, then filters, samples and normalizes the histogram values automatically. Next, the histogram data is recognized by the network and an output answer is generated.

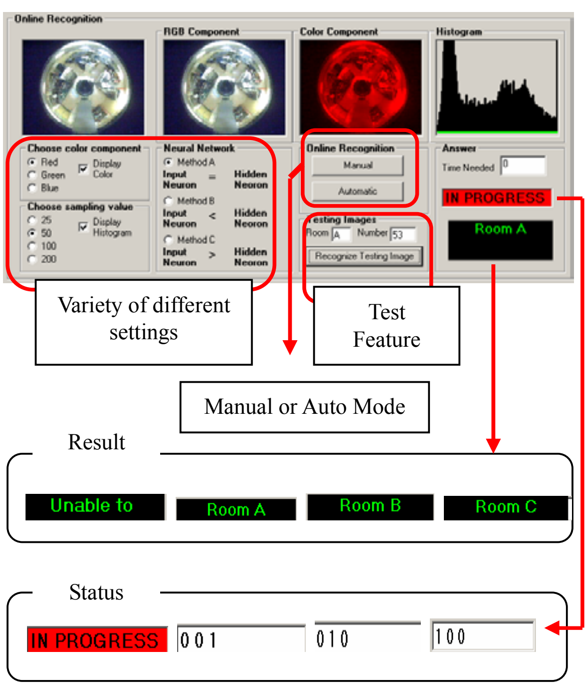


Fig 16: GUI for Real Time Room Recognition

For both the manual and automatic mode, a user can choose the color component, the sampling rate and the type of network for room recognition. The original image, the image after pre-processing and the corresponding histogram will be displayed as shown in Figure 16. A status bar also shows the progress of recognition. Recognition result is displayed at the bottom right corner, whether image is recognized as Room A, B or C.

Another extra feature in this GUI is the single image testing using Test Images saved in database. This feature is similar to the single image testing feature in offline recognition and is used to check and monitor this online recognition software.

4. Experimental Results

This section presents the results for the room recognition system performance analysis. A few experiments were carried out to examine the performance of the system under varying conditions and to validate the feasibility of appearance based room recognition system for real time mobile robot localization. The experiments can be categorized into two main approaches – offline and real time. Performance of the offline and real time experiments were measured in terms of accuracy and recognition time.

The offline room recognition system was evaluated in two sets of experiments to compare the potential of each color component and different network shapes. A total of 300 images were tested with the system. The experiment field used was the Robotic Laboratory located at Block P08, Faculty of Electrical Engineering, Universiti Teknologi Malaysia. The laboratory consists of three rooms which are the robotic research room, laboratory and pantry. All these rooms are connected.

Based on the results, the red color component histogram was found to give the most promising recognition result in this system compared to using blue or green color component. As for network shape, the most favorable result was achieved from Method A where the number of hidden neurons equaled the number of input neurons. The time taken to train the network was 4 minutes and the offline recognition rate achieved using this structure was 92.67%, the highest among the three network structures. Although the short training time of Method C may pose attractive, the low recognition rate makes it unfavorable.

Table 1 Performance Comparison Based on Color Different Components

Color Component	Recognition Rate
Red	92.67%
Green	85.67%
Blue	74.33%

Table 2 Comparison of Training Time and Accuracy Based on Different Network Shapes

Network Shape	Training Time	Recognition Rate
Method A	4 mins	92.67%
Method B	8 mins	83.67%
Method C	40 seconds	84.67%

The system was also tested in real time and gave reliable room recognition. A recognition rate of 90.67% was achieved in random real time testing with average recognition speed of 6.2s.

In continuous real time testing, recognition rate was an average of 92%. The system could even make reliable recognition when it passed through the opening that connects Room A and Room B. As for Room B and Room C, the recognition during the transition was less smooth. The system sometimes could only recognize the transition to Room C only on the second instant. This was accomplished using the following combination: the input data was the red component color and the number of hidden neurons equaled the number of input neurons (Method A). Overall, it can be said that the system can be used reliably in real time and suitable for room recognition to be used by a mobile robot.

5. Conclusion

The main objective of this work is to develop a room recognition system using appearance based method. A few problems in robot localization have been identified and tackled with this system. First is the dynamism of environment where furniture may be rearranged. This issue is overcome by using color histogram to represent a room due to the rotation invariant property of an image. Furthermore, the catadioptric sensor is used so that one image is sufficient to capture the whole room environment. Using images to globally localize a room overcome the 'kidnapped' robot problem as a robot does not rely on its previously known location to calculate for its new location.

In this system, the color images are replaced with color histograms. Color histograms require less memory and histogram matching is a much faster process than image matching. The color histogram data is further reduced by plotting single color component histogram or one dimensional RGB color histogram. The color histogram is then fed into the Multi Layer Perceptron (MLP) neural network and trained using backpropagation (BP) method. The recognition of room is achieved by matching the color histogram of a momentary view with the histogram in database using the same MLP network.

This system requires no modification of environment as is needed in the case of using active beacons, and no tedious mapping is needed as in the case of metric-map based localization. Although the research has been successful in room recognition on a mobile robot, there are still several constraints identified in the system for example, the system is suitable to be used in rooms with more color variations. Rooms with very similar color, furniture and little decorations will be harder to differentiate using this system.

References

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