https://doi.org/10.17576/apjitm-2013-0202-03

http://www.ftsm.ukm.my/apjitm
Asia-Pacific Journal of Information Technology and Multimedia
Jurnal Teknologi Maklumat dan Multimedia Asia-Pasifik
Vol. 2 No. 2, December 2013 : 27 - 38
e-ISSN: 2289-2192

SIMULTANEOUS LOCALIZATION AND MAPPING TRENDS AND HUMANOID ROBOT LINKAGES

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ABSTRACT

Simultaneous localization and mapping (SLAM), also known as concurrent mapping and localization (CML), is an important topic or robotics files. This method produces a real-time map of an environment and finds the current position of a robot on that map. This method is generally used to solve the problem of "Where am I?" for localization, "Where do I go?" for goal determination, and "How do I go there?" for robot motion planning. Recently, the number of studies in this area has increased rapidly and expanded to different areas. In this paper analyzes SLAM or CML, which is currently a hot topic in the field of robotic research. In addition, this paper describes methods for solving SLAM problems, presents evaluation methods for SLAM, analyzes recent research on SLAM worldwide, and studies the academic importance of SLAM. This paper also reviews the use of SLAM for humanoid robots and aims to address the issue of the significance of SLAM engine in the future of stereo vision on humanoid robots.

Keywords: Visual Simultaneous Localization (Localisation) and Mapping, VSLAM, Concurrent Mapping and Localization (CML), humanoid robot, stereo vision on SLAM, 3D vision

INTRODUCTION

Simultaneous localization and mapping (SLAM), also known as concurrent mapping and localization (CML), is a significant issue in the field of robotics. The SLAM acronym was first presented in a mobile robotics survey paper at the International Symposium on Robotics - Research in 1995 (Durrant-Whyte & Bailey, 2006; Durrant-Whyte, Rye & Nebot, 1996). The main idea of SLAM is to deal with the localization and map building problem in an unknown environment (Kovacs & Tevesz, 2012). SLAM addresses the problem of the possibility for a mobile robot to be placed in an unknown location and environment, where it will incrementally build a consistent map of the environment while determining its location within this map. SLAM method generates a real-time map of an environment and finds the position of a robot on that map. This method solves the problem of localization, goal determination, and motion planning of robots. Recently, studies in this area have increased rapidly and expanded to different areas. In addition, the number of ISI papers, patents, and theses based on SLAM gradually increases each year.

SLAM can be applied to real-life problems such as natural disasters. During an earthquake, SLAM can be used to create a map that will allow a rescue agent to help victims find their way back or locate the right path. This method can also be used to find victims in a collapsed building. In the medical field, SLAM can be used to create a map for endoscopy activities. SLAM is implemented in some real-life applications, such as oil pipeline inspection, ocean surveying and underwater navigation, mine exploration, coral reef inspection, military applications, and crime scene investigation. Other studies have discussed the use of SLAM in other real-time applications (Davison et al., 2007) (Chang et al., 2007).

Solving the SLAM problem has become a popular area of research in the past years. SLAM problems generally include four major units, namely, sensor uncertainty, correspondence problem, loop-closing problem, and time complexity (Begum, Mann & Gosine, 2008). Sensor uncertainty explains the noise of each instrument used. The correspondence problem is the difficulty of different viewpoints and the finding of a similarity between the same object from each viewpoint. Data association is particularly important when a vehicle returns to a previously mapped region after a long excursion, which is called “loop closing” problem. Loop closing explains how the loop completes the process. The time complexity clarifies how fast the processing algorithm needs to be to perform and produce results in real time.

However, SLAM has some limitations. One such limitation is the need for quadratic scaling against the number of landmarks in a map. For real-time implementation, this scaling is potentially a substantial limitation in the use of SLAM methods. Environment modeling depends on both environment complexity and sensing modality limitations (Bailey & Durrant-Whyte, 2006). In addition, current approaches cannot perform consistent mapping for large areas given their high computational cost and uncertainties (Aulinas et al., 2008a; Aulinas et al., 2008b). Every sensor carries certain errors, which are often referred to as measurement noise. Sensors also have several range limitations. For instance, light and sound cannot penetrate walls, thereby requiring navigation through the environment (Aulinas et al., 2008a; Aulinas et al., 2008b).

The rest of the paper is organized as follows: Section 2 presents several methods used to solve SLAM problems, such as Kalman filter (KF) and grid-based methods. Section 3 elucidates evaluation methods for SLAM. Section 4, analyzes popular studies in the area of SLAM that have been conducted worldwide. The academic importance of SLAM is emphasized in Section 5 and Section 6 deals with conclusion and future works.

COMPARISONS AMONG SLAM METHODS

In this section, the four widely used SLAM methods, namely KF, particle filter, feature-based SLAM, and graph-based SLAM is elucidated.

KF AND ITS VARIATIONS

This probabilistic technique is popular because robot mapping is characterized by uncertainty and sensor noise. Probabilistic algorithms solve these problems by explicitly modeling different sources of noise and their effects on measurements. KF is a Bayesian filter that represents posteriors by using Gaussians, that is, unimodal multivariate distributions that can be represented compactly by a small number of parameters. KF SLAM assumes that state transition and measurement functions are linear with added Gaussian noise and the initial posteriors are also Gaussian. According to Chen (2012), more than 20 research have presented to improve the KF method in SLAM. In this paper, some important methods, such as extended KF (EKF), unscented KF (UKF), extended information filter, and sparse-extended information filter (SEIF) is shown.

KF has high convergence, is capable of handling uncertainty, reduces memory usage, and handles large areas. However, this method also has some drawbacks. For long missions, the number of landmarks will increase and computer resources will be insufficient for real-time map updating (Aulinas et al., 2008a; Aulinas et al., 2008b). The Gaussian assumption is slow in high-dimensional maps, requires highly robust features, and includes data association problems (Aulinas et al., 2008b). EKF-based approaches have a limited number of 3D points that can be tracked, apart from divergence from the true solution because of linearization errors

(Alcantarilla et al., 2013). Nevertheless, Kalman-based solutions that rely on landmarks have been modified to reduce the complexity of general EKF from O (L^3) to O (L^2) (Holmes & Murray, 2013).

PARTICLE FILTER

Particle filter is a non-parametric and recursive algorithm based on Bayesian filters. Some researchers have applied particle filter in their SLAM, including (Aulinas et al., 2008b; Tornqvist et al., 2009). Particle filter can handle non-linearity and non-Gaussian noise. This method can also solve optimal map building and data association. However, particle filter results in inefficient cost increase, is more complex, and is unstable for large scenarios. This method also requires a large number of particles to track systems with diffuse posterior distributions (Eliazar & Ronald, 2006). Among the well-known methods based on particle filter are FastSLAM (Montemerlo et al., 2002) and FastSLAM2 (Montemerlo et al., 2003). The FastSLAM algorithm utilizes an important characteristic of the SLAM problem. The FastSLAM complexity is $O(P \log L)$ in the number of landmarks L, with a particle filter with P particles used to represent the trajectory (Holmes & Murray, 2013).

GRAPH-BASED SLAM

Every node in the graph corresponds to a pose of a robot during mapping. The edge between two nodes corresponds to the spatial constraints between them. Graph-based SLAM methods have undergone a renaissance and are currently among the state-of-the-art techniques with respect to speed and accuracy. A graph-based SLAM approach constructs a simplified estimation problem by abstracting raw sensor measurements (Grisetti et al., 2010). This method uses the divide-and-conquer approach in which the world is divided into equally spaced cells. Each cell stores the probability of the corresponding area that has been occupied by an obstacle. The cells are assumed to be conditionally independent. Graph-based SLAM methods are easy to use in robotic applications if a known mapping is given in advance.

FEATURE-BASED SLAM

SLAM relies on simple point features for describing an environment (Pedraza et al., 2009). However, two main drawbacks occur when relying solely on this representation. The first and obvious problem emerges when the environment does not have a sufficient structure to extract feature points robustly, for example, an underground mine. The second and more significant issue is the use of only a small fraction of information available from popular sensors, such as laser-range finders, is exploited. Most data that do not correspond to the expected features are discarded (Pedraza et al., 2009). Laser ranging systems are accurate active sensors that mostly operate on the time-of-flight principle by sending a laser pulse in a narrow beam toward the object and measuring the time used by the pulse to reflect the target and return to the sender (Aulinas et al., 2008a; Aulinas et al., 2008b). Feature-based SLAM is widely used in image processing to find and select a landmark. Some image processing methods can also be used to define a landmark.

EVALUATION METHODS

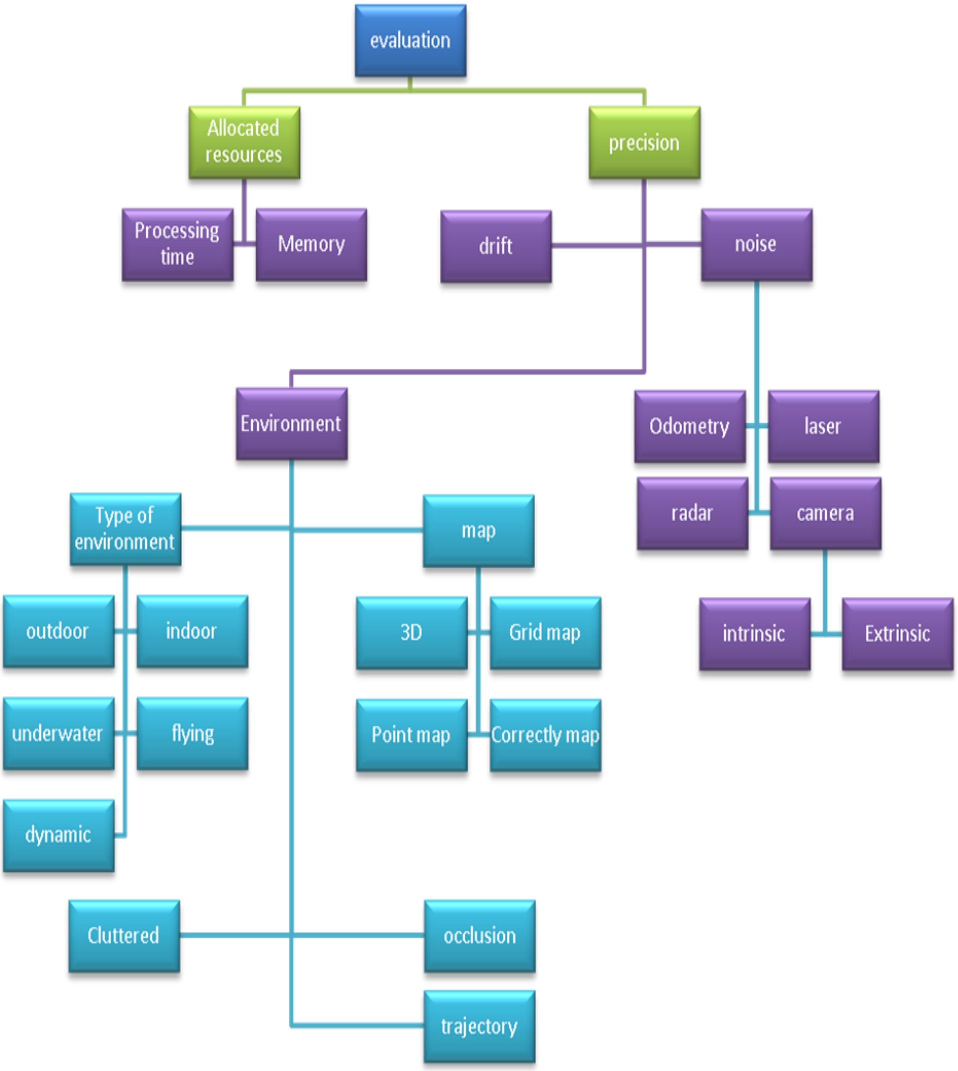

FIGURE 1. Flowchart of the evaluation methods for SLAM application.

Figure 1 shows the evaluation methods for SLAM application. The evaluation methods are divided into two parts, namely, allocated resource and precision. Time processing and memory usage are sub-evaluation methods in the allocated resource category. Tuna et al. (2012) compared the performances of EKF, compressed EKF (CEKF), and UKF in terms of their processing times; CEKF outperformed the EKF and UKF. UKF is based on unscented transform. This method reduces estimation errors and is more computationally costly than EKF. UKF differs from EKF and CEKF in that it does not require deriving Jacobian matrices. The computational complexity of UKF is $O(K)$, where K is the number of landmarks. For memory evaluation, He et al. (2011a) compared SEIF-SLAM and EKF-SLAM in terms of their average memory usage against the number of landmarks. SEIF-SLAM requires lower computational cost than EKF-SLAM. However, SEIF-SLAM is less efficient than EKF-SLAM when fewer than 1,000 features exist in the map. The reduced efficiency of SEIF-SLAM is mainly due to the significantly greater effect of computation in the scarification step than that of the sparse property when only few features are available. As the number of features increased over 1,000, SEIF-SLAM became more efficient than EKF-SLAM. In addition, SEIF-SLAM needs lesser storage than EKF-SLAM, and the gap increases when the number of features increases. SEIF-

SLAM maintains an information matrix, which is sparse and more superior to the non-sparse matrix in storage (He et al., 2011a).

Precision and recall are the common sub-evaluation methods for drift (Botterill et al., 2013), noise, and environment. Odometry and velocity measurements provide an estimate of a vehicle's motion. The error in the estimated pose drifts with time because of noise that corrupts data. Reducing drift and noise elements created by used sensors, such as laser, radar, odometry, and camera, is critical in any SLAM application. Precision is the measure of the ability of SLAM application to present only relevant drift or noise items. Recall measures the ability of SLAM application to present all relevant drift or noise items. Noise can also be measured by peak signal–noise ratio, distance error (Tutar et al., 2006), or adaptive online estimate for the SLAM problem by using the mean and variance of innovation (Won-Seok, Jeong-Dwan & Se-young, 2009).

Environmental issues also affect SLAM evaluation. Different environments, such as dynamic (Yaghmaie, Mobarhani & Taghirad, 2013), outdoor, indoor, underwater (Kim & Eustice, 2013), and in-air, need different methods of evaluating SLAM algorithms. Precision and recall are essential methods for verifying SLAM algorithms' robustness to environmental factors. Researchers have used different types of maps, such as 3D, map, and point maps, to measure environmental factors. Some SLAM methods for different environments are 3D (Aghili, 2011; Cole & Newman, 2006; Olivier et al., 2006; Tong, Barfoot & Dupuis, 2012; Weingarten & Siegwart, 2005), stereo (Ngo et. al, 2006), indoor (Hwang & Song, 2011; Lee & Song, 2010), outdoor (Abdallah, Asmar & Zelek, 2007), underwater (Eustice, Pizarro & Singh,. 2008; Eustice, Singh & Leonard, 2006; Fraundorfer & Scaramuzza, 2012; Jaulin, 2009; Kumagni, 2007; Mahon et al., 2008; Olson, Leonard & Teller, 2006), aerospace (Grzonka, Grisetti & Burgard, 2012; Saeedi et al., 2011; Steder et al., 2008), and dynamic (Yaghmaie, Mobarhani & Taghirad, 2013). Cole and Newman (2006) used laser for 3D outdoor SLAM and presented an algorithm for segmenting 3D laser-range data from a moving platform into distinct 3D point clouds referenced to vehicle poses. The processors of some robots work with mobile embedded systems that have limited processing power. This limited power must be devoted to interpret visual frames and to the robot application. This feature limits the computational ability of SLAM algorithm and compounds the previous problem that a low frame rate exists for vision and greater noise exists in visual interpretation.

So far, no researcher has evaluated 3D SLAM performance based on cluttered, occlusion, and trajectory tolerances, which have been used widely in motion tracking algorithms (John, Trucco & Ivekovic, 2010; Khosravi & Safabakhsh, 2008; Zin, Abdullah & Abdullah, 2013). This measurement method can define the robustness of SLAM mapping tracking to external environmental behaviors. It is suggested that this evaluation method is used in future SLAM research.

ONLINE DATASETS

Table 3 presents online datasets applicable for SLAM research until 2013, such as indoor and outdoor datasets. Most datasets focus on outdoor environments because they need extensive research and are difficult to evaluate. Outdoor datasets with ground truth are difficult to create and need considerable information and equipment. Some well-known datasets are the datasets of the Intel research lab, FHW Museum, Belgioioso, MIT CSAIL, MIT Killian Court, and Freiburg Bldg. 79. The website http://www.openslam.org provides a collection of open-source SLAM packages that include many algorithms and datasets.

TABLE 3. Online Datasets in the area of SLAM until year 2013.

Dataset Name or authors	Description	Link
Eduardo Nebot(Durrant-Whyte, Rye & Nebot, 1996; Nieto, Bailey & Nebot, 2007; Nieto, Guivant & Nebot, 2006)	Numerous large-scale outdoor datasets, notably the popular Victoria Park data.	http://www.acfr.usyd.edu.au/homepages/academic/enebot/dataset.htm
Chieh-Chih Wang (Durrant-Whyte & Bailey, 2006; Lin et al., 2012; Wang et al., 2007)	Three large-scale outdoor datasets are collected by the Navlab11 testbed.	http://www.cs.cmu.edu/~bobwang/datasets.html
Radish, (He et al., 2011b; Pedraza et al., 2009; Valencia et al., 2013) (The Robotics Data Set Repository)	Many and varied indoor datasets, the Intel Research Lab in Seattle, the Edmonton Convention Centre, and more.	http://radish.sourceforge.net/
IJRR (The International Journal of Robotics Research)	IJRR maintains a Web page for each article, often containing data and video of results. A good paper example is by Bosse et al. [3], which has obtained benchmark dataset from Killian Court at MIT.	http://www.ijrr.org/contents/23_12/abstract/1113.html
Michael Montemerlo, Nicholas Roy et al.	Radish: The Robotics Data Set Repository Standard data sets for the robotics community	http://radish.sourceforge.net/

One of the well-known benchmark datasets for evaluating SLAM method was presented by (Kümmerle et al., 2009), but it requires an expert to set the ground truth manually for the dataset. Another benchmark dataset by (Burgard et al., 2009) uses an error metric to determine translational and rotational errors and weighting factor.

Few studies on SLAM methods for stereo humanoid robots have been conducted. Figure 4 shows the relationship among localization, mapping, robotic, and stereo vision. The combination of localization, mapping, and stereo vision on humanoid robots is a new research area that needs more attention.

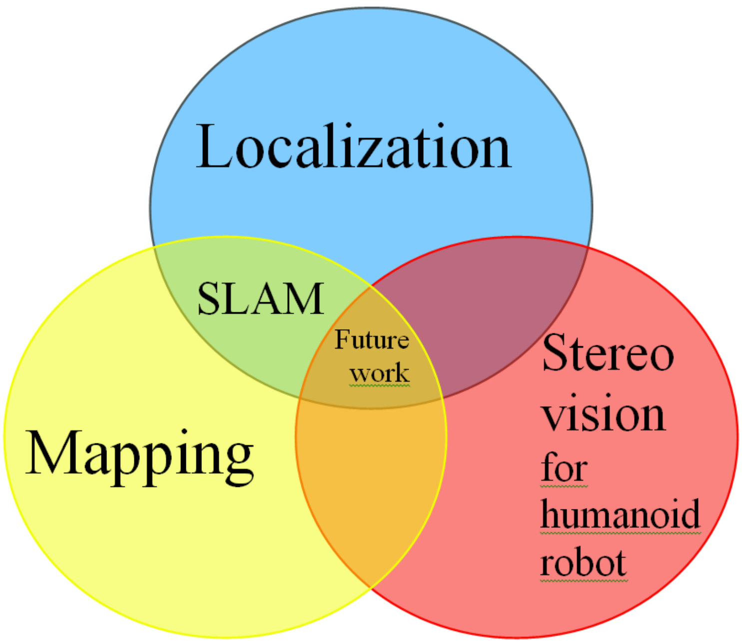

FIGURE 4. Relationship among localization, mapping, robotic, and stereo vision for SLAM application.

Research on humanoid robots based on SLAM approach is one of the recent explorations in the field of robotics. Most well-known approaches of SLAM were created and demonstrated on wheeled robots on flat and even surfaces. However, humanoid robots have many degrees of freedom in their physical construction. Thus, the position of a camera attached to the robot will vary significantly (e.g., as the robot bends to take a step) even if the robot is on a flat surface, thereby leading to more noise and difficulty in interpreting a stream of images. This issue makes the SLAM problem for humanoid robots significantly more challenging.

Alcantarilla et al. (2013)proposed a real-time VSLAM which uses a single camera based on HRP-2. Their method is efficient, easy to implement, robust, and accurate. They also suggest the combination of vision and odometry information for localization for future work. Ozawa et al. (Ozawa et al., 2005) proposed the use of stereo visual odometry to create local 3D maps for online footstep planning. Among the advantages of utilizing visual odometry is that it is computationally inexpensive and the robot can use the method online. However, this approach cannot close loops, and the local nature of the obtained 3D maps prevents the maps from life-long mapping. For future work, the authors recommend the implementation of an intelligent gaze control and more efficient footstep planning to gather better information and enhance the robot's capabilities.

For GPU (Michel et al., 2007) presented a fully integrated online perception planning execution system for humanoid robots, which employs a GPU-accelerated model-based 3D tracker for perception. They recovered the robot's pose and localized the robot with respect to the object. However, this method greatly depends on the 3D object for tracking, and the 3D model is relatively small. Hence, their method should be expanded to make it applicable for visual serving, grasping, or human tracking for human–robot interaction applications. This method can also be useful for more challenging humanoid robot scenarios, such as stair climbing.

Davison et al, (2007) proposed a real-time algorithm for SLAM with a single and freely moving camera. A persistent map permits drift-free, real-time localization over a small area. However, accurate results were obtained only when the pattern generator, robot odometry, and inertial sensing were fused to aid visual mapping into the EKF framework, as shown in Holmes & Murray (2013) whereby they suggest extending the algorithm for a significantly large-scale environment. A network of accurate small-scale maps can be successfully combined by a relatively loose set of estimated transformations provided that the sub-maps in the background can be "map-match." This feature is closely related to being able to solve the "lost robot" problem of localizing against a known map with only a weak prior position and has proven by 2D laser data to be relatively straightforward. With vision-only sensing, this type of matching can be achieved with invariant visual feature types, such as SIFT, or by matching higher-level scene features, such as gross 3D surfaces.

One of the most successful monocular SLAM approaches is the parallel tracking and mapping (PTAM) approach proposed by Klein and Murray (2007). PTAM was originally developed for augmented reality in small workspaces and combines the tracking of hundreds of features between consecutive frames for accurate camera pose estimation and non-linear map optimization. Map optimization uses a subset of all camera frames of special importance in the reconstruction (key frames) to build a 3D map of the environment (Alcantarilla et al., 2013). However, this approach does not perform well enough to enable an untrained user to learn this approach and apply it in an arbitrary environment. Future studies should address the shortcomings of the system and to expand its potential applications.

Several studies based on SLAM application on biped-walking robots have been conducted (Alcantarilla et al., 2013; Dai, Xiong & Li, 2011; Ruiz, 2011; Seung-Joon et al., 2011; Shamsuddin et al., 2011; Yeon Geol et al., 2011; Yi et al., 2011) Some problems encountered in these studies include noisy odometer, inaccurate 3D data, complex motions, motion blurring caused by fast robot motion, and large jerks (twitches, jolts) caused by the landing of the robot feet. The processes that apply SLAM on humanoid robots are as follows:

1. Establishing stereo vision
2. Building a 3D map of environment
3. Stereo visual SLAM techniques and bundle adjustment (BA)
4. Local and global BA to obtain accurate 3D maps with respect to global coordinate frame
5. Data association between a large map of 3D points and 2D features perceived by a camera
6. Random sample consensus framework
7. Perspective-n-point to camera pose

CONCLUSION AND FUTURE WORKS

New combinatory methods, such as grid-based FastSLAM (Stachniss et al., 2005) and graph-based SLAM, with landmarks (Grisetti et al., 2010), have been proposed recently. Some recent studies on stereo vision SLAM, such as near real-time learning of 3D point-landmark and 2D occupancy-grid maps that use particle filters laser-range data usage for 3D SLAM in outdoor environments (Cole & Newman, 2006), detailed 3D mapping based on image edge-point ICP and recovery from registration failure (Tomono, 2009), gamma-SLAM that uses stereo vision and variance grid maps for SLAM in unstructured environments (Marks et al., 2008), and SLAM for autonomous mobile robots that use a binocular stereo vision system (Lu-Fang, Yu-Xian & Sheng, 2007), have also been reported. The grid-based FastSLAM solves the loop-closure problem in SLAM. The graph-based SLAM with landmarks increases map accuracy as well as solve loop closure. The occupancy grids divide the environment into small cells with a predefined size and classify them as occupied or not, and its variants would result in an impracticably large-state vector. The importance and effectiveness of these techniques are undeniable.

However, less effort has been dedicated to the area of 3D SLAM on humanoid robots. One study used Rao-Blackwellized particle filter (Kwak et al., 2009) on a humanoid robot (Kaneko et al., 2004), and another used stereo vision (Tomita et al., 1998). These studies found that map and stereo vision are very noisy (Kwak et al., 2009) and need to be improved. One cause of noisy vision is shaky video caused by the movement of a humanoid robot, which causes difficulties in recognizing and detecting objects. This is one issue that should be addressed because the real world is full of moving objects.

Future work should be devoted to the application of the system to stereo vision SLAM for humanoid robots in real 3D environments. The robots have to interact with a 3D environment and need metric data to conduct path planning; thus, they require a 3D environment map. Among SLAM methods, the grid-based method is suitable for our humanoid robot. The feature-based SLAM is efficient for localization but cannot work properly for unknown features and path planning (Kwak et al., 2009). For the stereo vision, the first step is to set up a stereo camera on a fixed baseline and calibrate it. As the robot moves, the camera needs to be stabilized to ensure more accurate vision. Hence, a 3D feature should be included to ensure correct recognition and localization of objects. A landmark that will be used for SLAM will then be selected based on 3D features. KF will be applied to SLAM by using landmark selection, and a 3D environment map can then be created. Research on SLAM can greatly benefit the field of robotics and should be given more attention. Future studies can involve stereo video stabilization as well as focus on SLAM with 3D vision for humanoid robots. Highly critical places should be a focus of attention; for example, during natural disasters, a highly critical place is one where people are located.

ACKNOWLEDGEMENTS

This research was funded by the FRGS/1/2012/SG05/UKM/02/8 grant entitled "Generic Object Localization Algorithm for Image Segmentation" and UKM-PTS-2011-047 Grant entitled "Empowering Robot Soccer among Faculty of Information Science and Technology students".

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