Vol.17 Iss.3 pp.25-31 International Journal of Scientific Research & Engineering Technology (IJSET)

Vision based Simultaneous Localization and Mapping in a light intensity Static Environment

Jabulani K. Makhubela[#1], Tranos Zuva[*2], Olusanya Yinka Agunbiade[#,*3]

[#]Department of Computer Science, Tshwane University of Technology
Pretoria, South Africa
[1]makhubelaJK@tut.ac.za
[3]sanyaYinka@gmail.com

[*]Department of Information and Communication Technology, Vaal University of Technology
Vanderbijlpark, South Africa
[2]tranosz@vut.ac.za

***Abstract*— Visual Simultaneous Localization and Mapping (VSLAM) has seen an incredible interest amongst research community in recent years due to its capability to make the robot truly independent in navigation. In this paper we present a framework for Visual Simultaneous Localization and Mapping (VSLAM) to address the challenge of light intensity in an environment The framework addresses this challenge by introducing image filtering algorithm, together with the Extended Kalman Filter (EKF) algorithm for localization and mapping and A* algorithm for navigation into the VSLAM framework to improve the robustness of the system in a static environment. The methodology used to perform experiment in research is simulation. Experimental results show a root mean square error (RMSE) of 0.13m, which is minimal when compared with other SLAM systems from literature. The inclusion of an Image Filtering Algorithm has enabled the VSLAM system to navigate in a noisy environment.**

Keywords*—*Navigation, Sensor, Vision, light intensity, mobile robot, Simultaneous Localization and mapping (SLAM)

I. Introduction

The capability of an autonomous mobile robot to create a model of an unknown surrounding and estimate its position at the same time is described SLAM [1]. SLAM technique has been common challenge for autonomous robots to navigate and accomplish mobile operational activities [2]. According to [3] technique has been a prosperous for solving autonomous robot shortcomings for research community; it has attracted many research studies, and main reasons for robotics accomplishment [3].

The key reason for SLAM technique success it is better than others in removing the artificial infrastructures of the location [3]. For an autonomous robot to navigate the environment, majority of systems use wide range of sensors such as laser scanner, sonar, acoustic etc. which can be very large and expensive [3]. [4] Endorses the operation of camera into the SLAM technique, which can deliver extra information on the location than other sensors. [3] State that the benefits of a camera are compact, precise, low-priced, non-invasive and pervasive. Camera as vision sensors are favored because people and animals seems to be navigating effectively in a complicated locations using a vision as prime sensor [4].

Various researchers [5] have presented leading methods in SLAM technique such as extended Kalman filter (EKF), FastSLAM, GraphSLAM, and Rao Blackwellized Particle filter (RBPF) SLAM. Numerous researcher have concentrated on making the vision SLAM technique to operate on more, challenging environment [6]. However the problem of environmental noise like light intensity in static environment has been a matter that causes error on the VSLAM technique [7].

In the attempt to solve this challenge in our study, we have introduce image filtering algorithm into the VSLAM framework to increase the effectiveness of the system. The outcome of this study has improved VSLAM to enable an autonomous mobile robot application to navigate the static environment where environmental noise exists, without causing an error. A reminder of this paper is organized as follows: - section II discusses the methodology of proposed VSLAM framework. Section III discuss experiments & results and finally conclusion is drawn in section IV.

II. Methodology of a Proposed VSLAM Framework

For an autonomous robot to localize its position and successfully build a map in unfamiliar location, it needs to follow a method called SLAM [7]. VSLAM arise when a mobile robot uses a vision sensor as their eye(s) to map and navigate the environment [2]. In our effort to address the challenge of environment noise such as light intensity in VSLAM, we have chosen simulation as our methodology in this study.

"Simulation is defined as a method for using computer software to model the operation of real world processes, systems, or events" [8]. The proposed VSLAM framework in a noisy environment is simulated by using Matlab. Matlab stands for Matrix Laboratory, a fourth generation programming language commonly utilized for technical calculation, programming and conceptualization of data [9].

The VSLAM proposed framework comprised of five phases: Image Acquisition Phase, Pre-processing Phase, Light Filtering Algorithm, Localization and Mapping Phase and Navigation Phase. Figure 1 shows the graphical structure of the proposed VSLAM framework. The phases below will be discussed in detail later in the section. This section also discusses the dataset that is used to simulate the proposed VSLAM framework and evaluation metrics.

ISSN: 2356-5608

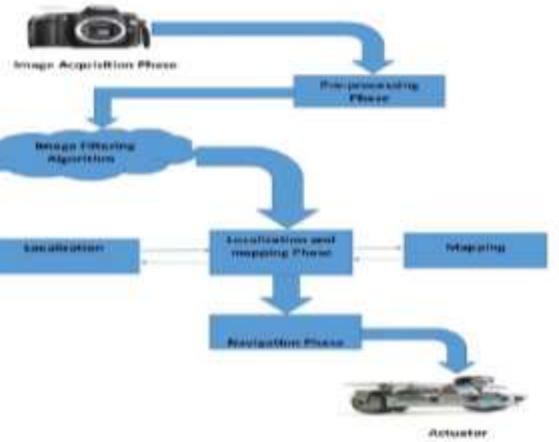

Fig 1: Proposed Framework of VSLAM framework [3]

A. *Sensors (acquisition stage)*

Before image processing can start, a picture must be received by a sensor and transformed into a controllable object; this method is called image acquisition [10]. According to [10] the image acquisition procedure involves three phases: energy reflected from the entity of concern, an optical system which emphasizes the energy and a sensor which calculates the quantity of energy. The energy of interest is normally electromagnetic waves [10] and the light reflected from the object has to be taken by the sensor. If a material sensitive to the reflected light is located near to the entity, a picture of the entity will be taken [10]. The light reflected from the object of concern is focused by some optics and now must be logged by the sensor [10]. The image will then be sent to pre-processing stage for further processing.

B. *Pre-process Algorithm*

The second phase in our method is Image pre-processing, since the major part of the genuine information from camera sensor are noisy, incomplete and inadequate, so pre-processing from acquisition stage becomes essential [11]. Image pre-processing was one of the preparatory stages which were very required to guarantee the high exactness of the subsequent stage [11]. [12] defined Image Pre-processing as a procedure to enhance crude pictures caught from cameras/sensors situated on satellites, space tests and air ships or pictures caught in standard day by day life for various frameworks. The reason for pre-pre-processing was an upgrade of the picture data that overwhelms unfavorable misrepresentations or enhances some picture features pertinent for extra processing with and analysis work [13]. The photos taken from the vision sensors experience pre-process stage to be prepared, analyzed for an autonomous robot to extract the landmarks on the picture. In our work to improve VSLAM, at the pre-processing stage, we had introduced a noise filtering algorithm to remove the noise on pictures which were harmed by higher light intensity in the Acquisition stage. The next section introduces the filtering algorithm to remove the environmental noise such as light intensity had been removed from acquired image.

C. *Image Filtering Algorithm*

An Image filtering algorithm is vital to our framework as it is utilized to lessen environmental noise, clean and improve the pictures that are as of now influenced by environmental noise, for example, light intensity, shadow, rain and so forth. Environmental noise, for example, light variety are common noise most particularly in office territories [7] and can cause the VSLAM method to fail, because as mentioned early in the study the environmental noise can harm picture, degenerate the Red Green Blue (RGB) shading value and bring decreased vision [14]. As mentioned early, in our pre-processing stage we had introduced a noise filtering algorithm, but in this research our attention is only focused on light intensity because of its common occurrence on a daily basis. Filtering algorithms are vital method in image processing, they are used to decrease noises in image. Environmental noise has the competency to destroy image, corrupt the RGB color value and bring poor vision that makes the image content interpretation difficult to analyses [14]. According to [14] they are several types of Environmental noises (snow, Shadow, fog, humility, rain, dew) exist, but in this research out attention is only focused on light intensity because of its common occurrence on a daily basis. Below is the illustration of a light intensity filtering algorithm

Light intensity algorithm has the capability to minimize the effect of light intensity affecting the image [9]. The framework is first carried out on modelling the object reflected by camera based on dichromatic reflection represented as I(x).

Thus, the light intensity detection method is based on the use of dark channel shown in equation (1) and automatic thresholding illustrated in equation (2) is used to label high light reflection in image. This two framework is used for identification for high light area because the intensity value of such are in the dark channel will be having high intensity value while non-area affected with light will be having low intensity value.

I^{dark} of **I** can defined as follows:

$$I^{dark}(X) = \min_{y \in \Omega(x)} \left(\min_{c \in \{r,g,b\}} (I^c(y)) \right) \qquad (1)$$

$\Omega(X)$ is a local patch cantered at x,x = {x,y} is the image coordinates, I^c is a color channel of I

$$t^* = ArgMax \ \{(1 - p_t)(\omega_1(t)\mu_1^2(t) + \omega_2(t)\mu_2^2(t))\} \qquad (2)$$

Where t is a threshold value, p is the probability of occurrences at threshold value t, the smaller the Pt is, and the larger the weight will be.

In the mark image generated by automatic thresholding of dark channel image, the area labelled as 1 signifies the area affected with light intensity and 0 signifies area that are not affected with light intensity. Illustration for these expression is given in equation (3).

$$masmask(x) = \{^1_0 \ if \ I(x) > t^* \qquad (3)$$

In the removal process of Light intensity, Specular to diffuse mechanism is proposed in this framework, illustration of the image with minimal light intensity effect I^D is given in equation (4).

ISSN: 2356-5608

$$I^{D}(\wedge_{\max}) = I - \frac{\max_{c\in(r,g,b)} I_c - \wedge_{\max}\sum_{c\in(r,g,b)} I_c}{1-3\wedge_{\max}} \tag{4}$$

After filtered images with uncorrupted features generated will now be sent to localization and mapping for further processing of the image which will lead to minimum error in the estimation of the environment.

D. Localization and mapping

The third phase of our framework localization and mapping, the whole procedure and motivation behind simultaneous Localization and Mapping (SLAM) is develop a model of its location and estimate the robot position inside location simultaneously [7]. This cannot be accomplished until the point that robot can refresh its odometry which gives guidance to the robot [15]. Odometry it is continually deceptive in begin of the robot navigation, so the robot needs to explore location in order for vision sensor as an exteroceptive sensor to obtain the scene of the environment in order to redress the robot position [15]. The vision sensor gives scene of the location in form of a picture which needs to go pre-processing phase to filter environmental noise acquired on acquisition phase [15]. The robot would extricate the features from the obtained picture of the earth and re-observing the scene the robot returns to the territory [16].

According to [17] the original SLAM posterior is given as follows:

$$p(x_{1:t}, l_{1:m} \mid z_{1:t}, u_{o:t-1}) \tag{5}$$

where $x_{1:t}$ represents the path of the robot, $l_{1:m}$ represents the landmarks,

$z_{1:t}$ represents the measurements and $u_{o:t-1}$ represents the commands given to the robot.

As for static landmarks, the landmark will be defined as follows:

$$l_{1:m} = \{l^{s}_{1:m_s}\} \tag{6}$$

where m represents the number of landmarks, static landmarks. Static landmarks are separated from static as follows. Then (5) is divided into two parts as follows:

$$p(x_{1:t}, l_{1:m} \mid z_{1:t}, u_{o:t-1})$$

$$= p(x_{1:t}, l^{s}_{1:m_s} \mid z_{1:t}, u_{o:t-1}).$$

$$= p(x_{1:t}, l^{s}_{1:m_s} \mid z_{1:t}, u_{o:t-1}) \tag{7}$$

Also Static landmarks can be independent from each other as it's shown below:

$$p(x_{1:t}, l^{s}_{1:m_s} \mid z_{1:t}, u_{o:t-1})$$

$$= p(x_{1:t}, l^{s}_{1:m_s} \mid z_{1:t}, u_{o:t-1}). \tag{8}$$

E. Navigation Algorithm

Another fundamental phase in our proposed approach is Navigation phase which is responsible for robot movement around the environment. Navigation is a science of getting mobile robots from place to place [18], the ability of a mobile robot to navigate without external aid [19]. The autonomous navigation of robots in uncontrolled environments is a challenge because it requires a set of subsystems to work together. It requires building a map of the environment, localizing the robot in that map, making a motion plan according to the map, executing that plan with a controller, and other tasks; all at the same time [20]. According to [21] a robot application utilizes path planning and local motion controls to navigate the unknown territory. Path planning studies a model or a map of the location to decide on the regular path points for an autonomous robot to trace from a start site to its destination. Local motion utilizes sensory data to decide a movement that will evade crash with unknown objects or objects whose station in the location had changed [21]. After path planning and local motion, the navigation algorithm will send a command to actuator to instruct the movement of the robot within the unknown location. There are many navigation algorithms which are available from literature each with its strengths and drawbacks however in our method, A* Algorithm is adopted this study to plan a local optimal collision-free path from the current location of the robot to because of its ability to reduces the number of node explorations with respect to Breadth- and Depth-First [20].

F. Dataset

The dataset used was developed from the data used for a PhD Thesis by [23] as cited by [22] on efficient SLAM. "It was documented at the DLR Institute of Robotics and Mechatronics building using a mobile robot controlled by hand. The building covers a region of 60m x 45m and the robot path consists of three large loops within the building (plus a small outside path) with a total length of 505 meters. The robot moved around in the building with artificial landmarks (white/black circles) placed on the ground. The image data has been pre-processed and the relative positions of the observed landmarks with respect to the observation point are provided." [22]. Figure 2 depicts the architectural diagram of the DLR Institute of Robotics and Mechatronics building.

ISSN: 2356-5608

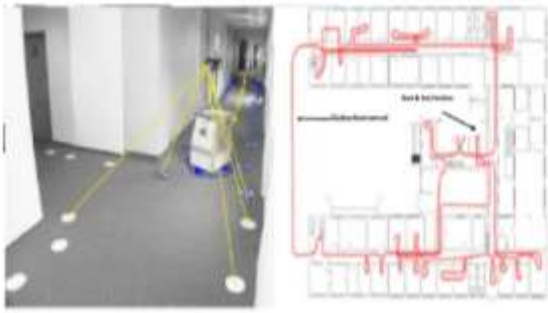

Figure 2: Architectural Diagram of DLR Building [22]

Figure 3 shows a simulated map of the DLR building. The simulated map was also acquired from the study of [22]. The dataset is publicly available, and all the model measurements and set-up of the dataset can be acquired from this "Website, http://www.sfbtr8.spatial-cognition.de/insidedataassociation/, 6 2008" [22].

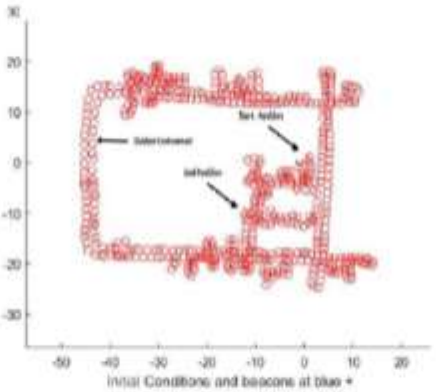

Figure 3: Simulated Map of DLR Building [22]

G. Evalution metrics

The Robot Position of the proposed VSLAM system will be evaluated by employing/calculating the Root mean Square Error (RMSE) and comparing RMSE Robot Position of the proposed system with RMSE of the system from literature. This will be supplemented by calculation of the Robot Position Square Error of the proposed VSLAM system.

The formulation for RMSE is specified in equation (9) as:

$$RMSE = \sqrt{\frac{1}{T}\sum_{k=1}^{T}\left[(X_k - X_k)^2 + (Y_k - Y_k)^2\right]} \tag{9}$$

where $(Y_k - Y_k)$ refers to difference between the actual and $(X_k - X_k)$ refers to estimated distance in Y-direction and refers to difference between the actual and estimated distance in X-direction

The formulation for Square Error at Y-direction is specified in equation (10) as:

$$E^2 = (Y_A - Y_E)^2 \tag{10}$$

where E^2 refers to the calculated square error, Y_A refers to the actual distance in Y-direction, and Y_E refers to estimated distance in Y-direction.

X-direction is specified in equation (11) as:

$$E^2 = (X_A - X_E)^2 \tag{11}$$

where E^2 refers to the calculated square error, X_A refers to the actual distance in X- direction, and X_E refers to estimated distance in X-direction

III. EXPIRIMENTS AND RESULTS

A. Results and Ecaluation Scheme

This chapter defines the experimental methods utilized to evaluate the proposed VSLAM framework that was introduced in the previous chapter. It is imperative to evaluate reliability and viability of the framework and ensure that objectives of the study are accomplished. To validate the proposed VSLAM framework, we compare the proposed VSLAM framework with existing SLAM system result(s) from literature. Utilizing these experimental procedures, the outcomes accomplished are contrasted and examined to perceive how effectively the framework we proposed has improved the VSLAM effectiveness.

Our experimental methods are executed for the determination of error of a proposed VSLAM framework in estimating robot posture in X-direction within the environment and error of a proposed VSLAM framework in estimating the robot posture in Y-direction within the environment.

In uncovering the framework capacity and execution, we evaluated the proposed VSLAM framework using a simulation mathematical software known as Matlab. In comparing a VSLAM framework with existing SLAM systems' results from literature, a study done by [24] on the application of square-root Cubature Kalman filter in SLAM for an underwater robot is utilized to compare for mobile robot position. The next section, Section B, describes the parameters that we are using in our experimental set-up. That is followed by a presentation of simulation results in Section C and then the rest of the chapter presents quantitative results of the simulated VSLAM framework.

B. Expirimental Parametes

In this study, we simulate the proposed VSLAM framework using a vision camera sensor in a pre-defined environment called a DLR building dataset. Table 4-1 presents the parameters employed to simulate the proposed Visual VSLAM framework.

Parameters	Values
Robot Speed	0.93 m/s
Maximum Sensor Range	12 m
Camera Field of View	±75°
Image Resolution	320 x 240

Table 1: Parameters

ISSN: 2356-5608

C. Simulation

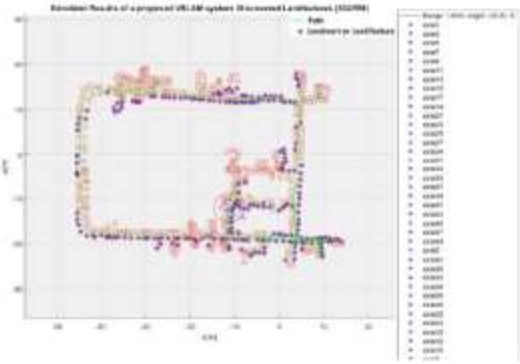

Figure 4-: Simulation Results of a proposed VSLAM system

The simulation map comprises unregularly dispersed landmarks or landfeatures. The mobile robot starts to move at point (0; 0) coordinates and ends at point (-11; -12) coordinates of the simulation map, which is towards middle-left of the simulation map in Figure 4. The mobile robot utilizes the odometry data to predict its movement along the simulation map. In Figure 4, the path of the robot and all the landmarks or landfeatures discovered by the mobile robot are depicted in the map. The light-green line in the simulation map in Figure 4 indicates the path that the robot travels on when navigating the environment. Figure 4 illustrates the linearized least squares result with ground truth of the landmark locations. The Blue stars are the ground truth of landmark or landfeature locations. The ground truth of landmarks and poses of the mobile robot are utilized to update the odometry data as the mobile moves on the simulation environment.

D. Quantitative Analysis of Robot Position

Figure 5: Graphical Results of Robot Position at X-direction

Figure 6: Graphical Results of Robot Position at Y-direction

In Figure 5 and Figure 6, we measure the proposed VSLAM framework robot position towards the true position within a pre-defined environment in X-direction and Y-direction. This experiment is very important because it displays the effectiveness of the proposed VSLAM framework towards Localization. Localization is when a robot it able to estimate its position which is a requirement for building an accurate map for navigation, therefore it is crucial for a mobile robot to know where it is inside the environment at all times. In both Figure 5 and Figure 6, the x-Axis represents iterations whereas the y-Axis represents the robot location in metres within a simulation map. The orange colour line on Figure 5 and Figure 6 represents robot position of a proposed VSLAM framework and the blue colour line represents the true robot position. Both Figure 5 and Figure 6 show minimal deviation between the robot position of a proposed VSLAM framework and the true robot position. Next, we look at the amount of square error between the robot position of a proposed VSLAM framework and the true robot position in X-direction and Y-direction.

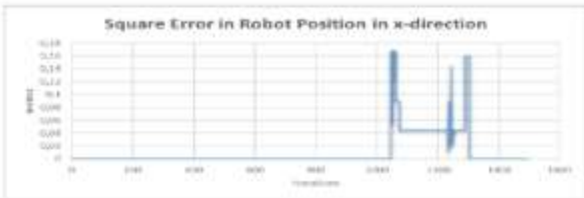

Figure 7: Graphical Results of Error in Robot Position Estimate for X-direction

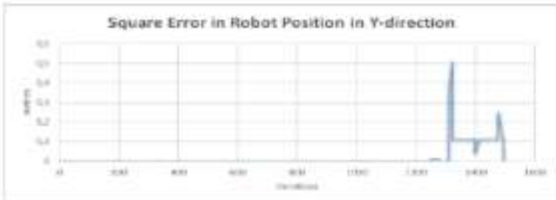

Figure 8: Graphical Results of Error in Robot Position Estimate for Y-direction

Figure 7 and Figure 8 show the amount of square error between the proposed VSLAM framework robot position and the true position within a pre-defined environment in X-direction and Y-direction. Figure 7 shows the minimum error of 0 meters and maximum error of 0,168m in X-direction whereas Figure 8 shows the minimum error of 0 meters and maximum error of 0,494 meters in Y-direction. These errors are mostly due to large odometry data error and loop closure challenges affected when the robot enters and re-enters the outdoor environment.

RMSE in Robot Position	
SLAM System	**RMSE**
Proposed VSLAM System	0.13 m
Cubature Kalman Filter (CKF) SLAM [24]	0.19 m
Square Root Cubature KF (SRCKF) SLAM [24]	0.15 m

ISSN: 2356-5608

Table 2: Comparison of Root Mean Square Error in Robot Position

Table 2 shows a tabular comparison of a RMSE in robot position of a proposed VSLAM system and SLAM using CKF and SRCKF SLAM algorithm from the study that was done by [24]. Both algorithms, CKF and SRCKF as well as Extended Kalman Filter are extensions of Kalman Filter. Table 4-2 compares RMSE of the two systems. The results on Table 2 show that a proposed VSLAM system RMSE in robot position Estimation is lesser than systems done in the study by [24] simulated using the CKF and Square SRCKF SLAM algorithms. However, both systems utilized different parameters and were tested under different conditions. We can only speculate that our algorithm has a lower RMSE due to the noise filter we used.

IV. CONCLUSION

SLAM is a capability of an autonomous mobile robot to create a map of an unknown environment and localise itself at the same time. VSLAM is when an autonomous robot utilizes the operation of a vision sensor or camera to navigate and create a model of an unknown environment. SLAM framework permits an autonomous robot to operate self-sufficiently and cleverly. The utilization of a camera in SLAM allows a mobile robot to have vision capability similar to human beings and/or animals. The purpose of our study is to address the difficulties of environmental noise such as light intensity in a stationary/static environment to enhance the execution of a VSLAM system. In our efforts to address this challenge an image filtering algorithm has been applied into a VSLAM framework to reduce the effects of environmental noise such as light intensity coming from a vision sensor. EKF SLAM has also been applied in the proposed framework to localize the mobile robot and map the environment together with A* algorithm to assist the mobile robot in navigation. The image filtering algorithm was able to minimise the amount of high light intensity within an image. The proposed VSLAM framework has been extensively experimented for robot position estimation in both Y-direction and X-direction and we have demonstrated the performance of experiments, and the outcomes achieved of the proposed VSLAM framework. After minimising the effects of light intensity by using the Light Filtering Algorithm, the proposed VSLAM system was able to depict a RMSE of 0.13, which is less than the study done by [24]. The proposed Visual Simultaneous Localization VSLAM system is able to obtain better results in mapping the location, locating the mobile autonomous robot and navigating the location. Our improved VSLAM system was able to better classify the position of a robot.

REFERENCES

[1] S. Khan, D. Wollherr, and M. Buss, "Modeling laser intensities for simultaneous localization and mapping," IEEE Robotics and Automation Letters, vol. 1, no. 2, pp. 692–699, 2016.

[2] L. Xiang, Z. Ren, M. Ni, and O. C. Jenkins, "Robust graph slam in dynamic environments with moving landmarks," in Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference on. IEEE, 2015, pp. 2543–2549.

[3] J.K. Makhubela, T. Zuva, and O.Y. Agunbiade. "Framework for Visual Simultaneous Localization and Mapping in a Noisy Static Environment." In 2018 International Conference on Intelligent and Innovative Computing Applications (ICONIC) IEEE, 2018 pp. 1-6.

[4] C. Park and J.-B. Song, "Illumination change compensation and extraction of corner feature orientation for upward-looking camera-based slam," in Ubiquitous Robots and Ambient Intelligence (URAI), 2015 12th International Conference on. IEEE, 2015, pp. 224–227.

[5] S. Oh, M. Hahn, and J. Kim, "Simultaneous localization and mapping for mobile robots in dynamic environments," in Information Science and Applications (ICISA), 2013 International Conference on. IEEE, 2013, pp. 1–4.

[6] B. Clipp, C. Zach, J. Lim, J.-M. Frahm, and M. Pollefeys, "Adaptive, real-time visual simultaneous localization and mapping," in Proceedings of the 2009 Workshop on Applications in Computer Vision. IEEE, 2009.

[7] X. Gao and T. Zhang, "Robust rgb-d simultaneous localization and map-ping using planar point features," Robotics and Autonomous Systems, vol. 72, pp. 1–14, 2015.

[8] Davis, J. P., Eisenhardt, K. M., Bingham, C. B. 2007 "Developing theory through simulation methods." Academy of Management Review, 32:480–499.

[9] Okereke, M., Simeon K.2018 "A Brief Introduction to MATLAB™." *Finite Element Applications*. Springer, Cham, 2018. 27-45.

[10] T. B. Moeslund, Introduction to video and image processing: Building real systems and applications. Springer Science & Business Media, 2012.

[11] N. Shameena and R. Jabbar, "A study of preprocessing and segmentation techniques on cardiac medical images," 2014.

[12] A. Ballabeni, F. Apollonio, M. Gaiani, and F. Remondino, "Advances in image pre-processing to improve automated 3d reconstruction." International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences, 2015.

[13] M. Sonka, V. Hlavac, and R. Boyle, Image processing, analysis, and machine vision. Cengage Learning, 2014.

[14] A. O. Yinka, S. M. Ngwira, Z. Tranos, and P. S. Sengar, "Performance of drivable path detection system of autonomous robots in rain and snow scenario," in Signal Processing and Integrated Networks (SPIN), 2014 International Conference on. IEEE, 2014, pp. 679–684.

[15] H. Williams, "Human inspired robotic path planning and heterogeneous robotic mapping," 2016.

[16] F. Heukels, "Simultaneous localization and mapping (slam): towards an autonomous search and rescue aiding drone," Master's thesis, University of Twente, 2015.

[17] S. Oh, M. Hahn, and J. Kim, "Simultaneous localization and mapping for mobile robots in dynamic environments," in Information Science and Applications (ICISA), 2013 International Conference on. IEEE, 2013, pp. 1–4.

[18] U. Frese and G. Hirzinger, "Simultaneous localization and mapping-a discussion," in Proceedings of the IJCAI Workshop on Reasoning with Uncertainty in Robotics. Seattle, 2001, pp. 17–26.

[19] G. Kosuru, "Design and implementation of an ekf based slam algorithm on a mobile robot," Ph.D. dissertation, International Institute of Infor-mation Technology Hyderabad-500 032, India, 2011.

[20] E. Z. Gomez," "Map-building and planning for autonomous navigation of a mobile robot," Ph.D. dissertation, Center for Research and Advanced Studies of the National Polytechnic Institute, 2015.

[21] A. Bircher, M. Kamel, K. Alexis, M. Burri, P. Oettershagen, S. Omari, T. Mantel, and R. Siegwart, "Three-dimensional coverage path planning via viewpoint resampling and tour optimization for aerial robots," Autonomous Robots, vol. 40, no. 6, pp. 1059–1078, 2016.

[22] J. Kurlbaum, U. Frese, "A benchmark data set for data association". Technical Report, University of Bremen, available online: http://www.sfbtr8.uni-bremen.de/reports.htm. Data available on http://radish.sourceforge.net/

[23] U. Frese.2004. "An O(log n) Algorithm for Simultaneous Localization and Mapping of Mobile Robots in Indoor Environments". PhD thesis, Technische Fakultat Universit " at Erlangen-N " urnberg.

[24] Li, X., Feng, Y., Huang, R., Zhang, X., Liu, S., & Ai, J. 2017 "The application of square-root cubature Kalman filter in SLAM for underwater robot." *2017 Chinese Automation Congress (CAC)*. IEEE.

ISSN: 2356-5608