Data association of RF-VSLAM for ocean observation using blimp

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Graphical abstract
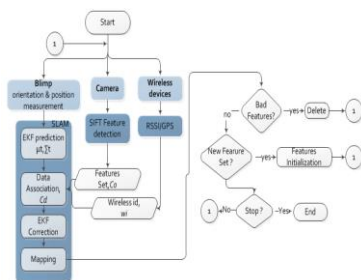
Abstract

This paper describes a selection of features for potential landmarks for ocean observation system using radio frequency visual simultaneous localization and mapping (RF-VSLAM) framework. Due to dynamic changes of the ocean surface caused by the ocean gyres, the features selection is difficult. Therefore, the tendency for vehicles to drift is high. As a solution, we introduced the beacons as an anchor node as an aid to correct the navigation and improve data association. We investigated the data association stage of the RF-VSLAM system which improved the state estimator for the aerial vehicle. The goal is to produce a correct association to the landmarks, since wrong data association will produce inaccurate maps. The points features were extracted from a monocular camera using SIFT as detector and descriptor. The experimental data of the dynamic changes of water surface has been evaluated. The result showed that the data association method was able to produce correct and accurate landmarks selection.

Keywords: Visual SLAM, beacon, buoy, feature, SIFT, data association

Abstrak

Kertas kerja ini menerangkan pemilihan beberapa ciri sebagai mercu tanda yang berpotensi untuk sistem pemerhatian lautan menggunakan rangka kerja frekuensi radio penyetempatan serentak dan pemetaan (RF-VSLAM). Disebabkan perubahan dinamik pada permukaan lautan yang disebabkan oleh gyres lautan, pemilihan ciri ini susah. Oleh itu, kecenderungan untuk melayang adalah tinggi. Sebagai penyelesaian, kami perkenalkan suar sebagai nod utama untuk membantu membetulkan pandu arah dan membaiki hubungan data. Kami mengkaji peringkat hubungan data pada sistem RF-VSLAM yang membaiki penganggar keadaan untuk kenderaan udara. Tujuannya ialah untuk menghasilkan hubungan yang betul kepada mercu tanda, kerana hubungan data yang tidak betul akan menghasilkan peta yang tidak tepat. Ciri titik-titik diekstrak daripada kamera monocular menggunakan SIFT sebagai pengesan dan penghurai. Data eksperimen daripada perubahan dinamik permukaan air telah dinilai. Dapatan kajian menunjukkan bahawa kaedah hubungan data dapat menghasilkan pemilihan mercu tanda yang betul dan tepat.

Kata kunci: Penglihatan SLAM, suar, boya, ciri, SIFT, hubungan data

1.0 INTRODUCTION

The oceans cover greater than 70% of the earth surface which consists of 99% of living space on earth. The coral reefs, salt marshes, estuaries, mangrove and sea grass beds are the ocean environments which support a large number of different types of organisms. Without healthy ocean space for the organisms to survive, there would be five decreasing phyla of animals on the earth. Therefore, continuous ocean observation system will help to protect the oceans and preserve the biodiversity which will sustain earth food chain [1]-[3]. A number of researchers have investigated the ocean issue with platform such as the ship[4], autonomous underwater vehicle (AUV) [5]-[6], remote operated vehicle (ROV) [7], and ODAS buoy [8]-[9]. In this work, we propose a cooperative decentralized observation system using Ariel vehicle known as blimp and buoys as the beacons. Both platforms offer an environmental friendly observation system which preserves natural value of the selected area. In addition, the cooperative system offers larger bandwidth of data covering the underwater data, ocean surface data and aerial image [10].

The RF-visual simultaneous localization and mapping (RF-VSLAM) algorithms are used for estimating the pose on moving blimp; RF-VSLAM technique perform localization and mapping problem of navigation in an unknown environment using the IMU, camera and RF devices. The visual information from the camera provides lots of information with less payload. The buoys are introduced as landmarks and also as a device to record the ocean underwater and surface. There are two fundamental issues for the visual SLAM system which are to detect new features and finding matching between frames [11]-[12]. Therefore, the features point selection is important to improve the decision in order to add the landmark into the map; while correct data association is important to ensure consistent estimates of the vehicles. The contributions of this paper are divided into two parts. First, we proposed the approach of ocean observation for the coral reefs area using RF-VSLAM. To the best of our knowledge, this is the first work that uses water surface and buoy for feature extraction using blimp. Second, we introduced data association framework for RF-VSLAM. The features selection is important to produce a correct association to the landmarks, since wrong data association will produce inaccurate maps. The rest of the paper is structured as follows. Section 2 presents the approach and method as well as the details of data association method. Section 3 presents the experimental setup. Finally, Section 5 concludes the paper.

2.0 PROPOSED METHOD

The ocean surface is affected by the dynamic changes of environment such as ripple of water reflecting the sun and different level of sun light spread. Furthermore, the number of static features is less and the most prominent features are waves and ripple. Figure 1 shows the sample of ocean surface images.

Figure 1 Sample of ocean surface scenes

The landmarks should contribute to the most prominent features point. In this work, we used visual landmarks as the point in space. As the blimp moved, the monocular camera captured the ocean surface images and the database of landmark will be updated over selected frames. In this case, it was difficult to use the ocean surface for landmark initialization since the dynamic changes of ocean surface. In consequences, it contributed to complex data association problem. Therefore, the buoys were used as beacons to introduce reliable features point to improve data association capability. There were several detectors and descriptor method used for visual SLAM such as MSER, Harris-Laplace, SIFT and SURF. However, the SIFT detector and descriptor were chosen due to their capability to produce the highest key point number and matching pairs compared to MSER and SUFT[12].

2.1 Data Association

In order to choose a valid landmark to be added in the database, the following criteria were considered. When the features point is not found or visible in the current frame, the landmark is not valid. If the features point is found as expected in the current frame, the landmark is valid. If the landmark is found as expected in the current frame, and in the threshold range, the landmark is added in the database. If the landmark is found as expected in the current frame, and in the threshold range, the landmark is considered partially valid and will be analyzed using data association method before being added in the database. If the landmark is found as expected in the current frame and in the threshold range with valid wireless identification, the landmark is added in the database. Therefore, a new feature is initialized. Figure 2 shows the data association method proposed.
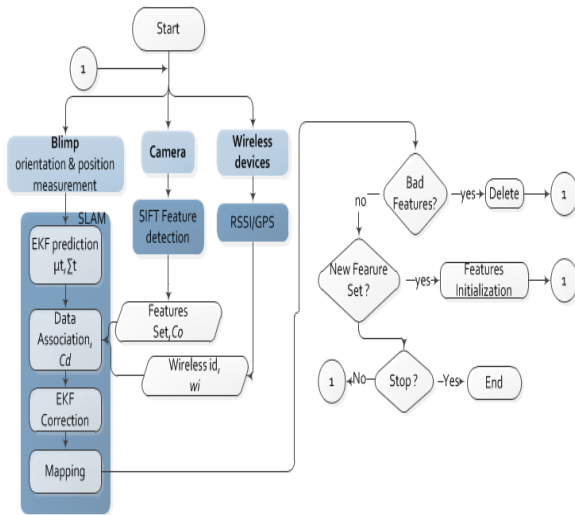
Figure 2 Data association method

3.0 EXPERIMENTAL SETUP

In order to validate the selection of RF-VSLAM landmarks, we have recorded the real time video on sequences of the movement on water surface and processed them using Matlab™. Figure 3 shows the platform used in the experiments
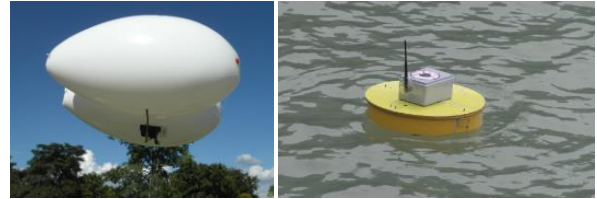

Figure 3 Platform (a) Double hull Blimp (b) Beacon with wireless coverage

As a blimp explores the environment, the landmarks are updated based on the EKF equation. An EKF state consists of state vector X_i of the blimp and landmark state vector X_m with a set of landmark coordinates. State vector Xi is given by

$$X_i^T = [x \quad y \quad \varphi] \tag{1}$$

State vector Xm for the landmark is given by

$$X_m^{\ T} = [m_1^w \quad m_2^w \quad \ldots\ldots\ldots \quad m_N^w \quad] \tag{2}$$

where *i* is the order of landmarks added and *N* is the number of landmarks. In EKF prediction, the blimp heading is updated and estimated based on data association method using heading reading, landmark coordinates and wireless id.

The SLAM prediction step is as follows:

$$X_{ik} = F_v(X_{ik-1}, u_{ik}) + w_{ik} \tag{3}$$

$$u_{ik} = [\delta_h]^T \tag{4}$$

where w_{ik} is the process noise, u_{ik} is the process input and δ_h is the compass output representing blimp heading. Therefore, the state k in EKF at prediction is given by

$$X_i = \begin{bmatrix} x_{k|k-1} \\ y_{k|k-1} \\ \varphi_{k|k-1} \end{bmatrix} \tag{5}$$

However, it must decide the correct observation. The corresponding to the features selection, C_d is given by

$$C_d = [C_o \quad w_i]^T \tag{6}$$

In the experiments, we aim to select features points that reappeared in the next selected frame in a range of threshold as landmarks. We have considered a sequence of images which captured the sea surface view with sequence of 30 frames per second (fps). Since all feature points were tracked over time, the beginning and the last frames were selected to be sampled to reduce computational cost. As SIFT features were extracted from the video frames, the best candidates for each point was identified using the minimum euclidean distance.

$$d = \sqrt{\sum_{i=1}^{128} \left(d_1^n(i) - d_2^n(i) \right)^2} \tag{7}$$

When a new landmark is detected and added into the EKF states, variance and covariance of the landmark are calculated and updated in the EKF. We assumed that, the wireless id was known in advance, to enable the evaluation the data association specifically for features point.

Two types of scene were considered in the experiment; (1) Clear water (2) Dark water.

3.1 Scenario 1-Clear Water

In order to proof the concept, the experiment was done in a pool area with a confine setup as shown in Figure 4. This is due to several issues such as deploying the autonomous blimp which suffered high instability issues especially to strong wind. The blimp logged its own position and orientation data from the IMU sensor, and flied in predefined waypoint. At the same time, it performed feature detection and extraction from video captured by the downward looking camera attached to the blimp.

Figure 4 Experimental setup

3.2 Scenario 2-Dark Water

In this scenario, several images were captured near Penang, Malaysia coastal marine waters. The blimp was not capable to be deployed due to strong wind. Therefore, a sequence of image was used to proof the capability of the algorithms to produce correct and accurate landmarks selection with dynamic background of ocean water. It should be noted that the same camera and buoy were used in the setup.

4.0 RESULTS AND DISCUSSION

In this section, we will present the data association performance for two types of water scene as mentioned previously. The data association performances were examined in a several of numbers of features points and view angles to analyze the extraction performance.

4.1 Feature detection

Table 1 shows, three sample of images selected from video sequence which were used to evaluate features detection performance using SIFT descriptor. As can be observed, five key point of detection numbers for an image were analyzed. The selected features number used to evaluate the capability of the data association to select the most reliable feature point in each image frame and the effect on the buoy extraction performance. The results showed that for each image frame, different detection points were obtained. This is due to the effect of water surface changes. When the number of features to be detected is small, the algorithms are not capable to detect the buoy as main interest point because the water dynamic produces more prominent feature point in the image frame. As the number of features points increase the features detection becomes more reliable and include the buoy as the interest point. Therefore, increasing the chance of buoy to be considered in the extraction. Qualitatively, the results of the detection produced good features detection output.

Table 1 Samples of features detection performed by SIFT detector–Clear Water

Feature no.	Detection Sample 1	Detection Sample 2	Detection Sample 3
10			
50			
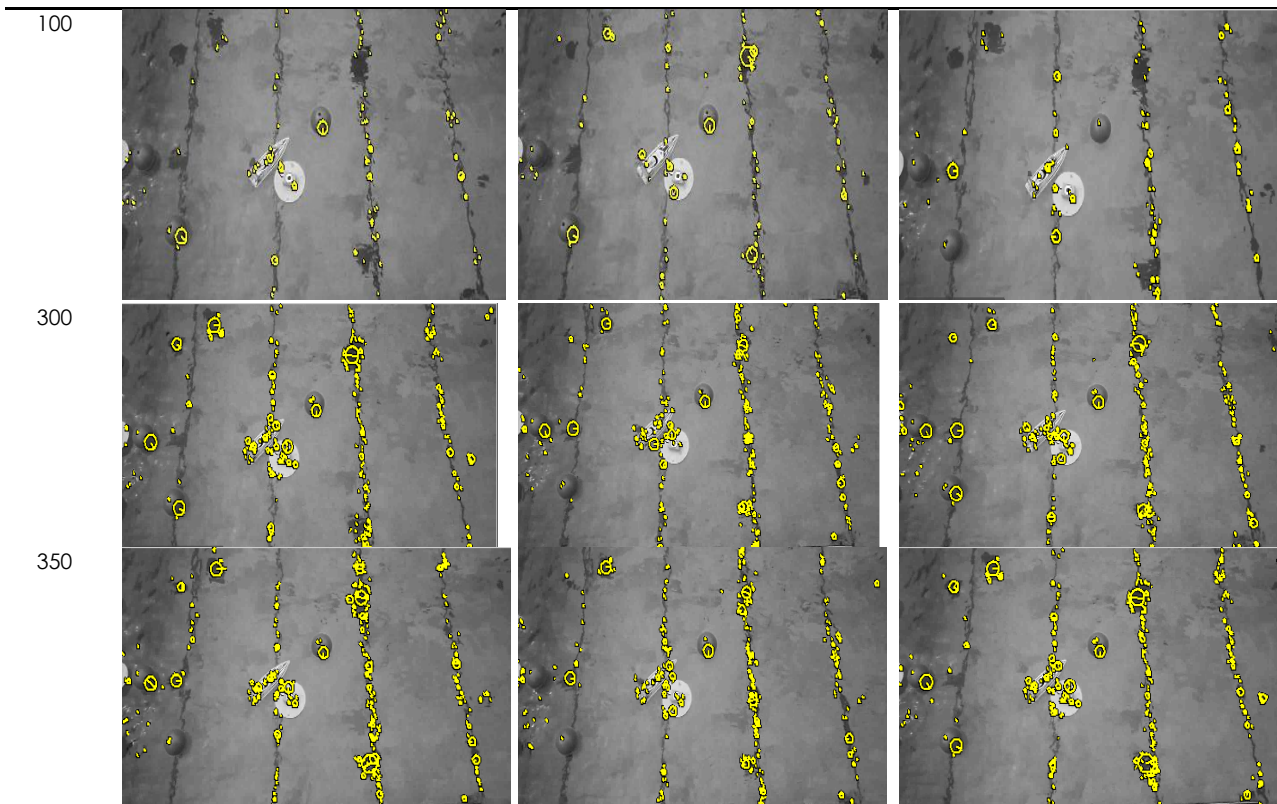
4.2 Feature Extraction

To avoid considering the unreliable features and temporary features, the descriptor selected the buoy as the final interest features. Figure 5 shows, a sample of process that has successfully detected the buoy as required. Each detection included feature frame information denoted as [X; Y; S;θ], where X,Y is the center of the frame, S is the image scale and θ is the orientation. The results of buoy extraction are presented in Figure 6. It can be observed that as number of key point detection increased, the number of beacon detected also increased. In fact, a fine linear trend was shown with R^2 value of 0.926. This reveals that, using a large number of key points in the detection, has improved the quality of extraction results. However, with more landmarks in the map, finding the correct data association becomes computational expensive. In order to overcome this issue, we can reduce the number of observation by selecting appropriate time sample for the frames.
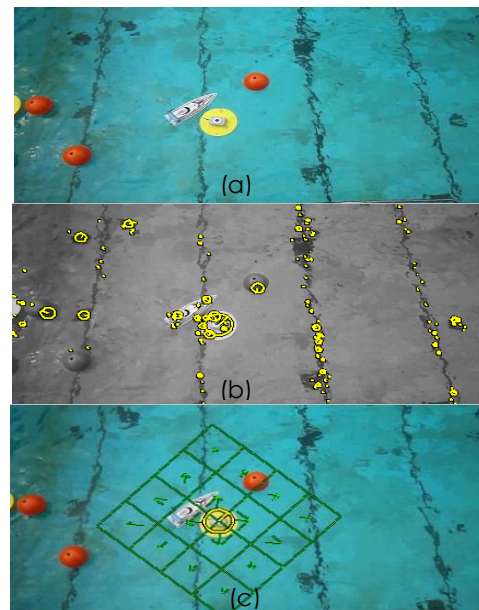

Figure 5 Sample of detection and extraction based on 150 features point in an image(a) Features point : 150 (b) Features Detection (c) Extraction of beacon features
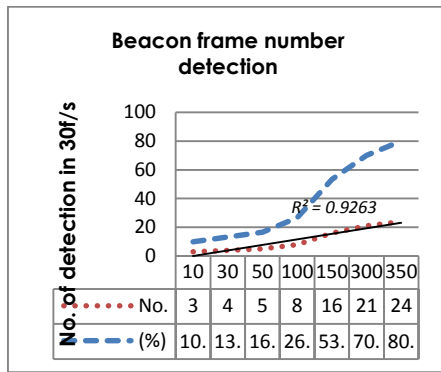
**Figure 6** An analysis of buoy extraction

4.3 Ocean Surface

In our final experiment, the performance of data association was evaluated with video of dynamic ocean surface. The data association method from the previous example was applied in the experiment. However, several issues need to be considered since the features extraction of the ocean surface environment was difficult due to less number of static features, changes of waves, ocean colour, and sunlight reflection. Figure 7 shows feature detection of ocean surface for two different image frames. The feature detection was prone to select the sunlight reflection on the surface as the interest point compared to surface without sunlight reflection. Therefore, appropriate numbers of features to be detected need to consider to ensure that the desired interest point were detected. The incoherent detection for each image frame, suggesting that there should be adequate features to be introduced on the surface, hence buoy was used to increase the static texture on the environment. Table 2 shows the sample of detection and extraction of buoy from different angle with ocean surface background. In this experiment, we have set key point detection numbers of 50. Although, each image frame was affected by sunlight reflection, the method was able to detect the buoy as final interest point. The results showed that the data association method was able to select the correct features to be registered as landmark.

Table 2 Detection and extraction of buoy from different angle with ocean surface background-Dark water

Sequence	Image	Features Detection	Buoy Extraction
1			
2			
3			
4			

5

6

7
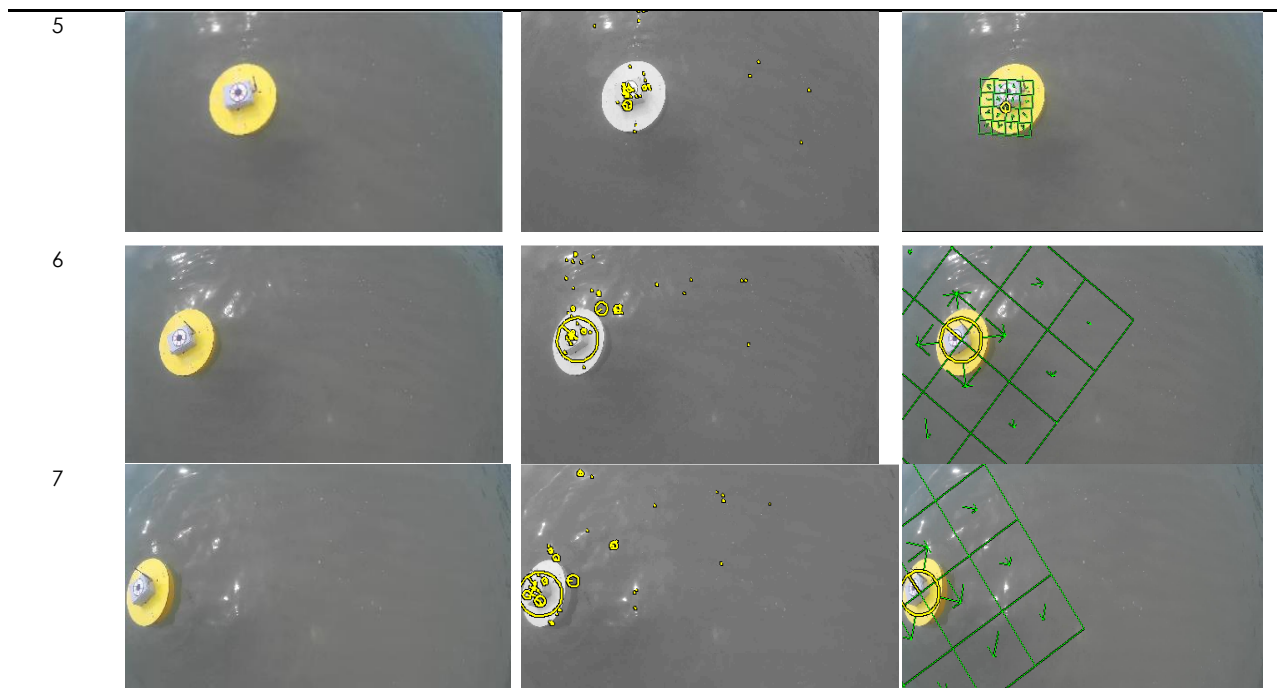
4.0 CONCLUSION

We have presented an approach of ocean observation using a blimp and buoys. Despite the difficulties of landmark selection on the ocean surface, the buoys were introduced to improve the capability of data association capability. The features selections for data association produced correct association throughout all experimental analysis. However, with more landmarks in the map, finding the correct data association becomes computational expensive. In order to overcome this issue, by selecting appropriate time sample for the frames can reduce the number of observation. As a future work, we plan to extend this work by including ocean experimental data. Also extension of this idea to other platform can also be a potential future direction.

Acknowledgement

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