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Estimating Object Location using Particle Clustering on Rotating Sonar Detection

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Abstract
Particle filter been used for localization and position estimation with various applications. Several method applied in order to reduce the complexity of particle information to lower processing resource requirement while providing a precise map. Sonar sensor provide a range precision with poor bearing. Partial observation applied to gain estimation of object location using several measurement from multiple vantage point. This paper propose grouping of detection particle from sonar sensor using clustering method in order to provide estimated object position from a single vantage point. The approach estimate objects using euclidean distance treshold to separate one object detections from the other and group all the detection particle into cluster containing a set of number. As a result of particle clustering, object location can be estimated with their respective weight of certainty as an attribution for further decision making.

Keywords: sonar, particle filter, clustering, slam

1. Introduction

Simultaneous localization and mapping (SLAM) has been widely developed and implemented using several method and approach. SLAM main purpose is to compose an environment map using a mobile robot while estimating it's location on the map simultaneously. Ref [1] state that SLAM problems is successfully solved over last decade using various available approaches and methods.

The essential of SLAM methods use estimation and probability to solve its problem [1]. Statistic calculation used to analyze large amount of data gathered by SLAM system. The SLAM data consist of object and environment detection from robotic sensors and movement data from robotic actuators feedback. Particle filter approach used to manage uncertainty in SLAM data to estimate the robot and objects location on the map. Ref [2] compare various approach of location estimation based on bayesian filters.

2. Sensor Characteristic

SLAM method result highly related with the sensors accuracy and detection modeling [3]. Different sensors produce different output according to its characteristic and measurement method. Surface roughness of material detected also interfere the data acquired [4]. Sensor measurement often uses time of flight method. Equation (1) shows that distance traveled between sensor to object and back to sensor in *d* is the speed of signal in *c* times the flight duration in *t*.

$$d = c.t \tag{1}$$

Sonar typically has the cheapest price compared to others [3]. Sonar sensor return an accurate ranging measurement but poor bearing due to the wide beam and side lobes [5]. Figure 1 shows sensitivity pattern of sonar sensor from different angles [6]. Due to the low speed of sound wave compared with the speed of light, sonar sensor response are slower compared with others [3].
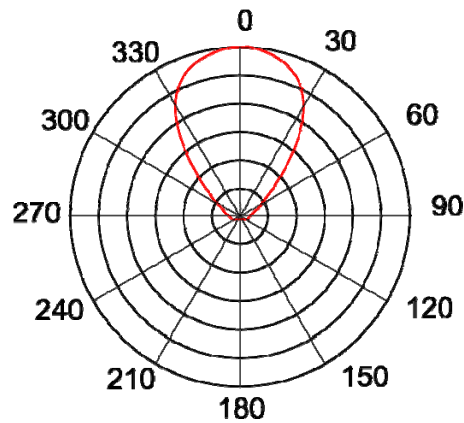
Figure 1. Sonar sensor sensitivity pattern

Laser ranging had the most accurate measurement and also the fastest sensor available in market [3]. Typical laser ranging sensor does detection up to 200m with 0.1^0 resolutions [3]. Disadvantages of using laser ranging are that it is expensive and spent high energy consumption [3]. Laser ranging sensor also had problems with reflecting surface such as mirrors, windows etc [3].

Visual sensor like camera provides a better bearing with poor range [5]. The visual SLAM method locate feature from image captured by the camera as reference for localization and further mapping. Ref [7] describes the application of active vision approach within SLAM systems. Visual approach in SLAM require easily distinguished landmark from their environment [7]. Using available object as landmark generate more object detected and more computation complexity required.

Sensor used in this research is HC-SR04 low cost sonar sensor working on 40 kHz frequency with effective measurement up to 8inch [8]. The servo mounted on top of hxt900 micro servo that provides 180^0 rotation for observation purpose. Sensor mounted on robotic chassis shown on Figure 2.

Figure 2. Sonar sensor mounted on servo

3. Object Localization Approaches

Due to limitations of sensors available, many localization methods introduced. Some system use partial observation with delayed mapping in order to estimate object location from several vantage point [5], [9]. Ref [10] specifically propose robust mapping using sonar data. As described in previous section, sonar sensor provide a precise ranging with poor baring while visual imaging had better baring with poor ranging.
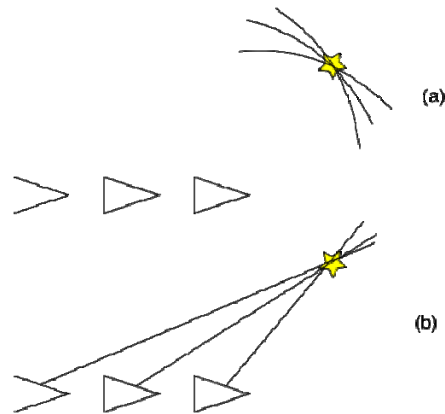
Figure 3. Partial observation (a) range-only (b) baring only

Figure 3 display partial observations which use range only sensor and bearing only sensor [5]. As the robot move, more object detection with more vantage points acquired, resulting a more accurate estimation of object location. Partial observation method requires detection data from at least two vantage points. All the information from every detection vantage point carried along the delayed mapping progress to estimate object location. The large sets of data carried increase computing complexity and spent more resource and energy.

3.1 Particle Clustering
Clustering been introduced as mass dataset grouping method. Ref [11] describes clustering method as an examination process towards collections of data sets and groups them into several clusters with certain similarities between its members. Ref [12] applies clustering for effective and efficient data mining approach based on random search by analyzing spatial distribution.

Rotating sonar sensor generates huge sets of data that are the rotation angle over the resolution. In this research, 180^0 degrees data with 1^0 resolutions generate up to 180 particles for each step. Some angle might return no value because there is no object detected. Ref [13] describe about building a simple SVG map to represent spatial information as a result of non destructive observation of robotic system. Figure 4 display a sample map containing spatial distribution of sonar sensor detection particle.

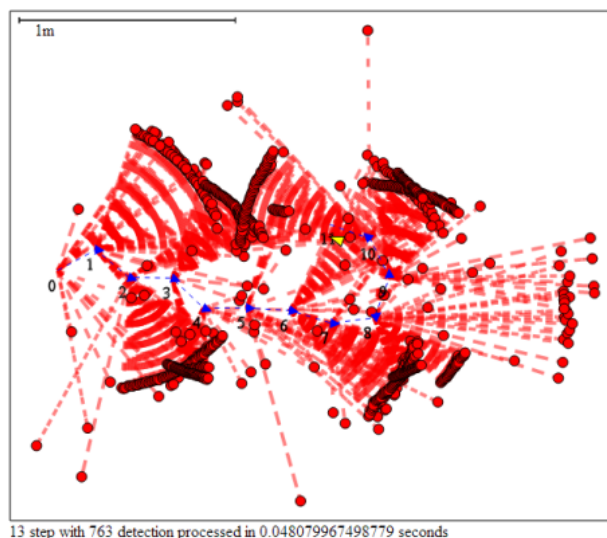13 step with 763 detection processed in 0.048079967498779 seconds

Figure 4. Sonar detection sample data

This paper propose clustering of detection data for each step resulting estimated object position and the weight of object location certainty to represent the amount of particle providing the estimation. Cluster generated by separating detection data using predefined amount of Euclidean distance threshold.

Figure 5 shows the clustering process flow. The process calculates Euclidean distance between two particles and compares it with predefined threshold to determine whether they belong to the same cluster or not. Object location can be estimated as the average location of every particle in one cluster. This research use polar coordinate system to represent spatial information. Euclidean distance on polar coordinate system also called radial distance. Radial distance of two particle *p* and *q* are described in (2).

$$d_{p \to q} = \sqrt{r_p^2 + r_q^2 - 2 r_p r_q \cos(\theta_p - \theta_q)}$$

(2)

The number of particle in the cluster represent certainty of the location that increased along with additional measurement data especially from different vantage point. To preserve cluster complexity, particle data can be stored with their respective cluster membership relation for further analysis such as determining object shape, planning obstacle avoidance save path, etc.
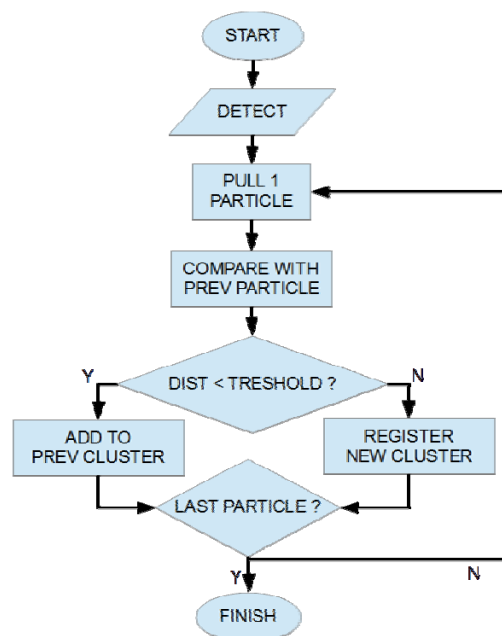

Figure 5. Clustering process flow

3.2 Clustering Result

The estimated object location after particle clustering plotted into two dimensional maps with exact same scale and center point to compare with the particle distribution before clustering. As an example, particle clustering with threshold 10cm and no minimum certainty weight displayed in Figure 6.

Figure 6 shows less detection particle and detection line compared with Figure 4. As the distributed particle clustered, the object estimated position can be pointed on the map based on single vantage point detection. Certainty value displayed as the weight of the object point and the detection line. The weight can be filtered to ignore detection error shown as cluster with less than certain value of certainty.
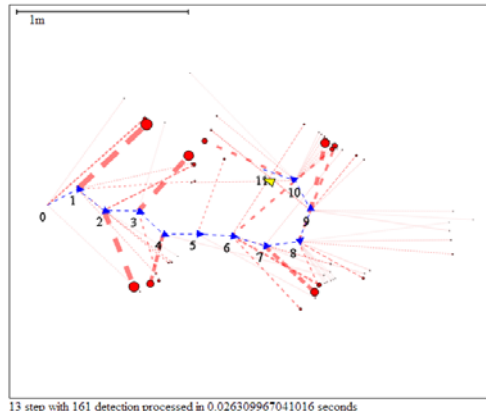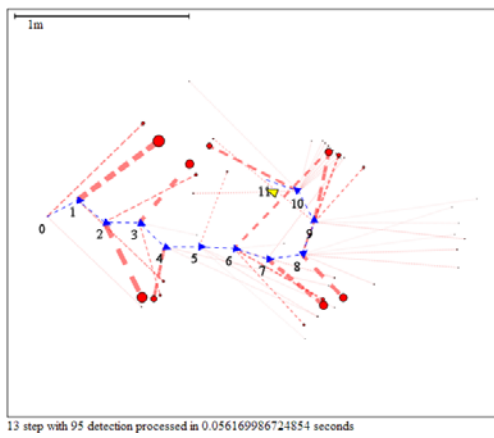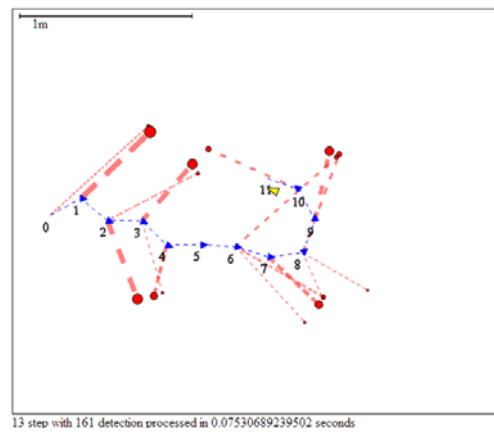
13 step with 161 detection processed in 0.026309967041016 seconds

Figure 6. Sonar detection after clustering

13 step with 95 detection processed in 0.056169986724854 seconds

(a)

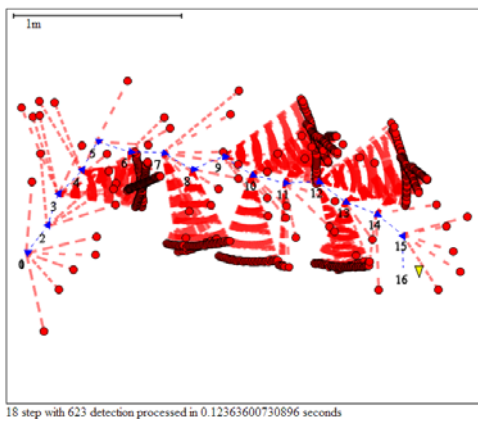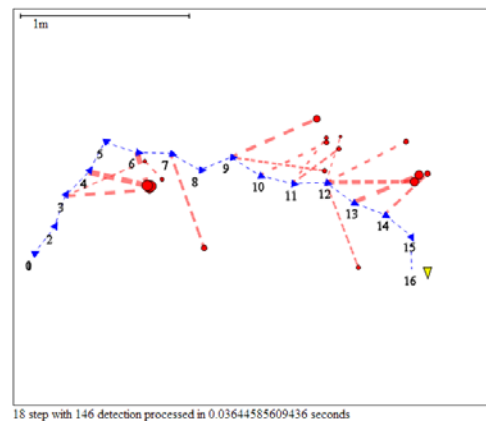13 step with 161 detection processed in 0.07530689239502 seconds

(b)

Figure 7. Sonar experiment data using different parameter (a) 20cm threshold and no minimum weight. (b) 10cm threshold and minimum weight 10.

18 step with 623 detection processed in 0.12363600730896 seconds

(a)

18 step with 146 detection processed in 0.03644585609436 seconds

(b)

Figure 8. Different data also shows less noisy map (a) before clustering (b) after clustering

The value of Euclidean distance threshold and minimum weight of certainty can be defined as fix number or dynamically change along with the maturity of the data and object certainty. Further artificial algorithm can be added for object localization decision making based on the location cluster. Figure 7 and Figure 8 display the result of experiment using different

value of threshold and minimum certainty weight.

The larger value of threshold resulting larger coincidence of two particles grouped into single cluster, therefore it generate less cluster but may accidentally recognize two different object as one. With various weight of certainty, the higher minimum weight will eliminate more uncertain cluster resulting less cluster displayed on the map.

Ref [14] describes the complexity of tracking 3-dimensional object using 2-dimensional visual. The clustering method generates single feature point for every objects reducing computation complexity.

4. Conclusion

This research successfully simplified distributed particle and form estimations of object location as single feature point for every step of robot position. Particle clustering allows better view of the map displaying less data and more information.

The higher value in threshold and certainty weight, the less cluster generated lowering further computation complexity but may resulting multiple object recognized as one.

Further research can be applied using several sensor like laser, imaging and inertial measurement unit.

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