Tracking Objects Using PHD Filter for USV Autonomous Capabilities

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Abstract. Most of the work on automatic detection tracking and classification of unmanned applications over the past twenty years has been focused on ground and aerial vehicles. Recently, the research has also focused on unmanned surface and underwater vehicles for autonomous capabilities.The ability to recognize and identify obstacles becomes more essential with USVs autonomous capabilities, such as obstacle avoidance, decision modules, and other Artificial Intelligence (AI) abilities using low cost sensors. This paper presents multi-target automatic algorithm stages to acquire, identify, and track targets from an Unmanned Surface Vehicle (USV) located in marine environments with LIDAR sensor challenging clutter. We present several clutter models and formulations to handle clutter phenomena. We propose the Probability Hypothesis Density (PHD) Bayes filter, challenging clutter for multi-target tracking.

1 Introduction

One of the most difficult challenges for USV navigation is the recognition of obstacles around the vehicle without human intervention. This task is known as Automatic Target Detection (ATD). An efficient ATD system should achieve a high detection percentage for targets while maintaining a minimal false-alarm rate. This means that it must preserve an optimal balance between a high detection rate and a low error probability. However, ATD algorithms are very sensitive and unstable regarding clutter elements, i.e. elements that are not targets but still part of the scenes with similar characteristics to the targets. Dealing with clutter in ATD algorithms and multi-target environments have been extensively studied [5, 6, 7, 8, 9]. Common, well-known methods try to separate between the targets and noises with Blind Source Separation (BSS) [9, 10, 11].

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Several methods with advanced filter characteristics proposed over the last few years, such as the Joint Probabilistic Data Association Filter (JPDAF) [5], Multiple Hypotheses Tracking (MHT) [6], and the multi-target particle filter [7, 8] use observations weighted by their association probabilities. A new and efficient formulation without an explicit base between measurements and targets is Random Finite Sets (RFS) [9], demonstrated in [10]. The main idea behind RFS is based on two different kinds of collections. The first consists of the individual targets and is called the 'set-valued state', while the second consists of the individual observations and is called the 'set-valued observation'. This kind of modeling allows allows the estimation of the targets in the presence of clutter in a Bayesian filtering framework [9, 10, 11]. Advanced RFS-based filters such as the multi-target Bayes filter, the Probability Hypothesis Density (PHD) filter [9, 10, 12] and their implementations [12], have also generated substantial interest.

In our paper we demonstrate tracking and decluttering targets in marine environments by using these kinds of filters. One of the key tasks which intelligent autonomous marine craft have to perform is safe and efficient navigation, which depends directly on the reliable perception of the environment. A high quality sensor is required for close to mid ranges, as a substantial part of the detection and alert belt of the USV lies within this range. As with many other sensors, the primary limitations of LIDAR sensors in marine environments are related to clutter.The Velodyne HDL-64E 3D-LIDAR provides 3D range scans [1]. Typical data in marine environments with sea clutter can be seen in Fig. 1. Therefore, it ought to be either filtered, or the obstacles distinguished by an efficient algorithm using a PHD filter to detect and track multiple targets.

2 Advanced Clutter Models

Exact knowledge of sea clutter is highly important in target detection and classification, and of course permits an efficient tracking. Many algorithms use static clutter models for target detection; an extensive study can be found in [14]. We introduce the main concepts of clutter models which aim to predict sea clutter. First, the 1D Stochastic model, which is an extension of the classical approach. It relies on the phenomenological model of the dynamics of the sea, as can be seen in Fig. 2. Basically, two kinds of waves are encountered at the surface of the sea, generated by two different mechanisms, capillary waves and gravity waves. Capillary waves are generated by the influence of the wind and express the surface tension of the water, while gravity waves are mainly generated by the accumulation of gravitational forces and are the main energy carrying factor. The combined effects of capillary and gravity waves over the scattered electromagnetic waves translate into a composite echo, which is the sum of two components- one having a Gamma PDF (Probability Density Function), corresponding to a large scale, slow varying physical structure, and the other having a Rayleigh PDF, corresponding to a small scale, rapid varying physical structure as can be seen in Fig. 3. The advantage of this model is the compatibility with the existing radar processor and detection algorithms [4]. However,

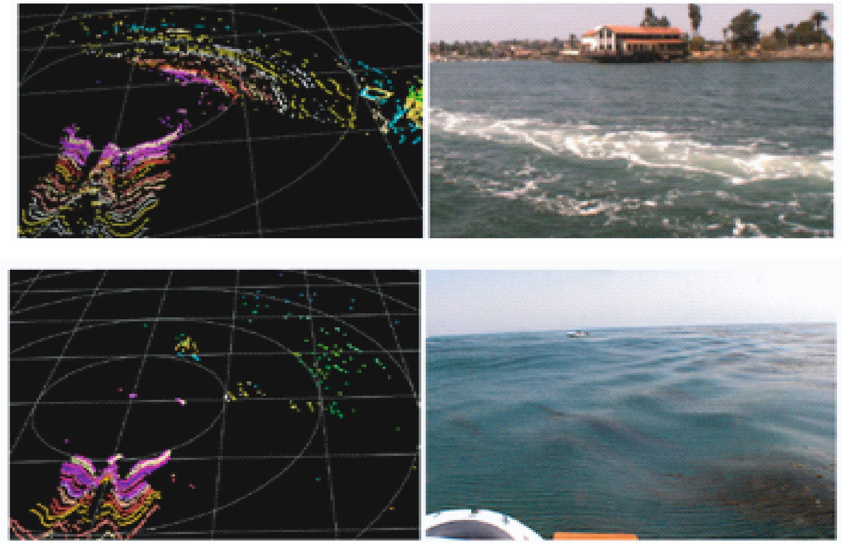

Fig. 1 Velodyne HDL-64E 3D laser scanner LIDAR in Marine Environment [Velodyne Records]

this model has been stretched to the limit- it's quite difficult to obtain a valid set of parameters for an assumed PDF from recorded sea clutter samples, leading to poor results. Moreover, it is not logical to describe the sea using one variable. However, adding more dimensions removes simplicity.

Second, is Texture Realization, which ignores the classic detection algorithms. A set of real data representing measured sea clutter samples is recorded. Then, this information is used to extract a "mask" filter of the clutter, which would permit the reproduction of its stochastic and correlation properties, using a completely new technique. This approach seems quite promising, even though it depends on the training performance of neural networks. More work on real data is required before credibly validating it.

The third is the chaotic model, which assumes that the processes involved in sea clutter generation are non-random, but purely deterministic phenomena. This approach also requires a new radar processor paradigm. Results obtained from one of the prototypes of this model seems are very promising [15], achieving perfect detection. More real data validation and noise robustness are required for credible validation. Moreover, this model involves fractals (non-integer dimensions). The chaotic model is not a trivial one for the standard detection models, due to the statistical character of the model. The classic chaotic model introduced by [15] also known as the Exponential Sensitivity to Initial Condition (ESIC) claims that two systems governed by similar terms will have divergent evolutions, even in similar initial conditions. The model can be expressed as an exponential relation. Let $c(0)$

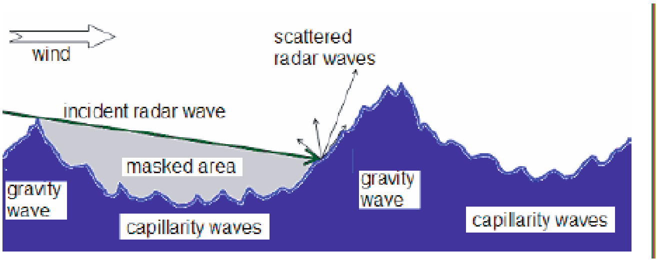

Fig. 2 The phenomenological model of sea surface and interaction with electromagnetic waves [14].

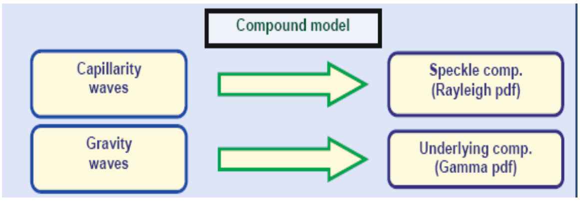

Fig. 3 The compound model of the sea clutter [14].

be the small separation between the initial condition of the two systems (at time $t = 0$). Then, the separation between their states at the time t can be written as:

$$c(t) \approx c(0)e^{\lambda t} \tag{1}$$

where λ is a positive quantity known as the Lyapunov exponent.

3 PHD Object Tracker

As a result of the inefficiency and inaccuracy of all the models above, there is a need for a different approach to track multi-objects. The objective of the multi-object tracking problem is to estimate the state of an unknown number of objects, based on the measurements of the objects corrupted by noise, in the presence of clutter. The classical approach for solving this problem is to apply a stochastic filter such as the Kalman filter [2, 3] or its variants to each object, and use a data association technique such as the Nearest Neighbor to assign the appropriate measurement to each object and track each object separately. An alternative and a more elegant approach is to consider the multi-object set as a single meta-object and the measurements received by the sensor as a single set of measurements, and model them as Random Finite

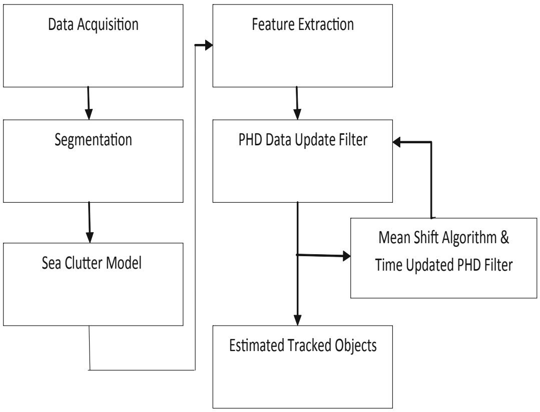

Fig. 4 Block diagram of PHD Tracker Filter

Sets (RFS). This allows multiple objects to be estimated in the presence of clutter, and any data association uncertainty to be cast in a Bayesian filtering framework. Optimal Bayesian multi-object tracking is not yet practical due to its computational complexity. However, a practical alternative to the optimal filter is the Probability Hypothesis Density (PHD) filter, which propagates the first order statistical moment of the full multi-object posterior distribution. The original algorithm is intractable, thus a recursive algorithm which propagates the posterior intensity is employed, which involves Gaussian mixtures. The different stages of this method are described in Fig. 4. We tested our algorithm in simulations with recorded data from Velodyne LIDAR using 1.8GHz Intel Core CPU.

3.1 Stabilized 3D LIDAR

The Velodyne HDL-64E provides 3D range scans by rotating an array of 64 beams around its vertical axis producing around 1.2 million points per second. Usually, the sensor is mounted and stabilized on top of the mobile platform providing range scans with a full FOV in horizontal direction. In case of unstabilized LIDAR, USVs roll pitch and heave are compensated for using IMU measurements and the GPS location is part of the Lidar inputs . In the horizontal direction, the array provides 360 degrees field of view (FOV) with an angular resolution of approximately 0.09 degrees. Vertically, the pitch angles range from -24.8 to +2 degrees. The Velodyne HDL-64E LIDAR can detect a target of one meter in length from a distance of 100 meters. Its range measurement accuracy typically is within 10 cm.

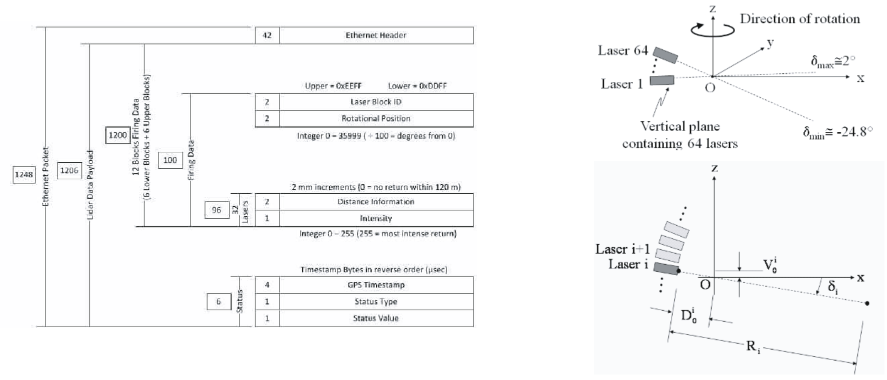

Fig. 5 The UDP Packets Structure and Axes Parameters [1]

3.2 *Data Acquisition*

The 3D point cloud data from each scan is projected onto a cylinder whose axis is the rotational axis of the LIDAR. This projection yields a range image, whose pixel intensity values correspond to the distance measurements. This is a standard way to represent LIDAR data in different terrain, commonly used in applications such as aerial vehicles for urban terrain modeling [1]. The LIDAR use UDP structure data to the main computer, UDP packets structure and axes parameters on the USVs can be seen in Fig. 5.

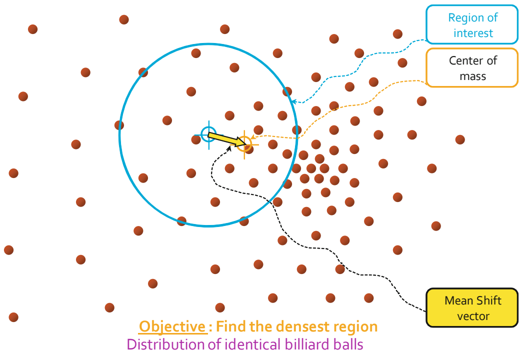

Fig. 6 Mean Shift Algorithm Illustration - Step 1

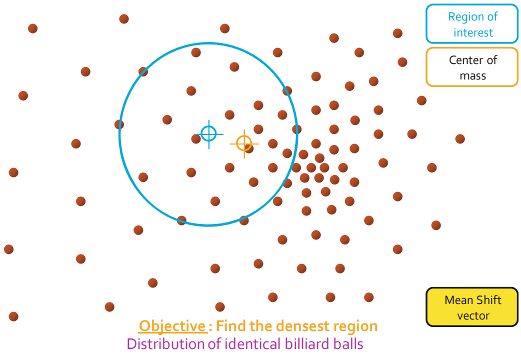

Fig. 7 Mean Shift Algorithm Illustration - Step 2, Location of center of mass and center of region

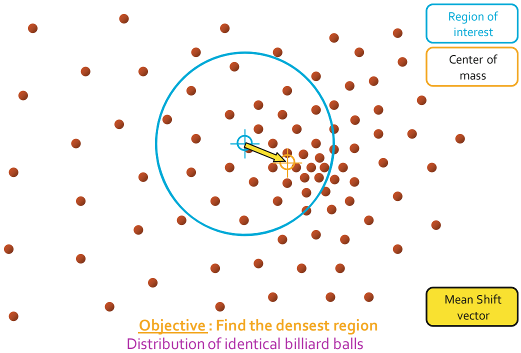

Fig. 8 Mean Shift Algorithm Illustration - Step 3, Mean shift vector from center of mass and center of region

3.3 Segmentation

The range image is segmented using a mean shift segmentation technique. It consist of two steps: mean shift filtering of the original range image data, followed by clustering of the filtered data points. The centroids of the segmented cluster are used as measurement z axis values to update the PHD filter prediction. We illustrate our mean shift algorithm on a distribution of identical billiard balls, which is identical to LIDAR 3D range scans. We can see in Fig. 6 the region of interest as same as the range of the LIDAR in our case, and the center of mass (such as the 3D range scans). Mean Shift is proportional to the normalized density gradient estimate

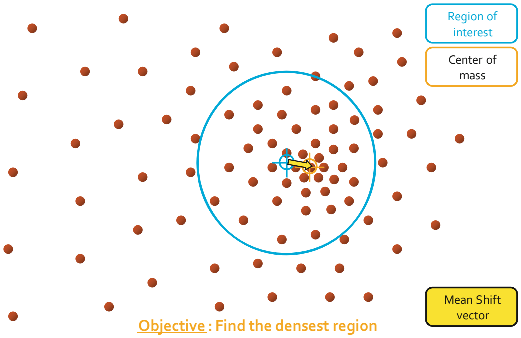

Fig. 9 Mean Shift Algorithm Illustration - Step 4, Mean shift vector from center of mass and center of region

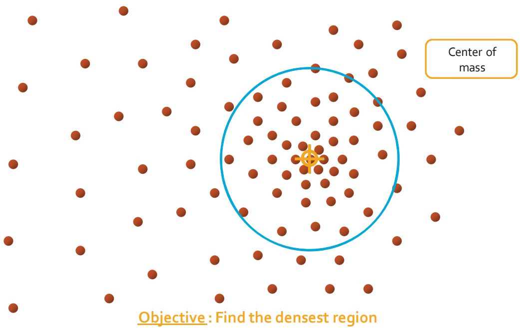

Fig. 10 Mean Shift Algorithm Illustration - Step 5, Convergence of center of region to center of mass

obtained with kernel. The mean shift vector is change as can be seen in Fig. 7 - Fig.9, until convergence can be seen in Fig. 10.

We introduce our initial results of mean shift segmentation implemented on two test cases. In Fig. 11 and Fig. 12 the noises from the background are cleaned, and the points related to the object are connected successfully. Our next is to test our implementation on real records from LIDAR with our mean-shift segmentation.

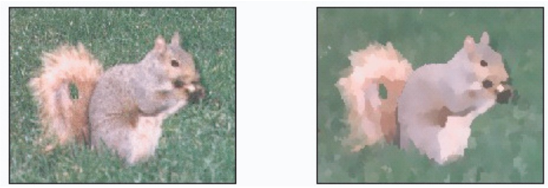

Fig. 11 First Test Case Mean Shift Algorithm. The original picture can be seen at the left, and the one with mean shift algorithm on the right.

Fig. 12 Second Test Case Mean Shift Algorithm. The original picture can be seen at the left, and the one with mean shift algorithm on the right.

4 Conclusion

This paper presents an initial research direction for tracking multi-targets in marine environments for USV autonomous capabilities. LIDAR sensors are very precise, however, they are challenged by clutter and moving platforms for target detection and tracking in real time. We present several models for clutter formulation as an options for decluttering LIDAR measurements. Additionally, we propose the PHD filter, which is an advanced RFS-based filter. We describe the main stages for multi-object detection and tracking using this filter. We demonstrated our segmentation and mean-shift implementation on two test cases. Future work will focus on testing our implementation on sea records and sea experiments with the LIDAR sensor and PHD filter for testing and validation of our concept testing algorithm efficiency and power consumption integrated into small USV.

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