Surface Ship Location Based On Active Sonar Image Data

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Abstract

A human observer can locate surface ships in sequences of active sonar images based on intensity features due to the ship's hull, wake, and its emitted cavitation noise. Three different sector-scan sonar image target detection and tracking algorithms are examined here that will inform further research towards the goal of developing a computer algorithm to perform the surface ship detection.

Introduction

Active sonar emits an acoustic pulse into a body of water and collects signals from an array of hydrophones (underwater microphones) in a finite time after the pulse. Given a constant speed of sound, the range to a given target can be calculated from the time it takes the emitted acoustic pulse to travel from the sonar to the target and back, divided by 2, and multiplied by the speed of sound in water. Match filtering the hydrophone data with the the transmitted pulse increases the time resolution, and thus the range resolution, that can be extracted from the signal data containing reflections of the transmitted pulse. Beamforming "points" the response of the hydrophone array in a specific direction, or usually, many specific directions. Such conventional signal processing produces an bearing versus range intensity response image per emitted pulse. From emitted pulse to the beamformed result, the cycle for one emitted pulse is referred to as a "ping," for historical reasons (reference?).

In addition to the acoustic reflections, the hydrophones also receive other acoustic energy, including cavitation noise produced by a ship's propeller. Despite a signal processing chain tuned to detect reflections of a transmitted pulse, this energy shows up in the resulting images.

A human observer can visually locate surface ships in the bearing vs. range sonar images images by a combination of their characteristics. An acoustic reflection from the the hull of a

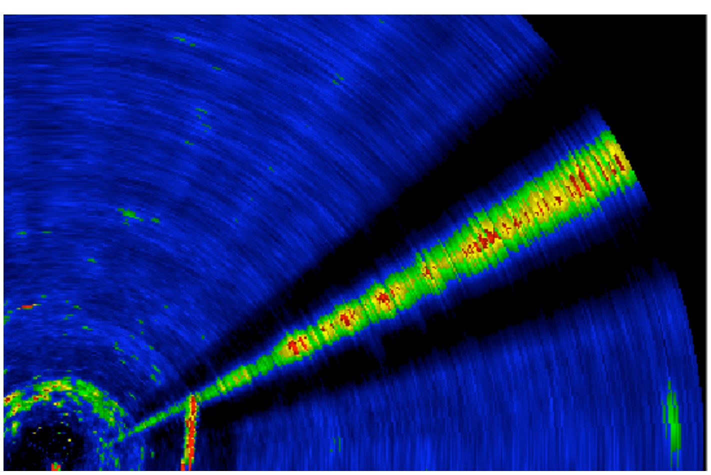


Fig. 1.
Portion of active sonar image showing radial cavitation noise spoke and reflection from boat wake. Source: ARL:UT

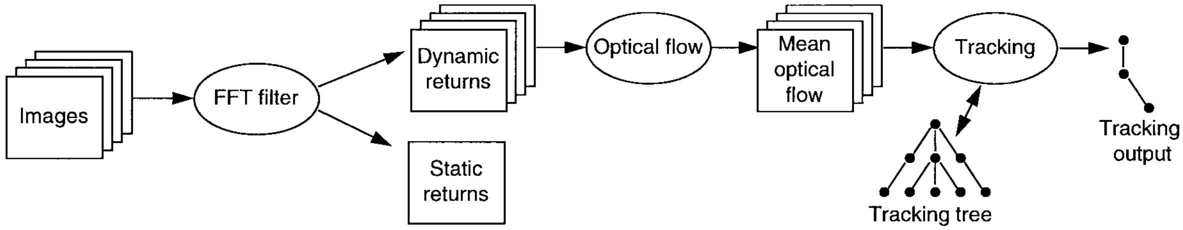
stationary, silent ship becomes an intensity point in the sonar image. However, if the ship is moving under it's own power, such a point is swamped by other features. An acoustic reflection from the persistent air bubbles in the ship's wake appears as an intensity line according to the wake's position. Constant acoustic noise produced by the ship appears as a radial line in the image according to the ship's bearing. See Figure 1 for an example of an active sonar image with a wake reflection and a noise spoke (beam vs. time plotted as azimuth vs. distance).

A variety of applications could benefit from a computer algorithm that could automatically locate surface ships from sequential active sonar data. In particular, underwater vehicles must be able to avoid collisions with ships when surfacing. This requirement is well illustrated by the disastrous February 2001 collision between the USS Greenville nuclear submarine and a Japanese fishing boat. An autonomous underwater vehicle does not have the luxury of a human operator, but must still avoid such collisions whether surfacing or docking with a larger ship or submarine.

Much work has been published on active sonar image feature tracking. Much of it is devoted to features that appear on the bottom or in the water column, and not to the specific problem of avoiding surface ships. However, many of the concepts studied may be applicable to the problem at hand.

In general, target tracking from sonar data has two main parts. First is a filtering stage to refine the sensor data and extract target candidates, and second is a correlation stage to associate target candidates with a track. A matched filter and beamformer, as described above, will assumed to be the first part of the filtering stage for the purposes of this paper. The implementation of the rest of the system varies widely depending on methodology and application.

Fig. 2. Simplified block diagram for optical flow method [1-2].



Optical Flow Method:

Chantler, et. al. devised a method that works over multiple pings to to separate stationary targets from moving ones, and then calculate the optical flow of the moving targets [1-2]. First, a 1-D Fast Fourier Transform (FFT) is applied to the the time sequence of each image pixel across multiple pings. A band pass filter and inverse FFT is applied to obtain images containing the dynamic targets, and a low pass filter and inverse FFT is applied to obtain an image with the static targets (See Figure 2). Each image is thresholded to obtain binary images containing distinct objects.

The apparent motion of the brightness patterns, or optical flow, of the objects in the dynamic images is used to segment the image into significant objects and provide motion information about those objects. These observations are used to find possible associated objects in the next image frame; a tracking tree is constructed by progression through multiple frames and recording multiple possible paths. For each branch of the tree (a possible track), a compatibility measure is computed based on the expected position of the object in the next frame. A cumulative compatibility measure, or confidence value, is recomputed for each branch of the tracking tree with each new ping, where the maximum value is reported as the object's actual track.

Experiments were done with scuba divers moving among a group of pier legs, demonstrating low confidence measures assigned to tracked noise, and high confidence assigned to the divers for a fixed position sonar, a fast sonar ping repetition rate, and smooth target motion.

When these latter assumptions are violated, the algorithm gives significantly degraded performance. However, the algorithm was applied to a moving sonar platform, detecting fixed position objects (the pier legs), which were tracked with high confidence.

Recurrent Neural Network method:

Perry and Guan developed a method to detect small man-made objects from a moving sonar platform [3]. First, the motion of the sonar platform is estimated by tracking a bright seafloor object, along with input from other shipboard navigational systems. Five successive sonar images are aligned based on the motion information and averaged together to enhance contrast and reduce clutter. An adaptive threshold, based on the mean and standard deviation of a local window of pixels, is applied to each pixel in the averaged image to segment it into objects of interest.

The first neural network (a multilayer perceptron, or MLP) operates on the preprocessed images selects target candidates using pre-defined geometric, statistical, and texture-based features, which the authors selected based on previous work. Up to 20 target candidates are tracked, each with a Kalman filter that looks for a matching candidate objects in the next preprocessing image. When multiple candidates are found, it picks the closest one, called the "nearest neighbor" algorithm. These tracked candidates are fed into another neural network to provide final tracked target detection. The authors note that an object is more likely to be detected in the present if it has been in the past; thus their primary innovation is to use a recurrent MLP neural network, with the addition of delay lines (see figure 1), rather than a simple non-recurrent, non-temporal MLP, as this final detection stage.

The authors trained their neural networks with data sets where human analysis of the sonar images was known to correspond to the real world. The version of the algorithm using the

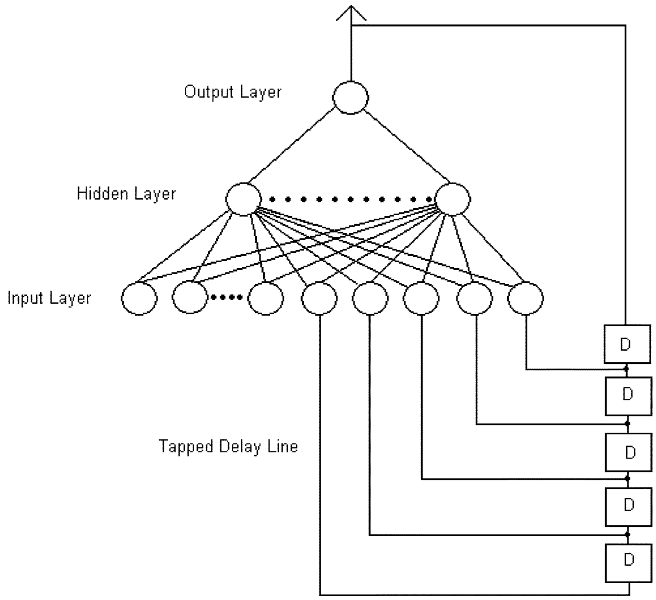


Fig. 3.
Example of a recurrent neural network

recurrent neural network was shown to have superior probability of detection and false alarm rates compared with non recurrent networks.

Surface Watercraft method:

Lo and Ferguson's algorithm detects and tracks a single surface ship from a fixed sonar platform [4]. First, the sonar images are preprocessed by integrating over range cells at a given bearing to achieve a 1m range cell. Then, the image intensity at a given range is normalized by the median intensity over all bearings at that range to reduce effect of beampattern sidelobes and increase contrast.

Target position measurement is obtained by looking for the direction of arrival of the surface ship's emitted cavitation noise. This is done by integrating the image intensity over range per bearing, and looking for the bearing with the maximum energy. Range measurements are only looked for at the measured target angle. To prevent the cavitation noise present in the range profile from giving false target range measurements, a moving window median normalizer is used along the target range. Further false detection is prevented with a geometric fading algorithm that subtracts out the weighted intensities of previous pings from the current processed image. The first two strongest peaks are taken as range estimates.

Initial detection occurs if the range measurement peak intensity exceeds a threshold for a set number pings, and the angular positions of those potential target measurements are in ascending or descending order. The initial target track start is short linear feature determined from the maximum cost function computed from the sum of every combination of peaks in a line between two adjacent target bearings. A Kalman filter is used to maintain the target track by providing an estimate of where to look for the target in the next ping, and then gating the range and bearing measurements in the next ping according.

Conclusion

Three different sonar target tracking algorithms have been examined towards the end goal of locating surface ships from an underwater moving sonar platform. The algorithm presented by Lo and Ferguson is an ideal stepping off point for further research towards this goal, perhaps incorporating optical flow or neural network methods to improve performance on a moving platform in a wider variety of circumstances. Should adequate performance not be achieved with these methods, other areas of literature to investigate include particle filtering [6-7] or radar-oriented detection and tracking methods like those in [5] and [8]. Research in the immediate future will implement focus on implementing a variant of Lo and Ferguson's algorithm that compensates for the motion of the sonar platform and testing it on existing data sets collected with an ARL:UT sonar.

Algorithm	Advantages	Disadvantages
optical flow + compatibility measure	robust, self-correcting	computationally expensive
neural networks + Kalman filter	superior detection, low false alarm, allows for moving platform	detects static objects only
geometric fading + Kalman filter	relatively simple, applies directly to application of interest	assumes one target with very specific properties

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