# POST PROCESSING OF SONAR IMAGERY USING RECURSIVE HIGH ORDER CORRELATION METHOD

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## ABSTRACT

In processing of sonar data, beamforming process plays a central role in reducing the effects of the surface and bottom reverberation. In shallow water environments where the reverberation is dominant, target detection from the beamformed results is not effective and may lead to significantly high false alarm rate. This paper presents a novel approach for post-processing sonar beamformed imagery in order to improve the detectability of the targets while substantially reducing the occurrence of the false detection. This is done using the recursive high order correlation (RHOC) method which exploits the spatial-temporal correlation between consecutive pings of the beamformed images. Test results on several sets of sonar data show the great efficiency and power of the proposed method especially in very high cluttered environments.

## 1. INTRODUCTION

The problem of ocean mines is a real and ongoing threat to the safety of naval vessels especially in shallow water environments [1], [2]. Due to the vastness of the ocean, the small size of mines, the acoustically reverberant environment and the frequent occurrence of biologics or magnetic clutter, which can mask the presence of mines and present false detection, the development of advanced signal processing schemes for underwater target detection from sonar data becomes of utmost importance. Considerable attention has been recently focused on this area and numerous approaches have been developed to aid in detection of underwater targets/mines. Generally, these research efforts have been concentrated on three major topics: Pre-processing, Beamforming and Post-processing. The post-processing scheme is addressed in this paper. In post-processing, the beamformed output image is further processed to find additional clues to distinguish targets from the background clutter. This facilitates the sonar operator’s decision making task and helps to provide higher target detection rate while reducing the false alarm rate. In [3], statistical features, i.e., mean, standard deviation, skewness and kurtosis were calculated for target size windows in the digitized beamformed sonar imagery. The combination of these statistical measures provides an additional clue about the presence of a target versus clutter. In [4], several methods including energy detector, sliding matched filter, skewness matched filter and dispersion-based reconditioning were applied to the Toroidal Volume Search Sonar (TVSS) [1],[2] beamformer output in order to increase the signal-to-reverberation ratio. It was reported that while the skewness matched filter offers some improvements, the dispersion-based reconditioning provides considerable improvements. However, the common drawback of these post-processing schemes is that the spatial-temporal correlational information of the target in several consecutive pings of the sonar system is ignored.

In this paper, a novel method based on recursive high order correlation (RHOC) is developed. The original RHOC method was developed [5] to detect multiple dim target tracks in heavily cluttered background from infrared (IR) satellite data. This method is extended in this paper for post-processing of highly cluttered beamformed sonar images of several pings. The basic assumption behind this approach is that target should consistently appear in a limited area (beam x range) in several consecutive pings. The effectiveness of the proposed scheme is demonstrated on several sonar images with different clutter density and target characteristics.

## 2. Recursive High Order Correlation (RHOC) Method

Target detection schemes such as spatio-temporal filtering, maximum likelihood (ML) estimation and recursive Kalman filtering [8], [9] generally use certain assumptions about the target signatures and the background clutter in order to reduce the computational requirements. For applications where such assumptions are valid, these methods perform well. However, if no a priori information about the statistics of signals and clutter and/or noise is available and further the signals are not simply distributed or are highly correlated, these methods may give inferior results. On the contrary, RHOC method does not make any a priori assumption about the number of targets, target's dynamical information and initial conditions and background clutter. Using RHOC as a post-processor for beamformed sonar data was initiated by the following facts. First, the along track coverage of the sonar system widens with distance hence causing a target to be present in multiple consecutive pings. RHOC is capable of determining the temporal and spatial dependencies of consecutive pings of data. Second, no a priori information is available about the targets and clutter/noise in the sonar data.

These two reasons make the application of RHOC very attractive for post-processing sonar imagery.

## 2.1 RHOC for Sonar Imagery

Since the target is stationary in the water column and the vehicle moves toward certain direction, there is a time-dependency between the adjacent pings of data. To find these dependencies, cross-correlations between adjacent pings can be calculated. In the conventional cross-correlation method, only spatio-temporal information between two consecutive pings can be determined. RHOC method solves this problem by allowing one to calculate the correlations among several consecutive pings recursively [5] as opposed to only two pings.

The basic assumptions behind this approach are: targets should consistently appear in a limited area (beam x range) in several consecutive pings and there might be more than one target in the searching region. In addition, the targets may be low observable or even missing in certain pings due to the movement of the vehicle on which the sonar system is deployed.

The first order correlation can be calculated using:

$$R^1(k,l,n) = g\left[\sum_{i=-M}^{M}\sum_{j=-N}^{N} B(k,l,n)B(k+i,l+j,n+1)\right] \qquad (1a)$$

where $g(\cdot)$ is the standard hard limiter thresholding function, i.e.,

$$g(x) = \begin{cases} 1 & x > 0 \\ 0 & x \le 0 \end{cases} \qquad (1b)$$

B(k, l, n) is the beamformed result of ping n at position (k, l), i.e., beam k and range l. Thus, $R^1(k, l, n)$ which represents the result of first order correlation provides information on how the points of B(k ,l ,n) at ping n are correlated to their neighboring points B(k+i, l+j, n+1) at ping n+1. The correlation is evaluated in a window of size (2M+1) x (2N+1). This window size is chosen under the assumption that the target location changes (due to vehicle's movement) from one ping to the next do not exceed certain limits. In order to calculate the $1^{st}$ order correlation of ping n and ping n+1 at (k, l), the products of B(k, l, n) and B( k+i, l+j, n+1), $i, j \in$ window, are summed and thresholded. It is quite obvious that if $R^1(k,l,n) = 1$, then there is a two-point spatio-temporal sequence initiated at location (k, l) of ping n to location (k+i, l+j) of ping n+1. Although this process can be repeated to identify all such two-point sequences, it can not provide correlational information of more than two pings of data. However, in order to declare a detection, we need to verify if the target shows consistently in three out of four consecutive pings of data. To calculate the higher order correlation in more than two consecutive pings, RHOC builds memory into the process and computes correlations of R recursively using:

$$R^p(k,l,n) = g\left[\sum_{i=-M}^{M}\sum_{j=-N}^{N} R^{p-1}(k,l,n)R^{p-1}(k+i,l+j,n+1)\right] \qquad (2)$$

where p is the order of the correlation, n is the index of pings which varies from 1 to $n_{max}$. When the order p increases, $n_{max}$ should decrease such that $p + n_{max} = n_0$ for computing correlations among $n_0$ consecutive pings. The initial condition for the above recursive equation is $R^0(k,l,n) = B(k,l,n)$. If $R^p(k,l,n) = 1$, that means a possible target location appears consistently in (p+1) consecutive pings. The entire process is illustrated in Figure 1.

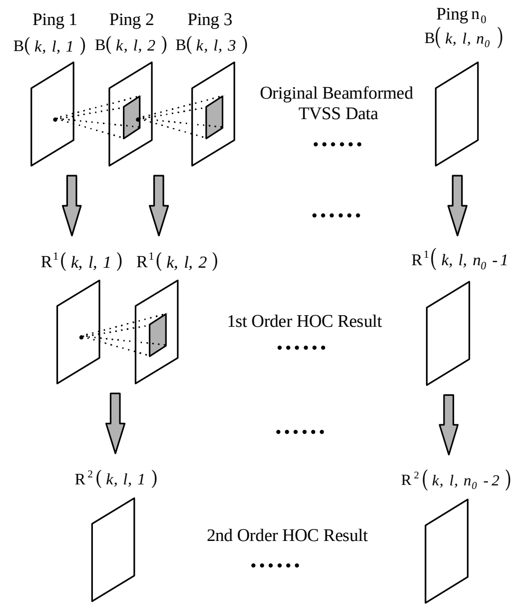


**Figure 1. RHOC for Different Orders.**

The choice of p is very critical in the RHOC process since it presents a trade-off between clutter removal capability of the RHOC and its sensitivity to missing target peaks at certain pings. More specifically, large p gives better clutter rejection but at the same time increases the likelihood of losing the target peak in the final RHOC result when there are several missing target peaks in some of the pings. The effect of p will be shown clearly in the testing results of Section 4.

# 3. TVSS Sonar System and Beamforming [1]

The Toroidal Volume Search Sonar (TVSS) is an active sonar, designed for detection of all types of targets located in water column including volume, close tethered, and close-close tethered [1],[2]. It provides a detection range of 675 meters with resolution of 3 cm [1],[2]. This mine hunting sonar contains 120 receive elements arrayed in a band around a 21" section [1],[2]. The array configuration produces a toroidal search pattern about the major axis of the towbody. TVSS can operate at a search speed of up to 8 knots to provide area coverage rates approaching 6 square nautical miles per hour with a probability of detection and classification greater than 0.85 [2].

A phase shift beamformer [7] is used for the TVSS. The beams are narrow and each 3 degrees wide in the azimuthal and transverse directions. The 120 beams are formed simultaneously to provide 360 degree coverage on each ping. Each $3^o$ beam is formed in the radial plane by focusing one quarter of the array (30 elements) centered about the beam origin. The beams are defined counterclockwise with beam one pointing directly upward toward the sea surface (assuming a stable tow platform). Beam 1 is then formed by focusing the 30 elements, 1 through 15 and 106 through 120. Under this convention the "port side" beam 31 (formed by focusing elements 16 through 45) and the "starboard side" beam 91 (formed by focusing elements 76 through 105) are defined to focus directly along the channel.

## 4. Test Results

A search window of size 100 range cells x 4 beams was used in the RHOC process. This accounts for approximately 3 meters range variations in 3 consecutive pings. The original processed TVSS beamformed data had to be converted to binary data prior to applying the RHOC method. In the following test results, the top pre-defined ( by *top_pick* ) number of peaks in each beamformed image were retained and set to 1 while all the others were set to zero. The three data sets used in this testing contained five, six and ten consecutive pings of the TVSS data, respectively. The target locations in these cases were in range cell 9119, 1693 and 2392, respectively.

Figures 2(a)-2(c) show the original beamformed image, first order and second order RHOC results on beamformed data set 1 with *top_pick*=50. As can be seen, this data set is quite noisy and the target return is not obvious in the unprocessed beamformed images. Since it is substantially dimmer than the clutter, in the first and second order RHOC results of Figure 2, though most of the clutter was removed by the process, the correct target return was not picked up. This is due to the choice of parameter *top-pick*. When *top_pick*=50, we assume that the target return is among the top 50 valuess. In most cases, this is true. Nevertheless, sometimes when the raw data is too noisy like this case, the assumption is no longer valid. To achieve better RHOC results, one needs to increase *the top_pick* value. Figures 3(a)-3(c) show the RHOC results with *top_pick*=100. This time one can see that the target return was correctly picked up. Though there are still a few clutter remained, the target becomes much more obvious comparing with the unprocessed case.

Figures 4(a)-4(c) show the RHOC results on data set 2. Comparing with the previous data set, the unprocessed modified beamformed result is much cleaner. Apart from several dim clutter, the target return is one of the most prominent returns in the image. However, right beside the true target location, one can clearly see another competing target-like return. It is hard to distinguish the target return from the competing clutter. To process this data set, *top_pick*=50 was first used. From the 1st and 2nd RHOC results in Figure 4, one can see that the only prominent return was the target return while the competing clutter was removed. Figures 5(a)-5(c) shows the RHOC results with *top_pick*=100. In this case, apart from the correct target return, the competing clutter was also picked up. However, one can see that the true target return is much stronger than the clutter. Thus, a too aggressive choice of *top_pick* faces the danger of losing the real target return while a too conservative choice degrades the ability of clutter removal. The optimal value of *top_pick* may be chosen empirically.

Figure 6 and Figure 7 show the RHOC results on data set 3 with *top-pick*=50 and *top_pick*=100, respectively. Similar to the previous cases, there is also a competing clutter (in range cell 5000-6000). In both results, one can see that apart from the correct target, the competing clutter was also picked up. However, we can see that the target return is much more prominent and more consistent.

## 5. Conclusion

The proposed RHOC method for post-processing of sonar data showed the ability to remove the competing clutter and at the same time boost the target return in several consecutive pings. The algorithm is simple, easy to implement and fast. For example, processing a set of 31 pings of TVSS beamformed data took only about 18 seconds CPU time on a HP 700 series workstation. However, from the results, we also find some limitations of the RHOC method. Apart from the window size which constrains the maximum deviation of the vehicle motion, no other constraints pertaining to the dynamic information of the vehicle, such as velocity and direction, are incorporated into the process. For the TVSS shallow water application, if the vehicle's dynamic information is available, the RHOC results may be significantly improved by building the vehicle's motion as well as the constraints on the target peak locations into the process.

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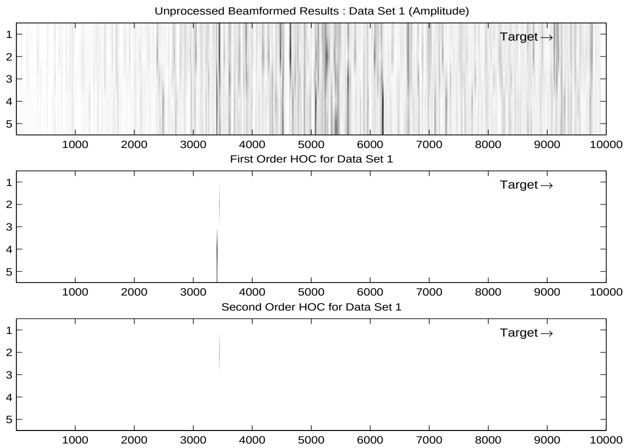


Figure 2. RHOC Results on Data Set 1 ( *top_pick*=50 ).

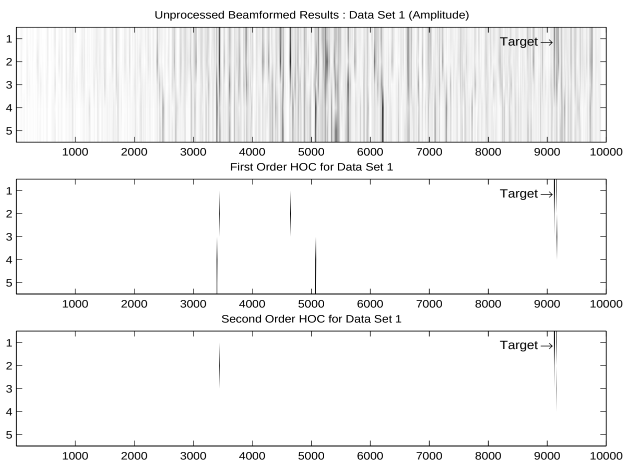


Figure 3. RHOC Results on Data Set 1 ( *top_pick*=100 ).

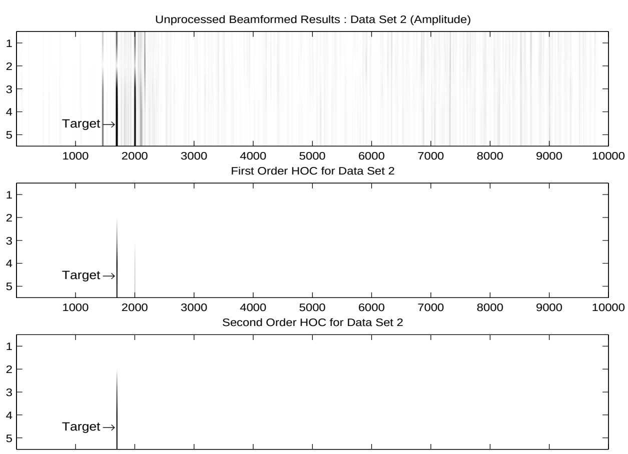


Figure 4. RHOC Results on Data Set 2 ( *top_pick*=50 ).

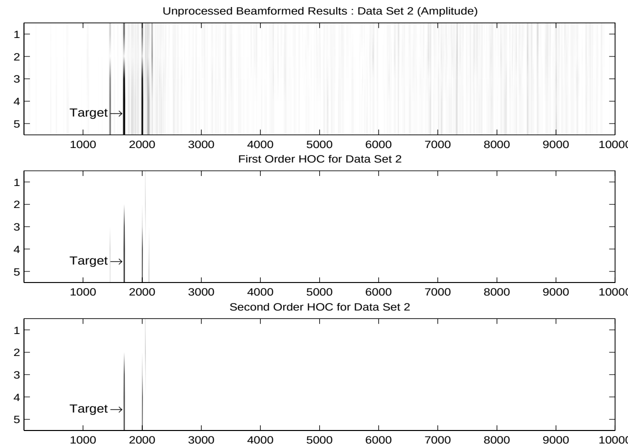


Figure 5. RHOC Results on Data Set 2 ( *top_pick*=100 ).

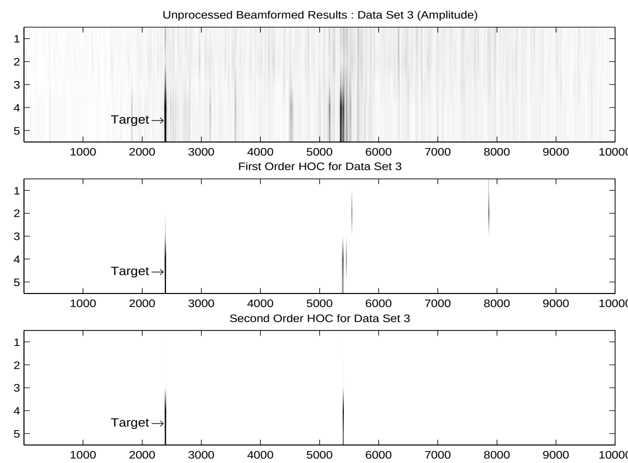


Figure 6. RHOC Results on Data Set 3 ( *top_pick*=50 ).

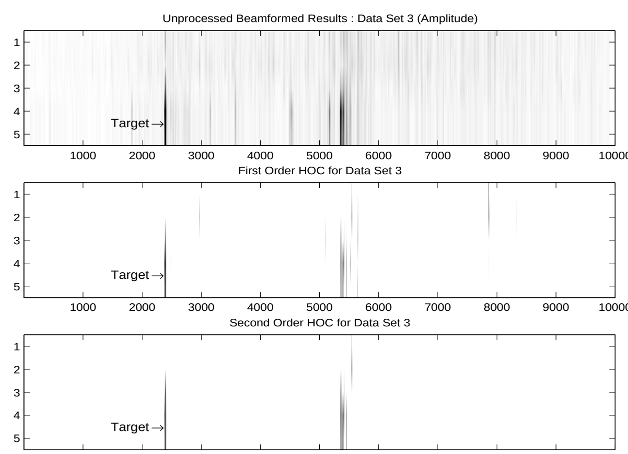


Figure 7. RHOC Results on Data Set 3 ( *top_pick*=100 ).