Clutter Reduction in Active Sonar Using a Clustering Method

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Abstract: *In shallow-water environments, active sonar pulses are repeatedly reflected off the seabed and sea surface as they travel to underwater targets. This generates heavy clutter and multiple measurements from targets, making it challenging to design algorithms that effectively remove clutter while preserving target measurements for tracking. Clutter reduction methods, such as k-means clustering method and hough transform-based track initialization method, have been proposed to mitigate heavy clutter. However, these approaches rely on the assumption that targets follow constant-course maneuvers to distinguish them from clutter, which limits their effectiveness in scenarios involving random target maneuvers. In this paper, we propose a novel clutter reduction method to address heavy clutter in shallow-water multipath detection environments. It applies HDBSCAN clustering method to segment measurements into multiple clusters, followed by a cluster classifier to differentiate target clusters from clutter clusters. The cluster classifier considers the spatial and temporal consistency of accumulated measurements to distinguish between target clusters and clutter clusters. The performance of the proposed clutter reduction method is evaluated using sea trial data collected near Jeju Island, South Korea, with an Active Towed Array Sonar system deployed from ADD Research Vessel CheongHae.*

Keywords: *Active sonar, Clutter rejection, Clustering, Classification, Multipath, HDBSCAN*

1 INTRODUCTION

Active sonar has become the preferred method for detecting submarines in modern ASW. The traditional method of detecting active sonar targets is the thresholded matched filter detector. The conventional thresholded matched filter detector declares a target present when the normalized matched filter output exceeds a predefined threshold [1]. However, this approach has limitations, particularly in complex underwater environments, as it results in a higher incidence of false alarms, generally called clutter. When real targets and clutter are detected simultaneously, operators should manually distinguish between them. Manually classifying sonar signals by operators can cause delays in target declaration and increase a system's workload.

In previous studies, researchers attempted to remove clutter by tuning thresholds based on the signal characteristics of clutter [2]. However, this approach has limitations, as it is not robust account for the highly variable nature of clutter, which differs significantly depending on the underwater environments. In particular, the Yellow Sea and South Sea of Korea are shallow-water environments where multipath detection is prevalent. In such shallow-water environments, heavy clutter is generated by underwater objects and seabed reflections, further complicating the distinction between targets and clutter. In shallow-water environments, active sonar pulses are repeatedly reflected off the seabed and sea surface as they travel to targets. It generates heavy clutter and multiple measurements from targets, making it challenging to design algorithms that effectively remove clutter while preserving target measurements for tracking.

Recently, clustering-based clutter removal methods, such as k-means clustering method and hough transform-based track initialization method, have been proposed for heavy clutter environments [3],[4]. However, previous methods often require predefined parameters and operate under the assumption that target movement follows a constant course and speed. This assumption limits performance in multipath detection environments and during random target maneuvers.

In this paper, a novel clutter removal algorithm is proposed. The proposed method is independent of target movement and remains effective in multipath detection environments, where a target produces multiple measurements amidst high-density clutter. The proposed clutter removal method distinguishes targets from clutter by analysing the spatial and temporal consistency of accumulated measurements. It employs clustering techniques to group measurements into clusters and applies a cluster classifier, based on their temporal and spatial distribution, to differentiate target clusters from clutter clusters. The performance of the proposed clutter removal technique has been validated using sea experimental data, demonstrating its effectiveness.

2 PROPOSED METHOD

2.1 Sea Trial Data

Sea experiment was conducted at the eastern sea of Jeju Island in september 2022, as depicted in Fig.1. The sea trial data was obtained using the Active Towed Array Sonar installed on the Research Vessel (RV) CheongHae of Agency for Defense Development (ADD). The towed active sonar system consists of a variable-depth active sensor for transmitting signals and a towed linear array of sensors for receiving signals. The active sensor used a LFM pulse with a bandwidth of *400* Hz and a pulse length of *1* second. The transmission frequency was similar to that used in Murphy's research [5]. The receiving sensor is an array of triplet sensors designed to receive signals within the transmission frequency range. The sea experiment was conducted in a shallow environment at a depth of approximately *150* meters, with active and passive sensors' depth of *50* meters. The submarine involved in the sea experiment was a medium-sized submarine. In the sea experimental environment, the sound propagation path involved repeated reflections from the sea bottom and the surface, resulting in a multipath detection environment, as shown in Fig.1. After obtaining the beamformed sensor signals from the sea experiment, matched filtering and two-dimensional normalization using CFAR are performed. Measurements exceeding a specific SNR threshold are extracted, and the accumulated results over a total of *120* pings are shown in Fig.1. The target moved in a clockwise circular motion at approximately *9* km and a speed of about *4* knots, while the RV CheongHae moved westward at a constant speed of *5* knots.

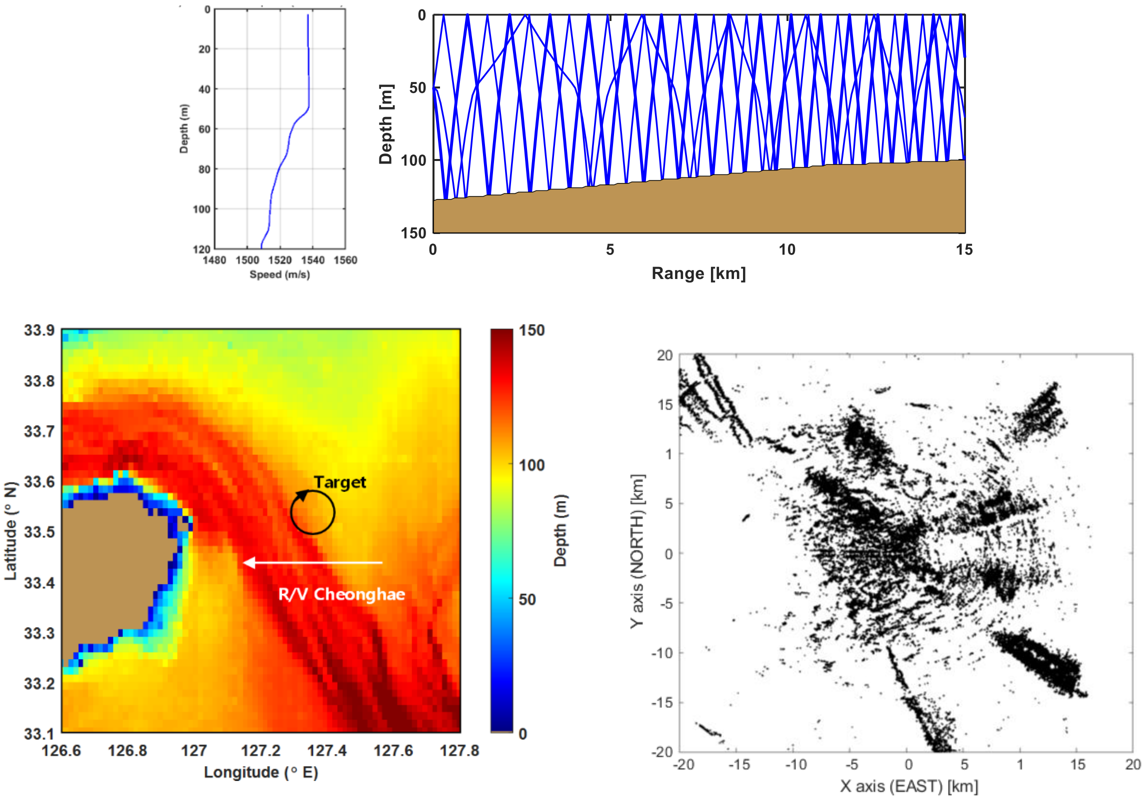

Fig.1: The top graph shows sound velocity profile and the ray trace. The bottom left panel shows rendering of the bathymetry data and navigation path. The bottom right panel shows accumulated measurements (120 pings) which exceed a predefined SNR threshold.

2.2 Clustering Method

HDBSCAN (Hierarchical Density-Based Spatial Clustering of Applications with Noise) is a type of density-based clustering technique that, unlike DBSCAN, effectively groups data with varying characteristics by allowing different densities for each cluster [6]. Moreover, it offers the advantage of lower tuning costs due to fewer parameters compared to DBSCAN. It is not necessary for the HDBSCAN method to define a minimum distance ε to determine core points; instead, only the minimum number of neighbors *minPts* needs to be defined. The HDBSCAN technique uses mutual reachability distance between all points to form a hierarchical structure rather than the DBSCAN method checks whether the Euclidean distance between data points is less than the minimum distance ε. The mutual reachability distance is defined as shown in equation (1).

$$d_{mreach,k}(a,b) = \max\{core_k(a), core_k(b), d(a,b)\} \tag{1}$$

where, $core_k(a)$ is the core distance of a point, indicating the radius of a cluster that contains at least k points surrounding the core point. $d(a,b)$ is the distance between the core point and the center of the cluster. The hyperparameter k is typically set to the same value as *minPts*. A hierarchical structure of data points can be established by gradually reducing the mutual reachability distance from a value large enough to group all points into a single cluster to a smaller value where each point is classified as its own cluster. The hierarchical structure can be visualized as branches extending from a single cluster to multiple clusters when represented using the inverse of the mutual reachability distance, arranged in ascending order from smaller to larger values. The HDBSCAN technique identifies long-length branches as valid clusters while disregarding clusters with short-length branches within the tree-like hierarchical structure.

2.3 Classification of Each Cluster

After clustering, the proposed method extracts features from each cluster. Using these features, a classification algorithm determines whether each cluster represents a target or clutter. The proposed classification method utilizes a combination of three features to differentiate between target clusters and clutter clusters. The first feature is temporal and spatial distribution characteristics. The second feature is the number of measurements within a cluster. The third feature is ping consistency of measurements within a cluster.

The first feature indicates whether the spatial and temporal distribution of accumulated measurements can be approximated by a polynomial function. The polynomial f approximates time intervals as a function of space i.e. cartesian coordinates of measurement x_n and y_n. Since M accumulated measurements over N pings have a time interval t_n, it is calculated by multiplying the ping number by the sonar pulse repetition interval, the residual r can be obtained using the difference from the polynomial approximation.

$$r = \sum_{n=1}^{M} (t_n - f(x_n, y_n))^2, \tag{2}$$

In this paper we choose the polynomial as $f(x_n, y_n) = ax_n + by_n + c$. But it can be expended in the quadratic form as $f(x_n, y_n) = ax_n{}^2 + by_n{}^2 + cx_n y_n + dx_n + ey_n + f$. Then, target clusters and clutter clusters can be distinguished by comparing their residuals. The coefficients of the polynomial can be easily obtained by the least square method.

$$\boldsymbol{X} = (\boldsymbol{A}^T\boldsymbol{A})^{-1}\boldsymbol{A}^T\boldsymbol{b}\text{ , where }\boldsymbol{A} = \begin{bmatrix} x_1 & y_1 & 1 \\ \vdots & \vdots & \vdots \\ x_M & y_M & 1 \end{bmatrix},\ \boldsymbol{b} = [t_1\ t_2\ \cdots\ t_M]^T \tag{3}$$

The second feature, the number of measurements within a cluster, is influenced by the probability of consistently detecting a submarine over N pings, leading to the accumulation of at least Np_c measurements, where p_c represents the average continuous detection probability for the target over pings. The maximum number of measurements within a target cluster could be as high as m_tN, where m_t represents the number of multiple measurements from a target obtained from a single ping. These multiple measurements are caused by multipath detection environments. Clutter clusters caused by high ambient noise often contain an excessive number of measurements, exceeding m_tN.

The third feature, the ping consistency between measurements within a cluster, indicates that measurements originating from a target are likely to follow a consistent sequence of ping numbers. In contrast, measurements within clutter clusters may lack a consistent sequence of ping numbers due to variable SNR and a spatially uniform distribution. Although ping consistency can be incorporated into distance calculation for clustering, situations may arise where too many measurements are detected from a single ping or where sequence of ping numbers in the measurements in a cluster is inconsistent.

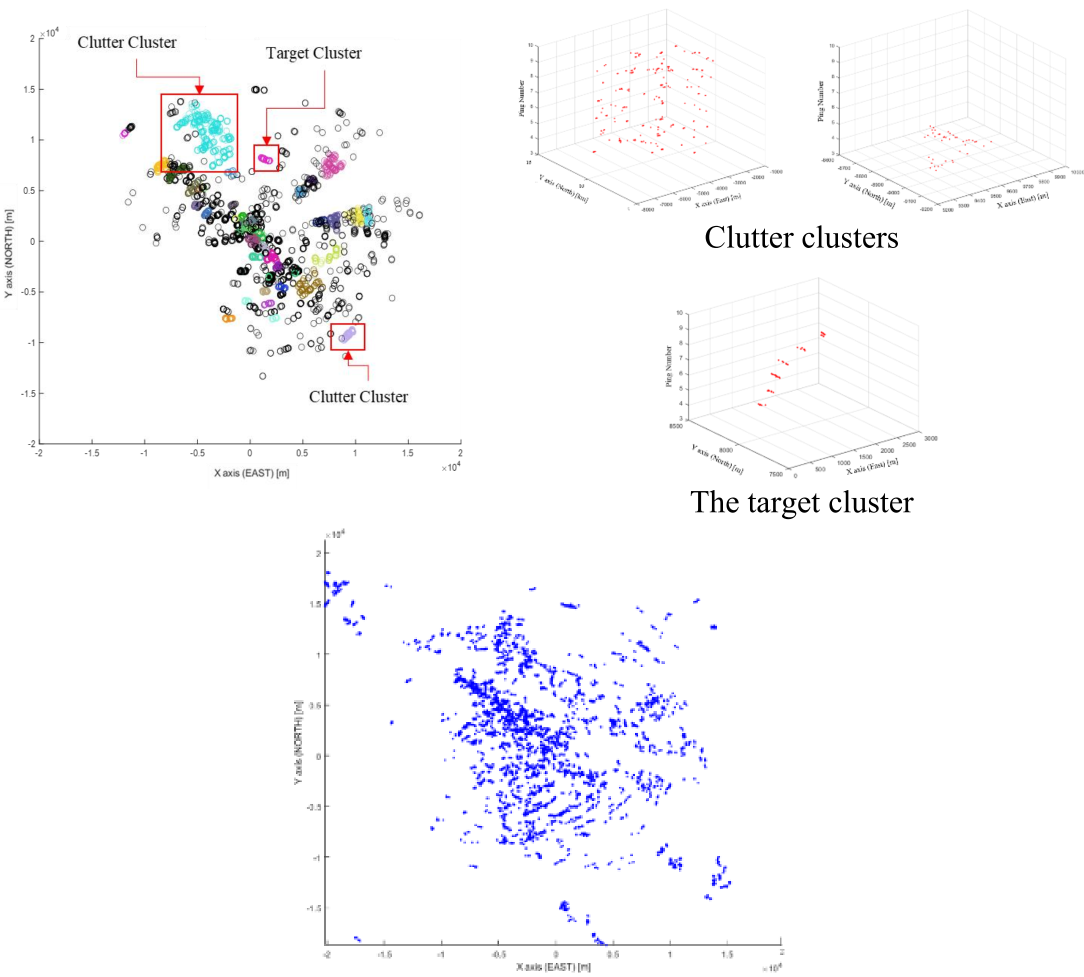

Fig.2: The top left panel shows the clustering result of accumulated measurements (ping #4~9), different color for each cluster. The top right panel shows temporal and spatial distribution of clutter clusters and the target cluster. Red dots are accumulated measurements within a cluster. The bottom panel shows clutter reduction result.

3 RESULTS

The clutter removal performance of the proposed algorithm was evaluated in two stages. First, the performance was analysed using the HDBSCAN clustering method alone. Then, we investigated the cluster classification results after the clustering. By removing non-clustered measurements, it was observed that 36% of clutter was reduced using the clustering method alone. The parameter $minPts$ for the HDBSCAN was set to *3*, which is the half of the number of accumulated pings. In the second stage, we classified every cluster, and 85% clutter measurements were reduced. The parameters used to distinguish between target clusters and clutter clusters were as follows: the polynomial approximation residual threshold for temporal and spatial distribution characteristics was *3*. The accumulated number of pings N was *6*, and the number of measurements in an extended target form m_t was set to *10* based on the analysis of the sea experimental data. The average continuous detection probability p_c between pings was set to *0.5*. The ping consistency was set to *2*, meaning the proposed method allows for one missing ping. The results of clustering and cluster classification process are presented in Fig.2.

4 CONCLUSION

A novel method employing density-based clustering combined with cluster-specific classification has been proposed for effective clutter removal in heavy-clutter active sonar detection environments. The proposed approach simplifies clustering application in real systems by requiring only the definition of the minimum number of neighbors. The cluster classification algorithm is generalized and adaptable to various target maneuvers and underwater acoustic conditions. However, optimization of certain algorithm parameters is necessary, considering the specific characteristics of active sonar detection. Furthermore, a comprehensive performance evaluation using diverse sea trial datasets is required, as the current analysis is based on only a single set of sea trial data.

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