Clustering-Based Maximum Likelihood Estimation: Application to Sensor Fusion in UXO detection

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Abstract: This paper describes our approach of applying clustering techniques in the detection of UXOs (Unexploded Ordances). The clustering algorithms help us to integrate information from various sensors. Because of the specific characteristic of our application, a new MLE (maximum likelihood estimation) method is designed. The MLE is integrated into the clustering algorithm whose inputs are the extracted features of targets. This approach is tested on one of the MTADS (Multi-Sensor Towed Array Detection System) data. Good performance has been achieved. Finally, it should be pointed out that further improvements could be achieved when better feature extractions become available.

1. *Introduction*

Sensor fusion is found to be necessary in UXO (Unexploded Ordance) detection systems in order to achieve better performance. It can offer robust operational performance, extended spatial coverage, extended temporal coverage, increased confidence, reduced ambiguity, enhanced resolution and improved system reliability. In a word, the advantages using sensor fusion can be significant. However, situation is usually complicated in applying sensor fusion techniques in the detection of UXOs. Part of the reason is that sensor outputs are affected by various factors in reality, which make the boundary between targets and clutters ambiguous.

In recent years, a lot of progress has been made on the detection of UXOs [1][2][3][4]. Various methodologies have been used, including Bayesian decision theory (maximum likelihood), Markov random fields, neural network, fuzzy logic and etc. While in this paper, our approach is to apply clustering techniques to integrate information from different sensors. There are basically two phases in this approach: the training phase and the detection phase. In the training phase, target features are combined as inputs to the clustering algorithm. In the detection phase, the distance between the object features and the clusters calculated from previous phase is computed. Based on this distance, decision can be made on whether a object belongs to targets or not.

The approach described is tested on one of the MTADS (Multi-Sensor Towed Array Detection System) data collected by naval research lab. Our goal is to achieve high detection rate P_d and low false alarm rate P_f. The final results show substantial improvements over simple Bayesian methods or ISODATA algorithm.

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Section 2 reviews the ISODATA algorithm, which is the starting point of this paper. Section 3 discusses the new clustering-based maximum likelihood estimation method. Section 4 presents the testing results of this method on one of the MTADS (Multi-Sensor Towed Array Detection System) data. Concluding remarks are collected in Section 5.

2. *ISODATA algorithm*

Now suppose we have a set of training data $\{X_j\}$, where each $\{X_j\}$ is a vector whose components are features extracted from sensor outputs of targets. Assume that $\{X_j\}$, $j = 1 \cdots n$ belong to m categories. Now the objective is to search for the m clusters representing these categories. The ISODATA algorithm is one of the algorithms accomplishing this objective. Compared to the well-known K-means algorithm, ISODATA provides a means to automatically determine the optimal number of clusters by splitting and merging clusters. The flowchart of the training phase in ISODATA algorithm is shown in the figure below. Detailed discussion can be found in [6][7].

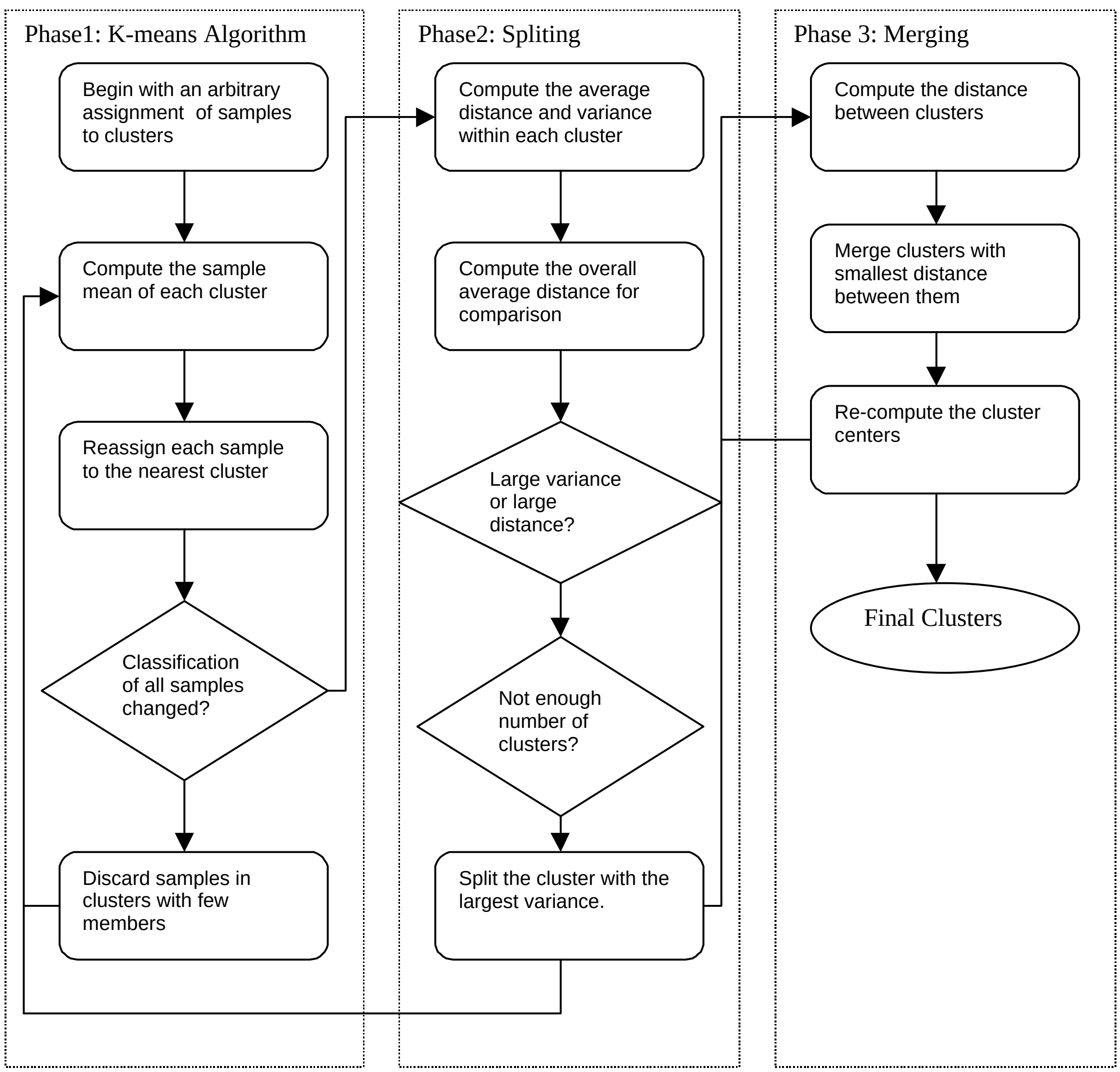

Figure 1. ISODATA algorithms

After the training phase, all the clusters representing the training data have been determined. Now we are able to determine whether an object is similar to a target or not. To do that, we will first calculate the minimum distance between the object's feature vector and clusters. Then we will put a threshold on this distance. If it is less than a pre-defined threshold, we will declare it as a target. Otherwise, we will claim it as a clutter.

3. Clustering-based Maximum Likelihood Estimation

In ISODATA algorithm, there are two assumptions implied [5][8]. The first assumption is that clusters can not overlap. The second assumption is that covariances within clusters are the same. Therefore, it can only handle situations shown in the figure below.

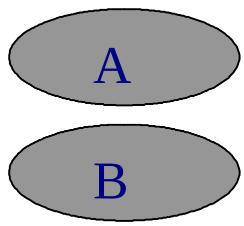

Figure 2: Clusters in ISODATA algorithm

While in UXO detection, these two assumptions may be violated. Two cases are shown here. In the first case, the clusters overlap with each other. In the second case, the covariances within clusters are not the same. If we simply apply the ISODATA algorithm to these two cases, the clusters generated will be incorrect. Thus, it is necessary to modify the ISOATA algorithm to handle situations like these.

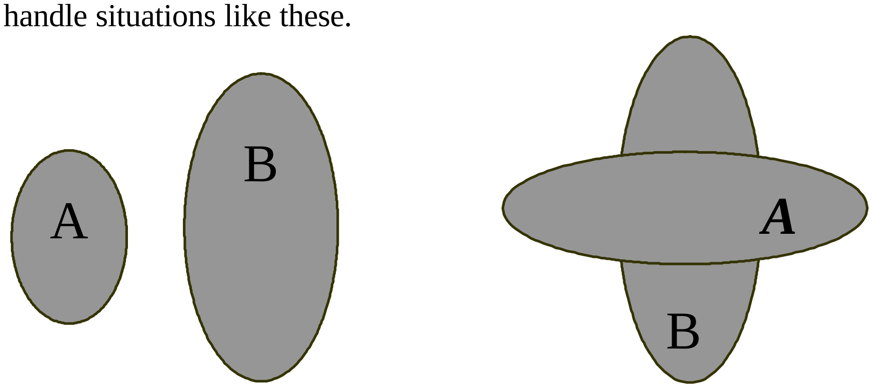

Figure 3: Situations where ISODATA algorithm is not applicable

In this paper, we will combine the maximum likelihood test together with the ISODATA algorithm. Suppose now, we have training data $\{X_j\}$ and cluster centers V_i obtained from ISODATA algorithm, where $j = 1 \cdots n$ and $i = 1 \cdots k$. We will also define the variables as follows:

$h(i \mid X_j)$: Probability for X_j to be in the ith cluster
P_i : Priori probability of selecting the ith cluster
F_i : Covariance of the ith cluster
V_i : Cluster center of the ith cluster

Before the running of the algorithm, these variables are initialized as:

$$h(i \mid X_j) = 1 \quad i = \underset{i=1\cdots k}{\text{argmin}}\, d(X_j, V_i)$$

$$Pi = \frac{\sum_{j=1}^{N} h(i \mid Xj)}{N}$$

$$F_i = \frac{\sum_{j=1}^{N} h(i \mid X_j)(X_j - V_i)(X_j - V_i)^T}{N}$$

Then, the algorithm consists of an iterative procedure shown in the figure below.

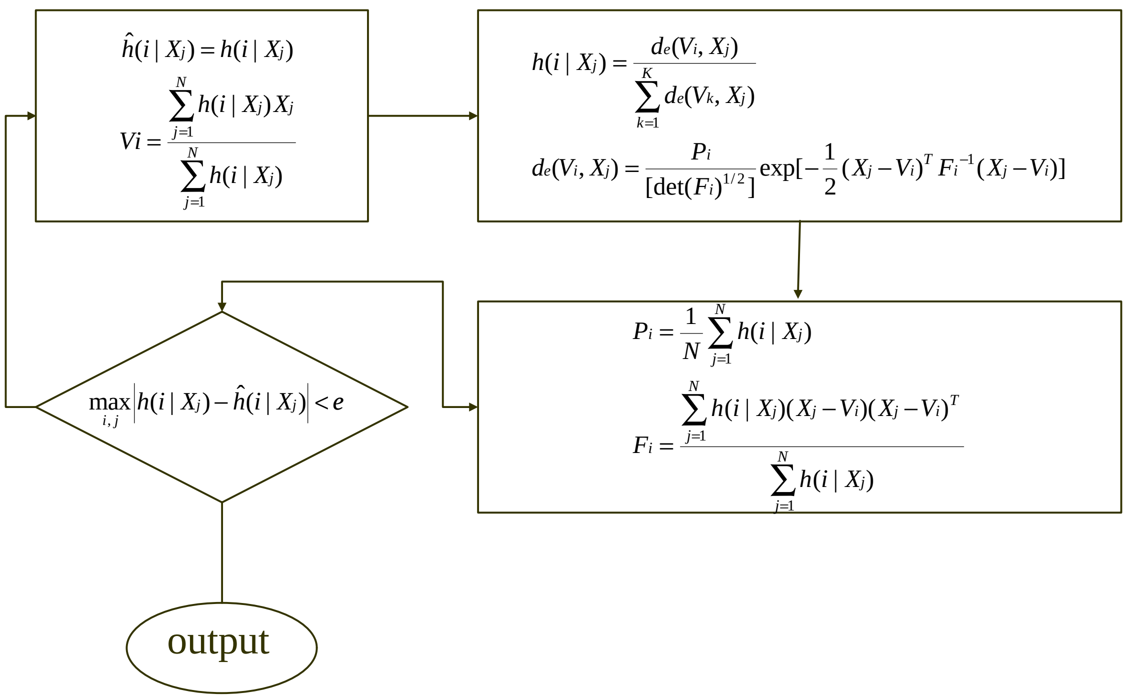

Figure 4: Maximum Likelihood Estimation Based on Clustering

[Remark:] The major advantage of this algorithm is that it can obtain good partition results in cases of unevenly feature distributions. Since exponential distance function is incorporated, the algorithm seeks an optimum in a narrow local region. Therefore, it may be unstable when the initial condition was not properly chosen. That is the reason why we need ISODATA algorithm as the first layer.

Similar to the ISODATA algorithm, in the detection phase, we will first calculate the minimum distance between the feature vector and the clusters. Then, the probability for the feature data to be in each cluster is calculated. In particular, given feature vector y, $h(i \mid y)$, the probability for y to belong to the ith cluster will be calculated as follows:

$$h(i \mid y) = \frac{d_e(V_i, y)}{\sum_{k=1}^{K} d_e(V_k, y)}$$

$$d_e(V_i, y) = \frac{P_i}{[\det(F_i)^{1/2}]} \exp[-\frac{1}{2}(y - V_i)^T F_i^{-1}(y - V_i)]$$

where $d_e(V_i, y)$ stands for the distance between y and the ith cluster . It is noted that in the calculation, both the priori probability P_i and the covariance F_i have been used. After that, we will compare this new probability $h(i \mid y)$ with a pre-defined threshold l . If it is greater than l , we will claim that it belong to the ith cluster. Since there are k clusters, the final detection procedure can be written as:

Declared as target if $\max_i h(i \mid y) > l$

4. Results

The algorithm described in this paper has been tested on one of the MTADS (Multi-Sensor Towed Array Detection System) data. It was collected by naval research laboratory at the Badlands Bombing Range (on Pine Ridge Reservation in South Dakota). The data available now covers an area of 150(m) x250 (m). The target (Buried and surface UXO) dropped there are primarily M38 (100 lb. sand-filled bombs). There are 25 labeled target in the field. The number of labeled clutter is 19. However, many clutters are not listed in the ground truth table. The system consists of a specially designed tow vehicle and tow platform that supports arrays of total field magnetometers and pulsed-induction sensors. The pulsed induction array uses modified Geonics EM-61 sensors for EMI (electromagnetic induction) sensors and Geometrics Model 822ROV sensors for magnetometer sensors.

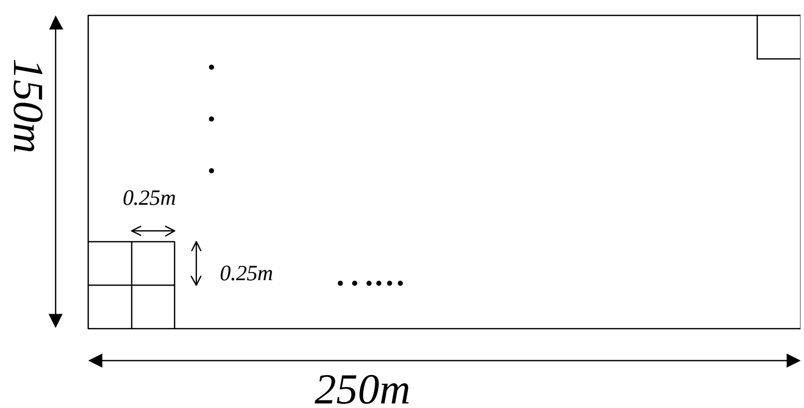

Figure 5. Fitting data into grid

There are several steps in extracting features from the data. The first step is to fit data into grids as shown in the figure above. After that, we are able to associate each EMI data with each magnetometer sensor data. The second step is to combine EMI data and magnetometer sensor data into feature vectors. It is noted that the position of EMI peak for a target is usually not the same as the position of the magnetic peak. So instead of using sensor data collected at the same point, it is more appropriate to use separate peaks in EMI sensor data and magnetometer sensor data in a small region as feature components.

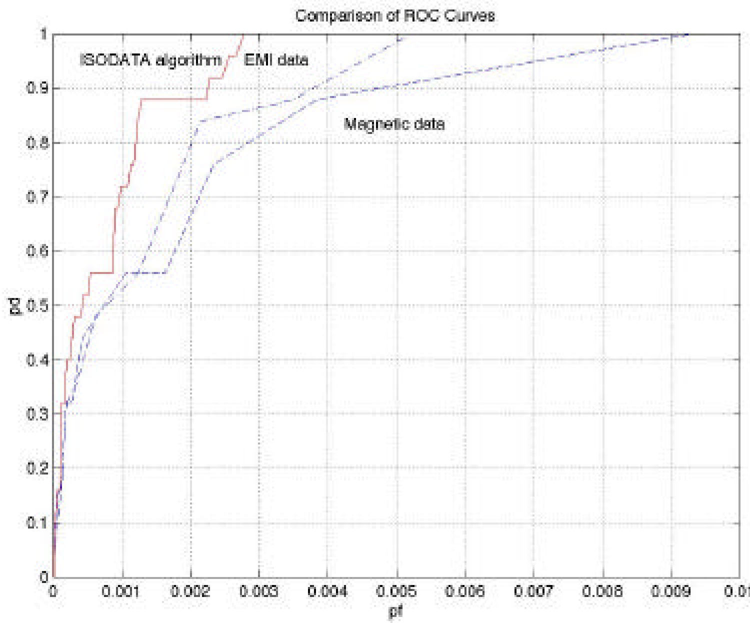

Figure 6. Comparison between ISODATA and Threshold Tests
--: Threshold Tests. --: ISODATA

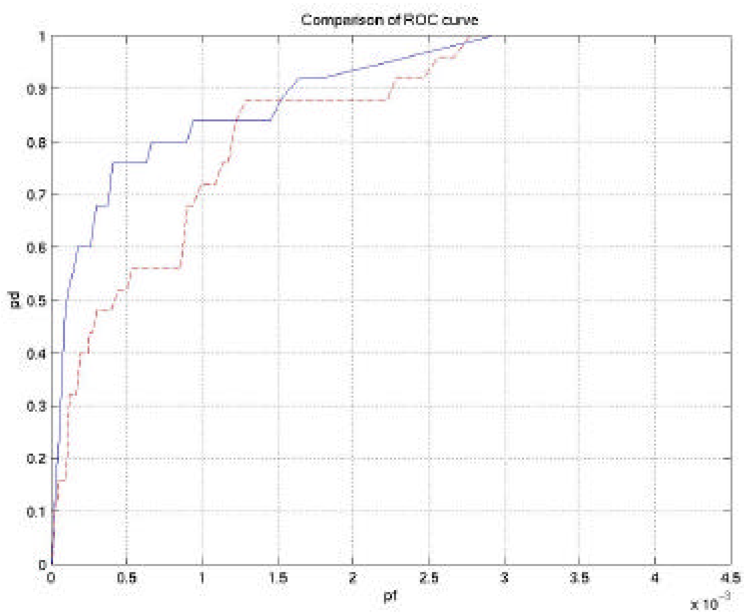

Figure 7. Comparison between Clustering-based MLE and ISODATA.
-: Clustering-based MLE. --: ISODATA

First, comparisons between ISODATA algorithm and threshold tests based on EMI (Magnetometer) data are shown in Fig 6, which proves the benefit of using multiple sensors. Then, the comparison between clustering-based maximum likelihood estimation and ISODATA algorithm is shown in Fig. 7. This result clearly demonstrates the effectiveness of the new clustering-based maximum likelihood estimation.

5. *Conclusion*

It should be pointed out that our results in this paper only serve as a start point of the research along this line. Further improvement can be achieved as more salient features become available. As several basic sensor models become available recently, it is now possible to roughly estimate some physics parameters of objects based on these models. Supervised clustering may also be needed to match the models with the clustering results. Even without any explicit models, a good understanding of the physics behind the data is helpful in selecting features.

Acknowledgement:

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