



## WOA based Selection and Parameter Optimization of SVM Kernel Function for Underwater Target Classification

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**Abstract:** The identification and classification of noise sources in the ocean is a challenging task due to a myriad of impediments introduced by the complicated oceanic environment. The underwater target recognition system essentially has to identify underwater targets of interest that are heavily masked by the oceanic noise. The characteristic acoustic signatures of the underwater targets of interest, are patterned by feature recognition algorithms operating on data captured by hydrophone. In this paper, an SVM based classifier is used to distinguish between 4 classes of acoustic targets and attempt is made towards improving the performance of the classifier by automating the selection of kernel and algorithmic parameters of the underlying classifier through Whale Optimization Algorithm (WOA).

**Keywords:** Underwater target classifier, Support Vector machines, Kernel Function, Whale Optimization Algorithm.

### I. INTRODUCTION

Underwater target classification is a challenging and complex task due to a myriad of underwater noise sources imposed by the ever changing and complicated oceanic environment. Underwater target activity is reflected by acoustic events with each target having its own 'acoustic signature', and heavily masked in the background noises imposed by the ocean. In the very basic form, an underwater target classification system is an acoustic recognition system, but the multitude of noises makes their recognition and classification difficult. This makes fast and accurate underwater target classification for military purposes in the interference filled ocean difficult.

The classification problem concerns the construction of a procedure that will be applied to a variety of acoustic signals, in which each new signal is assigned to one of a set of pre-defined classes on the basis of observed features [1]. The classification problem, in general, can be decomposed into two steps *viz-a-viz* estimating features or signatures of the source from a set of received signals by applying suitable feature extraction technique; and applying a pattern recognition algorithm to the estimated source signatures, for final classification. A number of techniques have been developed for extracting features of the acoustic clips, with cepstral techniques outperforming feature extraction by classical power spectral techniques. Many pattern recognition algorithms exist which include Gaussian Mixture models, Naive Bayes classifiers, Decision trees, Artificial Neural Networks (ANN) and Support Vector Machines (SVM). SVM classifier which is recognized as one of the powerful techniques in supervised classification, is adopted in this work.

The advantage of using SVM based classification technique is that SVM's are relatively easy to implement, very robust due to its sound theoretical background and has high generalization ability. Any dimensional problem is easily solvable with SVM, keeping the model complexity relatively simpler, when compared to other approaches.

The performance of a classifier depends on a variety of factors including selection of the underlying classification algorithm and the choice of algorithmic parameters and the

feature extraction method used. This paper deals with the selection of optimal SVM algorithmic parameters, kernel and kernel parameters.

Several attempts have been made for automatic kernel selection and parameter optimization, including meta-heuristic algorithms such as genetic algorithms (GA), particle swarm optimization (PSO), BAT algorithm etc. This paper attempts selection of SVM parameters, kernel and kernel parameter optimization using Whale Optimization Algorithm proposed by Seyedali Miralili [2]. The attempt has been carried out over four classes of acoustic targets, namely, humpback whale, sea lion, ship and boat. The results indicate higher classification accuracy when compared to BAT algorithm based selection and optimization.

### II. THEORY AND DEFINITIONS

#### A. Support Vector Machines(SVM)

Support Vector Machine is a supervised learning technique which has proved to be powerful on a wide range of classification tasks. SVM is a statistical binary classification technique that has stemmed from the theory of Structural Risk Minimization.

The three key ideas [3] on which SVM relies on are converting complex non-linear classification problems into simpler linear classification problem by mapping data to a higher dimensional space so that the non-linear classification problem transforms to be a linearly separable one, using the training patterns that are near the decision surface referred to as Support Vectors for classification and finding the hyperplane referred to as the Optimal Separating Hyperplane (OSH) that separates the data with the largest margin.

The learning problem setting for SVM can be formulated as follows: there is some unknown and nonlinear dependency,

$$y = f(x) \quad (1)$$

between a high-dimensional input vector  $x$  and an output  $y$ . There is no a-priori information about the probability distribution of the input and hence a distribution free learning must be performed. The only information available is a training data set belonging to two linearly separable classes,

$$\{\chi = [x(i), y(i)] \in \mathbb{R}^m \times \mathbb{R}, i=1, \dots, n\} \quad (2)$$

where  $n$  stands for the number of the training data pairs and is therefore equal to the size of the training data set  $\chi$ .

The set of all linear separating hyperplanes which can separate the data classes can be represented as

$$y_i(w^T x_i + b) \geq 1, i = 1, \dots, n \quad (3)$$

and with a margin defined to be  $2/\|w\|$ .

The problem of finding the optimal separating hyperplane is to maximize the margin  $2/(\|w\|)$  or minimize  $\|w\|^2/2$ . This is a quadratic optimization problem with linear constraints defined by inequalities i.e: Find  $w$  and  $b$  such that  $\|w\|^2/2$  is minimized for all  $(x_i, y_i)$  and such that (3) is satisfied.

Table I. Standard Kernel Functions

| Kernel Functions                             | Type of Classifier       |
|----------------------------------------------|--------------------------|
| $K(x, x_i) = (x^T x_i)$                      | Linear, dot product      |
| $K(x, x_i) = [(x^T x_i) + 1]^d$              | Polynomial of degree $d$ |
| $K(x, x_i) = \exp(-[ x - x_i ^2]/2\sigma^2)$ | Gaussian RBF             |

As with most real-world classification problems, when the classes are separated in a nonlinear way and a linear boundary becomes inappropriate, the input vectors are mapped to a higher dimensional feature space via a mapping function  $\phi$ , where they are linearly separable. The mapping function,  $\phi$  is called kernel function and can be any symmetric function that satisfies the Mercer's conditions [4]. Commonly used kernel functions are summarized in Table (I).

### B. Multiclass SVM

SVM was originally proposed to solve binary classification problems. Though originally proposed as a binary classification problem, SVM's can be extended to solve multiclass problems also. Algorithms for solving multiclass problems are built upon the binary SVM classifier by reducing the multiclass problem to multiple binary classification problem.. Two commonly used algorithms for multi-class classification with SVM are one-against-all (1-a-a) proposed by Vapnik and one-against-one (1-a-1) method proposed by Knerr. In the first approach,  $K$  classifiers are constructed to solve a  $K$ -class problem. The  $n^{\text{th}}$  classifier constructs a hyperplane between class  $n$  and the  $K-1$  other classes. The second approach involves constructing  $(K(K-1)/2)$  hyperplanes separating each class from every other class.

### C. Whale Optimization Algorithm

Whale Optimization Algorithm (WOA) is a meta-heuristic algorithm inspired by the foraging behaviour of humpback whales [2]. Their foraging behaviour can be

described in three phases 1. searching for prey (exploration) 2. encircling the prey 3. Bubble net feeding behaviour.

In the first phase, humpback whales search for prey randomly which can be modeled by the following equations.

$$\bar{D} = |\bar{C}\bar{X}_{rand}(t) - \bar{X}(t)| \quad (4)$$

$$X(t+1) = \bar{X}_{rand}(t) - \bar{A}\bar{D} \quad (5)$$

where  $t$  indicates the current iteration,  $\bar{A}$  and  $\bar{C}$  are coefficient vectors,  $\bar{X}_{rand}(t)$  is a random position vector and  $\bar{X}(t)$  is the current position vector.

In the encircling phase, the best search agent is defined, and other agents will update their positions towards the best search agent according to the following equations.

$$\bar{D} = |\bar{C}\bar{X}^*(t) - \bar{X}(t)| \quad (6)$$

$$X(t+1) = \bar{X}^*(t) - \bar{A}\bar{D} \quad (7)$$

where  $\bar{X}^*(t)$  is the position of the best solution obtained so far.

The coefficient vectors  $\bar{A}$  and  $\bar{C}$  are calculated as

$$\bar{A} = 2\bar{a}\bar{r} - \bar{a} \quad (8)$$

$$\bar{C} = 2\bar{r} \quad (9)$$

where  $\bar{r}$  is a random vector and  $\bar{a}$  is decreased from 2 to 0.

The humpback whales also exhibit an interesting hunting technique called bubble-net feeding mechanism. They forage by creating distinctive bubbles along a circle or 9-shaped path. To mathematically model this mechanism the distance between the whale located at  $(X, Y)$  and prey located at  $(X^*, Y^*)$ . A spiral equation is then created between the position of whale and prey to mimic the helix-shaped movement of humpback whales as follows

$$\bar{X}(t+1) = \bar{D}.e^{bl}.\cos(2\pi l) + \bar{X}^*(t) \quad (10)$$

where  $\bar{D} = |\bar{X}^*(t) - X(t)|$  indicates the distance between the whale and the prey,  $b$  is a constant for defining the shape of the logarithmic spiral,  $l$  is a random number in between -1 and 1.

## III. METHODOLOGY

The database consists of 114 real backscattered signals of four classes of acoustic targets. Two targets namely, humpback whale and sea lion belong to the mammalian class while the other two, namely, ship and boat are of mechanical origin. Classification of the four target types is done using multiclass SVM employing 1-a-a approach.

The classification involves training and testing phases. In the training phase the characteristic features of labeled acoustic signals are extracted based on which a reference model of each category is created. In the testing phase, test signals are fed to the classifier which uses the reference model created in the training phase to identify their category. Though the ratio of the acoustic files selected for training and

testing are user-selectable, an intensive training phase will certainly improve the performance of the classifier.

In the proposed classifier features are extracted through Mel Frequency Cepstral Coefficients (MFCC) as spectral techniques cannot often reliably perform to derive the characteristics of underwater signals in the presence of composite ambient noise and varying environmental parameters. To make the classification process more robust and reliable, nonlinear techniques such as cepstral analysis is used. One of the important properties of the cepstrum is that it is a homomorphic transformation in which the output is a superposition of the input signals. A more systematic approach for extracting the cepstral features makes use of the estimation of Mel Frequency Cepstral Coefficients (MFCC), which is a measure of the perceived harmonic structure of sound. A Mel is a psychoacoustic unit of frequency which relates to the human perception of audio and is approximated using the expression

$$m = 2595 \log_{10}[1 + f/100] \quad (11)$$

where  $f$  is the frequency in Hz. Mel filter banks, which is a row of triangular filters overlapping at Mel-spaced intervals are used to transform the spectrum emphasized at Mel intervals. MFCC's are obtained by taking Discrete Cosine Transform (DCT) of the logarithm of the short-term energy spectrum obtained after the Mel-scale filtering.

The proposed classifier has a feature extractor based on the Mel Frequency Cepstral Coefficients (MFCC). The target specific features extracted using spectral estimation of the noise emissions alone cannot always perform reliable classification especially, in the presence of composite ambient noise and varying environmental parameters. To make the classification process more robust and reliable, those feature components are incorporated by exploiting the other unexplored features of the noise sources. A variety of signal processing applications use the collection of nonlinear techniques known as cepstral analysis which is capable of yielding potential features that can aid in the process of classification. One of the important properties of the cepstrum is that it is a homomorphic transformation in which the output is a superposition of the input signals. A more systematic approach for extracting the cepstral features makes use of the estimation of Mel Frequency Cepstral Coefficients (MFCC), which is a measure of the perceived harmonic structure of sound. A Mel is a psychoacoustic unit of frequency which relates to the human perception and is approximated using the expression

The efficiency of the proposed SVM classifier depends profoundly on (i) proper setting of SVM parameters, (ii) selection of the apt kernel function, and (iii) finding the optimal kernel parameters. In the proposed classifier, BAT algorithm is employed to find the apt kernel function for the problem in hand and set the optimal parameters for the chosen kernel function and the SVM classifier.

The pseudocode of the WOA algorithm is shown in figure 1. The parameters which are optimally found from the WOA algorithm is tabulated in table (II). Each solution encodes 7 parameters  $a_1, a_2, a_3, a_4, a_5, a_6$ , and  $a_7$ .

The fitness function is used to define a fitness value to each candidate solution. Accuracy, defined as the percentage

of samples correctly classified is the most common performance criterion, is used as the fitness function.

Table II. Standard Kernel Functions

| Attribute | Parameter                                               |
|-----------|---------------------------------------------------------|
| $a_1$     | Kernel (linear, quadratic, rbf, polynomial, mlp)        |
| $a_2$     | KKT violation level                                     |
| $a_3$     | Method used to find separating hyperplane (QP, LS, SMO) |
| $a_4$     | MLP kernel parameter $p1$                               |
| $a_5$     | Sigmoid kernel parameter $p2$                           |
| $a_6$     | Polynomial kernel parameter, polynomial order           |
| $a_7$     | RBF kernel parameter, RBF sigma                         |

#### IV. RESULTS AND DISCUSSIONS

A multiclass SVM classifier with 1-a-a approach is employed in the proposed classifier. Classification of 4 classes of acoustic signals are attempted, namely humpback whale, sealion, ship and boat. As discussed earlier the classification has a training and testing phase. We have used 70% data for training and 30% for testing. The training data set is again divided into two sets for fitness calculation. 70% of the training data set is given to multiclass SVM to train the classifier and the remaining 30% is used to calculate the fitness values during the training phase.

The performance of multiclass SVM classifier is improved by incorporating automatic parameter and kernel selection. This is done using WOA algorithm. The results are compared with BAT algorithm based automatic parameter and kernel selection which was done in an earlier work. The fitness function is the accuracy obtained from the evaluation of solutions. Fitness function  $F$ , is defined as

$$F = (TP + TN)/(FP + FN + TP + TN) \quad (12)$$

where

TP = True Positive

TN = True Negative

FP = False Positive

FN = False Negative

The fitness function of the each solution is calculated from (12), using training dataset. The candidate solutions are initialized randomly, and the performance of the algorithm is calculated for varying population size of 10, 15, 20 and 25.

The results of the experiments are tabulated in table (III) and table (IV) and indicate a clear improvement in the performance metrics when the WOA algorithm is used compared with the performance obtained with the BAT algorithm.

Table III. Performance of WOA with various population sizes

| Population Size | $a_1$       | $a_2$ | $a_3$ | $a_4$  | $a_5$    | $a_6$        | $a_7$ | % Accuracy   |
|-----------------|-------------|-------|-------|--------|----------|--------------|-------|--------------|
| 10              | <b>poly</b> | 0.589 | 5.880 | -4.662 | <b>6</b> | 3.305        | 0.043 | 65.71        |
| 15              | <b>rbf</b>  | 0.895 | 9.35  | -9.432 | 2        | <b>6.858</b> | 0.047 | 71.42        |
| 20              | <b>rbf</b>  | 0.161 | 3.026 | -5.088 | 3        | <b>5.581</b> | 0.036 | <b>74.28</b> |
| 25              | <b>rbf</b>  | 0.229 | 2.714 | -6.462 | 5        | <b>6.605</b> | 0.027 | 62.85        |

Table IV. Performance of BAT algorithm with various population sizes

| Population Size | $a_1$       | $a_2$ | $a_3$ | $a_4$  | $a_5$    | $a_6$        | $a_7$ | % Accuracy |
|-----------------|-------------|-------|-------|--------|----------|--------------|-------|------------|
| 10              | <b>rbf</b>  | 0.77  | 8.165 | -7.735 | 11       | <b>8.6</b>   | 0.013 | 71.42      |
| 15              | <b>poly</b> | 0.684 | 2.138 | -1.929 | <b>9</b> | 8.33         | 0.064 | 71.42      |
| 20              | <b>rbf</b>  | 0.241 | 5.91  | -3.83  | 4        | <b>2.713</b> | 0.008 | 60         |
| 25              | <b>rbf</b>  | 0.524 | 8.45  | -9.992 | 9        | <b>5.98</b>  | 0.054 | 54.25      |

```

Initialize the whales population  $X_i(i=1,2,...,n)$ 
Calculate the fitness of each search agent
= the best search agent
While( $t < \text{maximum number of iterations}$ )
    For each search agent
        Update  $a, A, C, l$ , and  $p$ 
        if ( $p < 0.5$ )
            if2 ( $|A| < 1$ )
                Update the position of the current search agent as in encircling phase
            else if ( $|A| \geq 1$ )
                Select a random search agent ( $X_{rand}$ )
                Update the position of the current search agent as in exploration phase
            end if
        else if ( $p \geq 0.5$ )
            Update the position of the current search agent as in bubble-net phase
        end if
    end for
    Check if any search agent goes beyond the search space and amend it
    Calculate the fitness of each search agent
    Update  $X^*$  if there is a better solution
     $T = T + 1$ 
end while
return
    
```

Figure 1. Pseudocode of Whale Optimization Algorithm

## V. CONCLUSIONS

The performance of a classifier greatly depends upon the parameter setting. Parameter tuning to obtain best classification results is attempted in this paper. We have used Whale Optimization Algorithm for automatic kernel and parameter selection. WOA gives reasonably good classification accuracy when classifying underwater acoustic audio clips and also shows improvement over BAT algorithm based optimization.

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## VII. REFERENCES

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