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Performance of fusion algorithm for active sonar detection in underwater acoustic reverberation environment

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ABSTRACT

In the active SONAR system, the detection of a target is performed by Matched-Filter processing proceeded by a Constant False Alarm Rate (CFAR) thresholding method. CFAR alone is a not a competent method, to annihilate the invalid echoes. This method on sole does not attain the best pursuance under the reverberation scenario in the non-homogeneous condition of the acoustic environment. In this, the paper Fusion algorithm is recommended for active sonar application, where the CA-CFAR and Support Vector Machine (SVM) based classification method are together used to annihilate the invalid echoes and simultaneously improve the detection of valid echoes. In this paper, a comparison of linear and non-linear SVM with the CA-CFAR method is proposed for elevating the performance of detecting the valid echoes and annihilates the invalid echoes. The interpretation of the algorithm is accomplished using measured data.

Keywords*— CA-CFAR, SVM*

1. INTRODUCTION

In SONAR applications, when the signal is transmitted into the underwater medium, the signal hits the main target and other objects (such as surface and bottom parts of the ocean etc.), and some part of the signal is reflected back, which is known as echo signal. The echo signal consists of actual target information, which is buried in noise and reverberation. In some cases, to detect the target accurately, thresholding method is used, to select the valid echo. In most simple CFAR detection schemes, the threshold level is calculated by estimating the level of the noise floor around the Cell Under Test (CUT). This can be done by considering a block of cells around the CUT and calculating the average power level. In homogeneous condition, CA-CFAR processor is the best CFAR processor to improving the detection of valid echoes. But, CA-CFAR method on sole does not attain best pursuance under the reverberation scenario in the non-homogeneous condition of the acoustic environment. In reverberation environment, this method will improve the detection of valid echoes but also upsurge the false alarm rate in different channels. As, CA-CFAR method does not attain best pursuance in non-homogeneous condition, a latest algorithm, SVM (Support Vector Machine) classifications are chosen and are used eloquently for an immense range of applications, such as, text (and hypertext) categorization, image classification, bioinformatics (Protein classification, Cancer classification), hand-written character recognition. SVM method is used to map the data into higher-dimensional feature space, where, the data is linearly separable. For classifying the non-linear data, SVM kernel methods are used to differentiate the valid and invalid echoes.

This paper starts with the introduction of the topic in section I. Section II presents a typical under water Electric field measurement facility. Analysis of underwater Electric fields is presented in Section III. Proposed algorithm is developed to find the target motion (Approaching/Receding) in Section IV and algorithm is developed to find the location of target location (Port/Starboard) in Section V.

2. SVM (SUPPORT VECTOR MACHINE)

Support Vector Machine method is a powerful algorithm for classifying the data based on different classes. This paper uses two class SVM problems. The main intention of this algorithm is to differentiate the data using two classes, which are both linear and non-linear separable data by using optimum hyperplane. In non-linear case, initially, SVM method transforms the data into higher dimensional space, where the data is linearly separable. Mainly, linear and non-linear SVM has two stages, training and testing stage.

2.1 Linear Case

Given, a training vectors belonging to two separate classes,

$$D=\{(x^1,y^1),\ldots\ldots,(x^l,y^l)\},\qquad x\in R,\ y\in\{-1,1\}.$$

In the first stage, training is done to separate the data by a separating hyperplane.

Assume training set is linearly separable case, that is exist w and b ЄR such that

$$w^Tx_i+b>0 \text{ for all i, } y_i=+1$$

$$w^Tx_i+b<0 \text{ for all i, } y_i=-1$$

$w^Tx+b=0$, the equation for separating hyperplane.

We can scale w and b such that

$$w^T x_i + b > +1 \text{ for all i, } y_i = +1$$

$$w^T x_i + b < -1 \text{ for all i, } y_i = -1$$

Or equivalently,

$$y_i(w^T x_i + b) \geq 1, for\ all\ i$$

The set of vectors is said to be optimally separated by the hyperplane if it is separated without error and the distance between the closest vectors to the hyperplane is maximal.

Hence the hyperplane that optimally separates the data is the one that minimizes $\frac{1}{2}\|\boldsymbol{w}\|^2$

The decision boundary can be found by solving the following constrained optimization problem

Minimize $\frac{1}{2}\|W\|^2$
Subject to $y_i(W^T x_i + b) \geq 1, i = 1,2, \ldots n$

One method of solving the constrained optimization problem is Lagrangian equation, which is used to solve the w and b values.

$$L(w, b, \mu) = \frac{1}{2} w^T w + \sum_{i=1}^{n} \mu_i [1 - y_i(w^T x_i + b)]$$

The L is called the Lagrangian of the problem and μ_j is called the lagrangian multipliers, w is the weighted vector, b is the bias value, y_i is two classes, and n is the no. of support vectors. One method of solving the constrained optimization problem is Lagrangian equation, which is used to solve the w and b values.

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, where L is called the Lagrangian of the problem and μ_j is called the lagrangian multipliers, w is the weighted vector, b is the bias value, y_i is two classes, and n is the no. of support vectors.

Weighted and bias parameters are obtained by differentiating the lagrangian equation w.r.t to w and b and set it to zero.

$$\boldsymbol{w} = \sum_{i=1}^{n} \mu_i y_i x_i\ ,\ \ \boldsymbol{b} = \frac{1}{y_i} - \boldsymbol{w}^T \boldsymbol{x}_i$$

In second stage, for an unknown X (test data), the decision is given by,

$$\boldsymbol{F} = \boldsymbol{W}^T \boldsymbol{X} + \boldsymbol{b}$$

2.2 Non-Linear Case

SVM can dexterously perform a non-linear classification known as the kernel trick i.e., implicitly mapping the inputs into higher dimensional feature space. Compared to linear case, it is clear that a full separation of two classes would require a curve (which is more complex than a line). The process of rearranging the objects is known as mapping (transformation). Note that in this new setting, the mapped objects is linearly separable and thus instead of constructing the complex curve, all we have to do is to find the optimal line that can separate the objects. Given, a training vectors belonging to two separate classes,

$$D = \{(x^1, y^1), \ldots \ldots .., (x^l, y^l)\}, \quad x \in R, y \in \{-1,1\}.$$

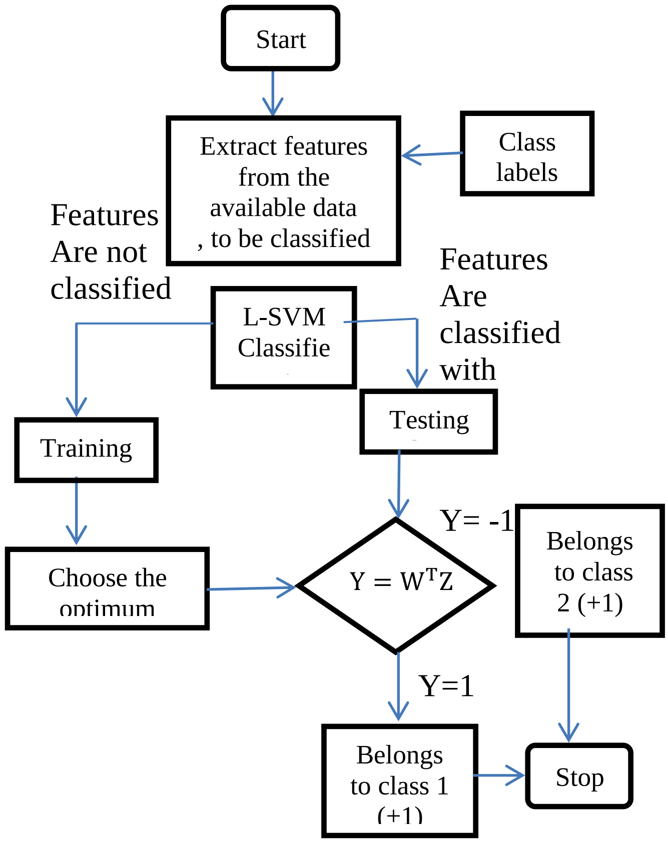
In non-linear case, these training vectors should be transformed into higher dimensional feature space $\varphi(x)$.

$\Phi: \longrightarrow$ x
$\{\boldsymbol{x1.^2}, \boldsymbol{x2.^2}, \boldsymbol{x3}, \ldots \ldots \boldsymbol{xd.^2},, \boldsymbol{x1x2}, \ldots \ldots \ldots \boldsymbol{x1}, \boldsymbol{xd}, \ldots \ldots \ldots \boldsymbol{xd} - \boldsymbol{1}, \boldsymbol{xd}\}.$

For each x_i, we have to calculate $\varphi(x_i)$, that may be costly calculation and then we have to calculate w (weighted vector), which is a lot of computation. So, in order to overcome this computation, kernels are introduced in SVM classification method. Suppose we have a function, k: R^m dimensional $\rightarrow$ R,

Such that, $k(x_i, x_j) = \varphi(x_i)^T \varphi(x_j)$, called as kernel function.

The following are the most popular kernels for real valued vector inputs.



2.1.1 Polynomial kernel of degree d

$$\mathrm{K}(x, z) = (sv^T z + 1)^d$$

where sv=support vectors

And z=new unknown test vector

2.1.2 RBF (Radial Basis Function) kernel

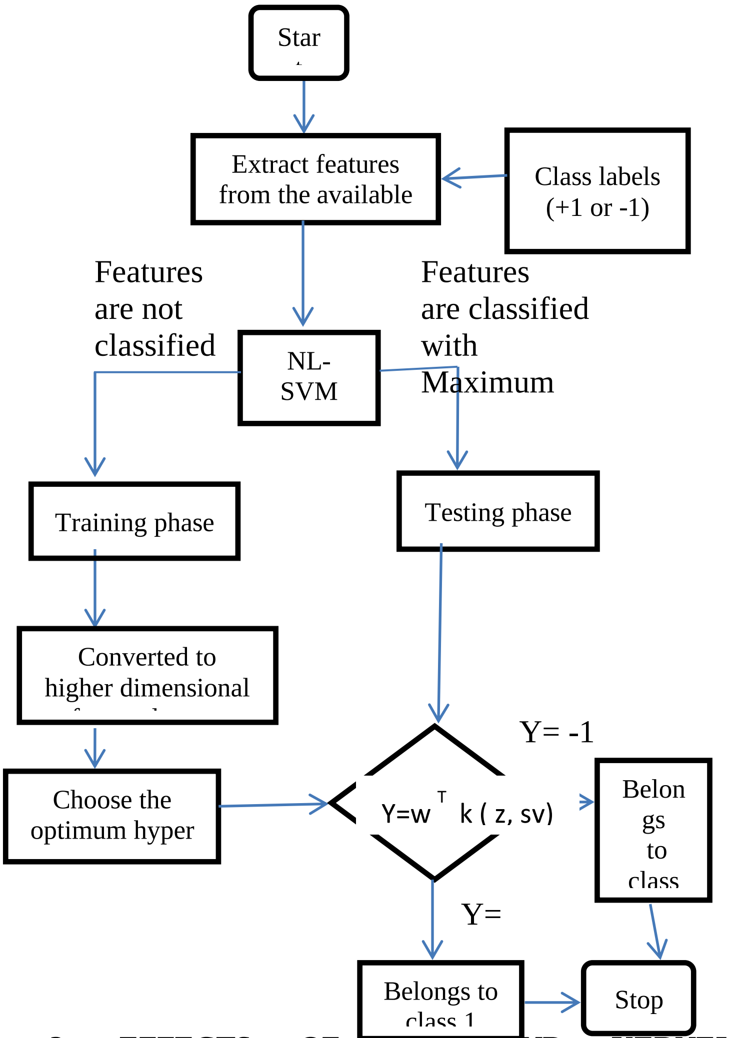
Radial basis function (RBF) is based on Gaussian Curve. It takes a parameter that determines the center (mean) value of the function used as a desired value. Aradial basis function (RBF) is a real-valued function whose value depends only on thedistance from the origin,

$$k(x, z) = \exp\left(-\gamma \|sv - z\|^2\right)$$

$$where\ \gamma = 1/2\ \sigma\text{\^{}}2$$

In Training stage, different kernels are selected at a time, in which, input vector is mapped into higher dimensional space.

Different kernels have different parameters, which are to be considered.



3. EFFECTS OF SVM AND KERNEL PARAMETERS

Training an SVM finds the large margin hyper-plane i.e. sets the values of the parameters alpha and bias. The SVM has another set of parameters called hyper parameters i.e. soft-margin constant C and any parameters in kernel function such as width of the Gaussian kernel or degree of a polynomial kernel. For large values of C, a large penalty is assigned to errors/ margin errors; the hyperplane is close to several data points, which affects its orientation. When C is decreased, the position of the hyperplane is changed, results high margin for the rest of the data. Kernel parameters also play a crucial role on deciding the decision boundary. The degree of the polynomial kernel and width of the Gaussian kernel control the flexibility of the resulting SVM in fitting the data. If the degree is more, then it over fits the data, so the degree and the soft margin C of the polynomial kernel depends on the training data, which fits the data, resulting the optimum decision boundary.

The parameter γ in the RBF kernel is increased, the locality of the support vector expansion increases, leading to greater curvature of the decision boundary. Where

$$\gamma = 1/2\,\sigma\text{^}2.$$

Largeσ^2, features x_i vary more smoothly.
Smallσ^2, features x_i vary less smoothly

We recommend a grid search on C and γ using cross validation. Various pairs of (C, γ) values are tried and the one with the best cross-validation accuracy is picked. Trying exponentially growing sequences of C and γ is an practical method to identify good parameters (C=$2^{-5}, 2^{-3}, \ldots \ldots, 2^{15}$ and $\gamma = 2^{-15}, 2^{-13}, \ldots \ldots, 2^{3}$)

Grid search method is applied to the measured data, and best (C=2e3, γ=2e5) is chosen best pair in RBF-SVM kernel, which fits the data. Polynomial order d=3 and soft margin C=2e-5 are chosen best pair in polynomial kernel-SVM, which fits the data.

4. THE FUSION ALGORITHM

Captivating CA-CFAR or SVM individually in detection of valid targets is improved only to an extent. The observation in detection of targets is accomplished but the false rate is increasing simultaneously. In order to improve the decrease in false rate, Fusion algorithm is proposed. In this, we take CA-CFAR and SVM together. If the data in CA-CFAR and SVM is valid, then the target is to be considered in-turn rest of false echoes fetching zeros. This decrease in false rate and increase in detection of valid targets becomes faultless. To increase the detection of targets even more accurate, different combinations of SVM kernels are performed and the result is fused with CA-CFAR and the performance is validated.

Tab1e 1: Performance comparison of SVM, CA-CFAR and Fusion Algorithm

Algorithm	Detection of Valid Target	Detection of Invalid Target
CA-CFAR	17.55%	3%
-SVM	14.5%	7.633%
RBF-SVM	19.84%	10.68%
Polynomial-SVM	10.68%	4.58%
Fusion1 (CA-CFAR & L- SVM)	14.5%	0
Fusion 2 (CA-CFAR & RBF-SVM)	17.55%	0
Fusion 3 (CA-CFAR & Polynomial-SVM)	10.68%	0
Fusion 4 (CA-CFAR & OR b/w RBF-SVM and Polynomial-SVM)	18.32%	0
Fusion 5 (CA-CFAR & OR b/w between RBF and Linear SVM)	18.32%	0
Fusion 6 (CA-CFAR & OR b/w L-SVM and Polynomial-SVM)	14.5%	0

5. EXPERIMENTAL RESULTS

A sequence of experiment in mono-static condition is conducted to verify the effectiveness of the algorithm. Different pings of Linearly Modulated Signals (LFM) are transmitted from a moving platform against a moving target approximately 80m long. Transmission pings of duration 50ms and 100ms are used throughout the experiment. Different geometries of transmitter and target are also considered to get different aspect combinations. All the data collected during the trial is recorded. The recorded data is passed through a matched filter to get the row data for processing. The range cells are manually labeled as Class1 (actual target echo) and Class 2 (reverberation signal). This is not a complex task since geometry of the transmitter target position is known a priori. From the data sets, 100 Class1 data sets and 100 Class 2 data sets are chosen randomly as the training set for SVM. Using the training set the weight vector and bias are computed. The weight vector and bias is used to verify the performance on the remaining data set. The same test data set is used to verify the performance of CFAR algorithm. Further, the results of fusion method is also computed and tabulated. Table 1 indicates the performance comparison of SVM, CA-CFAR and Fusion algorithms. Different scenarios to illustrate the performance of CFAR, SVM and fusion algorithm are shown in figure 1 to 4.

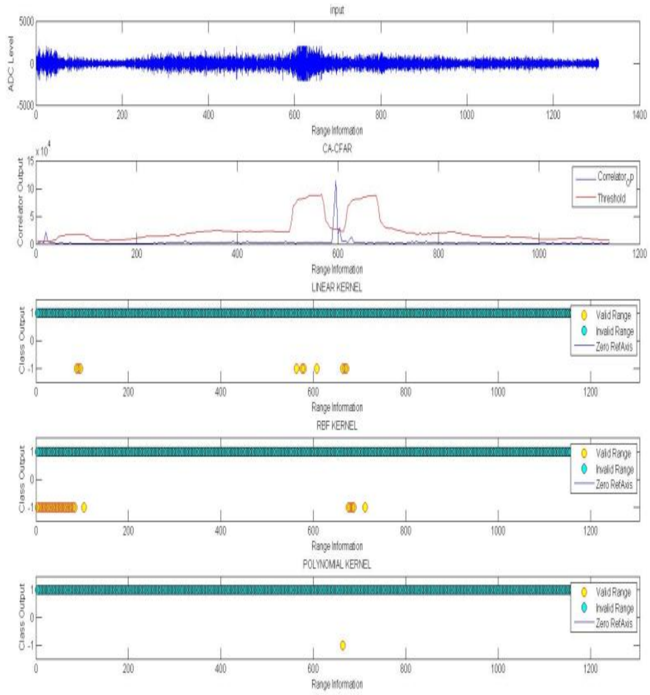


Fig. 1: Indicates that in the L-SVM, Non-L-SVM and CA-CFAR, the command is declared as one

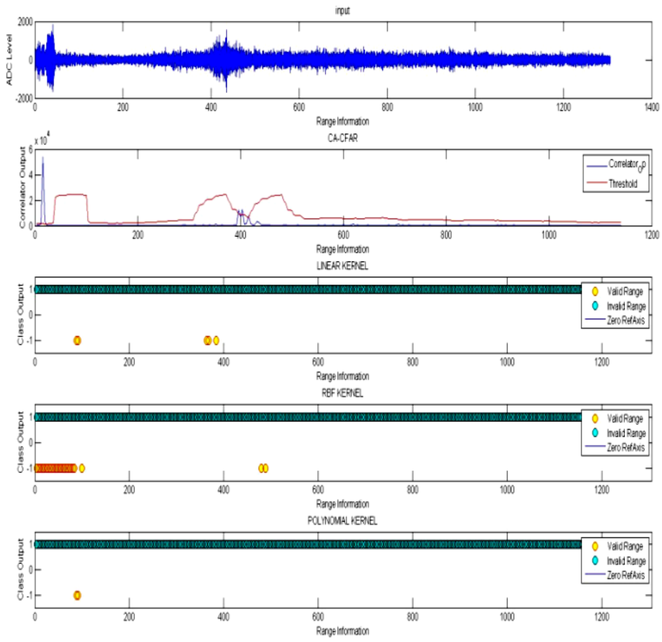


Fig. 2: Indicates that in both L-SVM and RBF-NL-SVM and CA-CFAR the command declared as one, but in polynomial-NL-SVM, the command is declared as zero.

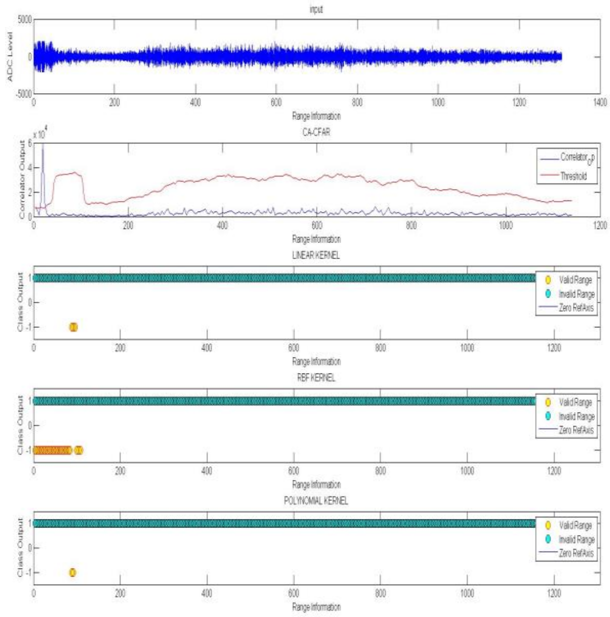


Fig. 3: Indicates that in L-SVM, Non-L-SVM kernels and CA-CFAR the command declared as one.

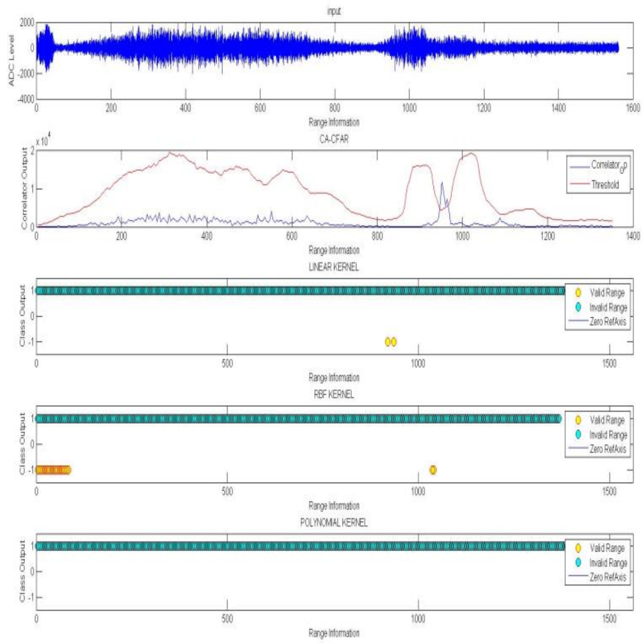


Fig. 4: Indicates that in CA-CFAR, and L-SVM, RBF kernel target is declared where as in Polynomial kernel SVM, target is not declared.

6. CONCLUSION

From the experimentation results on real data and tabulated results, POLYNOMIAL kernel-SVM gives the better performance, when the target has high energy power. If the target has low energy power, then polynomial kernel does not give better performance i.e. it cannot detect the valid target. So, in the case where, the target has low energy power, we should switch to RBF-SVM. From, the tabulated results, Fusion 4 and 5 give the better results i.e. it improves the performance detection of valid target and suppress the invalid target.

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