Classification Of Ground Moving Object Using Coefficient Of Integrated Bispectrum For Doppler Radar

Munesh Singh, Srinivasa Rao Katuri

Abstract: This paper considers the classification of radar target using Backscatter Doppler signature of moving object. Classification performance evaluated by the integrated Bispectrum based technique of feature extraction and compared it with Cepstrum based feature extraction technique. Classifier performance is tested by GMM (Gaussian Mixture Model) and ML (Maximal Likelihood) decision making method. Classifier is trained and tested by distinct target echoes such as single human, double human, and triple human set. Proposed classification results shows the superiority of integrated Bispectrum method over Cepstrum method and classification rates are up to 82% to 87% at different feature sets.

Index Terms: ATR (Automatic Target Recognition), SNR(Signal to Noise Ratio) , Features extraction , Result

1 INTRODUCTION

Radar is a remote-sensing system that is widely used for surveillance, tracking and imaging application for both civilian and military needs. Apart from its day/night and all weather surveillance capability make it robust for a perfect ATR(Automatic Target Recognition) .it also provides valuable information that can be helpful for monitoring the target activity, its speed, its location and its direction. Enormous amount of research is going on development of enhanced radar surveillance system that can avoid the human involvement [1]. Human involvement never been able to give perfect surveillance in varied type of conditions. In order to avoid human involvement, we need a perfect ATR (Automatic Target Recognition) System that can able to give surveillance in all variety of varied conditions that was not possibly by the human. The perfect surveillance possibly only if Radar working capability depends on its signal processing capability and the feedback from the receiver to the transmitter. The radar target classification using Doppler signature in ground moving object depends on better classification algorithm. Many types of classifier algorithms are present such as target classification using Gaussian Mixture Model(GMM) [2], A hidden Markov Model (HMM) [3].However ,the development of effective radar classification of object needs a better classifying feature that can be helpful for recognition of object at certain approximation.

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In this paper we are using integrated Bispectrum coefficient as a classifying feature that is compared with cepstrum based feature extraction at various SNR (Signal-to-Noise Ratio). Classifying performance is trained and tested using Gaussian Mixture Model .GMM based classification methods are majorly applied in speech recognition system [4]. The advantages of using GMM is that it can estimate any density at any degree of approximation that are not possible by single Gaussian .Here estimation of mixture parameter is largely depending on famous iterative Expectation Maximization (EM) algorithm. Performance of this algorithm depends on its initialization. In this work we are using the integrated Bispectrum coefficient that having its own advantages and disadvantages important properties of the Bispectrum such as detection of quadratic phase coupling and suppressing zero mean additive gaussian noise. The main limitations of Bispectrum-based techniques are that they are computationally expensive and the variance of the Bispectrum estimators is much higher than that of power spectral estimators for identical data record size.

2 CLASSIFICATION SCHEME

2.1 TARGET CLASSIFICATION STRATEGY

Radar target classification is carried by Maximum Likelihood (ML) rule and Gaussian Mixture Model [5]. GMM are used for estimation of Bispectrum feature an estimate of its robability density of each component in the mixture of gaussian expression as-

$$p(\mathbf{x};\theta) = \sum_{c=1}^{C} \alpha_k N(\mathbf{x}; \boldsymbol{\mu}_c, \boldsymbol{\Sigma}_c) \qquad (1)$$

GMM is a set of several Gaussians which try to represent groups or clusters of data, therefore they represent different subclasses inside one class .The probability density function (PDF) is defined as a weighted sum of Gaussians where $N(\mathbf{x}; \boldsymbol{\mu}_C, \boldsymbol{\Sigma}_C)$ represent the gaussian mixture of *c* component mean and covariance matrix. α_k is the mixing weight. Multi-dimensional case: μ becomes vector μ, σ becomes covariance matrix Σ.

$$N(\mathbf{x},\boldsymbol{\mu},\Sigma)=\frac{1}{\sqrt{(2\pi)^{D}\,|\Sigma|}}\,e^{-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^{T}\Sigma^{-1}(\mathbf{x}-\boldsymbol{\mu})} \qquad (2)$$

number of components such as means and covariance matrices of the Gaussian component and weight (height) of each component. These parameters are tuned using an iterative procedure called the Expectation Maximization (EM). EM algorithm: recursively updates distribution of each Gaussian model and conditional probability to increase the maximum likelihood. Whole process is divided into two parts one called training part and another called testing part, at the training time Training dataset is applied to the algorithm and Initialize the initial Gaussian means μ_i using the K-means clustering algorithm and Initialize the covariance matrices of distance to the nearest cluster, Initialize the weights covariance matrix, so that all Gaussian are equally likely and then apply EM algorithm .EM algorithm have an iterative steps.

E step: Computes the conditional expectation of the complete log-likelihood, (Evaluate the posterior probabilities that relate each cluster to each data point in the conditional probability) assuming the current cluster parameters to be correct

M step: Find the cluster parameters that maximize the likelihood of the data assuming that the current data distribution is correct, then recomputed $w_{n,c}$ using the new weights, means and covariance's. Stop training if

$$w_{n+1,c} - w_{n,c} < \text{threshold}$$

or when number of component completed.

2.2 Feature Extraction

The classification features in this work are coefficient of integrated Bispectrum [6]. The Bispectrum is defined as the two dimensional Fourier transforms of third order cumulate of the data. Cumulate represent the triple correlation of the data sequence and are usually a function of time. The third order cumulate of *{x(k)}* is defined as-

$$T(\mu,\nu) = E(\xi(\kappa)\xi(\kappa+\mu)\xi(\kappa+\nu)\} \qquad (3)$$

Assuming that the sequence *{x(k)}* is third order stationary .The Bispectrum of *{x(k)}* can be obtained from T(m,n) using Fourier transform. m and n is lags.

$$B(\omega1,\omega2)=\sum_{m}\sum_{m} T(\mu,\nu)\Omega(\mu,\nu)\varepsilon\xi\pi\{-\varphi(\omega1\mu+\omega2\nu)\} \qquad (4)$$

Where *W(m,n)* is two dimensional window that has the same symmetry properties as T(m,n).The backscatter signal from the target is recorded as frequency, so third order cumulate is defined in terms of frequency as-

$$T(\phi1,\ \phi2) = E\{Z*(\phi)Z(\phi+\phi1)Z(\phi+\phi2)\} \qquad (5)$$

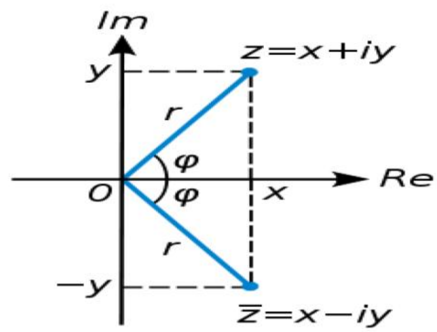


Fig.1.Complex conjugate

Where *Z*(f)* is complex conjugate *Z(f)* of backscatter response of radar target as seen in fig(1) and E{.} denote statistical expectation. Bispectrum is short term Fourier transform at variant angular frequency it depends on multiple frequency component *(f,f+f1,f+f2)* based on its phase relation. As compared to Bispectrum, power cepstrum method independently treats the frequency component and its second order cumulate also known as autocorrelation is defined as-

$$\Delta(\mu) = E(\xi(\kappa).\xi(\kappa+\mu)\} \qquad (6)$$

Power cepstrum is obtained by taking the Fourier transformation of *D(m)* as-

$$X(\omega) = \sum_{\mu} \Delta(\mu)\Omega(\mu)\,\varepsilon\xi\pi(-\varphi(\omega\mu) \qquad (7)$$

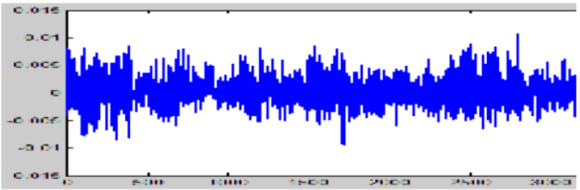
Where W(m) is single dimension window that has same symmetric properties as D(m).Second order cumulate of backscatter signal of radar target is recorded in term of frequency define as-

$$\Delta(\phi) = E\{Z*(\phi).Z(\phi) \qquad (8)$$

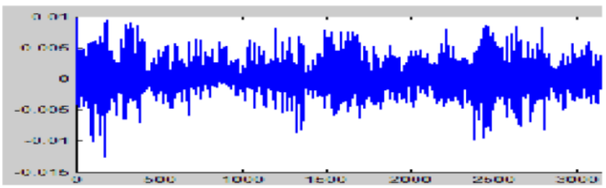
We can also define third order and second order cumulates in terms of time.

$$B(\tau1,\ \tau2) = \sum_{\phi 1}\sum_{\phi 2} T(\phi1,\ \phi2)\,\varepsilon\xi\pi\{-\varphi(\tau1\ \phi1+\tau2\ \phi2)\} \quad (9)$$

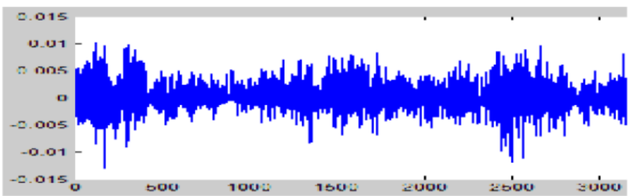
The Bispectrum can also be expressed in terms of range (r1,r2).Bispectrum derived from above definition in (5) signifies that it implicit depends on multiple frequency response [7]. In our case radar backscatter signals from the object holds variety of information at different-different frequency responses from the body part of the moving target [8]. Majorly in human body scattering part is torso and swinging legs and arms scattering is not that much significant because every parts of body independently scatter phase coupled information.



a) Preprocessed Echo of single Person



b) Preprocessed Echo of Double Person



c) Preprocessed Echo of Triple Person

Fig.2

Here in fig (2) we can see the dropper signals sets of one, two and three human approaching toward the radar. We can easily see that most dominant part of the body torso showing the uniformity but independent part showing frequency response varies.

3 RESULT

Classification of radar target model is estimated at various SNR (Signal-to-Noise Ratio) and compared it with power cepstrum and integrated Bispectrum methods. Classification results are modeled in two different ways, first by adding the additive white gaussian noise (AWGN) and second one without adding any noise; in both type of classification integrated Bispectrum method gives an excellent result of classification. Performance results comparisons are carried out by considering various classifying feature vectors at various SNR. The highest classifications results of 87% had been achieved with integration times of 16 seconds by considering a 35 features vector on the other hand Power Cepstrum method had gave 80% classification result without considering noises. Result of Radar classification at various SNR is given below. Target Echo at various SNR can be seen in fig (3).

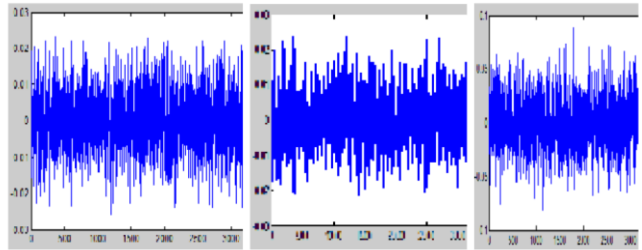


Fig.3.Doppler Echo of three class of object After adding additive white gaussian (AWGN).

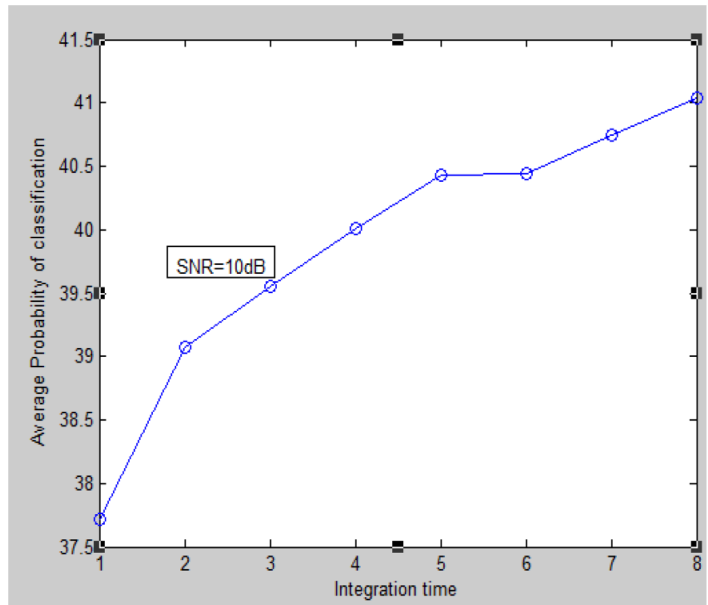


Fig.4. Classification rate of Bispectrum at 5 Feature vector at 10dB of SNR

TABLE 1
CLASSIFICATION TABLE OF BISPECTRUM

SNR(dB)	Classification rate in %	Integration time	Feature size
10	39%	8	5
20	51%	8	5
30	65%	8	5

Here in table average probability of classification rate is shown. Classification rate can be increased if increase the size feature vector as well as integration time or both individually increased. Both are interrelated quantity with classification rate.

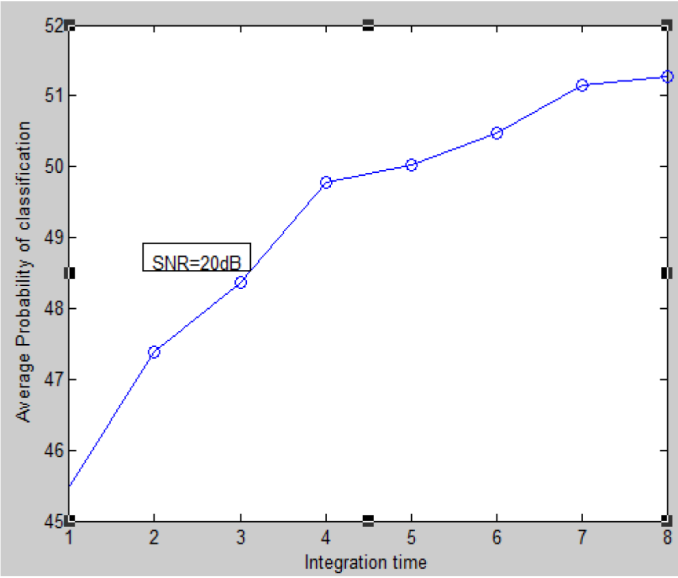


Fig.5. Classification rate of Bispectrum at 5 Feature vector at 20dB of SNR

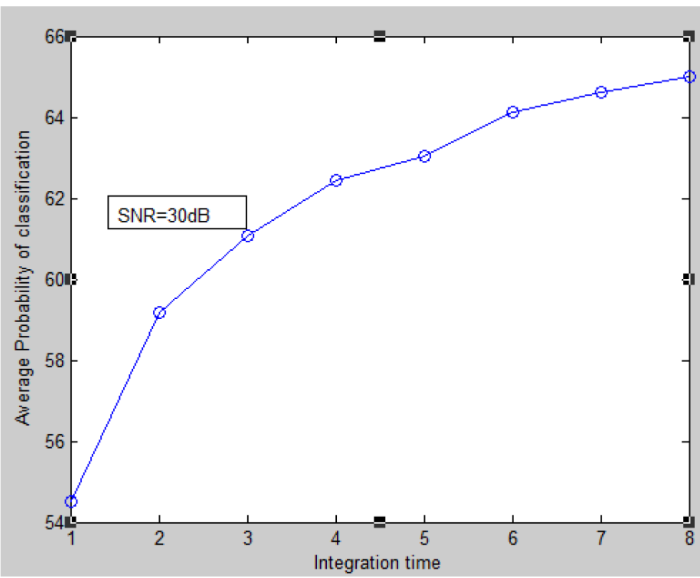


Fig.6. Classification rate of Bispectrum features 5 feature vector at 30 dB of SNR.

TABLE 2
CLASSIFICATION TABLE OF BISPECTRUM

SNR(dB)	Classification rate in %	Integration time	Feature Size
10	40%	8	10
20	53%	8	10
30	69%	8	10

Classification performance of power cepstrum method at various SNR are given below-

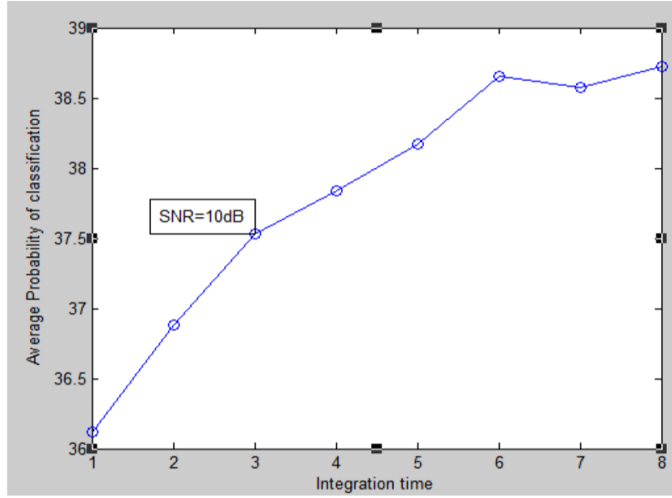


Fig.7.Classification rate of cepstrum at 5 Feature vector at 10dB of SNR.

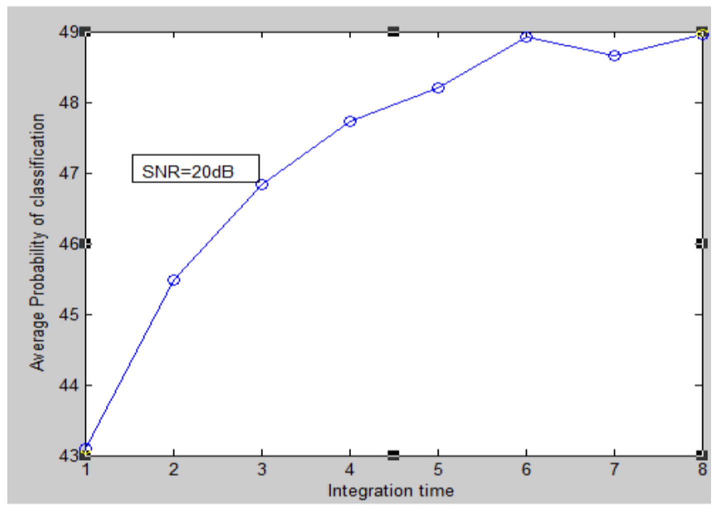


Fig.8.Classification rate of cepstrum at 5 Feature vector at 20dB of SNR

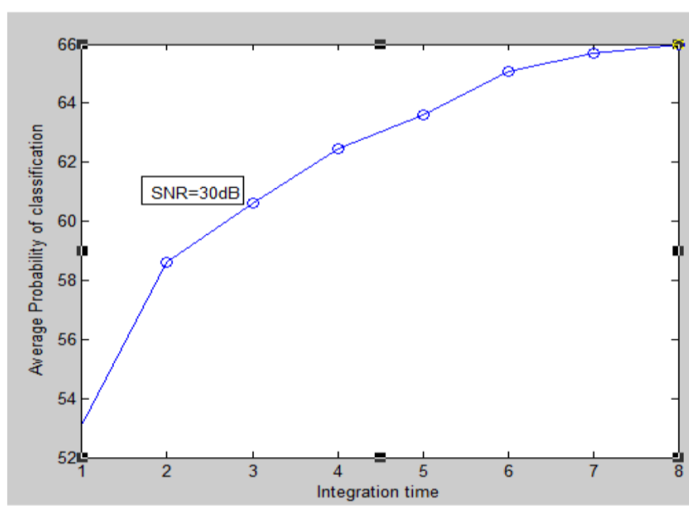


Fig.9.Classification rate of Cepstrum at 5 Feature vector at 30dB of SNR.

TABLE 3
CLASSIFICATION TABLE OF CEPSTRUM

SNR(dB)	Classification Rate in %	Integration Time	Feature Size
10	39%	8	5
20	49%	8	5
30	66%	8	5

Classification rate of power Cepstrum method at 10 size of feature vector given below.

TABLE 4
CLASSIFICATION TABLE OF CEPSTRUM

SNR(dB)	Classification Rate in %	Integration Time	Feature Size
10	38%	8	10
20	50%	8	10
30	68%	8	10

4 CLASSIFICATION PERFORMANCE

The classification performance of Bispectrum method and Cepstrum method had analyzed without considering any noise addition into the signal. The below simulation results shows at various size of feature vector at 16 sec of integration times.

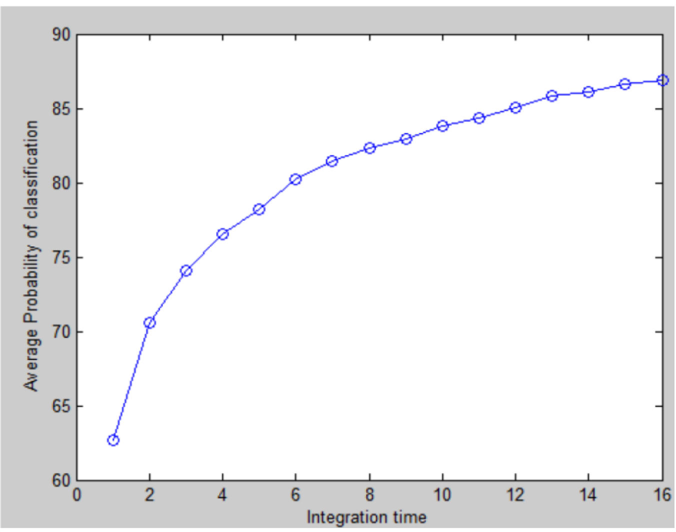


Fig.10.Classification rate of Bispectrum feature at 16 sec of integration time with 35 feature vector.

TABLE 5
CLASSIFICATION PERFORMANCE OF BISPECTRUM

Classification Rate in %	Feature Size	Integration Time
82%	5	16
86%	15	16
87%	35	16

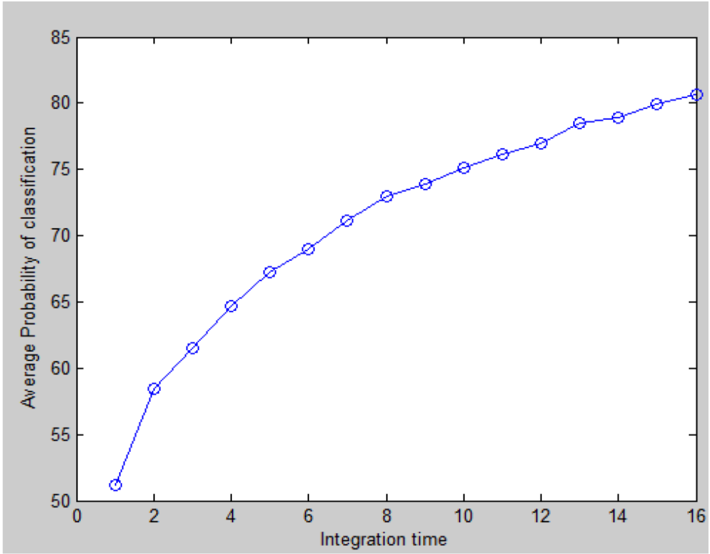


Fig.11.Classification rate of cepstrum feature at 16 sec of integration time with 35 feature vector. If we increase the feature vector size up to 50, then the classification results goes up to 90%.

TABLE 6
CLASSIFICATION PERFORMANCE OF CEPSTRUM

Classification Rate in %	Feature Size	Integration Time
73%	5	16
78%	15	16
81%	35	16

The simulation results concludes that Bispectrum method of classification is robust than Cepstrum method. Also the analyses show how integration time and feature vector size effect the classification performance rate.

5 CONCLUSION

In this paper we showed the superiority of the Integrated Bispectrum method over Cepstrum method by considering various parameters. So as we seen various parameter effect the classification performance that we can overcome it by applying various technique of signal processing to make a robust ATR system for ground based surveillance[13]. Here in our work we tried to support the optimization of ATR System.

Acknowledgment

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