RADAR SIGNAL RECOGNITION METHOD BASED ON GAUSSIAN MIXTURE MODELS

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Abstract: This paper describes an automatic recognition method of radar signals. The modern radar systems utilize many heterogeneous signals and corresponding number of various recognition methods exist. Nevertheless, this paper is focused on an automatic target recognition method based on calculation of the Gaussian Mixture Models because they can be widely used and theirs parameters are easy to change. These abilities predetermine the Gaussian Mixture Models recognition method to cover the most of the radar signals recognition tasks. The Gaussian Mixture Models were obtained for a wide range of heterogeneous radar signals. The Maximum-likelihood criterion was applied to these models and algorithm performance was examined.

Keywords: Gaussian Mixture Model, GMM, radar signal, recognition.

1 INTRODUCTION

The main task of ground surveillance radar is detection and recognition of the moving targets. Typical radar system can detect and track targets automatically however target recognition is unable to do without cooperation with the target [1]. If a plane is not equipped by a transponder of secondary surveillance radar (SSR) the human operator is necessary for moving targets recognition. Human based automatic target recognition (ATR) systems have as many advantages as disadvantages. The major advantages of the human operator are learning and adapting abilities. However, it may be concern even as a disadvantage because human operators require adequate training to become well experienced. Other disadvantages could be actual mental conditions, illness, individual experiences and knowledge etc. Various studies have shown that human operators can manually track only a few targets [2]. These reasons lead to unsatisfactory performance limited by human operator's senses and forms demand for an automatic target recognition system which can operate without any human involvement. Performance of such systems should exceed performance of experienced operators and could be much more cost-effective.

2 GAUSSIAN MIXTURE MODELS

The modern radar systems are very complex devices and deal with enormous number of various signals from different sources. The signal source can be an aircraft, missile, boat or vehicle equipped with Identification Friend or Foe (IFF) system, SSR transponder, on-board radar system or any radio transmitter [3]. Every specific signal emitted by target can be used for its recognition and that is the reason why the most general method of signal recognition is essential. One of a suitable method is based on calculation of Gaussian mixture models (GMM) which is regularly used for speech recognition [4].

General mixture model $F_k(\mathbf{x})$ can be represented as [5]

$$F_k(\mathbf{x}) = \sum_{k=1}^{K} c_k f_k(\mathbf{x}) \tag{1}$$

and $c_k \geq 0$, $\sum_{k=1}^{K} c_k = 1$, where K is the number of mixture components, $\mathbf{x}$ is an input data vector, c_k stand for the weight coefficient and $f_k(\mathbf{x})$ represent distribution function. Mixture model type is determined by kind of distribution function so Gaussian mixture model contains normal distribution function, known as the Gaussian function

$$f_k(\mathbf{x}) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{2}$$

where parameter σ^2 is the variance and μ is the mean value or expectation (location of the peak) of one mixture component.

For illustration, the two dimensional Gaussian mixture models are depicted in Figure 1. This Gaussian mixture model is composed of five mixture components. Every component is defined by its own mean value and variance in each dimension. Every evaluated parameter is described by mean value and variance so in Figure 1 every mixture component is described by two mean values and two corresponding variances. The variances pertain to the parameter sweep and parameter inaccuracy. In general, The Gaussian mixture model can be n-dimensional depending on the number of parameters. The parameter can be any feature of the analyzed signal like an amplitude, frequency, pulse width, periodicity etc. Desired parameters are analyzed in a certain range and can be defined as a global mean of the mixture model so parameter values can be positive or negative.

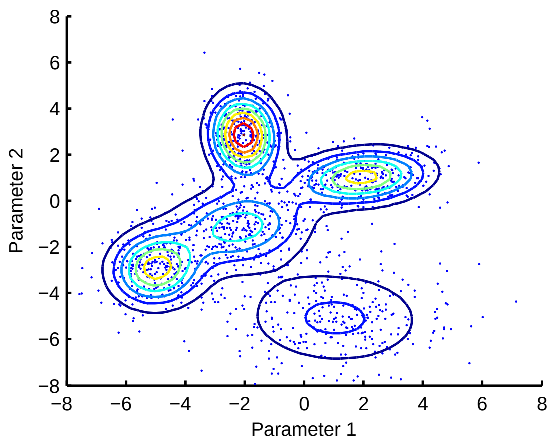

Figure 1: 2D PDF of GMM

3 RECOGNITION SCHEME

The signal processing block diagram is shown in Figure 2. First, the received signal is sampled and quantisated, depending on the desired precision can be down sampled to reduce computational complexity. Then it is possible to extract the required parameters from the received signal. The parameter can be any signal characteristic such as carrier frequency, modulation frequency, pulse width, repetition period, cyclic prefix and many others [7]. The modern radar systems are often reconfigurable [8] so the recognition method must be easily reconfigurable too. Gaussian mixture models can be composed of many parameters and in case of major changes of only one parameter, the probability of recognition may be still sufficient due to statistical character of recognition method. Block GMM calculate Gaussian mixture model which is compared to predefined database of Gaussian mixture models. Final decision is based on maximum-likelihood criterion, as in [1]

$$\hat{m} = \arg \max_{m=1,2,\ldots,M} f_{K(m)}\left(\mathbf{x}, H_m\right), \tag{3}$$

where $f_{K(m)}\left(\mathbf{x}, H_m\right)$ is probability density function of input data vector $\mathbf{x}$ under hypothesis H_m of the predefined mixture model.

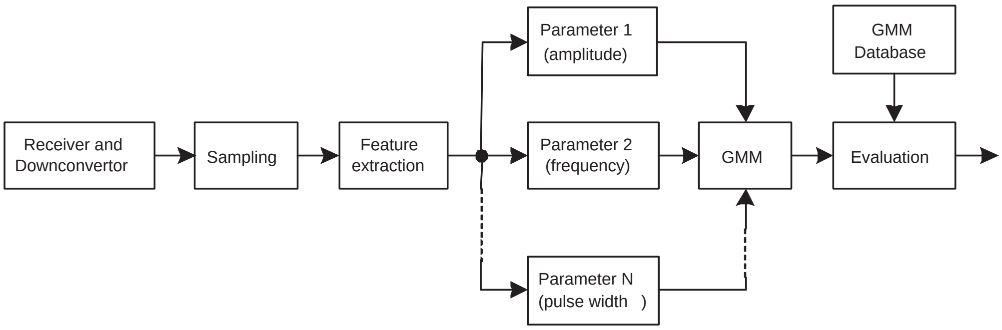

Figure 2: Block scheme of recognition system

4 ALGORITHM CONVERGENCE

The most popular algorithm for GMM parameters estimation is the Expectation–Maximization (EM) algorithm [1]. The popularity of the EM algorithm is due to its simple implementation and nondecreasing likelihood maximization. However, limitation of the EM algorithm is prior knowledge of components number. It is not acceptable condition for initializing the parameters. An solution for initialization problem is the greedy learning EM algorithm for GMM [9]. This method start with only one mixture component and estimate the EM algorithm. Second mixture component is inserted and the EM algorithm is re-estimated. If likelihood criterion increased significantly another mixture component is inserted. This procedure is performed until the convergence condition is met. The entire algorithm was implemented in Matlab and its performance was investigated using simulated data. The parameters of simulated GMM model are presented in Table 1. The procedure of the greedy learning algorithm is illustrated in Figure 3. In each diagram the inserted mixture component is added after partial EM algorithm has converged. The resulted numbers of necessary iterations and corresponding values of log-likelihood for different numbers of mixture components are presented in Table 2. The greedy learning algorithm does not require prior knowledge of the number of mixture component K.

Mixture component	Param. 1		Param. 2	
	μ_x	σ_x^2	μ_y	σ_y^2
1.	-5	1	-3	1
2.	-2	2	-1	1
3.	-2	0.5	3	1
4.	1	4	-5	2
5.	2	2	1	0.5

Table 1: Mixture components parameters

Mix. comp.	Iters	Log-likehood
$K = 1$	3	-7496
$K = 2$	49	-7263
$K = 3$	26	-6953
$K = 4$	62	-6734
$K = 5$	53	-6684
$K = 6$	92	-6758

Table 2: Algorithm convergence results

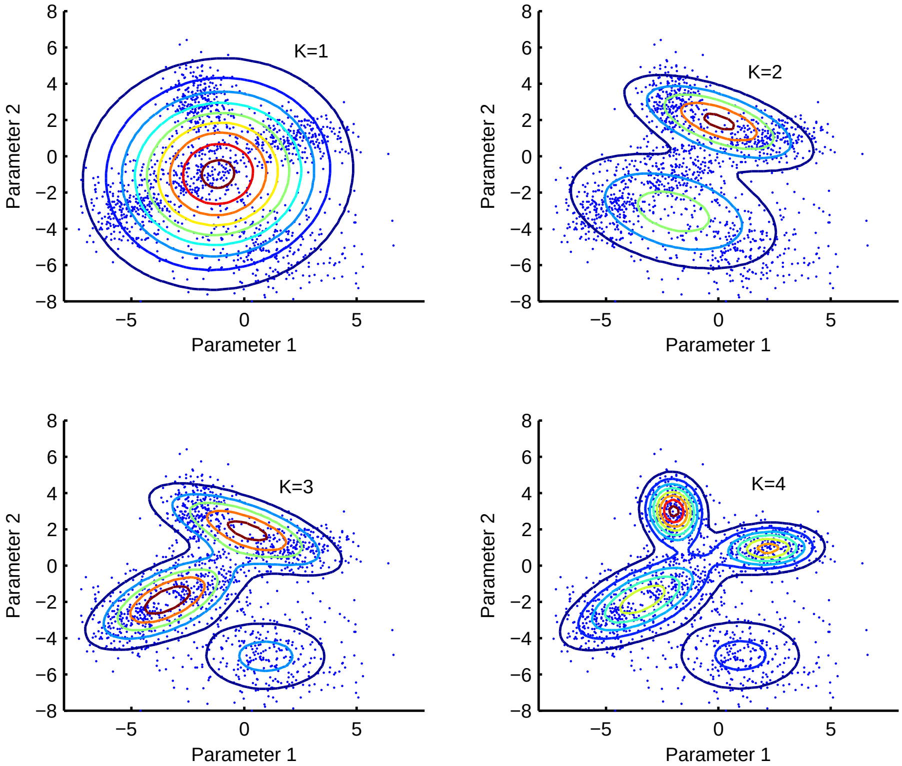

Figure 3: Component allocation steps

The Gaussian mixture model calculation is iterative process and its convergence depends on the position of starting point. The starting point position is picked out of the search-space at random so necessary number of iteration to successful algorithm convergence may differ between realizations. The number of iteration dependence on a mean to variance ratio for 4 realizations is shown in Figure 4. The number of iterations necessary to convergence of algorithm steadily decreases while the mean to variance ratio grow. However, the number of iteration varies with each calculation. For example, if mean to variance ratio is equal to 5 the number of iterations varies from 10 to almost 70 iterations to successful convergence. If mean to variance ratio is less than 4 algorithms converges insufficiently because it is very complicated to determine corresponding mean values. The processing performance requirements are extremely demanding.

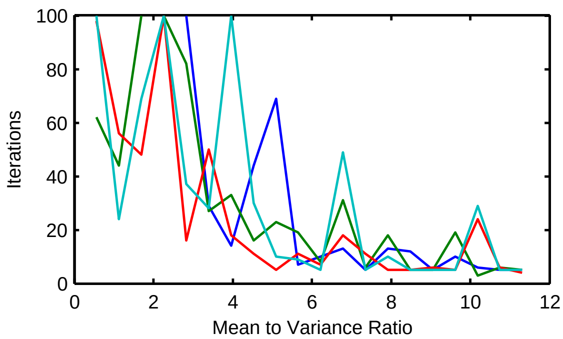

Figure 4: Algorithm convergence

5 CONCLUSION

In this study, we introduced the radar signal recognition method based on the Gaussian mixture models. The Gaussian mixture models are calculated using iterations. Based on a simulation, the algorithm attempts to iteratively determine the mean values and variances require specific number of the iterations depending on mean to variance ratio. The number of iteration is volatile and so the algorithm performance. The goal for our further study is to investigate a new mathematical method to examine fitness function. We will focus on speeding up and increasing the reliability of the algorithm convergence and the calculation of The Gaussian mixture models.

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