An Application of Entropy Approach for Moving Object Detection

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Abstract **— Doppler radar signal analysis based on information entropy is presented. Aim of the analysis is moving object detection. Entropy is calculated using the normalized eigenvalues of the covariance matrix of Doppler radar signal samples. The proposed algorithm is applied on real-world data acquired by ground surveillance Doppler radar. Appearance of the moving object during the observation process by radar results in decreasing entropy. Results are compared to those obtained by Fourier transform. Computational complexity of the proposed algorithm is discussed.**

Keywords **— Doppler radar, signal detection, entropy, covariance matrices.**

I. Introduction

RADAR is basically an object detection and measuring instrument. If the object is moving, radar produces an audio signal from the Doppler frequency of moving object. The important classes of moving objects (pedestrian, vehicle …) can be distinguished by their audio Doppler radar signatures. For most applications in radar data processing, the Fourier transform performs satisfactorily. However, other methods of spectral analysis can offer some advantages when a data set is too short for a Fourier transform to resolve or detect important spectral features.

In the technical literature, several alternative techniques have been proposed and analyzed: hidden Markov models [1, 2], circular Gibbs-Markov model [3], neural networks [4], fuzzy logic [5] and entropy spectral analysis [6,7]. Although the entropy has been already used in analysis of Doppler radar signals, previously reported algorithms are based on maximum entropy criterion and verified by computer simulation results [6] or applied on ST radars [7].

In this paper, we present a new algorithm for Doppler radar signal analysis based on entropy. We show that the use of information entropy as a quantitative measure of uncertainty can be very useful in detection of moving objects. It is well known that vector space of the noise audio signal, such as Doppler radar signal, can be decomposed into a signal-plus-noise subspace and a noise subspace [8]. The main assumption in this paper is that the energy of the noisy Doppler radar signal is mainly localized in the signal-plus-noise subspace. Presented algorithm is applied on real-world Doppler radar data. Obtained results are compared to those calculated using Fourier transform and presented on spectrogram. Computational complexity of the algorithm is discussed.

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II. Concept

A. Structure of the algorithm

Let us define incoming signal as the set of Doppler radar signal samples. Incoming signal is passing through analog tapped-delay line containg (*M-1*) delay elements, as is shown on Fig. 1. Delay τ is equal to the time difference between two succesive signal samples. Signals at the outputs of delay elements are denoted with s(1), s(2), ... s(*M*-2), s(*M*-1), respectively, while s(*M*) denotes signal at the input of tapped-delay line.

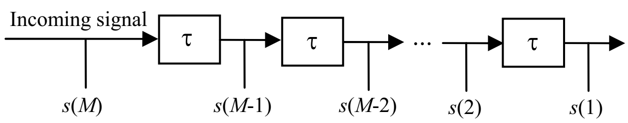

Fig.1. Analog tapped-delay line

All samples of the incoming signal within a certain time interval we call sequence. That sequence is divided into *K* subsequences which we call frames. Length of the frame is *N* elements (samples). Elements of each frame are multiplied by Caiser window of the same length N to obtain *n*-th sample of the signal *x(n),* where $1 \le n \le N$.

Set of the first M samples constitutes the first column of matrix *X*. At the following time interval, samples are shifted for time interval τ and this set of M samples constitutes the secound column of *X*, etc. Thus, each of the following columns is delayed to preceded one for time interval τ . So, dimension of the matrix X is $M \times (N-M+1)$:

$$X = \begin{bmatrix} x(1) & x(2) & x(3) & \cdots & x(N-M+1) \\ x(2) & x(3) & x(4) & \cdots & x(N-M+2) \\ x(3) & x(4) & x(5) & \cdots & x(N-M+3) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x(M) & x(M+1) & x(M+2) & \cdots & x(N) \end{bmatrix} \quad (1)$$

Each row of matrix *X* can be considered as individual random variable. Thus, the matrix *X* represents *M*-dimensional random vector [9, Ch. 2]. Corresponding covariance matrix *C* is defined as:

$$C = E\left\{\left(X - M_X\right)\left(X - M_X\right)^T\right\}, \qquad (2)$$

where $M_X = E\{X\}$ represents the expected value of X and T denotes transpose. Hence, each component of vector M_X is calculated as the expected value of an individual random variable of vector X. The diagonal components of the covariance matrix are the variances of individual random variables and the off-diagonal components are the covariances of two random variables. Thus, C is symmetric square matrix $M \times M$.

The characteristic equation of covariance matrix C is:

$$\left|C - \lambda I\right| = 0, \qquad (3)$$

where I denotes unity matrix of the same dimension as matrix C. The solutions λ of the characteristic equation are called eigenvalues, and are extremely important in the analysis of signal. Calculated eigenvalues are ordered $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_M$ and used to make a vector $\Lambda = \left[\lambda_1, \cdots, \lambda_M\right]$. Since the eigenvalues represent energy's magnitude of each dimension of the eigenspace, they are real numbers.

Eigenvalues λ_i are than transformed into probabilities p_i according to the following relation:

$$p_i = \frac{\lambda_i}{\sum_{i=1}^{M} \lambda_i}, \quad i = 1, \ldots, M \qquad (4)$$

where p_i represents the normalized eigenvalue, i.e. relative ammount of Doppler radar signal energy in i-th dimension while $\sum_{i=1}^{M} p_i = 1$. According to formal definition from information theory [10], corresponding entropy of k-th frame, where $1 \leq k \leq K$, may be defined by using p_i as:

$$H_k = -\sum_{i=1}^{M} p_i \, \boldsymbol{log} \, p_i \qquad (5)$$

B. Real-world data acquisition

The next step in signal analysis is data acquisition. The real-world Doppler radar data set used herein is acquired by Ku-band short-range ground surveillance Doppler radar. Maximum Doppler radar frequency is equal to 2 KHz and sampling frequency is 4 KHz. Amplitude of the raw Doppler radar data is in the range ±1V. Sequence consists of 20000 samples.

Since the length of the frame is $N=200$, it means that $K=100$ frames are analyzed. Elements of each frame are multiplied by Kaiser window function of the same length N, while parameter $\beta=3\pi$ is assumed. Eqns. (4) and (5) are used to produce numerical results, which are compared to those obtained by Fourier transform and presented on spectrogram. For spectrogram calculations following parameters are used: discrete Fourier transform in 1024 points, Kaiser window function length 512 and parameter $\beta=3\pi$, while overlapping between adjacent windows is 256 samples.

C. Numerical results

Numerical results obtained for the man walking, who appears at $t_0=1.7s$ (it corresponds to 34-th frame of recorded signal), where $M=15$, are presented on Fig. 2. Normalized eigenvalues of covariance matrix C versus ordinal number of the frame are presented on Fig.2.A. Corresponding entropy is shown on Fig. 2.B. From Fig. 2.A and Fig. 2.B one can conclude that appearance of man who is walking causes significant increase of the first and second eigenvalues and decrease of entropy. Spectrogram of the same analyzed sequence, shown on Fig. 2.C, is used for verification of results presented on Fig. 2.A and Fig. 2.B.

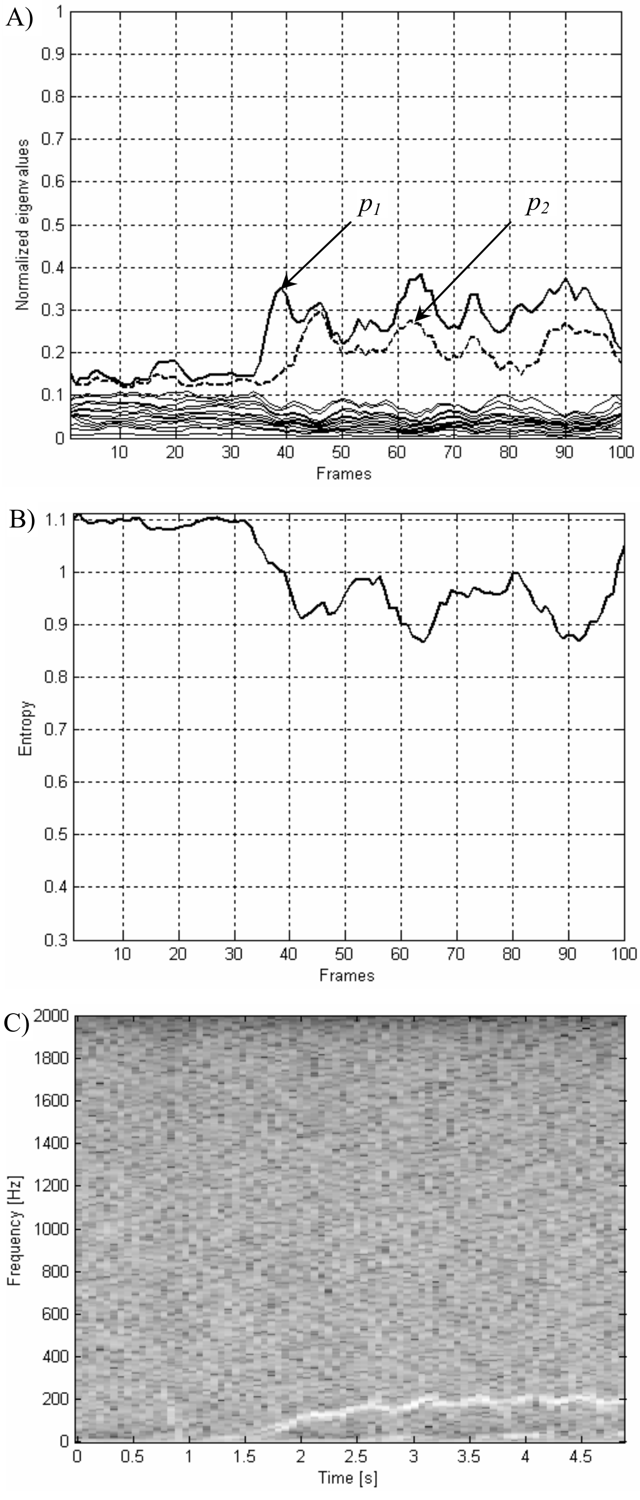

Fig. 2. Man walking: A) Normalized eigenvalues versus ordinal number of the frame, M=15; B) Entropy versus ordinal number of the frame; C) Spectrogram

Normalized eigenvalues of covariance matrix C versus ordinal number of the frame, in the case of man walking where M is varied, are presented on Fig. 3. For low values of M (i.e. M=3 and M=5), the moment of man walking appearance is followed by significant increase of the first normalized eigenvalue in comparison to other eigenvalues. Simultaneously, the values of other normalized eigenvalues are reduced in comparison to their values before appearance of man who is walking, as is shown on Fig. 3.A and Fig. 3.B. Based on results presented on Fig. 3.A, one can conclude that analog tapped-delay line, consisting of two delay elements only, could detect presence of the moving object. In that case, dimension of the covariance matrix C is 3×3 .

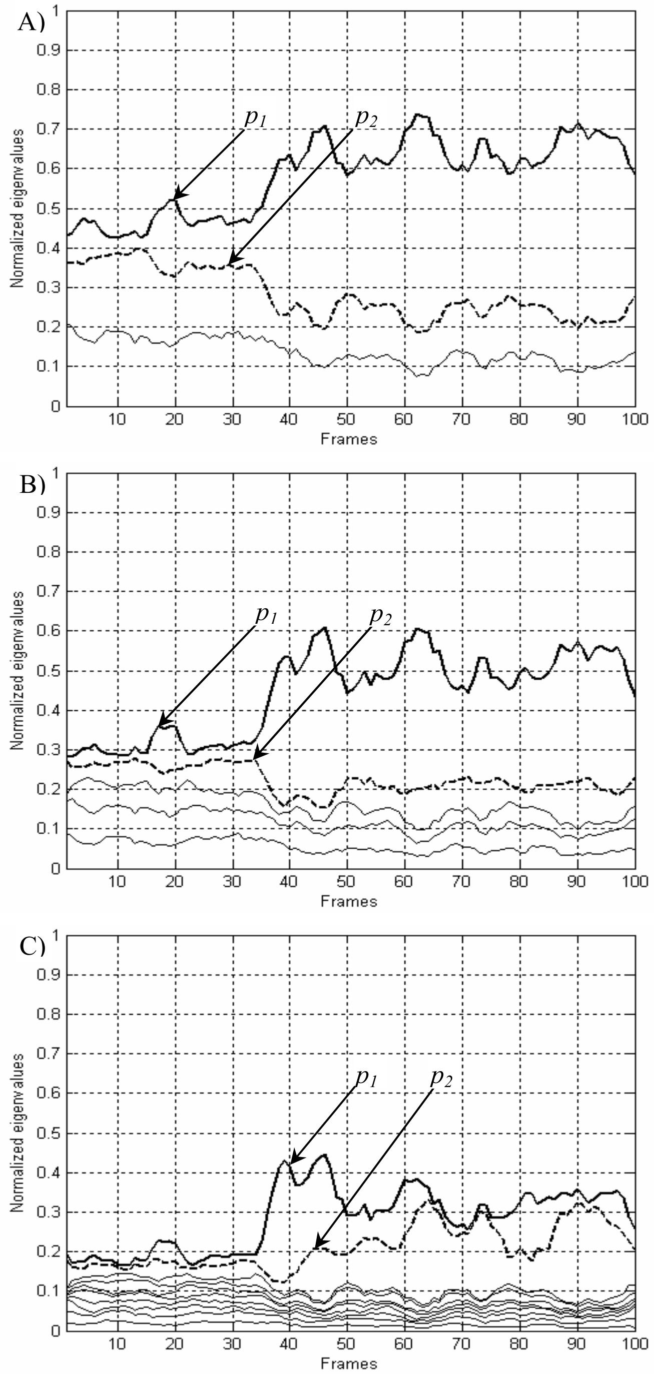

Fig. 3. Man walking: Normalized eigenvalues versus ordinal number of the frame A) M=3; B) M=5; and C) M=10

For higher values of M (i.e. M=10), besides the first normalized eigenvalue the second normalized eigenvalue is increased as well, as is shown on Fig. 3.C.

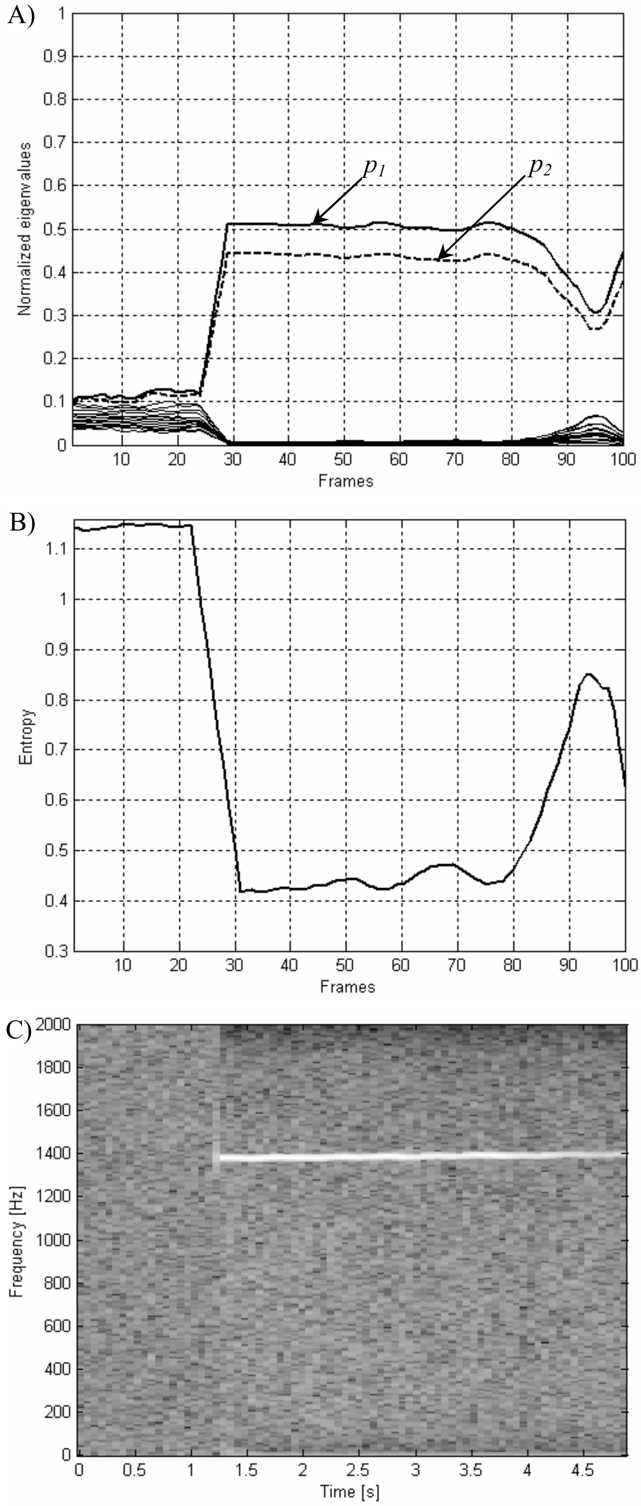

Fig. 4. Vehicle: A) Normalized eigenvalues versus ordinal number of the frame, M=15; B) Entropy versus ordinal number of the frame; C) Spectrogram

Numerical results obtained for the vehicle, which appears at $t_0=1.2s$ (it corresponds to 24-th frame of recorded signal), where M=15, are presented on Fig. 4. This is an example of moving object appearance with a large radar cross-section (RCS). Increasing RCS causes a significant increase in the first and second normalized eigenvalues and significant decrease of entropy.

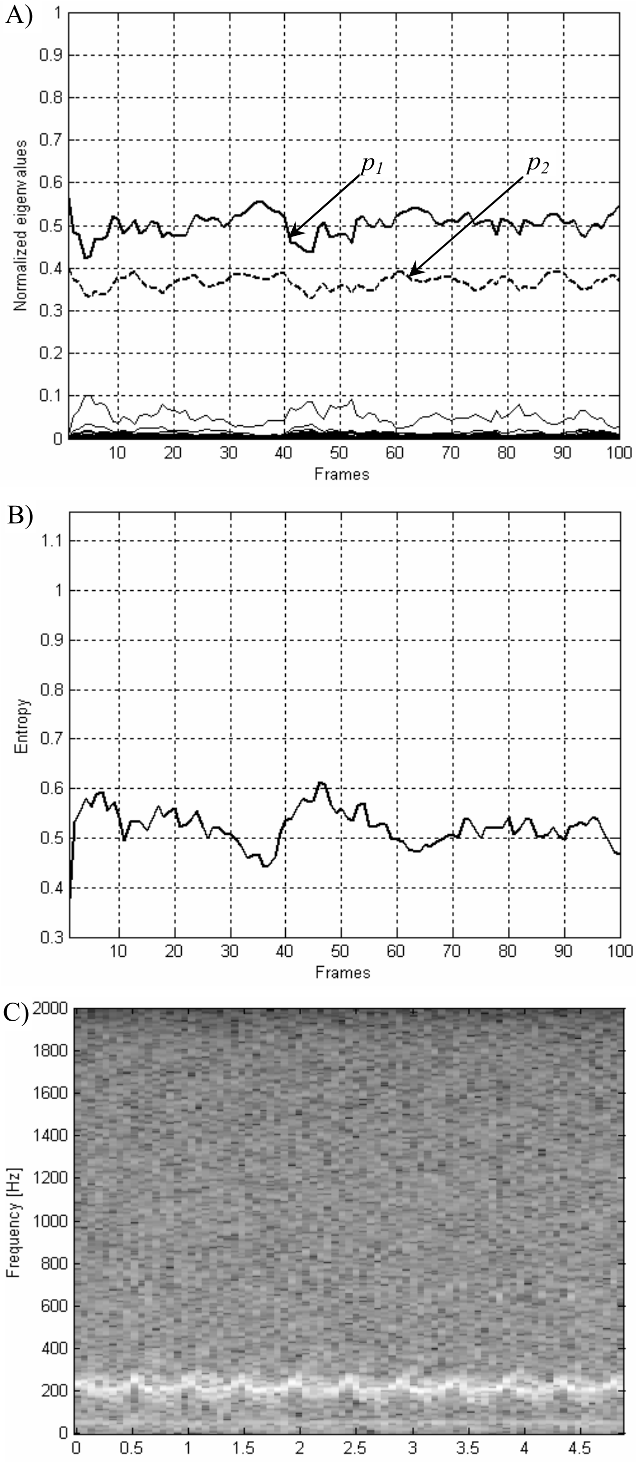

Fig. 5. Man walking (all the time): A) Normalized eigenvalues versus ordinal number of the frame, M=15; B) Entropy versus ordinal number of the frame; C) Spectrogram

Figure 5 illustrates the situation when the man is walking during all the time of radar observation. Based on the results presented in figures Fig. 5.A and Fig. 5.B we can conclude that it is the moving object with significant RCS.

III. Conclusion

We showed that information entropy is an important signature of Doppler radar signal that can be used for process of moving object detection. Entropy is calculated using the normalized eigenvalues of the covariance matrix of Doppler radar signal samples. The proposed algorithm is applied on real-world data acquired by ground surveillance Doppler radar. Results obtained by the proposed algorithm and their comparison to results obtained by Fourier transform and presented on spectrogram confirm that entropy approach can be useful in detection of moving objects.

Proposed algorithm is not computationally demanding. As opposed to Fourier transform, it doesn't require signal transform in frequency domain. Calculations assume matrix operations in time domain with real numbers exclusively: addition, subtraction, multiplication and transpose. Since the covariance matrix of dimension $M=3$ is enough for moving object detection, required computational complexity is very low.

Although in this paper the entropy approach is applied on Doppler radar signal analysis, it may be used in many other applications, e.g. for medical signal analysis. It is particularly appropriate for sensor systems in general, which have as their objective the acquisition of information.

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