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NON-PARAMETRIC SIGNAL PROCESSING IN NOISE RADAR

R. B. SINITSYN AND F. J. YANOVSKY

Noise radar is one of the most interesting technical and scientific ideas implemented in modern radar design. Nonparametric methods of signal processing, with some loss in efficiency, give us the opportunity of providing the synthesis of procedures that are invariant to changes in the signal form and changes of the interference situation. The use of statistical methods for the noise signal processing is closely linked with the latest digital signal processing achievements, which give us the possibility of simplifying the technical implementation of the noise radar as well as signal processing. Thus the use of digital processing techniques can technically implement the idea of noise radar.

Keywords: Noise radar, permutation statistics, copula, rank, permutations, ambiguity function.

1. INTRODUCTION

Noise radar is one of the most interesting technical and scientific ideas implemented in modern radar design.

Scientific interest in the noise radar is associated with the form of the sounding signal (waveform). Typically, the properties of the sounding signal are connected with its shape, which is characterized by its radar ambiguity function. The form of the ambiguity function is connected with the possibility of simultaneous measurement of spatial coordinates and velocity of the target.

If we use a random process with uniform spectrum (a white noise) as a sounding signal, we can obtain almost a unique form of the ambiguity function, which tends to a delta function. This allows us to make simultaneous measurement of distance and speed with maximum resolution. Certainly, such results can also be obtained by using other signals, but in our opinion, it is essentially more complicated. The selection of the waveform creates a coordinate system in which the radar measurements exist. The choice of a rational system of coordinates simplifies obtaining the necessary resolution.

Radar targets are always observed on the background of random noise, and this requires the use of statistical methods for signal processing. Only the statistical approach allows us to implement scientifically optimal signal processing with a fixed level of error.

Nonparametric methods of signal processing, with some loss in efficiency, give us the opportunity of providing the synthesis of procedures that are invariant to changes in the signal form and changes of the interference situation.

In recent years, these methods have been based on the use of the rank procedures, as well as some relatively new methods, such as kernel estimates of the probability density and on such notion as the copula.

The use of statistical methods of processing for a random sounding signal is natural for the noise radar. This allows us to obtain the most efficient use of statistical and non-parametric methods with a random coordinate system and the random noise generated by the radar.

In this paper we will discuss all possible statistical methods of noise radar signal processing. Among them there are the following.

Classical parametric methods of signal processing. Rank signal processing techniques. Processing methods based on permutation statistics. Processing methods, based on kernel estimates of the probability density, as well as methods using copulas, which enable us to generalize the concept of the ambiguity function.

The use of statistical methods for the noise signal processing is closely linked with the latest digital signal processing achievements, which give us the possibility of simplifying the technical implementation of the noise radar as well as signal processing. Thus the use of digital processing techniques can technically implement the idea of noise radar.

2. GENERAL DETECTION PROBLEM DEFINITION

We can divide the signal space observed by the radar into two areas. In one area, as supposed, there is a useful signal, in the other there is interference: noise or clutter. Signal detection is achieved by using a difference of a multivariate probability density in observed areas. Thus, the task of detection is reduced to checking the hypothesis H_0 about the equality of probability density functions and alternative hypothesis H_1 :

$$H_0 : f_S(\mathbf{x}) = f_N(\mathbf{x}) \quad (1)$$

$$H_1 : f_S(\mathbf{x}) \neq f_N(\mathbf{x}), \quad (2)$$

where $f_S(\mathrm{x})$ is a probability density function of a signal in the area where we are trying to find a target, $f_N(\mathrm{x})$ is a probability density function of a received signal in the area where there is no target.

Let us assume that from the samples received from signal and noise (or clutter) areas, it is possible to generate the mixed sample

$$\mathbf{x} = \{x_1, x_2, \ldots, x_m, \ldots, x_n\} \quad (3)$$

where $x_1, x_2, \ldots, x_m$ are samples received from the noise or clutter area, and $x_{m+1}, \ldots, x_n$ are samples received from the signal area. We will suppose that the signal and noise (or clutter) samples are statistically independent.

Then the task of testing the hypothesis is reduced to checking the hypothesis about the form (shape) of the density function of the mixed sample

$$H_0: f_0(\mathbf{x}) = \prod_{i=1}^{n} f_N(\mathbf{x}) \qquad (4)$$

$$H_1 :. \; f_1(\mathbf{x}) = \prod_{i=1}^{m} f_N(x_i) \prod_{i=m+1}^{n} f_S(x_i).$$

The problem of the signal detection in this case is reduced to the problem of the form of the probability density function.

3. RANK AND PERMUTATION ALGORITHMS

3.1. Similar Test

If we compare the likelihood function $f_1(x)$ with the solution threshold obtained with the help of the empirical permutation distribution, which is derived by substituting all permutations of the vector x in the likelihood function, we will obtain the most powerful similar test. Such a test has the property of similarity, i.e. a fixed level of error of the first kind. The detection algorithm built on the basis of this test has stability of the false alarm probability.

However, it has an essential disadvantage. The number of all permutations is too great, it increases with the increase of a number of samples and is equal to $n!$. This fact hampers the practical use of the devices, which have been designed on the basis of using the permutation test.

3.2. Permutation Algorithm

Thus, the suggested algorithm for detecting signals is reduced to the following procedure:

The likelihood function from the accepted signal is computed

$$l(\mathbf{x}) = \prod_{i=1}^{m} f_N(x_i) \prod_{i=m+1}^{n} f_S(x_i), \qquad (5)$$

which, after some of identical conversions, can be reduced to the following expression

$$l(\mathbf{x}) = \prod_{i=1}^{m} f_N(x_i) \prod_{i=m+1}^{n} f_S(x_i) \prod_{i=m+1}^{n} \frac{f_N(x_i)}{f_N(x_i)} = \prod_{i=1}^{n} f_N(x_i) \prod_{i=m+1}^{n} \frac{f_S(x_i)}{f_N(x_i)} \qquad (6)$$

Let us take into account only those permutations of samples x_i, which require the modification of the statistic $l(\mathbf{x})$. We will remark, that for all permutations of the statistics $\mathbf{x}$, the product $\prod_{i=1}^{n} f_N(x_i)$ remains constant. Therefore in the procedure of decision making it is possible not to take into account the whole set of $n!$ permutations, it is enough to consider $\binom{n}{m} = \frac{n!}{m!(n-m)!}$ permutations and the following statistics

$$L(\mathbf{x}) = \prod_{i=m+1}^{n} \frac{f_S(x_i)}{f_N(x_i)} = \prod_{i=m+1}^{n} \lambda(x_i), \qquad (7)$$

where $\lambda(x_i) = \frac{f_S(x_i)}{f_N(x_i)}$ are partial likelihood ratios.

Using the statistics $\lambda(x)$, we will suggest the rank test, which is based on permutations of the partial likelihood ratios $\lambda_i = \lambda(x_i)$. We will use the vector statistic

$$\lambda = \{\lambda_1, \lambda_2, \ldots, \lambda_m, \ldots, \lambda_n\}.$$

Variables λ_i are independent and have the same distribution if the hypothesis H_0 is true. We can construct a permutation test using permutations of the variables λ_i but not x_i.

Ranking the variables λ_i we obtain the vector of ranks of variables λ_i

$$\mathbf{r} = \{r_1, r_2, \ldots, r_m, \ldots, r_n\}$$

On the basis of statistic $\mathbf{r}$ many different rank hypothesis tests and corresponding to them signal detection algorithms can be constructed. For example, a rank test which is similar to the Vilkokson criteria

$$Q_1 = \sum_{i=m+1}^{n} r_i.$$

This statistic is not optimal, but has sufficient efficiency, and an algorithm, based on this statistic is attractively simple.

Rank tests are using the empirical distribution function as a functional transform. We suggest using smoothed estimates of this function, among them kernel estimates.

The kernel estimate of a cumulative distribution function is constructed by using of the partial likelihood ratios $\lambda_i = \lambda(x_i)$. The following functions will be used as the kernels

$$K_i(\lambda) = \frac{1}{n} W(\lambda - \lambda_i), \qquad (8)$$

where $W(\lambda)$ is some cumulative distribution function, λ_i is a value of the partial likelihood ratio.

The estimate of a cumulative distribution function for noise area is determined by the expression

$$\widehat{F}(\lambda) = \sum_{i=1}^{n} K_i(\lambda). \qquad (9)$$

After the functional transform we obtain the vector of transformed partial likelihood ratios

$$\mathbf{l} = \{l_1, l_2, \ldots, l_m, \ldots, l_n\},$$

where $l_i = \widehat{F}(\lambda_i)$. Density function of transformed statistics for hypotheses H_0 and H_1 can be calculated, using following approach.

The density function of the vector of the initial samples can be represented as

$$f_l(l_1, l_2, \ldots, l_m, \ldots, l_n) = \prod_{i=1}^{m} f_{Nl}(l_i) \prod_{i=m+1}^{n} f_{Sl}(l_i).$$

The density function of the vector 1 coordinates l_i is described by the integral

$$f_l(l_i) = \int_{-\infty}^{\infty} \ldots \int_{-\infty}^{\infty} \prod_{j=1}^{m} f_N(\lambda_j) \cdot f_S(\widehat{F}^{-1}(l_i; \lambda_1, \ldots, \lambda_m)) \cdot \frac{1}{\widehat{f}(\widehat{F}^{-1}(l_i; \lambda_1, \ldots, \lambda_m))} d\lambda_1 \ldots d\lambda_m, \qquad (10)$$

where $\widehat{F}^{-1}(\mathbf{l})$ is the function, inverse to $\widehat{F}(\lambda)$, $\widehat{f}(\lambda)$ is the derivative of the $\widehat{F}(\lambda)$.

When $N \to \infty$ estimate $\widehat{F}(\lambda) \to F(\lambda)$

$$f_l(l_i) = \frac{f_S\left\{F^{-1}(l_i)\right\}}{f_N\left\{F^{-1}(l_i)\right\}}.$$

This vector can be used as a statistic for designing an ordinary Neyman-Pearson test and a signal detection algorithm.

For hypothesis H_0 the distribution $f_l(l_i)$ asymptotically tends to the uniform distribution. In the case of the alternate hypothesis H_1 validity the statistics distribution $f_l(l_i)$ of the signal aria elements differs from the distribution of the elements of the noise area. It is determined by the presence of the desired signal.

The decision statistics is defined by the likelihood ratio, which is in this case equal to the likelihood function (Fig. 1.)

$$\ell(l) = \prod_{i=n+1}^{n} f_l(l_i) . \tag{11}$$

If the density function of reflections from the guessed target coincides with the density function of the interference, the density function of references l is asymptotically uniform. Thus, in the case of validity of the hypothesis H_0, i.e. in the no-signal condition the density function is equal to 1. In the case when the hypothesis H_1 is valid (when the desired signal is available) the density function of converted references l also lies in the interval [0,1], but it is not uniform.

The solution about a desired signal is made by comparing $\ell(l)$ with the solution threshold (Fig. 2). This threshold has a constant value and depends only from the false alarm probability for all signal and interference probability densities.

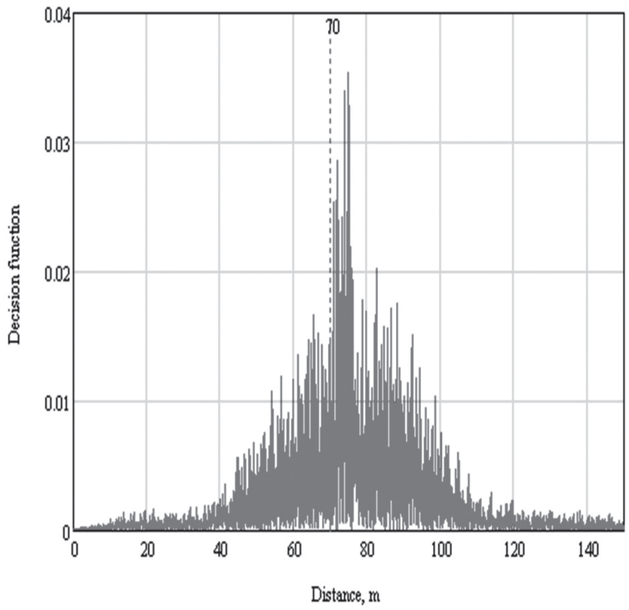

Fig. 1. Dependence of the decision function for the algorithm, based on the kernel estimate from distance. Number of samples is 111891

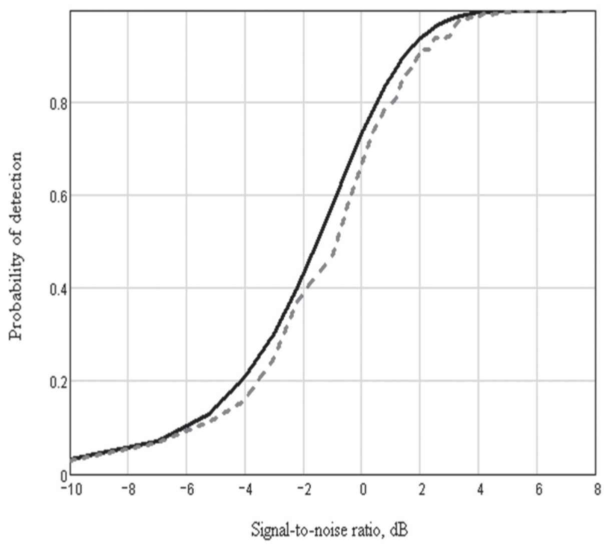

Fig. 2. Dependence of the detection probability on SNR for the algorithm, based on permutations of partial likelihood ratios (the dashed curve) and the optimal algorithm (the solid curve). Number of samples is 16. Size of the noise area is 128. False alarm probability is 0.01

4. COPULA DETECTION ALGORITHM

4.1. Copula Transform

We can transform the vector (x, y) to a new a random variable (x_T, y_T), using two marginal cumulative distribution functions $x_T = F_x(x)$, $y_T = F_y(y)$ as functional transforms. It is easy to prove that vector (x_T, y_T) has uniform distribution if random variables x and y are independent. The bivariate cumulative distribution function of the transformed variables (x_T, y_T) is called a copula of these variables [2] and according to the Sklar's theorem

$$F(x, y) = C(F_x(x), F_y(y)),$$

where $F(x, y)$ is a bivariate cumulative distribution function of (x, y).

The density function, corresponding to the copula $C(x_T, y_T)$ is

$$c(x_T, y_T) = \frac{\partial C(x_T, y_T)}{\partial x_T \partial x_T}.$$

If a useful signal is absent the copula density function has a uniform distribution on $[0, 1]^2$.

If a useful signal is present a copula density function has some other distribution on $[0, 1]^2$.

A copula density function can be estimated using kernel estimates.

Let us replace the cumulative distribution functions $F_x(x)$ and $F_y(y)$ by their estimates $\hat{F}_x(x)$ and $\hat{F}_y(y)$. It is assumed, that if the size of a sample is increased, the estimate converges to a cumulative distribution function. Transformations of the sounding and reflected signals

$$x_{Ti} = \hat{F}_x(x_i), \; y_{Ti} = \hat{F}_y(y_i)$$

will be used later.

4.2. Copula Estimates

The kernel estimates of the cumulative distribution functions will be used as this transform [3], [4].

Thus the estimate of a bivariate copula density function $c(x_T, y_T)$ will look like the total of the kernels $K_i(x_T, y_T)$

$$\hat{c}(x_T, y_T) = \sum_{i=1}^{n} K_i(x_T, y_T), \quad (12)$$

where n is the sample size, which is the basis for finding an estimate.

Let's assume, that the kernels look as follows

$$K_i(x_T, y_T) = \frac{1}{n}\omega(x_T - x_{Ti}, y_T - y_{Ti}), \quad (13)$$

where $\omega(x_T, y_T)$ is some probability density, for example, normal, (x_{Ti}, y_{Ti}) is the sample unit i, which is the basis for an estimate.

For the estimate $\hat{F}_x(x)$ of one-dimensional cumulative distribution function the kernels look as follows

$$P_i(x) = \frac{1}{n}\int_{-\infty}^{x}\int_{-\infty}^{\infty} \omega(u - x_i, v - y_i)\,du\,dv. \quad (14)$$

4.3. Decision Rule

To synthesise the decision rule on the basis of **x** and y statistics it is necessary to obtain the density function of these statistics under competing hypotheses H_0 and H_1. The detection procedure is based on testing the hypotheses about the density function of transformed signals on the basis of Neyman – Pearson criterion. In this case, the distribution of a transformed statistics tends to be uniform if we increase a sample size. Thus the distribution of the converted statistics $(\mathbf{x_T}, \mathbf{y_T})$ under the hypothesis H_0 (no target) is asymptotically uniform. Thus testing the hypothesis about the presence of the target is reduced to testing the hypothesis about uniformity of distribution of the transformed statistics and likelihood ratio - to the likelihood function of the statistics $(\mathbf{x_T}, \mathbf{y_T})$. The likelihood function is substituted by its estimate (12) obtained with the help of the kernels, such as (13) and (14)

$$\lambda_T(\mathbf{x}_T, \mathbf{y}_T) = \prod_{i=1}^{n} \hat{c}(x_{Ti}, y_{Ti}), \quad (15)$$

where

$$\hat{c}(x_{Ti}, y_{Ti}) = \sum_{j=1}^{m} K_j(x_{Ti}, y_{Ti}),$$

where m is a sample size of the test statistics obtained on the basis of reflections from the target. After taking the logarithm of expression (15) we obtain the final formula of decision rule enabling us to detect the target

$$\lambda_T(\mathbf{x}_T, \mathbf{y}_T) = \sum_{i=1}^{n} \ln(\hat{c}(x_{Ti}, y_{Ti})). \quad (16)$$

This result can be simply extended to MIMO [8] variant

$$\lambda_T(\mathbf{x}_T, \mathbf{y}_T) = \sum_{k=1}^{m}\sum_{j=1}^{m}\sum_{i=1}^{n} \ln(\hat{c}(x_{Tij}, y_{Tik})).$$

For making a decision $\lambda_T(\mathbf{x}_T, \mathbf{y}_T)$ is compared with the invariable threshold C. The invariability of the threshold for decision making providing stable error probability of first kind, is ensured by the uniform distribution of statistics under the hypothesis H_0. In particular, to simplify the practical realization of the method the kernels are decomposed into a trigonometric series, and the algorithm of fast Fourier transform is used.

The relationship between the detection probability and signal to noise ratio expressed in power units is represented in Fig. 3. These characteristics are obtained as a result of Monte-Carlo simulation, α is the false alarm probability, the sample size is 100.

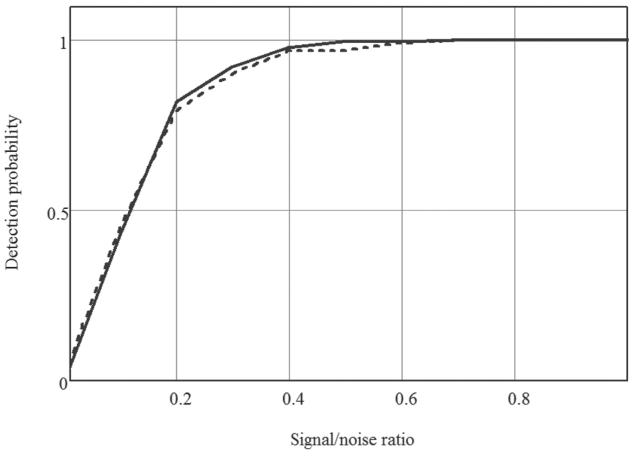

Fig. 3. Performance of detection as a dependence from signal-to-noise ratio . Signal and noise with Gaussian distribution. Solid curve – parametric algorithm, dashed curve – nonparametric algorithm $(\alpha = 0.01, \quad N = 100)$

In Fig. 3 parametric and nonparametric algorithms are presented. As we can see the results for parametric signal processing algorithm are slightly better. But we must understand that simulation was made in the case of the prior certainty of the signal and noise probability densities. In the real situation for unknown signals and noises the nonparametric algorithm must be better.

5. COPULA AMBIGUITY FUNCTION

5.1. Ambiguity Function

The cross-ambiguity function [1] for two random processes $X(t)$ and $Y(t)$ can be defined as an average

$$\chi(\tau, \alpha) = \sqrt{|\alpha|}E\left\{(X(t)) - m_x)(Y^*(\alpha(t - \tau)) - m_y)\right\},$$

where $\alpha = \frac{c - v}{c + v}$ is a scale coefficient, c is the velocity of the wave, v is the target velocity, $Y^*(t)$ is a complex conjugate of the random process $Y(t)$, m_x and m_y are mathematical expectations of $X(t)$ and $Y(t)$. This variant of the ambiguity function can be simply recalculated in the range/velocity coordinates. For the ergodic process we can consider, that the cross-ambiguity function is (17). This expression looks like an ordinary wideband ambiguity function definition for deterministic signals

$$\chi(\tau, \alpha) = \lim_{T \to \infty} \frac{\sqrt{|\alpha|}}{T}\int_{0}^{T}(x(t) - m_x)(y^*(\alpha(t - \tau)) - m_y)dt. \quad (17)$$

The example of the calculation of the cross-ambiguity function estimate for the noise acoustic radar is presented in Fig. 4.

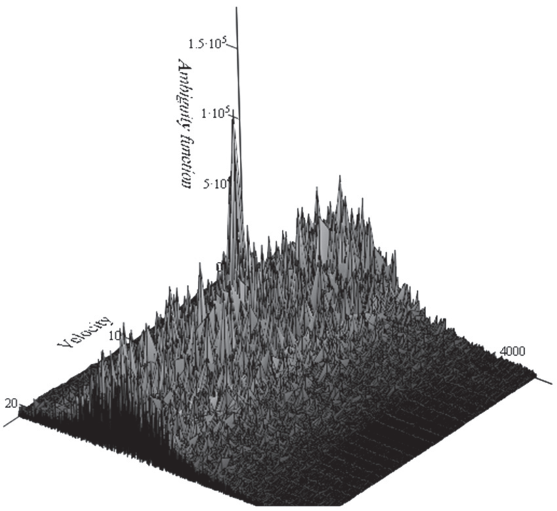

Fig. 4. Estimate of the cross-ambiguity function for the acoustic radar. Range in distance samples and velocity in ADC digits. One digit for velocity is 1 m/s, number 11 corresponds to zero velocity, one digit for distance is equal to 0.0038820862 m

The sounding signal in this radar is a discrete white noise with a normal distribution. The ambiguity function is calculated in range/velocity coordinates. The sampling frequency is 48 kHz.

5.2. Estimates

The kernel estimates of the cumulative distribution functions will be used as this transform. Thus the estimate of a bivariate copula density function $c(x_T, y_T)$ will look like the total of the kernels $K_i(x_T, y_T)$

$$\hat{c}(x_T, y_T) = \sum_{i=1}^{n} K_i(x_T, y_T) \,,$$

where n is the sample size, which is the basis for finding an estimate [3].

The copula kernel estimate, calculated for the signal of the acoustic noise radar(which samples which are shown in Fig. 5), is presented in Fig. 6.

Let's assume, that the kernels look as follows

$$K_i(x_T, y_T) = \frac{1}{n} w(x_T - x_{Ti}, y_T - y_{Ti}) \,,$$

where $w(x_T, y_T)$ is some probability density, for example, normal, (x_{Ti}, y_{Ti}) is the sample unit i, which is the basis for an estimate.

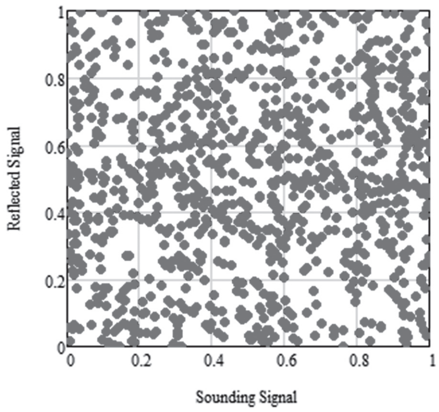

Fig. 5. Sounding and reflected signal samples

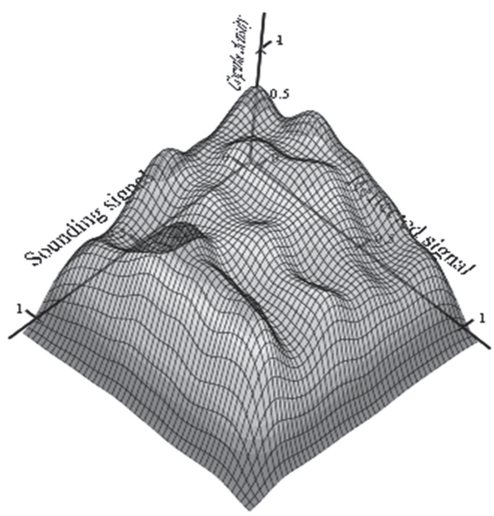

Fig. 6. The kernel estimate of a bivariate copula density for the acoustic radar signal

For the estimate $\hat{F}_x(x)$ of one-dimensional cumulative distribution function the kernels look as follows

$$P_i(x) = \frac{1}{n} \int_{-\infty}^{x} \int_{-\infty}^{\infty} w(u - x_i, v - y_i) du dv \,.$$

The kernel estimate for the copula itself is presented in Fig. 7.

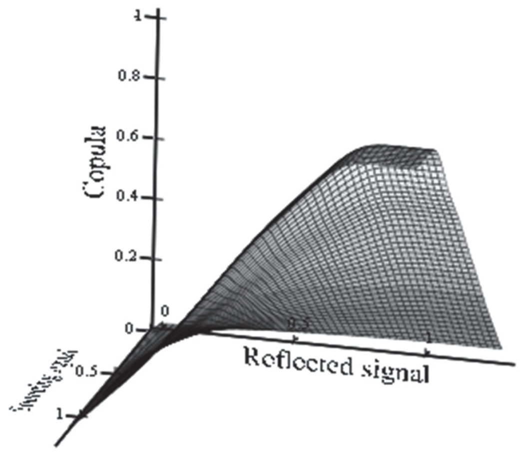

Fig. 7. The kernel estimate of a bivariate copula for acoustic radar signal

5.3. Copula Ambiguity Function

Using the copula density function we can define its copula ambiguity function [9] as a second mixed central moment of the copula density

$$\chi(\tau, \alpha) = \sqrt{|\alpha|} E\left\{(F_x(X(t)) - m_x)(F_y(Y^*(\alpha(t-\tau))) - m_y)\right.$$

or for the ergodic process

$$\chi(\tau, \alpha) = \lim_{T \to \infty} \frac{\sqrt{|\alpha|}}{T} \int_0^T (F_x(x(t)) - m_u)(F_y^*(y(\alpha(t-\tau))) - m_v) dt.$$

Using the kernel estimates of the cumulative density function we can obtain the copula ambiguity function kernel estimate in some finite time interval

$$\chi(\tau, \alpha) = \sqrt{|\alpha|} \int_{t_1}^{t_2} (\hat{F}_x(x(t)) - m_u)(\hat{F}_y^*(y(\alpha(t-\tau))) - m_v) dt \,. \quad (18)$$

The authors also are suggesting in heuristic variant of the function (19). In this formula we are using an estimate of the moment of the second order for the uniform distribution. For obtaining the statistics, which depends from two parameters, we will use an additional functional transform, transforming the copula statistic to a normal distribution

$$\chi(\tau,\alpha)=\sqrt{|\alpha|}\int_{t_1}^{t_2} F_N^{-1}(\hat{F}_x(x(t)))F_N^{-1}(\hat{F}_y^*(y(\alpha(t-\tau))))dt \quad (19)$$

where F_N^{-1} is an inverse cumulative function of a normal distribution.

With the help of the noise acoustic radar, designed and constructed by authors [4, 5, 6, 7], the copula ambiguity function was measured for real signals. The acoustic radar sounding signal is a wideband random signal with a normal distribution. The signal reflected from the solid object at the distance equal to 70 m from the radar. For this signals the copula ambiguity functions were calculated. The results are presented in Fig. 8 and in Fig. 9.

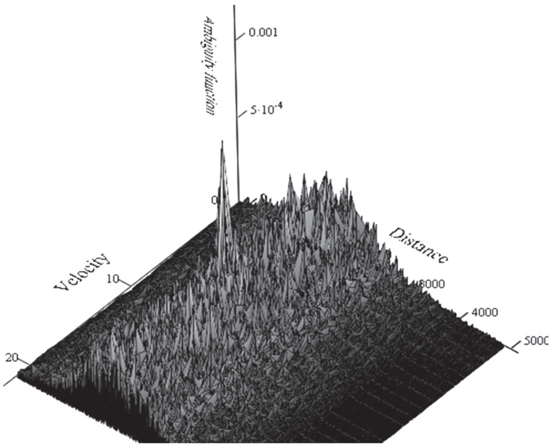

Fig. 8. Estimate of the copula cross-ambiguity function for the acoustic radar. Range in distance samples and velocity in ADC digits. One digit for velocity is 1 m/s, 11 corresponds to zero velocity, one digit for distance is equal to 0.0038820862 m

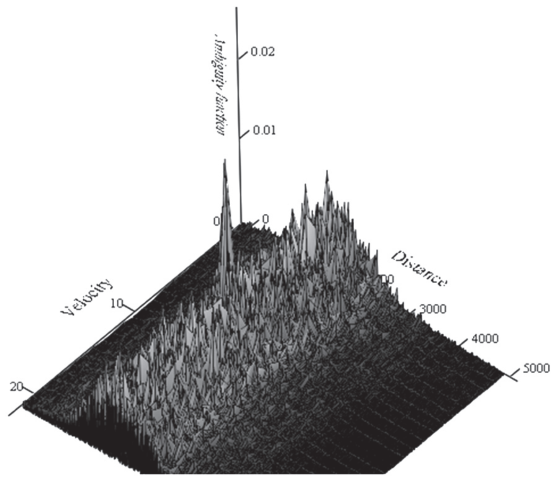

Fig. 9. Estimate of the copula cross-ambiguity function (with an aditional functional transform) for the acoustic radar

The cross section of the ambiguity function in time area (or in distance area) for zero velocity of the target propagation is the correlation function. The result of the calculations is presented in Fig. 10. The same calculations were done for the cross section of the copula ambiguity function. The result is presented in Fig.11.

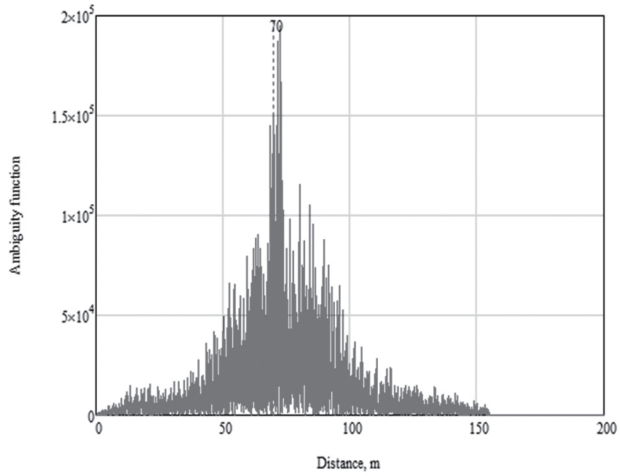

Fig. 10. Estimate of the cross-ambiguity function cross section (cross-correlation function) for the acoustic radar

The shape of the suggested variant of the ambiguity function does not depend on the probability density functions of the sounding and reflected signals. That is why signal detection algorithms, which are based on this notion are distribution free and have a constant level of the false alarm probability. The detection can be done with the help of the simple threshholding of the copula ambiguity function.

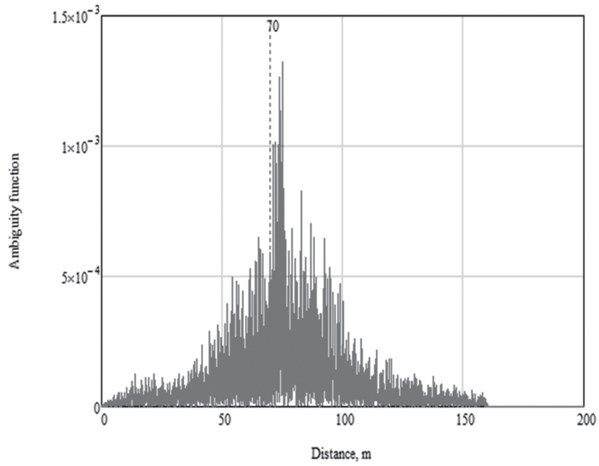

Fig. 11. Estimate of the copula cross-ambiguity function cross section (cross-correlation function) for the acoustic radar

CONCLUSION

In this paper different aspects of the signal processing algorithms for random signal radars were discussed.

We believe that the random signal radar is one of the most interesting types of radar. It combines properties of UWB radar with some additional features, based on random nature of the sounding waveform. This new properties allows us to simplify signal detection algorithms and measure a distance, an azimuth and a target velocity simultaneously with high resolution and accuracy because of the noise sounding waveform. Nonparametric algorithms have wonderful properties of invariance to the group of the noise and signal transforms and stable level of the false alarm probability. It is important to remember that all these good properties exist only in the case when we have independent samples. The noise signal forms the independent samples because of its nature.

The generalization of the radar ambiguity function has been suggested. In contrast to classically defined ambiguity function, new one does not dependent on the signal PDF. It can be used as a pure measure of the relation between sounding and reflected signals as well as for the analysis of potential properties of waveforms.

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Непараметрическая обработка сигналов в шумовом радаре / Р.Б. Синицын, Ф.И. Яновский // Прикладная радиоэлектроника: науч.-техн. журнал. – 2013. – Том 12. – № 1. – С. 72–78.

Рассмотрены различные алгоритмы обработки сигнала шумового радиолокатора. Разработана теория и алгоритмы непараметрической обработки сигналов, которые с некоторой потерей эффективности дают возможность обеспечить синтез процедур, обладающих свойством инвариантности по отношению к изменениям формы сигнала и помеховой обстановки. Синтезированные непараметрические алгоритмы обеспечивают также стабильный уровень вероятности ложной тревоги. Указанные свойства существуют только в случае независимых выборок, что в шумовом локаторе обеспечивается естественным образом в силу характера генерируемого шумового сигнала. В работе также предложено обобщение функции неопределенности, которая, в отличие от классической, не зависит от плотности вероятности сигнала и может быть использована как чистая мера связи между зондирующим колебанием и отраженным сигналом. Она также обеспечивает анализ потенциальных свойств зондирующего сигнала. Предложенные статистические методы обработки шумового сигнала в сочетании с новейшими достижениями цифровой обработки обеспечивают упрощение технической реализации шумовой радиолокации.

Ключевые слова: шумовой радиолокатор, статистики перестановок, копула, ранжирование, функция неопределенности.

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Розглянуто різні алгоритми обробки сигналу шумового радіолокатора. Розроблено теорію і алгоритми непараметричної обробки сигналів, які з деякою втратою ефективності дають можливість забезпечити синтез процедур, що мають властивість інваріантності по відношенню до змін форми сигналу і завадової обстановки. Синтезовані непараметричні алгоритми забезпечують також стабільний рівень ймовірності хибної тривоги. Зазначені властивості існують лише в разі незалежних вибірок, що в шумовому локаторі забезпечується природним чином в силу характеру генерованого шумового сигналу. В роботі також запропоновано узагальнення функції невизначеності, яка, на відміну від класичної, не залежить від щільності ймовірності сигналу і може бути використана як чиста міра зв'язку між зондувальним коливанням і відбитим сигналом. Вона також забезпечує аналіз потенційних властивостей зондувального сигналу. Запропоновані статистичні методи обробки шумового сигналу в поєднанні з новітніми досягненнями цифрової обробки забезпечують спрощення технічної реалізації шумової радіолокації.

Ключові слова: шумовий радіолокатор, статистики перестановок, копула, ранжування, функція невизначеності.

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