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KOHONEN NEURAL NETWORK IN WEATHER CLUTTER STATISTICS CLASSIFICATION

Система прийняття рішень, яка базується на нейронній мережі Кохонена LVQ2, була використана для класифікації статистики відбитків від метеорологічних об'єктів. Розрізняють між собою три класи розподілів: log-нормальий, Вейбулла і K.Data, які аналізувались з використанням L смугового радара. Показано, що виміряні амплітуди екземплярів відбитків, згідно з класифікацією, підпорядковуються розподілу Вейбулла.

A decision system based on Kohonen LVQ2 neural network was used to classification of weather clutter statistics. Three classes of distributions were distingished: log-normal, Weibull and K.Data were observed using L band radar. It was shown that the measured clutter amplitude samples obey a Weibull distribution, according to the classifier decision.

Introduction

In radar signal processing an important problem is the suppression of clutter, which is defined [1] as "confused unwanted echoes on radar display". Such waves, reflected for example from the ground surface, sea waves, clouds or raindrops, make the detection of wanted (target) echoes more difficult or impossible. The classification procedure allows to identify the radar clutter and it could considerably improve radar detection performance [2].

The clutter classification is important not only in the classical radar systems but also in more sophisticated applications, like meteorological radars or teledetection satellite systems. Many identification techniques are used for the classification purposes: visual examination of radar display, spectral analysis, autoregressive modelling, pattern recognition, amplitude distribution analysis, parametric and nonparametric statistical decision rules and recently neural networks [3,4].

Our previous work [5] has demonstrated some successful results in introducing the Kohonen neural network for distinguish between several classes of clutter statistics. The probability of correct decision of the proposed classifier was evaluated for clutter samples, modelled with given Non-Rayleigh amplitude distribution and different values of correlation coefficient.

In this paper the results of real data classification by using the mentioned Kohonen neural network are presented. A brief review of the classifier structure is given in Section II. Section III provides a description of the experimental data, which represents weather clutter samples. The results, discussed in section IV, allow to fit the Weibull model for observed data.

The neural network classifier

Kohonen neural networks are used mostly to the classification problems [2]. Fig. 1 shows the classifier structure based on an LVQ2 neural network, presented and evaluated in [5]. In our work we have concentrated on an LVQ2 architecture (LVQ stands for Linear Vector Quantization). The network contains J nodes, each of them being a prototype vector (so called weight vector) $\mathbf{w}^{(j)}$ of a j-th class. After feeding the network with an input $\mathbf{x}$, a winning node j* is calculated as the closest to the output such that

$$\forall \mathbf{j} \left\| \mathbf{w}^{(j^*)} - \mathbf{x} \right\| \leq \left\| \mathbf{w}^{(j)} - \mathbf{x} \right\|. \tag{1}$$

During the training phase, the classification of the input vector is apriori known, and the following weight adjustment is performed after selecting the winner j*:

$$\mathbf{w}^{(j^*)} := \mathbf{w}^{(j^*)} + \eta_1 \mathbf{x} \qquad \text{if the resulting class equals the expected} \qquad (2)$$

$$\mathbf{w}^{(j^*)} := \mathbf{w}^{(j^*)} - \eta_2 \mathbf{x} \qquad \text{otherwise} \qquad (3)$$

where η_1 and η_2 are training factors, gradually decreased to provide convergence. In the recognition phase, weight vectors $\mathbf{w}^{(j)}$ are frozen and the class of the winner j* is reported as a result.

The LVQ2 network was employed as a part of the system given in Fig.1.

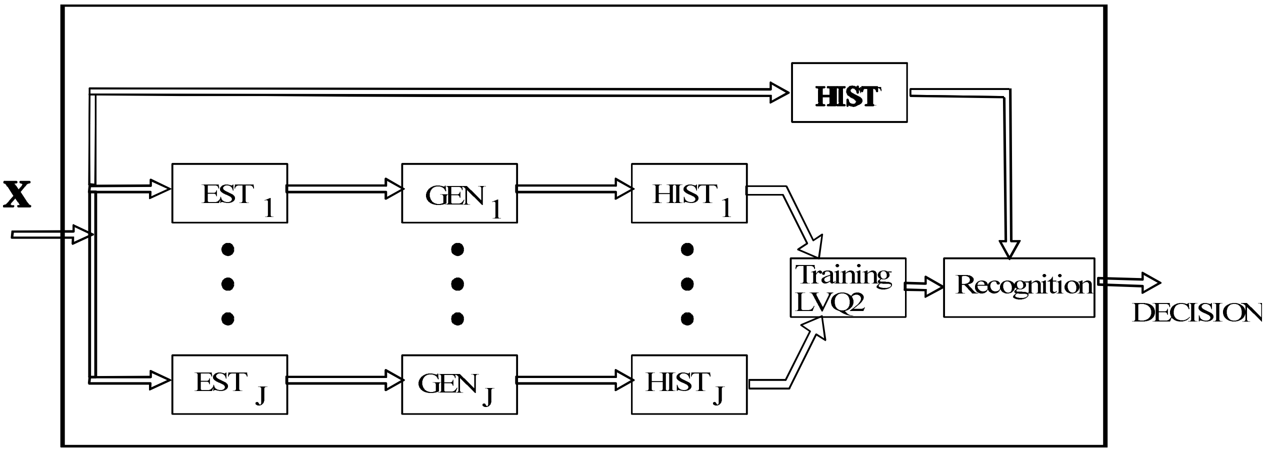


Fig. 1. Clutter classifier system based on the Kohonen neural network

An input to the system is a vector $\mathbf{x} \in R^n$ of samples of a random variable; the output is the decision, which distribution type it resembles mostly. The number J of classes the network can recognise is predefined, there is no "don't know" class.

For each "suspected" distribution we calculate (in the block EST_j) its parameters by their estimation based on data input. Then we generate (in the block GEN_j) a sample set of random variables with assumed distribution and estimated parameters. Based on this we create the histograms ($HIST_j$) of the generated set of samples. The histograms are used to train LVQ2 network. Simultaneously, the block **HIST** creates a histogram of empirical data with an unknown distribution. Finally, having presented the empirical histogram as an input vector to the previously trained LVQ2 network we obtain the resulting class as an answer.

Let an input to the system is a set $\mathbf{X}=\{X_i ; i=1,...., N\}$ of clutter samples with unknown amplitude probability density function (APDF) p_j. The otput is the decision which distribution class p_j (j=1,...., J) the radar clutter belongs to. The number J and type of APDF is predefined. In recent years non-Rayleigh models have received much attention [6] and we assumed log-normal, Weibull or K-distributed models (J=3). The APDF for these models are respectively
for log-normal:

$$p_1(X) = \frac{1}{\sigma X \sqrt{2\pi}} \exp \frac{-(\ln X - m)^2}{2\sigma^2} \qquad (1)$$

where X>0 and m, σ are clutter distribution parameters,
for Weibull:

$$p_2(X) = \alpha\delta(X)^{\alpha-1} \exp(-\delta X^{\alpha}) \qquad (2)$$

where X>0 and α, δ are clutter distribution parameters,
and for K-distributed:

$$p_3(X) = \frac{2\beta}{\Gamma(M)} \left(\frac{\beta X}{2} \right)^M K_{M-s}(\beta X) \qquad (3)$$

where X>0 and β, M are clutter distribution parameters, Γ is the gamma function, K_s is the s-order modified Bessel function.

The estimators of distribution parameters, obtained by moments method, are for log-normal:

$$\hat{m} = \frac{1}{N}\sum_{i=1}^{N} \ln x_i \,, \tag{4}$$

$$\hat{\sigma} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (\ln x_i - \hat{m})^2} \,, \tag{5}$$

for Weibull:

$$\hat{\alpha} = \frac{\pi}{\sqrt{6}\hat{\sigma}} \,, \tag{6}$$

$$\hat{\delta} = \exp(-\frac{\pi\hat{m}}{\sqrt{6}\hat{\sigma}} - \gamma \,), \tag{7}$$

where $\hat{m}$, $\hat{\sigma}$ are given by (4) and (5) respectively,
for K-distributed:

$$\hat{\beta} = 2\hat{m}\sqrt{\frac{2}{\hat{E}\{x^2\}[\hat{E}\{x^2\} - 2\hat{m}]}} \tag{8}$$

$$\hat{M} = \frac{2\hat{m}^2}{\hat{E}\{x^2\} - 2\hat{m}} \tag{9}$$

where $\hat{m} = \frac{1}{N}\sum_{i=1}^{N} x_i$ and $\hat{E}\{x^2] = \frac{1}{N}\sum_{i=1}^{N} x_i^2$.

For each of assumed APDF its parameters are estimated in the block EST_k based on data input. Then in the block GEN_k a sample set of random variable with distribution p_k and estimated parameters is generated. Based on this a histogram of the generated set is created in block $HIST_k$. The histograms are used to train LVQ2 network. Simultaneously the block **HIST** creates a histogram of empirical data as an input vector to the previously trained network.

Experimental data

Weather clutter was observed using an L band long range air-route surveillance radar (ARSR) of the beamwidth 1.2 ^{O}, pulsewidth 0.45 μs, pulse-repetition frequency 500 Hz. Data were taken from the centre of the rain-cloud in a range about 40 km. Each sample X_i is a 12 bits word that represents clutter envelope fr

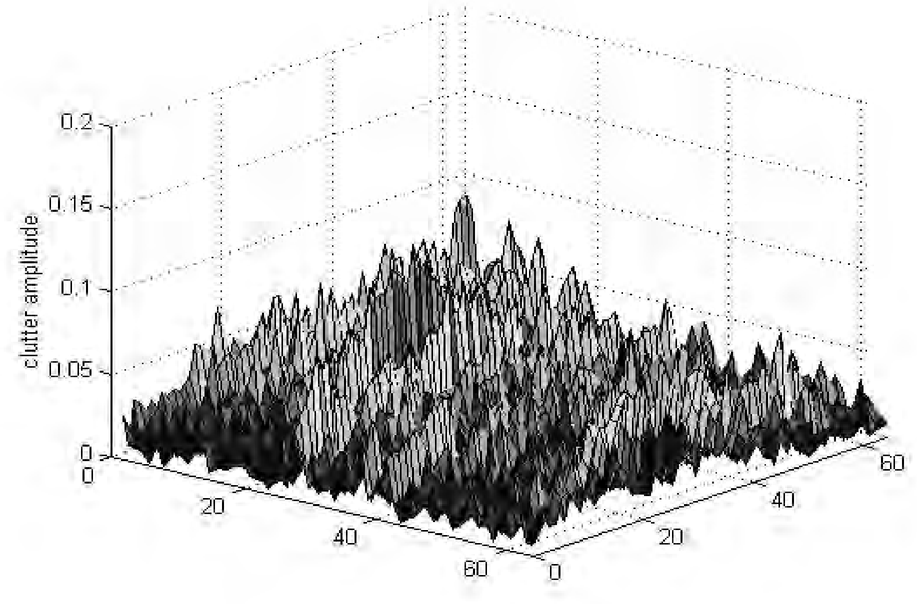
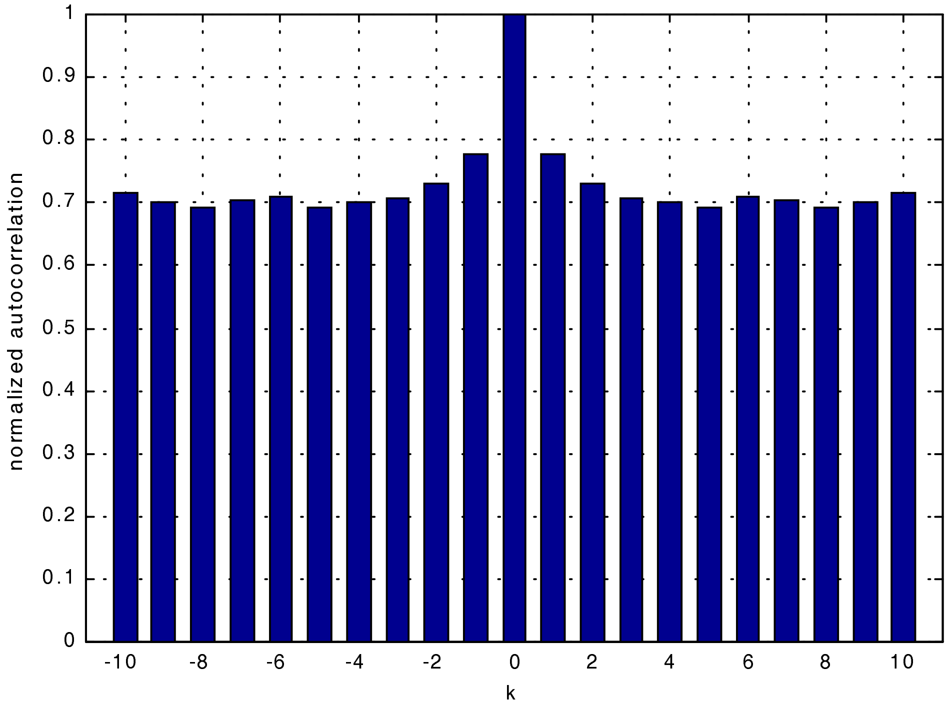
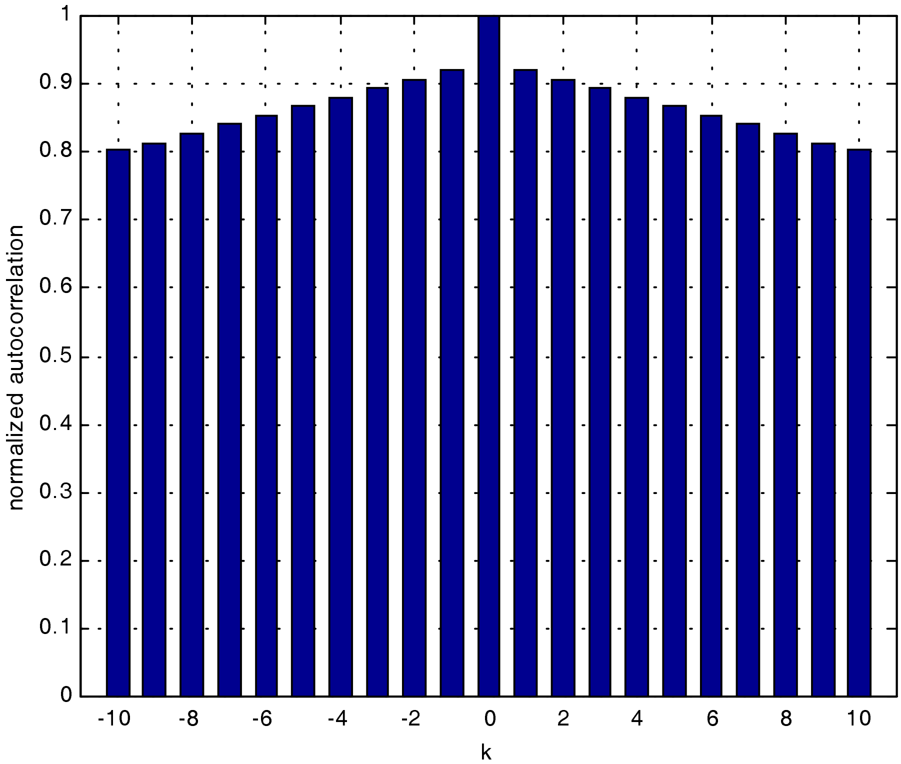


Fig. 2. Recorded weather clutter area



a



b

Fig. 3. Normalized autocorrelation of clutter samples (a) in range, (b) in azimuth

Fig. 3 shows the correlation properties of weather clutter in a range and in an azimuth. It must be emphasized that the correlation between samples is comparatively high . The correlation coefficient, given by

$$\rho_j = \frac{\left\langle (X_i - m)(X_{i+j} - m) \right\rangle_{\text{all } i}}{\operatorname{var}(X)}, \tag{10}$$

where $< . >_{\text{all } i}$ denotes the average taken over all cells and m is the mean value of X taken over all cells, for j=1 takes the value of 0.86.

Results

A set of 4096 amplitude clutter samples, described in previous section, was taken as an input data of the considered classifier. The system should decide which APDF: log-normal, Weibull or K-distributed is the most appropriate to the weather clutter amplitude statistic.

The classifier decided that **Weibull model**, with APDF given by the equation (2), represents a distribution of observed weather clutter. A histogram of recorded samples is shown in Fig. 4. A solid line fits a Weibull distribution with α parameter of 1.39 and δ parameter of 0.08 . The estimation of distribution's parameters was performed by using moments method.

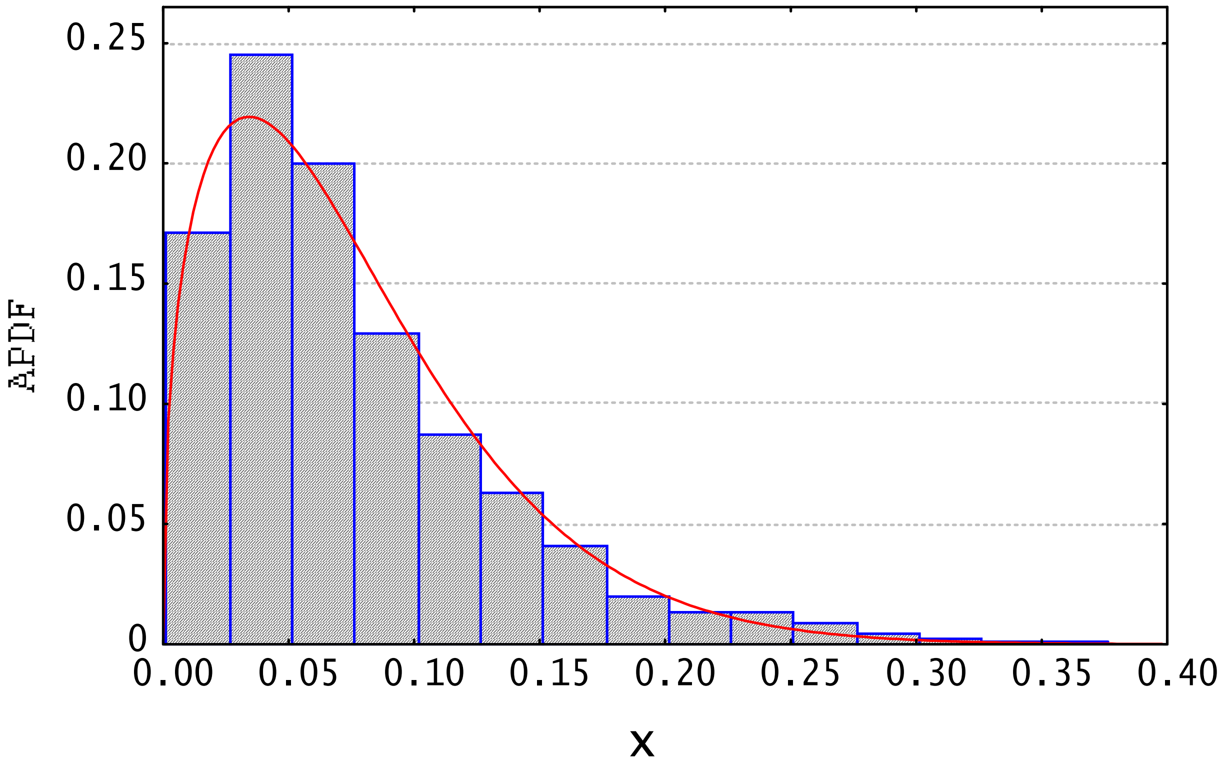


Fig. 4. Histogram and APDF (solid line) of weather clutter

The probability of the correct classification, approximated from results obtained in [5], takes the value between 0.95 and 0.99. The more precise value was evaluated by using Monte Carlo method. 1000 trials of N=4096 Weibull distributed clutter samples with α=1.39 ; δ=0.08 and ρ_1=0.86 were generated. For such input signal the probability of correct decision of the classifier was 0.98 .

Conclusion

As a result of observation of weather clutter it was found that clutter samples of the rain-cloud obey a Weibull distribution with a very high probability. This result and the value of the shape parameter α is similar to that obtained in [7].

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MODELLING OF GEOMETRIC DEPENDENCIES OF PARASITIC CAPACITANCES IN INTERCONNECTION BUSES

Зростання складності сучасних інтегральних схем призводить до зростання важливості таких ефектів, що виникають між з'єднаннями, як затримки та перехресні завади. Ці ефекти визначаються паразитними елементами відповідно до з'єднувальних ліній. Аналізується вплив геометричної конфігурації шин на паразитні ємності. Для цього була виведена формула для покращання точності ємнісних моделей.

Increasing complexity of modern integrated circuits causes that importance of effects occurring in interconnections, such as delay and crosstalk, grows. These effects are determined by parasitic elements corresponding to the connection lines. In this paper we discuss influence of geometrical configuration of the bus on parasitic capacitances. Suitable formulas improving accuracy of capacitance models have been developed.

Introduction

Continuous progress in VLSI technology enables increasing of the circuits' scale of integration. Modern chips including millions of transistors become more and more complex and their area grows. As a result, complexity of the net of conductive lines connecting devices in the subcells and leading signal between the subcells rapidly grows too. In effect propagation parameters of the interconnections are even crucial for performance of the circuit. These parameters strongly depend on values of parasitic elements corresponding to the interconnection lines. For this reason availability of effective models allowing to determine parasitic capacitances is indispensable for correct verification of the circuit.

In our previous works [1-3] we discussed some problems of interconnection capacitance modelling. Numerical methods, used in such computer programmes as CAPCAL [4] and FastCap [5-7] are too time-consuming for verification of large circuits, especially during statistical verification. For such purposes empirical models have to be used. But existing empirical models [8-12] determine the capacitance values basing only on line dimensions (width (W) and thickness (T)) and on spacing between the line and closest neighbours (spacing between lines (S) and distance to the plane (H)). In our works we have shown this approach is not justified for lines on one plane (Fig. 1). In such a case further lines intercept part of the flux and influence the values of *Caf* (capacitance between the line and the plane) and *Ccoup* (capacitance between the lines). It is less important for connections inside the subcells, because of their relatively low lengths. But lines leading signal between subcells may be long (even several centimetres) and these effects should not be neglected.