APPLICATION OF RANDOM DECISION RULES IN LASER LOCATOR IMAGE OPTIMAL SEGMENTATION ALGORITHMS

V. M. Lisitsyn, N. N. Pasechny, V. A. Stefanov, V. P. Samoilov, D. A. Lukanidin
The State Research Institute of Aviation Systems, Moscow, Russia

Commission III, Working Group 3

KEY WORDS: Mathematics, Algorithms, Image Processing, Radar, Pattern Recognition

ABSTRACT:

The method of speckled laser radar image segmentation based on the criterion of a maximum *a posteriori* probability is considered. Laser radar images are described by using the hierarchical two level stochastic model based on Markov random fields. The higher level of the model is a Gibbs random field which describe the whole laser image as a composition of the regions of different shapes and types and at the lower level each region is modelled within its borders by the Gaussian random field with known statistical characteristics. The grouping of pixels into different regions of image is governed by the new iterative segmentation algorithm. This algorithm has very low sensitivity to initial segmentation quality of the image and has the ability to achieve the global optimum in sense of probability. As belonging on each step of the iterative segmentation process the classification of the tested pixel to one of several region classes is made by random decision. The result of decision making is the value of the specific discrete random variable which distribution is equal to the *a posteriori* probabilities of belonging the tested pixel to the different regions. This probabilities are recursively estimated by taking into account only the nearest neighbourhood group of pixels and the results of the previous decisions. To provide a stochastic algorithm convergence (in probability) to a global maximum it is necessary to obtain a smooth transition from completely random estimations to deterministic ones. Thus, during initial iterations the algorithm searches for global maximum regions compensating the low quality of the initial segmentation and then tends to a deterministic form and provides the optimal image segmentation.

INTRODUCTION

The segmentation is one of steps in pattern recognition, scene analysis and image description problems solution which consists in image partitioning into homogeneous regions by some attribute. The segmentation task, for example, may involve the highlighting of objects images in a scene and the suppression of insignificant details (Duda, R., 1973; Borisenco, I., 1987).

The problem is considered of optimal segmentation of extended uncertain objects images generated by 10.6 mkm coherent IR laser locator (Dansac, J., 1985 Wang, J., 1984). By segmentation we mean the partitioning procedure of an image presented in the form of brightness matrix into a number of mutually disjoint regions corresponding to objects patterns and to the background. The pixels belonging to different image regions are assigned different states and pixels belonging to one region are assigned identical states. The total number of states is equal to a number of image region types (Therrien, C., 1986; Derin, H., 1986).

MODELS FOR IMAGE DESCRIPTION

To describe laser locator images a two-level composite Markov random model is used according to which the transitions from image region to another (pixel state change) are described by discrete Markov random field with Gibbs distribution and pixel brightness within each region is described by two-dimensional correlated Gaussian random process (Derin, H., 1986; Hanson, F., 1982; Kelly, P., 1988; Lisitsyn, V., 1995). The probability characteristics of the processes of both types are assumed to be specified a priori and to correspond to the characteristics of observable object and background patterns. Fig.1 showing the two-level composite model illustrates the description of images.

The segmentation problem under consideration consists in optimal in stochastic sense estimation of pixels of observable laser locator image based on a priori specified stochastic characteristics of the two-level Markov random-field model employed. In this case the regions of a segmented image coincide in form with observable objects and background patterns.

The Problems of Image Segmentation

The well-known iterative image segmentation algorithms (Kelly, P., 1988; Derin, H., 1986; Lisitsyn, V., 1991; Lisitsyn, V., 1995) based on sequential pixel state updating by *a posteriori* probability maximum criterion (probability of current pixel belonging to different regions with neighbouring pixels states) have two grave disadvantages. Firstly, because of deterministic nature of decision making these algorithms yield the same result under equal initial conditions. Secondly, the algorithms are highly sensitive to initial conditions: the resulting segmentation quality heavily depends on initial segmentation quality especially when signal-to-noise ratio is low. This is because in pixel-by-pixel optimization, i.e. when at each step *a posteriori* probability local maximum is searched for with a single pixel state variation, the algorithm provides process conver-

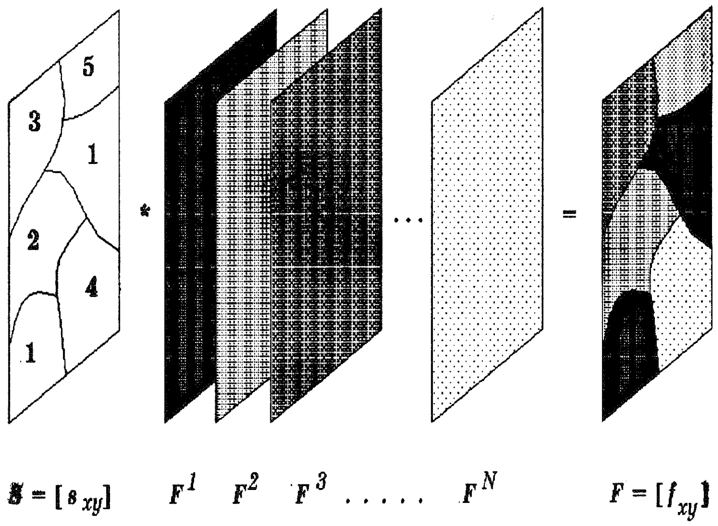

Fig.1. Two-level composite model.

gence to a maximum which is closer to the states of pixels corresponding to initial segmentation. Thus, in case of inadequate initial segmentation the process will converge not to a global but to some local maximum. Another drawback of the algorithms is the necessity of careful matching of Markov random field model parameters with really observable image parameters.

SEGMENTATION ALGORITHM CONSTRUCTION

To overcome the above-mentioned drawbacks a new approach to the synthesis of laser locator image iterative segmentation algorithms is proposed based on random decision rules.

The pixel-to pixel iterative segmentation of laser locator images based on stochastic decision rules represents a step-by-step nondeterministic procedure of a global maximum search where each pixel state is randomly update at each iteration step from neighbouring pixels states based on calculated *a posteriori* probabilities of a considered (current) pixel belonging to different regions. The algorithm is stochastic in its nature and can be written in the following form

$$\hat{S}^{i}_{xy} = \mathrm{rand}\left\{S^{i}_{xy} \middle| P(S^{i}_{xy})\right\}$$

where $\hat{S}^{i}_{xy}$ - an update (random) estimation of a current pixel state (x, y) at i-th iteration step $\mathrm{rand}\left\{S^{i}_{xy} \middle| P(S^{i}_{xy})\right\}$ is the result of a random value generation (a pixel state estimation) S^{i}_{xy} with a probability distribution $P(S^{i}_{xy})$; $(x, y) \in \{(0,0), \ldots, (M, N)\}$, $M \times N$ - number of pixels.

$P(S^{i}_{xy})$ probability distribution with completely stochastic decision making algorithm is the usual *a posteriori* probability distribution of a (x, y) pixel state at i-th iteration step. In this case the algorithm gives a random (close to optimal) result of segmentation and does not converge to any state. To provide a stochastic algorithm convergence (in probability) to a global maximum it is necessary to obtain a smooth transition from completely random estimations to deterministic ones. The above-mentioned laser locator image segmentation algorithms can be used as determenistic algorithms (Lisitsyn, V., 1991, Lisitsyn, V., 1995).

For considering models the transitions from image region to another are described by discrete Markov random field with Gibbs distribution

$$p_t(S) = \frac{1}{Z_0} \exp\left\{-\frac{U(S)}{T(t)}\right\}$$

where $T(t) \to 0$ at $t \to \infty$ and $T(t) \geq \dfrac{R\Delta}{\ln t}$ for $\forall t \geq t_0$; R – total number of pixels; t – iteration number; $U(S)$ – potential function depending on region types; Z_0 – normalization factor; $\Delta = U_{\max} - U_{\min}$.

It was shown that in this case the convergence is provided if

$$P(S^{i}_{xy}) = K P_B^{T(i)}(S^{i}_{xy} | \hat{S}^{i-1}_{(xy)})$$

where $P_B(S^{i}_{xy} | \hat{S}^{i-1}_{(xy)})$ - *a posteriori* probability of (x, y) current pixel state. On condition that B brightness image is observed and neighbouring pixels at the previous iteration step had $\hat{S}^{i-1}_{(xy)}$ states; K - normalization factor and $T(i)$ must tend to infinity with an unlimited increase of i, but no quicker than $T(i) \leq k\ln(i+1)$: k - a parameter, depending on specific characteristics of two-level Markov random field.

If the above conditions are met, then the random estimation of $\hat{S}^i_{xy}$ pixel state in the limit with an unlimited increase of i transforms into an ordinary estimation by *a posteriori* probability maximum criterion and random estimation sequence of pixels states

$$\hat{S}^1_{xy}, \hat{S}^2_{xy}, \ldots, \hat{S}^i_{xy}, \hat{S}^{i+1}_{xy}, \ldots$$

is a nonstationary Markovian chain of the first order with a single absorbing state corresponding to the global optimum.

Thus, during initial iterations the algorithm searches for global maximum regions compensating the low quality of the initial segmentation and then tends to a deterministic form and provides the optimal image segmentation.

MODELLING RESULTS

Figs 2-5 illustrate the implementation of algorithms with random decision rules. The algorithm described in (Lisitsyn, V., 1991) was considered as deterministic algorithm. Fig. 2 shows reference synthesized laser locator image with superimposed speckled noise. Fig. 3 shows the result of initial segmentation. Fig. 4 presents the result of deterministic segmentation algorithms implementation. Fig. 5 shows the result of segmentation algorithms implementation with random decision rules.

Mathematical modelling results have shown that in case of proper initial segmentation the stochastic and deterministic algorithms implementation yields equal results while in case of improper initial segmentation, the resulting image provided by stochastic algorithm implementation much better agrees with the ideal segmentation. Besides, algorithm implementation time increases by 30–35%.

The proposed approach is of general nature and can be applied not only to laser locator image segmentation but also to other similar cases.

REFERENCES

Boriseneo, I., Zlatopolsky, A., Muchnic, A., 1987. Segmentaciya izobrajeniy (Image Segmentation). Avtomatica i telemechanika, N 7, pp. 4–25.

Dansac, J., Meyzonnette, J.,1985. CO_2 -laser doppler rangefinding with heterodyne detection and chirp pulse compression. Proceedings of the SPIE, V. 590, pp.380–388.

Derin, H., Cole, W.S., 1986. Segmentation of textured images using Gibbs randomfield. Computer vision, graphics and image processing, V. 35, pp.72–98.

Duda, R.O., Hart, P.E.,1973. Pattern classification and scene analysis. John Wiley, New York.

Hanson, F.R., Elliott, H., 1982. Image segmentation using simple Markov fields models . Computer vision, graphics and image processing, V. 20, pp.101–132.

Kelly, P.A., Derin, H., Hartt, K.D., 1988. Adaptive segmentation of speckled images using a hierarchical random field model. IEEE Transactions on Acoustics, speech, and signal processing, V. 36 (10)

Lisitsyn, V., Obrosov, K., Pasechny, N., Stefanov, V., 1990. Laser radar images iterative segmentation for dynamic scenes. In: Archives of ISPRS, Victoria, Canada, Vol. XXVIII, Part 7–1, pp. 716–723.

Lisitsyn, V., Obrosov, K., Pasechny, N., Stefanov, V., 1991. Doppler optical image segmentation algorithm. Soviet journal of computer and systems sciences, V. 29 (1), pp. 33–42.

Lisitsyn, V., Obrosov, K., Pasechny, N., Stefanov, V., 1995. Iterative algorithm for segmenting multidimensional images. Journal of computer and systems sciences international, V. 33 (5), pp. 89–98.

Therrien, C.W., Quatiere, T.F., Dadjion, T.E., 1986. Statistical model-based algorithm for image analysis. Proceeding of the IEEE, V.74 (4), pp. 532–551.

Wang, J.Y.,1984. Imaging CO_2 - laser radar field test. Applied optics, V. 23 (15), pp. 2565–2571.

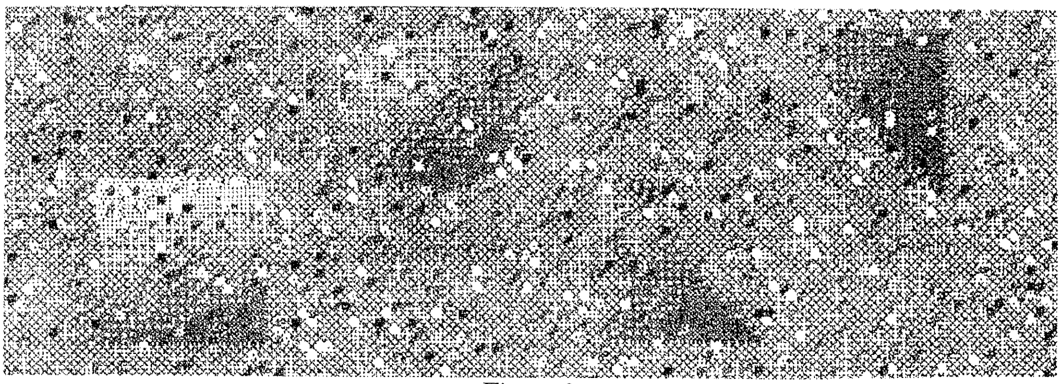

Figure 2.

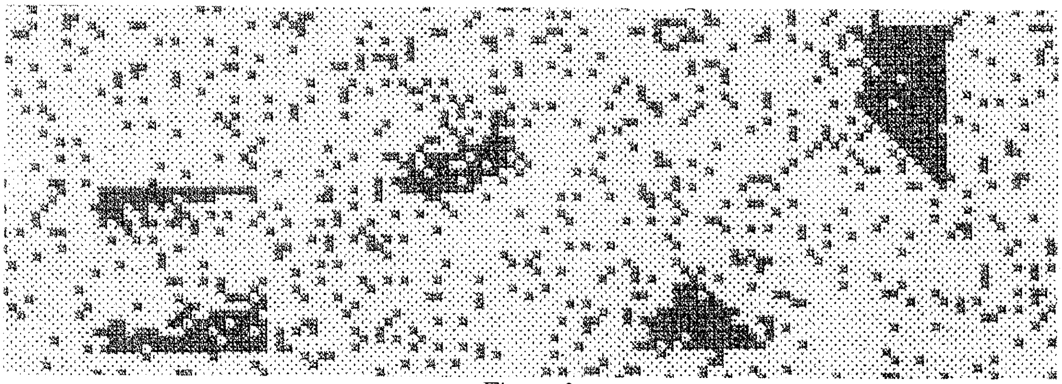

Figure 3.

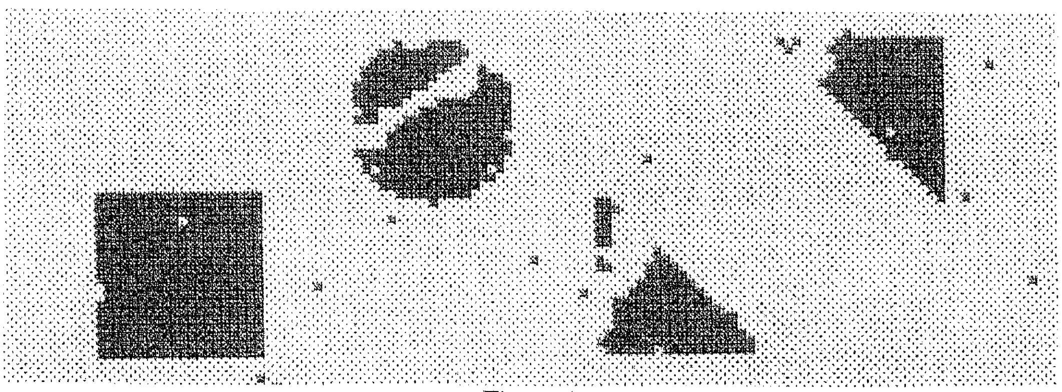

Figure 4.

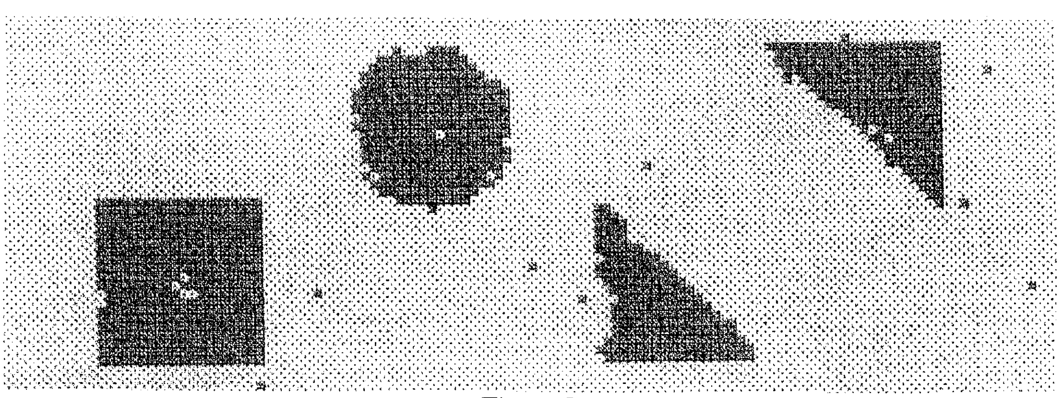

Figure 5.