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R. N. KVETNYY, O. YU. SOFINA, YU. A. BUNYAK

TEXTURED PATTERNS RECOGNITION BASED ON EIGEN HARMONIC DECOMPOSITION

Vinnitsa National Technical University,
95 Khmelnitske sh., Vinnitsa, Ukraine 21021
E-mail: olyasof@mail.ru

Анотація. У статті представлено новий підхід до розв'язання задач розпізнавання об'єктів на текстурованому фоні за допомогою власного гармонійного розкладання. Було використано набір власних (резонансних) гармонік коливань сигналу текстурованого зображення для апроксимації та фільтрації структури зображення.

Аннотация. В статьи представлено новый подход к решению задач распознавания объектов на текстурированном фоне с помощью собственного гармонического разложения. Набор собственных (резонансных) гармоник колебаний сигнала текстурированного изображения был использован для аппроксимации и фильтрации структуры изображения.

Abstract. An approach to textures pattern recognition based on eigen harmonic decomposition (EHD) is considered. A set of principal eigen (resonance) harmonics (EH) of textured image signal fluctuations is used for the image structure approximation and filtration.

Key words: pattern recognition, eigen harmonic decomposition, linear symmetry, inverse filtration.

INTRODUCTION

Textured images pattern recognition is one of the main problems in visual basing measurement and control systems. Main methods of texture analysis and modeling are presented in reviews [1-3]. Most of the methods are based on statistical analysis, spectral transforms and dynamic models of images signal. Method choosing depends on the texture type – regular, quasi-regular, stochastic or dynamic.

The main purpose of the texture analysis consists in obtaining the minimal number parameters that are invariant to spatial and temporal image transforms. The models of linear and nonlinear autoregression can represent correlation relation of texture structure. The correlation can be used directly too. It is used in the most known the method of co-occurrence matrices. Another approach is based on the images signal spectral transforms (ST) into spatial frequency domain where spectral parameters of the image have simple statistic in narrow range [4,5]. The newest methods combine statistical models and ST using a set of some type functions. For example the wavelets represent well a local geometry feature of textures with minimal number of significant coefficients however they do not represent as well the textures periodicity because are intended for presentation of transient signals. The eigenvector decomposition (EVD) of texture kernel and filters that are resonance to some type of image eigenmodes are most informative when texture is dynamic [6,7]. The EVD is computationally complicate and therefore independent component analysis, empirical mode decomposition (EMD) and singular values decomposition (SVD) are using instead of it [8,9]. However, the decompositions usually are using for projection transform of full image space that complicates their application in real time systems. Another way is based on using of filters banks. The filters banks are synthesized with the help of Fourier transform, wavelets and Gabor functions [1-3,10,11]. The wavelets and Gabor functions have parameters that are polysemantic and unique technique for their estimation according to texture structure does not exist. This complicates the problem of filters banks design. In the case of dynamic textures the decompositions are used for synthesis of texture model which generates an original like texture [12,13]. The textures correlation matrix often serves as object of the decompositions because it represents dynamic properties of large image in compact form. The asymptotic correlation matrix of a stationary process has Toeplitz structure and its eigenvectors have harmonic nature [14]. Therefore the harmonic decomposition is natural approximation of EVD or EMD. The parameters of harmonics can be agreed with periods of texture spatial structure.

The brief survey of the textured images analysis methods allows to make the following conclusions.

The most informative is decomposition that is invariant to texture spatial and temporal dynamic. The wavelets and SVD ignore signal structural information because are not shift invariant. The EVD and EMD have not analytical definition that complicates their use for approximation and interpolation of the image fragments. In contrast to mentioned decompositions, the EHD has simple analytical definition and joins capabilities for approximation and interpolation of 2D fields [15]. And so the EHD is appropriate functions basis for approximation of textured image fragment and for interpolation of its pattern for comparative analysis of rest image part. Another way of this procedure implementation is based on suppression of the texture pattern by EHD and obtaining of approximately flat signal. The signal flatness level points on recognized pattern or on the foreign object. Such spectral transform can be realized in spatial domain by convolution scheme which can be defined as inverse resonance filter (IRF).

HARMONIC MODEL OF TEXTURED IMAGE

Ideal textured image of size $N \cdot P \times M \cdot Q$ can be represented as tensor product of two matrices,

$$\mathbf{X} = \mathbf{T} \otimes \mathbf{B}, \tag{1}$$

where matrix $\mathbf{T}$ of size $N \times M$ includes unit elements with insignificant fluctuations and matrix $\mathbf{B}$ of size $P \times Q$ is the texture kernel, $\otimes$ – tensor product. Let's the texture (1) is changing by moving of the matrix $\mathbf{B}$ along t rows and τ columns. The model of such shift is the following: rows (columns) of the matrix move cyclically but instead last row (column), which becomes first, new row (column) is introduced as linear combination of previous ones. This shift is presented by the operator

$$\mathbf{K}_P = \begin{bmatrix} 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \\ -a_P & -a_{P-1} & \cdots & -a_1 \end{bmatrix} \tag{2}$$

that can be called as linear shift operator (LSO), its characteristic polynomial

$$1 + \sum_{i=1}^{P} a_i z^i = 0 \tag{3}$$

has the roots $z_i = \exp(\iota 2\pi f_i)$, f_i – eigen or resonance frequencies, $i = 1 \ldots P$. The LSO (2) can be defined for two image coordinates. The spectral factorization of the LSO can be written for both coordinates as

$$\mathbf{K}_{xP}^t = \mathbf{Z}_{xP} \mathbf{diag}\left[z_{xi}^t\right]_{i=1\ldots P} \mathbf{Z}_{xP}^{\#};$$
$$\mathbf{K}_{yQ}^t = \mathbf{Z}_{yQ} \mathbf{diag}\left[z_{yi}^t\right]_{i=1\ldots Q} \mathbf{Z}_{yQ}^{\#}, \tag{4}$$

where $\mathbf{Z}_{xP} = \left[z_{xi}^t\right]_{i=1\ldots P}^{t=0\ldots P-1}$, $\mathbf{Z}_{yQ} = \left[z_{yi}^t\right]_{i=1\ldots Q}^{t=0\ldots Q-1}$, # – pseudoinversion. The linear shifted kernel matrix can be presented using (4) in the manner

$$\mathbf{B}^{t,\tau} = \mathbf{K}_{xP}^t \mathbf{B} \mathbf{K}_{yQ}^{\tau T} == \mathbf{Z}_{xP} \mathbf{diag}\left[z_{xi}^t\right]_{i=1\ldots P} \mathbf{Z}_{xP}^{\#} \mathbf{B} \mathbf{Z}_{yQ}^{\# T} \mathbf{diag}\left[z_{yi}^{\tau}\right]_{i=1\ldots Q} \mathbf{Z}_{yQ}^{T} =$$
$$= \mathbf{Z}_{xP} \mathbf{diag}\left[z_{xi}^t\right]_{i=1\ldots P} \mathbf{A} \ \mathbf{diag}\left[z_{yi}^{\tau}\right]_{i=1\ldots Q} \mathbf{Z}_{yQ}^{T}, \tag{5}$$

where

$$\mathbf{A} = \mathbf{Z}_{xP}^{\#} \mathbf{B} \mathbf{Z}_{yQ}^{\# T} \tag{6}$$

– spectrum of the matrix $\mathbf{B}$ in the basis $\mathbf{Z}$, T – transposition. Expression (5) shows the spectrum invariance to LSO – spectral matrix of the shifted kernel in (5) differs from the original one by phase multiplies. The periodicity of kernel in textured image is defined by condition

$$\mathbf{B}^{mP,nQ} = \mathbf{B}, \tag{7}$$

where m and n arbitrary integer values. This condition allows to present the full ideal textured image (1) by overdetermined matrices.

$$\mathbf{X} \approx \widetilde{\mathbf{Z}}_{xP}\mathbf{A}\ \widetilde{\mathbf{Z}}_{yQ}^{T}, \tag{8}$$

where $\widetilde{\mathbf{Z}}_{xP} = \left[z_{xi}^{t}\right]_{i=1...P}^{t=0...NP-1}$, $\widetilde{\mathbf{Z}}_{yQ} = \left[z_{yi}^{t}\right]_{i=1...Q}^{t=0...MQ-1}$.

The expression (8) has approximate invariance to linear shift transforms because the pseudoinversion of overdetermined matrices is approximative. The linear shift is natural for many models of texture, static and dynamic. And so the EHD (8) provides informative presentation of the image model on condition the parameters of the LSO are estimated correspondingly to texture structure.

HARMONIC DECOMPOSITION AND TEXTURES FILTERING

The harmonic decomposition of image type signals. The problem of texture filtering and recognizing can be considered as coherent suppression of its structure. The filtered signal must be flat as possible with the additive error noise. The flatness level is characterized by noise dispersion value. The filtration is based on two transforms (6), (8) using square or overdetermined matrices $\mathbf{Z}$ and modification of the spectral matrix $\mathbf{A}$. The first step of the filter design is estimation of the LSO (2) parameters and definition of its characteristic polynomial (3) roots. There is known a series of methods for estimation of 2D data resonance frequencies [14]. In the case of texture EHD it is necessary to take into account important restrictions to model parameters:

- The texture model is considered as stationary process with approximative pattern periodicity (7). As it follows from condition (7) the roots of characteristic polynomial (3) must be placed on the unit circle.
- Texture can be not smooth 2D function and the method must be not-sensitive to signal breaks.
- The order of the LSO must corresponds to texture structure – the matrix $\mathbf{A}$ must not includes zero components. But if the EHD order is understated the spectrum will be corrupted.
- The high order filter is required when texture is quasi-regular, dynamic or corrupted by noise spikes.

As it was shown in [15] the eigen harmonics of two one-dimensional data vectors along coordinates can be used for 2D data representation by EHD approximation (11). Therefore usual methods of harmonic decomposition can be used for LSO parameters estimation [14]. The methods of spectral parameters estimation are based on the idea of correlation relation between two mutually shifted data sets. The linear parameterization of this relation yields the linear prediction (LP) model and its various implementations. The LP based methods are sensitive to signal phase, usually it becomes apparent in splitting of spectral lines. The image signal breaks can be considering as phase interruptions. We enforce the LP model by condition of invariance to shift operations with the purpose of reducing sensitivity to data breaks. This invariance may be determined as linear symmetry (LS) [16]. The LS of correlation matrix $\mathbf{R}_p$ of size $p \times p$ has the manner

$$\mathbf{R}_p = \mathbf{K}_p \mathbf{R}_p \mathbf{K}_p^H \tag{9}$$

and it differs from usual LP as superposition of direct and conjugate (H – Hermitian conjunction) LP that removes depending on signal phase. The equation (9) provides unitarity of LSO, the roots of polynomial (3) are placed on unit circle, but it is valid on condition of Toeplitz structure of correlation matrix. Therefore the exact LS (9) can be changed by the approximative condition of LS that is optimized accordingly to maximal likelihood criteria,

$$\frac{\partial}{\partial a_i} tr(\mathbf{R}_p^{-1}\mathbf{K}_p \mathbf{R}_p \mathbf{K}_p^H) = 0;\ \ i = 1, \ldots, p\ . \tag{10}$$

The equation (10) has simple solution

$$a_{p-i} = -\rho_{i,p}\rho_{p-1,p-1}^{-1},\ \ i = 1...p-1;\ \ a_p = 1,$$

where $\rho_{\cdot,p-1}$ are elements of the last column of the inverse matrix $\mathbf{R}_p^{-1}$, the dispersion of LS model error is estimated as $\sigma^2 = \rho_{p-1,p-1}^{-1}$. As it follows from this solution the LS model order p must be chosen such that element $\rho_{p-1,p-1}$ is the maximum or local maximum of the function $\rho_{\cdot,p-1}$. In the case of LS (10) the condition of unitary symmetry can be achieved by additional relations between LSO parameters: $a_p = 1;\ a_i = a_{p-i}$,

$i = 1 ... p/2 - 1$. Taking into account this polynomial symmetry the expression (25) can be written as equation system with respect to the polynomial coefficients.

$$\sum_{i=1}^{q-1} a_i (r_{i,k} + r_{p-i,k} + r_{i,p-k} + r_{p-i,p-k}) + a_q (r_{k,q} + r_{p-k,q}) =$$

$$\rho_{p-1,p-1}^{-1} \sum_{i=0}^{p-2} \rho_{i,p-1}(r_{k,i+1} + r_{p-k,i+1}) - r_{k,0} - r_{p-k,0}, \quad (11a)$$

where p is even and $k = 1...q-1$, $q = p/2 - 1$, for $k = q$

$$\sum_{i=1}^{q} a_i (r_{i,q} + r_{P-i,q}) + a_q r_{q,q} = \rho_{p-1,p-1}^{-1} \sum_{i=0}^{p-2} \rho_{p-1,i} r_{i+1,q} - r_{q,0}. \quad (11b)$$

Analogues equation can also be written for the odd model order. But the case of even order is preferable because polynomial (3) gives $p/2$ pairs of mutually complex conjugated significant roots. In the case of odd order the equation (11) yields the polynomial (3) with one insignificant root, usually equal to constant value. The spectrum component of this root is undesirable for texture filtering because it is presented in filtered signal.

If image signal is homogeneous than the first data moments of some row and column can be used for estimation of LSO parameters. In other case the 2D correlation matrix

$$\mathbf{R}^{(2)} = \left[r^{(2)}_{i_x,k_x,i_y,k_y} \right]_{i_x,k_x=0...P-1}^{i_y,k_y=0...Q-1} = \left[\sum_{m=0}^{n_x-P} \sum_{n=0}^{n_y-Q} u_{m+i_x,n+i_y} u_{m+k_x,n+k_y} \right]_{i_x,k_x=0...P-1}^{i_y,k_y=0...Q-1} \quad (12)$$

is more informative The correlation matrices that characterize data along coordinates in (10) may be defined as

$$\mathbf{R}_x^{(2)} = \left[r^{(2)}_{i_x,k_x,0,0} \right]_{i_x,k_x=0...P-1}^{i_y,k_y=0}; . \mathbf{R}_y^{(2)} = \left[r^{(2)}_{0,0,i_y,k_y} \right]_{i_x,k_x=0}^{i_y,k_y=0...Q-1} \quad (13)$$

and can be used as $\mathbf{R}_p$ in (10).

Texture Filtering. The textured image region of size $n_x \times n_y$: $n_x > P$; $n_y > Q$, that covers texture kernel can be presented by the EHD like (8), its pixels values are the following.

$$d_{i,k} \approx \sum_{m=0}^{P-1} \sum_{n=0}^{Q-1} A_{m,n} z_{xm}^i z_{yn}^k, \quad (19)$$

where $i(k) = 0...n_{x(y)} - 1$, $A_{m,n}$ – spectral coefficients that are found by inverse to (19) transform like (6). The spectral coefficients of filtered image can be found as

$$E_{m,n} \approx \sum_{i=0}^{n_x-1} \sum_{k=0}^{n_y-1} E \ \bar{z}_{xm}^i \bar{z}_{yn}^k, \quad (20)$$

where E – some constant value, $\bar{z}_{xm}^i$ and $\bar{z}_{yn}^k$ – elements of matrices $\mathbf{Z}^{\#}$ in (6). From (19) and (20) it follows that for obtaining of the flat signal the image spectrum must be transformed by the filter with spectrum

$$H_{m,n} = E_{m,n} A_{m,n}^{-1}. \quad (21)$$

The procedures of filtration in spectral domain by (6), (8) and (21) can be changed by filtration in spatial domain by the filter with the transient characteristic

$$h_{i,k} = \sum_{m=0}^{P} \sum_{n=0}^{Q} H_{m,n} z_{xm}^i z_{yn}^k. \quad (22)$$

This procedure seems as convolution operation

$$\sum_{m,n=0}^{P-1,Q-1} h_{m,n} d_{m+i,n+k} = E + \varsigma_{i,k} , \tag{23}$$

where $\varsigma_{i,j}$ – error noise.

The statistical analysis of the filtered signal was made using the dispersion of the noise of base region filtering. It was estimated as

$$\sigma_{\varsigma}^2 = \frac{1}{n_x n_y} \sum_{i,j=0}^{n_x-1,n_y-1} \left(\tilde{d}_{i,j} - E\right)^2 , \tag{24}$$

where $\tilde{d}_{i,j}$ – filtered values of image signal. Texture pattern can be recognized using the condition

$$\textbf{if} \ \bigcup_{j=1}^{3} \left(| \tilde{d}_{i,k}^{[t]} - E | > 3\sigma_{\varsigma}^{[t]} \right) \ \textbf{then} \ v_{i,k}^{[t]} = d_{i,k}^{[t)]} \ \textbf{else} \ v_{i,k}^{[t]} = 0; \ t = 1,2,3 \ ,$$

where top indices in the brackets point on colors, the dispersion (24) was estimated for each color components, $d_{i,k}^{[t]}$ – initial image pixels values, $v_{i,k}^{[t]}$ – filtered image pixels values.

The filter (23) suppresses eigen or resonance harmonic modes of textured image signal. As it follows from expressions (21) and (22) the transient characteristic of the filter relates with inversion of texture spectrum and therefore the filter can be classified as inverse resonance filter.

Filtered Texture Abnormalities Analysis. The IRF, statistical (24) and logical analysis (25) recognize own texture, foreign objects and textures of another types. The filtering may gives errors because oftexture heterogeneity. The errors removing can be executed by account of other image properties. We will consider the approach that can be implemented for removing errors of dynamic textures filtering.

When texture is dynamic and characterized by nonstationary surges the application of filtration (23) and algorithm (25) does not provide high quality of the filtering and recognition. If texture tracking is continuous it is possible to remove false foreign objects by binary correlation of objects that are found in consequent frames.

The method of binary correlation filtration includes:

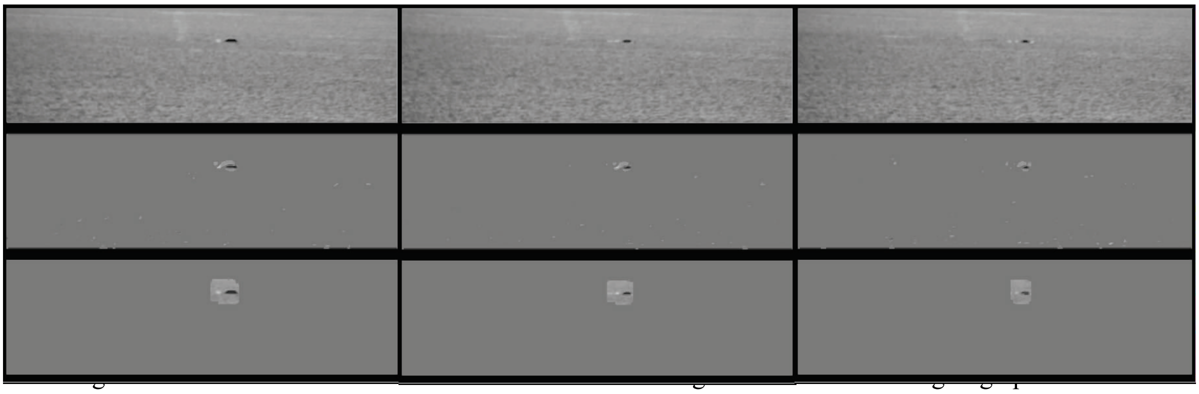
1. the objects size and geometrical centre estimation;
2. the correlation coefficient estimation using L consecutive frames,

$$r = \frac{\sum_{t=0}^{L-1} \sum_{i=-Sx/2}^{Sx/2} \sum_{k=-Sy/2}^{Sy/2} \left\{ v_{I+i,K+k}^{(0)} > 0 \right\} \wedge \left\{ v_{I+i,K+k}^{(t)} > 0 \right\}}{\sum_{\tau=0}^{L-1} \sum_{i=-Sx/2}^{Sx/2} \sum_{k=-Sy/2}^{Sy/2} \left\{ v_{I+i,K+k}^{(t)} > 0 \right\}} , \tag{26}$$

where $\{\cdot\}$ denotes the logical function, if condition in the brackets is true then it equal to one, else to zero, I, K – the coordinates of the object centre of the frame number in top brackets, $Sx \times Sy$ – the object size.

1. if the correlation coefficient (26) exceeds threshold level then the object is true else false;
2. true object is redefined with surround background for further classification.

The L frames running time must be much smaller in comparison with the time of target object moving outside of the rectangle of the size $Sx \times Sy$.



initial images; middle positions – images filtered by IRF; low positions – images filtered by correlative filter

Three consecutive frames of marine surface filtering are shown in Figure 1 [17]. The base region of size 32×32 in left high image corner was used for design of the IRF of the order 8×8 (full frame size is 200×600). First frame of the series free from foreign objects was used for filter design. The binary correlative filter (26) with parameters $L=3$, $r=0.3$ was also used. As it follows from Figure 1 some mistakes of filtering by IRF were removed well by correlative filter.

CONCLUSIONS

Nowadays methods of texture analysis are found on the decompositions and integral transforms that have the same symmetry as texture in respect to shift and rotate transforms. The moving in some direction is natural for many types of static and dynamic textures. This type of transforms can be represented by linear shift operator that modeling step-type changes and simultaneously periodicity of the texture. The eigenvectors of LSO can serve as basis for EHD of the texture with the invariance to shift transforms.

The problem of pattern classification can be considered as inverse problem of recovering of known signal with flat surface. The dispersion value of the surface fluctuations points on recognized texture or foreign objects.

The IRF in conjunction with correlative filtering in the case of dynamic textures series successfully removes textured signal and recognizes foreign objects boundaries.

The considered above method of textured image filtering for foreign objects recognizing or textures classification differs from other known methods by the following features:

- simplicity – each texture is characterized by its own filter and dispersion of the error;
- ability of implementation in real time using arithmetic units array;
- regulated resolution and quality;
- invariance to image moving changes;
- it is based on principal harmonic decomposition that is simpler and more convenient than EMD or EVD because has simple analytical form and may be simply adapted to image and its fragments size.

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КВЄТНИЙ РОМАН НАУМОВИЧ – д.т.н., професор, Вінницький національний технічний університет, завідувач кафедри автоматики та інформаційно-вимірювальної техніки, Вінниця, Україна.

СОФИНА ОЛЬГА ЮРІЇВНА – аспірант кафедри автоматики та інформаційно-вимірювальної техніки, Вінницький національний технічний університет, Вінниця, Україна.

БУНЯК ЮРІЙ АНАТОЛІЙОВИЧ – к.т.н., головний спеціаліст ТОВ «ІВП ІнноВінн», Вінниця, Україна.