phasor voltages at the x- and z-terminal of the kth current conveyor. \(I_{ax} = I_{x}(j\omega)\) is also the phasor current through the x-terminal of the kth current conveyor. \(V_{ax}, V_{az}\) and \(I_{ax}\) are the bounds of the linear region obtained from the transfer characteristics or from the linear operation conditions, and these are termed the saturation voltages and current of the kth current conveyor. When the CCII-s are implemented using the above mentioned CMOS configurations, then saturation voltages and current of

\[
V_{ax} = 6.7 \text{ V} \quad V_{az} = 7.17 \text{ V} \quad I_{ax} = 204 \mu \text{A}
\]

are obtained from eqn. 2 for the CCII+, and values of

\[
V_{ax} = 7.94 \text{ V} \quad V_{az} = 9.1 \text{ V} \quad I_{ax} = 116 \mu \text{A}
\]

are obtained from eqn. 3 for the CCII-.

Eqn. 4 places the following constraints on the input current amplitude for \(\omega \in \Omega_k (\alpha_k, \beta_k)\):

\[
|I_{in}| \leq \frac{V_{ek}}{Z_{ek}}|I_{in}| \leq \frac{V_{ek}}{Z_{ek}}|I_{in}| \leq \frac{V_{ek}}{|A_{ek}|} \quad k = 1, 2, \ldots, n
\]

where \(|A_{ek}|\) is the amplitude of the filter’s input current, and \(Z_{ox}, Z_{oz}\), and \(A_{ek}\) are the transfer functions defined as

\[
Z_{ek} = \frac{V_{ek}(j\omega)}{Z_{ek}} \quad Z_{ek} = \frac{V_{ek}(j\omega)}{I_{in}} \quad A_{ek} = \frac{I_{ek}(j\omega)}{I_{in}} \quad k = 1, 2, \ldots, n
\]

In other words, \(Z_{ox} = Z_{o}(j\omega)\) is the transfer impedance which is defined as the ratio of the kth current conveyor’s x-terminal phasor voltage to the phasor input current. \(Z_{oz} = Z_{o}(j\omega)\) is also the transfer impedance defined as the ratio of the kth current conveyor’s z-terminal phasor voltage to the phasor input current. \(A_{ek} = A_{ek}(j\omega)\) is the current transfer function which is defined as the ratio of the kth current conveyor’s x-terminal phasor current to the phasor input current.

In inequalities exist in eqn. 7, and their common solution which gives the maximum value of input current that does not cause nonlinear distortion (clipping and slew-rate limiting) can be expressed as

\[
|I_{in}|_{\text{max}} = \min \left\{ \frac{V_{ek}}{|Z_{ek}|_{\text{max}}}, \frac{V_{ek}}{|Z_{ek}|_{\text{max}}}, \frac{|I_{ek}|_{\text{max}}}{|A_{ek}|_{\text{max}}} \right\}
\]

where \(|Z_{ek}|_{\text{max}}\), \(|Z_{oz}|_{\text{max}}\), and \(|A_{ek}|_{\text{max}}\) are, respectively, the maximum values of \(|Z_{ek}|\), \(|Z_{oz}|\), and \(|A_{ek}|\) for the specified frequency band \(\omega \in (\alpha_k, \beta_k)\). Note that the saturation voltages and currents are known from the current conveyor topologies used in the design, and the values of \(V_{ax}, V_{az}\) and \(I_{ax}\), \(k = 1, 2, 3, \ldots, n\) are equal to each other if identical current conveyors (CCII+ or CCII-) are used in the realisation of the filter. Note also that \(Z_{ek}, Z_{oz}\), and \(A_{ek}\) in eqn. 9 are to be calculated from the given network topology of the filter involving the current conveyors, by the use of eqn. 8.

\[
\text{Fig. 3} \quad \text{Third order all-pole bandpass filter using four current conveyors}
\]

**Example:** In the following, as an example, the maximum input signal level is calculated for the all-pole bandpass filter shown in Fig. 3. This filter realises

\[
\frac{I_{out}}{I_{in}} = \frac{\sqrt{2}S^2}{S^3 + 2S^2 + 2S + 1}_{\text{in}}
\]

with unity gain at a resonant frequency of \(\omega_0 = 10^6 \text{ rad/s}\). This circuit uses only CCII-s and they are designed using the CMOS configuration in [1, 2]. Their saturation currents and voltages are given in eq. 6. \(Z_{ox}, Z_{oz}\), and \(A_{ek}\) for \(k = 1, 2, 3, 4\), which are necessary for determining \(I_{in}\) are obtained from the filter topology of Fig. 3, by the use of eqn. 8, for the 3 dB passband region.

\[
Z_{ox}(j\omega)_{\text{max}} = 0, i = 1, 2, 3, 4 \quad |Z_{oz}(j\omega)|_{\text{max}} = 20 \Omega
\]

\[
Z_{ox}(j\omega)_{\text{max}} = 20.19 \Omega \quad |Z_{oz}(j\omega)|_{\text{max}} = 10 \Omega
\]

\[
Z_{oz}(j\omega)_{\text{max}} = 0 \Omega \quad |Z_{oz}(j\omega)|_{\text{max}} = 10 \Omega
\]

\[
A_{ek}(j\omega)_{\text{max}} = 1.11 \quad |A_{ek}(j\omega)|_{\text{max}} = 1.56
\]

\[
A_{ek}(j\omega)_{\text{max}} = 1.17 \quad |A_{ek}(j\omega)|_{\text{max}} = 0.69
\]

Substitution of eqns. 6 and 11 into eqn. 9 yields

\[
|I_{in}|_{\text{max}} = \min \{\infty, \infty, \infty, 397 \mu \text{A}, 450 \mu \text{A}, 388 \mu \text{A}, \infty, 104.6 \mu \text{A}, 74.4 \mu \text{A}, 99.3 \mu \text{A}, 167 \mu A\} = 74.4 \mu \text{A}
\]

This result is verified by the SPICE simulations of the filter by simulating the output response of the filter to a sinusoidal input current at several signal levels of \(I_i < 74.4 \mu \text{A}\) and \(|I_i | > 74.4 \mu \text{A}\) with angular frequency of \(\omega_0\), respectively. For \(|I_i | < 74.4 \mu \text{A}\), the total harmonic distortion (THD) at the output is less than 1.1%. It is observed that THD rapidly increases with increasing input amplitude for \(|I_i | > 74.4 \mu \text{A}\).

**Conclusion:** In this study the maximum input signal level that does not cause nonlinear distortion is investigated for current-mode active-RC filters involving second generation current conveyors; eqn. 9 has been derived in order to determine this level. Note from eqn. 9 that the input signal level can be optimised and hence the behaviour of the filters can be improved by using impedance scaling since impedance scaling does not scale the current transfer function \(A_{ek}\), while the transfer impedances \(Z_{ox}\) and \(Z_{oz}\) are scaled for \(k = 1, 2, \ldots, n\).

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C. Acar and H. Kurntman (Istanbul Technical University, Faculty of Electrical and Electronics Engineering, Department of Electronics and Communication Engineering, 80626, Maslak, Istanbul, Turkey)

**References**


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**Image block classification using stochastic image segmentation**

Chee Sun Won and Yoonsik Choe

**Indexing terms:** Segmentation (image processing), Image coding

The authors propose a new image block classification method. The proposed algorithm incorporates image context into the classification via pixel-based segmentation. To obtain a segmented image they adopt the stochastic model-based unsupervised image segmentation algorithm. Since the block classifier considers the grey level distribution in the block, it can differentiate edges from textures. Also, since the segmentation is executed independently at each small block, a parallel processor can be applied to obtain a real-time block classification.
Introduction: Image block classification is a very useful task for image compression purposes; e.g., having classified each image block into one of monotone, texture, and edge blocks, we can apply such compression methods as vector quantisation [1], DCT [2], lapped orthogonal transforms [3], or fractal-based image coding [4]. Despite the importance, however, few improvements have been made to efficiently classify a given image block. Usually, block variance has been used as the criterion for the classification [1]. However, as also pointed out in [5], block variance (the mean squared deviation from the block mean) does not consider the pixel value distribution within the block. Therefore, to differentiate a monotone block with an edge from a textural block, we have to take into account the pixel value distribution in the block. To consider the contextual information of the block, we propose the use of a pixel-based stochastic image segmentation.

Image models and segmentation: We partition the given image space into non-overlapping blocks of size \( N_x \times N_y \). Now, the image data in each block is assumed to be a realisation \( y = (y_i) \in \Omega \) from a random field \( Y = (Y_{ij}) \in \Omega \), where \( \Omega \) is a discrete rectangular lattice denoted as \( \Omega = \{(i,j): 1 \leq i \leq N_x, 1 \leq j \leq N_y\} \). For each pixel \( i \in \Omega \), the region-type that the pixel belongs to is specified by a region label. The region label at a pixel \( i \) is modelled as a discrete-valued random variable \( X \), taking values in \( \{1, \ldots, G\} \), and the set of region labels \( X = \{x_i, 1 \leq i \in \Omega\} \) is assumed to be a realisation from a Markov random field (MRF) \( X = \{x_i, t \in \Omega\} \). Then, we can specify the region process \( X \) through a Gibbs random field (GRF) distribution [6, 7].

Having defined stochastic models, our goal is to segment the given image block into \( g' \in \{1, \ldots, G\} \) distinct regions. To achieve this goal, we can apply an unsupervised image segmentation algorithm [6, 7]. For complete unsupervised segmentation, we can also estimate the optimal number of regions \( g' \) in the block by adopting the model selection criterion [6]. One difference in adopting the previous model selection criterion in [6] is that the number of regions to be segmented starts from one (i.e., homogeneous region) instead of two. Therefore, we need to check the model selection criterion for \( g = 1, 2, \ldots, G\). However, since it is meaningless to include a priori probability distribution in \( P(x) \) in the log-likelihood of the model selection criterion for \( g = 1 \), it should be modified as follows in our problem:

\[
g^* = \arg\max_{g' \in \{1, 2, \ldots, G\}} \left[ \log P(Y|\theta^*, X^*) - N \log m(g) \right] \quad (1)
\]

where \( \theta^* \) is the ML estimate of the noisy model parameter with the segmented region label configuration \( \hat{s} \); \( m(g) \) represents the number of model parameters to be estimated for the \( g \)-region segmentation and \( c \) is a constant to correct the bias of the AIC criterion [6]. Note that as \( c \) increases we will have more homogeneous regions.

Block classification: Once we have a \( g' \) segmentation for each block, we can now classify it by the segmented result, i.e., if the block has \( g' = 1 \), then it is a homogeneous block. In this case, if the block variance \( \sigma^2 \) exceeds a threshold \( V_{TH} \), then it is further classified as a textural block. Otherwise, it belongs to a monotone block. If \( g' > 1 \), then it must contain more than two regions. Therefore, it contains an edge. The edge block can be further partitioned into four square regions to check the homogeneity to yield a variable size block segmentation.

Experimental results: Suppose that the noisy model \( Y \) has an IID Gaussian distribution. That is, the grey level \( x_i \) at \( t \in \Omega \) is assumed to be corrupted by independent Gaussian noise. More specifically, at \( t \in \Omega \), \( y_i \) is Gaussian with mean \( r_t \) and variance \( \sigma^2 \) for \( x = g \in \{1, \ldots, G\} \). Then

\[
P(Y|X) = \prod_{t \in \Omega} P(Y_t|X_t, x_t) \quad (2)
\]

where

\[
P(Y_t|X_t, x_t) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y_t - \theta_t)^2}{2\sigma^2}} \quad (3)
\]

where \( \theta_t = (\sigma^2, r_t, \ldots, r_t) \) represents the set of noisy image model parameters associated with \( Y \). For the region process \( X \), we adopted the isotropic pair-clique parameter \( \beta \) with the second order neighbourhood system. Since the model parameter for the region process \( X \) is relatively insensitive to the segmentation result [6], it is assumed to be known as \( \beta = 0.8 \). Therefore, \( m(g) \) in eqn. 1 should be \( (g+1) \). For the block segmentation we used the unsupervised segmentation in [6] with the model selection criterion in eqn. 1.

Fig. 1 shows segmented results for a \( 256 \times 256 \) Lena image. For the experiment, we used \( N_x = N_y = 8, G = 2, V_{TH} = 125 \) and \( c = 0.8 \). As can be seen in the Figure, the proposed algorithm segments the given image into monotonic, textural, and edged regions quite well.

Conclusion: A segmentation-based block classifier has been proposed. Since the image contextual information, as well as the block variance was used for the block classification, edges can be differentiated from textures. Also, since the segmentation can be executed at each small block independently and in parallel, we can obtain real-time block classification.

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