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Providing an Algorithm for Improvement of Wavelet-Based Moving Object Segmentation for Noisy Video Sequences

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ABSTRACT

Technology advancement has allowed large amount of video data to be used in multimedia systems, digital TV, and information systems. Since access to the information in the huge video database and its modification (manipulation?) is difficult and time-consuming, video object segmentation is of immediate importance for the purpose of information analysis. Considering that in many segmentation algorithms pre-processing issues such as denoising are not included, in this paper, while random noise is applied to video object sequence and harmonic filters, Wiener-DWT and Median Filtering techniques of denoising are implemented. Comparing IQI and PSNR parameters at RGB and YUV color spaces on the improved moving images, best quality from among the filtered images are selected and after removal of background to expedite segmentation operation and its transform into color sphere of black-and-white, texture and gradient values together with the obtained values from the Dual-Tree Complex Wavelet Transform are extracted. The obtained results indicate desirable efficiency and performance of wavelettrans form in the area of denoising and segmentation improvement compared to image processing tools.

KEYWORDS: Segmentation, Wavelet Transform, Denoising, Background Estimation, Moving Objects.

1. INTRODUCTION

Next to discrete Wavelet Transform (DWT), in 1998 Complex Wavelet Transform (CWT) [1, 2] was suggested by Kingsbury, which takes account of essential features, shift-invariance, and good directional selectivity through brief calculations in two or more dimensions. However, CWT encountered some barriers, including decomposition of more than one input layer and complexity in its regeneration. Hence, Kingsbury presented Dual-Tree Complex Wavelet Transform[3, 4]. The purpose in object segmentation is division of image into areas of pixels related to each other in terms of structure, color and intensity. Huang and Hsieh proposed a wavelet-based technique called Simple Change Detection (SCD) method for moving object segmentation [5] which was found more efficient compared to Kim's method [6]. Huang and Hsieh modified their method by introducing Double Detection technique to make improvement in correct detection of number of threshold points [7]. For the issue of moving object segmentation, like the issue of denoising, using multi-wavelet transfers and dual-tree complex wavelet transfer suitable solutions are suggested [8, 9, and 10]. Sendur and Selesnick demonstrated that dual-tree complex wavelet transfer performs more effectively relative to Scalar's wavelet-based methods for denoising [10]. Therefore, dual-tree complex wavelet transform is expected to be of high efficiency in segmentation operation for object detection.

1.1 Energy and power signals

Consider the given continuous time signal of *X(t)* which can be either real or complex. If the signal energy is defined by the following relation:

$$E_x = \int_{-\infty}^{+\infty} |x(t)|^2 \, dt \qquad (1)$$

It is regarded an energy signal. If the energy is infinite but the average power:

$$P_x = \lim_{T\to\infty} \frac{1}{T} \int_{\frac{-T}{2}}^{\frac{T}{2}} |x(t)|^2 \, dt \qquad (2)$$

is finite, *X(t)* is called a power signal. Most of the introduced signals to technical applications belong to one of the two classes.

The second major classification of signals is their referral to signal space $L_P(a, b)$, where *a* and*b* are the points of an interval within which the signal lies. From $L_P(a, b)$ with $1 \leq P \leq \infty$, we understand that its Lebesgue integral, i.e.

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$\int_a^b |x(t)|^P\, dt$, is infinite. If the distance between *a* and**b** infinitely extends, we write $L_P\,(\infty)$ or $L_{P(R)}$. According to this classification, defined energy signals on the real axis belong to $L_{2(R)}$ group.

1.2 Energy density and correlation

1.2.1 Continuous time signals

Considering relation (1) we have:

$$E_x = \int_{-\infty}^{+\infty} |x(t)|^2\, dt \qquad (3)$$

According to Parseval'sTheorem, it can be written:

$$E_x = \frac{1}{2\pi}\int_{-\infty}^{\infty} |x(\omega)|^2 d\omega \qquad (4)$$

In which, $x(\omega)$ is Fourier transform of $x(t)$. Quantity $|x(\omega)|^2$ represents signal energy distribution in time t, which is correspondingly known as Energy SpectralDensity.

1.2.2 Discontinuous time signals

All the previous considerations are properly applicable to discontinuous time signals as well. X(t) signals can be either real or complex. According to continuous time signals, we start the argument with signal energy:

$$E_x = \sum_{n=-\infty}^{+\infty} |x(n)|^2 \qquad (5)$$

Based on Parseval's theorem, for Fourier transform of discontinuous time, E_X can be calculated from $X(e^{\omega})$:

$$E_x = \frac{1}{2\pi}\int_{-\pi}^{\pi} \left|X(e^{jw})\right|^2 \; dw \qquad (6)$$

The expression $\left|X(e^{j\omega})\right|$ in the above relation is referred to as discontinuous time signal spectral density.

1.3 Random signals

Random signals are present in all domains of signal processing. For example, in transmission of signals, they appear as turbulence. Even the transmitted and received signals from telecommunication are random information carriers. In recognition of the pattern, the patterns which are to be distinguished are modeled through random processes. In face and image speech coding, the signals which should be compressed are modeled the same way.

First of all, random variables and processes are distinguished. A random variable is the product of attributing a real or complex number to each attribute of m_i from the set of M attributes.Attributes (events) occur randomly. Note that the attributes themselves may be non-numeric.

If from a function $i_x(t)$ is attributed to each feature of m_i, the set of all possible functions is called a random process. Attributes occur randomly, while the ratio $i_x(t) \rightarrow m_i$is definitive. Function $i_x(t)$ is called realization of $X(t)$ random process. Figure 1.1 gives a schematic view of random variables and processes.

1.3.1 Properties of random variables

Properties of a random variable x is described via Cumulative Distribution Function $F_x(a)$ and Probability Density Function (pdf) $p_x(a)$. A probability density (p) expresses whether random variable x is smaller than or equal to a given a value.

$$F_x(\alpha) = P(x \leq \alpha) \qquad (7)$$

According to general laws of probability, for $\alpha_1 \leq \alpha_2$, the following relations apply:

$$\lim_{\alpha\to-\infty} F_x(\alpha) = 0, \lim_{\alpha\to\infty} F_x(\alpha) = 1, F_x(\alpha_1) \leq F_x(\alpha_1)$$

Given the distribution and differentiating it, pdf is obtained:

$$P_x(\alpha) = \frac{d}{d\alpha} F_x(\alpha) \qquad (8)$$

Since the function is a non-decreasing function, $P_x(\alpha) \geq 0$.

3.2 Noise reduction of moving images

Images mostly at transmission or receiving point get noise and damaged. Noise includes a range of Additive Gaussian Noise in natural images to speckle noises in ultrasound medical images, radar aerial images, and SAR. One of the main ways of image improvement is denoising to the extent that main features of image are not affected. The first customary denoising methods were based on statistical filters which despite low cost and simplicity of their implementation they create flat and occasionally mat (dull) pictures. Upon emergence of Time-Frequency techniques in signal analysis with introduction of the Wavelet Threshold Concept by Donoho and Johnstone, a new window was opened to denoising in the wavelet domain [11, 12] on which still investigations are carried on [13, 14]. Threshold selection methods for image denoising in the wavelet domain are divided into three general techniques: *Universal Threshold* in which for coefficients of noisy image wavelet-based transform subbands one single threshold is considered [12]; *Subband Adaptive* in which for each detail band a separate threshold is allocated; and Spatially Adaptive methods where for every single coefficient or group of coefficients a distinct threshold is dedicated [15].

Most of the signal energy is only concentrated on several wavelet coefficients and in the remaining coefficients, quantity ofthis energy is often insignificant, whereas noise energy is distributed among all coefficient in wavelet domain.

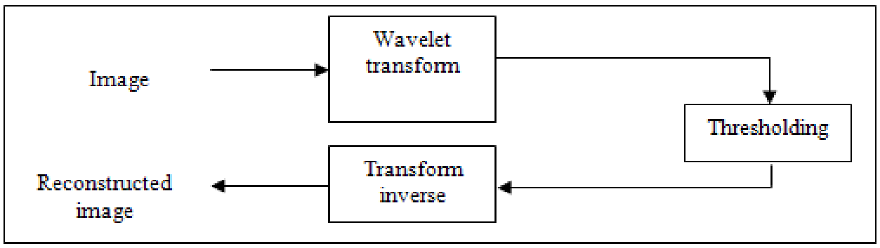

Fig 1. Diagram of denoising system in wavelet domain

In (Fig. 1), the general denoising diagram block in wavelet area is presented. For Gaussian denoising, first, noise image is broken down into several surfaces and then using VisuShrink Universal Threshold for all detail coefficientsbased the noise estimationa single threshold is selected and based on the Thresholding Law these coefficients are changed. Finally wavelet transform inverse gives the denoised image. In this method, value of universal threshold is obtained from the following relation.

$$thr_{universal} = \sigma\sqrt{2\log(n)} \qquad (9)$$

In which, *n* is signal length representing product of image dimensions and σ is standard deviation of noise which is often estimated due to lack of information and the most frequently applied estimators for this purpose is MAD estimation [2] which is expressed in the relation below.

$$\sigma = \frac{\text{median}\{y_{i,j}: i,j \in HH_1\}}{0.6745} \qquad (10)$$

In the nominator of which median of the horizontal detail subband coefficients of first decomposition level (HH)are brought.

Wavelet transform stages, thresholding, and wavelet inverse are similar to the applied Gaussian noise, and after application of the wavelet inverse operator, the obtained image passes through the final function and the work outcome is the final denoised image.

2.1 Harmonic Mean Filter

Harmonic filtering is carried out based on the following relation:

$$f'(x,y) = \frac{mn}{\sum_{(s,f)\in s_{xy}} \frac{1}{g(s,t)}} \qquad (11)$$

This filter works properly for salt noise but it is not suitable for pepper noise. This filter is also suitable for other types of noise such as Gaussian noise.

2.2 Contra-Harmonic Mean Filter

Contra-harmonic mean filter gives the restored image as follows:

$$f'(x,y) = \frac{\sum_{(s,f)\in s_{xy}} g(s,t)^{q+1}}{\sum_{(s,f)\in s_{xy}} g(s,t)^{q}} \qquad (12)$$

In which, *q* is the order of the filter. This filter is suitable for reduction of pepper-salt noise effect. For positive values of *q*, the filter eliminates the pepper noise, and for negative values of *q*, the filter eliminates the salt noise.

The filter is not able to eliminate the both noises at the same time. If q = 0, this filter turns into Arithmetic Mean Filter and if q = -1, it turns into harmonic mean filter.

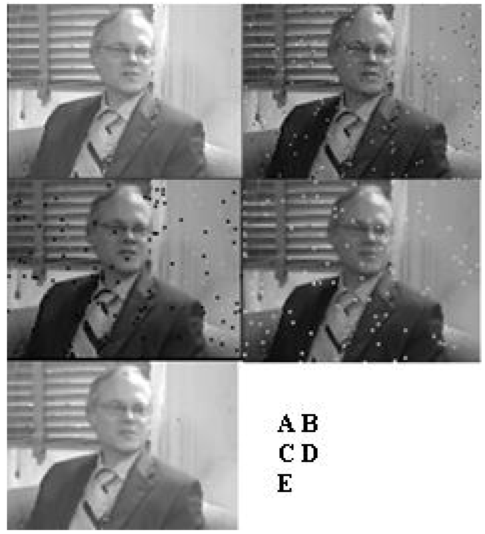

Fig 2. (A) Preliminary image; (B) Image polluted with pepper noise at YUV color space (Y matrix); (C) Harmonic Filter; (D) Contra-Harmonic Filter; and (E) Median Filter

2.3 Inverse filtering

The simplest recovery method is application of mat inverse filter. In doing so, estimate of the main image transform f'(u, v) is found by dividing degraded function G(u, v) by degradation function H(u, v).

$$F'(u,v) = \frac{G(u,v)}{H(u,v)} \qquad (13)$$

This division is an array operation. The above equation can be written as follows:

$$F'(u,v) = F(u,v) + \frac{N(u,v)}{H(u,v)} \qquad (14)$$

This is an interesting expression and states that even if the degraded function is known, still due to noise indistinctness the not-degraded (intact) image cannot be exactly retrieved. Another negative point is that if the degradation function contains zero or very small values, the expression N(u, v) / H(u, v) easily affects f'(u, v) estimation.

One way to resolve the problem of small or zero values is restriction of the filter frequencies to the frequencies round the axis. Hence, by limiting the analysis to frequencies round the axis, we reduce the probability of encountering zero values.

2.4 Minimum Mean Square Error (Wiener) Filtering

Inverse filtering application method is not of specific use in dealing with noise. In this section, we discuss a method which engages both degradation function and noise statistical specifications in the recovery process. In this method, we consider images and noise as random variables. This filtering technique seeks estimate $f'$of the main image f in a way that minimum mean square error (MMSE) exists between them.

$$e^{2=E\{(F-F')^2\}} \qquad (15)$$

In which, *E{0}* is the mathematical expectation. It is assumed that noise and image are uncorrelated; one of the two has zero mean and illumination levels in estimation of linear functions from illumination intensity are degraded images. Given this condition, the minimum error function in the above equation in frequency domain is given by the following function.

Table 1. Results of PSNR parameter on Wiener-DWT Filtering (**Wavelet settings**: Wavelet family name: db4; MASKL: Low-frequency sub-band; MASKH: High-Frequency sub-band)

PSNR			**Factor**	**Noise Variance**
[MASKL][MASKH]				
[2 2][3 3]	[2 2][2 2]	[3 3][2 2]		
21.4	21.5	17.2	0.1	0.1
21.2	21.6	17.4	0.2	
21.2	21.7	17.5	0.3	
21.03	21.2	17.2	0.1	0.2
21.04	21.3	17.4	0.2	
20.9	21.4	17.4	0.3	
20.7	20.8	17.2	0.1	0.3
20.7	20.9	17.3	0.2	
20.6	21.03	17.3	0.3	

3. Moving object segmentation

Video segmentation algorithms can be divided into four sub-groups: first group segmentation depends on motion estimation and closed regions. These constraints help precision of object segmentation; second group of algorithms were proposed for improvement of the first group's weak points. Spatial information in combination with motion information further strengthens and stabilizes extraction of object thresholds. These two techniques are not suitable for content applications since they require such features as color, intensity or motion. Third group of algorithms determines segmentation first based on difference in grey-level image between two frames and then by identification of moving regions of absolute difference. If moving objects are not exclusively composed of texture, the closed thresholds remain as variable and inside the objects as invariable. In this way, stationary and immovable objects are eliminated over time.

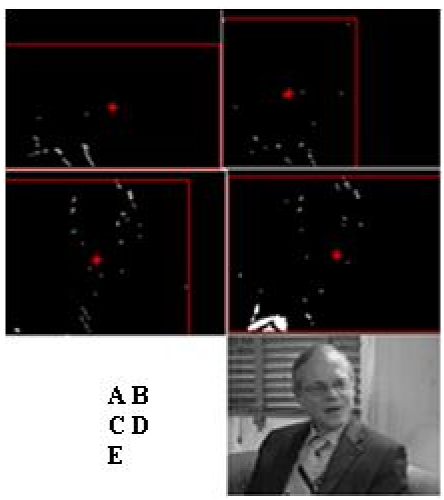

Fig 3. (A – B – C – D) Sequence of the extracted background moving frames for segmentation; (E) Filtered image by Wiener-DWT

3.1 Structure of Dual-Tree Complex Wavelet Transform for segmentation

Huang and Hsieh in the article of 2004 by introduction of the approach Double Change Detection (DCD) corrected their earlier proposed method Dual-Tree Complex Wavelet Transform (DT-CWT), resulting in improvement in number of threshold points detection. DCD has superseded dual tree method in techniques of change detection. The issue of denoising in moving object segmentation using multiple wavelets was raised by Strela et al (1999). Later on, Baradarani and Yu (2008) propose dual-tree complex wavelet method for moving objects detection and segmentation transform.

In this paper, the used methodin filter specification is based on change detection in wavelet domain the approach of which is enriched using DCD and Denoising Function.

3.1.1 Suggested algorithms

Our purpose is providing a wavelet-based algorithm for improvement of moving object (such as human) segmentation speed and precision. In this algorithm, after receiving the input, first, structure of color video is transformed into grey range. Since noise usually appears as random static (color dots) over the picture, preprocessing operation is carried out to soften input image for denoising and elimination of unwanted signals and details. The implementation phases are as follows:

1. Extraction of moving image frames
2. Denoisingon images
3. Background estimation for the purpose of foreground segmentation (assuming background as constant) and detection of bodies in movement with low resolution
4. Moving object segmentation
5. Execution of morphologic operation on foreground

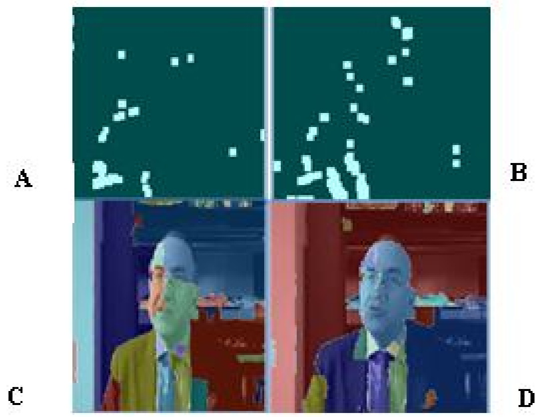

Fig 4. (A – B) Segmentation after background extraction at YUV space; (C – D) Filtered image segmentation by Wiener – DWT at RGB space

4. Conclusion

In this article, wavelet-based combined algorithm for the purpose of denoising and moving object segmentation, assuming a constant background, was treated [16]. Results of the proposed technique at two RGB and YUV spaces are presented. It is made use of the DCD based dual-tree complex wavelet transform for segmentation after denoising by the combined Wiener-DWT filter at three sequential frames of f_n, f_{n+1} and f_{n-1}. Results presented in table 1 indicate study of the noise application parameters in discontinuous wavelet domain, including wavelet name, power of the applied noise, and the selected mask at low and high frequencies. By extraction of the highest PSNR which is underlined we have applied the selected filter to the noisy image, and in the end, on the obtained video, background estimation takes place and segmentation operation of video image sequence is implemented.

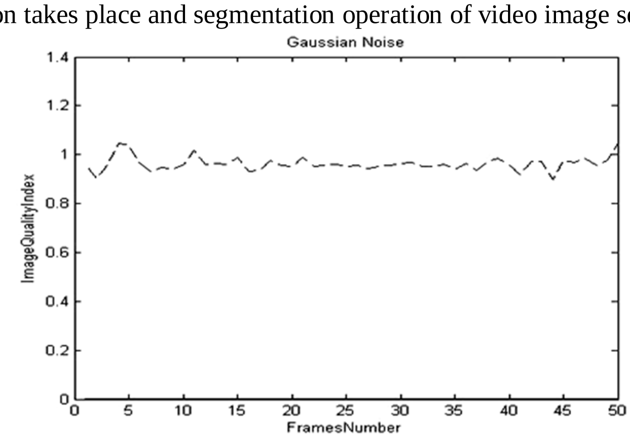

Fig 5. Results on improvement of Gaussian denoising by wavelet transform (horizontal axis: frame sequence; vertical axis: IQI value

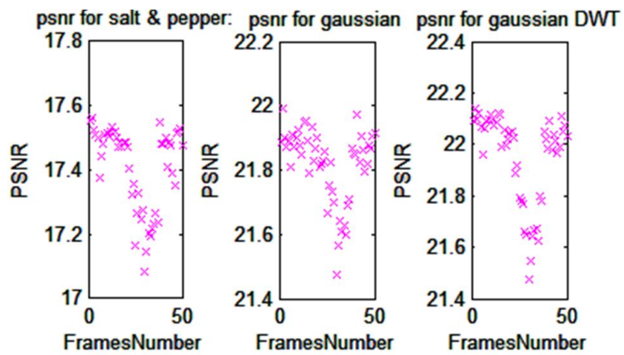

Fig 6. Results on improvement of PSNR parameter by DWT

Figures 5 and 6 suggest desirable performance and efficiency of the combined algorithm using wavelet transform in the area of denoising and segmentation improvement.

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