Proceedings of the 2007 IEEE Symposium on Computational Intelligence in Image and Signal Processing (CIISP 2007)

Daubechies Complex Wavelet Transform Based Moving Object Tracking

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Abstract -**This paper describes a new method for moving object tracking, using complex wavelet transform. Real-valued wavelet transform is widely used in tracking applications, but it suffers from shift-sensitivity. Daubechies complex wavelet transform is more suitable for tracking due to approximate shift-invariance nature. The proposed method is intelligent enough to segment the object from a scene. Segmentation in the first frame has been done by computing multiscale correlation of imaginary component of complex wavelet coefficients and then object is tracked in next frames by computing the energy of complex wavelet coefficients corresponding to the object area and matching this energy to that of the neighborhood area. The proposed method is simple and does not require any other parameter except complex wavelet coefficients for segmentation as well as tracking.**

I. Introduction

Object tracking is an important problem in computer vision [1]. Object tracking is needed in many applications such as sport video analysis to extract highlights, human-computer interface to assist visually challenged people, medical image analysis, etc. Object tracking requires the segmentation of the object from scene followed by tracking.

The most popular method for tracking is based on a moving object region tracking [2]. The method identifies and tracks a bounding box, which is calculated for connected components of moving objects in 2D space. These methods have a major shortcoming that they rely on many properties of object such as size, color, shape, velocity, etc. For avoiding this shortcoming feature based tracking is used. Feature selection of the object requires some heuristic. We have used complex wavelet coefficients of the object as a feature. Although real-valued wavelet transform can be a useful tool for object tracking among several frames, but it suffers from shift-sensitivity [3,4]. Use of complex wavelet transform will reduce this shortcoming. Several complex wavelet transforms like dual tree complex wavelet transform (DTCWT) [5], projection-based complex wavelet transform [6], steerable pyramid complex wavelet transform [7], etc. have been proposed. These transforms are approximate shift-invariant but in all of the above transforms, the use of real filters make them not a true complex wavelet transform and due to the presence of redundancy, they are also computationally costly. For avoiding this, Daubechies complex wavelet transform [8] can be used which is also approximate shift-invariant.

In the present paper complex wavelet coefficient has been used in an effective manner to first segment the object followed by tracking. Literature for tracking using complex wavelet transform is few and far between. Magarey and Kingsbury [9] described a motion estimation algorithm, using a separable 2-D DWT, which is based on complex-valued pair of 4-tap FIR filters with Gabor-like characteristic. A more efficient motion estimation algorithm using complex wavelet transform is given by Yilmaz and Severcan [10]. Not many researchers have applied complex wavelet transform with the assumption that, by adding imaginary component, the algorithm will not be suitable for real-time applications. We have shown that due to reduced shift-sensitivity property, complex wavelet transform is quite helpful for tracking. We have used imaginary components of complex wavelet coefficients in an intelligent manner to segment and thereby tracking the object in the sequence of frames. Further use of only one feature for segmentation as well as tracking makes the algorithm appropriate for real time applications.

The rest of paper is organized as follows: Section II describes reduced shift-sensitivity property of complex wavelet transform. Section III deals with the proposed segmentation and tracking algorithms. Experimental results and conclusions are given in section IV and V respectively.

II. Reduced Shift-Sensitivity Of Daubechies Complex Wavelet Transform

Object tracking is a problem where moving object may be present in translated as well as rotated form among different frames. Thus any object feature which remains invariant by translation and rotation of the object will be helpful for tracking. Most of the transform features vary by translation and rotation of the object. We have found that Daubechies complex wavelet transform of the object remain approximately invariant in such conditions. The approximate shift invariance property of Daubechies complex wavelet transform is described below.

The basic equation of Multiresolution theory is the scaling equation [11]

$$\phi(t) = 2\sum_n a_n \phi(2t - n) \qquad (1)$$

where, a_n s are coefficients. The a_n s can be real as well as complex valued and $\sum a_n = 1$.

Daubechies's wavelet bases $\{\psi_{j,k}(t)\}$ in one dimension are defined through the above scaling function and multiresolution analysis of $L_2(\Re)$ [11]. She has given the general solution for standard Daubechies scaling function. During the formation of solution if we relax the Daubechies condition for a_n to be real [12], it leads to complex valued scaling function. The orthogonal wavelet basis $\{\psi_{j,k}(t), j \in \mathbb{Z}, k \in \mathbb{Z}\}$ and generating wavelet $\psi(t)$ is given by,

$$\psi(t) = 2\sum_{n}(-1)^n \overline{a_{1-n}}\phi(2t-n) \qquad (2)$$

and $\psi(t)$ and $\phi(t)$ shares the same compact support [-N, N+1].

Any function $f(t)$ can be decomposed into complex scaling function and a mother wavelet as:

$$f(t) = \sum_{k} c_k^{j_0}\phi_{j_0,k}(t) + \sum_{j=j_0}^{j_{\max}-1} d_k^j \psi_{j,k}(t) \qquad (3)$$

where, j_0 is a given low resolution level, $\{c_k^{j_0}\}$ and $\{d_k^j\}$ are known as approximation and detail coefficients.

The Daubechies complex wavelet function can be made symmetric. The symmetry property of filter makes it easy to handle the boundary problems of the object [12]. We have used symmetric Daubechies complex wavelet (SDW) transform for segmentation as well as tracking. SDW is also in linear phase and its linear phase property allows it to retain the shape of the object during reconstruction [12].

A transform is shift sensitive if an input signal shift causes an unpredictable change in transform coefficients. Real valued wavelet transforms are shift-sensitive. Fig. 1 illustrates the reduced shift-sensitivity of symmetric complex Daubechies wavelet (SDW) transform. Fig. 1(a) is an input signal while fig. 1(b) is the shifted form of the signal by one sample. Fig. 1(c) and 1(d) are high-pass wavelet coefficients of signals using real wavelet transform (db4) while fig. 1(e) and 1(f) show the magnitude of high-pass wavelet coefficients using complex wavelet transform (SDW6). This figure indicates that the nature of magnitude and energy of complex wavelet coefficients remain approximately same by shifting the input signal and the energy is also approximately invariant. Thus magnitude and energy of complex wavelet coefficients remain approximately invariant by translating the object in different frames of a video. To perform a precise detection of any feature, a transform should not "miss" the feature due to such shifts. Fig. 2 shows the sensitivity of different wavelet transforms to shifts of the input image. It shows an image shifted by 0, 1 and 2 pixels to its right and its Daubechies real and Daubechies complex wavelet based reconstruction at 2 levels. From the figure it is clear that complex wavelet transform is less sensitive to shift and it does not miss the features of image. Fig. 2 also has a circular edge structure and as the circular edge structure moves through space, the reconstruction using real discrete wavelet transform coefficients changes erratically, while complex wavelet transform reconstructs all local shifts and orientations in the same manner. This indicates that complex wavelet transform is also rotational invariant. Thus rotation of object in different frames keep magnitude and energy of complex wavelet coefficients approximately same. This property is very much useful for detection of same object in different frames.

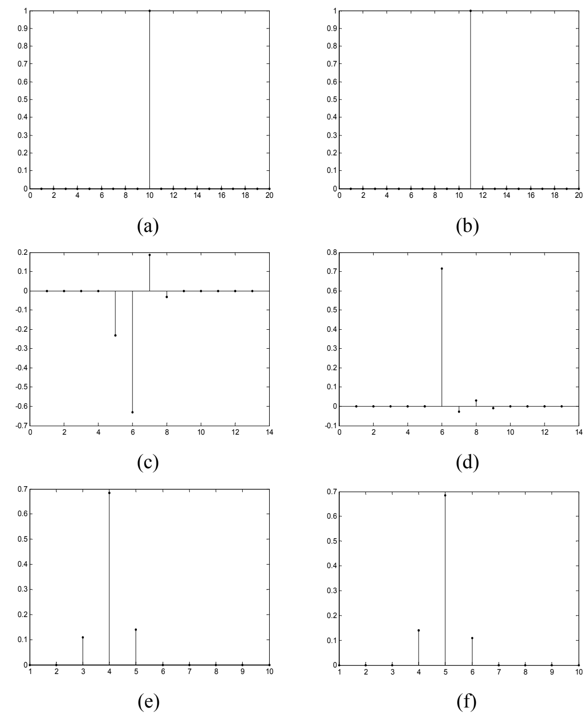


Fig. 1. (a) Original Signal, (b) signal shifted by one sample, (c)-(d) high-pass wavelet coefficient of original signal and shifted signal using real db4 wavelet, (e)-(f) Magnitude of complex wavelet coefficients of original signal and shifted signal using SDW6 wavelet.

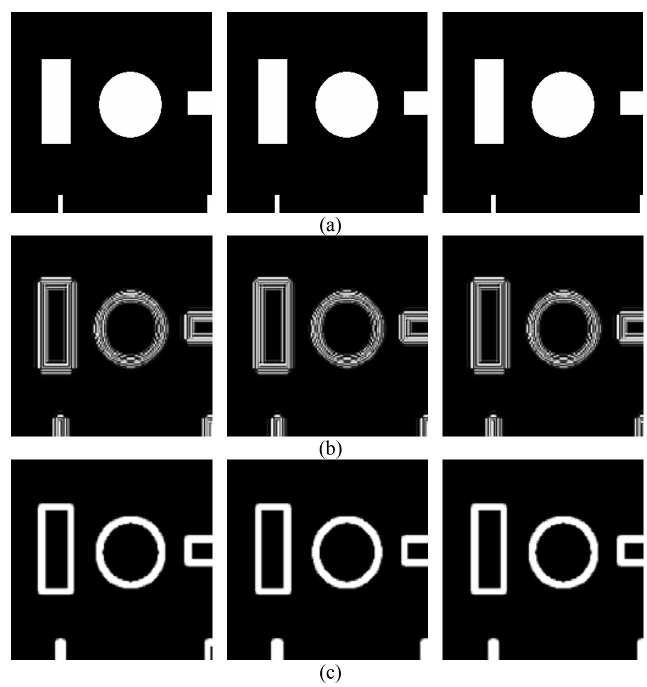


Fig. 2. (a) Image shifted by 0,1 and 2 pixels to the right. Image reconstructed from 2 levels of wavelet coefficients using (b) Real db6 wavelet and (c) Complex SDW6 wavelet.

III. THE PROPOSED OBJECT TRACKING METHOD

The proposed method consists of two steps –

A. *The Segmentation Algorithm*

Segmentation of object has been done in complex wavelet domain. The proposed segmentation algorithm uses imaginary components of multiscale complex wavelet coefficients. The intelligence of algorithm lies in the fact that the segmentation process is automatic in nature and require no intervention. The algorithm is based on the concept that multiscale scaling and wavelet projection of the function $f(t)$ carries edge information in its imaginary components [12,13].

Let $\phi(t) = k(t) + i\,l(t)$ be a scaling function and $\psi(t) = u(t) + i\,v(t)$ be a wavelet function. Let $\hat{l}(\omega)$ and $\hat{k}(\omega)$ are Fourier transforms of $l(t)$ and $k(t)$. The ratio

$$\alpha(\omega) = -\frac{\hat{l}(\omega)}{\hat{k}(\omega)} \tag{4}$$

is strictly real-valued and behaves as ω^2 for $|\omega| < \pi$ [13]. This observation relates the imaginary and real components of scaling function: $l(t)$ accurately approximates the second derivative of $k(t)$, up to some constant factor. Similarly for wavelet function $\psi(t)$, the ratio

$$\beta(\omega) = -\frac{\hat{v}(\omega)}{\hat{u}(\omega)} \tag{5}$$

is also real valued.

Equations (4) and (5) indicate $l(t) \approx \alpha\,\Delta k(t)$ and $v(t) \approx \beta\,\Delta u(t)$. This gives multiscale projections of a function $f(t)$ as,

$$\left\langle f(t), \phi_{j,k}(t) \right\rangle = \left\langle f(t), k_{j,k}(t) \right\rangle + i \left\langle f(t), l_{j,k}(t) \right\rangle \approx \left\langle f(t), k_{j,k}(t) \right\rangle + i\alpha \left\langle \Delta f(t), k_{j,k}(t) \right\rangle \tag{6}$$

$$\left\langle f(t), \psi_{j,k}(t) \right\rangle = \left\langle f(t), u_{j,k}(t) \right\rangle + i \left\langle f(t), v_{j,k}(t) \right\rangle \approx \left\langle f(t), u_{j,k}(t) \right\rangle + i\alpha \left\langle \Delta f(t), u_{j,k}(t) \right\rangle \tag{7}$$

From (6), it can be concluded that the real component of complex scaling function carries averaging information and the imaginary component carries Laplacian (i.e. edge information). Similarly from (7), it can be concluded that the imaginary component of complex wavelet function also carries edge information. We exploited this property of Daubechies complex wavelet coefficients for detection of edges. For edge detection, we used interscale product of imaginary component of wavelet coefficients i.e. direct multiplication of imaginary components of the subband decomposition, similar to noise filtration technique developed by Xu et.al. [14]. Large values of direct multiplication locate important edges. This approach is straightforward, easier to implement and robust.

In order to calculate edge coefficients, correlation among imaginary component of wavelet coefficients at adjacent scales has been computed. In the 1-D case, the correlation is defined as

$$C_L\left(2^j, k\right) = \prod_{r=0}^{L} \mathrm{Im}\left(Wf\left(2^{j+r}, k\right)\right) \tag{8}$$

where $\mathrm{Im}\left(Wf\left(2^{j+r},k\right)\right)$ denotes imaginary component of complex wavelet coefficient at k^{th} point and $j+r$ $^{\text{th}}$ level. Since wavelet coefficients of actual edges propagate well across scales, while noise dies out swiftly with increasing scale, the above correlation enhances major edges. Instead of choosing a threshold from each subband $\mathrm{Im}\left(Wf\left(2^{j+r},x\right)\right)$, the method extracts gradually more and more edge coefficients. The procedure for edge detection is as follows –

Step 1. Rescale the power of $\left\{C_L\left(2^j,k\right)\right\}_{1\le k\le n}$ to that of $\left\{Wf\left(2^j,k\right)\right\}_{1\le k\le n}$.

Step 2. Identify an edge at position k if $\left|C_L\left(2^j,k\right)\right| > \left|Wf\left(2^j,k\right)\right|$.

This procedure can be easily extended for detection of edges in 2-D images. By means of experiments, we found that the choice for $L = 3$ gives good results.

After detecting strong edge points, a simple hysteresis based thresholding [1] has been used for segmentation and a square bounding box has been made to cover the object. The result of the segmentation algorithm described above is shown in fig. 3 for cameraman image.

(a) (b)

Fig. 3. (a). Cameraman image and
(b). Segmented image by the proposed segmentation method

B. *The Tracking Algorithm*

The proposed tracking algorithm uses the advantage of approximate shift-invariance property of Daubechies complex wavelet transform, described in section II. The shift-invariance property makes the feature vectors independent of precise location and rotation. If the object is moving (equivalently shifted in frames), then the nature of complex wavelet coefficients in the region where object is placed will not change. This has been shown in fig. 1 and fig. 2. The tracking algorithm searches the object in next frame according to the value of current velocity, which is computed from the previous three frames and direction of movement. In all the computations, it has been assumed that the frame rate is adequate and the size of the object should not change between adjacent frames. However our algorithm is capable of tracking an object whose size changes within a range in various frames.

Calculation of velocity of the moving object is based on object position coordinates. For this, we have computed centroid of the object. This computation makes each object correspond to a single point. Further, we assume that the movement of object in a few adjacent frames is close to straight line. The object centroids from previous three frames are used to predict new centroid in the next frame.

The tracking algorithm does not require any other parameter except complex wavelet coefficient. Complete tracking algorithm is as follows –

Step 1. Segment the first frame, by the method described in subsection III.A. Make a square bounding box to cover the object with centroid at (C_1,C_2) and compute the energy of complex wavelet coefficients of the square box, say E, as

$$E = \sum_{\substack{(i,j)\\ \in \text{bounding box}}} \left| w_{i,j} \right|^2$$

where $w_{i,j}$ is complex wavelet coefficients at $(i,j)^{\text{th}}$ point.

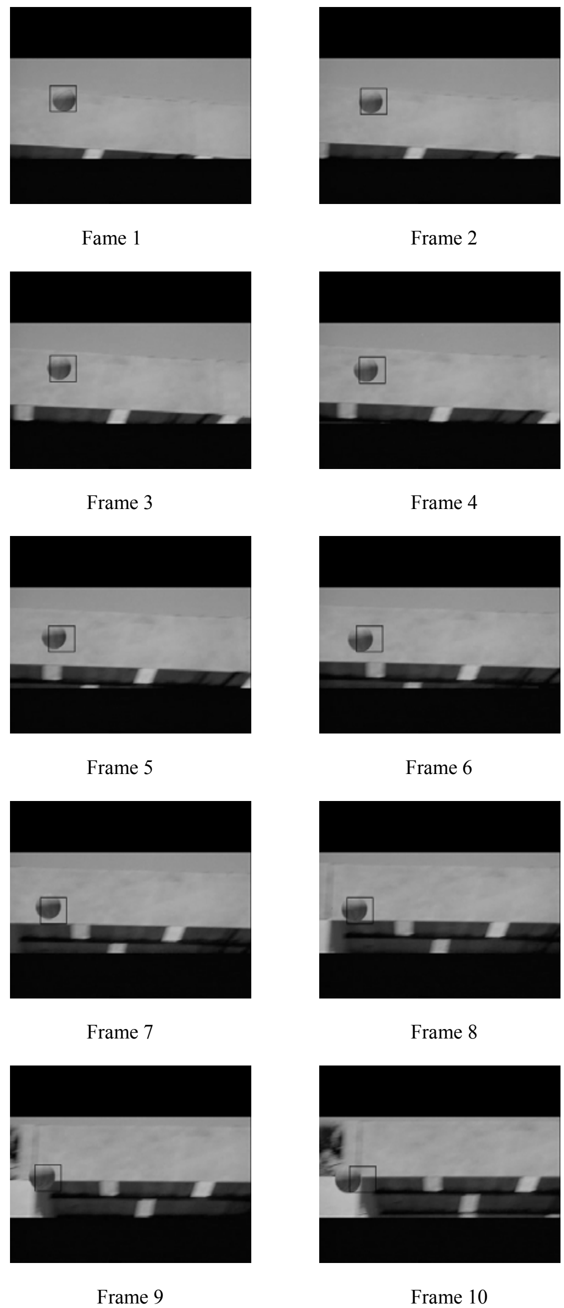
Step 2: for *frame_no* = 2 to *last* do
compute the complex wavelet coefficients of the frame, say $w_{i,j}$.
if *frame_no* = 2 or 3
search_length = 10.
else
search_length = 4.
Predict the centroid (C_1,C_2) of the current frame with help of centroids of previous three frames and basic equations of straight line motion.
endif
for i = - *search_length* to +*search_length* do
for j = - *search_length* to +*search_length* do
$C_{new1} = C_1 + \text{i}$; $C_{new2} = C_2 + \text{j}$;
Make a bounding box with centroid (C_{new1}, C_{new2}).
Compute the difference of energy of wavelet coefficient of bounding box, with E, say $d_{i,j}$.
end
end
Find minimum of $\{d_{i,j}\}$ and its index, say (m,n).
$C_1 = C_1 + m$; $C_2 = C_2 + n$.
Mark the object in current frame with bounding box with centeroid (C_1,C_2) and energy of bounding box E as

$$E = \sum_{\substack{(i,j)\\ \in \text{bounding box}}} \left| w_{i,j} \right|^2$$

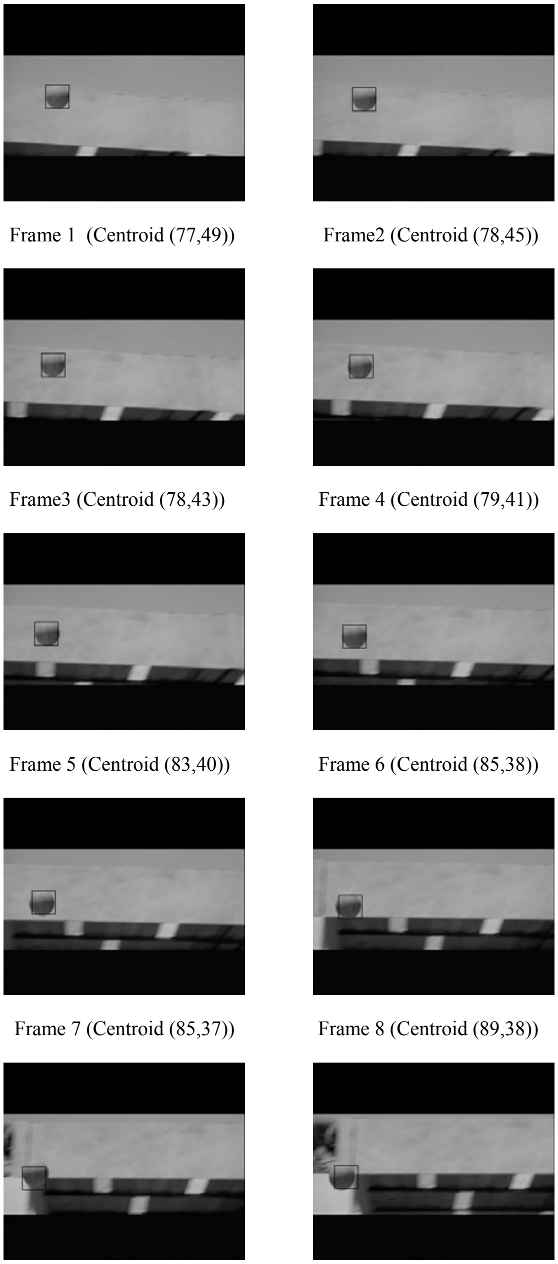
end.

IV. Experiments And Results

To evaluate the proposed tracking method, we applied it to several video clips of football match, for tracking football. The frame size is 256 by 256. For one representative video clip of ten frames, we have compared the results of the proposed method with the tracking results of Magarey [9] by our own program. The results are shown in fig. 4. It illustrates the result of the method applied on the sequence. Here SDW14 Daubechies complex wavelet transform is used, as it is reported as an optimal choice [4,15]. From fig. 4, it is quite clear that the proposed tracking method performs well. The proposed method process 14 frames/second, while method of Magarey [9] process 16 frames/second but the proposed method does more accurate tracking as evident from the fig.4. Centroid values of the tracked object are also given. We have traced the position of centroid in complex wavelet domain, as it gives information about the locality of object. It is also evident that the tracking method can track the object efficiently even in the presence of background, whose intensity is very similar to the object intensity. This indicates the robustness of the proposed method.



(a)



(b)

Fig. 4. Tracking of football in 10 consecutive frames by (a). Motion estimation [9] method and (b). the proposed method

V. Conclusions

Wavelet transform is known to provide position localized information. This information can be obtained at various levels depending on the resolution we require. However for moving objects the use of real valued wavelet transform is not appropriate because of its shift-sensitivity. We have shown that the reduced shift sensitivity of complex wavelet transform can be used for tracking the moving object in video clips. The reduction of search space has been done intelligently based on the two properties –

1. The object boundaries and hence the centroid of the object can be computed with the help of imaginary component of complex wavelet coefficients of the object only (not the whole image). The image is segmented in the first frame to object and background in the complex wavelet domain.
2. The total energy computed with the help of modulus of complex wavelet coefficient remains approximately constant in various frames.

In addition, the rigid body assumption and smooth velocity change assumption provide extra reduction in search space. The method is simple, efficient and robust. The tracking algorithm does not require any human intervention. However for asymmetrical shapes of the object the method may require some change. Similarly the method may also require improvement for a very complex background. The paper is the first step towards exploration of new application of Daubechies complex wavelet transform.

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