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Video Object Extraction using the Curvelet Transform

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Abstract: In this paper a novel scheme for video object extraction based on the second generation of the curvelet transform which is called Fast Discrete Curvelet Transform (FDCT) via wrapping is introduced. The main advantages of using FDCT are the approximate properties and the high directional sensitivity of this transform. An imaginary component of the curvelet coefficients to extract the moving objects in the video sequence is used. The proposed algorithm is mainly divided into two steps. The first step is based on estimating the static background from the initial frames using FDCT, the seconded step is based on subtracting the background from each video frame for obtaining the moving objects. Experimental results show a promising results than traditional wavlelet transform, where the accuracy ratios of each video frame is maximized while the error ratios are minimized compared with the wavelet transform.

Keywords: Curvelet transform, Canny edge detector, Background subtraction, Video object extraction

1 Introduction

Object extraction plays an important role in an intelligent surveillance. In video object segmentation, the foreground object (moving object) is extracted from each frame of video sequence, making it one of the most challenging tasks in intelligent surveillance which has attracted a lot of attention in recent years. The increasing demand for safety and security has resulted in more research in intelligent surveillance. It has a wide range of applications such as event detection [1,2], tracking and identification of moving persons [4] and face detection [3]. Video object segmentation can also be applied to some interesting and powerful applications, such as video editing [5], behaviour analysis of sport video [6] and advanced story retrieval [7]. Furthermore, the importance of digital media, rapid searching and retrieval of multimedia data is extended from the importance of video object extraction. Where, the mentioned applications are active to industries such as communications, education, and entertainment.

One application can be related directly to the advantage of video object extraction is video compression and video coding. A video compression engine can selectively compress objects with high bit-rates to produce subjectively pleasing results. But lowering the bit-rates used to compress less important regions to maintain storage and transmission efficiently.

One of the most important video compression formats are H.261, H.263, MPEG-1, MPEG-2, MPEG-4 and MPEG-7 where the research community focused on the standards MPEG-4/H.264 and MPEG-7. After 30 years of video coding research and development, standards are moving towards a more general and powerful way of coding visual contents in which data is described in terms of ”objects”. Object-based standard, such as MPEG-4 video coding standard, enables object-based Video Coding (OBVC) which offers the flexibility of coding video objects separately. Where, the coder may perform a locally defined preprocessing, aimed at the automatic identification of the objects appearing in the video sequence. In general, object segmentation is a key issue in efficiently applying the MPEG-4 coding scheme. In [8,9,10,11] an overview of the advanced video coding standards is introduced. On the other hand, in applications [12,13] performing detection, monitoring and tracking, only the VOs with spatial or unique features are in the focus of observation, these VOs are considered to be more important for observers and are expected to be coded with different distortion scales according to their visual ”priority of interests [14]. To achieve priority-based object coding quality, firstly the priority of the video objects has to be formulated according to their

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individual's semantic importance and physical prosperities, then the distortion of each object under the bit budget constraint needs to be defined and hence more bits can be distributed to the objects that are of interest in the scene and improved.

In this paper, we present a new approach for video object extraction based on the second generation of the curvelet transform [15]. In the wavelet transform there is an inability to represent edge discontinuities along the curves. Due to the large or several coefficients are used to reconstruct edges properly along the curves. For this reason, it needs a transform to handle the two dimensional singularities along the sparsely curve. This is the reason behind the birth of curvelet transform.

This paper is organized as follows: in section II we introduce a brief introduction to the curvelet transform. Section III describes in details the proposed method of extracting moving objects using the second generation of the curvelet transform via wrapping. Experimental results are presented in section IV and section V is the conclusion.

2 Fast Discrete Curvelet Transform (FDCT)

Curvelet transform is developed to overcome the limitation of wavelet and Gabor transforms. Although, wavelets are widely used in image processing, but it failed to handle randomly oriented edges of the object and the singularities of the object. Gabor filters overcome the limitation of wavelet transform and deal with the oriented edges, but it loses the spectral information of the image. Curvelet transform is used to overcome these problems of the wavelet and Gabor filters. It can obtain the complete spectral information of the image and handle with the different orientations of the image edges as shown in Figure 1. The initial approach of curvelet transform implements the concept of discrete ridgelet transform [16]. Since its creation in 1999 [17], ridgelet based curvelet transform has been successfully used as an effective tool in image denoising [18], image decomposition [19], texture classification [20], image deconvolution [21], astronomical imaging [22] and contrast enhancement [23], etc. However, ridgelet based curvelet transform is not efficient as it uses complex ridgelet transform. In 2005, Candès et al. proposed two new forms of curvelet transform based on different operations of Fourier samples [15], namely, unequally-spaced fast Fourier transform (USFFT) and wrapping based fast curvelet transform. Wrapping based curvelet transform is faster in computation time and more robust than ridgelet and USFFT based curvelet transform.

The idea of curvelets [15] is to represent a curve as a superposition of functions of various lengths and widths obeying the scaling law width 2248 length2. This can be done by first decomposing the image into subbands, i.e. separating the object into a series of disjoint scales. Then, each scale is analyzed by a local ridgelet transform.

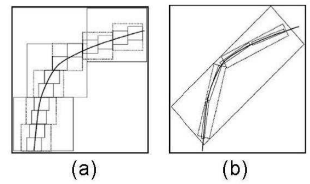

Fig. 1: Comparison between wavelet and curvelet transforms in (a) and (b) respectively.

The newly constructed and improved version of the curvelet transform is known as Fast Discrete Curvelet Transform (FDCT). The new constructed version is faster, simpler and less redundant than the original curvelet transform, which based on Ridgelets. As mentioned, according to Candès et al. in [15] two implementations of FDCT are proposed:

1. Unequally spaced Fast Fourier Transform (USFFT).
2. Wrapping Function.

Both implementations of FDCT differ mainly in choosing the spatial grid that used to translate curvelet at each scale and angle. Both digital transformations return a table of digital curvelet coefficients indexed by scale, orientation and location parameters.

The new implementation of curvelet transform, based on wrapping of Fourier samples, takes a 2D image as input in the form of a Cartesian array , $f[m,n]$ where $0 \leq m < M$, $0 \leq n < N$ and M,N are dimensions of the array. As illustrated in equation (1) the output will be a collection of curvelet coefficients $c^D(j,l,k_1,k_2)$ indexed by a scale j, an orientation l and spatial location parameters k_1 and k_2.

$$c^D(j,l,k_1,k_2) = \sum_{0\leq n<N}^{0\leq m<M} f[m,n]\varphi^D_{j,l,k_1k_2} \qquad (1)$$

where $\varphi^D_{j,l,k_1k_2}[m,n]$ is the curvelet waveform. This curvelet approach implements the effective parabolic scaling law on the subbands in the frequency domain to capture curved edges within an image more effectively. Curvelets exhibit an oscillating behaviour in the direction perpendicular to their orientation in the frequency domain.

Wrapping based curvelet transform is a multi-scale pyramid which consists of different orientations and positions at a low frequency level. Basically, multiresolution discrete curvelet transform in the spectral domain utilizes the advantages of fast Fourier Transform (FFT). During FFT, both the image and the curvelet at a given scale and orientation are transformed into the

Fourier domain. At the end of this computation process, we obtain a set of curvelet coefficients by applying inverse FFT to the spectral product. This set contains curvelet coefficients in ascending order of the scales and orientations.

Candès et al. [15] describe the discrete curvelet transform as follows:

curvelet transform = IFFT [FFT (curvelet) x FFT (Image)],

and the product from the multiplication is a wedge.

The following steps of applying wrapping based fast discrete curvelet transform via frequency wrapping:

1. Apply the 2D fast Fourier transform (FFT) and obtain Fourier samples

$$\hat{f}[n_1,n_2], -n/2 \leq n_1,n_2 < n/2 \tag{2}$$

2. For each scale j and angle l form the product

$$\tilde{U}_{j,l}\ [n_1,n_2]\ \hat{f}[n_1,n_2]$$

Where $\hat{U}$ is the “Cartesian” window.

3. Wrap this product around the origin and obtain

$$\hat{f}_{j,l}[n_1,n_2] = W(\tilde{U}_{j,l}\ \hat{f}\ )[n_1,n_2],$$

Where, the range for n_1 and n_2 is $0 \leq n_1 < L_{1,j}$ and $0 \leq n_2 < L_{2,j}$ (for θ in the range $(-\frac{\pi}{4}, \frac{\pi}{4})$).

4. Apply the inverse 2D FFT to each $\hat{f}_{j,l}$, hence collecting the discrete coefficients $c^D\,(j,l,k)$.

This set contains curvelet coefficients in ascending order of the scales and orientations. Clearly, this algorithm has computational complexity $O(n^2 log\ n)$.

There is a problem in applying inverse FFT on the obtained frequency spectrum. The frequency response of a curvelet is a trapezoidal wedge which needs to be wrapped into a rectangular support to perform the inverse Fourier transform. The wrapping of this trapezoidal wedge is done by periodically tiling the spectrum inside the wedge and then collecting the rectangular coefficient area in the origin. Through this periodic tiling, the rectangular region collects the wedge’s corresponding fragmented portions from the surrounding parallelograms. For this wedge wrapping process, this approach of curvelet transform is known as the ‘wrapping based curvelet transform’. The wrapping is illustrated in Figure 2. In order to do IFFT on the FT wedge, the wedge has to be arranged as a rectangle. The idea is to replicate the wedge on a 2-D grid, so a rectangle in the center captures all the components a, b, and c of the wedge. Wedge wrapping is done for all the wedges at each scale in the frequency domain, so we obtain a set of subbands or wedges at each curvelet decomposition level. These subbands are the collection of the discrete curvelet coefficients.

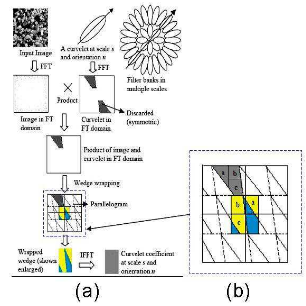

Fig. 2: Fast discrete curvelet transform.

3 The Proposed Method

A novel approach to automatic video object segmentation is proposed in the following subsections. The proposed segmentation is mainly depending on the second generation of discrete curvelet transform via wrapping which represents edges and singularities of the object more accurately than other transforms. Also, it can obtain the complete spectral information of the image and handle with the different orientations of the image edges as mentioned in details in Section II. This method presents a temporal-to-spatial segmentation technique to extract moving objects from a video sequence which is described in details in the following sub sections.

The simple idea of extracting moving objects from the video frames is depending on subtracting of the current frame from the static background. The proposed method focuses on estimating the static background. The background is estimated from the first N frames (N depends on the sequence motion which is obtained in Table1). The proposed algorithm will be compared with object extraction in wavelet domain.

The proposed algorithm can be subdivided into the following steps:

1- Background Estimation.

2- Background subtraction.

The proposed algorithm can be summarized in the following flowchart in Figure 3.

1. Background Estimation

To begin the object extraction process, the original N frames are decomposed into the second generation of curvelet transform via wrapping (FDCT). For each frame we used Canny edge detector to detect the edges for each resulting sub band from the curvelet transform. The resulted N frames which represent the object edges are collected using the OR logical operator to obtain one image. The obtained image is processed using some morphological operators to obtain mask1.

Estimating the second mask using the following steps:

1-In this step the differentiation of the first N frames is performed by subtracting the current frame from each

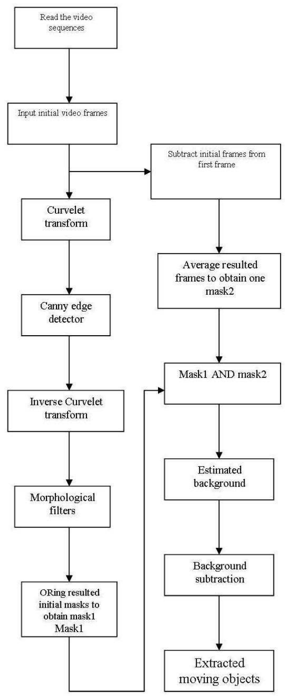

Fig. 3: Major steps in the proposed algorithm.

Table 1: The results for the lag number estimation.

Video sequence	Claire	Mother & Daug	Akiyo	Grand- mother	MissAm.
Estimated lag number	6	4	2	8	8

of the other frames and threshold $T1$ is used to generate an initial mask for each subtraction. This operation can be written in the following equation:

$$mask\_df_k(i,j) = \begin{cases} 1 & if \quad |x_k(i,j) - x_1(i,j)| > T_1 \quad k \neq 1 \\ 0 & otherwise \end{cases} \tag{3}$$

The k represents the frame numbers in equation 3 which is called lag, it will depend on the kind of motion as shown in Table1. i.e. it will be small for fast motion video sequences while it needs to be large for slow motion video sequences. 2- The resulted frames are averaged for each pixel over these initial masks and a certain threshold T2 is used to generate the second mask which is called mask2 as shown in equation 4.

$$mask2 = \begin{cases} 1 & if \quad \text{average } (mask\_df(i,j)) > T_2 \\ 0 & otherwise \end{cases} \tag{4}$$

The AND logical operator is used to Combine mask1 and mask2 and obtaining the final mask3 then thresholding mask3 with threshold T3 to have the final filtered mask3. Then, the object in the final mask3 will be represented with binary 0 value and the background will be represented with binary 1 value. This mask is multiplied with the original frame to represent the pixels of moving object with 0 values and the background with the value of the original frame. 0 values will be replaced with the average of two values which are on the edge of the binary object in mask3. The final image is the estimated background which is called background bg. The visual steps of estimating the background is illustrated in details in Figure 4.

Fig. 4: (a) Original image for Akyio, Clair, Grandmother, Mother & doughter and Miss America. (b) Binary image with 0 value of the object and 1 for the background. (c) Binary image multiplied with original image. (d) The estimated background.

2. Background subtraction

In this step the moving object is extracted by subtracting the current frame from the estimated background and thresholding the absolute value of the subtraction with threshold T4 give the moving object for each frame in the video sequence which acted as mov_obj. This step is illustrated in equation 5.

$$mov\_obj(i,j) = \begin{cases} 1 & |bg(i,i) - f(i,j)| > T_4 \\ 0 & otherwise \end{cases} \tag{5}$$

$mov\_obj(i,j)$ is the extracted moving object, it results from the current frame $f(i,j)$ and the estimated background $bg(i,j)$.

4 SIMULATION RESULTS

The proposed algorithm is applied to a number of videos such as Akyio, Grandmother, Mother & Daughter Claire and Miss America video sequences with a QCIF format with size of (144x176). In our algorithm we specified the following parameters to the curvelet domain, the number of scales = 2 and the number of angles=16 and all resulting 32 subbands are used. Our results are compared with the results of extracting moving objects using region growing, fuzzy and rainfalling watershed techniques in the wavelet domain.

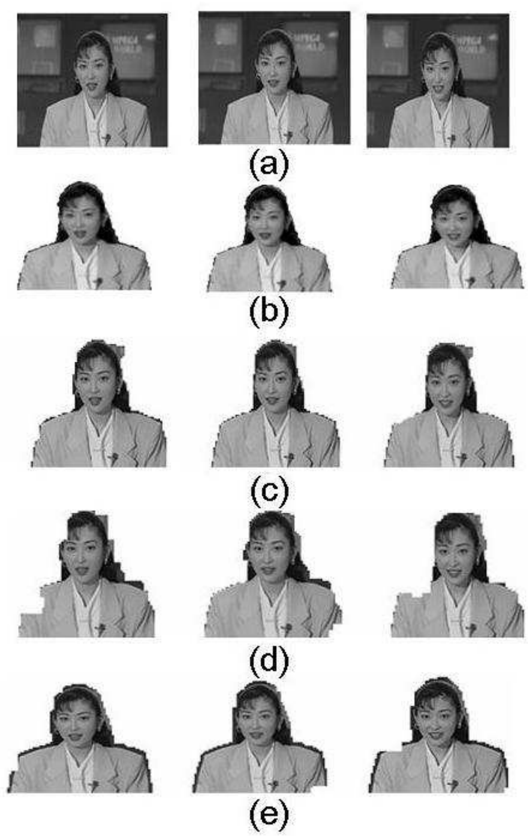

Fig. 5: The results of 4^{th}, 11^{th} and 19^{th} frames of Akyio video sequence (a) Original frames (b) The proposed method (c) Region growing method in wavelet domain (d) Watershed method in wavelet domain (e) Fuzzy method in wavelet domain.

1) Visual results

The frame number 4^{th}, 11^{th} and 19^{th} is selected to indicate the visual quality of the proposed method compared with the region growing, the rainfalling watershed and the fuzzy techniques in wavelet domain. As shown in Figure (5), for Akyio video sequence the proposed method in Figure (5-b) shows excellent complete extraction of the object while in Figure (5-c) using region growing in the wavelet domain there is small part of the background is taken with the extracted object that represents the famous problem in the wavelet transform and is called over-segmentation. In Figure (5-d) and Figure (5-e) using watershed and fuzzy c-mean respectively a missing part of the object is considered as background which is called sub- segmentation problem, (a part of the background considered as object). Figure (6) represents Claire video sequence in Figure (6-b) the proposed algorithm has completely extracted the moving object and the edges of the object are smooth. Although, in Figure (6-c) and Figure (6-d) for region growing and watershed respectively the extracted object is good but the edges are not smoothed, (this is the main difference between the cuvelet domain and the wavelet domain).

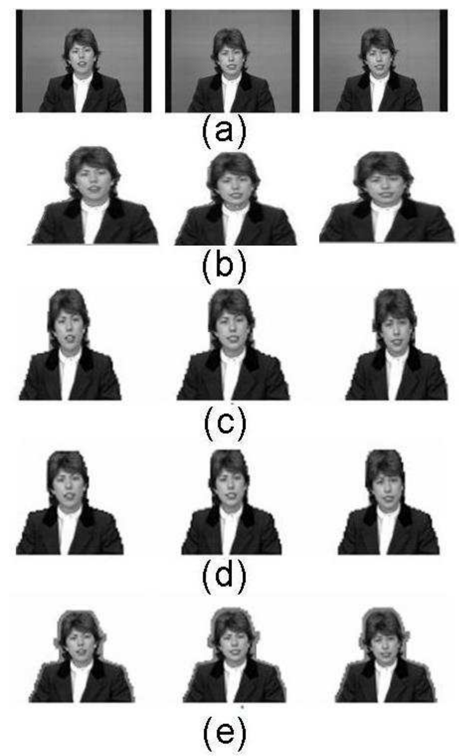

Fig. 6: The results of 4^{th}, 11^{th} and 19^{th} frames of Claire video sequence (a) Original frames (b) The proposed method (c) Region growing method in wavelet domain (d) Watershed method in wavelet domain (e) Fuzzy method in wavelet domain.

While, in Figure (6-e) for fuzzy c-mean algorithm the surrounded background of the object is taken as a part of the extracted moving object. In Figure (7-b, 8-b) for Mother & daughter and Grandmother video sequences respectively the extracted objects using the proposed method is more accurate and the boundaries are smoother than the extracting objects using region growing, watershed and fuzzy c-mean respectively in Figure (7-c), Figure (7-d), Figure (7-e), Figure (8-c), Figure (8-d) and Figure (8-e).

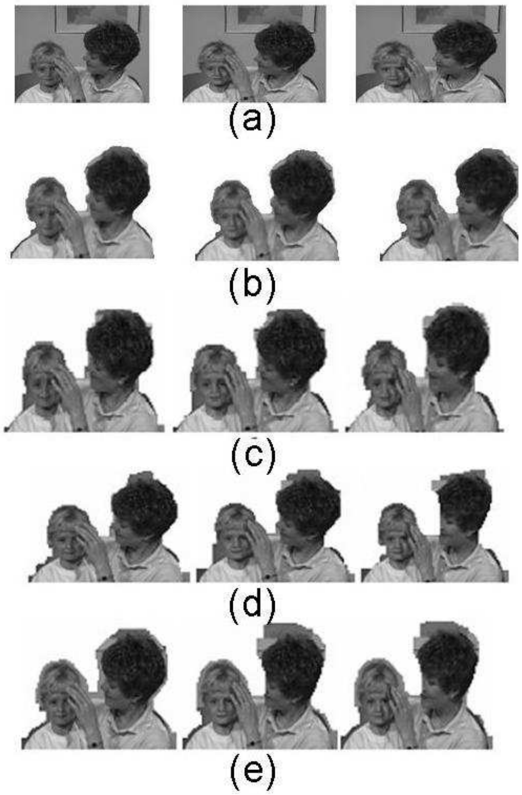

Fig. 7: The results of 4^{th}, 11^{th} and 19^{th} frames of Mother & daughter video sequence (a) Original frames (b) The proposed method (c) Region growing method in wavelet domain (d) Watershed method in wavelet domain (e) Fuzzy method in wavelet domain.

2) Numerical results

As mentioned in the simulation results the proposed algorithm is applied to number of video sequences such as Akyio, Claire, Mother & daughter, Grandmother and Miss_Am with QCIF format and size (144x176). We selected the first 30 frame to be tested. The accuracy and spatial error are measured for these videos sequences. Firstly, we measured the performance of the proposed algorithms using the accuracy (s) tests which is represented by equation 6. In the simulation results, a prior known segmentation object (reference object) is used in calculating the accuracy (s) of the segmented object and is represented by *Aref*.

$$S = \frac{A \cap A_{ref}}{A \cup A_{ref}} \quad (6)$$

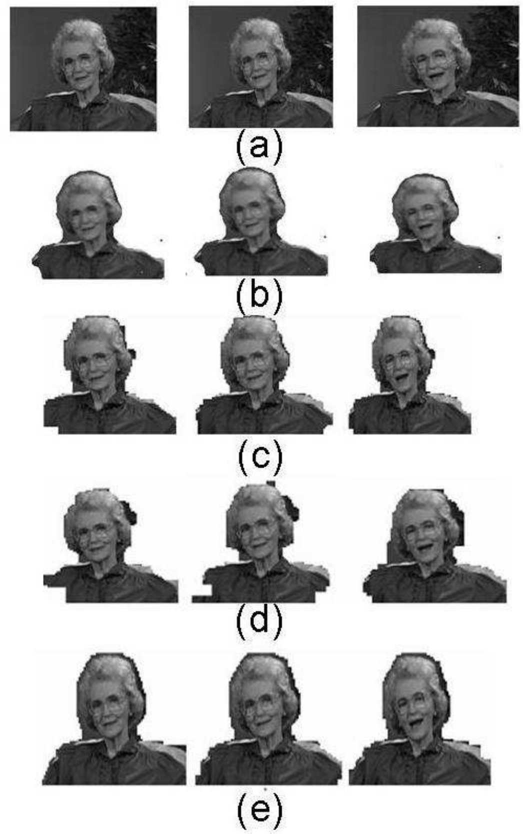

Fig. 8: The results of 4^{th}, 11^{th} and 19^{th} frames of Grand Mother video sequence (a) Original frames (b) The proposed method (c) Region growing method in wavelet domain (d) Watershed method in wavelet domain (e) Fuzzy method in wavelet domain.

Where A represent the object extracted using the proposed algorithm. To prove high accuracy rate of the proposed algorithm as shown in Table 2 for the frames number 10^{th}, 20^{th}, 25^{th} and 50^{th} respectively, the accuracy rate is grater than 90%. Secondly, temporal error measurement (vQM) which is represented in equation 7 is measured in this algorithm the temporal errors are directly detectable by the variation of the sQM value along time (vQM). If one calls QMF and QAB the effect of, respectively, MF and AB points on the final measure, vQM is given by:

$$vQM(t) = |Q_{MF}(t) - Q_{MF}(t-1)| + |Q_{AB}(t) - Q_{AB}(t-1)| \quad (7)$$

Is measured for the proposed method and compared with the results of Fuzzy c-mean, watershed and region growing in wavelet domain. As shown in Figure (9) for Claire video sequence almost frames of our algorithm proved less vQM error than other methods in the wavelet transform. The temporal error for another video like Akyio video sequence is shown in Figure (10). the

Table 2: The results of the accuracy measurement.

Image name	Accuracy %			
	Frame no. 10	Frame no. 20	Frame no. 25	Frame no. 50
Grand mother	93.29	91.44	80.89	90.98
Claire	91.48	91.34	89.70	90
Miss_Am	93.31	90.93	93.16	92.98
Akyio	97.74	94.13	92.55	94.87
Mother& daughter	90.50	92.86	86.41	83.44

average of vQM values of Akyio is less than the average values of other methods.

5 Conclusion

In this paper, a novel algorithm for moving object extraction from video sequence based on the second generation of the curvelet transform is introduced. In the proposed method, the first moving objects masks are primary obtained using canny edge detector in the curvelet transform. Using the OR logical operator for collecting obtained masks to get the first mask to be combined with the second obtained mask from subtracting the initial frames from the first frame and averaging the subtraction results. After combining the first and the second masks using the AND logical operator, to replace edge values of the moving object by the average of the two values on the moving object edges. Thus, the estimated background is obtained and is used in subtraction of each frame in the video sequence from the estimated background to get the moving parts. A comparison study has been introduced between the proposed algorithm and the common fuzzy c-mean, watershed and region growing techniques in the wavelet domain. Visually and numerically comparison via accuracy and vQM measures is also introduced. The simulation results indicated that the proposed method has better performance for both visual and numerical results than the traditional methods.

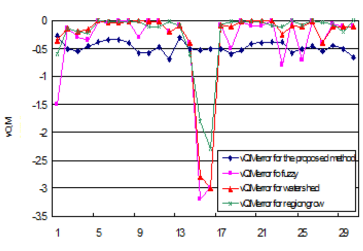

Fig. 9: Comparison between vQM error in dB for the proposed method in curvelet domain, fuzzy, watershed and region growing in wavelet domain for Clair video sequence.

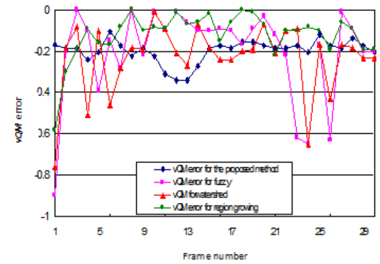

Fig. 10: Comparison between vQM error in dB for the proposed method in curvelet domain, fuzzy, watershed and region growing in wavelet domain for Akyio video sequence.

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