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Active Mesh Based Motion Compensation Algorithm for Video Compression in Wavelet Sub Bands

Vidyasagar K N, Bharathi S H, Vinay N A

Abstract: ***The method of assessing the motion vectors is termed as Motion Estimation and consequently reconstructing the original frame using these motion vectors is termed as Motion Compensation. In this paper a new active mesh based Motion estimation and compensation algorithm in wavelet domain at subpixel level is proposed. To achieve the accuracy in estimating the motion vector from reference frame to predicted frame in sub pixel level a Wavelet based Counterlet transform is used. This new mesh based method is based by minimizing the mesh energy with energy functions as its input coefficients. The accuracy of the estimation and the compensation is improved by the feature points obtained by the energy functions. The analysis of the experimental results describes that there is improvement in the distortion of the performance rate for the video compression and this is achieved by the generation of the structured and the unstructured active mesh motion techniques in the wavelet sub-bands. The energy criteria of the input coefficients helps to retain the energy in the sub-bands which is a condition that helps in significant gaining of the PSNR required for better outcome.***

Index Terms: ***Motion Estimation,Motion Estimation,Active mesh.***

I. INTRODUCTION

The present technology is mainly based on the digital processing and many applications like digital television, cathode-ray oscilloscope displayer, computer media devices such as laptops, tablets, notepads, and video conference belongs to the field of video storage and video communication. These applications require less bandwidth for the transmission of data and process the video data. Hence the necessary condition is to compress the data by application of the various compression algorithm techniques. This application of video compression techniques helps in the reduction of the storage capacity and hence the transmission bandwidth is decreased. In many digital applications, the digital video is first divided into many frames[1]. Each of these divided frames is considered as input images, which contain the information that has to be processed under many various techniques of video compression[3].

The main goal in the video compression algorithm is to decrease or attenuate the redundancy information and hence remove the redundant data from the image frame. The redundancy can be minimized by representing the input data by using fewer amounts of bits per second with respect to each frame [2]. The various redundancies such as spatial and temporal can be removed from the frames by using the quantization block and applying the discrete cosine transform (DCT) on the input data of eachframe [5]. The temporal redundancy between continuous frames of the video sequence can be minimized by utilization of motion estimation and motion compensation in the encoder of the MPEG application. The MPEG-4 is based on one of the block-based methods in the video coding techniques.

Recent compression algorithms in the digital video applications mainly prefer the Discrete Wavelet Transform (DWT) which has the principle of decomposing an image data into further levels [8].

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* Correspondence Author
Vidyasagar K N*, School of ECE, REVA Universty, Bengaluru, India.
Bharathi S H, School of ECE, REVA University, Bengaluru, India.
Vinay N A, School of ECE, REVA University, Bengaluru, India.

II. DISCRETE WAVELET TRANSFORM (2-D DWT)

The human visual method of processing can be incorporated by the usage of DWT. The computational complexity is reduced and thus an efficient design of quantization is obtained by the advantages of DWT. The quantization can be designed by decomposing a frame of image into the sub-bands of non-overlapping levels. The memory-efficient and the speed-efficient implementation of the wavelet filtering which is transversal with its specifications can be obtained by using the Lifting implementations.

The two successive 1-D transforms forms together and a 2-D discrete wavelet transform is formed. The transformation of an input frame of particular image in level-2 decomposition of the DWT is thus carried out by transforming the decomposed of the level-1 row and then followed by the level-1 decomposed transformation of the column. The set of the basis functions that are decomposed for level-2 are required to obtainDWT for an input image which is product of the two different 1-D basis functions.

The transform coefficients and the corresponding scaling function forms the decomposed levels of the sub-bands. Hence the LL sub-band contains the coarse coefficients, the LH sub band describes the vertical details, and the horizontal details are present in the HL sub-band. Finally the HH sub-band constitutes the horizontal details. Thus the analysis of the decomposition is shown in the Figure 1 and the process of the DWT and the IDWT using the filter bank is described in the Figure 2.

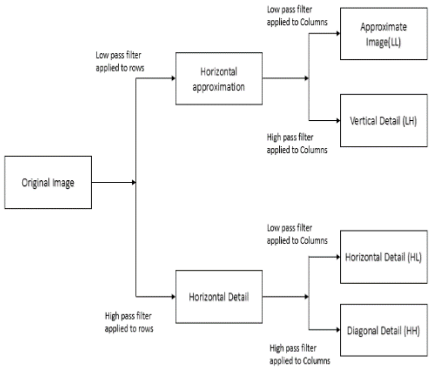


Figure 1: Wavelet analysis figure.

Let ψ(t) be the wavelet such that it scales and shifts the signal from orthonormal basis of square integral function. This is given as

$$\psi_{a,b}(t) = \frac{1}{\sqrt{2a}}\psi((t-2^{a}b)/2a) \qquad (1)$$

Where a and b are integers denoting scale and shift of the signal.

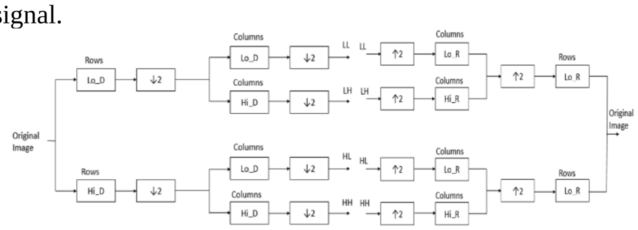


Figure 2: 2-D DWT and IDWT using filter bank

III. CONTOUR LET TRANSFORM

The transforms like Fourier and wavelets when applied for the signal, have failed to capture the geometry of image edges, hence the proposed algorithm contour let transform mainly aims at this problem and provides a better geometry at the contours of the image.

The improved transform will provide a smooth contours while representing the image. Consider the example where we have the representation of both wavelet and the contour let styles. The wavelets have limited style as seen in figure while the new transform provides the different shapes providing the smooth contours.

Thus the image represented by the new transform provides the better representation by local, directional and multiresolution properties. Multiresolution provides the fine resolution, then localized in both spatial and the frequency domains. Directionality provides orientation of elements at a variety of directions.

The Directional Filter banks (DFB's) act as maximally decimated while perfect reconstruction. It decomposes the image for l-level decomposition into binary tree of 2^{l} sub-bands with the cuneate frequency division as shown in Figure 3(a). While reconstruction the input is sent through the diamond shaped filters for modulation. This filter bank is called quincunx filter banks.

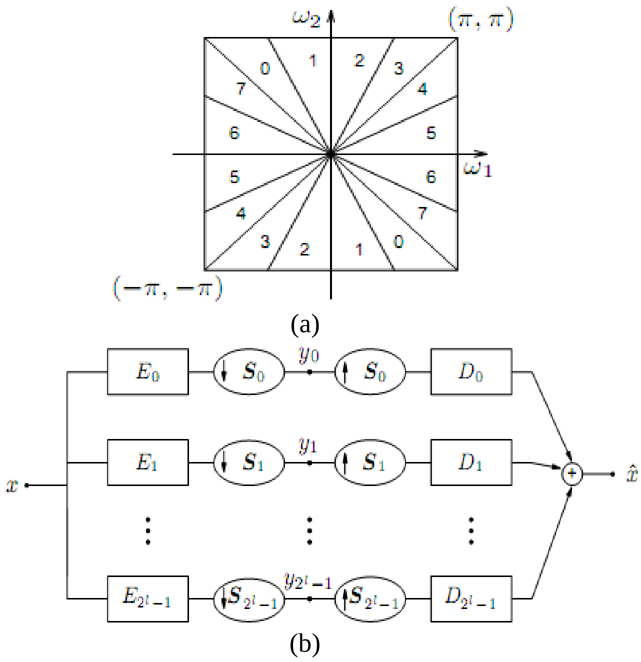


Figure 3: DFB. (a) Frequency Partitioning for l=3

(b) Multichannel view of l-level tree structure DFB

IV. WBCT

A pyramidal filter can be replaced by a wavelet filter and we can take directionality of CT as an advantage and at same time we can avoid redundancy. This is the fundamental idea behind WBCT (Wavelet Based Contourlet Transform) and it is a non-redundant transform. A perfect reconstruction of an image is very important in the best case of WBCT performance .This is the fundamental idea behind WBCT (Wavelet Based Contourlet Transform) and it is a non-redundant transform [6]. A perfect reconstruction of an image is very important in the best case of WBCT performance.

The non-redundant WBCT is as follows:

1. To an image DWT will applied in the following way
   - 1.1 Depending on the type of wavelet used, the low pass and high pass filters which are the decomposition filters will be designed
   - 1.2 To obtain the periodic extension of an image we have to compute the image convolution by selecting the image extension. Imext is the obtained result which is the extended image.
   - 1.3 Using the low pass filter perform convolution on the rows and columns of Imext. We obtain the image approximation LL after down-sampling the image.
   - 1.4 Using the low pass filter perform convolution on the rows of Imext and using the high pass filter perform convolution on the columns of Imext. We obtain the coefficients of horizontal component LH by down sampling the image.

1.5 Using the high pass filter perform convolution on the rows of Imext and using the low pass filter perform convolution on the columns of Imext. We obtain the coefficients of vertical component LH by down-sampling the image.
1.6 Using the high pass filter perform convolution on the rows and columns of Imext. We obtain the diagonal coefficients after down-sampling the image.
1.7 The LL will be decomposed again by repeating the steps from 1.2 to 1.6 until the required level of decomposition is reached.

2. The directional filters will be designed.
3. Using the LH, HL, HH components of an image the directional decomposition will be performed. This process is carried out using a bi-dimensional filter bank. This filter bank with decompose a image with maximum of 5 directions.
4. Step 3 will be repeated until we reach two directions with the LH, HL, HH images. At the final approximation the WBCT image is nothing but a pure wavelet.

V. METHODOLOGY

The new algorithm is proposed in video compression based on generating an active mesh for the given models. This method act as a solution for estimating the vectors which can be used to obtain motion estimation. The method is composed by utilizing the formed meshes and method of feature matching. Thus the feature points which are obtained by considering the interested region are extracted using the Kanade-Lucas-Tomasi (KLT) technique. These points will be further used for the input vertices in order to design the mesh structure based on principle of the Delaunay triangulation technique. The improved algorithm of feature matching is used to determine the matching points of the feature points. These matching points help to estimate the motion vectors. This improved algorithm uses the image pyramids in order to calculate the match points. This technique is applied for each individual feature point as to extract with respect to sub-pixel. The location of these points helps to define the mesh energy as to obtain the true match points. The accuracy is thus increased by mesh tracking which signifies the data content of changed motion features.

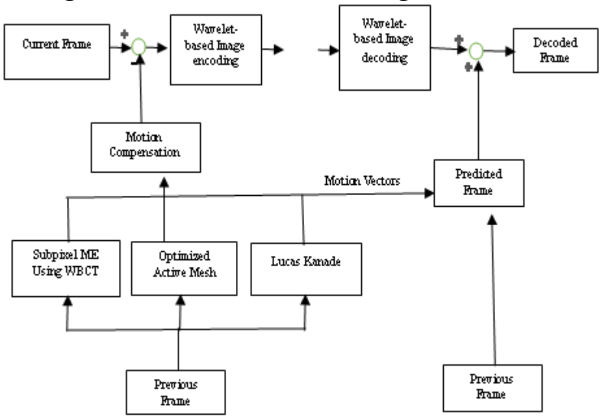


Figure 4:Motion compensation in spatial domain

The various algorithms of the video compression were tested in the domain of spatial were the coordinates are considered in the spatial analysis. As described in the Figure 4, the result obtained by considering the compensated frame which is resultant of subtraction of the frames of current frame with the previous one subsequently. The residue of the difference will be forwarded to the encoder. The limited quantity of information is sent to the decoder as the residue is obtained of the two sequences. The working principle of the wavelet transformation contributes for encoding and decoding the residual image using the SPIHT technique of image compression. Thus the estimation of motion is achieved by computing the vectors using the three methods as described further, are sent to the decoder. The decoder thus produces the restored image by considering previous frame as the reference frame with input parameters as motion vectors. Thus, this obtained image is further combined with the residual image original image is produced. The above explained procedure is carried for all the subsequent images and hence required results are restored.

A. Feature extraction based on technique of Kanade - Lucas – Tomasi

The tracking of the consequent frames and identification of the good features are major parameters for vision system in the process of extraction of feature points. The selection of the features which are used in tracking that seems to correspond to the points in the physical world is a tedious task. In order to achieve the optimality of the criterion in the task of feature selection, the process have to be carried out by construction including the detection of the disocclusions, working of the tracking and hence detecting the occlusions. The matching criterion is based on considering the image deformation which is linear, translation, window size which is adaptive with its specifications.

The cornerness and texturedness are the parameters used in selection of the feature windows where the intensity profile is processed in spatial domain. The measurement of dissimilarity in the feature specifies the change in the appearance and quality of a feature in referenced and the current frame.

The feature is abandoned when the rms residue of the dissimilarity is crossed the limited range. The accuracy of the tracker that can be optimized helps to obtain the feature points with the better properties of the texture. The desired result of extracting the features KLT is described in Figure 5

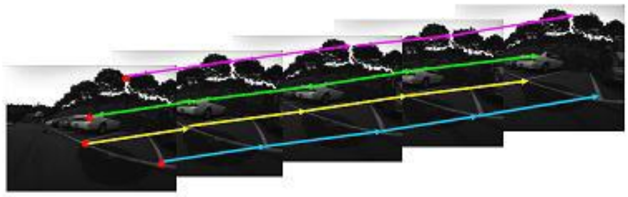


Figure 5: Feature point tracking

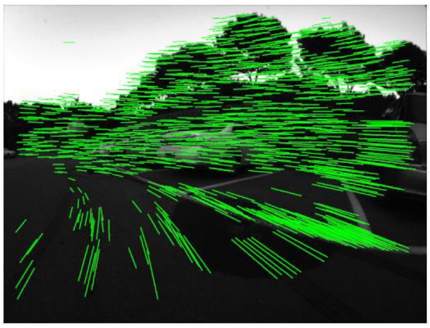


Figure 6: Tracking result

B. Improved Luca-Kanade technique

The intensity structure is present in the two images as to achieve the motion estimation and hence the motion correspondence can be established among the two image frames. The establishment occurs when the features are getting exposed or occluded, and this takes place rapidly and most of the information in the images are undefined i.e. the underlying motion. The solution is determined for this issue as when there is motion representation and the information is necessary for image compression at each position in the data. The error is minimized by defining the parameters and error norm of representation of the respective motion.

In the area of motion estimation that is mesh-based generation, the adaptation of the generated mesh topology is considered with the image content. There is increase in the computational complexity and there are issues in dealing the motion overhead rates. Thus these are the major limitations during this process is the estimation of motion vectors. In order to address these limitations and as to increase the efficiency of the compression, there is an introduction of an improved method for compensation of the motions based on mesh generation.

The proposed mesh topology for formation of the new triangular is used for shifting the node points of the mesh by half with respect to its inter nodal distance which results in construction of the mesh with the double - density around its frame boundary as shown in Figure 7. This topology prevents the outliers at the field boundary.

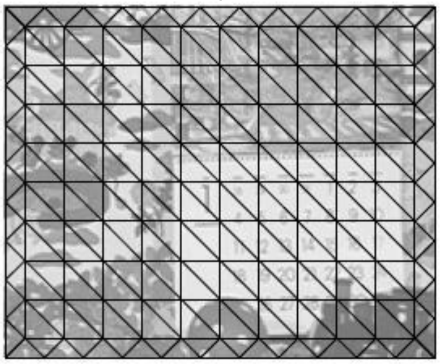


Figure 7: Model based on proposed mesh triangulation

C. Mesh Energy

The main task is to compute the match points which are true; this can be achieved bydefining the mesh energies based on the various criteria that mainly include the attributes that arerelated to the newly generated mesh and the match points are recognized between the videoframes. By reducing the quantity of the mesh energy defined, it is possible to track the objectsand reduces the mismatches and increase the accuracy.

Mesh energy can be defined by combining the two forms of energies, to be specific by combining the external energy and the internal energy of the nodes. There are various energy functions that are considered, to mention a few the model of mesh for the interest points, SSD, corner energies, and the correlation. Hence the energy is calculated for the neighbour hoods they are predefined and they include for the particular matched points. Thus the internal energy and the external energy are defined as described in the following description.

D. Internal Energy

Each vertex of a mesh is composed of the external energy that is normalized with its value and defined as:

$$E_{int} = \lambda L_{Cur}(x) + \lambda L_{Cur}(y) \qquad (2)$$

Where the parameters $Lcur\ (x)$, $Lcur\ (y)$ are known as the length of x and y apparatus of the meshed lines. The assessment of λ is outlined as

$$\lambda = \left[\frac{L_{pre}-L_{cur}}{\alpha_{Line}L_{cur}}\right] \qquad (3)$$

The length of previous frame and the current frame of mesh lines are denoted by the parameters$Lpre$, $Lcur$ respectively and the regularizing coefficient is denoted by the notation α_{line}.

By considering the internal energy for both the nodes of the origin and the destination node, it is defined as:

$$(i) = -E_{int} \qquad (4)$$

And for destination node:

$$(i) = +E_{int} \qquad (5)$$

E. External Energy

The normalization for this specific energy is defined for all vertex of the mesh is given as:

$$E_{Ext} = d(x)S_{FM}\left[\frac{r-d}{r}\right] + d(y)S_{FM}\left[\frac{r-d}{r}\right] \qquad (6)$$

The distance of the feature points between the current frame and the previous frame considering match points as a major parameter, are defined as the components of x and y.

Coordinates and are given by the notation (x), (y) respectively. The radius of the search region of the each individual frame is denoted as r. Finally the correlation criterion is defined as:

$$S_{FM} = \frac{F_{Corr}+1}{2} \qquad (7)$$

Where F_{corr} signifies the functionality of correlation coefficient between the true match points. The total sum of both computed internal as well as the external energy is defined as the node or mesh energy

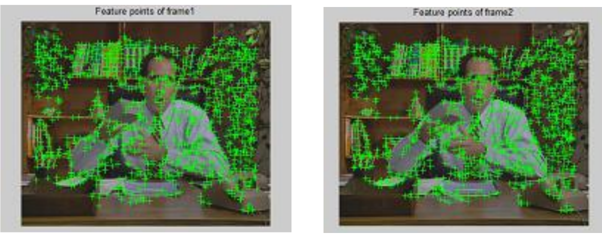
VI. EXPERIMENTAL RESULTS

The implementation is achieved using the proposed algorithm. This is accomplished using Matlab simulation of signal processing tool where the proposed algorithm is tested using various video frames as input.

The Subpixel Motion estimation is implemented as to estimate the motion vectors, by applying WBCT. Further the technique of feature matching is implemented as to find the true match points, this technique is known as Lucas-Kanade. The proposed active mesh algorithm has more efficiency. The first sequence of the video is having spatial resolution of value 352 × 288 pixels of dimensions and the next video frame of have a dimension of 352× 288. The corner points are detected using the KLT algorithm and these corner points are used to estimate the interested feature points of a specific frame as shown in the Figure 9. The feature points thus estimated act as an input vertices for generation of a triangular mesh using the Delaunay method as in the Figure 10. Finally the motion vectors are estimated by defining the mesh energy in order to determine the true match points. The motion vectors are estimated using the proposed method and can be observed that the Kanade method for estimating the vectors is quickest and have better execution speed. The results are shown in Figure 11.respectively.

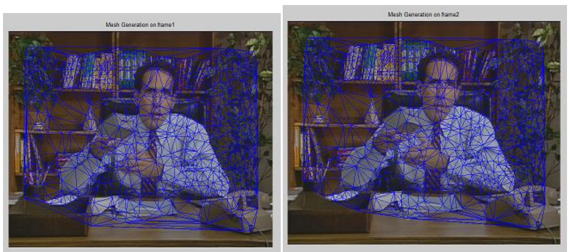
(a) (b)

Figure 8: (a) Detection of corner points of frame1. (b)Corner points of frame2 (using KLT)



(a) (b)

Figure 9: (a) Extraction of feature points (frame1). (b)Feature points of frame2 (KLT)



Frame 1 Frame 2

Figure 10: Mesh generated using DT algorithm

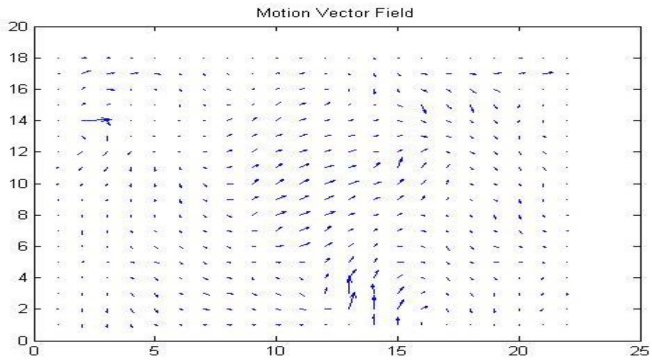


Figure 11: Estimated vectors for 2 frames based on improved algorithm of Kanade

VII. CONCLUSION

The motion vectors are estimated for the different video frames using the proposed technique of the active mesh based algorithm on different videos. The reconstruction is done by compensating the predicted frame and the vectors estimated to obtain the original frame. The energy functions and the mesh model are used as a major working principle. The energy minimization and the energy criteria are achieved as required for reducing the distortion. This algorithm is first applied for consecutive frames in the spatial domain, and the same proposed algorithm is applied in wavelet decomposed frame of the sub-bands in order to improve the sub-pixel accuracy by reducing the distortion. The final results of the experiment reveal that this active mesh methodology therefore increases the PSNR performance.

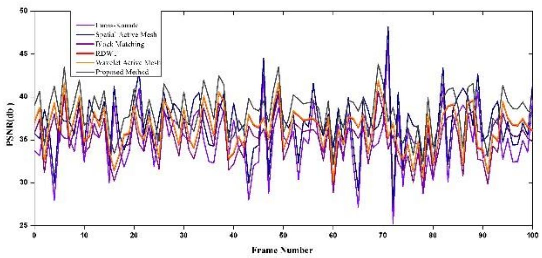


Figure 12: Graph of frame-by- frame PSNR values for sample video sales man.

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AUTHORS PROFILE

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Vidyasagar K N Received BE Degree in Electronicsand Communication Engineering from VTU Belgaum and M.Tech, in Digital Electronics and communication from VTU Belgaum. Presentlyhe is pursuing Ph.D from VTU, Belgaum, Karnataka, India. Heis working as faculty in School of Electronicsand Communication Engineering, REVA University,Bengaluru, India.His research interests Video Processing, Image processing, Signal Processing.,etc. He is a Associate MemberIETE of (AMIETE) INDIA.

Bharathi S.H has 26 years of teaching and research experience. Received her B.E. in Electronics and M.E. in Electronics and Communication, Bangalore University, Karnataka India. Dr. Bharathi S H was awarded the Ph.D. degree in 2013. Her work in the area of Sensors, VLSI, digital Signal Processing. Presently she is working as Professor, REVA University, Bangalore. She is a member of IEEE and Fellow of IETE societies. She is also a member of IEEE Women in Engineering.

Vinay N A Received BE Degree in Electronicsand Communication Engineering from VTU Belgaum and M.Tech, in Digital Electronics from India SAHETumkur. Presently he is pursuing Ph.D from, REVA University,Bengaluru, Karnataka, India. Heis working as faculty in School of Electronicsand Communication Engineering, REVA University,Bengaluru, India. His research interests Speech Processing, Image processing, Signal Processing.,etc. He is a Associate MemberIETE of (AMIETE) INDIA.