International Journal of Scientific and Technical Advancements

ISSN: 2454-1532

Decomposition of Dynamic Texture Using Diamond Search Algorithm

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***Abstract*—**Dynamic texture poses the problem of modelling, learning, recognizing and synthesizing dynamic textures on a firm analytical footing. A video file is taken for analysing the frames and to compress the video using H.264 encryption technique. After completing the video compression the video frames will be converted as inter frame and intra frame, and the motion of the video will be estimated as motion vector calculation. The motion of the video will be converted as lumachroma calculation, and its value is used to analyse the frames, and after the lumachroma value calculation PSNR value will be calculated. PSNR is used to analyse the motion in the frames and to extract motion in the video. Then the video will be encrypted and by using the diamond search algorithm the minimum blocks in the video will be decrypted. Thus the proposed system increases the processing speed and helps in identifying minute motions of the video.

***Keywords*—**Dynamic texture; diamond search algorithm.

I. INTRODUCTION

A dynamic texture poses the problem of modeling, learning, recognizing and synthesizing dynamic textures on a firm analytical footing. An image sequence analysis is the extension of static textures to the temporal domain, referred to as dynamic textures. A flag flapping in the wind, ripples at the surface of the water, fire, waving trees, smoke, or an escalator are all examples of dynamic textures that can be presented in real scenes are shown in figure 1 Consider a sequence of images of a moving scene. Each image is an array of positive numbers that depend upon the shape, pose and motion of the scene as well as upon its material properties (reflectance) and on the light distribution of the environment. It is well known that the joint reconstruction of photometry and geometryis an intrinsically ill-posed problem: from any (finite) number of images it is not possible to uniquely recover all unknowns (shape, motion, reflectance and light distribution).

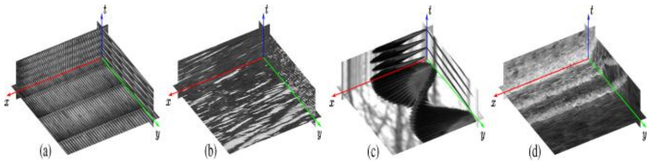

Fig. 1. 2-D+T sections of different dynamic textures. (a) Escalator, (b) Ripples at the Surface Water, (c) Endless Spiral, and (d) Wave Motion with sea Foam can be observed.

In the above figure each image sequence is viewed as a 3-D data cube where cuts enable us to observe motions occurring at different spatio-temporal scales.

II. DYNAMIC TEXTURE

Dynamic textures are sequences of image of moving scenes that exhibit certain stationary properties in time; these include sea-waves, smoke, foliage, whirlwind etc. Video containing dynamic textures are not all of the same nature. They can be natural (natural processes), artificial (created by humans), or synthetic (generated by a computer). An image sequence may contain static and/or dynamic texture components (the dynamic texture component of an image sequence contains at least one dynamic texture).

For example, a bridge, rocks or ivy are static textured patterns. Water and trees have a motion that generates two different dynamic textures. The following definitions of dynamic textures are, a natural, artificial or synthetic image sequence may contain a static texture component and/or a dynamic texture component. A dynamic texture is a textured pattern that can be rigid or deformable. This pattern has a motion induced by a force which can be internal, external or created by camera motions. This motion can be deterministic or stochastic.

III. A MODEL OF DYNAMIC TEXTURE

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Fig. 2. A Small Lake with water ripples.

Fig. 3. Fountain with water ripples.

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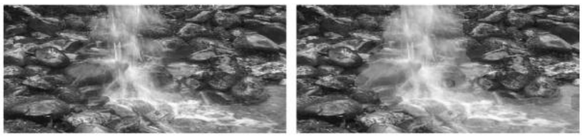
Fig. 4. Water falling over pebbles.


Fig. 5. Highway traffic.


Fig. 6. Duck floating on water.

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IV. Image Inpainting Using MCA

Filling-in-'holes' in images is an interesting and important inverse problem with many applications. Removal of scratches in old photos, removal of overlayed text or graphics, filling- in missing blocks in unreliably transmitted images, scaling-up images, predicting values in images for better compression, and more interest, and many contributions.

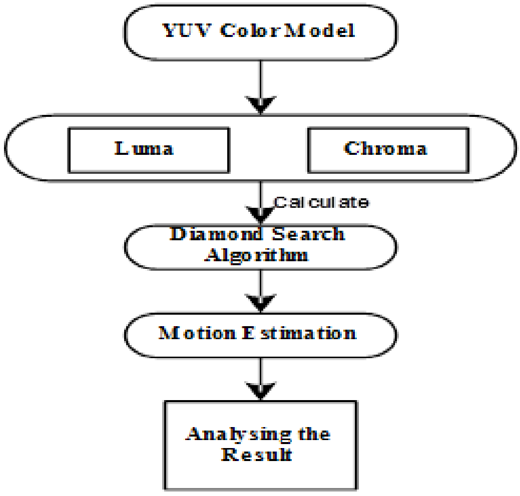
V. Diamond Search Motion Estimation Algorithm

The morphological component analysis (MCA), Independent component analysis (ICA) are failed to define textures when an image is sub-divided into 16x16 macro-blocks. Since the video consists of sequence of frames that have same characteristics for particular time with or without motion. Motion may be occurred in most of the pixels or smaller number of pixels. Under this condition we have to analyze every group of pixels in consecutive pixels. For this purpose, we propose a novel method Diamond search motion estimation algorithm which could divides the frames into 16x16 pixels that can make the decomposition faster when compared to existing MCA method.

The block displacement of real-world video sequences could be in any direction, but mainly in horizontal and vertical directions. Based on this crucial observation, our proposed method analyzes complete motion, and a new Diamond search (DS) algorithm is developed.

In DS the search basic point pattern is the diamond shape, and there is no limit on the number of steps that the algorithm can take. There are two different types of fixed patterns, one is Large Diamond Search Pattern (LDSP) and the other is Small Diamond Search Pattern (SDSP). The first step uses LDSP and if the least cost search point is at the center location we jump to fourth step. The consequent steps, except the last step, are also similar and use LDSP, but the number of search points where cost function is checked is reduced. The last step uses SDSP around the new search origin and the location with the least weight is the best match.

VI. Architectural Diagram



A. *YUV Color Model*

The YUV color model is the basic color model used in analogue color TV broadcasting. Initially YUV is the re-coding of RGB for transmission efficiency (minimizing bandwidth) and for downward compatibility with black-and white television. The YUV color space is derived from the RGB space. It comprises the luminance (Y) and two color difference (U,V) components. The luminance can be computed as a weighted sum of red, green and blue components; the color difference, or chrominance, components are formed by subtracting luminance from blue and from red.

The advantage of the YUV model in image processing is decoupling of luminance and color information. The importance of this decoupling is that the luminance component of an image can be processed without affecting its color component.

The Y'UV model defines a color space in terms of one luma (Y) and two chrominance (UV) components. Previous black-and-white systems used only luma (Y) information. Color information (U and V) was added separately via a sub-carrier so that a black-and-white receiver would still be able to receive and display a color picture transmission in the receiver's native black-and-white format.Y stands for the luma component (the brightness) and U and V are the chrominance (color) components; luminance is denoted by Y.

B. *Luma and Chroma*

Chrominance is the part of a video signal which carries information about the attributes of the colors being displayed.

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The development of a technique for transmitting information about color paved the way to color television, a move which revolutionized the television industry. Color values are given in the form of quantitative measurements against a standard reference color so that the signal is standardized, although properties of the display screen can change the way in which the color expresses.

Two different properties are expressed in the color part of a video signal, the hue and the saturation, with the color being defined by the red, green, blue (RGB) color metric for a quantitative description of the color. This information is also bundled with luma, which refers to brightness. Since the human eye is very sensitive to differentiations in brightness, chroma and luma can be balanced against each other to achieve a crisp, clear image with recognizable color patterns.

C. Motion Estimation

Motion estimation (ME) is the action of determining motion vectors that delineate the transformation from one 2D image to another; usually from adjoining frames in a video sequence. The problem of registering a sequence of images in a moving dynamic texture video. This involves optimization with respect to camera motion, the average image, and the dynamic texture model. To introduce powerful priors for this problem based on two simple observations:

1) Registration should simplify the dynamic texture model while preserving all useful information. It motivates us to compute a prior for the dynamic texture by marginalizing over specific dynamics in the space of all stable auto-regressive sequences;
2) The statistics of derivative filter responses in the average image can be significantly changed by registration, and better registration should lead to a sharper average image and superior motion estimation results are obtained by jointly optimizing over the registration parameters, the average image, and the dynamic texture model.

The temporal prediction technique used in MPEG video is based on ME. To send a full frame, the inherently have less energy and can be compressed by sending a encoded difference images, it need to save on bits. This is the idea of ME based video compression. From the video sequence, the ME takes out the motion information. Besides that, ME is a multistep action that combination of techniques, such as motion starting point, motion search patterns, and modify control to restrain the search, dodge of search stationary regions, etc. To find the most accurate motion vector (MV), the ME algorithm is an embodiment of several effective ideas and it also aim to maximize the encoding speed as well as the visual quality.

A video sequence can be considered to be a discretized three-dimensional projection of the real four-dimensional continuous space-time. The objects in the real world may move, rotate, or deform. The movements cannot be observed directly, but instead the light reflected from the object surfaces and projected onto an image. The objects may be transparent (so that several independent motions could be observed at the same location of an image) or there might be fog, rain or snow blurring the observed image.

Changes between frames are mainly due to the movement of objects. Using a model of the motion of objects between frames, the encoder estimates the motion that occurred between the reference frame and the current frame. This process is called motion estimation (ME).

VII. DIAMOND SEARCH (DS) ALGORITHM

The Full Search (FS) algorithm gives the global minimum SAD position which corresponds to the best matching block at the expense of highly computation. To overcome this defect, many fast BMAs are developed such as diamond search (DS) and the cross-search algorithm and new four step search.

The DS algorithm employs two search patterns. The first pattern, called large diamond search pattern (LDSP) shown in figure 8. (a) Comprises nine checking points from which eight points surround the center one to compose a diamond shape. The second pattern consisting of five checking points forms a small diamond shape, called small diamond search pattern (SDSP) shown in figure 8. (b). in the searching procedure of the DS algorithm, LDSP is repeatedly used until the minimum block distortion (MBD) occurs at the center point.

The search pattern is then switched from LDSP to SDSP when it reaches the final search stage. Among the five checking points in SDSP, the position yielding the minimum block distortion (MBD) provides the motion vector of the best matching block. The DS algorithm can not only provides similar or in many cases better results than NTSS, but also reduces complexity by as much as 75%. But it appears that DS has significant quality degradation with sequences containing significant global motion, or when coding higher resolution sequences.

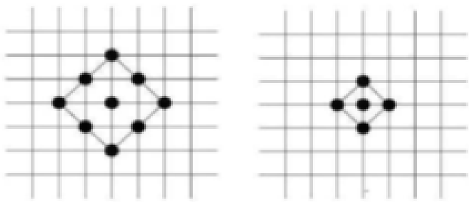

Fig. 8. (a) Large Diamond Search Pattern, (b) Small Diamond Search Pattern the large diamond search pattern (LDSP) contains 9 search points from eight surround to the center point for one and compose to a diamond shape and used at first and repeatedly until the minimum SAD point is the center point.

The small diamond search pattern (SDSP) contains 5 search points. The DS algorithm is summarized as follows.

Step 1: The initial LDSP is centered at the origin of the search window, and the 9 checking points of LDSP are tested. If the MBD point calculated is located at the center position, go to *Step 3*: otherwise, go to Step 2.

Step 2: The MBD point found in the previous search step is re-positioned as the center point to form a new LDSP. If the new MBD point obtained is located at the center position, go to Step 3; otherwise, recursively repeat this step.

Step 3: Switch the search pattern from LDSP to SDSP. The MBD point found in this step is the final solution of the motion vector which points to the best matching block.

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Implementing the DS algorithm is provided as follows. The compact shape of the search patterns used in the DS algorithm increases the possibility of finding the global minimum point located inside the search pattern. Therefore, the DS algorithm tends to produce smaller or at least similar motion estimation error compared with other fast BMAs. Unlike TSS, NTSS and 4SS, the search window size is not restricted by the searching strategy in DS algorithm.

DS algorithm greatly outperforms the well-known TSS algorithm and achieves close MSE performance compared to NTSS while reducing its computation by up to 22% approximately. The DS is implemented in the MPEG-4 video-encoding environment and its efficiency is demonstrated through core experimental results. Based on these results, it is adopted and incorporated in MPEG-4 verification model.

VIII. Result and Discussion

A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

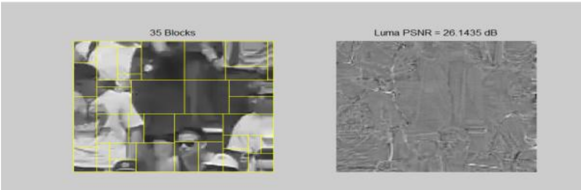

Fig. 9. 35 blocks, luma PSNR 26.1435 DB.

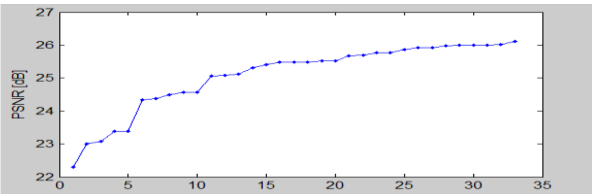

Fig. 10. Graph representing PSNR vs iteration.

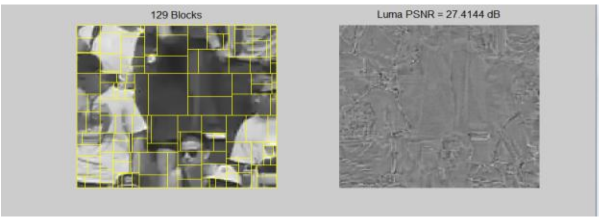

Fig. 11. 129 blocks, luma PSNR 27.4147Db.

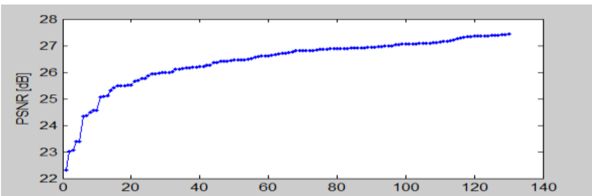

Fig. 12. Graph representing PSNR VS Iteration.

IX. Conclusion

Dynamic textures are complex sequence due the interaction between the multiple moving components in the scene. Examples of dynamic texture presented in this work including flickering fire, blowing leaves and water rising and falling in the fountain. To avoiding the segmenting, stracking and learning the trajectory of each of the individual components in the scene, a more appropriate representation of this class of sequence is the holistic interpretation. The dynamic are the scene are incorporated to the generative model which determines the state of the system. The order of the generative model is the number of previous states used in the deterministic components of the subsequent state prediction. Dynamic textured images exhibit statistical regularity over time. When the joint statistics of the frame from a sequence are time invariant, the sequence is stationary.

X. Future Extension

The small cross-center-biased characteristic of the real word video sequences, an improved version of the well-known cross diamond search algorithm is proposed in this paper. The new algorithm uses a small cross-shaped search pattern in the first two steps to speed up the motion estimation of stationary and quasi- stationary blocks. Experimental results show that this new cross- diamond search algorithm could achieve much higher computational reduction as compared with diamond search (DS) and Cross Diamond Search (CDS) while similar prediction accuracy is maintained, and it is especially suitable for videoconferencing sequences.

Acknowledgment

The authors would like to thank Dr. K. Malarvizhi, Head of Department, Electronics and Instrumentation, SNS College of Technology for her ideas in implementing this work.

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