Physical Sciences Section

Pak. j. sci. ind. res., vol. 32, no. 5, May 1989

FAST DETECTION, LOCATION AND TRAJECTORY TRACING OF MOVING TARGETS

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(Received June 26, 1988; revised April 1, 1989)

This paper describes a new time efficient technique for the analysis of time-varying images taken by a stationary camera. The proposed alogrithm consists of three stages, motion detection, object location, and trajectory tracing. These stages locate a local window containing the moving object in respective frames in both fast and slow motion cases. The described method has been tested on the real world complex images of moving objects. Experiments produced satisfactory results.

Key words: Motion analysis, Time-varying image, Trajectory tracing.

INTRODUCTION

Automatic analysis of time-varying images involves detection and description of the moving objects in a sequence of images recorded by visual sensors. A great deal of research has been devoted to different aspects of timevarying image analysis [1-3, 5]. This paper considers one of the fundamental problems in motion vision, which is the detection of moving object ard description of its motion. This problem has attracted considerable research efforts and several studies have been made. For example, Mosahako et al. [4] have described a system which detects and tracks moving objects from the videotape records of biological processes. Tsotsos and Mylopoulos [6] have developed a framework for motion extraction from a sequence of images using the semantic networks. Ayala et al. [7] have described a moving target tracking alogrithm at a symbolic level that performs image registration and motion analysis between pairs of frames using segmentation techniques.

The common procedures used in these studies is that two consecutive frames are compared and a difference image is created. The approach presented in this paper also uses the difference image only for detection of motion regardless of object contours. The proposed method takes maximum advantage of the information extracted from the difference image for further processing by using subimages and local windows without any loss or distortion of useful information about the object and its motion.

This new method can be used more efficiently as compared to other approaches for motion detection and trajectory tracing in 2-D images. There are two basic assumptions used in this research. First, the moving object is assumed to have a gray-level distribution different than that of the background. This is necessary to distinguish the object pixels from the background points. Second, it is assumed that there is no rotatory motion around the symmetry axis of the object. However the translational or angular motion can be in any direction on a 2-D plane in accordance with this condition. Motion detection and description using local windows. In this section we present a detailed description of the proposed three stage approach.

Motion detection stage. This is the initial stage in which two consecutive frames $(I_1 \text{ and } I_2)$ are compared to form a difference image $D(i, j) = 1 I_2(i, j) - I_1(I, j)I$, where l.l is the absolute value operator. A row and column search is then made in D(i, j) to find any non-zero elements whose values are equal to or greater than the given threshold, T. The threshold value is determined from the histogram of the difference image. The difference image gives the informaiton about any changes between the two images. If there is no any non-zero element detected in the difference image, it is then assumed that no motion existed within that time interval when these two images have been taken.

In the case that non-zero elements are found in D(i, j), the rows and the columns are marked as (i_1, i_2) and (J_1, j_2) such that they represent the locations of the first and the last detected non-zero elements. Using these marked rows and columns, we define a subimage A(i, j) in D(i, j) as A(i,j) = D(i, j) if $D(i, j) \ge T$ and A(i, j) = 0 if D(i, j) < T.

Object location stage. In this intermediate stage, A(i, j) is further processed to determine two local windows W, and W, for locating the moving object in two consecutive frames. Due to the fundamental difference between the fast and the slow motion, A(i, j) can possess two different forms. In the case of fast motion, non-zero elements A(i, j) describe the location of the moving object in I, and I, while all the other zero elements represent the background points. In the case of slow motion, however, all the zero elements of A(i, j) can either be due to the background points or to the overlapped portions of the moving object. In the latter case, zero points due to overlapping yield false results in the matching process. Moreover, when we place A(i, j) on I, and I, to find the actual locations of the object, it is not known which group of non-zero elements in A(i,j) belongs to W_1 and which group to W_2 Fig. 1. To overcome these difficulties, we obtain the gray-level (G_1, G_2)

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range of the background points from the original images. Let I'(i, j) be the gray-level value of the point (i, j) in the A(i, j) of the respective frames. Then pixels of A(i, j) are classified as follows; If I' (i, j) is in the range of (G_1, G_2) , then the corresponding image point (i, j) is considered as a background point and replaced by the code-1, otherwise it is classified as object point. Then W₁ and W₂ are defined in the corresponding subimages of the respective frames containing all the unreplaced elements which belong to the object.







Let (i_{1x}, i_{2x}) and (j_{1x}, j_{2x}) be the first and the last rows and columns of the unreplaced elements in the corresponding subimages of I_1 and I_2 , and x be the index number of the given frame. Then local windows are of the form $W_1(i, j) =$ $\{(i_{11}, i_{21}), (j_{11}, j_{21})\}$ and $W_2(i, j) = \{(i_{12}, i_{22}), (j_{12}, j_{22})\}$. These local windows give the locations of the moving object in the respective frames without any boundary analysis. However, if needed, the boundary information can easily be obtained from these windows.

Motion tracing stage. The local windows extracted in the previous stage are used for tracing the trajectory of the moving object. For this, the centers of the windows are computed as $\langle i \rangle = [i_2 - i_1]/2$ and $\langle j \rangle = [j_2 - j_1]/2$. These center points are ploted and pairwise joined using sraight lines to obtain the path of motion (Fig. 2).





RESULTS

The approach discussed above has been applied to several complex outdoor images acquired via VICOM imaging system.Images taken by the camera are digitized into 512x512 grid size with 0 to 256 gray-levels and stored into the host computer (VAX-11/750) for further processing (Fig. 3) presents the processing results of an image sequence showing a car moving out of its parked position. Motion of this car is correctly traced by the method. Images with multiple objects have also been studied. An attempt has been made to test the method for the cases where the camera is not stationary, and the background and/or the foreground is also changing. For such cases the proposed alogrithm should be modified by defining a pseudo referDetection, location and trajectory tracing of moving targets



Fig. 3. Sequence of images with a moving car and local windows containing object in each image.

ence point in the image. New techniques are needed to filter the effects of camera motion.

CONCLUSION

In this paper, we have presented a new time efficient technique to process a sequence of time-varying images to find the trajectory of a moving object. This method elminates the lengthy and difficult process of boundary analysis. Rather, it describes the motion in a compact form using the local windows. Another advantage of the discussed approach is that the data is reduced after every iteration without any loss or distortion of information about the object or its motion. While dealing with fast and slow motion, this method has overcome the difficulties due to the difference between their nature. A time domain filtering technique is needed to remove any noise present in the images.

tion of DDM the conversion comes down from 95 % to 10.6 %. In Fig. 2, curves of percentage conversion against time show that DDM lowers the polymerization rate without an inhibition period (Table 2). The lowering down of rate of polymerization is due to conversion of DDM into disulfide. It roacts with chain radicals (which are produced by reacting vinyl scetate and benzoyl peroxide) and yield propagating radicals of lower reactivity. These less efficient propagating radicals of now trap or stop the kinetic clustin but results in decrease in the rate of polymerization. The sonversion of DDM into disulfide might be due to oxygen

REFERENCES

- J.W. Roach and J.K. Aggarwal, IEEE Trans. on PAMI, 1(2), 127 (1979).
- 2. W. Thompson, IEEE Trans. on PAMI, 2(6), 543 (1980).
- J.W. Roach and J.K. Aggarwal, IEEE Trans. on PAMI, 2(6), 555 (1980).
- 4. Y. Mosahiko et al., IEEE Trans. on PAMI, 3(1), 12 (1981).
- 5. R.J. Schalkoff, Pattern Recognition, 20(2), 189 (1987).
- 6. J.K. Tsotsoc et al., IEEE Trans. on PAMI, 2(6), 563 (1980).
- 7. I.L. Ayala et al., IEEE Trans. on PAMI, 4(5), 515 (1982).

it is a good transfer agent for styrens monomer [8-9]. Thi paper deals with the benzoyl peroxides catalyzed poly merivation of vinyl acetate in the presence of dodecy mercapten using ethyl acetate as a diluent at 100°.

EXPERIMENTAL

Marerial Viayi acetate (E.Metok) was purified by distilling at 73°. Ethyl acetate and questing were distilled hefore use Dodecyl mercaptan (*n*-dodecanethiol) obtained from E.Metok ivas used as such. Benzoyi peroxide A it arade was recrystallised twice in chloroform.