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Efficiency Measurement of Various Denoise Techniques for Moving Object Detection Using Aerial Images

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***Abstract*— Noise reduction from aerial images is considered an image restoration mechanism in which it attempts to recover image from a degraded image. Denoising image is considered as the key factor for minimizing the functionality for piecewise smooth image intensity. Efficiency of various denoising techniques depends on frame rate and finally computation time for overall object detection mechanism. Moving object detection is the first step of image denoising as well as object detection. This technique uses segmentation, motion detection and feature extraction technique. The main goal of this paper is to compare various noise reduction techniques incorporated with various moving object detection methods along with various features like edges and corners based detection. Experimentation was done based on two parameters frame rate and computation time which initiate to choose the best denoising method for moving object detection.**

Keywords—Motion; Moving object; Computer vision

I. Introduction

With the development of technology, moving object detection from aerial images has played a vital role in modern wars and industries. In contrast to applications, such as traffic monitoring and building surveillance, aerial surveillance has the advantages of higher mobility and larger surveillance scope. Meanwhile, more challenges are involved in aerial image, such as changing background and low resolution. Therefore, much attention has been paid to moving object detection in aerial image.

The process of noise removal from aerial image is called Image Denoising, where noise reduction in image can be done through the image individually and between the frames collected from videos. Noise reduction from video sequence is used widely in traffic management, medical imaging and TV broadcasting applications. This technique uses segmentation of moving objects from stationary background objects [1]. This is focused on higher level processing and decreases computation time. This paper provides a detailed state of the art of different image denoising techniques. Overall image denoising is done for moving objects through motion detection, segmentation and feature extraction incorporated with various filtering approach. This paper is organized as follows. Section II describes previous research works, section III demonstrates research methodology, section IV depicts experimental results, analysis and finally, section V states conclusion.

II. BACKGROUND STUDY

High computation time is a fundamental problem for moving object detection in terms with frame rate in computer vision. There are several steps involves in moving object detection like frame difference, background subtraction, segmentation, feature extraction etc. Because of overall complicated methodology, computation time increases due to low level image processing. Moving object detection from image like aerial type which contains noises, requires more computation time demands for investigation on various types of denoising techniques.

Motion poses an important cue for object detection and recognition. While a number of techniques first estimate the motion field and segment objects later in a second phase [2], an approach of both computing motion as well as segmenting objects at the same time is much more appealing. First advances in this direction were investigated in [3] [4] [5] [6] [7] [8]. The idea of combining different image processing tasks into a single model in order to cope with interdependencies has drawn attention in several different fields. Recently, highly accurate motion detection [9] has been extended to contour based segmentation [10] following a well known segmentation scheme [11]. The authors demonstrated that extending the motion detection to edge detection in a variational framework leads to an increase in accuracy but still unable to reduce computation time. However, as opposed to proposed research methodology in this paper, the authors did not include image denoising in their framework. Including a denoising functional together with motion detection in a

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variational framework has been achieved by [12]. They reported significant increases in terms with the accuracy of motion detection, particularly with respect to noisy image sequences. In their approach, edges are not detected but errors of smoothing over discontinuities are lessened by formulating the smoothness constraint in a L1 metric.

This research investigates various denoising techniques for moving object detection which combines motion detection, image denoising, and various edge and corner detection in the same variational framework. Proposed investigation will enable to choose best denoising techniques for overall detection procedure.

III. RESEARCH METHODOLOGY

This research performed four types of denoising techniques to choose the best filtering approach i.e. Mean, Median, Adaptive and Bilateral filter shown in Fig. 1.

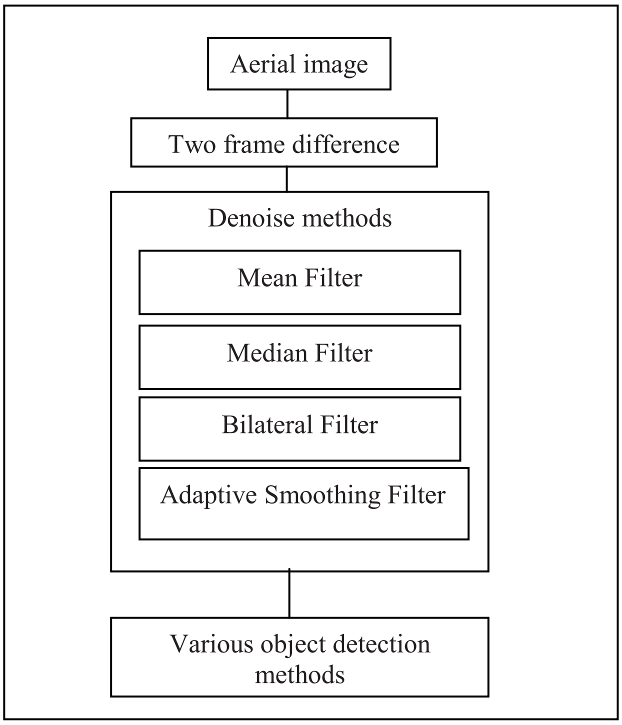

Fig. 1. Framework using four types of denoising techniques

Mean filtering is a simple, intuitive and easy to implement method of *smoothing images*, *i.e.* reducing the amount of intensity variation between one pixel and the next. It is often used to reduce noise in images. The idea of mean filtering is simply to replace each pixel value in an image with the mean (average) value of its neighbors, including itself. This has the effect of eliminating pixel values which are unrepresentative of their surroundings. There are two main problems with mean filtering, which are:

1. A single pixel with a very unrepresentative value can significantly affect the mean value of all pixels in its neighborhood.
2. When the filter neighborhood straddles an edge, the filter will interpolate new values for pixels on the edge and so will blur that edge. This may be a problem if sharp edges are required in the output.

Both of these problems are tackled by the median filter. The median filter is normally used to reduce noise in an image, somewhat like the mean filter. However, it often does a better job than the mean filter of preserving useful detail in the image. Each pixel of the original source image is replaced with the median of neighboring pixel values. The median is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value. Median filter is very effective in removing salt and pepper or impulsive noise while preserving image detail.

Adaptive smoothing filter is aimed to perform image smoothing, but keeping sharp edges. This makes it applicable to additive noise removal and smoothing objects' interiors, but not applicable for spikes (salt and pepper noise) removal.

Bilateral filter conducts "selective" Gaussian smoothing of areas of same color (domains) which removes noise and contrast artifacts while preserving sharp edges. Two major parameters Spatial Factor and Color Factor define the result of the filter. By changing these parameters noise reduction can be achieved with little change to the image or get nice looking effect to the entire image. Although the filter can use parallel processing, large Kernel Size values (greater than 25) on high resolution images may decrease speed of processing. Also on high resolution images small Kernel Size values (less than 9) may not provide noticeable results. Bilateral filtering can be decomposed into a number of constant time spatial filters [13]. The main advantages are higher PSNR, faster because of parallel implementation, and small memory footprint that is two percentages.

Let $I_1(x,y,t)$ and $I_2(x,y,t-1)$ are the two consecutive frames in t and $t-1$ time. Frame difference $I_f(x,y,t)$ from these two frames is defined by Eq. (1).

$$I_f(x,y,t) = round\left(I_2(x,y,t) - I_1(x,y,t-1)\right); \qquad (1)$$

$I_f(x,y,t)$ is experimented with four kind of filter which are mean filter, adaptive smoothing filter bilateral filter and median filter shown in Fig. 2, Fig. 3 , Fig. 4 and Fig. 5 respectively.

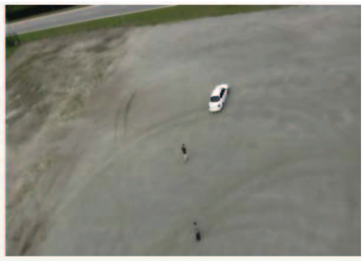

Fig. 2. Mean filter $I_f(x,y,t)$

Fig. 3. Adaptive smoothing filter $I_f(x,y,t)$

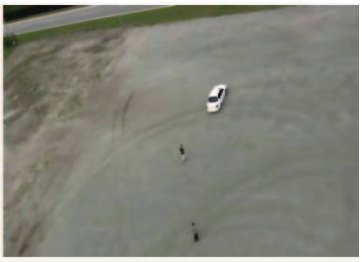

Fig. 3. Bilateral filter from $I_f(x,y,t)$

Fig. 5. Median filter from $I_f(x,y,t)$

Let $I_d(x,y,t)$ be the resultant denoised frame achieved from each of the denoise operation. Then $I_d(x,y,t)$ is through motion detection based moving object detection method. After moment based pixel intensity measurement is done, threshold set to 90.If threshold value decrease edge increase and if the threshold increases edge will decrease. Based on the same threshold, object $O(m,n)$ is achieved using different edge detector method.

$$Object(m,n) = P_{storge}(m,n);$$
$$if\,(P_{storge}(i,j) \quad P_{storge}(i \quad 1, j \quad 1)) > Threshold$$

Where for all pixels N of $s|P(m,n)|$ are stored in $P_{storage}(m,n)$.

Then, $I_d(x,y,t)$ is used for another segmentation method where edge difference is used for extraction of moving objects. After that, $I_d(x,y,t)$ is used for a new method where motion detection and edge difference based segmentation was done. Let M_T denotes total moment, F_T denotes total number of features, and W and H denotes width and height of $I_d(x,y,t)$, respectively. Based on motion detection and edge difference based segmentation method, moment weighting factor is defined by Eq. (2).

$$MWF = Math\log(M_T * F_T * W * H) \qquad (2)$$

Later, this research used $I_d(x,y,t)$ for edge based detection using Sobel, Prewitt, Canny edge and corner based detection using Moravec, Susan and Harris corner. For Sobel, Prewitt and Canny edge based detection Difference Edge Detector method is used for segmentation purpose while for each edge based detection threshold is set to 40. However, for Moravec, Susan and Harris corner based detection, this research used Difference Edge detection method while for Moravec and Harris threshold 40, for Susan threshold is set to 60.

IV. EXPERIMENTAL ANALYSIS AND DISCUSSION

This paper states performance measurement based on 1 frame per second and 3 frame per second. Experimentation was performed for various edges based detection like Sobel, Prewitt, Canny , corner based detection like Moravec , Susan and Harris corner, motion detection based method, edge difference based segmentation method and motion and edge difference based integrated method. Video dataset Actions1.mpg was collected from Center for Research in Computer Vision (CRCV) from University of Central Florida which was recorded using R/C controlled blimp equipped with HD camera and represents a diverse pool of action features at different aerial view points. From the dataset Actions1.mpg, frame 17 was taken for the experiment to evaluate various denoise effect for various moving object detection methods.

For 1 fps, computation time for edge based detection shown in TABLE I. Median filter shows the lowest computation time 53 ms for Prewitt edge detection while for Sobel uses 203 ms and Canny uses 95 ms. For corner based detection in TABLE II, almost all the filtering approach used short time like median filter. For Motion, Edge Difference and both of these methods using 1 fps are shown in TABLE III. Median filter uses the shortest computation time where Motion based detection uses 125 ms; Edge Difference based segmentation uses 211 ms and finally, Motion integrated with Edge difference based detection uses 97 ms.

TABLE I. Computation Time among various edge based detection

Denoising techniques	SOBEL	REWITT	CANNY
Mean Filter	907 ms	906 ms	89 ms
Median Filter	203 ms	53 ms	95 ms
Adaptive Smoothing Filter	550 ms	539 ms	103 ms
Bilateral Filter	871 ms	858 ms	86 ms

TABLE II. Computation Time among various corner based detection

Denoising techniques	MORAVEC	SUSAN	HARRIS
Mean Filter	126 ms	59 ms	121 ms
Median Filter	143 ms	56 ms	143 ms
Adaptive Smoothing Filter	122 ms	59 ms	117 ms
Bilateral Filter	137 ms	50 ms	135 ms

TABLE III. Computation Time among Motion based detection, Edge difference segmentation based detection and Motion + Edge difference segmentation based detection

Denoising techniques	Motion based detection	Edge Difference segmentation based detection	Motion + Edge Difference segmentation based detection
Mean Filter	86 ms	673 ms	467 ms
Median Filter	125 ms	211 ms	97 ms
Adaptive Smoothing Filter	147 ms	489 ms	488 ms
Bilateral Filter	105 ms	188 ms	84 ms

For 3 fps, computation time for edge based detection shown in TABLE IV. Median filter shows the lowest computation time 22 ms for Prewitt edge detection while for Sobel uses 38 ms and Canny uses 124 ms. For corner based detection shown in TABLE V, almost all the filtering approach used short time like median filter. However, computation time for Motion based, Edge Difference segmentation based and for both of these methods using 3 fps are shown TABLE VI. Median filter uses the least computation time where Motion based detection uses 128 ms, Edge Difference segmentation based detection uses 610 ms and finally, Motion and Edge difference based segmentation detection uses 98 ms.

TABLE IV. Computation Time among various edge based detection

Denoising techniques	SOBEL	PREWITT	CANNY
Mean Filter	540 ms	529 ms	88 ms
Median Filter	38 ms	22 ms	124 ms
Adaptive Smoothing Filter	558 ms	532 ms	84 ms
Bilateral Filter	554 ms	506 ms	87 ms

TABLE V. Computation Time among various corner based detection

Denoising techniques	MORAVEC	SUSAN	HARRIS
Mean Filter	121 ms	59 ms	130 ms
Median Filter	129 ms	61 ms	198 ms
Adaptive Smoothing Filter	137 ms	60 ms	116 ms
Bilateral Filter	132 ms	62 ms	120 ms

TABLE VI. Computation Time among Motion based detection, Edge difference segmentation based detection and Motion + Edge difference segmentation based detection

Denoising techniques	Motion based detection	Edge Difference segmentation based detection	Motion + Edge Difference based detection
Mean Filter	87 ms	560 ms	636 ms
Median Filter	128 ms	610 ms	98 ms
Adaptive Smoothing Filter	127 ms	553 ms	499 ms
Bilateral Filter	364 ms	743 ms	310 ms

V. CONCLUSION

This research demonstrated extensive experiments for best denoise technique selection for moving object detection using aerial images. Performed experiments are based on Motion detection based method, Edge Difference based segmentation method, Motion and Edge Difference based segmentation method, various edge and corner detection based methods. Based on the experimental results, medial filter required least computation time comparing with other filtering techniques. However, mean, adaptive smoothing filter and bilateral filter are not capable of holding of sharp edge from image like aerial image. In the meantime median filter is the best choice for preserving sharp edges for optimum detection performance. Based on comprehensive review on investigation results, this research states that median is the most preferred denoising technique to use for overall detection performance.

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