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ARTICLE

PERFORMANCE ANALYSIS OF FOREGROUND-ADAPTIVE BACKGROUND SUBTRACTION IN GRAYSCALE VIDEO SEQUENCES

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ABSTRACT

The paper proposes efficient motion detection and people counting based on background subtraction using dynamic threshold approach with mathematical morphology. Here these different methods are used effectively for object detection and compare these performance based on accurate detection. Here the techniques frame differences, dynamic threshold based detection will be used. After the object foreground detection, the parameters like speed, velocity motion will be determined. For this, most of previous methods depend on the assumption that the background is static over short time periods. In dynamic threshold based object detection, morphological process and filtering also used effectively for unwanted pixel removal from the background. The background frame will be updated by comparing the current frame intensities with reference frame. Along with this dynamic threshold, mathematical morphology also used which has an ability of greatly attenuating color variations generated by background motions while still highlighting moving objects. Finally the simulated results will be shown that used approximate median with mathematical morphology approach is effective rather than prior background subtraction methods in dynamic texture scenes and performance parameters of moving object such sensitivity, speed and velocity will be evaluated.

KEY WORDS
Fuzzy Color Histogram (FCH), Conventional Color Histogram (CCH), Peak Signal to Noise Ratio(PSNR), Root Mean Square Error(RMSE).

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INTRODUCTION

There are immediate needs for automated surveillance systems in commercial, law enforcement and military applications. Mounting video cameras is cheap, but finding available human resources to observe the output is expensive. Although surveillance cameras are already prevalent in banks, stores, and parking lots, video data currently is used only "after the fact" as a forensic tool, thus losing its primary benefit as an active, real-time medium. What is needed is continuous 24-hour monitoring of surveillance video to alert security officers to a burglary in progress, or to a suspicious individual loitering in the parking lot, while there is still time to prevent the crime. In addition to the obvious security applications, video surveillance technology has been proposed to measure traffic flow, detect accidents on highways, monitor pedestrian congestion in public spaces, compile consumer demographics in shopping malls and amusement parks, log routine maintenance tasks at nuclear facilities, and count endangered species. The numerous military applications include patrolling national borders, measuring the flow of refugees in troubled areas, monitoring peace treaties, and providing secure perimeters around bases and embassies [1-4].

In 1997, the Defense Advanced Research Projects Agency (DARPA) Information Systems Office began a three-year program to develop Video Surveillance and Monitoring (VSAM) technology. The objective of the VSAM project was to develop automated video understanding technology for use in future urban and battlefield surveillance applications. Technology advances developed under this project enable a single human operator to monitor actives over a broad area using a distributed network of active video sensors [5-7]. The sensor platforms are mainly autonomous, notifying the operator only of salient information as it occurs, and engaging the operator minimally to alter platform operations. A team composed of Carnegie Mellon University Robotics Institute and the Sarnoff Corporation were chosen to lead the technical efforts by developing an end-to-end test bed system demonstrating a wide range of advanced surveillance techniques: real-time moving object detection and tracking from stationary and moving camera platforms, recognition of generic object classes (e.g. human, sedan, truck) and specific object types (e.g. campus police car, FedEx van), object pose estimation with respect to a geospatial site model, active camera control and multi-camera cooperative tracking, human gait analysis, recognition of simple multi-agent activities, real-time data dissemination, data logging and dynamic scene visualization. Twelve other research contracts were awarded to university and industry labs to conduct research in focused technical areas that include human activity recognition, vehicle tracking and counting, airborne surveillance, novel sensor design, and geometric methods for graphical view transfer [8-12].

There are very few studies regarding the wearing and laundering of lab coats in hospitals and medical practice. This study highlights the role of lab coats acting as vector for transmitting health care infections to the patients and the common areas where contamination occurs.

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MATERIALS AND METHODS

Methodology

Proposed System

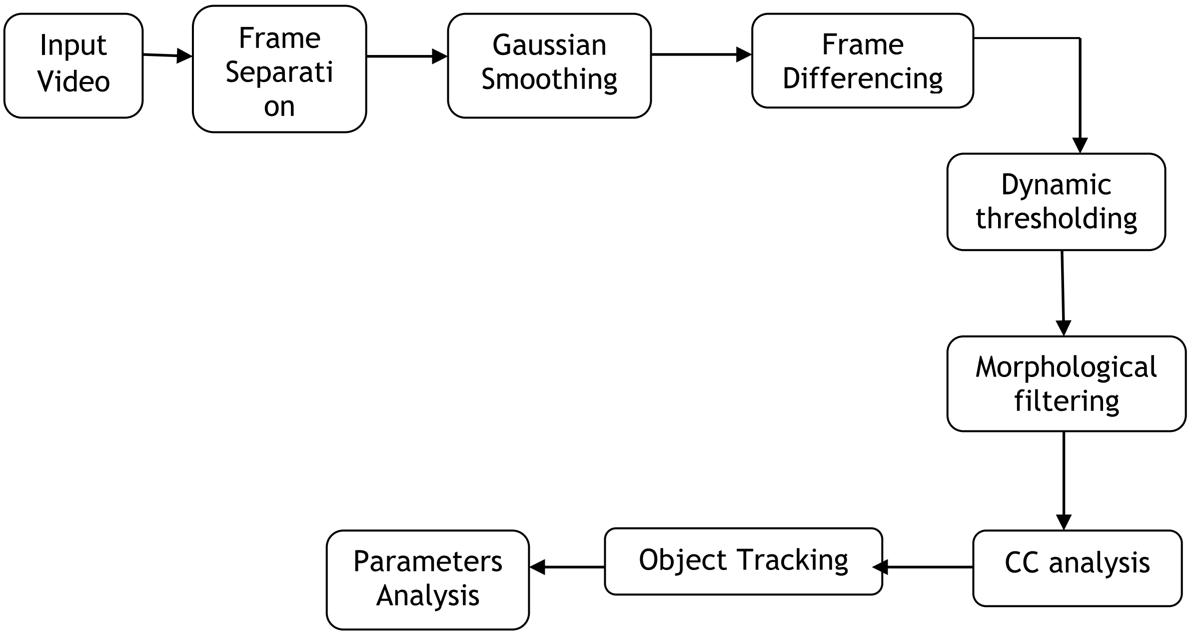

Fig.1: Block Diagram of Entire System

The paper proposes an effective scheme in order to enhance the detection of moving object and their respective tracking. There are various previous methods involved in object detection using background subtraction. The most important phase where they lag is about background motion and shadow elimination. Inspite of these, the system provides better detection and uses simple methodologies. Here the input video is fed to the system. The first process is to separate each frame of the video say for example, A video of 60 frames is converted to a series of 60 images of format .bmp and are stored in a folder. This is done by the Frame separation block. The next step involved in the process is to shape up the frames for further processing which is done by the Gaussian smoothing block. The sizes of the image are corrected to the dimensions that suit right for the process and sent to the Frame differencing block. Here the first image of the video or a series of images are considered to be the background model and each image in the sequence is subtracted from it as a loop of operation. For every loop of subtraction the background model is updated which helps in categorizing the motion involving the shadows and that of the real backgrounds. The next block in the process is the dynamic thresholding. It sets up a threshold value for intensity of the pixels and the size of object. The objects detected are compared with the given thresholds and the objects that do not match the criteria are eliminated from the output. Thus the required foreground is detected in this block. Morphological filtering is the block which involves the addition or removal of pixels in the fore ground detection which would later help in object counts.The CC analysis block compares the object detected with the ground truth (A rough sketch of object to be detected) and helps in measurement of parameters such as sensitivity, Correlation coefficient etc., Then the object tracking block shows the position of detected object in each frame in the video and thus provides an output of effective detection and tracking of object under changing illumination in background and background motions shown in [Fig. 1].

Frame Separation

An Input Video (.avi files) is converted into still images for processing it and to detect the moving objects. These sequences of images gathered from video files by finding the information about it through 'aviinfo' command. These frames are converted into images with help of the command 'frame2im'. Create the name to each images and this process will be continued for all the video frames. The following diagram represents the process flow of this separation shown in [Fig. 2].

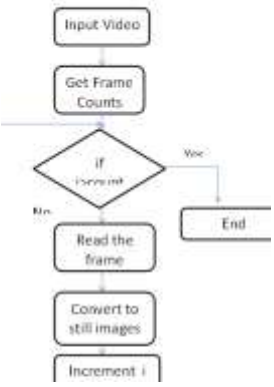

Fig.2: Process flow of Frame separation

Aussian Smoothing

Smoothing of the images can be used to reduce camera noise and remove transient environmental noise such as rain. Many algorithms use a Gaussian blur first to average out fluctuating pixel values to alleviate big differences.Alternatively, when temporal data can be exploited in a video, if a pixel's value is constantly changing over time then it can be assumed it is part of a non-static background object.

Frame Differencing

The moving object will be detected by frame subtraction. The frame subtraction is done by subtracting current frame and previous frame for detecting object from background. Then the background will be updated by comparing the process frame and background frame. This will be continued for all consecutive frames.

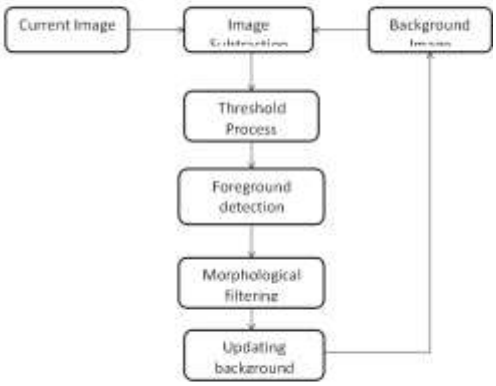

Fig. 3: Process flow of Frame subtraction, threshold process, morphological filtering and background update

Subtraction and Update of the background model

After initialization, temporally subsequent samples are fed to the network. Each incoming pixel P_t of the sequence Frame I_t is compared to the current pixel model C to determine if there exists a weight vector that best matches it. If a best matching weight vector C_m is found, it means that P_t belongs to the background and it is used as the pixel encoding approximation, and the best matching weight vector, together with its neighborhood, is reinforced. Otherwise, if no acceptable matching weight vector exists, we discriminate whether P_t is in the shadow cast by some object or not. In the first case, P_t should be still considered as background, but it should not be used to update the corresponding weight vectors, in order to avoid the reinforcement of shadow information into the background model; in the latter case P_t is detected as belonging to a moving object (foreground) shown in [Fig. 3].

Dynamic Thresholding

The moving object extraction from subtracted frames is done by dynamic thresholding method for foreground detection. The threshold value is set default as an approximate median of objects to be

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detected. The current image output is converted into gray scale and cut to desired sizes by the order of rows and columns. Now the difference image obtained is compared with the threshold value given in order to obtain the foreground detection. Each row and column pixel values are related to the assumed threshold and thus the extraction of objects whose pixel values exceed the threshold only are done. The other pixels are eliminated from the outcome.

Morphological Filtering

Morphological techniques probe an image with a small shape or template called a **structuring element**. The structuring element is positioned at all possible locations in the image and it is compared with the corresponding neighbourhood of pixels. Some operations test whether the element "fits" within the neighbourhood, while others test whether it "hits" or intersects the neighbourhood:

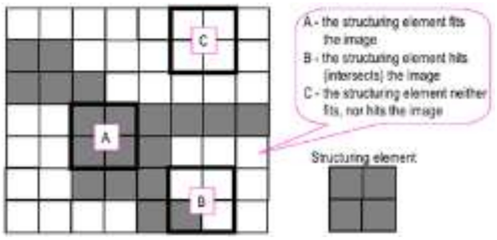


Fig. 4: Probing of an image with a structuring element.

A morphological operation on a binary image creates a new binary image in which the pixel has a non-zero value only if the test is successful at that location in the input image. The structuring element is a small binary image, i.e. a small matrix of pixels, each with a value of zero or one: The matrix dimensions specify the size of the structuring element. The pattern of ones and zeros specifies the shape of the structuring element. An origin of the structuring element is usually one of its pixels, although generally the origin can be outside the structuring element shown in [Fig. 4].

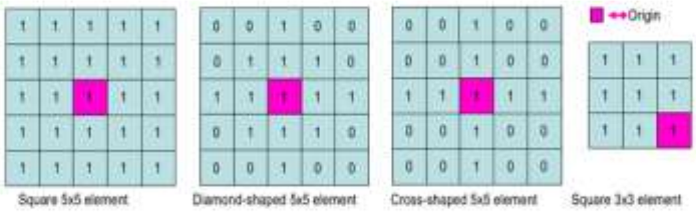
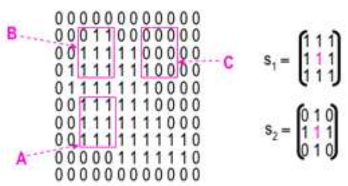


Fig. 5: Examples of simple structuring elements.

A common practice is to have odd dimensions of the structuring matrix and the origin defined as the centre of the matrix. Structuring elements play in morphological image processing the same role as convolution kernels in linear image filtering shown in fig 5.When a structuring element is placed in a binary image, each of its pixels is associated with the corresponding pixel of the neighbourhood under the structuring element. The structuring element is said to fit the image if, for each of its pixels set to 1, the corresponding image pixel is also 1. Similarly, a structuring element is said to hit, or intersect, an image if, at least for one of its pixels set to 1 the corresponding image pixel is also 1. Zero-valued pixels of the structuring element are ignored, i.e. indicate points where the corresponding image value is irrelevant shown in [Fig. 6].



		A	B	C
fit	s_1	yes	no	no
	s_2	yes	yes	no
hit	s_1	yes	yes	yes
	s_2	yes	yes	no

Fig. 6: Fitting and hitting of binary image with structuring elements s_1 and s_2.

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Parameters Evaluation

Velocity

The velocity of object is evaluated based on distance travelled by an object and frame rate

Velocity = Distance travelled / Frame rate (1)

Sensitivity

It measures the proportion of actual positives which are correctly identified in the detection process.

Sensitivity = Tp./(Tp + Fn) (2)

Where, Tp = True Positive: Object pixels correctly classified as object

Fn = False negative: Object pixels incorrectly classified as background.

RESULTS

Input Video

The input video is fed to the system and it is simulated through the matlab software. Here a graphical user interface panel is used in order to display the operations of blocks. The snapshot of the simulated result is shown [Fig. 7].

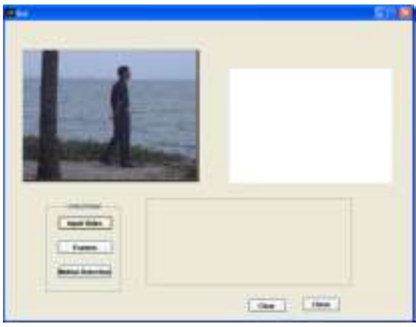

Fig.7: Input video

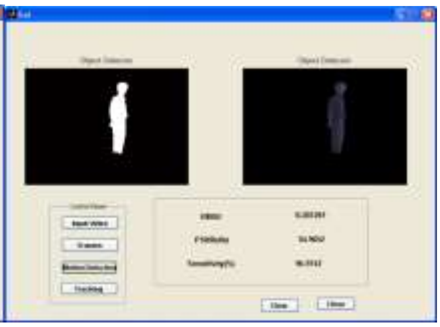

Fig.8: Object detection

Object Detection

The conversion of original frames to grayscale and the detection of the position of moving object in each frame is shown in the snapshot of simulated results. The values of Peak Signal to Noise Ratio (PSNR), Root Mean Square Error(RMSE), Sensitivity of detection are calculated and displayed in the [Fig. 8].

Object Tracking

The tracking of the moving object and the parameters of it such as speed, velocity and object count are determined and displayed in the [Fig.9]. The GUI panel helps in working the module easier. The parameters calculated are helpful in better comparative analysis of the proposed system with the other previously existing systems.

Fig.9: Object tracking

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CONCLUSION

The paper presented an efficient motion detection based on background subtraction using frame difference with thresholding and mathematical morphology. It will be enhanced with futures of connected component analysis and morphological filtering for tracking and counting moving objects. After the foreground detection, the parameters like Count, velocity of the motion was estimated and performance of object detection will be measured with sensitivity and correlation using ground truth. Finally the proposed method will be proved that effective for background subtraction in static and dynamic texture scenes compared to prior methods.The system can be programmed in integrated chip and can be inhibited into the camera itself, so that real time detection can be achieved. The threshold value which has been calculated manually in the process based on the approximate median of the object intensity can be automated in future for higher efficiency. More effective threshold techniques can be implemented for low quality videos which would help satellite surveillance applications.

CONFLICT OF INTEREST

There is no conflict of interest.

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None.

FINANCIAL DISCLOSURE

None.

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