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Development of a Novel Algorithm for Moving Object Tracking in Video Surveillance

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Abstract*: Video surveillance is a process of analyzing video sequences. It involves analysis, interpretation of object behaviors, as well as object detection and tracking. Video processing plays an important role in the industry and computer vision such as online monitoring of assembly processes, video surveillance security system, medical treatment, robot navigation and military, etc. Detection and tracking of human objects is one of the important studies in improving the ability of the surveillance system. The aim of this research work is to measure and analyze the application of background subtraction method and block matching algorithm to trace object movements through video-based. This research applies background subtraction method to detect moving object, assisted with block matching algorithm which aims to get good results on objects that have been detected. Performance evaluation is carried out to determine the various parameters. In this paper author design and develop a novel algorithm for moving object tracking in video surveillance also compares and analyse existing algorithms for moving object tracking. Author main aim to design and develop an algorithm for moving object tracking to handle occlusion and complex object shapes.

***Keywords* : Moving Object Detection; Background Subtraction, Kalman Filter, Video Surveillance.**

I. INTRODUCTION

Monitoring system is a system which is extensively applied to perform monitoring functions periodically to obtain the desired information, particularly for moving objects. Results of the system have significant role in improving various aspects that is identification, information, security, level of productivity, and performance. The example of monitoring system is the motion object detection application. Object occlusion is widespread in video surveillance due to the influence of angle and environment, which brings a great impact on the target tracking and makes the development of video object tracking encountered meeting many constraints. The challenge in video object tracking is how to track accurately when the target is obscured [1]. Detection of moving objects is an object detector which defines or extracts information from objects in a frame sequence.

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Detection of human objects both indoors and outdoors is the sample of object detection applications Detection of human objects is a significant aim of the research in order to improve the ability of the surveillance system in public spaces. In general, the mechanism of detecting human objects adapts the observing method in the real world through the human sight, starting from learning frame sequences and videos to obtain results those humans can do [2]. Besides, detection of human objects attempts to imitate the workings of human visual system which is currently known as computer vision technology. Several studies have been performed in order to apply techniques or methods to detect human objects. One of method is background subtraction for moving detection in a static environment. In this study, researchers perform the application of background subtraction methods to detect human objects in video files. Object detection has some basic formation; object detection is made from modeling the background and foreground. This modeling aims to distinguish pixels which will be the foreground-background. In the foreground-background modeling algorithm, the subtraction method or the difference of input frame is performed through background to obtain the foreground or moving objects [3]. In previous studies, the mathematical modeling of object detection has been divided into four principal quantities, using statistical methods to separate the background and foreground, examining for vectors representing the background and foreground, introducing the foreground (objects) with template matching, and applying the initiation of foreground features which based on uniqueness resulting from the transformation of frequency domain. In this paper the kalman filter will be applied to carry the performance improvements out in object tracking [4].

A. *Background*

Irene's research in performed a combination of Mean-shift and Kalman filters. This combination is assembled to obtain the power of the two algorithms aiming the mean-shift to perform tracking when there are no objects blocking the movement. When occlusion occurs, kalman filter is applied as a combination tracking. In another study, Pouya in proposed a Kalman filter method for tracking parts of the human body, by predicting the position and limbs. This method successfully identifies by various poses and conditions obstructed by objects. Dali Shu conducted a finger print data collection process with Kalman filter method to reduce noise, up and down signal and 2D signal mapping for fingerprints. The application of Kalman filter method, it results in the form of speed in the Gaussian weight, speed and track the target more accurately.

B. *Objectives*

- To design and develop a novel algorithm for moving object tracking in video surveillance.
-To compare and analyse existing algorithms for moving object tracking.
- To design and develop an algorithm for moving object tracking for complex object shapes.
- To design and develop an algorithm for moving objects tracking for occlusion handling in video surveillance.
- To compare and analyse various algorithms for performance measures with real time information.

II. REVIEW OF LITERATURE

Alexander Filonenko et al. [7] Smoke detection is a key component of disaster and accident detection. Despite the wide variety of smoke detection methods and sensors that have been proposed, none has been able to maintain a high frame rate while improving detection performance. In this paper, a smoke detection method for surveillance cameras is presented that relies on shape features of smoke regions as well as color information. The method takes advantage of the use of a stationary camera by using a background subtraction method to detect changes in the scene. The color of the smoke is used to assess the probability that pixels in the scene belong to a smoke region. Due to the variable density of the smoke, not all pixels of the actual smoke area appear in the foreground mask. These separate pixels are united by morphological operations and connected-component labeling methods. The existence of a smoke region is confirmed by analyzing the roughness of its boundary. The final step of the algorithm is to check the density of edge pixels within a region. Comparison of objects in the current and previous frames is conducted to distinguish fluid smoke regions from rigid moving objects. Some parts of the algorithm were boosted by means of parallel processing using CUDA GPUs, thereby enabling fast processing of both low-resolution and high-definition videos. The algorithm was tested on multiple video sequences and demonstrated appropriate processing time for a realistic range of frame sizes.

Santhoshkumar Sunderrajan et al. [8] tracking and re-identification in wide-area camera networks is a challenging problem due to non-overlapping visual fields, varying imaging conditions, and appearance changes. We consider the problem of person re-identification and tracking, and propose a novel clothing context-aware color extraction method that is robust to such changes. Annotated samples are used to learn color drift patterns in a non-parametric manner using the random forest distance (RFD) function. The color drift patterns are automatically transferred to associate objects across different views using a unified graph matching framework. A hyper graph representation is used to link related objects for search and re-identification. A diverse hyper graph *ranking* technique is proposed for person-focused network summarization. The proposed algorithm is validated on a wide-area camera network consisting of ten cameras on bike paths. Also, the proposed algorithm is compared with the state of the art person re-identification algorithms on the VIPeR dataset.

Liu Gang et al. [12] Moving target detection is an important part of video target tracking. Good moving target detection makes video track more effective. This paper proposes a new algorithm based on the traditional three-frame differential method comparison. The shortage of traditional three-frame differential method is pointed out. Combined with Canny edge detection algorithm, the improved three frame differential algorithm makes moving target detected containing more complete information. This new algorithm takes advantage of good performances of three-frame difference method and background subtraction method adequately. The proposed method is simple and experimental results show that it can accurately detect moving targets.

Jinhai Xiang et al. [14] moving object detection is a fundamental step in video surveillance system. To eliminate the influence of illumination change and shadow associated with the moving objects, we proposed a local intensity ratio model (LIRM) which is robust to illumination change. Based on the analysis of the illumination and shadow model, we discussed the distribution of local intensity ratio. And the moving objects are segmented without shadow using normalized local intensity ratio via Gaussian mixture model (GMM). Then erosion is used to get the moving objects contours and erase the scatter shadow patches and noises. After that, we get the enhanced moving objects contours by a new contour enhancement method, in which foreground ratio and spatial relation are considered. At last, a new method is used to fill foreground with holes. Experimental results demonstrate that the proposed approach can get moving objects without cast shadow and shows excellent performance under various illumination change conditions.

Erik Cuevas et al. [14] Block matching (BM) motion estimation plays a really vital role in video secret writing. in a very BM approach, image frames in a video sequence area unit divided into blocks. for every block within the current frame, the simplest matching block is known within a region of the previous frame, planning to minimize the total of absolute variations (SAD). sadly, the SAD evaluation is computationally high-ticket and represents the foremost intense operation within the BM method. Therefore, BM motion estimation may be approached as AN improvement downside, wherever the goal is to search out the simplest matching block among a search area. the only offered BM methodology is that the full search algorithmic program (FSA) that finds the foremost correct motion vector through AN thoroughgoing computation of unhappy values for all parts of the search window.

Yi Yao et al. [17] Demonstrated applications of video tracking to radiation detection, where a vision-based tracking system enables a traditional CZT (cadmium zinc telluride)-based radiation imaging device to detect radioactive targets that are in motion. An integrated real-time system consisting of multiple fixed cameras and radiation detectors was implemented and tested.
The multi-camera tracking system combines multiple feature cues (such as silhouette, appearance, and geometry) from different viewing angles to ensure consistent target identities under challenging tracking conditions.

Experimental results show that both the video tracking and the integrated systems perform accurately and persistently under various scenarios involving multiple vehicles, driving speeds, and driving patterns. The results also validate and reiterate the importance of video tracking as an enabling technology in the field of radiation imaging.

Yan Luo et al. [18] A significant body of literature on saliency modeling predicts where humans look in a single image or video. Besides the scientific goal of understanding how information is fused from multiple visual sources to identify regions of interest in a holistic manner, there are tremendous engineering applications of multi-camera saliency due to the widespread of cameras. This paper proposes a principled framework to smoothly integrate visual information from multiple views to a global scene map, and to employ a saliency algorithm incorporating high-level features to identify the most important regions by fusing visual information. The proposed method has the following key distinguishing features compared with its counterparts: (1) the proposed saliency detection is global (salient regions from one local view may not be important in a global context), (2) it does not require special ways for camera deployment or overlapping field of view, and (3) the key saliency algorithm is effective in highlighting interesting object regions though not a single detector is used. Experiments on several data sets confirm the effectiveness of the proposed principled framework.

Sebastian Hommel et al. [18] the architecture of an intelligent surveillance system installed at two reference airports. This architecture is developed to support the human operator and enables a multi-camera tracking of suspicious people in case of an alert. The described architecture is based on a network of non-overlapping cameras, each one connected to a self-developed recording tool which provides acquired images to different image processing modules. An efficient preprocessing makes it possible to analyze the data in real time. The system is able to detect, track and recognize people, but also enables the prediction of where a person will walk to by analyzing possible walking paths.

Murray Evans et al. [19] A number of multi-camera solutions exist for tracking objects of interest in surveillance scenes. Generally, the approach follows the idea of either early fusion (where all cameras are used to make a decision about detection and tracking) or late fusion (where objects are detected and tracked in individual cameras independently, and then the results combined). This paper describes an early fusion approach derived from the common approach of projecting foreground mask into a common coordinate system. The described approach extends prior work to suppress false detections and automatically estimate the size of the object under tracking, thus enabling it to work in environments containing a mix of people and vehicles.

Jiejun Xu et al. [20] Wide-area wireless camera networks are being increasingly deployed in many urban scenarios. The large amount of data generated from these cameras pose significant information processing challenges. In this work, we focus on representation, search and retrieval of moving objects in the scene, with emphasis on local camera node video analysis. We develop a graph model that captures the relationships among objects without the need to identify global trajectories. Specifically, two types of edges are defined in the graph: object edges linking the same object across the whole network and context edges linking different objects within a spatial-temporal proximity. We propose a manifold ranking method with a greedy diversification step to order the relevant items based on similarity as well as diversity within the database. Detailed experimental results using video data from a 10-camera network covering bike paths are presented.

S. Karthikeyan et al. [21] a novel and computationally efficient multi object tracking-by-detection algorithm with interacting particle filters. The proposed online tracking methodology could be scaled to hundreds of objects and could be completely parallelized. For every object, we have a set of two particle filters, i.e. local and global. The local particle filter models the local motion of the object. The global particle filter models the interaction with the other objects and scene. These particle filters are integrated into a unified Interacting Markov Chain Monte Carlo (IMCMC) framework. The local particle filter improves its performance by interacting with the global particle filter while they both are run in parallel. We indicate the manner in which we bring in object interaction and domain specific information into account by using global filters without further increase in complexity. Most importantly, the complexity of the proposed methodology varies linearly in the number of objects. We validated the proposed algorithms on two completely different domains 1) Pedestrian Tracking in urban scenarios 2) Biological cell tracking (Melanosomes). The proposed algorithm is found to yield favorable results compared to the existing algorithms.

Razali Yaakob et al. [22] Different block matching algorithms victimization motion estimation square measure evaluated wherever the results of the macro block size used are going to be reviewed to seek out the simplest formula among them is scrutinized to see the foremost optimum formula.Four completely different block matching algorithms square measure thought of and enforced. every formula is evaluated victimization completely different movies from the TRANS info [11] and comparisons square measure created through the height Signal to Noise magnitude relation (PSNR) and search points per macro block (i.e. computation time) for various sizes of macro blocks and search areas. The results recommend that among all the evaluated algorithms, ARPS has the simplest PSNR supported computation time.

Disha D. Bhavsar et al. [23] Includes algorithmic simulation of three-step search block matching algorithmic program for motion estimation. This methodology relies on the important world video frame sequence's feature of centre-biased motion vector allocation and uses centre-biased checking purpose patterns and alittle range of search locations to perform quick block matching. Many fast block matching algorithmic programs are developed to boost the serious computations of block matching algorithm. These

are supported numerous techniques like mounted search pattern, variable search vary, gradable and multi resolution algorithms, sub-sampling techniques, partial distortion elimination, spatio-temporal correlation etc. Among early block American state algorithms found in literature, mounted search pattern algorithms square measure the foremost famed, these algorithms scale back the machine requirement considerably by checking just some points within the search window, whereas keeping an honest error performance when compared with Full Search algorithmic program.

III. METHODOLOGY AND IMPLEMENTATION

The Proposed algorithm is mainly based on background subtraction and block matching algorithm for tracking. For software requirement MATLAB R2013a with operating system windows used for system implementation.
Input video Input is taken from camera. Video is changed into no. of frames are used by MATLAB as an information picture.

A. *Background Subtraction Tracking*

Removal of irrelevant background and detection of the object. It can also be utilized to detect the objects and capture the object's state in every frame. The standard initializing procedure for many more sophisticated tracking algorithms is given below:
Step 1: Compute the background image by averaging the first few frames contain only the static background.
Step 2: For each frame, we subtract background from it and obtain the difference image, then erode the difference
Image to remove small noise, finally select the largest, valid object from this difference image
Step 3: Compute the center of mass and radius of this largest, valid object and plot the contour of the object.
Background subtraction method is very sensitive to noise, random perturbation, motion blur and poor contrast.

B. *Object tracking by Kalman Filter algorithm*

The Kalman Filter calculation has a place with the state space approach class of tracking calculations. It takes care of the tracking issue in light of the state space condition and estimation condition. Kalman Filter partitions to two stages: prediction condition and correction condition. Kalman Filter gauges the speed, position, and increasing speed of the object in each edge of the succession yet it has been assumed that the changes in speed of the object are in restriction.

IV. BLOCK MATCHING ALGORITHM

A. *Proposed Algorithm:*

A Block Matching Algorithm is a way of locating matching macro blocks in a sequence of digital video frames for the purposes of motion estimation. The underlying supposition behind motion estimation is that the patterns corresponding to objects and background in a frame of video sequence move within the frame to form corresponding objects on the subsequent frame. This can be used to discover temporal redundancy in the video sequence, increasing the effectiveness of inter-frame video compression by defining the contents of a macro block by reference to the contents of a known macro block which is minimally different. A block matching algorithm involves dividing the current frame of a video into macro blocks and comparing each of the macro blocks with a corresponding block and its adjacent neighbors in a nearby frame of the video (sometimes just the previous one). A vector is created that models the movement of a macro block from one location to another. This movement, calculated for all the macro blocks comprising a frame, constitutes the motion estimated in a frame. The search area for a good macro block match is decided by the 'search parameter', p, where p is the number of pixels on all four sides of the corresponding macro-block in the previous frame. The search parameter is a measure of motion. The larger the value of p, larger is the potential motion and the possibility for finding a good match. A full search of all potential blocks however is a computationally expensive task.

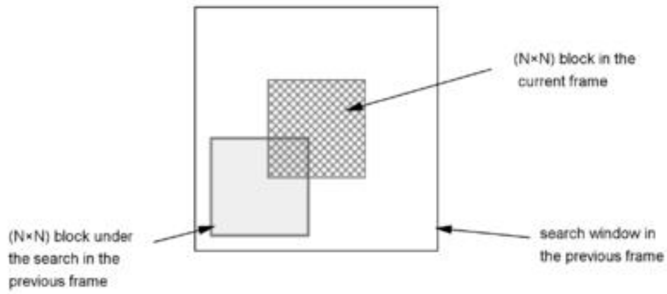


Fig.:1 Candidate block and its neighbor

Motion estimation is the process of determining motion vectors that describe the transformation from one 2D image to another; usually from adjacent frames in a video sequence. The motion vectors may relate to the whole image (global motion estimation) or specific parts, such as rectangular blocks, arbitrary shaped patches or even per pixel. The motion vectors may be represented by a translational model or many other models that can approximate the motion of a real video camera, such as rotation and translation in all three dimensions and zoom.

For matching difference between two blocks a metric used:

$$Mean\ Absolute\ Difference\ (MAD) = \frac{1}{N^2}\sum_{i-0}^{1-n}\sum_{j-0}^{1-n}|C_{ij} - R_{ij}| \quad ..(1)$$

Where 'N' is the size of macro-block.

Cij & Rij : Pixels being compared in current macro-block & Reference macro-block respectively.

For comparison between ground truth and predicted values:

The Euclidean distance between point's p and q is the length of the line segment connecting them.

If p=(p1,p2,….pn) and q=(q1,q2,….qn) are two points in Euclidean n-space, then the distance (d) from p to q, or from q to p is given by,

$$d(p,q) = d(q,p) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \cdots \ldots\ldots + (q_n - p_n)^2}$$

$$= \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2} \quad \ldots\ldots.. (2)$$

The algorithm can be described as follows:

Algorithm

1. Get two consecutive frames from videos.
2. Divide those frames into 100×100 macro-blocks.
3. Pickup first block from Frame 1 and match that with its same corresponding block of Frame 2
   - If match found between two blocks of two frames then there is no motion
   - If matching difference between two blocks found then motion is detected.
4. To determine direction and magnitude of motion vector, two blocks position difference is used.
5. To match correlation between two blocks FFT is used.
6. Direction and magnitude of motion vectors calculated in step 4. Their resultant shows net change in position.
7. Multiple such motion paths are joined together to find out tracking path of object.

Fast Fourier Transform

A Fast Fourier transform (FFT) is an algorithm that samples a signal over a period of time (or space) and divides it into its frequency components. These components are single sinusoidal oscillations at distinct frequencies each with their own amplitude and phase. Over the time period measured in the diagram, the signal contains 3 distinct dominant frequencies.

An FFT algorithm computes the discrete Fourier transform (DFT) of a sequence, or its inverse (IFFT). Fourier analysis converts a signal from its original domain to a representation in the frequency domain and vice versa. An FFT rapidly computes such transformations by factorizing the DFT matrix into a product of sparse (mostly zero) factors. As a result, it manages to reduce the complexity of computing the DFT from O (n^2), which arises if one simply applies the definition of DFT, to O (n log n), where n is the data size.

An FFT computes the DFT and produces exactly the same result as evaluating the DFT definition directly; the most important difference is that an FFT is much faster. In the presence of round-off error, many FFT algorithms are also much more accurate.

An FFT is any method to compute the same results in O(N log N) operations. All known FFT algorithms require O(N log N) operations, although there is no known proof that a lower complexity score is impossible.
FFT correlation between two images is given by:

$$P(x, y) = IF^{-1}\,[F^*(u, v)\,G(u, v) / \left|F^*(u, v)\,G(u, v)\right|] \quad \ldots.\ (3)$$

Where, F : FFT of image ‘f ’
G : FFT of image ‘g ’
IF^{-1}: Inverse of Fourier Transform

V. EXPERIMENTAL SET UP

Graphical Analysis

1. MOT WALK

A. *Qualitative Analysis*

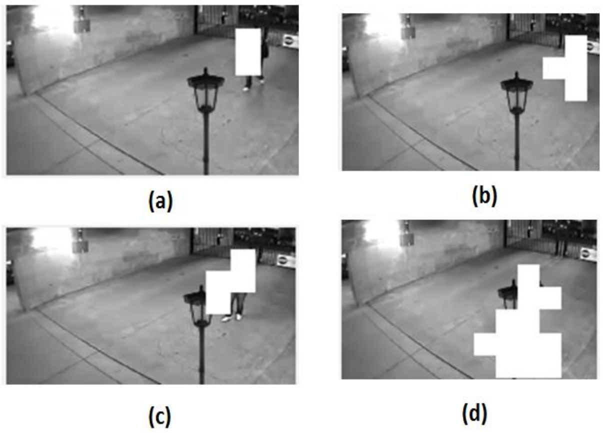


Fig:2 (a),(b),(c),(d) Row wise Block Matching

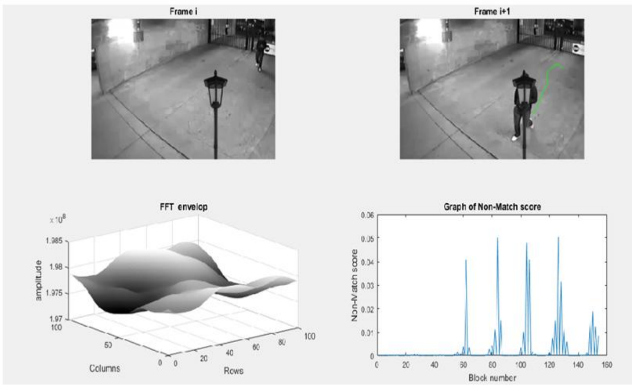
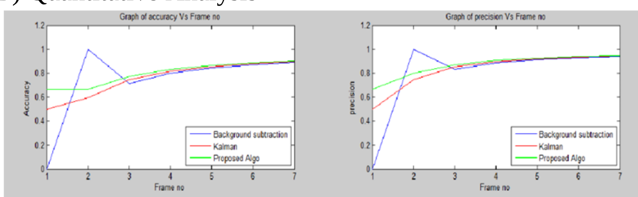
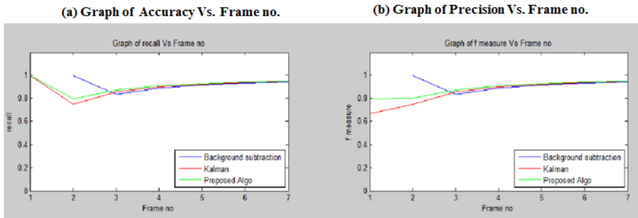


Fig:3 (a) frame i (b) frame i+1 (c) FFT envelope (d) Graph of Block no Vs Non Match score.

B) Quantitative Analysis



(a) Graph of Accuracy Vs. Frame no. **(b) Graph of Precision Vs. Frame no.**



(c) Graph of Recall Vs. Frame no. **(d) Graph of F-measure Vs. Frame no.**

2. CAR TURN

A) Qualitative Analysis

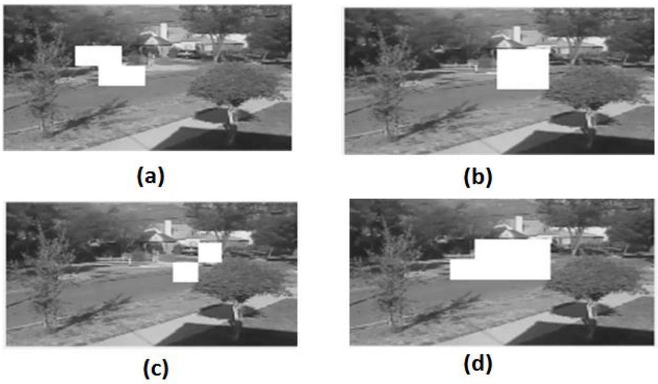


Fig:4 (a),(b),(c),(d) Row wise Block Matching

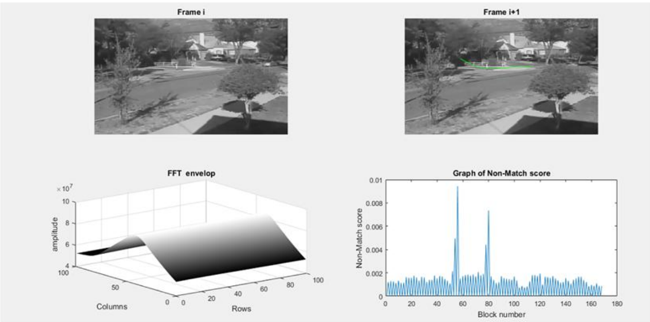
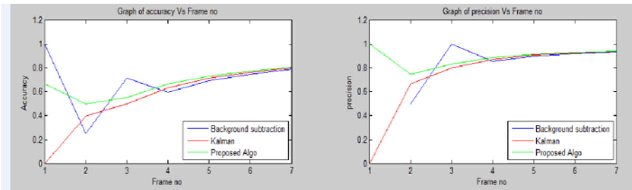
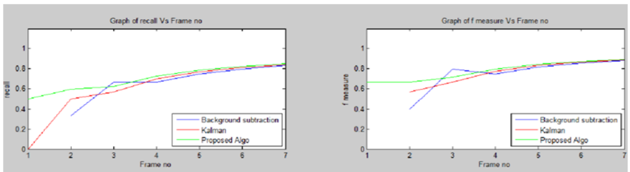


Fig:5 (a) frame i (b) frame i+1 (c) FFT envelope (d) Graph of Block no Vs Non Match score

B) Quantitative Analysis



(a) Graph of Accuracy Vs. Frame no. **(b) Graph of Precision Vs. Frame no.**



(c) Graph of Recall Vs. Frame no. **(d) Graph of F-measure Vs. Frame no.**

3. INSECT

A) Qualitative Analysis

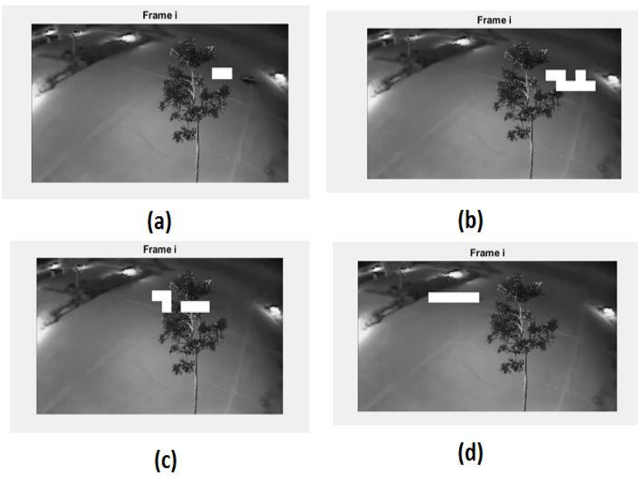


Fig: 5 (a),(b),(c),(d) Row wise Block Matching

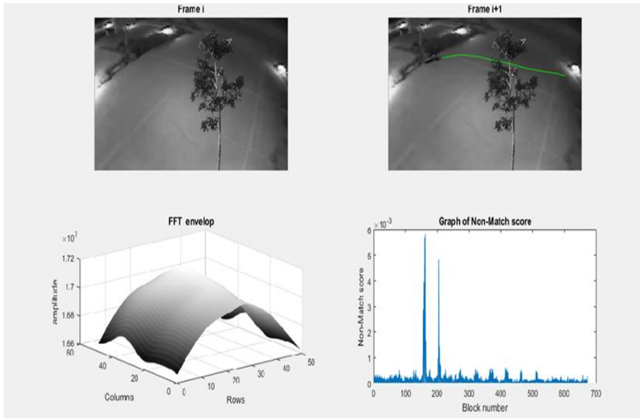
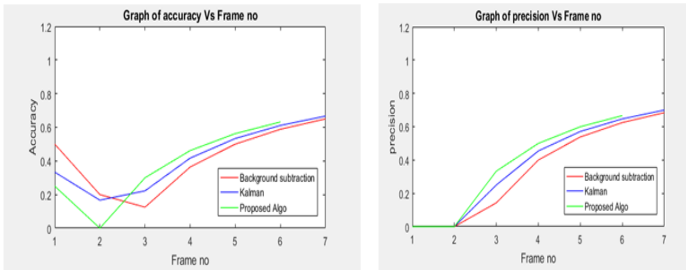
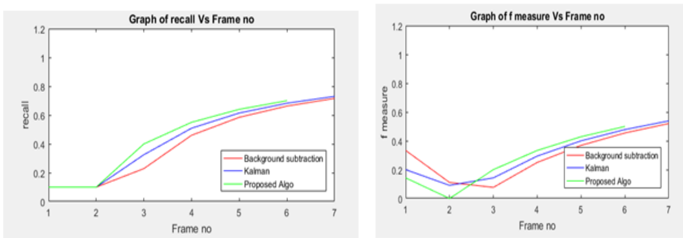


Fig: 6 (a) frame i (b) frame i+1 (c) FFT envelope (d) Graph of Block no Vs Non-Match score

B) Quantitative Analysis



(a) Graph of Accuracy Vs. Frame no. **(b) Graph of Precision Vs. Frame no.**



(c) Graph of Recall Vs. Frame no. **(d) Graph of F-measure Vs. Frame no.**

4. RAT

A) Qualitative Analysis

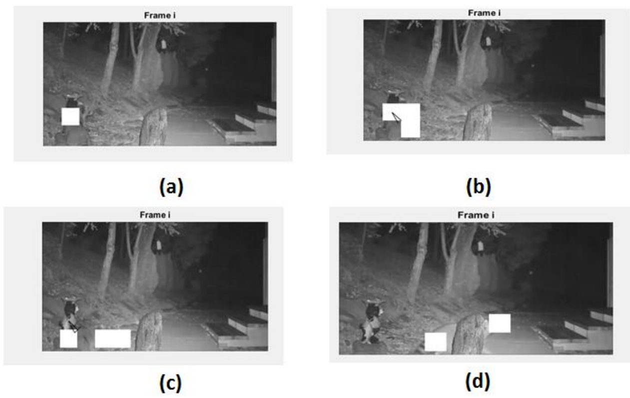


Fig: 6(a),(b),(c),(d) Row wise Block Matching

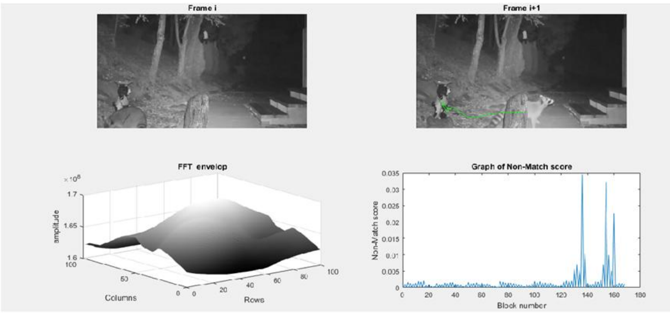
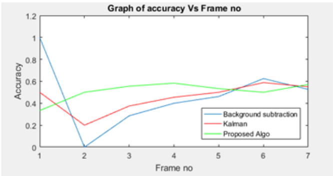
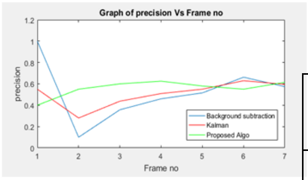


Fig: 7 (a) frame i (b) frame i+1 (c) FFT envelope (d) Graph of Block no Vs Non-Match score

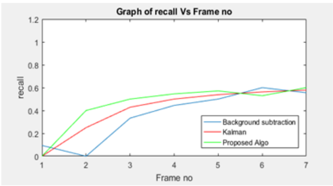
B) Quantitative Analysis



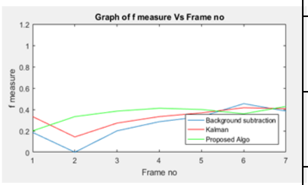
(a) Graph of Accuracy Vs. Frame no.



(b) Graph of Precision Vs. Frame no.



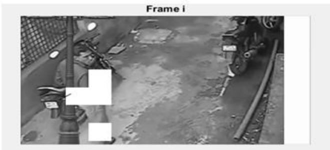
(c) Graph of Recall Vs. Frame no.



(d) Graph of F-measure Vs. Frame no.

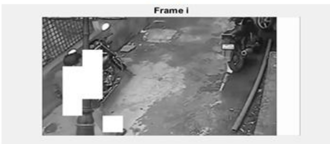
5. HUMAN

A) Qualitative Analysis



(a)

(b)



(c)

(d)

Fig: 8 (a),(b),(c),(d) Row wise Block Matching

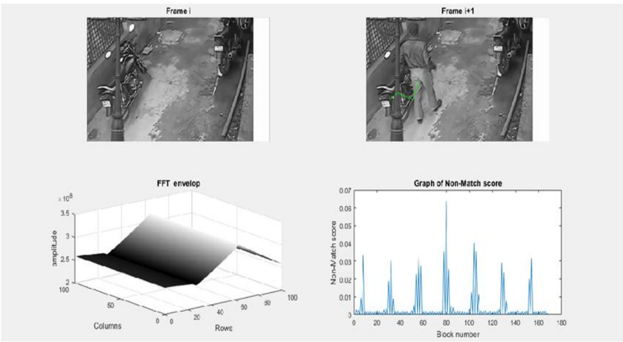
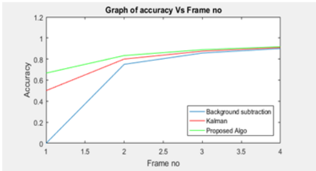
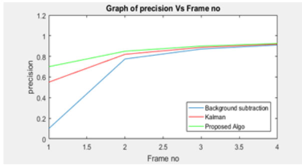


Fig: 9 (a) frame i (b) frame i+1 (c) FFT envelope (d) Graph of Block no Vs Non-Match score

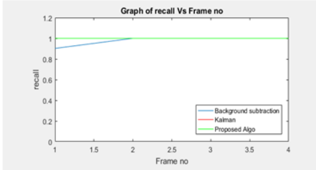
B) Quantitative Analysis



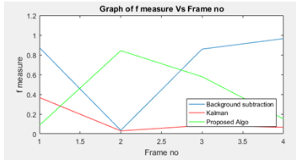
(a) Graph of Accuracy Vs. Frame no.



(b) Graph of Precision Vs. Frame no.



(c) Graph of Recall Vs. Frame no.



(d) Graph of F-measure Vs. Frame no.

VI. COMPARISON OF PERFORMANCE PARAMETERS

Table: 1. Comparison methods

	Parameters	Accuracy	Precision	Recall	F Measure
1. MOT WALK	Background Subtraction	0.72	0.90	0.81	0.85
	Kalman Filter	0.71	0.91	0.80	0.83
	Proposed Algorithm	0.80	0.97	0.89	0.90
2. CAR TURN	Background Subtraction	0.87	0.92	0.91	0.92
	Kalman Filter	0.77	0..91	0.89	0.91
	Proposed Algorithm	0.91	0.97	0.95	0.94
3. INSECT	Background Subtraction	0.67	0.73	0.69	0.65
	Kalman Filter	0.79	0.78	0.67	0.71
	Proposed Algorithm	0.90	0.80	0.75	0.82
4. RAT	Background Subtraction	0.61	0.63	0.69	0.65
	Kalman Filter	0.68	0.72	0.71	0.69
	Proposed Algorithm	0.69	0.74	0.82	0.68
5. HUMAN	Background Subtraction	0.62	0.64	0.50	0.71
	Kalman Filter	0.71	0.69	0.62	0.74
	Proposed Algorithm	0.80	0.81	0.79	0.84

VII. CONCLUSION

From the consideration of all the points we conclude that the Block Matching Algorithm method is simpler and gives good performance. The aspect of block matching is use of intelligent search strategies to reduce the computation complexity. Block Matching Algorithm met is more accurate and reliable method. Results are also improved. Kalman filter which is having probabilistic approach of point tracking is suitable for moving object tracking. Various performance measures are compared and analyzed between three methods. Accuracy, Precision, Recall and F-measure of Block Matching Algorithm are improved than the Kalman Filter Method and Background subtraction tracking method.

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