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Synthesized Performance Tuning towards Optimality in Identification and Tracking of Motion Detection for Video Surveillance System Using Image Processing Techniques

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Abstract

The identification of motion tracking is a complex procedure due to its immense density in clarifying the object position over time with proper care on pixel variations. The nest level of tracking the motion detection is a highly complicated procedure when the basic image processing approaches are only used. The composition of soft computing domains along with the image processing techniques plays the vital role in effective identification and tracking of motion detection in video surveillance system. The synthesized performance tuning approaches using image processing techniques are the desired way to obtain the optimal results in identification and tracking of motion detection in video surveillance system. The existing surveillance video object motion tracking approach methods fails in the areas of deep analysis in tracking and predicting the movements in an optimal way since they entirely depends on basic image processing procedures. The primary objective of this research is to focus on 3 main objectives such as optimal identification of motion detection, optimal tracking of motion detection and optimal prediction in identification, and tracking of motion detection along with the verification for optimality. This research article proposes a synthesized performance tuning towards optimality in identification and tracking of motion detection for video surveillance system using image processing techniques. In near future this research will be extended with the implementation of automated system using virtual reality for robotics.

Keywords: Image processing, CCTV, motion tracking, motion detection, video surveillance

I. INTRODUCTION

Synthesized Approach:

The mixture of different domain ideas used to solve a problem in other domain. It used the relation to attain the desired hypothesis.

Image Processing:

Image processing is the process of transforming an image into a digital form and performing certain operations to get some useful information from it [1]. The image processing system usually treats all images as 2D signals when applying certain predetermined signal processing methods [2].

Video Surveillance:

Video surveillance involves the act of observing a scene or scenes and looking for specific behaviors that are improper or that may indicate the emergence or existence of improper behavior [3].

CCTV:

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Closed-circuit television, also known as video surveillance, is the use of closed-circuit television cameras to transmit a signal to a specific place, on a limited set of monitors [4].

Motion Detection:

Motion detection is the process of detecting a change in the position of an object relative to its surroundings or a change in the surroundings relative to an object [5].

II. METHODOLOGY

The proposed methodology contains 4 stages of implementation. They are

Basic requirements:

- ✓ Legible quality of video content for processing.
- ✓ Proper image processing tools for image extraction from video sequences.
- ✓ Object identification using optimal criteria approach for tracking motion detection in video surveillance using image processing techniques.
- ✓ Structured video sequences are only taken into consideration.
- ✓ Deterministic fuzzy approach for tracking motion detection in video surveillance using image processing techniques.

Stage-1: Optimal identification of motion detection

The optimal identification of motion detection relies on 3 strategies based on the momentum of the object movement computed from Euclidean distance with reference to the specific interval of time. They are

a. Slower momentum objects use Image frame variations method.

b. Medium momentum objects use Pixel course layer method.

c. Rapid momentum objects use Object X-ray shots method.

Stage-2: Optimal tracking of motion detection.

The optimal tracking of motion detection is based on the object momentum in the identification of optimal motions detection with 3 cases of tracking.

Case-1: Grid based tracking

Case-2: Variant frame rate with grid based tracking

Case-3: Fuzzy grid based tracking.

Stage-3: Optimal prediction of motion detection & Motion tracking

The optimal prediction of motion detection and tracking depends on the following approaches based on the momentum of the object. They are,

Approach-1: Slow momentum linear average approach

Approach-2: Medium momentum linear regression approach

Approach-3: Rapid momentum multiple linear regression approach

Stage-4: Verification for optimality

The verification for optimality for synthesized performance tuning towards optimality in identification and tracking of motion detection for video surveillance system using image processing techniques include the numerical analysis based interpolation method.

The proposed methodology of synthesized performance tuning towards optimality in identification and tracking of motion detection for video surveillance system using image processing techniques is as follows in Fig-1.

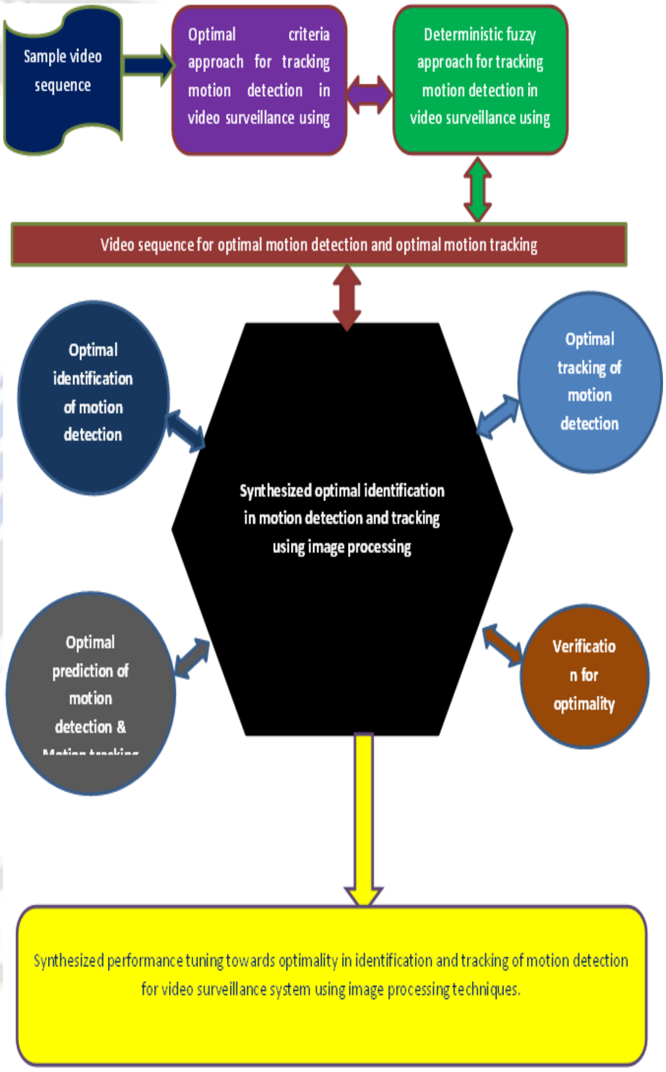

Fig-1: Proposed fuzzy deterministic approach for motion tracking

The flow chart for synthesized performance tuning towards optimality in identification and tracking of motion detection for video surveillance system using image processing techniques is as follows,

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Start
Input: *Sample video sequence for motion detection and tracking*
Step-0: *Apply optimal criteria approach for tracking motion detection in video surveillance using image processing techniques and deterministic fuzzy approach for tracking motion detection in video surveillance using image processing techniques.*
Step-1: *Compute the speed based on the Euclidean distance with reference to specific time intervals in order to compute the momentum of the objects.*
Step-2: Optimal identification of motion detection
Perform the following strategy based on the object momentum,
a. Slower momentum objects use Image frame variations method.
b. Medium momentum objects use Pixel course layer method.
c. Rapid momentum objects use Object X-ray shots method.
Step-3: Optimal tracking of motion detection.
Apply the appropriate case based on the object momentum as follows,
Case-1: Grid based tracking
Case-2: Variant frame rate with grid based tracking
Case-3: Fuzzy grid based tracking using dynamic programming.
Step-4: Optimal prediction of motion detection & Motion tracking
Execute the following approach based on the object momentum,
Approach-1: Slow momentum linear average approach
Approach-2: Medium momentum linear regression approach
Approach-3: Rapid momentum multiple linear regression approach
Step-5: Verification for optimality
Verification depends on the interpolation of data points for object positions.
End

III. IMPLEMENTATION

Step-1: *Compute the speed based on the Euclidean distance with reference to specific time intervals in order to compute the momentum of the objects.*
Consider the image frames from a video sequence [10] as in fig-2, fig-3, and fig-4.

Fig-2: Sample frame-0 of video surveillance sequence

Fig-3: Sample frame-1 of video surveillance sequence

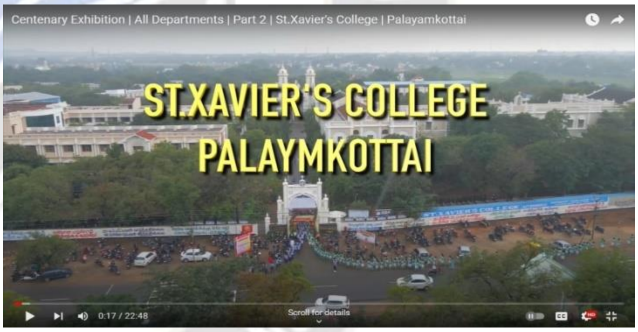

Fig-4: Sample frame-2 of video surveillance sequence

The following computations illustrate the momentum of the objects/persons.
Frame-0 as in fig-2
The girl student position= (A1, B1) = (200,300)
Right hand side white car on road position= (C1, D1) = (300,400)
Left hand side bike on road position= (E1, F1) = (50,350)
Frame-1 as in fig-3
The girl student position= (A2, B2) = (230,300)
Right hand side white car on road position= (C2, D2) = (220,400)
Left hand side bike on road position= (E2, F2) = (195,325)
Frame-2 as in fig-4
The girl student position= (A3, B3) = (250,300)

Right hand side white car on road position= (C3, D3) = (160,375)
Left hand side bike on road position= (E3, F3) = (320,275)

The Euclidean computations for momentum are represented in the following table-1

Table-1: Distance Computation table

Sl.No	Frame name	Object/Person	Distance	Time interval(S)	Speed P/S
1	Frame-0	Student	NULL	0	0
2	Frame-0	Car	NULL	0	0
3	Frame-0	Bike	NULL	0	0
4	Frame-1	Student	30	3	10
5	Frame-1	Car	80	3	26
6	Frame-1	Bike	154	3	51.3
7	Frame-2	Student	20	2	10
8	Frame-2	Car	65	2	32.5
9	Frame-2	Bike	135	2	67.5

Based on the table from Frame-1~Frame~2 and Frame-2~Frame~3, the results obtained are reliable for the momentum computation.
The results are as follows,
Student momentum (in this scenario) = [10, 10] =Slow momentum
Car momentum (in this scenario) = [26, 32.5] =Medium momentum
Bike momentum(in this scenario)=[51.3,67.5]=Rapid momentum

Step-2: Optimal identification of motion detection

Perform the following strategy based on the object momentum,

a. Slower momentum objects use Image frame variations method.

The following stages are involved in frame variation method, they are

Stage-1: Identify the source and destination frames as in fig-5.

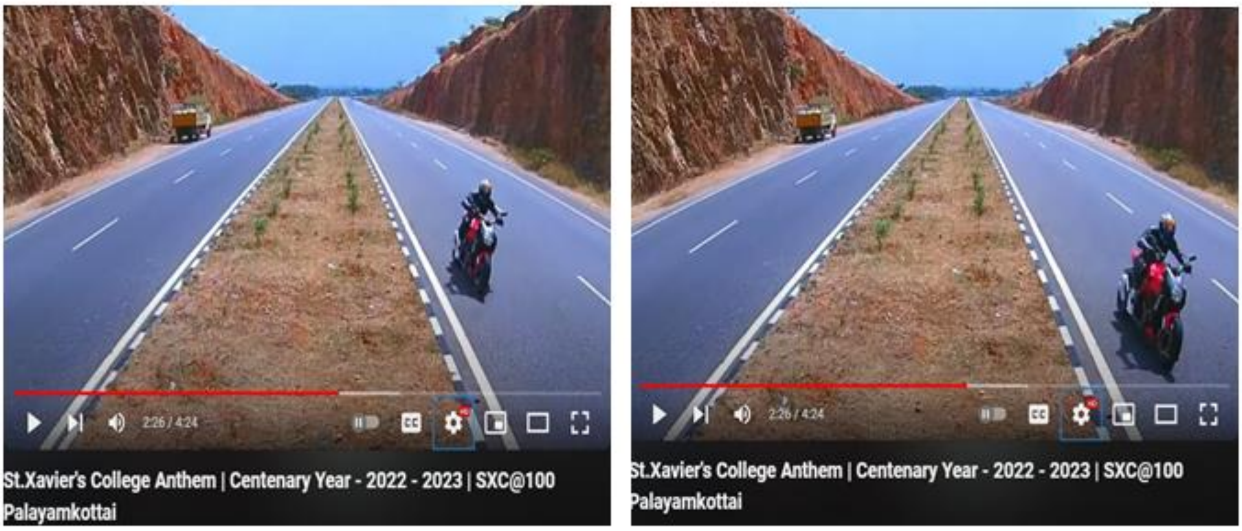

Fig-5: Source and destination frames

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Stage-2: Convert the source and destination frames to gray scale images as in fig-6.

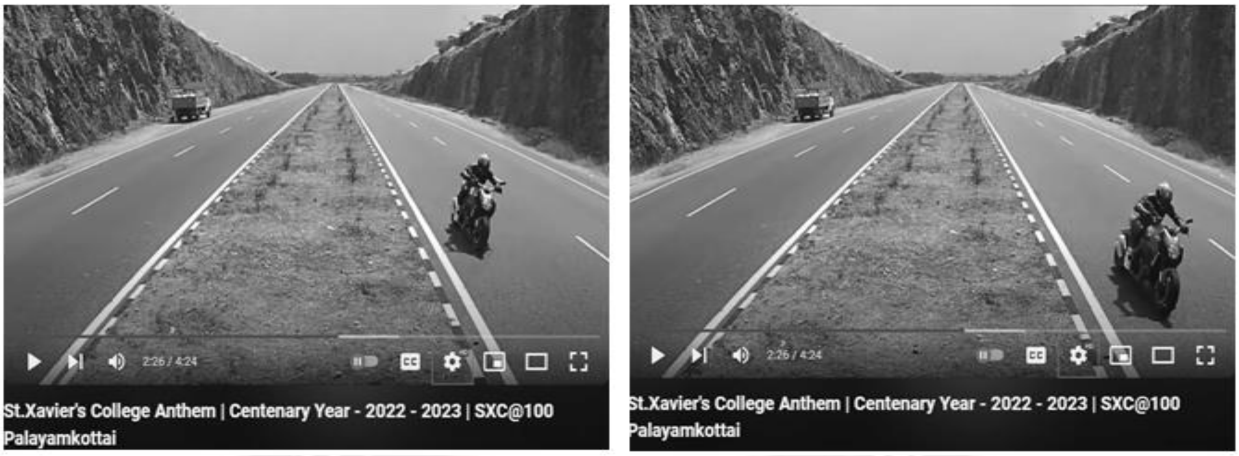

Fig-6: Gray scale frames

Stage-3: Compute the gray scale image frame variations as in fig-7:

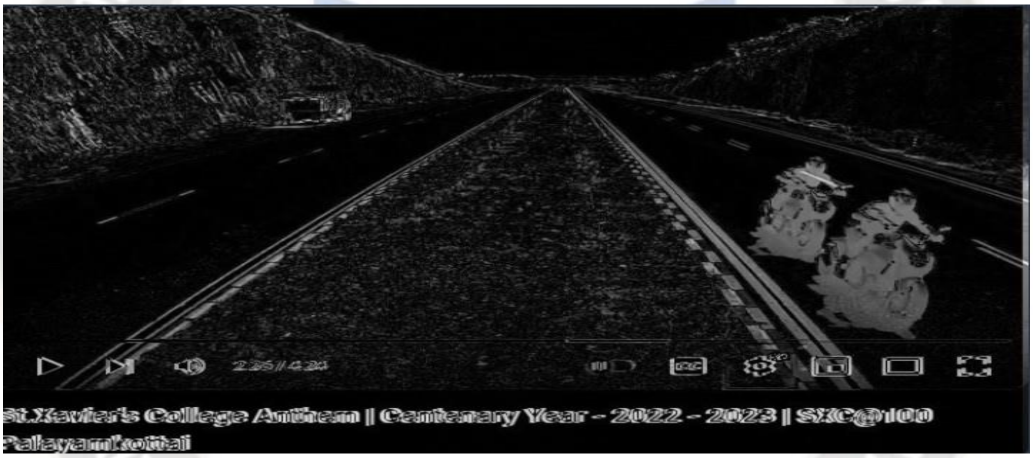

Fig-7: Gray scale comparison

Stage-4: Mark the object/person positions as in fig-8

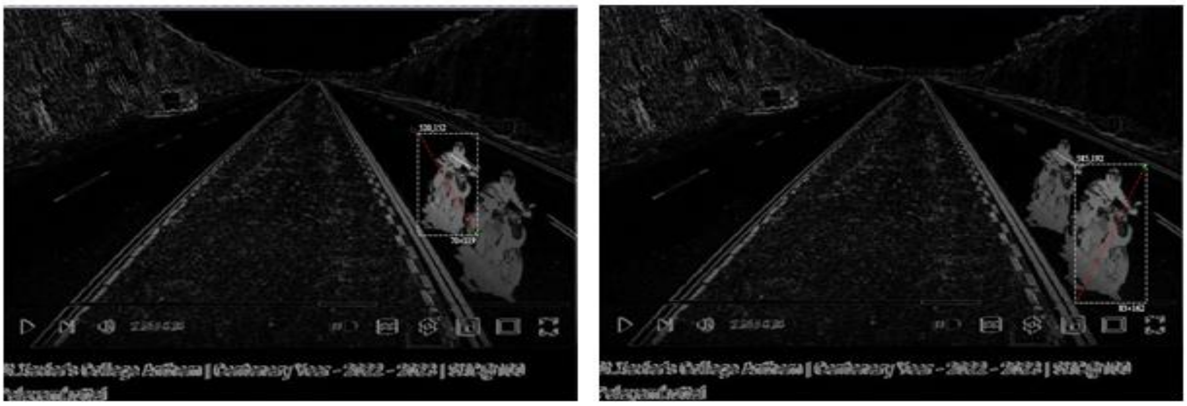

Fig-8: Object marking images

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Stage-5: Perform displacement computation:

The computation of displacement is calculated through the Euclidean distance as follows,

Object initial position= (520,152)

Object final position= (585,192)

Total distance of displacement = 76.32 pixels

b. Medium momentum objects use Pixel course layer method.

The following phases are involved in frame variation method, they are

Phase-1: Identify the source and destination frame with medium momentum object motion detection. The stick is in the medium momentum as in fig-9.

Fig-9: Source and destination frames

Phase-2: Perform the following tasks

Set initial frame=Frame-0

Set Final frame=frame-0

The pixel course layer for the initial frame is as in fig-10

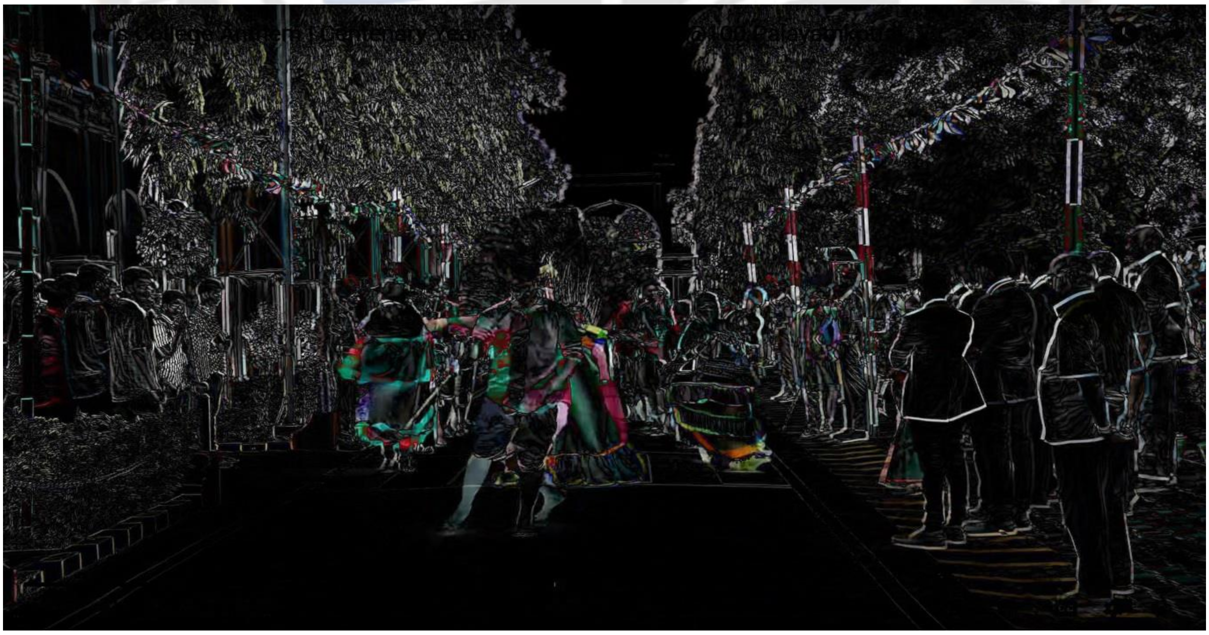

Fig-10: Pixel course layer

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Phase-3: Perform the following tasks

Set initial frame=Frame-0

Set Final frame=frame-1

The pixel course layer for the final state is as in fig-11

Fig-11: Pixel course layer

Phase-4: Identify the motion detection area as in fig-12

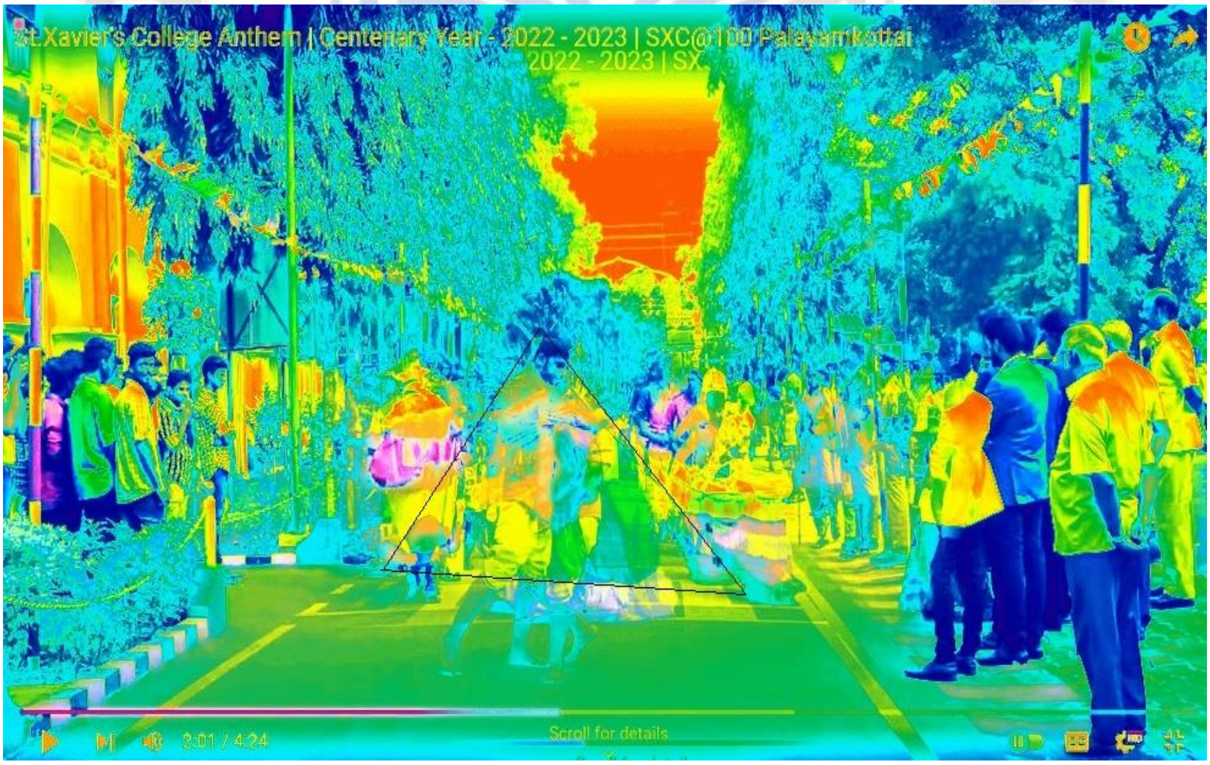

Fig-12: Motion detection area

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c. Rapid momentum objects use Object X-ray shots method.

The rapid momentum based X-ray shots method plays the vital role for optimal motion detection. It contains 3 tasks.

Task-1: Load the laser shots of rapid momentum within fractional time interval as in fig-13.

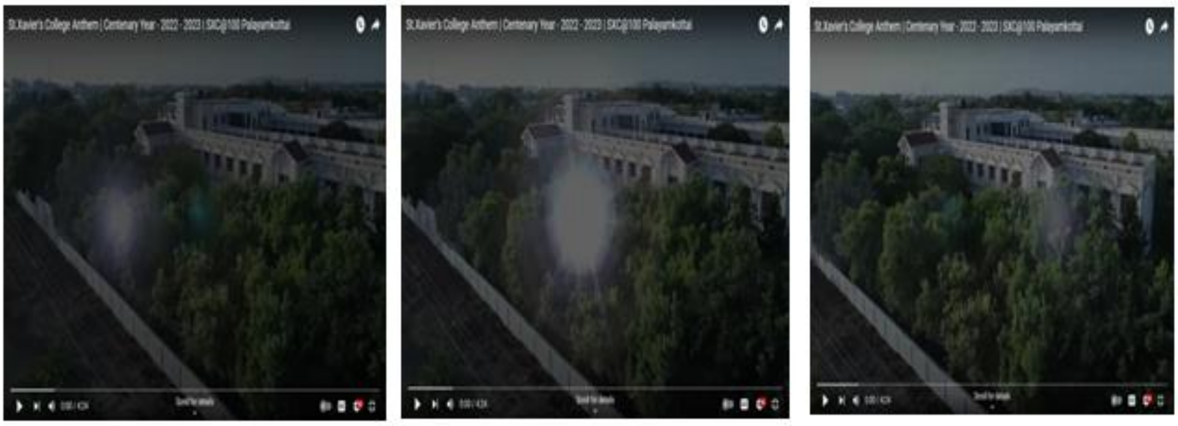

Fig-13: Laser X-ray shot frames for rapid momentum of sunlight

Task-2: Target the Object as in fig-14.

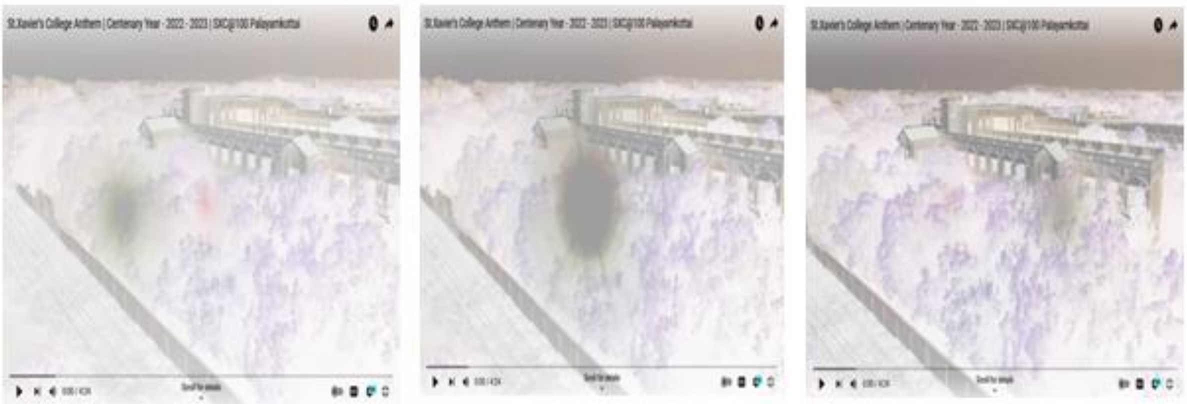

Fig-14: Target object identification

Task-3: Mark the Target object as in fig-15

Fig-15: Target marking frames

Task-4: Compute the distance

- Object initial position=(200,300)
- Object final position=(600,300)
- Time taken=250 Milliseconds
- Rapid momentum of the object=1600 Pixels/Second

Step-3: Optimal tracking of motion detection.

Apply the appropriate case based on the object momentum as follows,

Case-1: Grid based tracking

The slower momentum object tracking is completed through grid based tracking as in table-2.

Table-2: Grid structure for motion tracking

a1b1	**a1b2**	**a1b3**	**a1b4**	**a1b5**	**a1b6**	**a1b7**	**a1b8**	**a1b9**	**a1b10**
a2b1	**a2b2**	**a2b3**	**a2b4**	**a2b5**	**a2b6**	**a2b7**	**a2b8**	**a2b9**	**a2b10**
a3b1	**a3b2**	**a3b3**	**a3b4**	**a3b5**	**a3b6**	**a3b7**	**a3b8**	**a3b9**	**a3b10**
a4b1	**a4b2**	**a4b3**	**a4b4**	**a4b5**	**a4b6**	**a4b7**	**a4b8**	**a4b9**	**a4b10**
a5b1	**a5b2**	**a5b3**	**a5b4**	**a5b5**	**a5b6**	**a5b7**	**a5b8**	**a5b9**	**a5b10**
a6b1	**a6b2**	**a6b3**	**a6b4**	**a6b5**	**a6b6**	**a6b7**	**a6b8**	**a6b9**	**a6b10**
a7b1	**a7b2**	**a7b3**	**a7b4**	**a7b5**	**a7b6**	**a7b7**	**a7b8**	**a7b9**	**a7b10**
a8b1	**a8b2**	**a8b3**	**a8b4**	**a8b5**	**a8b6**	**a8b7**	**a8b8**	**a8b9**	**a8b10**
a9b1	**a9b2**	**a9b3**	**a9b4**	**a9b5**	**a9b6**	**a9b7**	**a9b8**	**a9b9**	**a9b10**
a10b1	**a10b2**	**a10b3**	**a10b4**	**a10b5**	**a10b6**	**a10b7**	**a10b8**	**a10b9**	**a10b10**

For forward motion

Horizontal motion tracking is a_ib_j to a_ib_{j+1}
Vertical motion tracking is a_ib_j to $a_{i-1}b_j$
Diagonal motion tracking is a_ib_j to $a_{i-1}b_{j+1}$

For 2 step pattern zigzag movement until it reaches the last column by reaching 8th column

Horizontal vertical=vertical Horizontal= a_ib_j to $a_{i-1}b_{j+1}$
Horizontal Diagonal=Diagonal Horizontal= a_ib_j to $a_{i-1}b_{j+2}$
Diagonal vertical=vertical Diagonal= a_ib_j to $a_{i-2}b_{j+1}$

For any other random movement as in fig-16

$a_{i-1}b_{j-1}$	a_ib_{j-1}	$a_{i+1}b_{j-1}$
$a_{i-1}b_j$	a_ib_j	$a_{i+1}b_j$
$a_{i-1}b_{j+1}$	a_ib_{j+1}	$a_{i+1}b_{j+1}$
Backward Motion	**Top down/Bottom up**	**Forward motion**

Fig-16: Random motion computation structure

Case-2: Variant frame rate with grid based tracking

For medium momentum motion objects the grid based tracking is implemented through variant frame rates as in table-3.

Table-3: Grid tracking table

Sl.NO	Direction	Speed=2X	Speed=3X
1	Forward	3 Frames skip	6 frames skip
2	Top	2 frames skip	3 frames skip
3	Down	3 frames skip	6 frames skip
4	Backward	2 frames skip	3 frames skip

Case-3: Fuzzy grid based tracking using dynamic programming.

The motion tracking for the objects with rapid momentum then the fuzzy logic based dynamic programming approach plays the important role.

i. Divide the entire frame into 10x10 cells as in Fig

ii. Locate the current object position $a_i b_j$

iii. Identify the motion direction from the next frame difference.

iv. Identify the object speed

v. Allocate the fuzzy membership values as follows in table-4

Table-4: fuzzy based grid tracking

Sl.No	Direction	Speed>20X	20X<Speed>10X	10X< Speed> 3X	3X < Speed > X
1	Forward	1.0	0.9	0.8	0.7
2	Top	0.8	0.6	0.4	0.2
3	Down	0.9	0.8	0.7	0.5
4	Backward	0.8	0.6	0.4	0.1

Step-4: Optimal prediction of motion detection & Motion tracking

Execute the following approach based on the object momentum,

Approach-1: Slow momentum linear average approach

The slower momentum uses the linear average approach for the prediction of next level. Consider the object with the following characteristics

Current position $=a_i b_j$ & Momentum rate=nX then the prediction for the next level is represented in the following equations.

Horizontal forward Prediction= $a_i b_{j+n}$ -------------------- (1)

Vertical forward Prediction= $a_{i-n} b_j$ --------------------------- (2)

Diagonal forward Prediction= $a_{i-n} b_{j+n}$ ------------------------ (3)

Horizontal backward Prediction= $a_i b_{j-n}$ ---------- (4)

Vertical backward Prediction= $a_{i+1} b_j$ ------------------------ (5)

Diagonal backward Prediction= $a_{i+n} b_{j-n}$ --------------------- (6)

Approach-2: Medium momentum linear regression approach

The linear regression approach for medium momentum objects for prediction provides the better results for any targeted value. Consider the speed of the object and corresponding changes in X and Y coordinates as in the following table-5

Table-5: Linear regression approach

Sl.No	Speed (X)	Change in X-Value	Change in Y-Value
1	1X	-20	-30
2	2X	-10	-20
3	3X	5	-5
4	4X	15	5
5	5X	25	15
6	6X	35	25
7	7X	45	35
8	8X	55	45
9	9X	65	55
10	10X	75	65

Now plot the data Points for X-axis as in fig-17

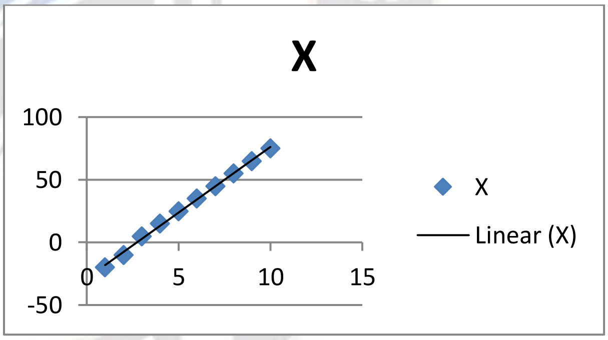

Fig-17: Plot for X-value

Now plot the data points for Y-axis as in fig-18

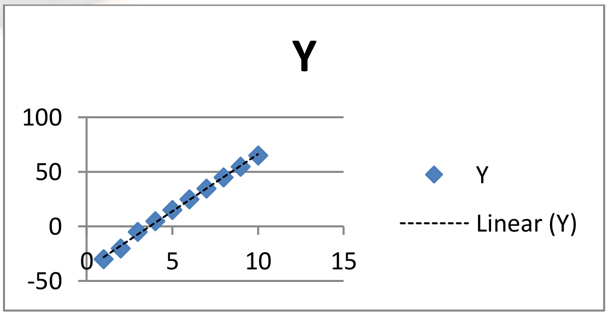

Fig-18: Plot for Y-value

Consider the required prediction target value of X axis is as in table-6

Table-6: Prediction for X-value

Sl.No	Required Speed(X)	Linear regression prediction	Prediction for Speed(X) in X-axis
1	1.5	FORECAST (Required value, X-start to X-final, Speed start to Speed final)	-12.9394
2	2.5		-2.45455
3	3.5		8.030303

Similarly Consider the required prediction target value of Y axis are as in table-7

Table-7: Prediction for Y-value

Sl.No	Required Speed(X)	Linear regression prediction	Prediction for Speed(X) in Y-axis
1	1.5	FORECAST (Required value, Y-start to Y-final, Speed start to Speed final)	-22.9394
2	2.5		-12.4545
3	3.5		-1.9697

The current position of the object as (Current-Current-Y) then the
The speed (3.5) predicts the position of the object as (Current-X+8.03, Current-Y-1.97)

Approach-3: Rapid momentum multiple linear regression approach

The rapid momentum uses the multiple linear regression approach in which,
One dependent variable= speed-(X) with two independent variable for prediction such as,
X-axis value and Y-axis value will be predicted.
The following results are obtained in a single computation as follows,
The current position of the object as (Current-Current-Y) then the
The speed (2.5) predicts the position of the object as (Current-X-2.45, Current-Y-12.45)
Similarly
The speed (1.5) predicts the position of the object as (Current-X-12.93, Current-Y-22.93)

Step-5: Verification for optimality

The verification of motion detection and tracking depends on the numerical analysis based interpolation method.
The value to be checked for X-axis=x (given or known)
The proposed methodology predicting or executing the corresponding Y-axis value=b
The verification for the value-y uses the following associative rule mining approach

Set-1: Hypothesis
Rule-1: *Predicted or executed b-value is correct*
Statement-1: *Verification success.*
Rule-2: *Predicted or executed b-value is wrong*
Statement-2: *Verification failed.*
Set-2: Assignment
Rule-3: *Set first coordinate=(x1, y1)*
Set second coordinate=(x2, y2)
Set-3: Computation
Rule-4: *Compute y*
y=y=y1+(x-x1) (y2-y1)/(x2-x1)
Set-4: Result
Rule-5: *If y=b then Rule-1 follows true*
Else rule-2 follows true

IV. RESULTS AND DISCUSSION

Consider the video collections from Kaggle standard data set [7], paper code [8], and real-time data sets with a collection of 75 videos.
The proposed methodology provides the optimal results in motion detection identification and motion tracking with better results.
This research article produces 96% (288 out of 300 video sequence sets) of success rate for the synthesized performance tuning towards optimality in identification and

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tracking of motion detection for video surveillance system using image processing techniques.
The parametric difference between the existing edge detection method and proposed methods with recall, precision and accuracy etc. are commutated in the below Table-8 format,

Table-8: Proposed methodology parametric comparisons

No	Approach	Accuracy	Precision	Recall	F1 score value
1	Edge detection based motion tracking approach.	67%	0.66	0.65	0.66
2	Synthesized performance tuning towards optimality in identification and tracking of motion detection for video surveillance system using image processing techniques	96%	0.96	0.95	0.97

The following fig-19 shows the performance comparison between the proposed and existing methodologies.

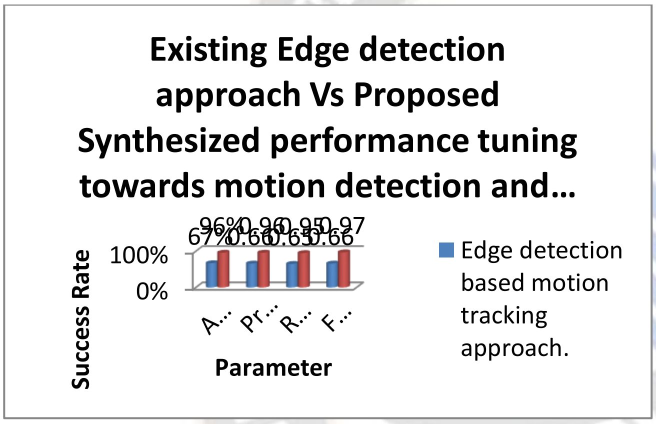

Fig-19: Proposed vs. existing methodology performance comparisons

V. CONCLUSION

The motion detection and tracking using image processing methods aloe is not sufficient due to the single faced domain touch for solving the problem in unidirectional way. In order to obtain the optimal results the incorporation of soft computing along with the mathematic logic play the vital role in achieving the goal for detecting and tracking the motion detection in video surveillance system..
The existing methodologies for edge detection approach directly apply the image handling approach irrespective of the event analysis and object movement analysis. The improper image handling tool implementation produces irrelevant outputs without any specific characteristics.
This research article focuses on the momentum computation and based on the momentum the next approach concentrates on optimal object motion detection followed by the optimal object motion tracking and with the optimal prediction for the next movement and finally with proper verification using mathematical structures for optimality. The proposed methodology produces 96% of success rate whereas the existing edge detection method gives only 67% of success which is low when compared with the proposed methodology. In future this research will extended with the automation schema for future implementation.

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