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Fast and Effective Motion Model for Moving Object Detection Using Aerial Images

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Abstract

Motion detection remains an unsolved issue for moving object detection using aerial images from moving vehicle like Unmanned Aerial Vehicle due to lack of motion model. Existing moving object detection methods do not provide motion model to detect motion pixels. In addition, previous research for moving object detection depends on either frame difference or segmentation methods. Frame difference based approaches can differentiate pixel motion but cannot extract the overall object whereas segmentation approaches can extract the overall object but cannot differentiate object motion. However, moving object performance depends on the feature type(s) employed, due to limited feature availability from aerial images. The purpose of the current research is first to select a new feature for overall detection procedures, second to propose a model for motion detection, and third to apply frame difference and segmentation methods together to achieve optimum detection performance. A new motion model, Advanced Moment based Motion Unification (AMMU) is proposed, where the moment feature is used for motion detection. Experimental results verify that the proposed AMMU model is successful at detection of moving objects.

Keywords: Frame difference, Motion detection, Segmentation

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1. INTRODUCTION

Moving object detection using aerial images extracts moving objects based on apparent movement relative to the background in image sequences using features such as corners and edges. Understanding objects activities moving in a scene from the use video is a challenging scientific problem and a very fertile domain with many promising applications in visual surveillance, intelligent transportation system, industrial vision, public and commercial security, smart video data mining, law enforcement, military security, etc. Thus, it has attracted significant research, institutions, and commercial companies. The main purpose of the current research is to detect and extract moving objects based on a new motion model, Advanced Moment based Motion Unification (AMMU), where pixel intensity is measured and segmentation and frame difference methods are applied simultaneously.

Accurate motion detection remains a problem for moving object extraction using aerial images in computer vision. Detection of motion and moving objects is coupled due to the coherence of pixel intensity. Image moments, from probability theory and leveraging computer vision research, are a particular weighted average of image pixel intensity which are rotation, translation and scale invariant, and provide a suitable candidate feature to develop a model for motion detection.

Section 2 reviews previous methods for moving object detection, Section 3 presents the proposed research methodology for AMMU, Section 4 describes experimental results and analysis and Section 5 summarizes the outcomes and conclusions.

2. BACKGROUND

Developing a motion model is difficult because the segmentation task increases computation time (CT) and decreases detection performance [1, 2]. Four approaches have

been used previously for moving object detection: illumination compensation, parallel filtering, and contextual information and long term motion analysis [3, 4, 5, 6, 7, 8, 9, 10]. None of these are suitable for moving object detection due to the large numbers of parameters, and excessive CT. There are four kind methods previously used for moving object detection mentioned below

1. Optical flow
2. Background subtraction
3. Frame difference
4. Segmentation

Optical flow identifies an apparent change of object location or deformation between frames [11, 12, 2]. The method has high detection accuracy, but cannot obtain an accurate outline of the moving objects. It is also very complex to calculate an optical flow field and consequently difficult to achieve optimum detection performance [11].

Background subtraction identifies moving objects from the frame portions that differ significantly from a background model. It is a popular motion detection technique [13, 14, 15]. However, the crucial challenge for background subtraction is the requirement to quickly establish the background image and timely update the background to remove influences of surrounding changes, such as lighting and other interferences.

Only the frame difference method provides a viable motion model [16, 17, 18, 19, 20]. Frame difference registers two consecutive frames first, then uses subsequent to find moving objects. The method can differentiate pixels or object portions in an image, but cannot extract a complete object.

Segmentation refers to extracting a moving object from an image where two adjacent frames are not similar [21, 22, 23, 24]. However, while segmentation can extract a complete object, it cannot differentiate moving regions from the image background.

Detection performance depends on the type of the features used. However, three types of feature previously used for moving object detection shown in Figure 1.

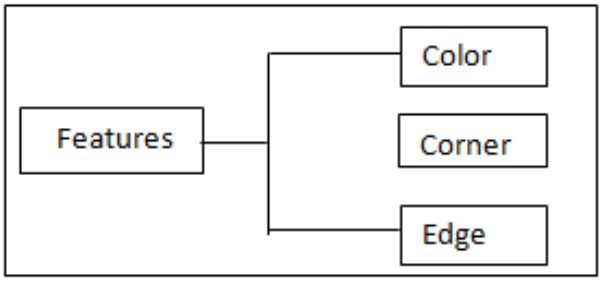

Figure 1: Types of features used for moving object detection

Hsu-Yung et al. (2012) [5] used color features by extending the pixel wise classification method, preserving the relationship among neighboring pixels in a region. Zezhong et al. (2012) [25] also used color features by identifying candidate key points of moving object pixels. They used a vector road map, similar to a training data set, for detecting a moving object. Use of a color feature meant the proposed research could not classify the same color but different objects in the same scene. Kembhavi et al. (2011) [26] used corner features with a larger feature set extracted from neighboring pixels, and also used a dual selection approach to reduce CT. Gleason et al. (2011) [11] used corner features to overcome system challenges addressing 3D image orientation. However, their proposed research rejected most background objects for their input aerial images, which was unrealistic. Oreifej et al. (2010) [27] used edge features for low quality images and posed variation across the set due to changes in object location and articulation. Their proposed method gave better performance for more persistency in high frame rate videos since it followed the assumption that an objects position in the next frame should be close to its position in the current frame. Bhuvaneswari and Rauf (2009) [16] used edge features by clustering single points obtained from motion detection. However, their research did not provide expected results due to the complexity of shortening the environment, and real time change of background and inconspicuous object features.

Moving object detection associates with motion, and motion itself needs to be modeled accurately to extract moving objects from aerial images. Motion represents the coherence of pixel intensity, so detection of motion will reinforce overall detection performance. However, none of the existing methods involve motion detection for moving objects. The lack of a suitable feature for analysis also impacts on overall detection performance. Motion detection means detection of motion pixels from images, which can be described as summing pixel intensity. Moments are means of the pixel intensity distribution, and so this research used moments for motion modeling and moving object detection from aerial images before segmenting individual objects to facilitate detection. Although the frame difference method can extract pixel motion, it cannot extract a complete object whereas segmentation can extract a complete object but cannot extract pixel motion. This research proposed to used frame difference and segmentation together in the AMMU model using moment for optimum detection performance.

3. RESEARCH METHODOLOGY

Overall research methodology is composed of two sections, i.e. Proposed Framework is depicted in section 3.1 and Proposed Methodology is depicted in section 3.2. Proposed framework illustrates summarizes overall methodology whereas proposed methodology depicts brief illustration of the proposed motion model.

3.1. PROPOSED FRAMEWORK

Let $P_A(x, y, t)$ and $P_R(x, y, t-1)$ be two consecutive frames at consecutive times t and $t-1$, and frame difference is denoted by $P_f(x, y, t)$. Let, $P_{df}(x, y, t)$ be the denoised image achieved by applying median filter. Moment estimation then provides the pixel intensity distribution, and pixel intensity difference (PID) is performed for each pixel. Based on a given threshold, pixels with lower intensities are ignored, while higher intensity pixels are retained for later segmentation, as flagged by PID. Finally, difference edge detector is used for segmentation to extract the moving object. The proposed framework is shown in Figure 2.

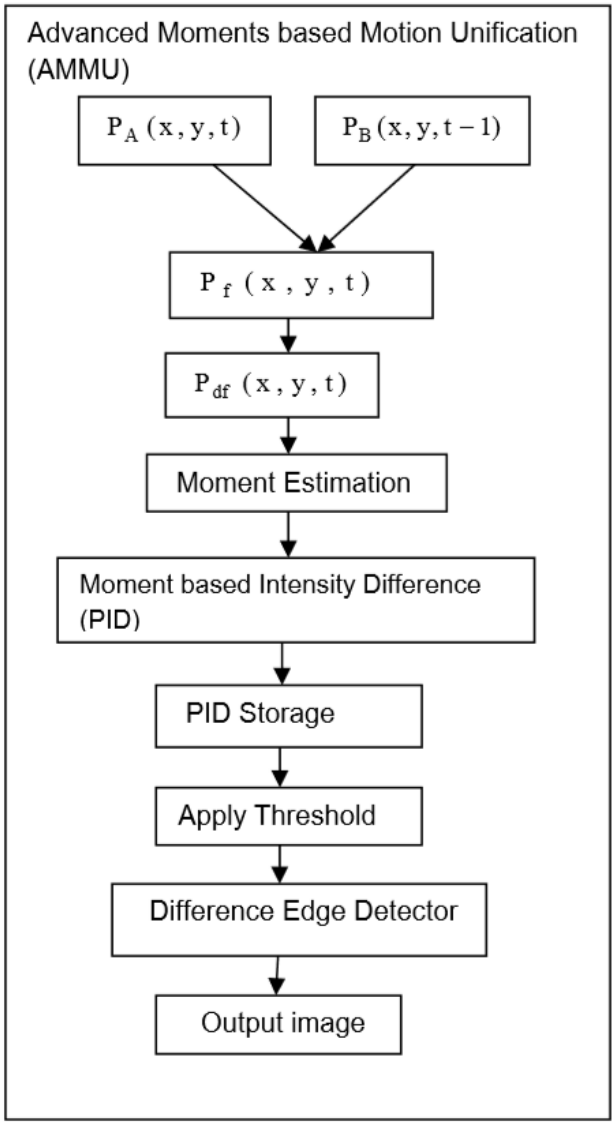

Figure 2: Advanced Moment based Motion Unification or (AMMU) framework

3.2. PROPOSED METHODOLOGY

Let, $F_A(m, n, t)$ and $F_B(m, n, t-1)$ be two consecutive frames at consecutive times t and $t-1$, as shown in Figure 3 and 4.

Figure 3: $F_A(m, n, t)$ at time t

Figure 4: $F_B(m, n, t-1)$ at time t-1 th time

The frame difference is

$$M_{df}(m, n, t) = round((F_A(m, n, t) - F_A(m, n, t-1))$$

Where

$$\left\{ \begin{array}{l} \mathrm{M}_{df}(m, n, t) = F_B(m, n, t-1); if(M_{df}(m, n, t) > 0) \\ \mathrm{M}_{df}(m, n, t) = F_A(m, n, t-1); if(M_{df}(m, n, t) < 0) \end{array} \right\}$$

as shown in Figure 5.

Let $M_{df}(m, n, t)$ be the median filtered image achieved from $M_f(m, n, t)$, shown in Figure 6.

3.2.1. MOMENT ESTIMATION

The two dimensional pixel intensity distribution of $P_{df}(x, y)$ for time t for order of $(r + s)$ is

$$K_{rs} = \int_{\infty}^{\infty} \int_{\infty}^{\infty} x^r y^s P_{df}(x, y) dx dy, ...(2)$$

Where $r, s = 0, 1, 2....$

K_{rs} is considered to be digital, so the double integral in

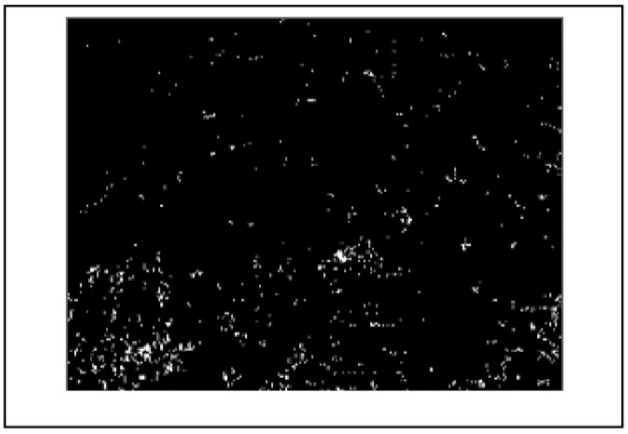

Figure 5: Frame difference

Figure 6: Frame difference

Eq. (2) can be replaced by a summation, and the zeroth moment of numeric integration is the best summation to use. The raw moment of K_{rs} for order of $(r+s)$ is

$$I_{rs} = \sum_r \sum_s x^r y^s P_{d,f}(x,y), ...(3)$$

Here summation extends over all the elements in $P_{d,f}(x,y)$. Where zeroth moments are defined by Eq. (4), $I_{00} =$ zeroth moment

$$I_{00} = \sum_r \sum_s x^0 y^0 P_{df}(x,y),$$

$$I_{00} = \sum_r \sum_s P_{df}(x,y).....(4)$$

$I_{rs}(x,y)$ is obtained after calculating the Zeroth moment pixel intensity distribution using Eq. (4).

3.2.2. MOMENT BASED PIXEL INTENSITY DIFFERENCE

The next step is to use the moment feature for PID measurement. Let

$$A_{pq} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix}$$

where A_{pq} represents $I_{rs} = (x,y)$ and each element a_{mn} represents the coordinate of the pixel in the form (i_m, j_n) , where $m, n = 1, 2, 3,$
Let, $A(i_m, j_n$ and $B(i_m, j_{n+k}$ be the rows that satisfy Eq. (5), where the intensity difference between $A(i_m, j_n$ and $B(i_m, j_{n+k}$ for red is denoted as $R(i,j)$, green as $G(i,j)$, and blue as $B(i,j)$, So that

$$|R(i,j)| = |G(i,j)| = |B(i,j)| \\ = |(i_m, j_{n+k}) - (i_m, j_n)|.....(5)$$

Therefore, the RGB intensity difference for each pixel can be expressed as

$$RGB_{rs}(i,j) = |R(i,j) + G(i,j) + B(i,j)|.....(6)$$

Let, for all pixels N of $I_{rs}(x,y)$ are kept in $P(m,n)$, if $RGB_{rs}(i,j) > Th$, where Th is a given threshold, set to Th = 40 here. Based on the same threshold, object is identified using the difference edge detector method from $P(m,n)$ that satisfy $|(P(m,n)| > Th$. The proposed AMMU model for moving object extraction is shown in Figure 7 and object $O(a,b)$ is shown in Figure 8.

The proposed AMMU model serves two purposes: moment estimation for motion pixel detection, and PID for each motion pixel using moment. The threshold is used with the difference edge detector method for final moving object extraction using segmentation.

4. EXPERIMENT AND DISCUSSION

Evaluation of the proposed AMMU method included two aspects, comparison with previous research, and comparison of hardware performance. Comparison with previous research was based on feature based comparison, and comparison with previous methods. Hardware comparison was performed for various edge and corner based detection methods to verify AMMU against known methods. Evaluation was based on standard performance metrics: detection rate, false alarm rate (FAR), and CT. Section 4.1 and 4.2 describes the datasets used, and presents the experimental results, and Section 4.3 provides analysis and discussion.

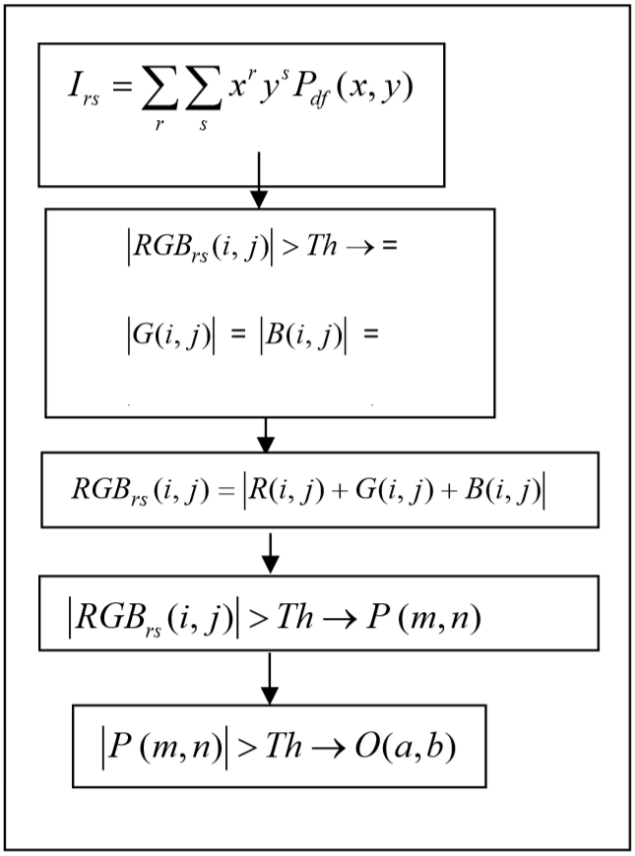

Figure 7: Proposed Advanced Moment based Motion Unification Model

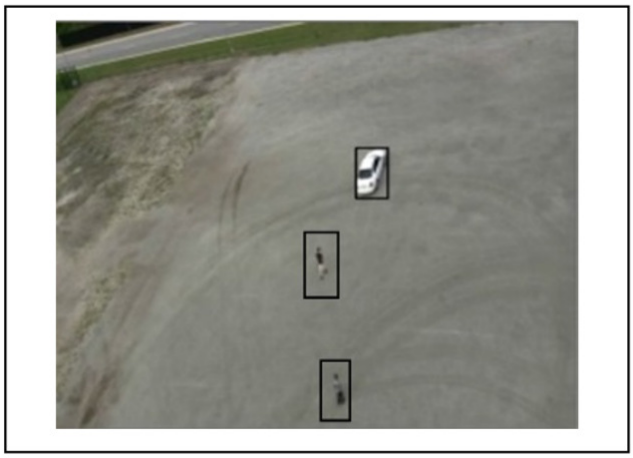

Figure 8: Object $O(a,b)$ using the proposed Advanced Moment based Motion Unification (AMMU)

Table 1: Detection Rate (DR), False Alarm Rate (FAR) and Computation Time of AMMU

Datasets	Detection Rate or DR (%)	False Alarm Rate or FAR (%)	Computation Time (ms)
Dataset 1	72.46	42.53	184.15
Dataset 2	76.42	34.01	171.17

4.1. DATASETS

Two data sets were provided by the Center for Research in Computer Vision (CRCV) at the University of Central Florida, USA. Dataset 1 and 2 contain 88 and 131 aerial images, respectively (219 images). Both data sets were obtained using R/C controlled blimp equipped with HD camera. The collection represents a diverse pool of action features at different heights and aerial view points. Multiple instances of each action were recorded at different altitudes 400500 feet and performed with different actors.

4.2. EXPERIMENTAL RESULTS

Advanced Moment based Motion Unification or AMMU is developed based on moment feature where motion model is provided to detect motion pixels. Experimental results of AMMU is shown in Table 1.Three performance metrics are used to evaluate AMMU which are Detection Rate or DR, False Alarm Rate or FAR and Computation Time. Computation Time is measured in Milliseconds. AMMU acquired Detection Rate of 72.46% and 76.42% for dataset 1 and dataset 2 respectively. False Alarm Rate for AMMU is 42.53% and 34.01% for dataset 1 and dataset 2 respectively. Computation Time or CT for AMMU is 184.15 ms and 171.17 ms using dataset1 and dataset 2 respectively.

5. ANALYSIS AND DISCUSSION

Analysis and discussion of Advanced Moment base Motion Unification is demonstrated based on three aspects; i) Previous research works, ii) Edge based detection and iii) Corner based detection. Section 4.2.1 demonstrates validation of AMMU in terms with Detection Rate (DR), Section 4.2.2 depicts validation of AMMU in terms with False Alarm Rate (FAR) and finally, Section 4.2.3 illustrates validation of AMMU in terms with Computation Time (CT).

5.1. DETECTION RATE

A. PREVIOUS RESEARCH RESULTS

AMMU uses the moment feature incorporated into a motion model. Therefore, detection rate (DR) from previous research is compared. Optical flow, proposed by Gaszczak et al. (2011)[17] and Pollard and Anton (2012) [19], and the background subtraction method, proposed by Cheraghi and Sheikh (2012) [28] were selected, as these methods do not included motion model.

a) FEATURE BASED METHODS

Figure 9 shows DR comparisons for edge feature based detection performed by Teutsch and Kruger (2012) [24], Oreifej et al. (2010) [27], and Gaszczak et al. (2011)[17]; and

corner feature based detection performed by Pollard and Antone (2012) [29], and Cheraghi and Sheikh (2012) [28] with AMMU.

AMMU achieved higher or comparable DR than previous research. Pollard and Antone (2012) received Detection Rate (DR) of only 50% using corner feature. However, Cheraghi and Sheikh (2012) [28] improved Detection Rate (DR) of 75% using corner feature. Oreifej et al. (2010) [27] achieved Detection Rate (DR) of 66% and Teutsch and Kruger (2012) [24] achieved Detection Rate (DR) of 56% using edge feature. However, Gaszczak et al. (2011)[17] received higher Detection Rate (DR) of 70% using edge feature. Advanced Moment based Motion Unification (AMMU) achieved higher Detection Rate (DR) of 76.42% using moment feature which indicates better performance than previous edge and corner feature based detection.

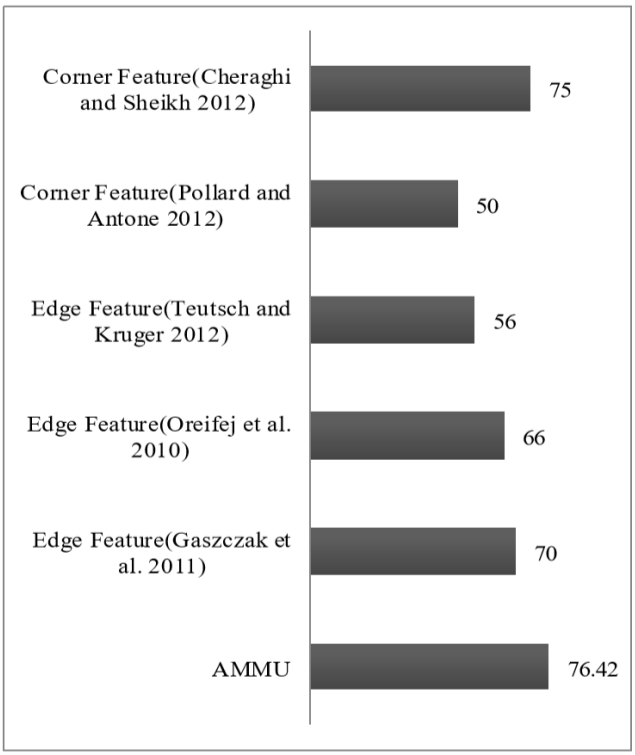

Figure 9: Detection Rate for AMMU and various feature based methods from previous research

b) COMPARISON BASED ON RELEVANCY WITH MOTION MODEL

Moment based Motion Unification or AMMU proposes motion model. Therefore, AMMU is validated with methods based on motion detection relevancy from previous research in terms with Detection Rate (DR). Optical flow method where any motion model does not exist performed by Pollard and Antone (2012) [29] achieved Detection Rate (DR) of 50% and Gaszczak et al. (2011) [17] achieved Detection Rate (DR) of 70%. However, Background subtraction method performed by Cheraghi and Sheikh (2012) [28] achieved Detection Rate (DR) of 75%. AMMU achieved higher Detection Rate (DR) of 76.42% than Optical Flow based method by Pollard and Antone (2012) [29] and Gaszczak et al. (2011)[17] and Background Subtraction based method by Cheraghi and Sheikh (2012) [28] shown in Figure 10.

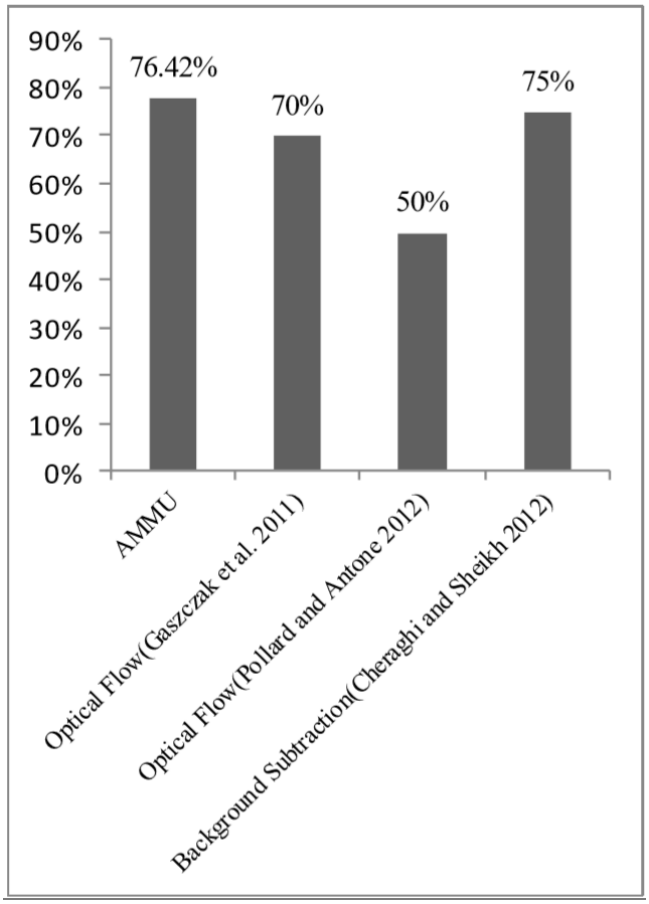

Figure 10: Detection rate for proposed AMMU and previous state of the arts

B. EDGE BASED DETECTION RATE

Three edge feature based detection methods are developed for same hardware performance measurement. Experimental results of three edge based detection methods i.e. Sobel edge based detection, Prewitt edge based detection and Canny edge based detection are compared to validate AMMU in terms with Detection Rate (DR) shown in Figure 11 and Figure 12. Detection Rate (DR) using Sobel edge based detection is 60.45% and Prewitt edge based detection is 60.08% for dataset 1. In addition, Canny achieved Detection Rate (DR) of 60.23% for dataset 1. However, AMMU achieved Detection Rate (DR) of 72.46%, which is higher than other edge based detection using dataset 1 shown in Figure 11. Higher DR indicates better performance from employing the moment feature to provide motion detection.

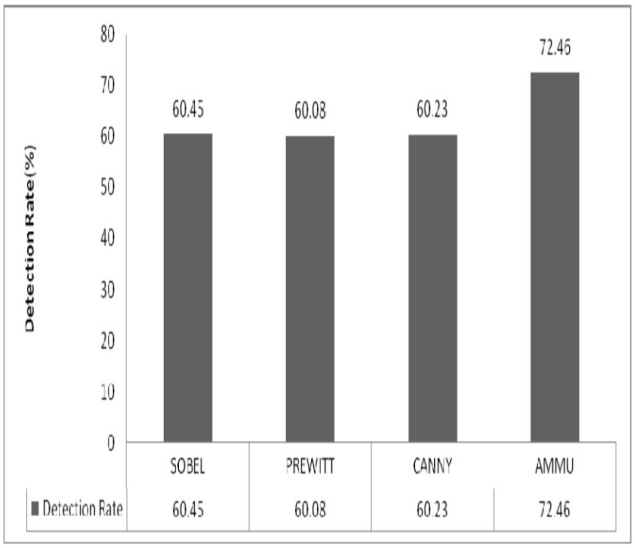

Figure 11: Detection Rate for AMMU and Edge based detection using dataset 1

For dataset 2, Sobel edge based detection achieved Detection Rate (DR) of 61.46% and Prewitt edge based detection is 64.16% shown in Figure 12. In addition, Canny edge based detection achieved Detection Rate (DR) of 64.36% for 3 fps. However, AMMU achieved Detection Rate (DR) of 76.42%, which is higher than other edge based detection using dataset 2.

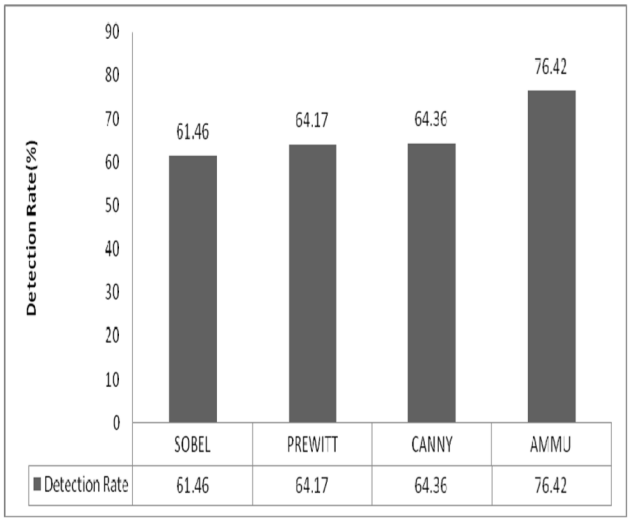

Figure 12: Detection Rate for AMMU and Edge based detection using dataset 2

C. CORNER BASED DETECTION RATE

Three corner feature based detection methods (Moravec, Susan, and Harris) were compared with AMMU for DR as shown in Figure 13 and 14 for datasets 1 and 2, respectively. AMMU shows superior DR to all previous models for both datasets, which indicates higher efficiency.

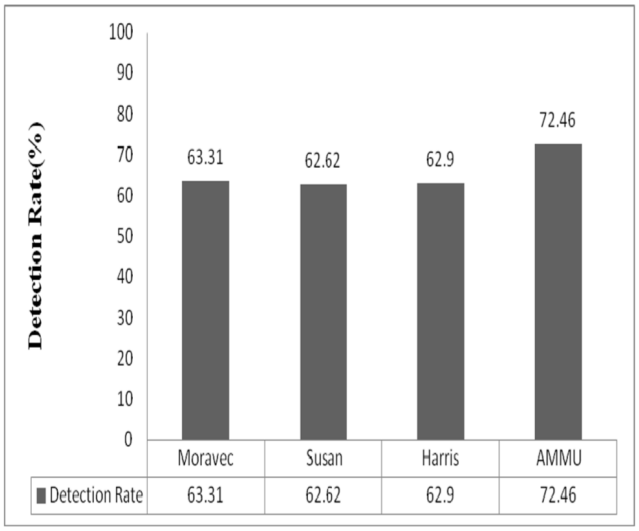

Figure 13: Detection Rate for AMMU and Corner based detection using dataset 1

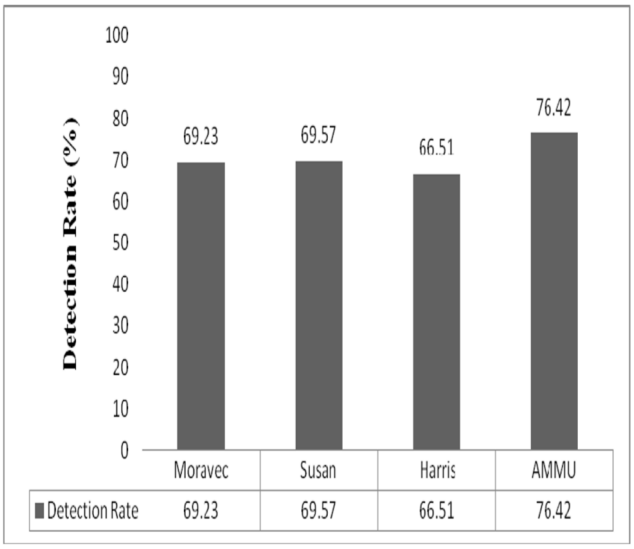

Figure 14: Detection Rate for AMMU and Corner based detection using dataset 2

5.2. FALSE ALARM RATE

FAR indicates the percentage of False Positive objects detected. AMMU was compared with the same three edge based detection methods and corner based detection methods for FAR as for DR.

A) PREVIOUS RESEARCH RESULTS

Since the proposed AMMU incorporates motion model, FAR metric is used to compare against optical flow [17, 29] mentioned by Gaszczak et al. (2011) [17] and Pollard and Anton (2012) [29] and background subtraction [28] method mentioned by Cheraghi and Sheikh (2012) [28], as based on the relevancy with motion model for motion detection. Optical flow based methods performed by Pollard and Antone (2012) [29] where motion detection was not included,

achieved False Alarm Rate (FAR) of 41% .However, Background Subtraction based methods performed by Cheraghi and Sheikh (2012)[28] achieved False Alarm Rate (FAR) of 25%. However, AMMU achieved False Alarm Rate (FAR) of 33% shown in Figure 15. AMMU was superior to optical flow, but inferior to background subtraction.

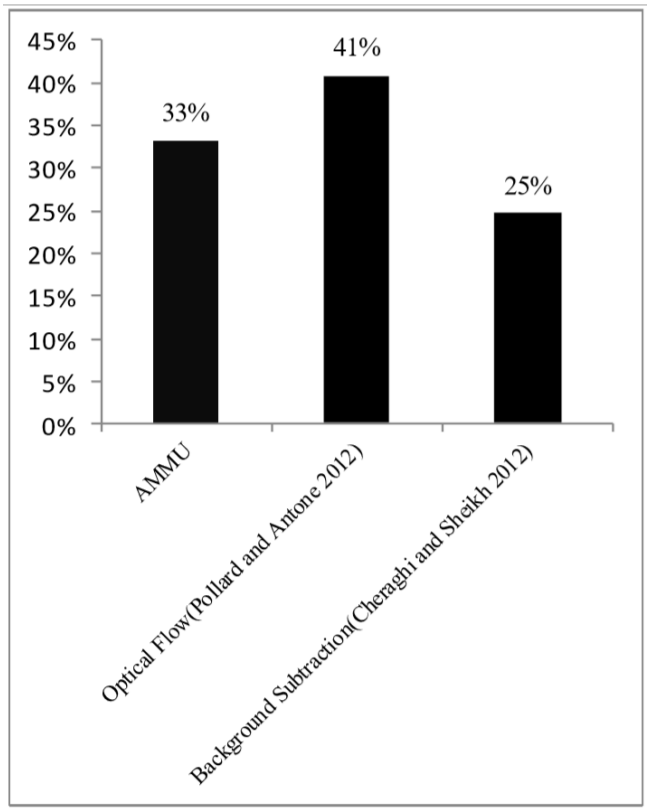

Figure 15: False Alarm Rate for AMMU and previous research results 2

B) EDGE BASED FALSE ALARM RATE

AMMU was compared to three edge based detection methods (Sobel, Prewitt, and Canny) for FAR, as for DR, as shown in Figure 15 and 17 for datasets 1 and 2, respectively. Low FAR indicates higher efficiency. AMMU produced lower FAR than all other edge based detection methods, which implies superior efficiency.

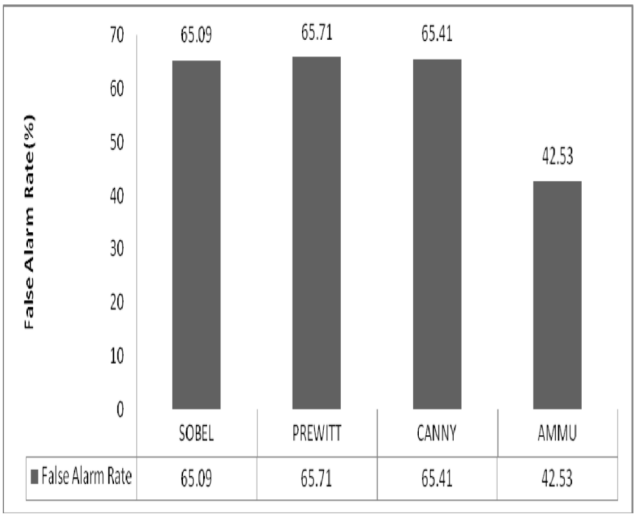

Figure 16: False Alarm Rate for AMMU and Edge based detection using dataset 1

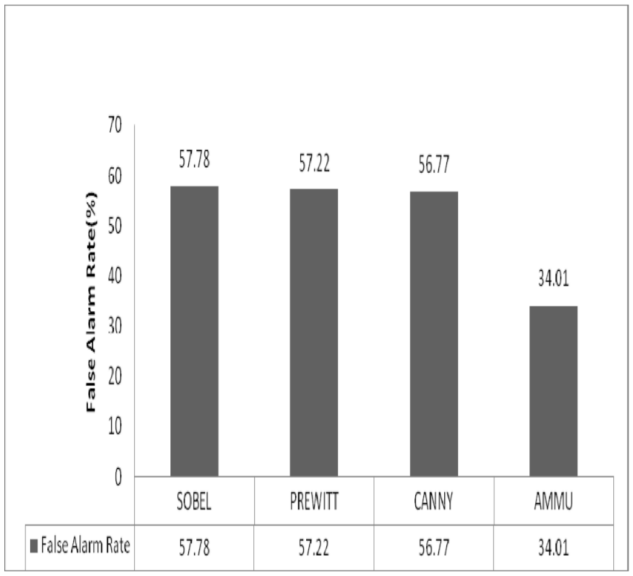

Figure 17: False Alarm Rate for AMMU and Edge based detection using dataset 2

C) CORNER BASED DETECTION PERFORMANCE FOR FALSE ALARM RATE

The three corner feature based detection methods as used for DR (Moravec, Susan, and Canny) were compared to AMMU for FAR, as shown in Figure 18 and 19 for datasets 1 and 2, respectively. AMMU always produced lower FAR than the other corner based detection methods, which indicates higher efficiency.

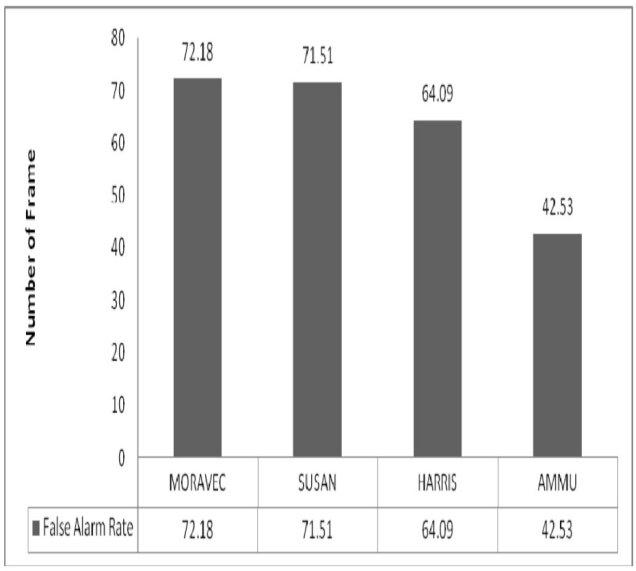

Figure 18: False Alarm Rate for AMMU and Corner based detection using dataset 1

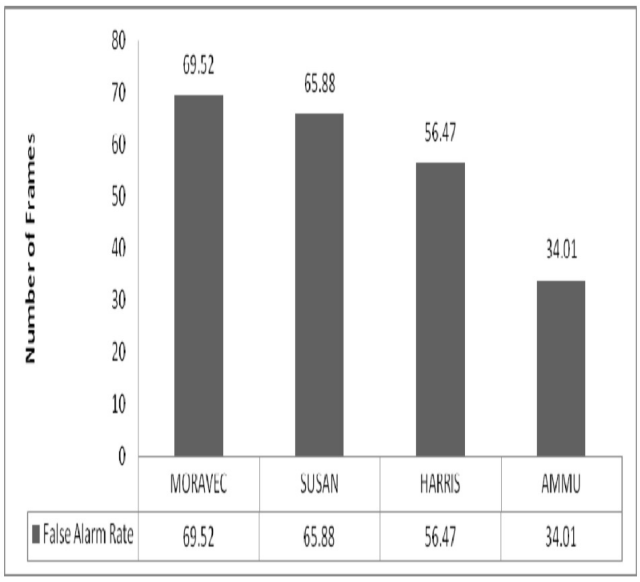

Figure 19: False Alarm Rate for AMMU and Corner based selection using dataset 2

5.3. COMPUTATION TIME (CT)

CT was compared for AMMU against previous research work, edge based detection methods (Sobel, Prewitt, and Canny), and corner based detection methods (Moravec, Susan, and Harris).

A) PREVIOUS RESEARCH RESULTS

AMMU required less CT than previous edge [30] and corner feature [1] based detection methods, as shown in Figure 20.

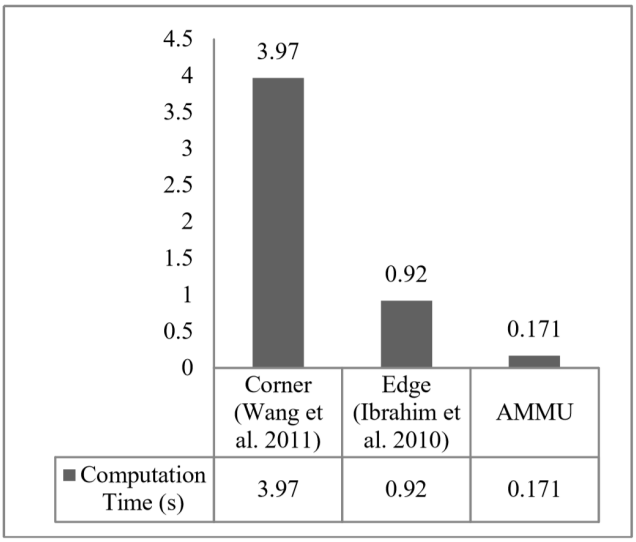

Figure 20: Computation Time for AMMU and Previous methods

B) EDGE BASED DETECTION PERFORMANCE FOR COMPUTATION TIME

The same three edge based detection methods (Sobel, Prewitt, and Canny) were compared against AMMU for CT, as shown in Figure 21 and 22. AMMU required less CT than other edge based detection methods for both datasets, which indicates lower processing time and higher efficiency.

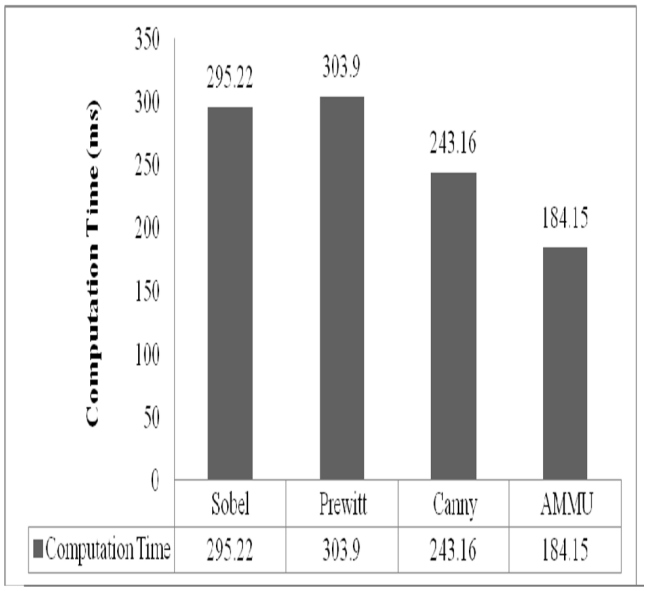

Figure 21: Computation Time (CT) of AMMU and Edge based detection using dataset 1

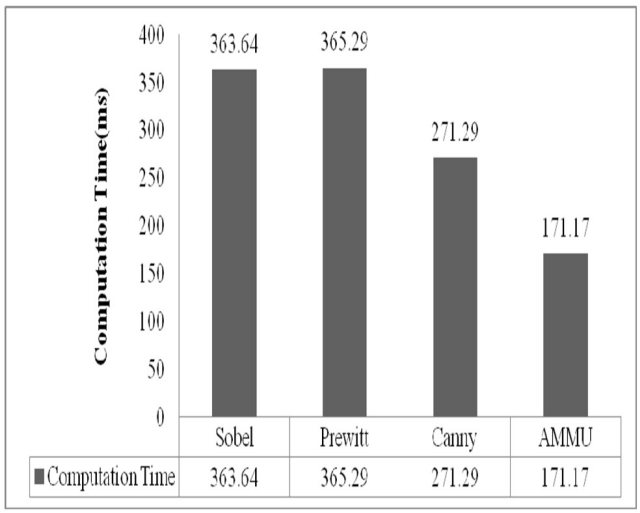

Figure 22: Computation Time of AMMU and Edge based detection using 3 fps

C) CORNER BASED COMPUTATION TIME

The same three corner based methods (Moravec, Susan, and Harris) were used to compare with AMMU in terms of CT, as shown in Figure 23 and Figure 24 for dataset 1 and 2, respectively. Although Harris corner based detection required less CT using dataset 1, as the number of images increased, AMMU required lower time than other corner based detection.

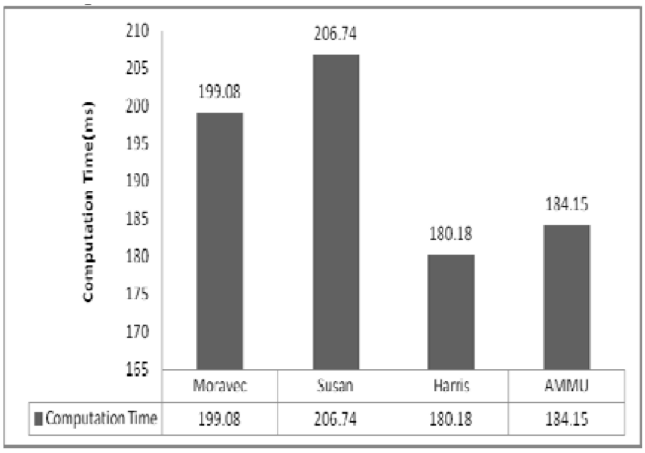

Figure 23: Computation for AMMU and Corner based detection using dataset 1

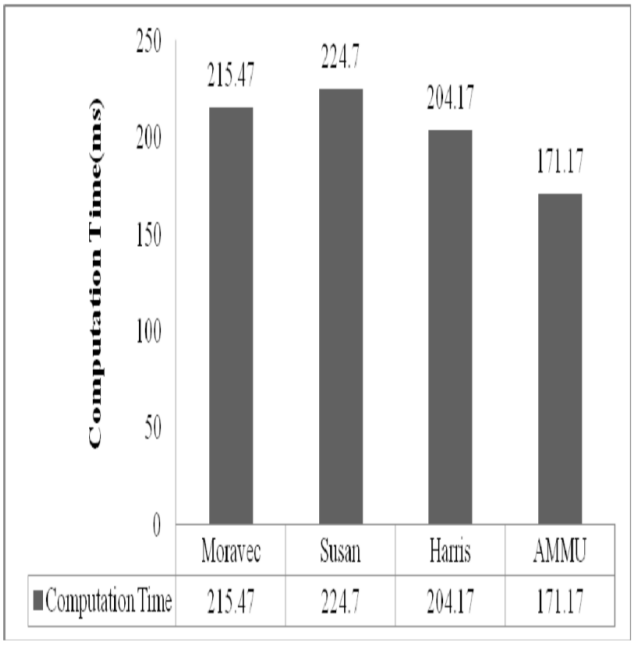

Figure 24: Computation Time for AMMU and for Corner based detection using dataset 2

6. CONCLUSION

Advanced Moment based Motion Unification or AMMU is developed based on two aspects i.e. i) AMMU is developed using the moment feature ii) AMMU provides motion model. The proposed AMMU model was validated against previous research results considering previous methods with motion detection, and previous edge and corner feature based detection. AMMU achieved higher detection rates than all previous models considered, indicates higher efficiency. Three edge based and three corner based detection methods were compared with AMMU for detection rate (DR), false alarm rate (FAR), and computation time (CT). AMMU achieved superior performance across the board, which indicates higher efficiency than previous research. Overall research methodology is composed of two sections, i.e. Proposed Framework is depicted in section 3.1 and Proposed Methodology is depicted in section 3.2. Proposed framework illustrates summarizes overall methodology whereas proposed methodology depicts brief illustration of the proposed motion model.

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