A Novel Region Growing Algorithm using Wavelet Coefficient Feature Combination of Image Dynamics

Tamanna Sahoo, Bibhuprasad Mohanty
Department of Electronics and Communication Engineering
ITER, Siksha 'O' Anusandhan, Deemed to be University, Bhubaneswar, India

***Abstract*—Moving object detection has versatile and potential applications in video surveillance, traffic monitoring, human motion capture etc., where detecting object(s) in a complex scene is vital. In the existing background subtraction method based on frame differencing, the false positive and misclassification rate increases as the background becomes more complex and also with the presence of multiple moving objects in the scene. In this piece of work, an approach has been made to enhance the detection performance of the background subtraction method by exploiting the dynamism available in the scene. The resultant differencing frame so obtained by the spatial background subtraction method is subjected to wavelet transformation. By extracting and combining wavelet features from the dynamics of the scene, a novel method of region growing technique has been further utilized to detect the moving object(s) in the scene. Simulation of various video sequences from CDnet, SBMnet, AGVS, I2R and Urban Tracker database has been applied and the method provides satisfactory detection of the moving object in a complex scene. The quantitative measure like Recall, Precision, F1-measure, and specificity computed for the algorithms, have indicated the algorithms can be a suitable candidate for surveillance applications.**

Keywords—Moving object; dynamism; wavelet transformation; region growing

I. Introduction

Identification of moving objects and localizing them in a video scene has become crucial as well as an initial task for many complex visual processing algorithms such as detection, classification, tracking, and analysis. This has lead researchers to work in this area and various models (parametric and non-parametric) have been already proposed in the spatial domain.

Using the benefit of the multiresolution analysis, two moving object detection methods have been proposed. The first one being object detection based on image dynamics subtraction [1], and the second one is to develop a novel region growing algorithms by extracting the wavelet features from the resultant subtracted image frames. In both algorithms, along with the dynamics creation, traditional background subtraction has been utilized in the transformed domain. In the second method, wavelet coefficient features of image dynamics are combined selectively to obtain a seed-based region growing process [2] for detecting the moving object in the scene. The methods have been applied to different video sequences available in CDnet [3], SBMnet [4], AGVS [5], I2R [6], and UrbanTracker [7] dataset. The result obtained by extensive simulation, has been compared with the reported results of several well-known techniques like ViBe [8], PCP [9] ,TD-2DDFT [10], and TD-2DUWT [11].

The rest of the paper is organized accordingly, wherein Section II provides survey papers related to both methods, Section III discusses the algorithm used in discrete wavelet transform domain and the creation of dynamics. Further in Section IV, the results of both the methods have been presented for various datasets and it has been discussed, both qualitatively and quantitatively using performance measure.

II. Related Work

Various techniques have been reported for the detection of moving object(s), such as, Paisitkriangkrai et.al.,[12] presents a study of moving targets like humans in pedestrian detection, using local feature extraction and support vector machine. In [13], a dual model (self and neighborhood model) which is a non-parametric-based background segmentation method has been proposed.

The generation of background becomes difficult for a complex scene or when there is a sudden change in illumination. This problem is tackled by Elharrouss et al., [14], by using the block-based Sum of Absolute Difference (SAD) method for background utilization as well as block-based entropy evaluation for background modeling purposes.

In the wavelet domain, the detection problem is addressed by Huang et al., [15], [16], by using change detection methods. Tsai et al., [17] applied 2-dimensional discrete Fourier transform (2D-DFT) where each Spatio-temporal slice of the gradient image is processed to detect the foreground objects.

According to Khare et al., [18], Daubechis Complex Wavelet Transform (DCWT) along with double change detection are the techniques used for detecting moving objects. Li et al. [19], estimated the models of foreground and background in wavelet domain using the likelihood of wavelet coefficients. Huntsberger et al. has used a wavelet-based algorithm for recognition and detection of objects in anti-submarine warfare using Logan radar data [20, 21]. Wavelet packet decomposition method has been applied for the analysis of sonar images, which are of quite large formats. Further, Tian et al. [22] have used wavelet coefficient characterization, namely spectral statistics and wavelet coefficients characterization (SSWCC) in spectral images for detecting targets. Boccigone et al., [23] have used Renyi's information as well as wavelet transform and region growing process for the detection in mammographic images. The camouflaged target images using wavelet coefficient features have also been proposed by Chennasetty et al., [24].

III. Proposed Methodologies

We have tried to obtain optimal detection results in the transformed domain by proposing a technique (Method I), named as Image Dynamic Subtraction (IDS). By utilizing this technique with the wavelet features, another novel region growing technique has been proposed (Method II), named as Image Dynamic Subtraction using Region Growing (IDS-RG). Below the detailed discussion has been presented.

A. Method I: Image Dynamics Subtraction (IDS)

The conventional background subtraction method suffers from the disadvantage of misdetection (detection of static object(s) along with moving object) which requires extensive further processing. First, the dynamics of the frame is created (Fig. 1) and then by using the algorithm of background subtraction, the difference is taken between the current dynamic frame and background dynamic frame.

1) Dynamic extraction: In a scene, when the dynamics, which is the motion of an object, are extracted by only using high-frequency components, is known as dynamic extraction. The high-frequency component gives information about the required edge and high contrast values of the moving objects.

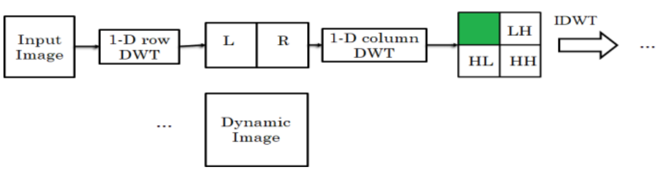

Fig. 1. Dynamic Extraction Process using Two-dimensional Discrete Wavelet Transform (2D-DWT).

Fig. 1 above depicts the dynamic extraction process using 2D-DWT where the decomposition of the image [25] is at a spatial level.

After decomposing into sub-bands (LL, LH, HL, and HH), the approximation coefficient (LL subband) is masked to zero and inverse DWT is applied to only higher frequency components to obtain the dynamics of that image. The following equation of creation of dynamics is presented below:

$$W^{-1} = [W] - F_{KA}^{-j}(x,y) \tag{1}$$

Where the F_{KA}, F_{KH}, F_{KD}, and F_{KV} represent the approximation, horizontal, diagonal, and vertical coefficient of the two-dimensional discrete wavelet transform at the j^{th} level. The W represents the wavelet decomposition and W^{-1} represents the inverse decomposition.

Fig. 2, shows the experimental setup of image dynamic subtraction (IDS) [19].

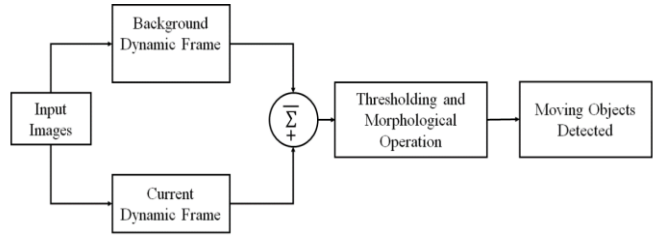

Fig. 2. Setup of Image Dynamic Subtraction using Two Dimensional Discrete Wavelet Transform (IDS-2DWT).

Group of frames is taken as input, the very first frame being referred as background frame. The dynamic extraction of background and the current frame is processed, using thresholding and morphological operation the detection result is produced. The advantage of this method is to avoid further processing of the detected result to get rid of misdetection due to the presence of a static object in the frame. The proposed method algorithm is provided below.

Step-1 Image Pre-processing

For input image

Do

- *Convert color image to grayscale image.*
- *Resize it to 512x512.*

End

Step-2 Frame selection

Do

- *Select B(x,y) as the background frame.*
- *F_k as the current frame.*

End

Step-3 Dynamic extraction of both frames

Do

- *Apply 2 level 2D-DWT.*
- *Mask LL subband to zero.*
- *Apply 2 level inverse 2D-DWT*

End

Step-4 Background Subtraction

Do

- *Using frame difference method*

$$D_K(x,y)=F_{kdy} - B_{dy} \tag{2}$$

End

Step-5 Thresholding and binarize

Do

- *Apply Otsu thresholding to $D_K(x,y)$.*
- *Get the value T_H.*
- *Binarize the difference image.*

$$D(x,y)=\begin{cases}1, D_k(x,y) \geq T_H \\ 0, \text{otherwise}\end{cases} \quad (3)$$

End

Step-6 Morphological Operation

Do

- *Using dilation operation.*

$$MO= D(x,y) \oplus B \quad (4)$$

- *Where B is the structuring element and MO is the moving objects detected.*

End

B. Method II: Image Dynamic Subtraction with Region Growing (IDS-RG)

The region growing process [26] is a technique where the regions are grown depending on some criteria. The most appropriate way to grow a region is by identifying the proper seed points.

1) Seed point computation: In this work, the selection of seed points is carried out based on the maximum featured value [27]. This present methodology avoids the Otsu thresholding and morphological operation that has been carried out in the previous method. After the selection, adjacent neighboring pixels which are satisfying the user-defined threshold condition, are included in the region.

A threshold value is taken to stop the region from growing and an optimal region is obtained. But one needs to keep in mind that the threshold value taken should be high enough so that the whole region is extracted [28]. This may also lead to the growth of a region much larger than the actual region, so the choice of threshold value must be a little higher than the optimal value so that the region grown is the actual region boundary.

The proposed technique of image dynamic subtraction using region growing is presented below in Fig. 3. In first step, a difference frame is computed by subtracting the reference background fame from the current frame. The difference input image of size N x M is then resized to 512x512. Image resizing is done so that the image can be divided into sub-region, in form of power 2 .Then it is converted to a gray-scale image (if the image is a color image). It is then divided into non-overlapping sub-blocks of 32x32 or 16x16.

Each of the above non-overlapping sub-block is converted to a 'dynamic' sub-block by adopting the procedure enumerated previously.

Wavelet coefficient features (WCF) like contrast, cluster prominence, energy, cluster shade, maximum probability, entropy, autocorrelation, variance, inverse difference normalized are extracted by using the popular GLCM method. With lots of experimentation, the initialization of the GLCM for 0-degree orientation, and separation vector (d) as one has been taken. The normalized linear values of contrast feature values are acquired along with normalized logarithmic values of cluster shade and cluster prominence, depending upon their dynamic ranges of the features. Three of the wavelet coefficient features are combined. From extensive possible combinations, it has been found that cluster shade, cluster prominence, and contrast combination provide maximum values for each sub-block as compared to other combinations.

For seed block selection, the selection is based on the criterion that the high value of the W.C.F represents the moving object in the spatial domain. Accordingly, the maximum of combined feature values is chosen as the reference seed sub-block. The purpose of selecting the seed block is that the higher value of the wavelet coefficient feature represents that it is a part of the target region. Then the coordinate of the seed point is computed based on the criteria that it is available at the midpoint of the seed sub-block at (r/2,c/2) point of the seed block[38], where r is the row and c is the column.

On selection of the seed block and subsequent seed point, the region [24] with the presence of the moving object is grown by selecting a suitable threshold value and merging the pixels with the seed points. The following Fig. 4 depicts the region growing algorithm undertaken for the purpose.

In the process, using the suitable pixel distance, pix_dist required is selected. It is done by creating a difference between the neighborhood pixels present in form of array in (k) and the R_mean (which is initially taken as the pixel value of seed point in I(r/2, c/2)) is satisfied for threshold. If the pixel distance is minimum of all and less than the threshold value (T) is added to the region. The next new R_mean is calculated using (5).

$$\text{New (R\_mean)}= \frac{R_{mean} \times R_{size} + k(\text{index})}{R\_size + 1} \quad (5)$$

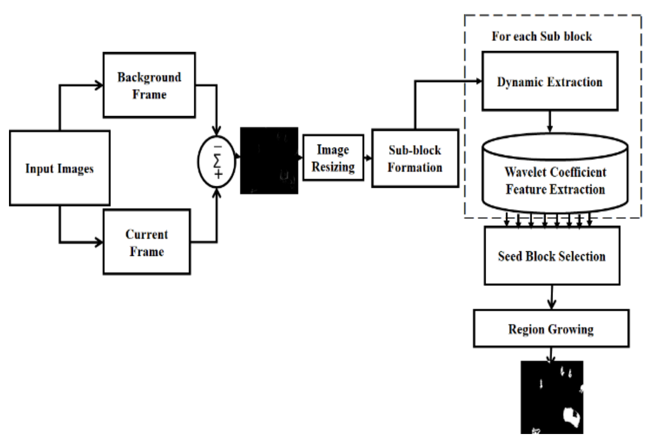

Fig. 3. General Setup of Image Dynamic Subtraction using Region Growing Algorithm.

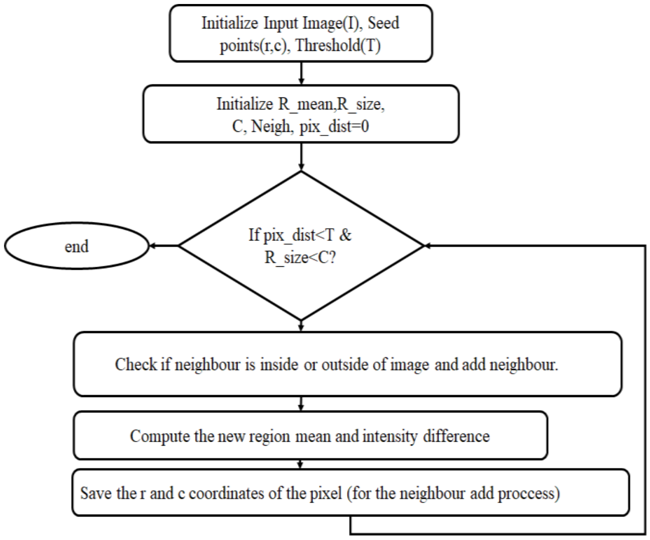

Fig. 4. Steps to Carry out Seed-based RGA.

Here R_size represents the number of pixels in the regions. The process continues until all the regions satisfying the threshold condition are added to the region.

IV. Result and Discussion

Extensive simulations are carried out on different video sequences with multiple and complex challenges for the detection of moving objects from a video frame. The experimentation is carried out on MATLAB environment (R2016a) by using Intel Core i5 CPU with 2.20GHz).

A. *Test Sequence*

Both of the methodologies are simulated on different frames of a particular test sequence, by carefully selecting the reference frames as background frames. The choice of sequence number, taken arbitrarily, but the complexity involved in the frames is considered. The major challengeable complexities are multiple moving objects, multiple static objects which changes as the sequences progress, camera movement, shadow for the static object occluding the moving object, complex background due to snowfall or rain, etc. In this paper, the detection results for different video sequences (one from CDnet [3], one each from UrbanTracker [7], I2R [6], AGVS [5], and SBMnet database [4] has been presented in this paper. Further, four more video sequences from CDnet has been compared with different state-of art methodologies.

B. *Experimental Results (Method-II)*

The next proposed method is image dynamic subtraction using a region growing algorithm. Here in this method, the current and reference frames are subtracted first. Then difference frame is divided into sub-blocks. The creation of dynamics (using 2D-DWT) is done on each sub-block, where wavelet coefficient features (WCF) using gray level co-occurrence matrix are extracted.

The maximum of each WCF from the sub-blocks is chosen as a seed block. The purpose of selecting the seed block is that the higher value of the wavelet coefficient feature represents that the region is part of the target. The moving object regions are grown using the seed point region growing algorithm from where the seed block the midpoint pixels are considered as the seed point. In the proposed technique, the combination of features like contrast, cluster prominence, and cluster shade are considered and the results are presented in Fig. 5 and Fig. 6.

1) Combined feature: The combination of features [32] is done to strengthen multiple complementary features and yield a more powerful feature. Features like contrast, cluster prominence, and cluster shade have been used.

The Contrast feature measures the local variations present in an image where it provides a correlation between the highest and lowest value of a continuous set of pixels [29]. Cluster shade is used for measuring the skewness of the matrix and is believed to gauge the perceptual concept of uniformity [30]. If the value is high the image is asymmetric [31]. Similarly, cluster prominence is the measure of asymmetry where if it is high, it is less symmetry.

2) Background updation: The process of background subtraction is about the difference between the current and reference (also known as background) image. Here for the experimentation, two types of reference or background image have been used where one is like the clear background image and the other one is the background updated reference image.

The need for background updation is in the practical application where the background of the frame changes with the change of light and the motion of the local background. Thus new background of moving objects becomes static. Thus the background should be updated in real-time [33].

Challenges like illumination change have to be overcome, for which the background is updated and it is given in (6):

$$B_{t+1}=(1-\alpha)\ B_t+\ \alpha.\ I_t \tag{6}$$

Where B_{t+1} is the updated background, It is the current video frame, B_t represents the previous background frame and α is the learning rate, ranging from [0, 1]. Here, the 'α' is chosen through trials. According to [34], the higher the value of alpha, the presence of foreground in the background is a must and the lower value cannot overcome the sudden change of illumination in a scene. This background model obtains a threshold that can be applied over the distance between corresponding pixel values of I_t and B_t. The method is best in terms of speed, simplicity, and memory requirements than other methods like mean, median, histogram, and Min-max. To elaborate the idea of background updation, in the next Fig. 5, an example of Rouen video has been presented.

The first row in Fig. 5 represents the original frames (27, 50, and 173). The second and third-row represent the detection result of the proposed method without and with background updation. Using without background updation, the presence of ghostly artifacts of moving pedestrians, present in the background frame, are also present in the detection result. But while using the method with background updation, only the moving objects of the current frame have been detected in the result.

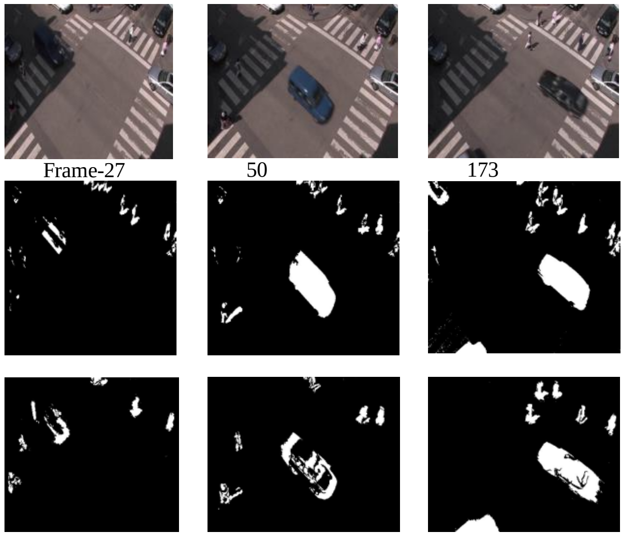

Fig. 5. Multiple Moving Object Detection using Method II .1st Row: Test Frames in Rouen (Traffic) Sequence,2nd Row: Corresponding Detection Results with Background Updation, and 3rd Row: Detection without Background Updation.

C. Qualitative Performance Measure

The visual comparison of the two methods of image dynamic subtraction using region growing algorithm (IDS-RG) with and without background updation with the ground truth has been presented in Fig. 6. The first row represents the original image of the current frames of test sequences, the second row represents the ground truth of that frame. The results of all frames are quite similar in this technique, that is, only the contours of moving objects are present and even the static lines of the background image are also present in the output detection result of IDS-RG without background updation. The method-II using a combined wavelet coefficient feature (WCF) with or without background updation has been applied to test sequences: Rouen (from Urban Tracker); bungalow (from CDnet); advertisement board (from SBMnet), bootstrap (from I2R) and S1 (from AGVS). The results with background updation are quite better than without background updation in Rouen, bootstrap, and bungalow video. The experimental results of IDS-2DDWT and IDS-RG are also compared with the four state-of-art background subtraction method below from Fig. 7 and Fig. 8 respectively.

Although in advertisement board and S1 video, without updation have shown a better result than with background updation as in later one only the contour is present but the presence of ghostly artifacts like snow and few static lines in the resulting image is also present. Further, addition of three crowded video sequences having complex scenario and multiple moving objects has also been used for comparison with the state-of-art results [37]. It includes skating sequence from bad weather category where snow is regarded as dynamic background, a tramcrossroad sequence from low frame rate category from the ChangeDetection.net (CD.net) benchmark dataset [3].

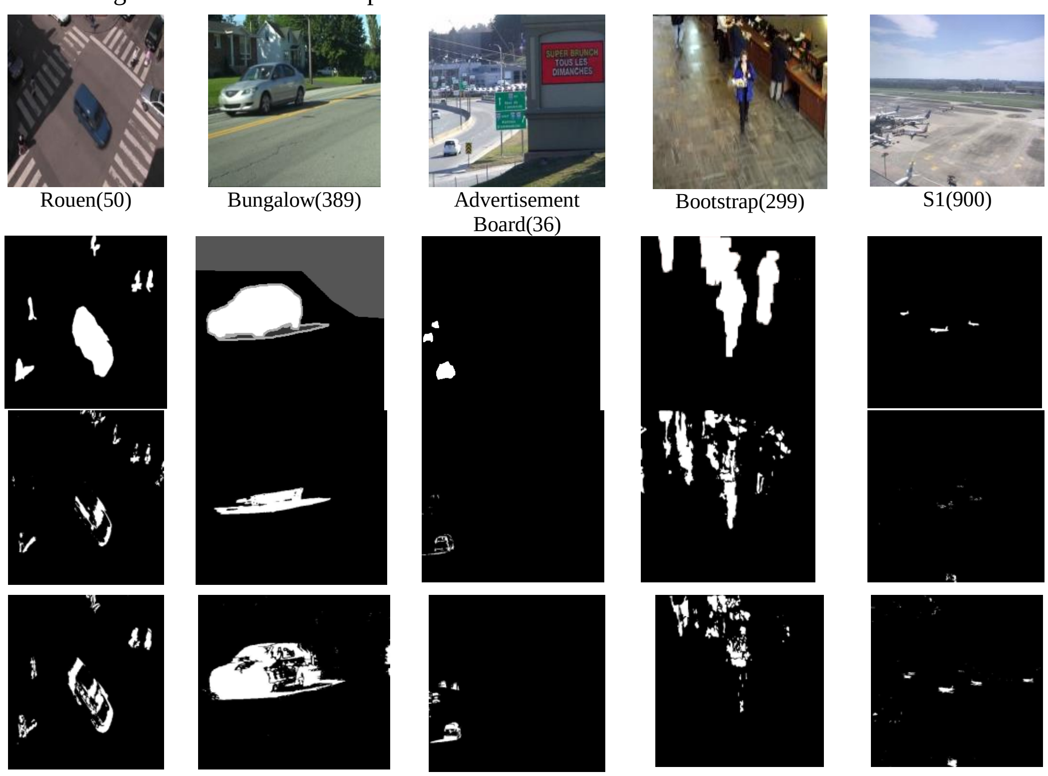

Fig. 6. More Detection Results for Algorithm II with different Datasets, 1st Row: Test Frames of Sequences (The Number in the Parenthesis Indicate the Frame Number of that Sequence), 2nd Row: Ground Truth of Frames, 3rd Row: Corresponding Detection Results without Background Updation and 4th Row: Detection with Background Updation.

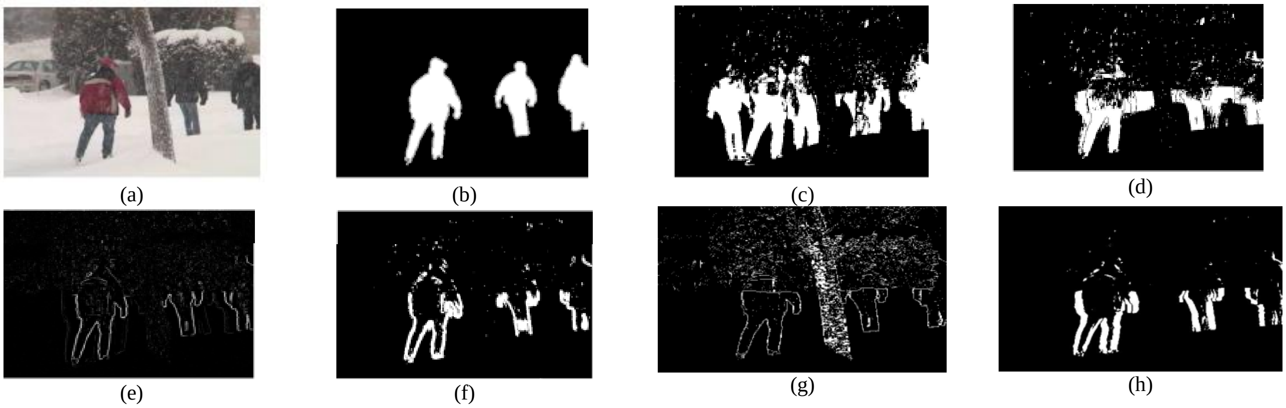

Fig. 7. Detection Result of Skating Frame (Frame Number-1953) (a) Input Frame (b) Ground Frame Reference; (c) ViBe; (d) PCP; (e) TD-2DDFT; (f) TD-2DUWT;(g) IDS-2DDWT;(h) IDS-RG + BU.

In Fig. 7 it has been shown that the proposed methodology (IDS-RG + BU) provides significantly better detection results than other methods. Since, the tree is available in the foreground, and is misdetected as in the Fig. 7(g) with IDS-2DDWT, the IDS-RG + BU method properly detects it as *not* moving object and hence clear detection of moving object (in this case, three human being in caps and gloves) are obtained. It is interesting to note that the proposed method is capable of eliminating the dynamic background due to continuous snowfall during the entire video sequence (as compared to ViBe and PCP). Due to low contrast the two human beings are not distinctly distinguishable against the black backdrops. Accordingly, the proposed method also fails to exhibit the entire contour of both persons in Fig. 7(h).

The video frame chosen for Fig. 8 is complex as it contains multiple numbers of moving small sized cars in the static background of high raising building and road with leveling as in Fig. 8(a). A careful observation of the frame reveals that the small sized moving cars are really indistinguishable against the backdrop. But the ground truth reference frame as obtained from the dataset [3], provides only the clearly visible and distinguishable three moving cars. It has been observed that both of our methods are capable of detecting almost all available moving objects [Fig. 8(g) and (h)]. But better visual representation is obtained in IDS-RG+BU method. The IDS-2DDWT method has some mis-detection and ghostly artefacts. The reported results of ViBe (c), PCP(d) and TD-2DDFT(e) have significant detection errors as shown.

D. Quantitative Performance Measure (QPM) Comparison

The performance of the proposed techniques and state-of-art is measured using four generalized metrics namely: Recall, Precision, F1- measure, and Specificity. Recall [35] can be defined by the percentage of detected true positive as compared to the total number of true positive in the ground truth which is given by (7). Precision [36] presented in (8), presents the percentage of true positives detected in comparison with the total number of items detected by the method. The above-mentioned metrics are used and usually, a method is considered to be good if it gives a high recall value without sacrificing the precision. F1-measure [39] is considered as the weighted harmonic mean of recall and precision using (9). Equation 10 is specificity which is defined as the number of correct negative predictions which is divided by the total number of negatives.

$$\text{Recall}=\frac{TP}{TP+FN} \tag{7}$$

$$\text{Precision}=\frac{TP}{TP+FP} \tag{8}$$

$$\text{F1-Measure}=\frac{2\times \text{Recall}\times \text{Precision}}{\text{Recall}+\text{Precision}} \tag{9}$$

$$\text{Specificity}=\frac{TN}{TN+FP} \tag{10}$$

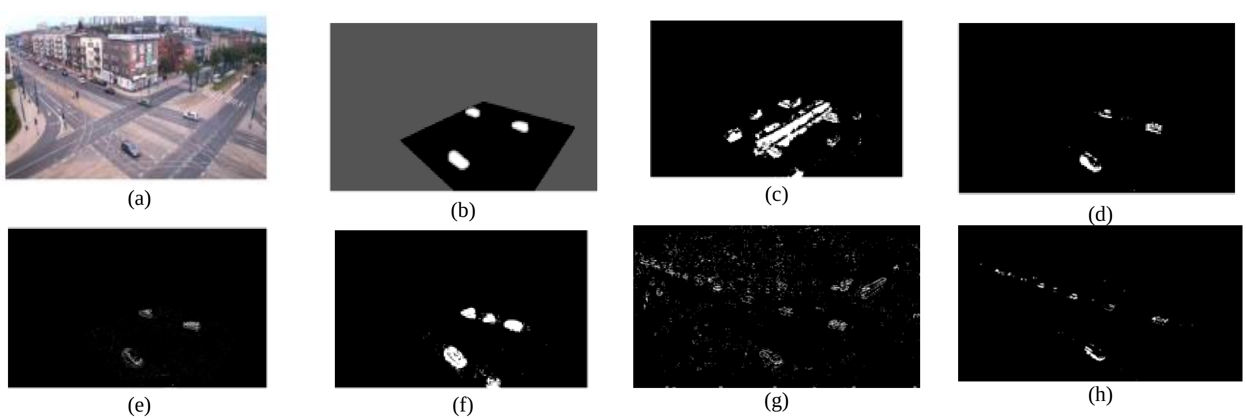

Fig. 8. Detection Result of Tramcrossroad Frame (Frame Number-502) (a) Input Frame (b) Ground Frame Reference; (c) ViBe; (d) PCP; (e) TD-2DDFT; (f) TD-2DUWT;(g) IDS-2DDWT;(h) IDS-RG + BU.

Table I presents the quantitative performance measure of videos of different datasets used for the experimentation purpose. The results of QPM determine that IDS-RG with background updation shows better results in most of the video sequences (Recall value of Rouen, Bungalow Advertisement board sequences is greater than IDS and IDS-RG (without background updation).

The results of IDS-2DDWT and IDS-RG with background updation are further compared with well-known state-of-art techniques. From skating and tramcrossroad test sequences, short clips of 96 frames are taken as input. To be specific, two short clips consist of 96 frames from skating sequence (from frames 1905 to 2000), from tramcrossroad sequence (from frames 413 to 508) and their quantitative performance measure has been presented Table II and Table III. In all videos, the result in IDS-RG has shown better. Table II and III presents the average metrics for all 96 frames, respectively. ViBe produces very low metrics especially in tramcrossroad video (as shown in Table III); further due to foreground aperture problem TD-2DUWT method also suffer as shown in Table II. Image Dynamic Subtraction using region growing with background updation metrics shows better result in overall indicators.

TABLE I. QPM RESULTS OF ALL DATASETS USED FOR THE PROPOSED TECHNIQUES

Dataset	**Method I**:Image Dynamic subtraction				**Method II:** Image Dynamic Subtraction using Region Growing(without Back- ground Updation)				**Method II:** Image Dynamic Subtraction using Region Growing(with Background Updation)			
	Recall	**Prec-ision**	**F1-Measure**	**Specif-icity**	**Recall**	**Precision**	**F1-Measure**	**Specif-icity**	**Recall**	**Precision**	**F1-Measure**	**Specif-icity**
Rouen (50)	0.9657	0.9957	0.9804	0.9960	0.9821	0.9843	0.9831	0.9845	0.9947	0.9929	0.9938	0.9931
Bung-alow (389)	0.8723	0.9904	0.9276	0.9903	0.9835	0.9875	0.9855	0.9864	0.9885	0.9918	0.9357	0.9917
Advertise-ment (36)	0.9598	0.9793	0.9695	0.9795	0.9681	0.9944	0.9811	0.9924	0.9705	0.9969	0.9884	0.9959
Boot-Strap (299)	0.9705	0.9390	0.9532	0.9365	0.9563	0.9635	0.9493	0.9127	0.9438	0.9512	0.9963	0.9925
S1 (900)	0.9880	0.9868	0.9824	0.9965	0.9968	0.9917	0.9943	0.9915	0.9957	0.9885	0.9963	0.9925

TABLE II. COMPARISON OF AVERAGE METRICS OF SKATING SEQUENCE (96 FRAMES)

Method	**Recall**	**Precision**	**F1-Measure**	**Similarity**
ViBe	0.5210	0.3779	0.4394	0.2816
PCP	0.4654	0.5205	0.4914	0.3257
TD-2DUWT	0.2266	0.6287	0.3332	0.1999
IDS-2DDWT	0.8937	0.9313	0.9121	0.8384
IDS-RG(with BU)	0.9656	0.9526	0.9442	0.9575

TABLE III. COMPARISON OF AVERAGE METRICS OF TRAMCROSSROAD VIDEO (96 FRAMES)

Method	**Recall**	**Precision**	**F1-Measure**	**Similarity**
ViBe	0.6095	0.0.0982	0.1692	0.0924
PCP	0.5939	0.8300	0.6924	0.5295
TD-2DUWT	0.5940	0.5574	0.5751	0.4036
IDS-2DDWT	0.9726	0.9666	0.9696	0.9410
IDS-RG(with BU)	0.9623	0.9567	0.9241	0.9338

V. Conclusion

Two new methods of multiple moving object detection in a video sequences have been proposed in this paper. Instead of adopting the conventional background subtraction method by means of frame differencing in spatial domain, the present work proposed the subtraction of dynamism available in the current and reference frame, thereby making it a potential technique for video surveillance. The use of discrete wavelet transform solves the localization of motion pixels associated in a frame by keeping those into high frequency subbands on decomposition. The exploration of these pixels are the dynamics of the frame which provide the necessary information of the moving object. Hence, instead of background subtraction, we refer to it as Image Dynamic Subtraction (IDS). The method of IDS exhibit better detection results both quantitatively (Table II and III) and qualitatively (Fig. 7 and Fig. 8). By suitably choosing wavelet coefficient feature (WCF), and adopting the region growing technique over and above it, the proposed method IDS-RG+BU exhibit enhanced detection results. The second method is capable of eliminating ghostly artefacts, occlusion, static lines, cluttering due to dynamic background as has been reported in this paper. Further, it has been observed that, the method of IDS-RG +BU is capable of detecting the moving object (even multiple objects) irrespective of size (for example tramcrossroad video). However, this method fails to provide the requisite results if the colours of the moving object and the background objects are the same and if the contrast between them is insignificant (for example skating video). In addition, this method fails to provide a complete binary image of the moving object(s) in some cases. Even if it detects the moving object by eliminating occlusion due to static object, the present proposed method does not exhibit acceptable result in case of occlusion made by another moving object. Attempts are being made to address these issues.

References

[1] T. Sahoo, B. Mohanty, “Moving object detection using background subtraction in wavelet domain,” 2nd International Conference on Data Science and Business Analytics (ICDSBA),2018.

[2] T. Sahoo, B. Mohanty, “Novel Region Growing Mechanism for Object Detection in a Complex Background,” In: Pradhan G., Morris S., Nayak N. (eds) Advances in Electrical Control and Signal Systems. Lecture Notes in Electrical Engineering, vol 665,2020.

[3] Y. Wang, P.M Jodoin, F. Porikli, J. Konrad, Y. Benezeth, and J. Ishwar , “ CDnet 2014: An Expanded Change Detection Benchmark Dataset,”in Proc. IEEE Workshop on Change Detection (CDW-2014) at CVPR-2014, pp. 387-394.

[4] P. M Jodoin, L. Maddalena, A. Petrosino, Y. Wang Y, “Extensive benchmark and survey of modeling methods for scene background initialization,” IEEE Trans. Image Process, vol. 26, no. 11, pp. 5244–5256,2017.

[5] http://www.agvscaac.com/pages/imagesDownload.html.

[6] L. Li, W. Huang, I. Y.-H. Gu, Q. Tian: ‘‘Statistical modeling of complex backgrounds for foreground object detection.’’ IEEE Trans. Image Process., vol. 13, no. 11, pp. 1459–1472, Nov. 2004.

[7] J.P Odoin, G.A Bilodeau, N. Saunier N, “Urban Tracker: Multiple Object Tracking in Urban Mixed Traffic,” Accepted for *IEEE Winter conference on Applications of Computer Vision (WACV14)*, Steamboat Springs.

[8] O. Barnich, M. van Droogenbroeck, “ViBe: A universal background subtraction algorithm for video sequences,” IEEE Trans. Image Process. Vol-20,pp- 1709–1724,2011.

[9] E.J Candès, X. Li, Y. Ma, J. Wright, “Robust principal component analysis?” J. ACM ,vol- 58, issue- 11,2011.

[10] D. Tsai, W. Chiu, “Motion detection using Fourier image reconstruction,” Pattern Recognit. Lett. Vol- 29, pp-2145–2155,2008.

[11] V. Crnojevic, B. Anti´c, D. Culibrk, “Optimal wavelet differencing method for robust motion detection,” In ´ Proceedings of the 16th IEEE International Conference on Image Processing (ICIP 2009), Cairo, Egypt, pp. 645–648,2009.

[12] B. Yin, J. Zhang, Z. Wang, “Background segmentation of dynamic scenes based on dual model,” IET Computer Vision, vol. 8, no. 6, pp. 545–555,2014.

[13] W. Liu, H. Chen, L. Ma, “Moving object detection and tracking based on ZYNQ FPGA and ARM SOC,”in Proc. IET Int. Radar Conf., pp. 1–4,2015.

[14] A.K Samantaray, P. Kanungo, B. Mohanty, “Neighborhood decision based impulse noise filter,” IET Image Process, vol. 12, no. 7, pp. 1222–1227,2018.

[15] J.C Huang, W.S Hsieh, “Wavelet-based moving object segmentation,” Electron.Lett.39 (19),2003.

[16] J. Huang, T. Su, L. Wang, W. Hsieh, “Double-change detection method for wavelet-based moving-object segmentation,” IET Electronics Letters, 40(13):798–199,2004.

[17] D.M Tsai, W.Y Chiu, “Motion detection using Fourier image reconstruction,” Pattern Recognition Lett. 29 (16) 2145–2155,2008.

[18] M. Khare, R.K Srivastava, A. Khare, “Moving object segmentation in daubechies complex wavelet domain,” Signal, Image and Video Processing. Accepted, doi: 10.1007/s11760-013-0496-4, Springer,2013.

[19] S. Li, D. Florencio, W. Li, Y. Zhao, C. Cook , “A fusion framework for camouflaged moving foreground detection in the wavelet domain,”IEEE Transactions on Image Processing, 27(8):3918–3930,2018.

[20] T.L Huntsberger, B.D Jawerth, “Wavelet based automatic target detection and recognition,” Annual Tech. Rep., University Research Initiative Program for Combat Readiness, University of South Carolina, Columbia, SC, USA,1998.

[21] T.L Huntsberger, B.D Jawerth, “Wavelet based algorithms for acoustic and non-acoustic antisubmarine warfare,” Annual Tech. Rep., University Research Initiative Program for Combat Readiness, University of South Carolina, Columbia, SC, USA,1998.

[22] Y. Tian, H. Qi, X. Wang, “Target detection and classification using seismic signal processing in unattended ground sensor systems,” in Proc. IEEE Int. Conf. Acoustics, Speech, Signal Processing (ICASSP’02),vol.4,p.4172,Orlando,Fla,USA,2002.

[23] G. Boccignone, A. Chianese, A. Picariello, “Using Renyi’s information and wavelets for target detection: an application to mammograms,” Pattern Analysis and Applications, vol. 3, no. 4, pp. 303–313,2000.

[24] N. Singh and S. Veenadhari, “Segmentation of Fuzzy Enhanced Mammogram Mass Images by using K-Mean Clustering and Region Growing,” International Journal of Advanced Computer Science and Applications(IJACSA), 11(5), 2020. http://dx.doi.org/10.14569/IJACSA.2020.0110546

[25] A. Jalal, V. Singh V, “A robust background subtraction approach based on Daubechies complex wavelet transform,”in: Advances in Computing and Communication, ACC 2011, pp. 516–524,2011.

[26] S. Paisitkriangkrai, C. Shen, J. Zhang, “Performance evaluation of local features in human classification and detection,”Iet Computer Vision, vol. 2, no. 28, pp. 236–246,2008.

[27] T. Bouwmans, “Traditional and recent approaches in background modeling for foreground detection: An overview,” Computer Science Review 11 (31- 66),2014.

[28] J. Yang, M. Shi, Q. Yi, “A New Method for Motion Target Detection by Background Subtraction and Update,”Physics Procedia, 33, pp 1768–17752012.

[29] M. Unser, “Sum and difference histograms for texture classification,” IEEE Trans. Pattern Anal. Mach. Intell. 8, 118–125 (1986).

[30] X. Yang , S. Tridandapani, J.J Beitler, D.S Yu , E.J Yoshida, W.J Curran, T. Liu, “Ultrasound GLCM texture analysis of radiation-induced parotid-gland injury in head-and-neck cancer radiotherapy: an in vivo study of late toxicity,” Med. Phys. 39 5732–9,2012.

[31] J. Wu, S. Poehlman, M.D. Noseworthy, M.V Kamath, "Texture feature based automated seeded region growing in abdominal MRI segmentation," In Proc. Int. Conf. BioMedical Engineering and Informatics, volume 2, pages 263–267,2008.

[32] R. Kalsotra, S. Arora, "A Comprehensive Survey of Video Datasets for Background Subtraction," IEEE Access, 2019.

[33] G. Takhar, C. Prakash, N. Mittal, R. Kumar, "Comparative Analysis of Background Subtraction Techniques and Applications," IEEE International Conference on Recent Advances and Innovations in Engineering, pp. 1-8,2016.

[34] J. Hou J, B.P. Zhang, N.M. Qi, Y. Yang, "Evaluating feature combination in object classification," in: International Symposium on Visual Computing, pp. 597–606,2011.

[35] Y. Lin, Y. Tong, Y. Cao, Y. Zhou, S. Wang, "Visual-Attention Based Background Modeling for Detecting Infrequently Moving Objects," in *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 27, no. 6, pp. 1208-1221,2017.

[36] S. Arivazhagan, L. Ganesan , "Automatic target detection using wavelet transform," EURASIP Journal on Applied Signal Processing, vol. 2004, no. 17, pp. 2663–2674.

[37] G. Han , J. Wang, X. Cai, "Background subtraction based on three-dimensional discrete wavelet transform," Sensors Basel 16(4):456,2016.

[38] A. Afifi, "A Hybrid Technique Based on Combining Fuzzy K-means Clustering and Region Growing for Improving Gray Matter and White Matter Segmentation" International Journal of Advanced Computer Science and Applications(IJACSA), 3(7), 2012. http://dx.doi.org/10.14569/IJACSA.2012.030716

[39] Mohana and H.V Ravish Aradhya, "Object Detection and Tracking using Deep Learning and Artificial Intelligence for Video Surveillance Applications," International Journal of Advanced Computer Science and Applications(IJACSA), 10(12), 2019. http://dx.doi.org/10.14569/IJACSA.2019.0101269.