Journal of Engineering and Applied Sciences 14 (12): 4043-4051, 2019
ISSN: 1816-949X

Moving Objects Detection Based on Bhattacharyya Distance Measurement

[1]Shahad Mahgoob Nafi and [2]Sawsen Abdulhadi Mahmood
[1]College of Medicine, University of Baghdad, Baghdad, Iraq
[2]Department of Computer Science, College of Education,
Al-Mustansiriyah University, Baghdad, Iraq

Abstract: Motion detection in video sequences is considered as a critical issue in video surveillance system. the key result of motion detection process is basically aims to extract and track the moving objects by segmenting the original frame into foreground part (moving objects) and background part in a video sequences. Practically, the moving objects may exhibit abnormal actions such as steady persons for while then moving. Meantime, the background may include periodic local actions such as waving arbor. Such intricacies may cause incorrect detection of moving objects based on the existing background subtraction approaches. In this study, we present a modified approach for moving objects detection based on Bhattacharyya distance measurement to detect the interaction between 2 sequence frames in a video sequences captured by static camera taking in consideration an indoor and outdoor scenes. A modified background subtraction method is adopted to extract the foreground parts in the video sequences (moving objects). The performance evaluation of the proposed approach was conducted using different video files taken from public video database with assist of several performance metrics. The experiments results proved the effectiveness of the proposed approach for moving objects detection.

Key words: Bhattacharyya distance, background subtraction, object detection, moving objects, detection, experiments

INRODUCTION

Motion detection is one of the significant tasks in video scene understanding and processing of the system. It helps to take out the important information from scenes that are used in several computer vision application, for example, object tracking, automatic video surveillance, classification and activity understanding. These make motion detection have a very high active research field in computer vision and its employment in automated visual and control surveillance system. Visual surveillance is the main technology to compact against crime, terrorism, public safety used in town centers, schools, transport networks and hospitals, proficient management of transport networks and public utility such as railway crossings and traffic light. In general, motion can be detected using different methods such as optic (detect video using cameras) infrared (employ passive and active sensors), sound and vibration (using magnetic measuring devices and magnetic sensors), radio frequency energy (microwave motion detection and radiography). But among these entire methodologies camera based method is usually intended for the improvement of computer vision based systems and for the detection of moving objects (Manchanda and Sharma, 2016). Moving object detection is the way to extract the moving part (region of interest) from all around (Hu *et al*., 2004). To take out the fore ground from the background at the beginning camera captured the video and then decompose into frames, the pixels from these frames are categorized into 2 groups, one belongs to the foreground and the second belongs to the background (Parekh *et al*., 2014). There are several traditional methods which are used to detect motion.

These methods can be categorized as frame difference, optical flow temporal difference and background subtraction methods (Shaikh *et al*., 2014) these are the essential methods for motion detection, these methods can be used separately or in grouping of each other to get the best recognition of motion; first, frame difference presence the calculation of the difference between 2 or more sequential images (Bouthemy and Lalande, 1993) but there is a problem in this method that the detected objects are imperfect and unwell presented. Second, method is the optical flow (Beauchemin and Barron, 1995) which gives totally information about the movement but the challenging in the real-time implementation because these methods calculated

Corresponding Author: Shahid Mahgoob Nafi, College of Medicine, University of Baghdad, Baghdad, Iraq

movement that is usually slow. Third, temporal difference this method is built on the pixel wise difference of the sequential frames. The result of this method does not good when the detection of object is either moving too fast or too slow and this is because of the little difference between video frames and this lead to the explanation of object is missing (Hu *et al*., 2004). Finally, background subtraction the implementation concerned in this method is also unpretentious in which the background frame is considered a reference, after that the difference between background frame and current frame is calculated. The resulting image acquired is the image of a movable object to be represented as the foreground object (Athanesious and Suresh, 2012).

Most motion detection algorithms used background subtraction techniques; in general they have 3 stages. First, it needs a static camera to develop a model of the background. Second, it computes the difference between current image and the background image; Finally, we must apply the threshold operation to select if a pixel takes place with the background or with the foreground. Detecting a moving objects in a video frames have always been a very essential research for several computer vision researchers because there are still various challenges that prevent the accurate and correct motion detection due to several complicated matters like shape, illumination change, speed, shadow and so forth. In the last years, there are many motion detection methods have been suggested.

Jain and Nagel (1979) proposed the most ordinarily utilized method temporal differencing. This method takes the current frame and compared it with the previous frame. The compared image is then thresholded to separation out foreground objects. This technique fails, if objects have uniformly distributed intensity values and if object stay not moving for more than a frame period (1/fps). There is another similar method which takes current frame and compared it with first frame. But this method fails if any organizational or lighting changes happen.

Another methods built on Gaussian Mixture Models (GMMs) (Stauffer and Grimson, 1999) are utilized as a part of higher multifaceted nature scenes in which each pixel is modeled as a mixture of Gaussian. This strategy is competent to redundant movements from mess, long period scene variations and illumination change. The Self-Organizing Background Subtraction (SOBS) algorithm (Maddalena and Petrosino, 2008) utilize neural system structure for background model by learning motion design in self-organizing technique. The model is strong for moving background, slow light variety, cast shadow and cover.

Kemoucheand Aouf (2009) suggested a new technique to distinguish the moving objects by incorporating the data in regards to the flow along with the RGB color information to determine the background form. Yatim *et al*. (2013) proposed a mechanized image based frame work to recognize the motions of the human in an intensive environment. At first using background forming for extracting and naming the target object and after that the centroid position of total objects are collective to calculate the motion vector. Hu *et al*. (2015) proposed a new technique for following and tracking the moving item in a video frame using dynamic camera. At first, the foreground object was separated with the assistance of the image differences scheme and regions related with the target object are acquired with the assistance of incorporation scheme. At last with the assistance of least bounding boxes they extracting moving object which are then followed with Kalman filter built on center of gravity. This method was good for real time application and prepared for following the covering objects.

MATERIALS AND METHODS

Various popular techniques initialize their model using a sequence of frames such as the presented research by Wang and Suter (2006). This technique seems to be resistant to environmental noise this happens because the approach provides enough information to further sequential frames. But the model fails and results in wrong detections if unexpected illumination changes occur through initialization. In such a case it is required to build another background model and the last whole model is required to be rejected. Another failing in the model if the length of analysis video is shorter than the training video, this happens due to inadequate information. The researchers in the presented research by Barnich and Van Droogenbroeck (2011) suggested a solution for this problem by initializing the background model from one frame. Initializing the model done by choosing pixel value in the spatial proximity. This leads to share the information with neighborhood pixel as in the situation in temporal distribution as one frame does not hold enough information about color or the variation of illumination in coming video sequences, thus, this process is liable to noise problems.

In this research, we suggest a suitable solution for this problem based on background subtraction, motion detection and foreground subtraction techniquesas illustrated in the following subsections.

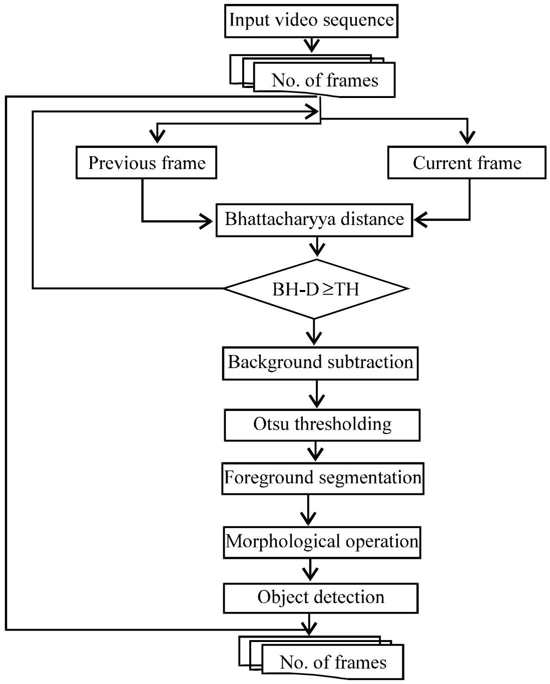

Fig.1: The block diagram of the proposed motion detection algorithm based moving object detection

Moving object detection approach: The framework of the proposed moving object detection is shown in Fig. 1 and relies on three main steps:

- Step 1: background model construction
- Step 2: botion detection approach
- Step 3: foreground extraction approach

Background model construction: In this step, the first frame was taken as initial frame, then background frame needs to be updated in real time in order to update the background frame in order to avoidlight changing and to extract the moving object accurately.

Motion detection: In this step, the human motion is detected based on the Bhattacharyya distance measure.

Foreground extraction approach: In this step, we use the background subtraction method for extracting the difference image and Otsu thresholding algorithm to calculate and determine the thresholding benchmarks to generate the binary image (binary mask process). Subsequently, the moving object can separated effectively with assist of foreground and background construction.

Background initialization: There are several ways to get the initial background image. Such that, put the first frame as the initial background or the background frame is constructed using the average of the first N frames or employ a background image sequences without the probability of dynamic object to evaluate the background model parameters. When we use a fixed camera, the simplest way is represented by adapting the first frame as background frame. In this way, this technique is effect significantly by outside location it is not good for changing in the environment with difficult background. The background frame configuration play an important role in the accuracy of object detection and updating the background image, a perfect background model is needed to extract the background accurately when there isa moving object in or out the background through the initialization. As the previous knowledge, we take first Frame (F1) of the input video sequence and supposed to be the initial background BC:

$$BC(x, y) = F1(x, y) \tag{1}$$

Background construction model: The background model needs to be updated throughout video sequences in order to avoid background scene changing, moving objects appearance throughout the scene, noise, lighting variations and fixed object for a long time, etc. Therefore, this stage is so, crucial to find a suitable solution for these challenges in real time objects detection and tracking. In this study, the background frame model is constructed based on the Blind Background theory (EL Baf *et al*., 2008) which is denoted by:

$$BC_{t+1}(x, y) = (1-\alpha) * BC_t(x, y) + (\alpha)C_t(x, y) \tag{2}$$

where, α is a scalar value within the range (0, 1) determined from the experiments. In this research, α = 0.8, (x, y) is a grey pixel value in the current frame, $BC_t(x, y)$ and BC_{t+1} (x, y) are the background value of current frame and next frame, respectively. In this research, the background model is constructed and updated at each 2 frames. The video sequences are acquired using fixed camera, so, the background model can stay relatively steady for a long period of time. Utilizing this method can effectively avoid the unexpected event of background like appearance of something sudden in the background that is not contained within the original background. Algorithm (1) illustrates the main steps of background model construction process.

Algorithm 1; (Background Construction):
Input: Video sample, frame-gap = 2, α = 0.8
Output: background

```
Begin
Count←-1
while not end ofvideo filedo
    current-frame←read frame from video sample
    ifframe = first video frame then
      background←current_frame
   Endif
  ifframe_gap = countthen
    background←(1-alpha) *background+
                (alpha* current_frame)
     count←-1
   End if
   count←count+1
  End while
End
```

Motion detection: Human motion analysis and detection is the first task in computer vision applications. Human detection aim to cutoff the corresponding area of people from the overall image it is a significant matter in human motion analysis systems followed by subsequent operations such as action recognition and tracking. There is several sequential process used in the motion detection algorithms and the foreground object extraction. In this study, the Bhattacharyya distance measure is utilized to measure the interaction between sequenced frames in real time video which represents the key point of moving objects detection methods.

Bhattacharyya distance measure: Bhattacharyya distance (BH) one of the statistical measures widely used for evaluating. It first discovered by Bhattacharyya (1946). It's a variation-type measurement between 2 populations and applied in multiclass classification (Choi and Lee, 2003) and computer vision (Aherne *et al.*, 1998). The Bhattacharyya distance between 2 continuous probability distributions (p, p_2) is defined as (AbdAllah and Shimshoni, 2013):

$$BH(p_1, p_2) = -In((BCH(p_i, p_2))) \tag{3}$$

where, BCH is the Bhattacharyya coefficient, a measure of the amount of overlaps between 2 statistical samples. For the discrete probability distributions the Bhattacharyya coefficient will be:

$$BCH(p_1, p_2) = \Sigma_{x \in x}\sqrt{p_1(x).p_2(x)} \tag{4}$$

And for continuous distribution it will be:

$$BCH(p_1, p_2) = \int\sqrt{p_1(x).p_2(x)}dx \tag{5}$$

Now, considering the special case of Gaussian distributions. Let, be 2 univariate Gaussian probability density functions where μ_1, μ_2 and $_{\circ 1}, _{\circ 2}$ and:

$$p_1(x) = N(\mu_1, \sigma_1^2) \tag{6}$$

$$p_1(x) = N(\mu_2, \sigma_2^2) \tag{7}$$

Then the Bhattacharyya coefficient is calculated as:

$$BCH(p_1, p_2) = \int\sqrt{p_1(x).p_2(x)}dx \tag{8}$$

$$\sqrt{\frac{2\sigma_1\sigma_2}{(\sigma_1^2+\sigma_2^2)}}\exp\left\{\frac{-(\pi_1-\mu_2)^2}{4(\sigma_1^2+\sigma_2^2)}\right\} \tag{9}$$

Therefore, the BH is:

$$BH_D(p_1(x), p_2(x)) = -In(BC(p_1(x), p_2(x))) \tag{10}$$

$$-In\left(\sqrt{\frac{2\sigma_1\sigma_2}{\sigma_1^2+\sigma_2^2}}\exp\left\{\frac{-(\pi_1-\mu_2)^2}{4(\sigma_1^2+\sigma_2^2)}\right\}\right) \tag{11}$$

$$\frac{1}{2}In\left(\frac{\sigma_1^2+\sigma_2^2}{2\sigma_1\sigma_2}\right)+\frac{1}{4}\frac{(\mu_1-\mu_2)^2}{\sigma_1^2+\sigma_2^2} \tag{12}$$

Motion detection description: In this study, the description and implementation of the proposed motion detection algorithm is presented and illustrated which is composed of the following main steps:

Algorithm 2; The proposed motion detection algorithm:

Step 1: Read video file sequences
Step 2: Take the previous frame and current frame
Step 3: Cconvert the 2 sequence frames into gray level and calculate the histogramfor both frames
Step 4: Calculate the Bhattacharyya distance between two successive frames as identified in Eq. 3
Step 5: If BH distance measure gives high difference between 2 successive frames and exceeds the given dynamic threshold then a motion is detected. Obviously, the estimation of an appropriate threshold level for the Bhattacharyya distance test is very critical to achieve the presented motion detection algorithm. Thus, the dynamic threshold level is adopted in this study based on the mean of the first 10 difference value obtained from BH-distance measure and weighted by a scalar value (β) determined from the experiments. In this research, β value is stand to (0.0001)

Additionally, to ensure accurate motion detection between the sequences frames, we adopt the Standard Deviation SD measure to discard the false positive status. The equation of the dynamic thresholding level is identified in Eq. 13:

$$\begin{aligned}\text{Threshold} &= \text{mean(differences buffer)}+\\ &\beta+\text{SD(differences buffer)}\end{aligned} \tag{13}$$

Algorithm 3 illustrates the main steps of calculating the differences between 2 sequence frames based on BH-distance. The dynamic threshold level value is determined and stated in algorithm 4. Finally, the workflow of the proposed motion detection algorithm based moving objects detection is stated and formulated in algorithm 5.

Algorithm 3; (Bhattacharyya distance measure):

```
Input: Video sample
Output: BH-distance
Begin
    while not end of video filedo
    current-frame←read frame from video sample
    if frame number greater than 1then
    BH-distance←Bhat (previousframe, curent-frame))
    End if
    Previous-frame←current-frame
    End while
End
```

Algorithm 4; (Motion detection algorithm):

```
Input: Video sample
    Output: Motion (if moving = 1 then motion detection,
if moving = 0 then no motion detection).
Begin
    while not end of video file do
    BH-distance←Distance measurement ( )
    threshodling dynamic←thresholding ( )
    if BH-distance>= thresholding then
    moving←1
    else
    moving←0
    End if
    End while
End
```

Algorithm 5; (Dynamic thresholding):

```
  Input: Video sample, β = 0.0001
  Output: Thresholding
Begin
Buffer [ ] ←0    // Create one dim buffer [10]
whilenot end ofvideo file do
    BH-distance←distance measurement ( )
    if frame number is <10then
       Right shifting for  buffer
        buffer (last right element )←BH-distance
    else
      Right shifting for buffer
      buffer (last right element )←BH-distance
    mean←Gaussian distribution (buffer)
    SD (standard deviation)←Gaussian distribution
    (buffer)
    thresholding←mean (buffer)+beta+SD (buffer)
    End if
End while
End
```

Foreground extraction scheme: The foreground extraction procedure essentially based on 2 main parameters; the background subtraction and binary masking procedures. In order to extract the foreground (moving objects) from the video sequence, the absolute difference D_i between the current frame and the background image is computed according to Eq. 14:

$$D_i(x, y) = \left|Cf_i(x, y)\text{-}B(x, y)\right| \tag{14}$$

where, i =1, 2, ... is the frame index in the video sequence frames. The difference D_i is calculated between the background image B and the current frame Cf when motion is detected as illustrated in algorithm 5. The binary masking procedure is performed according to the difference image D and determining the optimum threshold value specified from Otsu method (Gonzalez and Woods, 2006).

Otsu method is mainly formulated to implement clustering-based image threshold, once 2 pixel classe's background pixel and foreground pixel are supposed to be suitably differentiate as illustrated in Eq. 15. Otsu method computes the optimum threshold to split up the image into a foreground area, represented by F and a background area represented by G. Through the minimization of within-class variation, threshold can decrease the classification errors. To compute the "Within-class variance" this is simply done by the sum of the 2 variances multiplied by their related weights:

$$\sigma^1_w(g) = w_G(g)\sigma^2_G(g)+w_{(g)}\sigma^2_F(g) \tag{15}$$

w_G (g) and w_F (g) are the class probabilities at the intensity (g). And the 2 corresponding pixel classes σ^2_G and σ^2_F are the individual class differences. The formulas for element calculation are defined by AbdAllah and Shimshoni (2013). Threshold is computed in Eq. 16:

$$Oth = \arg\min\,(\sigma^2_w(g)) \tag{16}$$

The thresholding process is performed according to Eq. 17:

$$D(x, y) = \begin{cases} 1: D(x, y) \geq Oth \\ 0: D(x, y) < Oth \end{cases} \tag{17}$$

Morphological operation: Morphological operations (Opening, closing) are a useful mathematical tool (Pratt, 1991). Mathematical morphology applied on the segmented binary image for smoothening the foreground region and describes the shape of area from image.

RESULTS AND DISCUSSION

The demonstration of the experimental results of the proposed motion detection algorithm is presented in this section based on public video database. The performance evaluation of the proposed motion detection algorithm is conducted using indoor and outdoor video samples taken from the adopted public data set (Change Detection.NET, 2014). The comparison operation is specified with the ground truth of the data set. Two types of video sequences were handled; the first type is a colored video while the second video type is captured by a thermal vision-based monitoring camera. From the experiments, we noticed the effective performance of the Bhattacharyya distance measure based motion detection algorithm which is showed an independency behavior regardless the video type (colored or not). In addition, the accuracy of edge classification is coupled with the closeness of tracked object to the camera. Thus, whenever the moving object is close to the camera, the Bhattacharyya distance based motion detection algorithm produces high differences.

We have adapted some performance measures to evaluate the performance of the proposed motion detection algorithm which discussed by Sokolova *et al*. (2006) and by Eisner *et al*. (2005). These measures are:

True Not Moving (TNM): Based on the agreement of both the ground truth and the system result when there is no movement identified.

False Not Moving (FNM): Based on the disagreement of both the ground truth and the system result when there is no movement identified.

True Moving (TM): Based on the agreement of both the ground truth and the system result when there is movement identified.

False Moving (FM): Based on the disagreement of both the ground truth and the system result when there is movement identified. For comparison purpose, 2 state of art (motion detection) algorithms are adopted, the first algorithm is Mixture of Gaussian1(MOG1) and the second is adaptive background learning. The comparison results were obtained using atesting program designed and implemented in MATLAB language program in order to exhibit the main differences between the results of the proposed method and the state of art methods.

Table 1: The output results based on measurement tools

Video/Measurements tools	Proposed method	MOG1	Adaptive background
Thermal-library			
TM	6408096	661123	4026459
FM	636601	28060	2547850
FNM	973595	6720568	3355232
TNM	41084228	41692769	39172979
Baseline office			
TM	890911	4026459	793537
FM	285391	2547850	671305
FNM	205638	3355232	303012
TNM	18193300	39172979	17807386
Baseline-pedestrians			
TM	96663	80285	99951
FM	11917	4595	168877
FNM	14486	30864	11198
TNM	9312321	9319643	9155361

Table 2: The performance evalution of video samples

Video/Performance evalution	Proposed method	MOG1	Adaptive background
Thermal-library			
F-measure	0.8884	0.1638	0.5770
Precision	0.9096	0.9593	0.6125
Recall	0.8681	0.89	0.5455
Specificity	0.9847	0.9993	0.9389
Baseline office			
F-measure	0.7840	0.5770	0.6196
Precision	0.7574	0.6125	0.5417
Recall	0.8125	0.5455	0.7237
Specificity	0.9846	0.9389	0.9637
Baseline-pedestrians			
F-measure	0.8798	0.8191	0.5261
Precision	0.8902	0.9459	0.3718
Recall	0.8697	0.7223	0.8993
Specificity	0.9987	0.9995	0.9819

Obviously, in Fig. 5-7 the proposed method performance gives high level accuracy in compared with MOG1 and adaptive background learning. Table 1, illustrates the output results of the measurement tools for the 3 methods. Based on the above measurements, we used the following performance indicators of the proposed motion detection algorithm:

$$\text{Precision} = \frac{\text{TM}}{\text{TM+FM}}, \text{ Recall} = \frac{\text{TM}}{\text{TM+FNM}}$$

$$\text{Specificity} = \frac{\text{TNM}}{\text{TNM+FM}},$$

$$\text{F-score} = \frac{2\times\text{Precision}\times\text{Sensitivity}}{\text{Precision+Sensitivity}}$$

Table 2 gives a full description for the four perfmance evaluation metrics for video samples. An illustration of Bhattacharyya distance differences between the sequenced frames for a thermal-library video is presented in Fig. 2 with 1250 frames captured at thermal vision-based

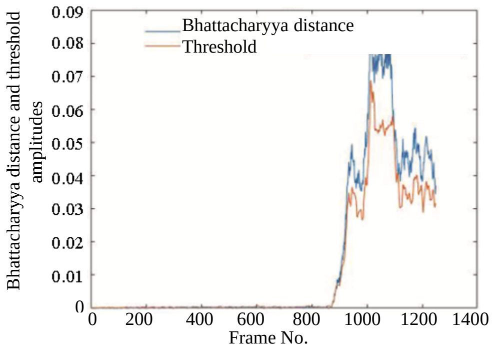

Fig. 2: BH-distance and thresholding amplitude for thermal-library video

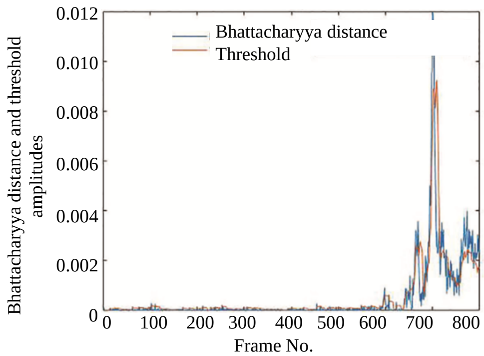

Fig. 3: BH-distance and thresholding amplitude for baseline office video

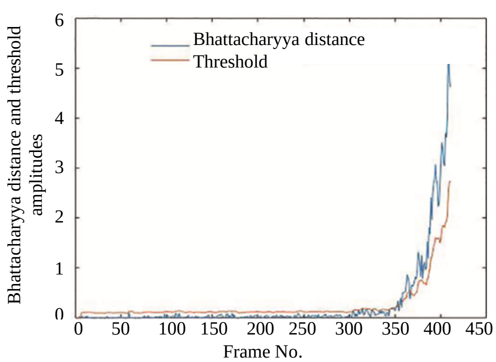

Fig. 4: BH-distance and thresholding amplitude for baseline pedestrians video

monitoring camera. Obviously, there is no movement at the beginning of video sequence, then the motion is detected at frame 861 based on BH-distance with dynamic threshold. The success of the presented detection algorithm depends basically on the dynamic threshold. Figure 3 shows the results for colored video sample (baseline-office) with 800 frames. Also, there is no

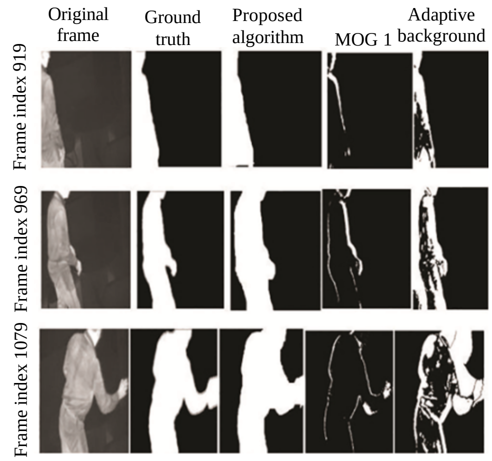

Fig. 5: Foreground extraction output result from thermal-library video

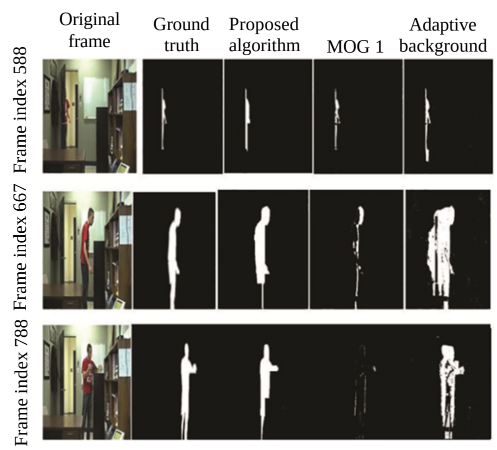

Fig. 6: Foreground extraction output result from baseline office video

movement at the beginning of video sequence, then the motion isdetected at frame 580 based on BH-distance with dynamic threshold.

The proposed motion detection algorithm detects the object in real time when the person interring the room as we see BH-distance give high difference when the object approaching the camera. Then settle on a certain range when the human remains standing. Figure 4 shows the results forcolored video sample outdoor (baseline pedestrians) with 410 frames. Also, there is no movement at the beginning of video, then the motion is detected at frame 305 based on BH-distance (Fig. 5-7) demonstrates the original video frame with its forground extraction in the ground truth and theproposed motion detection algorithm.using 3 video data set, thermal-library video, baseline office video and baseline pedestrians video, respectively.

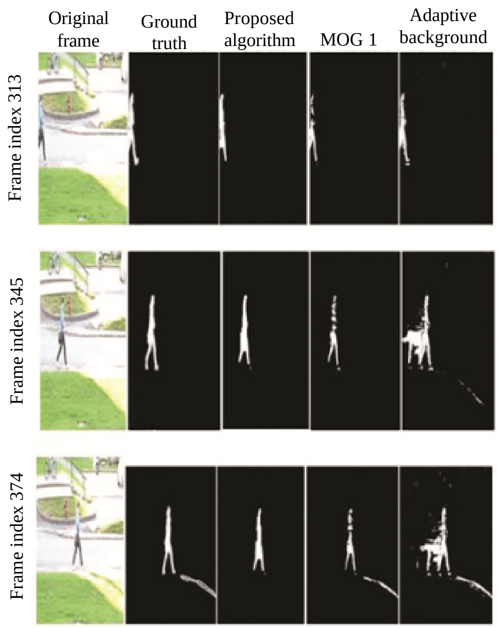

Fig. 6: Foreground extraction output result from baseline pedestrians video

CONCLISION

In our proposed method we defined a modified solution for human motion detection using BH-distance measure, background subtraction technique within indoor and outdoor environment to detect the moving object in a video sequence. The planned system was supported to eliminate processing requirements by eliminating analysis requests of unrelated background and reducing the processing time to detect motion in the successive frames. The results proved the efficiency of our method on scales of accuracy and low processing requirements. The proposed method can give perfect segmentation of the foreground-background in different situation and is study to illumination variation. We are supplementary working on other existing datasets to improve evaluation of the proposed algorithm.

REFERENCES

AbdAllah, L.K. and I. Shimshoni, 2013. A distance function for data with missing values and its application. World Acad. Sci. Eng. Technol. Intl. J. Comput. Inf. Eng., 7: 1312-1317.

Aherne, F.J., N.A. Thacker and P.I. Rockett, 1998. The Bhattacharyya metric as an absolute similarity measure for frequency coded data. Kybernetika, 34: 363-368.

Athanesious, J.J. and P. Suresh, 2012. Systematic survey on object tracking methods in videos. Intl. J. Adv. Res. C omput. Eng. Technol., 1: 242-247.

Barnich, O. and M. Van Droogenbroeck, 2011. ViBe: A universal background subtraction algorithm for video sequences. IEEE Trans. Image Process., 20: 1709-1724.

Beauchemin, S.S. and J.L. Barron, 1995. The computation of optical flow. ACM. Comput. Surv., 27: 433-466.

Bhattacharyya, A., 1946. On a measure of divergence between two multinomial populations. Indian J. Stat., 7: 401-406.

Bouthemy, P. and P. Lalande, 1993. Recovery of moving object masks in an image sequence using local spatiotemporal contextual information. Opt. Eng., 32: 1205-1213.

Choi, E. and C. Lee, 2003. Feature extraction based on the Bhattacharyya distance. Pattern Recognit., 36: 1703-1709.

Eisner, R., B. Poulin, D. Szafron, P. Lu and R. Greiner, 2005. Improving protein function prediction using the hierarchical structure of the gene ontology. Proceedings of the 2005 IEEE International Symposium on Computational Intelligence in Bioinformatics and Computational Biology, November 15, 2005, IEEE, La Jolla, California, USA., pp: 1-10.

El Baf, F., T. Bouwmans and B. Vachon, 2008. A fuzzy approach for background subtraction. Proceedings of the 2008 15th IEEE International Conference on Image Processing, October 12-15, 2008, IEEE, San Diego, California, USA., ISBN: 978-1-4244-1765-0, pp: 2648-2651.

Gonzalez, R.C. and R.E. Woods, 2006. Digital Image Processing. 3rd Edn., Prentice-Hall, Inc., Upper Saddle River, New Jersy, USA.

Hu, W., T. Tan, L. Wang and S. Maybank, 2004. A survey on visual surveillance of object motion and behaviors. IEEE. Trans. Syst. Man Cybern. C., 34: 334-352.

Hu, W.C., C.H. Chen, T.Y. Chen, D.Y. Huang and Z.C. Wu, 2015. Moving object detection and tracking from video captured by moving camera. J. Visual Commun. Image Represent., 30: 164-180.

Jain, R. and H.H. Nagel, 1979. On the analysis of accumulative difference pictures from image sequences of real world scenes. IEEE. Trans. Pattern Anal. Mach. Intell., PAMI-1: 206-214.

Kemouche, M.S. and N. Aouf, 2009. A Gaussian mixture based optical flow modeling for object detection. Proceedings of the 3rd International Conference on Imaging for Crime Detection and Prevention (ICDP 2009), December 3, 2009, IET, London, UK., ISBN:978-1-84919-207-1, pp: 1-6.

Maddalena, L. and A. Petrosino, 2008. A self-organizing approach to background subtraction for visual surveillance applications. IEEE. Trans. Image Process., 17: 1168-1177.

Manchanda, S. and S. Sharma, 2016. Analysis of computer vision based techniques for motion detection. Proceedings of the 2016 6th International Conference on Cloud System and Big Data Engineering (Confluence), January 14-15, 2016, IEEE, Noida, India, ISBN:978-1-4673-8204-5, pp: 445-450.

Parekh, H.S., D.G. Thakore and U.K. Jaliya, 2014. A survey on object detection and tracking methods. Intl. J. Innovative Res. Comput. Commun. Eng., 2: 2970-2979.

Pratt, W.K., 1991. Digital Image Processing. 2nd Edn., John Wiley & Sons, Hoboken, New Jersey, USA., ISBN:9780471857662, Pages: 720.

Shaikh, S.H., K. Saeed and N. Chaki, 2014. Moving Object Detection Using Background Subtraction. In: Moving Object Detection Using Background Subtraction, Shaikh, S.H., K. Saeed and N. Chaki (Eds.). Springer, Cham, Switzerland, ISBN:978-3-319-07385-9, pp: 15-23.

Sokolova, M., N. Japkowicz and S. Szpakowicz, 2006. Beyond Accuracy, F-score and ROC: A Family of Discriminant Measures for Performance Evaluation. In: AI 2006: Advances in Artificial Intelligence, Sattar, A. and B.H. Kang (Eds.)., LNCS. Vol. 4304, Springer, Berlin, Heidelberg, pp: 1015-1021.

Stauffer, C. and W.E.L. Grimson, 1999. Adaptive background mixture models for real-time tracking. IEEE Comput. Soc. Conf. Comput. Vision Pattern Recogn., 2: 246-252.

Wang, H. and D. Suter, 2006. Background subtraction based on a robust consensus method. Proceedings of the 18th International Conference on Pattern Recognition (ICPR'06), August 20-24, 2006, IEEE, Hong Kong, China, ISBN:0-7695-2521-0, pp: 223-226.

Yatim, H.S.M., A.Z. Talib and F. Haron, 2013. A practical and automated image-based framework for trackingpedestrian movements from a video. IERI. Procedia, 4: 181-187.