Dynamic Background Subtraction in Video Surveillance Using Color-Histogram and Fuzzy C-Means Algorithm with Cosine Similarity

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Abstract—The background subtraction is a leading technique adopted for detecting the moving objects in video surveillance systems. Various background subtraction models have been applied to tackle different challenges in many surveillance environments. In this paper, we propose a model of pixel-based color-histogram and Fuzzy C-means (FCM) to obtain the background model using cosine similarity (CS) to measure the closeness between the current pixel and the background model and eventually determine the background and foreground pixel according to a tuned threshold. The performance of this model is benchmarked on CDnet 2014 dynamic scenes dataset using statistical metrics. The results show a better performance against the state-of the art background subtraction models.

Keywords—Video surveillance, Background subtraction, Fuzzy C-Means (FCM), Fuzzy color histogram, Cosine similarity (CS), Dynamic background challenge

1 Introduction

In computer vision, detecting moving objects is one of the prominent areas due to the rapid increasing of security demands along with the wide spread of CCTV (Closed-Circuit Television Cameras) and sensors [1][2]. Foreground extraction can be applied in different real time applications and in various environment where there is a region of interest to be devoted for anomaly detection, synopsis and tracking [3]. There are several approaches to detect the moving objects, like frame differencing, optical flow, and background subtraction approach in which it is known for easy implementation in video surveillance systems [4]. Different environments of video surveillance system like human activities surveillance, Nature surveillance and transportation surveillance all come with a variety of challenges in the detection of moving objects [5]. In general, background subtraction approach is going through three pipelined stages, the ***Background initialization*** where the first background scene is generated from a number of video frames. ***Background modelling*** is the stage of demonstrating a representative scene to be compared with the current frame. ***Background maintenance*** is the stage of updating the background model upon frequent changes, the update is applied using the prior scene, foreground mask and the current scene. ***Foreground detection*** is the final stage, where a pixel classification is done, it is either foreground or background pixel according to the comparison between the background model and the current scene. In addition, some possible pre-processing and post-processing steps can be done like color space changing or video framing. On the other hand a post-processing steps might be taken to overcome a particular challenge [6]. Figure 1 depicts the outline of background subtraction stages.

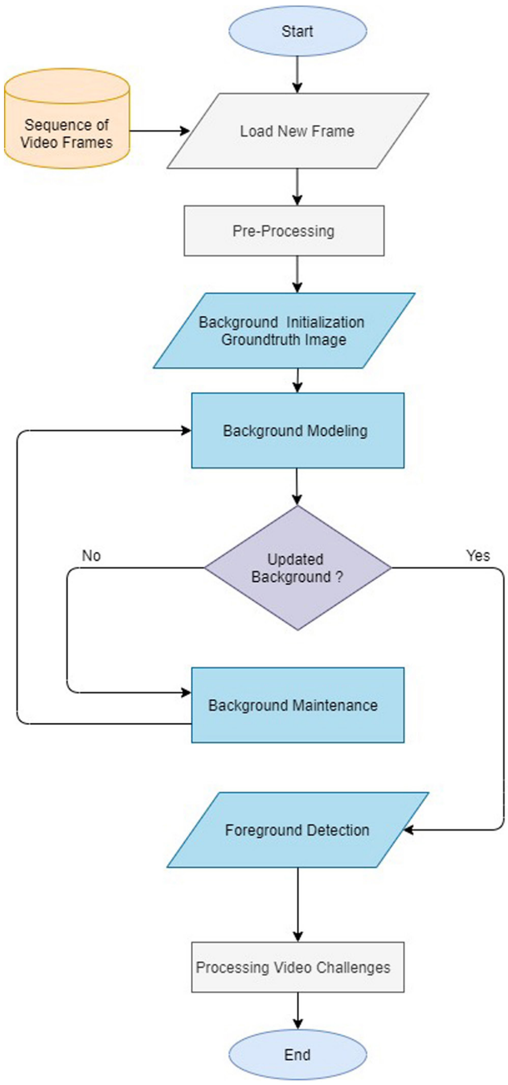

Fig. 1. The overview of background subtraction stages [7]

2 Related work

Through decades background subtraction methods have been developed and applied in many surveillances real time applications. ***Basic models*** like median [8], histogram [9] and mean [10] are examined earlier in the literature, they simply use threshold difference between the current scene and the obtained model to classify a pixel as background or foreground [11]. ***Mathematical models*** on the other hand are either parametrical or non-parametric, Gaussian Mixture Model (GMM) [12], Substance Sensitivity Segmenter (SuBSENSE) algorithm and Visual Background extractor (ViBe) [13] are examples of the parametrical models [14]. While, Pixel-Based Adaptive Segmenter (PBAS) [15] and kernel density estimation (KDE) [16] are examples of non-parametrical models. ***Clustering models*** are identifying a pixel as foreground by using the value of the color intensity for that pixel. Usually, two clusters are used for background and foreground pixels. Different algorithms have been applied in this model like ***Codebook model*** [17] and K-means algorithm [18]. ***Filter models*** predict the pixel value according to its history intensity [5], there are many examples of filters like Wiener filter [19], Tchebychev filter [20], Correntropy filter [21], optical flow [22] and Kalman filter [23].

More recently and due to the massive development of hardware processing and dataset availability, ***Machine learning models*** become the cutting edge models which encompass a variety methods like, support vector machines (SVM) [24], deep learning, neural network [25][26] and convolutional neural network (CCN) [27]. However, these models are still not preferable with real time applications in terms of the excessive processing time consumed [28]. Although, many studies have been done to design a background subtraction model, there is no single model can tackle all the challenges of background subtraction. Fusion of more than one model is another approach for enhancing the performance.

In background subtraction, a hard computation classification has been widely used, in which a pixel is binary classified into background or foreground. Consequently, any inaccurate classification for the pixel will critically affect the robustness of the background model after a number of iterations. Thus, the Fuzzy model [29] has broadly invited as a soft computing classification technique to address the uncertainty of a pixel value and come up with a better results performance in dynamic scenes, shadows and illumination changes [30].

Histogram as a conventional method has been used to calculate the pixel density distribution however, it is affected by the number of intervals and data noise. Though using fuzzy histogram can tackle these problems and has a valuable enhanced results [31]. Therefore, in this paper we propose FCM-CS using the algorithm of fuzzy c-means (FCM) to initiate the background model from fuzzy color histogram by computing each pixel membership to each histogram interval intensity. Cosine similarity (CS) were applied to measure the closeness between a membership of a current pixel and a background model to decide whether a pixel belongs to a foreground or background using tunned threshold.

3 The proposed FCM-CS

In this proposed algorithm FCM-CS, RGB color space is used, where fuzzy histogram for each pixel value in separate three channels (Red, Green, Blue) are computed. Each pixel membership to the FCM cluster center is calculated using Eq. (1),

$$M_{xy} = \frac{1}{\sum_{i=1}^{B}\left(\frac{\|p_y - v_x\|}{\|p_y - v_i\|}\right)^{\frac{2}{c-1}}} \tag{1}$$

M_{xy} is the pixel membership value, B is the total number of bins (histogram intervals), v_x is the cluster centre according to FCM where median value is used as a center and c is the fuzzification coefficient number.

The memberships are accumulated to form the fuzzy histogram background model (BGM) in Eq. (2),

$$\text{BGM} = \frac{\sum_{i=1}^{N} M(p_i)}{N} \tag{2}$$

Where **M** is the pixel membership value from Eq. (1), **N** is the total number of training frames. Then cosine similarity is used to compute the closeness between each pixel membership value and the fuzzy histogram background model using Eq. (3), for cosine similarity.

$$\text{Cosine Simmilarity} = \cos(\theta) = \frac{\text{M.BGM}}{|\text{M}||\text{BGM}|} \tag{3}$$

Detecting the foreground and background pixels is done using the following Eq. (4),

$$R_p = \begin{cases} 1, & \textit{if } CS\ (M_p, BGM) < \textit{threshold} \\ 0, & \textit{Otherwise} \end{cases} \tag{4}$$

Where, R_p is the result of pixel p whether it's foreground or background according to cosine similarity between membership pixel (M_p) and the histogram background model (BGM), threshold of 0.045 is used as a result of extensive trails. Background model is updated adaptively according to Eq. (5)

$$\text{BGM}^{k+1} = \text{R}^{f}\ \text{BGM}^{k} + (1-\text{R}^{f})\ ((1-\alpha)\ \text{BGM}^{k}) + \alpha\ \text{M}(p_{k+1}) \tag{5}$$

Where k = 1, 2, …, N, R^f is the final output, the background model is only updated when the final output is not foreground, the update will be according to the background model, the current membership value and the updating rate α which is set to 0.011 based on large scale testing.

The overall steps of the proposed model FCM-CS are illustrated in the Algorithm 1: and the experiment parameters for FCM-CS is listed in the following Table 1.

Table 1. FCM-CS experimental parameters

Parameters	Value	Parameters	Value
Total number of training frames (N)	100	Final result of pixel $\mathbf{R}^f$	{0,1}
Threshold used for detection	0.045	Histogram bins (B)	16
Background model update rate (α)	0.011	Fuzzification coefficient (c)	2

Algorithm 1: FCM-CS
Input: $VF^{ch}_{h,w,n}$ is the video frame image: w = 1, 2, … W: width of the video frame h = 1, 2, … H: height of the video frame n = 1, 2, … N: frame number of the video frame ch = The color channel.
Output: R^f = the final result of video frame
1. Initialization • Divide the **S** level histogram values to **B** histogram intervals. • Calculate the central values $\mathbf{v}_i$ i = 1, 2, … B. • Calculate the membership matrix **M** = $\{M_{xy}$ | x = 1, 2, … B, y = 1, 2, … S$\}$ using Eq. (1)
2. Modeling • Using the frame image and Eq. (2) to model the fuzzy background histograms **BGM** of the RGB color channels.
3. Foreground Detection • Fetch the membership vector M_p for the pixel value p. And use Eq. (3) to calculate the cosine similarity CS (M_p, BGM) between the current pixel membership and the background model. • The Pixel result obtained using Eq. (4)
4. Maintenance • Update the histogram background using the final output R^f value and the background model update rate (α) using Eq. (5)
5. Post Processing • Apply median blurring filter to the final output R^f
6. Return to 3

4 Experiments and analysis

In this article we compare the proposed algorithm against the cutting age background subtraction algorithms (GMM, KNN and ViBe). The models are tested using the CDnet 2014 [32] benchmark dataset considering the dynamic background challenge videos.

CDnet 2014 were chosen as the most well-known and preferable dataset due to providing a wide range of videos with several challenges as well as providing the ground-truth scenes which help in statistical evaluation. In these experiments we applied the model on dynamic background challenge scenes illustrated in Table 2 below.

Table 2. Dynamic background videos from CDnet 2014

Videos	Dynamic Challenge Description	Total Frames	Region of Interest Frames
Overpass	Large moving tree on the side of the frame	3000	1000–3000
Fall	Large moving tree in the center of the frame	4000	1000–4000
Boats	Moving water surface	7999	1900–7999
Canoe	Moving water surface	1189	800–1189
Fountain1	Random water movement	1184	400–1184
Fountain2	Random water movement	1499	500–1499

We are comparing the background subtraction image with the correspondent ground-truth image to evaluate the performance of each method in respect to quantitative evaluation metrics at the pixel level, and the background subtraction method classifies the pixels into background or foreground. Precision, recall and F-measures (F1) metrics are used for the performance evaluation according to the following formulas:

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + TN + FN} \tag{6}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{7}$$

$$\text{Recall(sensitivity)} = \frac{TP}{TP + FN} \tag{8}$$

$$F - \text{Measures(F1)} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{9}$$

$$FPR = \frac{FP}{FP + TN} \tag{10}$$

$$FNR = \frac{FN}{TP + FN} \tag{11}$$

$$\text{Error rate(PWC)} = \frac{FP + FN}{TP + FN + TN + FP} \times 100 \tag{12}$$

Where, **TP** is the number of foreground pixels correctly classified, **TN** is the number of background pixels correctly classified, **FP** is the number of background pixels incorrectly classified as foreground pixels, and **FN** is the number of foreground pixels incorrectly classified as background pixels.

Accuracy Eq. (6) indicates the correct classification for a pixel whether it is a foreground or a background pixel, **Precision** Eq. (7), indicates the proportion of truly detected foreground pixels to the number of all pixels classified as foreground pixels, **recall** Eq. (8), indicates the number of pixels that are correctly classified as a foreground of all the foreground pixels and the **F-measure** Eq. (9), is the harmonic mean of recall and precision. On the other hand, we have the metrics: (False Positive Rate) **FPR**

Eq. (10), is the ratio of background pixels that are misclassified as foreground pixels to the total actual number of background pixels, (False Negative Rate) **FNR** Eq. (11), is the ratio of foreground pixels that are misclassified as background pixels to the total actual number of foreground pixels, and (percentage weight loss) **PWC** Eq. (12), indicates the error rate which is the percentage of misclassified pixels to the original pixels.

Normally, we measure the relevance by recall and precision. A low recall is an indication of over segmentation of the foreground objects, where a low precision is an indication of under segmentation of the foreground objects. High F-measures is an indication of a robust background subtraction algorithm.

In the following Tables 3–6 the analytical metrics results of applying the GMM [33], KNN [9], ViBe [34] and the proposed FCM-CS models respectively on the CDnet 2014 dynamic background videos dataset are illustrated.

Table 3. Performance metrics results of applying GMM on CDnet 2014 dataset

Video	Accuracy	Precession	Recall	F1	FPR	FNR	PWC
Overpass	0.987	0.151	0.512	0.423	0.008	0.488	1.302
Fall	**0.979**	**0.146**	0.781	0.461	0.018	0.219	2.097
Boats	0.993	0.134	0.271	0.371	0.003	0.729	0.698
Canoe	0.968	0.297	0.402	0.407	0.014	0.598	3.245
Fountain1	0.987	0.027	0.631	0.209	0.013	0.369	1.307
Fountain2	0.996	0.095	0.663	0.508	0.004	0.337	0.427

Table 4. Performance metrics results of applying KNN on CDnet 2014 dataset

Video	Accuracy	Precession	Recall	F1	FPR	FNR	PWC
Overpass	0.988	0.173	0.703	0.549	0.008	0.297	1.180
Fall	0.968	0.119	0.699	0.377	0.029	0.301	3.210
Boats	0.995	0.142	0.318	0.426	0.002	0.682	0.528
Canoe	0.980	0.375	0.615	0.585	0.011	0.385	1.983
Fountain1	0.987	0.023	0.497	0.180	0.013	0.503	1.296
Fountain2	**0.997**	0.109	0.587	0.531	0.002	0.413	0.306

Table 5. Performance metrics results of applying ViBe on CDnet 2014 dataset

Video	Accuracy	Precession	Recall	F1	FPR	FNR	PWC
Overpass	0.989	0.164	0.564	0.157	0.006	0.436	0.111
Fall	0.967	0.125	0.570	0.129	0.026	0.430	3.311
Boats	0.992	0.129	0.371	0.088	0.004	0.629	0.824
Canoe	0.975	0.455	0.512	0.360	0.007	0.482	2.516
Fountain1	**0.991**	**0.055**	0.750	0.079	0.009	0.250	0.899
Fountain2	0.996	**0.126**	0.780	0.133	0.003	0.220	0.355

Table 6. Performance metrics results of applying FCM-CS on CDnet 2014 dataset

Video	Accuracy	Precession	Recall	F1	FPR	FNR	PWC
Overpass	**0.997**	**0.256**	**0.924**	**0.847**	**0.002**	**0.076**	0.301
Fall	0.918	0.096	**0.928**	**0.354**	0.083	**0.072**	8.187
Boats	**0.999**	**0.340**	**0.851**	**0.889**	**0.001**	**0.149**	**0.124**
Canoe	**0.997**	**0.676**	**0.947**	**0.958**	**0.001**	**0.053**	**0.298**
Fountain1	0.986	0.043	**0.881**	**0.318**	0.014	**0.118**	1.429
Fountain2	0.989	0.094	**0.986**	**0.614**	0.010	**0.014**	1.066

Table 7. Average performance metrics results of applying background subtraction models on CDnet

Model	Accuracy	Precession	Recall	F1	FPR	FNR	PWC
GMM [33]	0.985	0.141	0.543	0.396	0.010	0.456	1.512
KNN [9]	**0.986**	0.156	0.569	0.441	0.011	0.430	1.417
ViBe [34]	0.985	0.175	0.591	0.157	**0.009**	0.407	**1.336**
FCM-CS	0.981	**0.251**	**0.919**	**0.663**	0.018	**0.080**	1.901

Tables 3–6 shows a statistical result where, each model is applied individually on each dynamic background video available on CDnet 2014 dataset, the best performance is marked in bold. Proposed FCM-CS performs the best in almost all videos. Precession and recall are always the best and eventually F-measure (F1) results surpasses all other models results. However, FCM-CS relatively suffers from high but affordable FP pixels which increase the FPR and eventually the PWC results. Normally F-measure (F1) is one the most important metric to evaluate the model performance and assess the detection robustness. In this context we noticed that proposed FCM-CS on average surpasses all other models in quantitative evaluation as shown in Table 7.

Moreover, Figure 2 depicts the visual results comparison of the foreground results of applying the background subtraction models on the CDnet 2014 dynamic background scenes. Where (a) is the original scene, (b) is the ground-truth provided by the dataset, (c) is the foreground mask created by GMM model, (d) is the foreground mask created by KNN model, (e) is the foreground mask created by ViBe model and (f) is the foreground mask created by the proposed model FCM-CS. Looking at Figure 2 where qualitative evaluation is illustrated; one can see that the results generated by FCM-CS is visually the closest to the ground-truth frame.

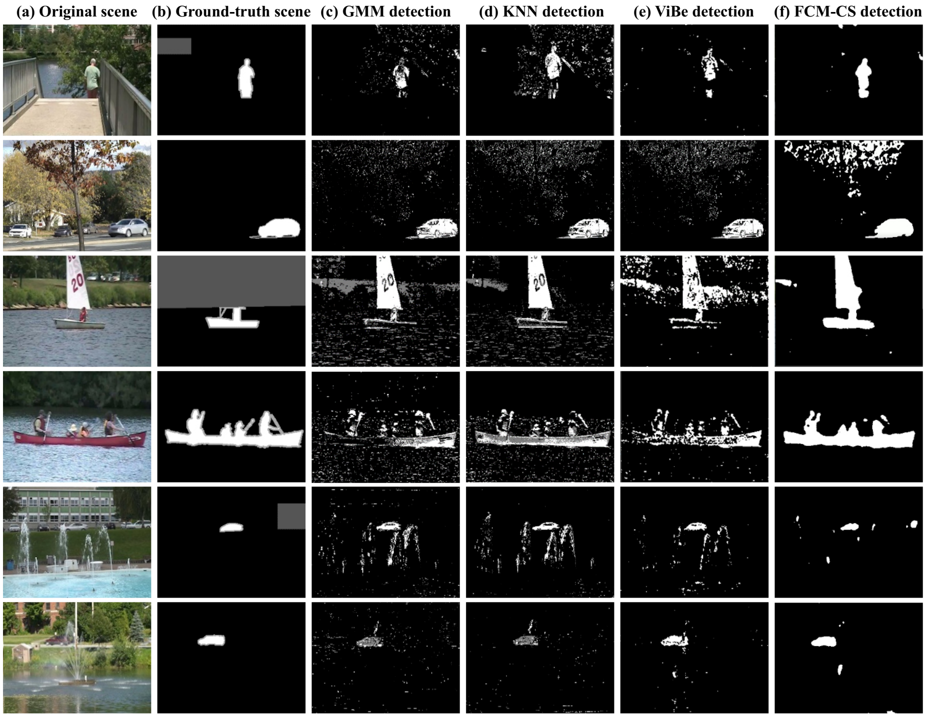

Fig. 2. Comparison of foreground detection results

5 Conclusion

In this paper, we built a novel and robust background subtraction model FCM-CS for video surveillance systems. The CDnet 2014 dataset was employed as a benchmark focusing on the dynamic background scenes. The fuzzy color histogram is computed to construct the background model and cosine similarity is applied to measure the closeness between the current pixel and the background histogram model to determine whether a pixel belongs to a background or foreground according to a tuned threshold. The background model is maintained adaptively to enhance the background subtraction process. Eventually a post-processing technique was applied to improve the final results. The model is compared against the state-of-the-art models using different evaluation metrics like accuracy, precession, recall, the harmonic means of precision and recall (F1), FPR, FNR and PWC to measure the accuracy of each model. The analysis showed that, FCM-CS algorithm is reliable and showed a robust performance in the dynamic background scenes.

6 References

[1] N. K. Jain, R. K. Saini, and P. Mittal, "A review on traffic monitoring system techniques," in *Soft Computing: Theories and Applications*, Springer, 2019, pp. 569–577. https://doi.org/10.1007/978-981-13-0589-4_53

[2] M. A. A. Hammoudeh, M. Alsaykhan, R. Alsalameh, and N. Althwaibi, "Computer vision: a review of detecting objects in videos—challenges and techniques," *Int. J. Online & Biomed. Eng.*, vol. 18, no. 1, pp. 15–27, 2022. https://doi.org/10.3991/ijoe.v18i01.27577

[3] D. Gutchess, M. Trajkovics, E. Cohen-Solal, D. Lyons, and A. K. Jain, "A background model initialization algorithm for video surveillance," in *Proceedings Eighth IEEE International Conference on Computer Vision, ICCV 2001*, 2001, vol. 1, pp. 733–740.

[4] D. Zeng, M. Zhu, and A. Kuijper, "Combining background subtraction algorithms with convolutional neural network," *J. Electron. Imaging*, vol. 28, no. 1, p. 13011, 2019. https://doi.org/10.1117/1.JEI.28.1.013011

[5] K. Goyal and J. Singhai, "Review of background subtraction methods using Gaussian mixture model for video surveillance systems," *Artif. Intell. Rev.*, vol. 50, no. 2, pp. 241–259, 2018. https://doi.org/10.1007/s10462-017-9542-x

[6] R. A. Hadi, L. E. George, and M. J. Mohammed, "A computationally economic novel approach for real-time moving multi-vehicle detection and tracking toward efficient traffic surveillance," *Arab. J. Sci. Eng.*, vol. 42, no. 2, pp. 817–831, 2017. https://doi.org/10.1007/s13369-016-2351-8

[7] M. Yasir and Y. Ali, "Review on real time background extraction: models, applications, environments, challenges and evaluation approaches," *Int. J. Online & Biomed. Eng.*, vol. 17, no. 2, pp. 37–68, 2021. https://doi.org/10.3991/ijoe.v17i02.18013

[8] M. Hadiuzzaman, N. Haque, F. Rahman, S. Hossain, M. R. K. Siam, and T. Z. Qiu, "Pixel-based heterogeneous traffic measurement considering shadow and illumination variation," *Signal, Image Video Process.*, vol. 11, no. 7, pp. 1245–1252, 2017. https://doi.org/10.1007/s11760-017-1081-z

[9] Z. Zivkovic and F. Van Der Heijden, "Efficient adaptive density estimation per image pixel for the task of background subtraction," *Pattern Recognit. Lett.*, vol. 27, no. 7, pp. 773–780, 2006. https://doi.org/10.1016/j.patrec.2005.11.005

[10] P. W. Power and J. A. Schoonees, "Understanding background mixture models for foreground segmentation," in *Proceedings Image and Vision Computing New Zealand*, 2002, vol. 2002, pp. 10–11.

[11] T. Bouwmans, "Recent advanced statistical background modeling for foreground detection-a systematic survey," *Recent Patents Comput. Sci.*, vol. 4, no. 3, pp. 147–176, 2011. https://doi.org/10.2174/2213275911104030147

[12] C. Stauffer and W. E. L. Grimson, "Adaptive background mixture models for real-time tracking," in *Proceedings. 1999 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (Cat. No PR00149)*, 1999, vol. 2, pp. 246–252.

[13] O. Barnich and M. Van Droogenbroeck, "ViBe: a powerful random technique to estimate the background in video sequences," in *2009 IEEE International Conference on Acoustics, Speech and Signal Processing*, 2009, pp. 945–948. https://doi.org/10.1109/ICASSP.2009.4959741

[14] P.-L. St-Charles, G.-A. Bilodeau, and R. Bergevin, "Subsense: a universal change detection method with local adaptive sensitivity," *IEEE Trans. Image Process.*, vol. 24, no. 1, pp. 359–373, 2014. https://doi.org/10.1109/TIP.2014.2378053

[15] S. Javed, S. H. Oh, and S. K. Jung, "An Improved Pixel-Based Adaptive Background Segmenter for Visual Surveillance System," pp. 579–582, 2014.

[16] M. Hua, Y. Li, and Y. Luo, "Robust background modeling with kernel density estimation," *Int. J. Online Eng.*, vol. 11, no. 8, 2015. https://doi.org/10.3991/ijoe.v11i8.4880

[17] L. Wang and C. Pan, "Effective multi-resolution background subtraction," in *2011 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2011, pp. 909–912. https://doi.org/10.1109/ICASSP.2011.5946552

[18] D. Butler, S. Sridharan, and V. M. J. Bove, "Real-time adaptive background segmentation," in *2003 IEEE International Conference on Acoustics, Speech, and Signal Processing, 2003. Proceedings.(ICASSP'03)*, 2003, vol. 3, pp. III–349. https://doi.org/10.1109/ICME.2003.1221318

[19] K. Toyama, J. Krumm, B. Brumitt, and B. Meyers, "Wallflower: principles and practice of background maintenance," in *Proceedings of the Seventh IEEE International Conference on Computer Vision*, 1999, vol. 1, pp. 255–261. https://doi.org/10.1109/ICCV.1999.791228

[20] R. Chang, T. Gandhi, and M. M. Trivedi, "Vision modules for a multi-sensory bridge monitoring approach," in *Proceedings. The 7th International IEEE Conference on Intelligent Transportation Systems (IEEE Cat. No. 04TH8749)*, 2004, pp. 971–976.

[21] G. T. Cinar and J. C. Príncipe, "Adaptive background estimation using an information theoretic cost for hidden state estimation," in *The 2011 International Joint Conference on Neural Networks*, 2011, pp. 489–494. https://doi.org/10.1109/IJCNN.2011.6033261

[22] X. Yu, X. Chen, and H. Zhang, "Accurate motion detection in dynamic scenes based on ego-motion estimation and optical flow segmentation combined method," in *2011 Symposium on Photonics and Optoelectronics (SOPO)*, 2011, pp. 1–4. https://doi.org/10.1109/SOPO.2011.5780637

[23] F. Lei and X. Zhao, "Adaptive background estimation of underwater using Kalman-Filtering," in *2010 3rd International Congress on Image and Signal Processing*, 2010, vol. 1, pp. 64–67. https://doi.org/10.1109/CISP.2010.5647080

[24] I. Junejo, A. Bhutta, and H. Foroosh, "Dynamic scene modeling for object detection using single-class SVM," in *Proc. of IEEE International Conference on Image Processing (ICIP)*, 2010, vol. 1, pp. 1541–1544.

[25] L. Maddalena and A. Petrosino, "Self-organizing background subtraction using color and depth data," *Multimed. Tools Appl.*, vol. 78, no. 9, pp. 11927–11948, 2019. https://doi.org/10.1007/s11042-018-6741-7

[26] T. Minematsu, A. Shimada, H. Uchiyama, and R. Taniguchi, "Analytics of deep neural network-based background subtraction," *J. Imaging*, vol. 4, no. 6, p. 78, 2018. https://doi.org/10.3390/jimaging4060078

[27] M. Braham and M. Van Droogenbroeck, "Deep background subtraction with scene-specific convolutional neural networks," in *2016 International Conference on Systems, Signals and Image Processing (IWSSIP)*, 2016, pp. 1–4. https://doi.org/10.1109/IWSSIP.2016.7502717

[28] T. Bouwmans, "Subspace learning for background modeling: a survey," *Recent Patents Comput. Sci.*, vol. 2, no. 3, pp. 223–234, 2009. https://doi.org/10.2174/2213275910902030223

[29] T. Bouwmans, "Background subtraction for visual surveillance: a fuzzy approach," *Handb. soft Comput. video Surveill.*, vol. 5, pp. 103–138, 2012.

[30] M. H. Sigari, N. Mozayani, and H. Pourreza, "Fuzzy running average and fuzzy background subtraction: concepts and application," *Int. J. Comput. Sci. Netw. Secur.*, vol. 8, no. 2, pp. 138–143, 2008.

[31] K. Loquin and O. Strauss, "Histogram density estimators based upon a fuzzy partition," *Stat. & Probab. Lett.*, vol. 78, no. 13, pp. 1863–1868, 2008. https://doi.org/10.1016/j.spl.2008.01.053

[32] Y. Wang, P.-M. Jodoin, F. Porikli, J. Konrad, Y. Benezeth, and P. Ishwar, "CDnet 2014: an expanded change detection benchmark dataset," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, 2014, pp. 387–394. https://doi.org/10.1109/CVPRW.2014.126

[33] Z. Zivkovic, "Improved adaptive Gaussian mixture model for background subtraction," in *Proceedings of the 17th International Conference on Pattern Recognition, 2004. ICPR 2004*, 2004, vol. 2, pp. 28–31. https://doi.org/10.1109/ICPR.2004.1333992
[34] M. Van Droogenbroeck and O. Paquot, "Background subtraction: experiments and improvements for ViBe," in *2012 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, 2012, pp. 32–37. https://doi.org/10.1109/CVPRW.2012.6238924

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