Detection of Moving Objects Using Fuzzy Color Difference Histogram Based Background Subtraction

Deepak Kumar Panda, *Student Member, IEEE*, and Sukadev Meher, *Member, IEEE*

***Abstract*—Detection of moving objects in the presence of complex scenes such as dynamic background (e.g, swaying vegetation, ripples in water, spouting fountain), illumination variation, and camouflage is a very challenging task. In this context, we propose a robust background subtraction technique with three contributions. First, we present the use of color difference histogram (CDH) in the background subtraction algorithm. This is done by measuring the color difference between a pixel and its neighbors in a small local neighborhood. The use of CDH reduces the number of false errors due to the non-stationary background, illumination variation and camouflage. Secondly, the color difference is fuzzified with a Gaussian membership function. Finally, a novel fuzzy color difference histogram (FCDH) is proposed by using fuzzy c-means (FCM) clustering and exploiting the CDH. The use of FCM clustering algorithm in CDH reduces the large dimensionality of the histogram bins in the computation and also lessens the effect of intensity variation generated due to the fake motion or change in illumination of the background. The proposed algorithm is tested with various complex scenes of some benchmark publicly available video sequences. It exhibits better performance over the state-of-the-art background subtraction techniques available in the literature in terms of classification accuracy metrics like MCC and PCC.**

***Index Terms*—Background subtraction, camouflage, color difference histogram, fuzzy c-means clustering, illumination variation, moving object detection, non-stationary background.**

I. Introduction

BACKGROUND subtraction [1], [2] is the most popular and robust method for detecting moving objects from static cameras. However, the challenges in background subtraction are still far from being solved due to the following reasons:

- Dynamic backgrounds [3]–[5] such as swaying vegetation, moving curtains, flowing water, sea waves, spouting fountain, ripple in water, etc.
- Gradual (cloud passing over the sun) or sudden change in illumination (switching on and off of light).
- Pixel characteristic of foreground object may be similar to that of the background.

In this paper, we address the above mentioned difficulties by building the background model using FCDH.

The different background subtraction techniques published in the literature can be classified depending on the features and procedures used to construct the background model.

- The **pixel-based** approaches [3]–[7] model observe scenes as a set of independent pixel processes.
- The **region-based** approaches [8]–[13] build background models by taking advantages of inter-pixel relations, demonstrating impressive results in handling non-stationary background.

Recently, fuzzy logic based background subtraction schemes have been reported in the literature [7], [11]–[13]. Employing the fuzy linking color histogram, proposed by Kucuktunc *et al.* [14] for video segmentation, in background subtraction applications, yields an average PCC of 98.25%, whereas FCH [11] algorithm yields 97.72%.

In this work, we propose to learn and maintain the dynamic models in the **difference domain**[1], whereas the earlier papers are based on pixel (color) domain processing. Ours is region-based approach, where the color difference is measured in a small local neighborhood. Since we process in difference domain, our scheme is quite robust under small variations, noisy conditions, illumination variation and camouflage. CDH was first reported in the literature for video segmentation [15] and then later it was used for content based image retrieval [16]. However, its adoption in background subtraction is not reported in the literature yet.

II. Proposed Approach

Our proposed algorithm comprises the following steps.

1) Determining color difference histogram (CDH).
2) Employing Fuzzy c-means clustering to obtain reduced-bin FCDH, i.e reducing feature space.
3) Background initialization.
4) Foreground detection using similarity matching.
5) Background maintenance.

To differentiate between the conventional color histogram and the CDH, which is employed here, we present the following.

A. Color Histogram Versus Color Difference Histogram

Let the intensity level of a color image, $I(m,n,ch)$, be quantized to W levels, i.e, $I \in \{0,1,\ldots,W-1\}$, where (m,n) is the location co-ordinate and ch is the color channel. The intensity of the ch^{th} color channel, centered at location (m,n) is denoted by $I(m,n,ch)$ whereas $I(p,q,ch)$ represents the intensity of a pixel in the neighborhood.

Manuscript received August 13, 2015; revised October 20, 2015; accepted October 23, 2015. Date of publication November 06, 2015; date of current version November 17, 2015. The associate editor coordinating the review of this manuscript and approving it for publication was Prof. Giuseppe Scarpa.

The authors are with the Image Processing and Computer Vision Lab. Department of Electronics and Communication Engineering, National Institute of Technology Rourkela, Rourkela 769008, Odisha, India (e-mail: deepakkumar.panda@gmail.com; sukadevmeher@gmail.com; smeher@nitrkl.ac.in).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/LSP.2015.2498839

[1]Analogous to differential domain

1) Color Histogram (CH): The color histogram, $hg(i,j,k)$, counts the occurrence or frequency of pixels in a local region of size $M \times M$, centered at location (m,n). It is given by:

$$hg(i,j,k) = \sum_{m=1}^{M}\sum_{n=1}^{M} \delta\left(I(m,n,ch) - (i,j,k)\right)$$
$$for\ 0 \leq i \leq W-1,\ for\ 0 \leq j \leq W-1,$$
$$for\ 0 \leq k \leq W-1\ and\ ch = \{L^*, a^*, b^*\} \quad (1)$$

2) Color Difference Histogram (CDH): The unique characteristic of CDH is that it counts the perceptually uniform color difference between two pixels. The color difference is computed in a small local neighborhood region of $R \times R$, which is given by:

$$d(m,n) = \frac{\sqrt{\sum_{p=m-\lfloor R/2 \rfloor}^{m+\lfloor R/2 \rfloor}\sum_{q=n-\lfloor R/2 \rfloor}^{n+\lfloor R/2 \rfloor}\left(\sum_{ch}\left(I\left(m,n,ch\right) - I\left(p,q,ch\right)\right)^2\right)}}{R \times R} \quad (2)$$

The color difference, d, is fuzzified according to the Gaussian membership function.

$$\mu_d(m,n) = e^{-\frac{1}{2}\left(\frac{d}{\sigma}\right)^2} \quad (3)$$

where σ is the standard deviation.

The color difference histogram (CDH) is computed in a local region of size $M \times M$, centered at location (m,n), as follows:

$$H(i,j,k) = \sum_{m=1}^{M}\sum_{n=1}^{M} \mu_d(m,n)\delta\left(I(m,n,ch) - (i,j,k)\right)$$
$$for\ 0 \leq i \leq W-1,\ for\ 0 \leq j \leq W-1,$$
$$for\ 0 \leq k \leq W-1\ and\ ch = \{L^*, a^*, b^*\} \quad (4)$$

B. Fuzzy Color Difference Histogram (FCDH)

We propose a novel FCDH by utilizing FCM clustering and CDH which are described, in details, below.

Fuzzy c-means (FCM) clustering [18] is used to classify the N bin local histogram $X = \{x_1, x_2, \ldots, x_N\}$ into c clusters, each centered at v_i. The bins are assigned to each cluster using fuzzy membership. It is achieved by iteratively minimizing the cost function, given by:

$$J = \sum_{i=1}^{c}\sum_{j=1}^{N} u_{ij}^{r}\|x_j - v_i\|^2 \quad (5)$$

A c-dimensional FCDH vector h is constructed from $c \times N$ dimensional membership matrix u and $N \times 1$ dimensional CDH vector H as follows:

$$h_{c\times 1} = u_{c\times N} H_{N\times 1} \quad (6)$$

The performance of FCH and FCDH is illustrated in Fig. 1 for "Fountains" and "Curtain" sequence. Since FCDH is based on color difference rather than color magnitudes, it does not change appreciably even for a non-stationary background. From Fig. 1 it is evident that the change in FCDH is almost zero for "Fountain" sequence and is negligible for "Curtain" sequence whereas change in FCH is quite noticeable for both the sequences. Hence FCDH is a more robust technique for background modeling and hence it is a better candidate for background subtraction compared to FCH.

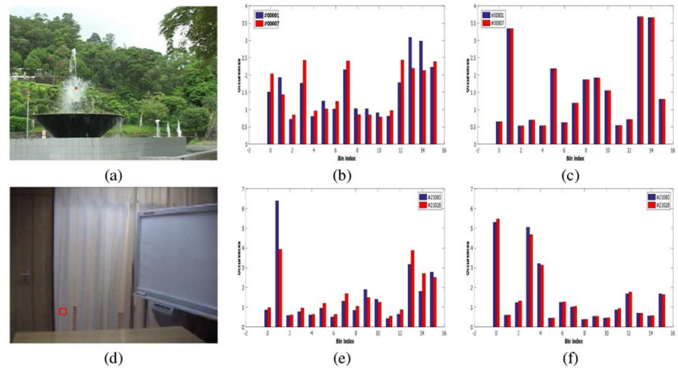

Fig. 1. Histogram comparison: (a) "Fountains"[17], (b) and (c): FCH and FCDH for (a), respectively for 1st and 7th frame. (d) "Curtain", (e) and (f): FCH and FCDH for (d), respectively for 1st and 29th frame.

C. Background Subtraction

The first frame of the video is used to initialize the background model and thereafter the model is updated in accordance with the feature computed from the current frame. The histogram intersection [19], used to measure the similarity, ρ, between the FCDH of the background model and the current frame, is given, in a normalized scale, by:

$$\rho(h^b, h) = \frac{\sum_{i=0}^{c-1}\min(h_i^b, h_i)}{\max\left(\sum_{i=0}^{c-1} h_i^b, \sum_{i=0}^{c-1} h_i\right)} \quad (7)$$

where h^b and h are the FCDH of modeled background frame and current frame and c is the number of histogram bins. The similarity function, ρ is binarized by choosing an appropriate threshold th to classify pixels with background flag, B given by:

$$B(t) = \begin{cases} 1, & \rho(h^b, h) > th \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

The background FCDH, h_i^b is updated with the new data by updating its bin for pixel labelled as background [3].

$$h^b(t) = \begin{cases} (1-\alpha)\, h^b\,(t-1) + \alpha h(t), & \text{background pixel} \\ h^b\,(t-1), & \text{otherwise} \end{cases} \quad (9)$$

where $\alpha \in [0,1]$ is the learning rate and t is the time index. The main steps of the proposed technique have been well summarized in Algorithm 1.

III. Experimental Results

The proposed technique is implemented in MATLAB, running on a 32-bit Windows7 platform with Intel Core i5-2400 CPU@3.10 GHz, 3.10 GHz and 4 GB RAM. The effectiveness of the proposed scheme is demonstrated on publicly available challenging video sequences such as "Campus" (CA), "Waving Trees" (WT), "Water Surface" (WS), "Curtain" (CU), "Lobby" (LO) and "PETS2006" (PE). The test sequences can be downloaded from [20]–[22]. The video sequences: CA, WT, WS, and CU have dynamic background such as waving trees (CA, WT), water surface (WS), moving Venetian blinds (CU). In

Algorithm 1 Background Subtraction Using Local FCDH

Calculate the membership matrix using FCM algorithm using (5) for $N(=W^3)$ bins.

Input: Data $X=\{x_1,x_2,\ldots,x_N\}$; $x=(i,j,k)$; $i,j,k=0,1,\ldots,W-1$; and initial cluster centers $V=\{v_1,v_2,\ldots,v_c\}$.

Output: Final fuzzy membership matrix. $U=[u_{ij}\in[0,1], i=1,\ldots,c, j=1,\ldots,N$.

for $t=1\rightarrow$ NoOfFrames **do**

Step 1: Determine color difference histogram.

(i) Quantize the color image to W levels.

(ii) Convert the RGB image to CIE $L^*a^*b^*$ color.

(iii) Compute the local *CDH* as per (4).

Step 2: Calculate *FCDH*; $h_{c\times 1}=u_{c\times N}H_{N\times 1}$.

if($t==1$) **then** //First frame

Step 3: Background initalization; $h^b=h$.

else

Step 4: Foreground detection.

(i) Calculate the similarity function using normalised histogram intersection given in (7).

(ii) Threshold the similarity function value as per (8).

Step 5: Update the background model for the background labeled pixels using (9).

end if

end for

TABLE I
NO OF GROUND TRUTHS USED IN DIFFERENT VIDEO SEQUENCES

	CA	CU	LO	WS	WT	PE	AVG
No of Ground truths	31	31	50	45	16	50	37.17

addition to this, WS, CU and LO have camouflage problem. The LO sequence also has the problem of illumination variation. The PE is a crowded sequence of a busy public railway station. We compare our proposed algorithm with GMM [3], LBP [8], STLBP [9], LIBS [6], FBS [7], FST [12], MCC [13] and FCH [11]. The ground truth sequences are obtained by manual segmentation of selected frames. On an average, 37 frames are used in performance evaluation. The number of ground truths used for the evaluation is given in Table I. No pre-processing (mean filtering) or post-processing (shadow removal, morphological filtering, etc.) operation is performed in any of the results for fair comparisons. The color difference is calculated in a local region of $(R=3)$. The Gaussian membership function employs $\sigma\in(1,2)$. CDH is measured in the neighborhood region of $M(=5)$ pixels. The RGB color space is quantized to $W(=16)$ levels. The parameters of FCM $(c=16, r=2.0, \varepsilon=1^{-5}, max\ iteration=100)$ are kept constant. The learning rate used for the updation of the background feature vector is set to $\alpha=0.01$. The threshold $th\in[0.4,0.7]$. The state-of-the-art algorithms are implemented using the optimized parameter values as specified in their publications [3], [6]–[9], [11]–[13].

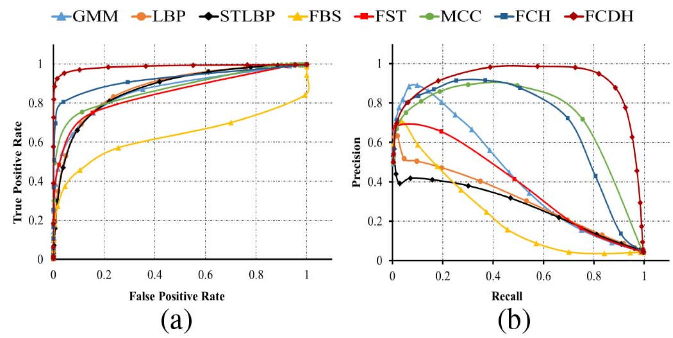

Fig. 2. Comparisons of algorithms in ROC and PR space for "Campus" sequence (a) ROC space (b) PR space.

TABLE II
QUANTITATIVE EVALUATION OF ROC AND PR CURVES USING AUC FOR CAMPUS SEQUENCE

	GMM	LBP	STLBP	FBS	FST	MCC	FCH	FCDH
ROC	0.8613	0.8743	0.8674	0.6289	0.8337	0.9119	0.9549	0.9853
PR	0.4408	0.3129	0.2767	0.2281	0.3864	0.7428	0.72	0.8944

TABLE III
QUANTITATIVE EVALUATION USING MCC

Algorithm	CA	CU	LO	WS	WT	PE	AVG
GMM	0.361	0.621	0.374	0.452	0.535	0.345	0.448
LBP	0.290	0.418	0.467	0.304	0.600	0.445	0.421
STLBP	0.379	0.455	0.519	0.434	0.699	0.377	0.477
LIBS	0.340	0.795	0.576	0.904	0.569	0.703	0.648
FBS	0.254	0.710	0.459	0.874	0.205	0.668	0.528
FST	0.358	0.809	0.591	0.927	0.637	0.804	0.688
MCC	0.617	0.557	0.536	0.593	0.722	0.620	0.608
FCH	0.608	0.731	0.547	0.887	0.864	0.607	0.707
FCDH	0.874	0.935	0.784	0.937	0.961	0.870	0.894

ROC and PR: The binary performance of our algorithm is evaluated using Receiver Operating Characteristic (ROC) and Precision-Recall (PR) curves [23] for CA sequence as shown in Fig. 2. Our proposed algorithm shows much improved performance in both the ROC and PR space. Area under the curve (AUC) is used as metric to measure the algorithm performance over the whole space. AUCs for both the ROC and PR curves are shown in Table II. The AUC-ROC and AUC-PR yielded by the proposed algorithm are 0.9853 and 0.8944 respectively, whereas those produced by the next best algorithm, FCH are 0.9549 and 0.72 respectively.

Quantitative Evaluation: The proposed algorithm is tested using metrics known as Matthew's correlation coefficient (MCC) [24] and the percentage of correct classification (PCC) [25]. Table III and Table IV show the effectiveness of our algorithm using MCC and PCC respectively. Our proposed algorithm, FCDH achieves an average MCC of 0.894 whereas next best is 0.707 for FCH. Similarly, FCDH yields an average PCC of 99.08% whereas next best is 97.72% provided by FCH. Thus, our algorithm demonstrates much better performance than the other state-of-the-art algorithms.

Qualitative Evaluation: Performance of the benchmark algorithms is shown in the Fig. 3. We can clearly infer that the FCDH algorithm provides fewer false positives for non-stationary background sequences such as CA, WT, WS, and CU. It also offers less false positives due to the illumination variation in LO sequence. FCDH gives minimal false negatives than other techniques for test sequences with camouflage problem

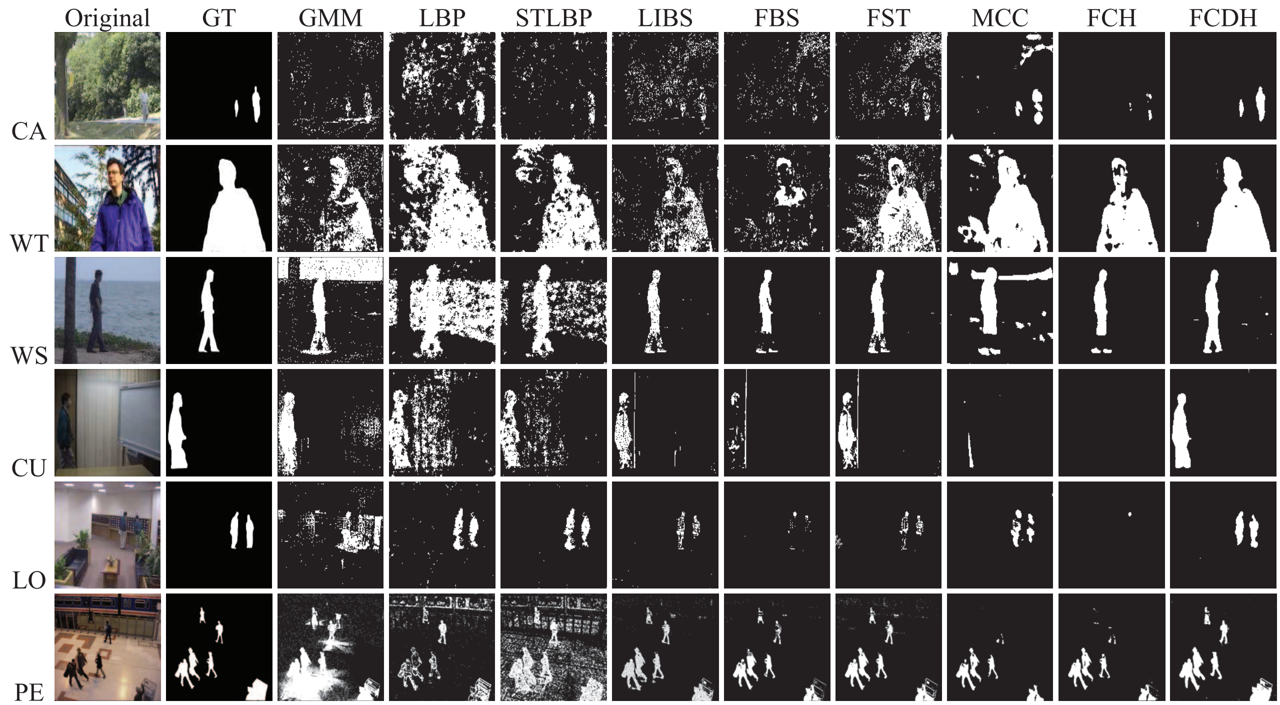

Fig. 3. Qualitative performance comparison of the state-of-the-art techniques for CA, WT, WS, CU, LO and PE sequences.

TABLE IV
QUANTITATIVE EVALUATION USING PCC

Algorithm	CA	CU	LO	WS	WT	PE	AVG
GMM	91.84	85.18	88.90	81.42	83.23	91.31	86.98
LBP	81.71	87.07	91.37	68.14	79.41	96.53	84.04
STLBP	93.22	91.91	92.79	84.15	88.21	87.92	89.70
LIBS	91.92	97.47	87.68	98.91	84.96	98.13	93.18
FBS	93.16	96.88	92.44	98.61	74.91	97.69	92.28
FST	92.34	97.56	96.46	99.15	86.08	98.18	94.96
MCC	95.70	92.61	95.96	92.82	88.03	97.60	93.79
FCH	98.07	97.44	99.10	98.75	95.41	97.56	97.72
FCDH	99.13	99.15	99.45	99.27	98.78	98.69	99.08

TABLE V
AVERAGE COMPUTAITON TIME PER PIXELS IN CLOCKS

Algorithm	CA	WT	WS	CU	LO	PE
GMM	61380	52824	59024	62651	61194	61442
LBP	276458	251410	259997	274381	271002	287060
STLBP	296453	279682	283433	287742	304637	314650
LIBS	4185	19220	8990	23126	3968	4743
FBS	16027	17298	15779	15686	15376	14260
FST	1373300	1376059	1370386	1370076	1368588	1371471
MCC	266042	266879	265236	264864	265329	290532
FCH	140740	141174	140740	140616	140554	139872
FCDH	136245	136834	136059	136090	136059	135129

(WS, CU, and LO). Further, FCDH is able to independently extract moving object from the crowded sequence (PE). The performance of FCDH is better than the other state-of-the-art algorithms since the traditional algorithms completely rely on color information, whereas ours employs the color difference between a center pixel and its neighbors. Thus, the color difference based background subtraction algorithm, FCDH is robust enough to discriminate a foreground pixel from a complex background with minimal false detections.

Time Complexity: To compare the performance of our algorithm with the existing algorithms, in terms of computational time requirement, we define the average computation time per pixel in clocks (ACTC) for a digital computing hardware platform as (10), shown at the bottom of the page. The time complexities are evaluated for FCDH and other existing algorithms and are presented in Table V. It is observed that our algorithm is quite fast compared to FST, STLBP, LBP and MCC algorithms, and is comparable with FCH technique. But it is slow compared to LIBS, FBS and GMM. Nevertheless, these three algorithms yield poor performance, in terms of MCC and PCC, compared to our algorithm, FCDH.

IV. CONCLUSION

The use of CDH in background subtraction reduces the number of false errors due to the illumination variation, non-stationary background and even when pixel characteristics of the foreground and background objects are similar. However, it fails to detect shadow cast by the object. Moreover, presence of a foreground object during the background initialization leaves ghost effect and different learning rates for foreground or background pixel do not eliminate this effect. From simulation, it is observed that our algorithm exhibits a considerable improvement in the moving object detection and hence it will be quite useful in applications like industrial automation, traffic monitoring, security and surveillance.

$$ACTC = \frac{Total\ computation\ time\ taken\ for\ a\ video\ sequence(in\ seconds)}{No.\ of\ frames \times Frame\, size \times clock\ period(in\ seconds)} \tag{10}$$

REFERENCES

[1] T. Bouwmans, F. E. Baf, and B. Vachon, "Background modeling using mixture of gaussians for foreground detection - a survey," *Recent Patents Comput Sci.*, vol. 1, no. 3, pp. 219–237, 2008.

[2] T. Bouwmans, "Recent advanced statistical background modeling for foreground detection: A systematic survey," *Recent Patents Comput Sci.*, vol. 4, no. 3, 2011.

[3] C. Stauffer and W. E. L. Grimson, "Learning patterns of activity using real-time tracking," *IEEE Trans. Patt. Anal. Mach. Intell.*, vol. 22, no. 8, pp. 747–757, 2000.

[4] A. Elgammal, D. Harwood, and L. Davis, "Non-parametric model for background subtraction," in *Computer Vision–ECCV 2000*, 2000, pp. 751–767, Springer.

[5] K. Kim, T. H. Chalidabhongse, D. Harwood, and L. Davis, "Background modeling and subtraction by codebook construction," in *Proc. ICIP*, 2004, pp. 3061–3064.

[6] K. K. Hati, P. K. Sa, and B. Majhi, "Intensity range based background subtraction for effective object detection," *IEEE Signal Process. Lett.*, vol. 20, no. 8, pp. 759–762, 2013.

[7] F. E. Baf, T. Bouwmans, and B. Vachon, "A fuzzy approach for background subtraction," in *Proc. ICIP*, 2008, pp. 2648–2651, IEEE.

[8] M. Heikkilä and M. Pietikäinen, "A texture-based method for modeling the background and detecting moving objects," *IEEE Trans. Patt. Anal. Mach. Intell.*, vol. 28, no. 4, pp. 657–662, 2006.

[9] S. Zhang, H. Yao, and S. Liu, "Dynamic background modeling and subtraction using spatio-temporal local binary patterns," in *Proc. ICIP*, 2008, pp. 1556–1559.

[10] V. M. Antoni, B. Chan, and N. Vasconcelos, "Generalized stauffer–grimson background subtraction for dynamic scenes," *Mach. Vis. Applicat.*, vol. 22, pp. 751–766, 2011.

[11] W. Kim and C. Kim, "Background subtraction for dynamic texture scenes using fuzzy color histograms," *IEEE Signal Process. Lett.*, vol. 19, no. 3, pp. 127–130, 2012.

[12] P. Chiranjeevi and S. Sengupta, "New fuzzy texture features for robust detection of moving objects," *IEEE Signal Process. Lett.*, vol. 19, no. 10, pp. 603–606, 2012.

[13] P. Chiranjeevi and S. Sengupta, "Detection of moving objects using multi-channel kernel fuzzy correlogram based background subtraction," *IEEE Trans. Cybern.*, vol. 44, no. 6, pp. 870–881, 2014.

[14] O. Küçüktunç, U. Güdükbay, and Ö. Ulusoy, "Fuzzy color histogram-based video segmentation," *Comput. Vis. Image Understand.*, vol. 114, no. 1, pp. 125–134, 2010.

[15] C. F. Lam and M.-C. Lee, "Video segmentation using color difference histogram," in *Multimedia Information Analysis and Retrieval*, ser. Lecture Notes in Computer Science. Berlin, Germany: Springer, 1998, vol. 1464, pp. 159–174.

[16] G.-H. Liu and J.-Y. Yang, "Content-based image retrieval using color difference histogram," *Patt. Recognit.*, vol. 46, no. 1, pp. 188–198, 2013.

[17] [Online]. Available: http://imp.iis.sinica.edu.tw/ytchen/testvideos.rar

[18] J. C. Bezdek, *Pattern Recognition with Fuzzy Objective Function Algorithms*. Berlin, Germany: Springer Science & Business Media, 1981.

[19] M. J. Swain and D. H. Ballard, "Color indexing," *Int. J. Comput. Vis.*, vol. 7, pp. 11–32, 1991.

[20] [Online]. Available: http://perception.i2r.a-star.edu.sg/bk_model/bk_index.html

[21] [Online]. Available: http://research.microsoft.com/en-us/um/people/jckrumm/WallFlower/TestImages.htm

[22] [Online]. Available: http://www.changedetection.net/

[23] J. Davis and M. Goadrich, "The relationship between precision-recall and roc curves," in *Proc. 23rd Int. Conf. Machine Learning*, 2006, pp. 233–240, ACM Press.

[24] A. D. L. Lacassagne and A. Manzanera, "Motion detection: Fast and robust algorithms for embedded systems," in *Proc. ICIP*, 2009, pp. 3265–3268.

[25] P. L. Rosin and E. Ioannidis, "Evaluation of global image thresholding for change detection," *Patt. Recognit. Lett.*, vol. 24, pp. 2345–2356, 2003.