Dynamic Background Subtraction using Local Binary Pattern and Histogram of Oriented Gradients

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***Abstract*—Moving object detection in the presence of complex dynamic backgrounds such as swaying of trees, spouting of water from fountain, ripples in water, flag fluttering in the wind, camera jitters, noise, etc., is known to be very difficult and challenging task. In addition to this, illumination variation, camouflage and real-time constraint aggravate the problem further. Background subtraction (BS) is a widely used algorithm for moving object detection in the presence of static cameras. Its performance purely depends on the choice of features used for background modeling. In this paper, we have proposed a novel multi-feature and multi-modal based background subtraction using Local Binary Pattern (LBP) and Histogram of oriented Gradients (HOG) for complex dynamic scene. Each pixel is modeled as a set of multi-feature calculated from its neighborhood and multi-modal BS is performed using Gaussian mixture model (GMM). To show its efficacy, the proposed algorithm is compared with some of the state-of-the-art BS techniques. In order to evaluate the algorithm in uncontrolled environments, a collection of publicly available database has been used. Quantitative and qualitative results justify our algorithm for efficient moving object detection in the presence of swaying of trees, camouflage and ripples in the water surface.**

***Index Terms*—Visual surveillance, motion detection, background subtraction, non-stationary scene, camouflage, illumination invariant.**

I. Introduction

In recent years, visual surveillance, especially of humans and vehicles has become an active area of research in the field of computer vision. Rising terrorist attacks and burglar have made the topic even more important. Visual surveillance includes wide range of promising applications such as human identification, crowd flux statistics, congestion analysis, detection of anomalous behavior, etc. The low cost digital video cameras and robust algorithms have catapulted the demand for automated surveillance system. The goal is to replace age old traditional methods which have been proven ineffective with the increase in cameras. The high density of people in religious places, important government buildings, busy market place, bus stand, railway stations and airports have made digital cameras omnipresent. Any untoward incident in these places can be a serious catastrophe with heavy loss to the property as well as to the people. Apart from visual surveillance, moving object detection in a video sequence is one of the primary task in many computer vision applications, such as transportation and industrial automation. The visual surveillance system first detects moving objects (i.e., humans) and then analyzes, understands and recognizes human behaviors for effortless and intelligent automated system. Detection of moving objects is one of the important steps in computer vision applications, like object classification, person identification, object tracking, behavior understanding and activity recognition. The task of moving object detection can be a challenging problem in the presence of illumination variation, swaying of leaves in tree, spouting fountains, ripples or sea waves in the water surface, camouflage, occlusion and crowded sequence. Moving object detection techniques can be divided into temporal differencing, background subtraction (BS) and optical flow. BS [1]–[3] is the most popular and widely used technique among the three for detecting foreground objects in the presence of stationary cameras. BS involves construction of background and then the modeled background is compared with every current frame of the video to detect changes associated with the foreground object. BS consists of following steps: background initialization, background modeling, foreground detection and finally background maintenance. Out of these four steps, background modeling is an important step in BS. Its performance purely depends on the choice of features used for background modeling. In this paper, we have proposed a novel multi-feature and multi-modal based background subtraction using Local Binary Pattern (LBP) [4] and Histogram of Gradients (HOG) [5] for complex dynamic scene.

In the last few years, several research papers have been published in the field of moving object detection based on BS algorithm. The literature can be grouped into pixel-based [6]–[10] and region-based [11]–[18], depending on the features used for background modeling. First, the pixel-based BS algorithms are discussed in detail. A unimodal BS technique is proposed by Wren et al. [6] using Gaussian distribution. However, a single Gaussian model fails in outdoor environment, as swaying vegetation in the background gives rise to multiple intensity for a single pixel. Stauffer and Grimson [7] have proposed BS approach using Gaussian mixture model (GMM). In this technique, each pixel is modeled independently using a GMM model and the parameters are updated in an online fashion. Although, it is a popular BS algorithm, still it suffers from several drawbacks. The limited number of components in GMM is not able to properly model the noise or non-stationary scene. Moreover, it does not consider the spatial correlation of pixels, which leads to false detections and Gaussian assumption for every background pixel does not always hold in dynamic scene. In spite of this, Gaussian distribution has become the de facto standard in background modeling. Many researchers have improved and extended GMM based BS. To overcome the problem of parametric BS [6], [7], Elgammal et al. [8] proposed a non-parametric BS using kernel density estimation. It does not require any presumption about the distribution of the background model but, requires a history of sample pixel values to closely estimate the model and hence involves huge computations, which makes the algorithm less efficient in real-time computations. Kim et al. [9] proposed a multi-modal BS using codebook model. Every background pixel is assigned some codeword during the training period, which depends on the background variation. The current codeword is compared with the codeword of background model. The dissimilar codewords are said to be ”Foreground” and similar codewords are classified as “Background”. However, a uni-modal background may have one or more codewords. The algorithm also suffers from highly dynamic background pixel, as it does not consider the spatial correlation between the pixels. Baf et al. [10] presented a fuzzy approach to background subtraction technique using Choquet integral.

Next, the region-based algorithm which uses features like edge histogram [11], contrast histogram [12], local binary pattern [13], co-occurrence matrix [17], correlogram [18], fuzzy color histogram [19], fuzzy color difference histogram [20], etc., in background modeling are discussed in detail. The work proposed in [14] uses covariance matrix descriptor and integrates multiple feature at both pixel level and region level. The pixel coordinate values, intensity, LBP and gradients are used to model each pixel. Marie et al. [15] proposed a new BS using invariant moments (i.e., Hu Set). The BS is done using codebook construction. Heikkila et al. [13] have used LBP, a novel powerful region based discriminative texture feature in background modeling. However, the algorithm fails in uniform region and a small change in intensity values of the pixel, give rise to different LBP code. Moreover, LBP histogram is not able to properly model the non-stationary scenes. Zhang et al. [16] have improved LBP based BS and coined a new term i.e., spatio-temporal LBP histogram for moving object detection. Chiranjeevi and Sengupta [17] have proposed fuzzy statistical texture features for moving object detection, derived from fuzzy transformed co-occurrence vector. The multiple features include intensity, energy, texture mean and local homogeneity. Furthermore, the authors have proposed a multi-channel kernel fuzzy correlogram based BS [18].

Even though, several researchers have proposed algorithms, which work well for static or near-static backgrounds, their performance degrades in the presence of real life scenario. Hence, the problem is still unsolved for dynamic backgrounds.

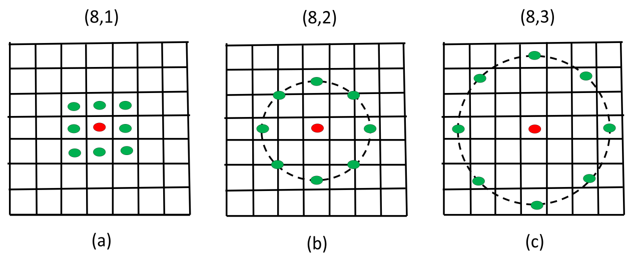

Fig. 2. Illustration of LBP; (a) circular LBP with P=8 and R=1; (b) circular LBP with P=8 and R=2; and (c) circular LBP with P=8 and R=3.

In this article, we have proposed a novel BS for complex dynamic background based on LBP and HOG. The combination of LBP and HOG has been used for person detection with partial occlusion in [21]. However, none of the research papers have used it in background subtraction for moving object detection. The originality of the work lies in the use of LBP and HOG for background modeling.

II. Proposed Algorithm

We have proposed a multi-feature background subtraction for dynamic scene using LBP and HOG. Each pixel is modeled with the multi-feature, which is calculated in the local neighborhood.

A. Local Binary Patterns (LBP)

The LBP [4] operator has some attractive properties such as gray scale invariance, non-parametric, illumination invariant, computational simplicity, and highly discriminative. The original version includes eight neighbors of a pixel, which can be easily extended to include a larger circular neighborhood with any number of pixels. In LBP the sign of difference between the central pixel and its P neighbors is thresholded to get the P-bit binary number, giving rise to 2^P discrete decimal values for the binary pattern. Thus number of bins used for histogram is 2^P-bins.

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{P-1} s(I_p - I_c)2^p, \quad s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0, \end{cases} \tag{1}$$

where I_c refers to the center value of the pixel with co-ordinate (x_c, y_c) and I_p to the neighboring values of the pixel in a circle of radius R.

B. Histogram of Oriented Gradients (HOG)

Dalal and Triggs introduced HOG [5], a popular feature descriptor for detecting objects in computer vision and image processing. The idea behind this is that local object appearance and shape can be described by counting occurrences of gradient orientation in localized portions of an image i.e., detection window.

Implementation of the HOG descriptor algorithm is as follows:

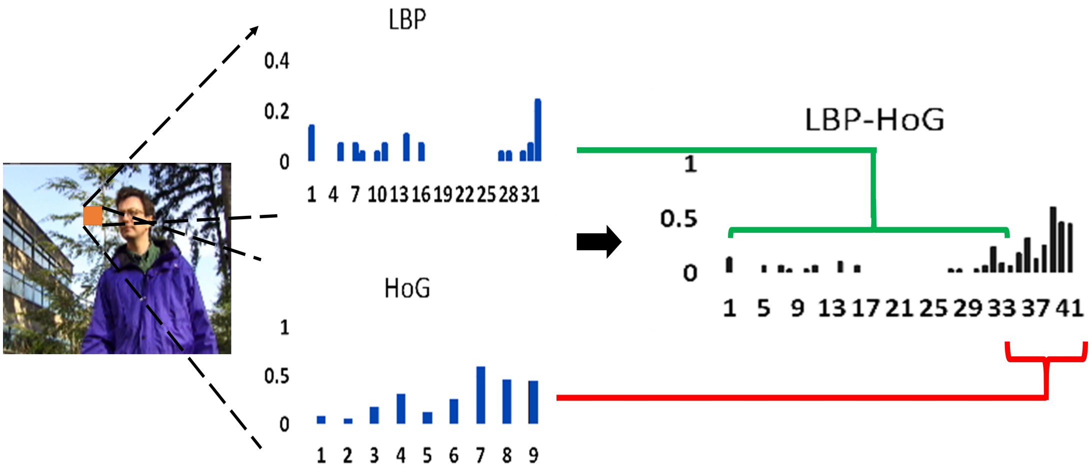

Fig. 1. Illustration of the proposed LBP-HOG based concatenation of histogram for background modeling. The LBP is calculate with $R = 2$ and $P = 5$, thus, number of bins used for histogram calculation is 32. The HOG is calculated with 9 bins.

1) The gray image is convolved with the filter kernels to get the derivative along both the horizontal and vertical directions.

$$D_x = [-1\ 0\ 1] \quad and \quad D_y = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \tag{2}$$

$$I_x = I * D_x \quad and \quad I_y = I * D_y \tag{3}$$

2) The magnitude of the gradient is given by:

$$I_g = \sqrt{I_x^2 + I_y^2}$$

3) The orientation of the gradient is given by:

$$\theta_g = \arctan\left(\frac{I_y}{I_x}\right) \tag{4}$$

4) Compute histogram of orientation gradient over a local neighborhood window for each pixel.

C. Background Modeling and Maintenance

Background construction is an important step in BS. Its performance purely depends on the choice of feature used for background modeling. Here, in this paper we have used multi-feature based background modeling using LBP and HOG. For every pixel, histogram of LBP and HOG are concatenated as a single histogram as shown in Fig. 1.

$$H = [hLBP(0),\ hLBP(1),\ \ldots,\ hLBP(2^P - 1), \\ HOG(1),\ HOG(2),\ \ldots,\ HOG(nbins)] \tag{5}$$

where LBP histogram is represented by $hLBP$. The number of bins required for the LBP image depends on the number of neighbors, P around the center pixel. HOG is computed using $nbins$. The number of bins required for the concatenated LBP-HOG histogram is $(2^P + nbins)$. The first frame of the video is used to initialize the background model using LBP-HOG histograms, $\{H_1^B, \ldots, H_K^B\}$. Here, K is the number of multi-modal component used for background modeling in GMM. Each background model is associated with a weight, whose value lies between 0 and 1. So that the sum of the weights of the K model histogram is 1. (i.e $\sum_{k=1}^{K} w_{k,t} = 1$). The weight of the kth model histogram is represented by w_k. The current LBP-HOG histogram H is compared against the K background model histogram, H^B using histogram intersection, ρ given by:

$$\rho(H^B, H) = \frac{\sum_i \min(H^B(i), H(i))}{(\sum_i H^B(i), \sum_i H(i))} \tag{6}$$

where $H^B(i)$ and $H(i)$ denotes respectively the histogram of the background model and the current frame. If the value of similarity measure is greater than a user-settable parameter T_p, a match is found. The highest value of histogram intersection, among the K model is chosen as the best match. We select the best match and update its background histogram and weight as follows:

$$H_{k,t}^B = (1 - \alpha_b)\, H_{k,t-1}^B + \alpha_b H_t \tag{7}$$

where $H_{k,t}^B$ represent the kth model of LGB-HOG histogram and current histogram is denoted by H_t.

$$w_{k,t} = (1 - \alpha_w) w_{k,t-1} + \alpha_w M_k \tag{8}$$

where α_b and α_w are the learning rate and M_k is chosen to be 1 for the best matching model and 0 for the rest.

If none of the K background model histogram matches with the current histogram, the least probable weight component in the background model is replaced with the current histogram. The weight associated with the model is replaced with low value of initial weight.

$$\begin{aligned} m &= \arg\min_{k=1,\ldots,K} w_{k,t} \\ H_{m,t}^B &= H \\ w_{m,t} &= 0.001 \end{aligned} \tag{9}$$

The weights associated with background model histogram are arranged in the descending order. This ordering moves the most likely background with high weight to the top. The first B model histogram which are greater than certain threshold T are retained for the background histogram.

$$B = \arg\min_{b} \left(\sum_{k=1}^{b} w_{k,t} > T \right) \tag{10}$$

where T is a user-settable threshold.

The main steps of the proposed BS using LBP-HOG is well illustrated in Alogrithm 1.

Algorithm 1 Multi-feature and Mulit-Modal Background Subtraction Using LBP-HOG Histogram

Step 1: The first frame of the video is used to initialize the K multi-modal background model using LBP-HOG histograms, $\{H_1^B, \ldots, H_K^B\}$ for every pixel.

Step 2:The current LBP-HOG histogram H is compared against the K background model histogram using histogram intersection given in (6).

Step 3: If the value of similarity measure is greater than T_p, match is found. For the best match model, its background histogram and weight are updated using (7) and (8) respectively.

Step 4: If none of the K background model histogram matches the current feature vector, update the background histogram and weight given in (9).

Step 5: The first B model histogram whose value exceeds T in (10) are retained for the background histogram.

Step 6: If the similarity function value is greater than T_p for any one of the background model histogram, then the pixel is classified as "background" or else the pixel will be marked as "foreground".

III. Result Analysis

Our results and discussion has been categorized into three subsections. In Section III-A, the state-of-the-art algorithm and publicly available test sequences used for the comparisons are described. Qualitative and quantitative comparison of the proposed algorithm with those of the state-of-the-art techniques is done in Section III-B and III-C respectively.

A. Experimental Setup

The efficacy of the proposed LBP-HOG based background subtraction (LBP-HOG BS) algorithm is compared with GMM [7], LBP [13], STLBP [16], FBS [10], MCC [18]. No pre or post-processing (median filtering, shadow removal and morphological operation) is performed on any of the results for fair comparisons. The parameters used for LBP calculation are set as $R = 2$ and $P = 6$. The number of bins for HOG calculation is kept constant as $nbins = 9$. The histogram of LBP and HOG are calculated in 5×5 overlapping window. The number of Gaussian has been fixed as $K = 3$. The learning rate for the updation of the weight and histogram is chosen as $\alpha_w = 0.001$ and $\alpha_b = 0.001$. The threshold for the background model is chosen to be $T = 0.7$ and threshold for similarity measure is judiciously varied between 0.3 to 0.6. The state-of-the-art algorithms used for comparison with our proposed approach are simulated using the optimized parameter values as specified in the publications [7], [10], [13], [16], [18].

The video sequences used for the performance evaluation contain various challenging situations faced during the moving object detection such as non-stationary background, camouflage, etc. The test sequences "Waving Trees" and "Camouflage" are taken from the publicly available walflower dataset [22]. The "Water Surface" sequence is downloaded from [23]. The database is recognized as standard in the research community for testing of moving object detection algorithm. In "Waving Trees" sequence, a person walks past a swaying tree. The video contains 287 images with a dimension of 160×120 pixels. This sequence is very challenging in the midst of non-stationary leaves of the tree. The goal is to detect the person and classify the swaying tree as "background". The "Camouflage" sequence is used to detect foreground object which have similar characteristics with the background pixel. It consists of a person walking in the room and comes in the front of flickering monitor. The video contains a total of 356 images with a dimension of 160×120 pixels. In "Water Surface" video, a person is walking on the bank of a river. There are many waves formed in the backdrop and this constitutes non-stationary background for the video. The lower half of the person, i.e. below the knee is having similar pixel characteristics with that of the bank of the river, giving rise to the problem of camouflage. It consists of a total of 633 frames each with a dimension of 160×128 pixels. The ground truth used for evaluation are manually segmented.

B. Qualitative Evaluation

The moving object detection results for complex video scenes like "Waving Trees", "Camouflage" and "WaterSurface" are shown in Fig. 3. The first row represents the original images and the hand segmented ground truth image is shown in the second row. The GMM and LBP BS technique is shown in the third and fourth row. The BS for these algorithm fails to provide true shape of the moving object. The algorithm shows rise in false errors in the detection results. The algorithm STLBP, FBS and MCC also shows false positives in the detection result. Our proposed algorithm is able to provide accurate silhouette with minimum false errors. The addition of HOG to the LBP based BS increases the discrimination power for moving object detection.

C. Quantitative Evaluation

To evaluate our method, we have used quantitative measure such as Average Classification Error (ACE), Precision (P_1), Recall (R_1), False Alarm Rate (FAR), F_1, Jaccard Coefficient(JC), Matthew's Correlation Coefficient (MCC) and

TABLE I
QUANTITATIVE MEASURE FOR WAVING TREES SEQUENCE

Sl. No	Algorithm	ACE	P_1	R_1	FAR	F_1	JC	MCC	PCC
1	GMM	198.21	0.69	0.60	0.09	0.64	0.47	0.54	83.23
2	LBP	229.65	0.56	0.94	0.26	0.69	0.54	0.60	79.41
3	STLBP	201.45	0.72	0.84	0.10	0.77	0.63	0.69	88.21
4	FBS	296.53	0.52	0.21	0.07	0.29	0.17	0.20	74.91
5	MCC	141.52	0.68	0.94	0.14	0.78	0.66	0.72	88.03
6	LBP-HOG	77.74	0.90	0.91	0.03	0.90	0.89	0.91	97.90

TABLE II
QUANTITATIVE MEASURE FOR CAMOUFLAGE SEQUENCE

Sl. No	Algorithm	ACE	P_1	R_1	FAR	F_1	JC	MCC	PCC
1	GMM	726.79	0.56	0.81	0.67	0.66	0.49	0.15	57.68
2	LBP	266.04	0.80	0.91	0.26	0.85	0.74	0.67	83.58
3	STLBP	206.60	0.82	0.90	0.03	0.85	0.88	0.88	86.79
4	FBS	98.29	0.95	0.94	0.05	0.94	0.89	0.88	94.27
5	MCC	410.21	0.70	0.95	0.43	0.80	0.67	0.56	76.11
6	LBP-HOG	83.69	0.95	0.94	0.10	0.94	0.93	0.90	96.10

TABLE III
QUANTITATIVE MEASURE FOR WATER SURFACE SEQUENCE

Sl. No	Algorithm	ACE	P_1	R_1	FAR	F_1	JC	MCC	PCC
1	GMM	1881.49	0.27	0.96	0.19	0.41	0.27	0.45	86.41
2	LBP	3043.88	0.16	0.93	0.33	0.27	0.16	0.30	81.54
3	STLBP	1513.99	0.27	0.87	0.16	0.41	0.265	0.43	90.05
4	FBS	140.44	0.96	0.80	0.001	0.87	0.78	0.87	91.20
5	MCC	726.44	0.47	0.83	0.06	0.59	0.42	0.59	93.02
6	LBP-HOG	133.79	0.93	0.90	0.12	0.91	0.83	0.88	95.60

Percentage of Correct Classification (PCC). The accuracy metrics [18] are given below:

$$ACE = \frac{f_p + f_n}{N_{GT}} \tag{11}$$

$$P_1 = \frac{t_p}{t_p + f_p} \tag{12}$$

$$R1 = \frac{t_p}{t_p + f_n} \tag{13}$$

$$FAR = \frac{f_p}{f_p + t_n} \tag{14}$$

$$F_1 = \frac{2 * R_1 * P_1}{R_1 + P_1} \tag{15}$$

$$JC = \frac{t_p}{t_p + f_n + f_p} \tag{16}$$

$$MCC = \frac{tp \times tn - fp \times fn}{\sqrt{(tp + fp)\,(tp + fn)\,(tn + fp)\,(tn + fn)}} \tag{17}$$

$$PCC = \frac{t_p + t_n}{t_p + t_n + f_p + f_n} \times 100 \tag{18}$$

Here, N_{GT} is the total number of groundtruth sequence used for the evaluation, true positive (t_p) represents the number of pixels classified correctly as belonging to the foreground and true negative (t_n), which counts the number of background pixel classified correctly. The false positive (f_p) is the number of pixels that are incorrectly classified as foreground and false negatives (f_n) represents the number of pixels which are wrongly labelled as background but should have been classified as foreground.

The quantitative evaluation for the proposed algorithm is done using test sequences like "Waving Trees", "Camouflage" and "Water Surface", which is given in the Table I, II and III respectively. The values of P_1, R_1, F_1, F_{joint}, $Similarity$, MCC and PCC should be higher, But ACE and FAR values should be lower for good detection result. The results of our proposed algorithm is better than other state-of-the-art methods.

IV. Conclusion

A novel moving object detection algorithm based on LBP and HOG is proposed. The detection of the LBP based BS is improved by concatenating HOG to the end of the LBP histogram. The proposed algorithm is able to detect accurate silhouette of the moving object in the presence of waving trees and camouflage. The qualitative and quantitative comparison with other state-of-the-art BS shows the efficacy of the proposed algorithm.

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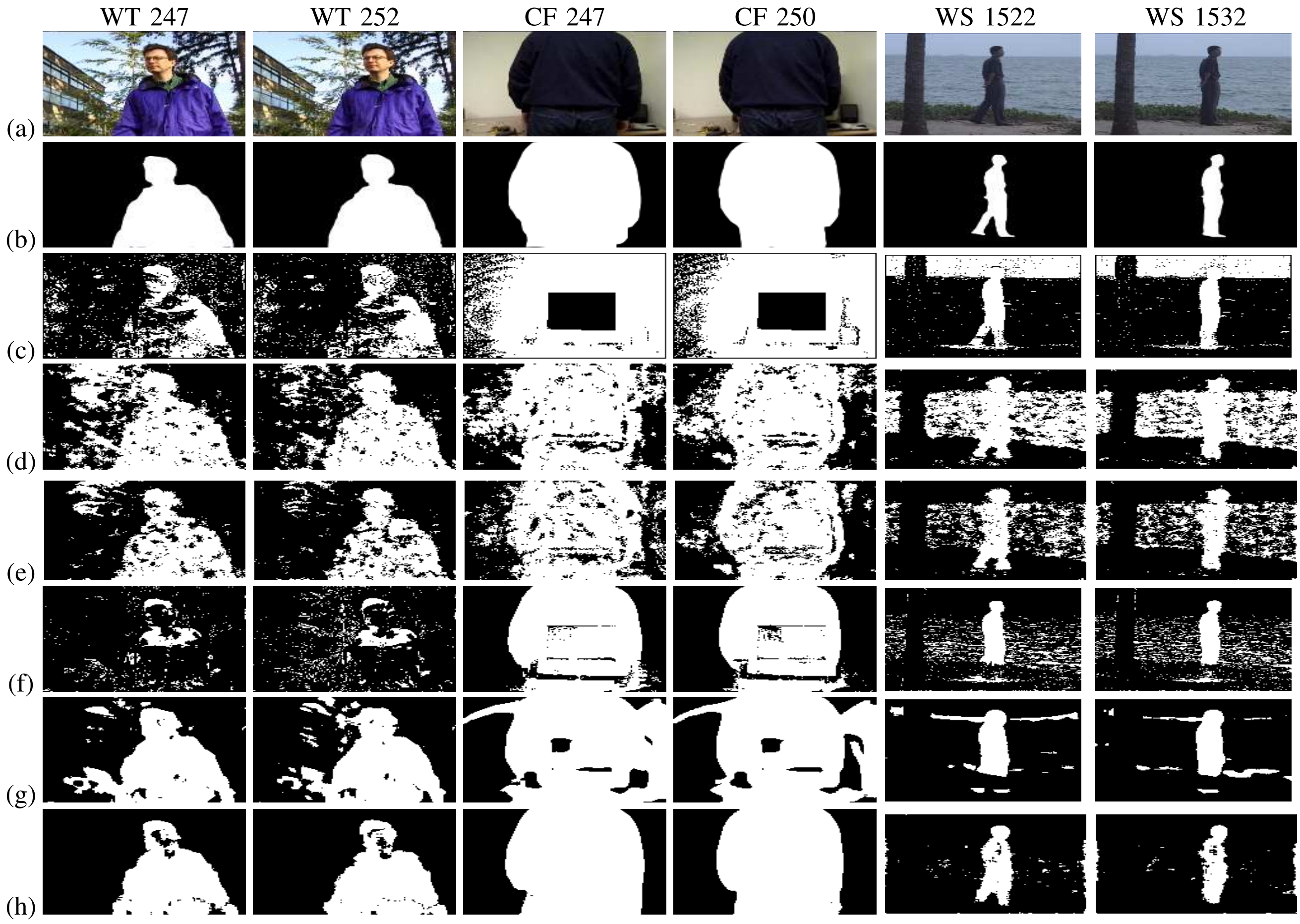

Fig. 3. Comparsion of experimental results. (a) Original images, (b) Ground truth, (c) GMM, (d) LBP, (e) STLBP, (f) FBS, (g) MCC, (h) LBP-HOG (proposed). (Note: No morphological operation have been used in any of these algorithms)

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