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Background Subtraction for Dynamic Texture Scenes Using Local FCH features With Adaptive Updating Procedure

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ABSTRACT: *Background subtraction is a very popular approach for vehicle detection in traffic surveillance systems. A conventional color histogram (CCH) considers neither the color similarity across different bins nor the color dissimilarity in the same bin. Therefore, it is sensitive to noisy interference such as illumination changes and quantization errors. Furthermore, CCHs large dimension or histogram bins requires large computation on histogram comparison. However, structured motion patterns of the background (e.g., Vehicular traffic videos, waving leaves, spouting fountain, rippling water, etc.), which are distinctive from variations due to noise, are hardly tolerated in this assumption. To address these concerns, we introduce a background subtraction algorithm for temporally dynamic texture scenes. Specifically, we propose to adopt a clustering-based feature, called fuzzy color histogram (FCH), which has an ability of greatly attenuating color variations generated by background motions while still highlighting moving objects. Experimental results demonstrate that the proposed method is effective for background subtraction in dynamic texture scenes using LFCH features with adaptive updating procedure compared to several competitive methods proposed in the literature.*

KEYWORDS : Background subtraction, Conventional color histogram, fuzzy c-means ,fuzzy color histogram, illumination changes, membership matrix, structured motion patterns.

1 INTRODUCTION

With increasing interest in high-level safety and security, smart video surveillance systems, which enable advanced operations such as object tracking and behavior understanding, have been in critical demand. For the success of such systems, background subtraction, one of essential tasks in video surveillance, has been studied in various environments. The basic idea of earlier work for this task is to evaluate the difference of pixel values between the reference and current frames. However, this approach is definitely sensitive to even small variations since it lacks adaptive updating of the reference background.

Stauffer and Grimson formulate the distribution of each pixel value over time as a mixture of Gaussians (MoG), which is adaptively updated in an online manner, and then classify incoming pixels into either background or not. Inspired by their probability model and on- line updating scheme, numerous variants have been proposed over the last decade. These approaches perform well for the static scene even containing gradual illumination changes, however, often fail to exclude various dynamic textures (e.g., Vehicular traffic videos, waving leaves and rippling water, spouting fountain etc).

Dalley *et al.* [6] propose a generalization scheme of the MoG model. In particular, they combine the relation between neighboring pixels in background likelihood estimation with the compactness of a semi-parametric MoG representation to classify the dynamic textures as being the part of the background.

Swain and Ballard have demonstrated the potential of using color histograms for color image indexing. Because each histogram bin represents a local color range in the given color space, color histogram represents the coarse distribution of the colors in an image. Two similar colors will be treated as identical provided that they are allocated into the same histogram bin. On the other hand, two colors will be considered totally different if they fall into two different bins even though they might be very similar to each other. This makes color histograms sensitive to noisy interference such as illumination changes and quantization errors.

In contrast with conventional color histogram (CCH) which assigns each pixel into one of the bins only, our FCH considers the color similarity information by spreading each pixel's total membership value to all the histogram bins. Furthermore, to save computation, we introduce an efficient method to compute these membership values using *fuzzy c-means* (FCM) clustering algorithm.

In this letter, we propose a simple and robust method for back- ground subtraction in dynamic texture scenes. The rationale behind our model is that color variations generated by background motions are greatly attenuated in a fuzzy manner. Therefore, compared to previous methods using local kernels, the proposed method does not require estimation of any parameters (i.e., nonparametric). This is fairly desirable for achieving the robust background subtraction in a wide range of scenes with spatiotemporal dynamics. Specifically, we propose to derive the local features from the fuzzy color histogram (FCH). Then, the background model is reliably constructed by computing the similarity between local FCH features with an online update procedure. To verify the superiority of the proposed method, we finally compare ours with competitive background subtraction models proposed in the literature using various dynamic texture scenes.

In the next section, we introduce related works of color histogram based methods for Dynamic texture scenes. The concept of FCH is introduced in Section III. Fuzzy color histogram and its application to Background subtraction is introduced in Section IV. In Section V, we analyze the experimental results of dynamic texture scenes using FCH with adaptive updating procedure. Section VII concludes the paper.

2 RELATED WORKS

Color histograms are easy to compute, and they are invariant to the rotation and translation of image content. However, color histograms have several inherent problems for the task of detecting moving objects. The first concern is their sensitivity to noisy interference such as lighting intensity changes and quantization errors. The second problem is their high dimensionality on representation. Even with coarse quantization over a chosen color space, color histogram feature spaces often occupy more than one hundred dimensions (i.e., histogram bins) which significantly increases the computation of distance measurement on the retrieval stage. Finally, color histograms do not include any spatial information and are therefore incompetent to support image indexing and retrieval based on local image contents. In the following, we briefly describe several existing approaches that have been attempting to address these concerns.

2.1 Sensitivity

Some approaches exploit the color histogram derived together with a similarity measurement chosen to make color histograms more robust to noisy interference. To identify objects based on their color histograms, Swain and Ballard propose a *histogram intersection* method which is able to eliminate the influence of color contributed from the background pixels during the matching process in most cases. Although their method is robust to object occlusion and image resolution, but it is still sensitive to illumination changes.

Funt and Finlayson propose a *color constant color indexing* method to extend Swain and Ballard's color indexing method to be illumination independent by establishing the histogram of color ratios. Since the illumination remains essentially constant locally, calculating the ratios of neighboring colors removes the illumination variation component. Similar extension can be found in Drew *et al.*'s work.

Cumulative color histogram utilizes the spatial relation-ship of the histogram bins in the color space. Consequently, it is slightly more robust with respect to illumination changes than CCH [8]. In Section V, we will show that it can be viewed as a special case of our FCH.

QBIC takes into account the perceptual color similarity between histogram bins through the measurement of *quadratic distance*, which is a weighted distance between two CCHs with each weight denoting the similarity between a pair of color histogram bins. It has been shown that such measurement is more closely related to human being's judgment on color similarity comparison, but on the expense of large computations.

2.2 Dimensionality

Many other approaches exploit their derived color histogram methods to facilitate the design of efficient database indexing schemes. Hafner *et al* generalize computationally simple similarity measures using *singular value decomposition* (SVD) method to compute quadratic histogram distance. It has been mathematically shown that SVD-based approach provides the lower bounds on the histogram distance measure. Mandal *et al.* reduce the computational complexity of color histogram comparison by representing the histogram in terms of its moments. Experimental results also indicate that Legendre moments provide superior retrieval performance compared to regular moments.

2.3 Spatial Information

Some approaches strive to incorporate spatial information into color histograms by dividing each image into sub regions and imposing positional constraints on image comparison in order to increase image discrimination power. Smith and Chang's method uses back projection of binary color sets to extract color regions. Each of these regions is efficiently represented by a binary color set and its location information as well Stricker and Dimai's method tessellates each image into five partially overlapping fuzzy regions and extracts the first two color moments of each region both weighted by the membership functions of the region, respectively, to form a feature vector for the image.

Other approaches augment histograms with local spatial properties. Pass and Zabih propose a split histogram, called *color coherence vector* (CCV), where image pixels in a given histogram bin are partitioned into two classes based on their spatial coherence. A pixel is considered as coherent pixel if it is part of a sizable contiguous region; otherwise, incoherent pixel. Huang *et al.* propose *color correlograms* to take into account the local color spatial correlation as well as the global distribution of this spatial correlation.

All the above-mentioned approaches made some improvements over the CCH for the task of detecting moving objects. Our FCH proposed in this paper makes improvement on robustness (less sensitive to interference), efficiency (reduced dimension), and computation (less online computation consumed).

2.4 Conventional Color Histogram(CCH)

The conventional color histogram (CCH) of an image indicates the frequency of occurrence of every color in an image. The appealing aspect of the CCH is its simplicity and ease of computation. There are however, several difficulties associated with the CCH viz .,a) CCH is sensitive to noisy interferences such as illumination changes and quantization errors; b) large dimension of CCH involves large computation on indexing, c)It does not take into consideration color similarity across different bins and cannot handle rotation and translation. To address the problem of rotation and translation an invariant color histograms based on the color gradients is used and to address the problem of spatial relationship fuzzy color histogram (FCH) is used.

The approach more frequently adopted for CBIR systems is based on the conventional color histogram (CCH), which contains occurrences of each color obtained counting all image pixels having that color. Each pixel is associated to a specific histogram bin only on the basis of its own color, and color similarity across different bins or color dissimilarity in the same bin are not taken into account.

Since any pixel in the image can be described by three components in a certain colour space(for instance, red, green and blue components in RGB space or hue, saturation and value in HSV space), a histogram, i.e., the distribution of the number of pixels for each quantized bin, can be defined for each component. Clearly, the more bins a color histogram contains the more discrimination power it has. However, a histogram with large number of bins will not only increase the computational cost, but will also be in appropriate for building efficient indexes for image data base. Quantization in terms of color histograms refers to the process of reducing the number of bins by taking colors that are very similar to each other and putting them in the same bin. By default the maximum number of bins one can obtain using the histogram function in MatLab is 256.

3 Fuzzy Color Histogram

In this paper, the color histogram is viewed as a color distribution from the probability viewpoint. Given a color space containing n color bins, the color histogram of image I containing N pixels is represented as s $H(I) = [h_1, h_2, \ldots\ldots h_n]$, Where $h_i = {}^{N_i}/_N$ is the probability of a pixel in the image belonging to the *i*th color bin, and N_i is the total number of pixels in the *i*th color bin. According to the total probability theory, h_i can be defined as follows:

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$$h_i = \sum_{j=1}^{N} P_{i|j} P_j = 1/N \sum_{j=1}^{N} P_{i|j}$$

Where P_j the probability of a pixel selected from image I being the jth pixel, which is 1/N, and $P_{i|j}$ is the conditional probability of the selected jth pixel belonging to the ith color bin.

In the context of CCH, $P_{i|j}$ is defined as

$$P_{i|j} = \begin{cases} 1, & \text{if the } j\text{th pixel is quantised into the } i\text{th color bin} \\ & 0, \text{otherwise.} \end{cases}$$

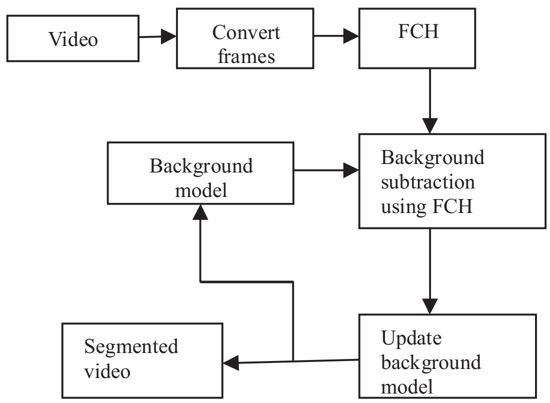

Fig 1:Fuzzy color histogram (FCH)

This definition leads to the boundary issue of CCH such that the histogram may undergo abrupt changes even though color variations are actually small. This reveals the reason why the CCH is sensitive to noisy interference such as illumination changes and quantization errors.

The proposed FCH essentially modifies probability $P_{i|j}$ as follows. Instead of using the probability $P_{i|j}$, we consider each of the N pixels in image I being related to all the n color bins via fuzzy-set membership function such that the degree of belongingness or "association" of the j th pixel to the ith color bin is detemined by distributing the membership value of the jth pixel, u_{ij} , to the ith color bin.

Definition (Fuzzy Color Histogram): The fuzzy color histogram (FCH) of image I can be expressed as $F[I] = [f_1, f_2, \ldots, f_n]$,where

$$f_i = \sum_{j=1}^{N} u_{ij} P_j = 1/N \sum_{j=1}^{N} u_{ij}.$$

P_j has been defined in h_i, and u_{ij} is the membership value of the j th pixel in the ith color bin.

In contrast with CCH, our FCH considers not only the similarity of different colors from different bins but also the dissimilarity of those colors assigned to the same bin. Therefore, FCH effectively alleviates the sensitivity to the noisy interference.

3.1 Fuzzy color histogram and its application to background subtraction

3.1.A Fuzzy Membership Based Local Histogram Features

The idea of using FCH in a local manner to obtain the reliable background model in dynamic texture scenes is motivated by the observation that background motions do not make severe alterations of the scene structure even though they are widely distributed or occur abruptly in the spatiotemporal domain, and color variations yielded by such irrelevant motions can thus be efficiently attenuated by considering local statistics defined in a fuzzy manner, i.e., regarding the effect of each pixel value to all the color attributes rather than only one matched color in the local region. Therefore, it is thought that fuzzy membership based local histograms pave a way for robust background subtraction in dynamic texture scenes. In this subsection, we summarize the FCH model and analyze the properties related to background subtraction in dynamic texture scenes.

First of all, in a probability view, the conventional color histogram (CCH) can be regarded as the probability density function. Thus, the probability for pixels in the image to belong to the *i* th color bin w_i can be defined as follows:

$$h_i = \sum_{i=1}^{N} P\left({}^{w_i}/_{x_{\cdot}}\right) P(x_i) = 1/N \sum_{i=1}^{N} P\left({}^{w_i}/_{x_{\cdot}}\right) \quad (1)$$

Where N denotes the total number of pixels. $P(x_j)$ is the probability of color features selected from a given image being those of the *j* th pixel, which is determined as 1/N. The conditional probability $P\left({}^{w_i}/_{x_i}\right)$ is 1 if the color feature of the selected *j* th pixel is quantized into the *i*th color bin and 0 otherwise Since the quantized color feature is assumed to be fallen into exactly one color bin in CCH, it may lead to the abrupt change even though color variations are actually small. In contrast to that, FCH utilizes the fuzzy membership to relax such a strict condition. More specifically, the conditional probability $P\left({}^{w_i}/_{x_i}\right)$ of (1) represents the degree of the belongingness for color features of the *j*th pixel into the *i*th color bin (i.e., fuzzy membership u_{ij}.) in FCH and it thus enables to be robust to the noise interference and quantization error.

Now, a rather critical issue is to efficiently compute such membership values. In this we employ a novel color quantization scheme based on the fuzzy c-means means (FCM) clustering technique. First, the RGB color space is uniformly and finely quantized into m histogram bins (e.g., 4096) and subsequently convert them into the MATLab color space. Note that the MATLab color space is adopted to correctly quantify the perceptual color similarity based on the uniform distance. Finally, we classify these m colors in the MATLab color space to c clusters (each cluster represents an individual FCH bin) using the FCM clustering technique ($m \gg c$). That is, by conducting FCM clustering, we can obtain the membership values of a given pixel to all FCH bins. More specifically, the FCM algorithm finds a minimum of a heuristic global cost function defined as follows:

$$\Gamma = \sum_{i=1}^{c} \sum_{i=1}^{m} \left| P\left(\tfrac{w_i}{-} \right) \right| \; \| x_i - v_i \| \text{^}2$$

Where x and v denote the feature vector (e.g., values of each color channel) and the cluster center, respectively. *b* is a constant to control the degree of blending of the different clusters and is generally set to 2. Then we have following equations, i.e.., where P_j denotes the prior probability of $P(w_j)$, at the minimum of the cost function. These lead to the solution given as

$$v_i = \frac{[illegible]}{[illegible]} \quad (3)$$

$$P\left({}^{w_i}/_{x_j}\right) = u_{ij} = \frac{[illegible]}{[illegible]} \quad (4)$$

Where $d_{ij} = ||x_j - v_i||$^2. Since (3) and (4) rarely have analytic solutions, these (i.e., cluster center and membership value) are estimated iteratively according to [13]. It is worth noting that these membership values derived from (4) only need to be computed once and stored as a membership matrix in advance. Therefore, we can easily build FCH for the incoming video frame by directly referring to the stored matrix without computing membership values for each pixel.

For the robust background subtraction in dynamic texture scenes, we finally define the local FCH feature vector at the *j*th pixel position of the *k*th video frame as follows:

$$F_j(k) = f_{j,1}^k, f_{j,2}^k, f_{j,3}^k, \ldots\ldots, f_{j,c}^k), f_{j,i}^k = \sum_{q \in w_j^k} u_{iq} \quad (5)$$

Where w_j^k denotes the set of neighboring pixels centered at the position j. u_{iq} denotes the membership value obtained from (4), indicating the belongingness of the color feature computed at the pixel position *q* to the color bin *i* as mentioned. By using the difference of our local features defined in (5) between consecutive frames, we can build the reliable background model. Fig. 1 shows the robustness of local FCH to dynamic textures compared to CCH. As can be seen, local CCHs obtained from the same pixel position of two video frames are quite different due to strongly waving leaves. In contrast to that, we confirm that FCH provides relatively consistent results even though dynamic textures are widely distributed in the background. There- fore, it is thought that our local FCH features are very useful for modeling the background in dynamic texture scenes. In the following, we will explain the updating scheme for background subtraction based on the similarity measure of local FCH features

3.1.B Background Subtraction With Local FCH Features

In this subsection, we describe the procedure of background subtraction based on our local FCH features. To classify a given pixel into either background or moving objects in the current frame, we first compare the observed FCH vector with the model FCH vector renewed by the online update as expressed in (6):

$$B_j(k) = \begin{cases} 1, \text{ if } S\left(F_j(k), F_j(k)\right) > \tau, \\ [illegible] \end{cases} \quad (6)$$

Where $B_j(k)$=1 denotes that the *j*th pixel in the *k*th video frame is determined as the background whereas the corresponding pixel belongs to moving objects if $B_j(k) = 0$. τ is a thresholding value ranging from 0 to 1. The similarity measure $S(.,.)$ used in (6), which adopts normalized histogram intersection for simple computation, is defined as follows:

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$$s\left(F_j(k), \hat{F}_j(k)\right) = \frac{[illegible]}{[illegible]} \tag{7}$$

Where $\hat{F}_j(k)$ denotes the background model of the jth pixel position in the kth video frame, defined in (8). Note that any other metric (e.g., cosine similarity, Chi-square, etc.) can be employed for this similarity measure without significant performance drop.

In order to maintain the reliable background model in dynamic texture scenes, we need to update it at each pixel position in an online manner as follows:

$$\hat{F}_j(k) = (1-\alpha).\hat{F}_j(k)(k-1) + \alpha.F_j(k), k \geq 1 \tag{8}$$

Where $F'j(0) = Fj(0).\alpha\epsilon[0,1]$ is the learning rate. Note that the larger α denotes that local FCH features currently observed strongly affect to build the background model. By doing this, the background model is adaptively updated.

For the sake of completeness, the main steps of the proposed method is summarized in fig 1 FCH Algorithm Algorithm 1 Background subtraction using local FCH features

Step 1. Construct a membership matrix using fuzzy c-means clustering based on (3) and (4) cluster
center and membership value(conducted only once).
Step 2. Quantize RGB colors of each pixel at the *k*th video frame into one of m histogram bins(e.g.,*r*th
bin where r=1,2,…..,m)
Step 3. Find the membership value u_{ir} at each pixel position (i=1,2,3,…....,c).
Step 4.Compute local FCH features using (5) at each pixel position of the *k*th video frame
Step 5. Classify each pixel into background or not based on FCH vector (6).
Step 6. Update the background model using (8).
Step 7. Go back to step 2 until the input is terminated *(k*=*k*+1).
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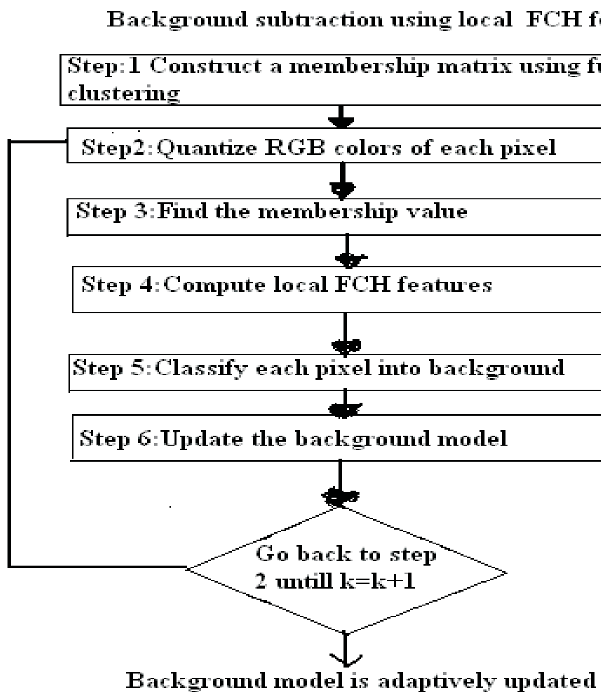

Fig 2:Flowchart for Fuzzy color histogram (FCH)

4 Experimental results

In this section, we demonstrate the relevance of local FCH features for background subtraction in dynamic texture scenes. Our experiments were conducted using traffic video sequences taken in outdoor environments with dynamic textures. We set the learning rate α=0.01 and used the local window w_i^k to extract local FCH features. m and c are set to 3 and 2.5,respectively.

Fig.2 shows several results of background subtraction. To confirm the superiority of the proposed method, we compared ours (we refer it as LFCH) with other competitive methods proposed in the literature, which are traditional MoG (t-MoG) method[1],generalized MoG(g-MoG) method and CCH-based method. To make fair comparisons, we report experimental results at a true positive (TP) rate of 0.8, which is good enough to correctly extract moving objects for further applications. As can be seen in Fig. 2, previous methods fail to reliably build the background model due to variability from temporally dynamic textures.

In particular, vehicular traffic videos widely distributed in the background lead to high-level false positive rates. Although some approaches (e.g., frame difference method and CCH-based methods) perform rather stably, those still suffer from abrupt changes in the background. In contrast to that, our approach provides reliable background models even in the presence of various dynamic textures. For the quantitative analysis, we evaluated the false positive (FP) rate at the TP rate of 0.8 based on 20 video frames randomly selected from each test video and corresponding results are shown in Table I.

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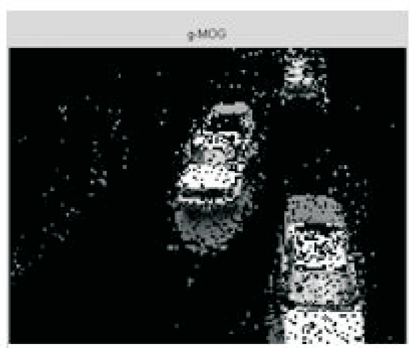
Moreover, we also plot the ROC curve using campus sequences in Fig. 3. From Table I and Fig. 3, we confirm that the proposed method is capable of correctly extracting moving objects with low false positives in dynamic texture scenes. Finally, the framework of the proposed method has been implemented by using MATlab version. The comparison of the processing time is shown in Table II. We can see that our method achieves about 0.027 s/frame (i.e., 37 fps) on average, which can be applied for various real-time applications, while providing much better background subtraction performance compared to previous methods.



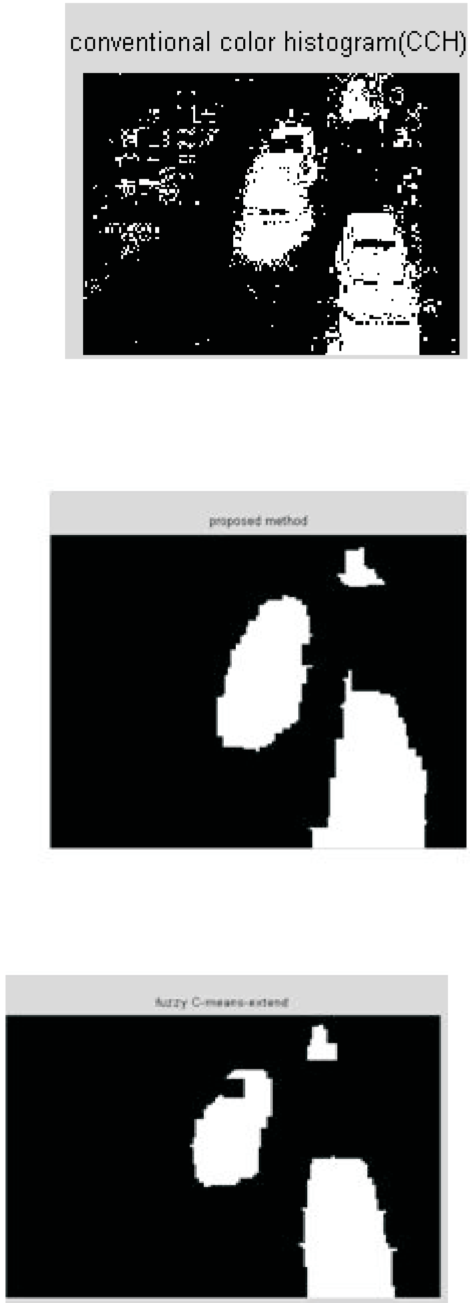


Fig. 3. Examples of background subtraction results obtained from vehicular video sequence. (a) Input video frames, (b)generalized MoG (g-MoG) method, (c) CCH-based method, and (d) proposed method (LFCH),(e)FCH method. Note that background subtraction results of each method are taken with the same level of detection rate(i.e.,true positive rate =0.8).

5 CONCLUSION AND FUTURESCOPE

In this paper, we introduce a novel descriptor on representing Background subtraction for dynamic texture using fuzzy c-means clustering algorithm, called *fuzzy color histogram* (FCH). For computing FCHs, we propose to adopt LFCH in a local manner to minimize color variations generated by background motions recorded in the perceptually uniform MATlab. Background subtraction is conducted by computing the similarity between the observed and the model FCH features, renewed by online update procedures.

Based on extensive experimental results, our FCH is less sensitive and more robust than CCH on dealing with illumination changes such as lighting intensity changes, quantization errors, region-of-interest background subtraction, and possibly other uncovered aspects in new applications. Our method achieves about 0.027 s/frame (i.e.,37 fps) on average, which can be applied for various real-time applications, while providing much better background subtraction performance in dynamic texture scenes compared to previous methods. Finally, exploiting FCH into other image processing frame- works and even extending similar soft clustering approach to other low-level visual features (e.g., shape, texture, etc.) are also recommended here

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