OBJECT IDENTIFICATION AND COUNTING BASED ON FOREGROUND DETECTION USING MORPHOLOGY IN DYNAMIC TEXTURE SCENES

Venkata Raviteja.M[1], Riyazuddin.K[2]

[1]*M.Tech Scholar, E.C.E, AITS, Rajampet, Andhra Pradesh, (India)*

[2]*Assistant Professor, E.C.E, AITS, Rajampet, Andhra Pradesh, (India)*

ABSTRACT

Background subtraction may be a very fashionable approach for police work moving objects from a still scene. For this, most of previous ways depend upon the belief that the background is static over short time periods. To adopt a clustering-based feature, referred to as fuzzy color bar chart (FCH). it's a capability of greatly attenuating color variations generated by background motions whereas still light moving objects. Background subtraction may be a procedure vision method of extracting foreground objects during a specific scene. A foreground object are often delineate as Associate in Nursing object of attention that helps in reducing the number data} to be processed likewise as offer necessary information to the task into account.

Key words: Background Subtraction, Fuzzy colour Histogram, Object Tracking

I. INTRODUCTION

Background subtraction, conjointly called Foreground Detection, may be a technique within the fields of image process associated pc vision whereby an image's foreground is extracted for additional process (object recognition etc.). distinctive moving objects from a video sequence may be a basic and vital task in several computer-vision applications. a typical approach is to perform background subtraction, that identifies moving objects from the portion of a video frame that differs considerably from a background model. There area unit several challenges in developing an honest background subtraction rule. First, it should be sturdy against changes in illumination. Second, it ought to avoid police work non-stationary background objects like moving leaves, rain, snow, and shadows forged by moving objects. Finally, its internal background model ought to react quickly to changes in background like beginning and stopping of vehicles. Our analysis began with a comparison of varied background subtraction algorithms for police work moving vehicles and pedestrians in urban traffic video sequences (Cheung and Kamath 2004). we have a tendency to thought-about approaches variable from straightforward techniques like frame differencing and reconciling median filtering, to a lot of refined probabilistic modeling techniques. whereas sophisticated techniques typically turn out superior performance, our experiments show that straightforward techniques like reconciling median filtering will turn out sensible results with abundant lower process complexness. usually associate image's regions of interest area unit objects (humans, cars, text etc.) in its foreground. once the stage of image preprocessing (which could embody image denoising, post process like morphology etc.) object localisation is needed which can create use of this method. Background subtraction may be a wide used approach for police work moving objects in videos from static cameras. The principle within the approach is that of police work the moving objects from the distinction between the present frame and a system, typically known as "background image", or "background model". Background subtraction is generally done if the image in question may be a a part of a video stream. Background subtraction provides necessary cues for varied applications in pc vision, as an example police investigation chase or human poses estimation. However, background subtraction is usually supported a static background hypothesis that is usually not applicable in real environments. With indoor scenes, reflections or animated pictures on screens result in background changes. in an exceedingly same manner, thanks to wind, rain or illumination changes brought by weather, static backgrounds strategies have difficulties with outside scenes **Fuzzy Membership Based Local Histogram Features.** In Our Project, color bar chart is viewed as a color distribution from the chance viewpoint. Given a color house containing color bins, the colour bar chart of image containing pixels is delineated as , wherever is that the chance of a constituent within the image happiness to the th color bin, and is that the total range of pixels within the th color bin. per the full applied mathematics, is outlined as follows:

$$\mathbf{h_i}=\sum_{j=1}^{N} \mu ij Pj = \frac{1}{N}\sum_{j=1}^{N} \mu ij$$

Where Pj is that the chance of a pel hand-picked from image I being the jth pixel, that is 1/N , and Pi/j is that the chance of the chose nth pixel happiness to the ith color bin. With in the context of CCH, is outlined as

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$$\mathbf{P_{i|j}} = \begin{cases} 1, if\ the\ jth\ pixel\ is\ quantized\ into\ the\ jth\ color\ bin \\ 0, otherwise \end{cases}$$

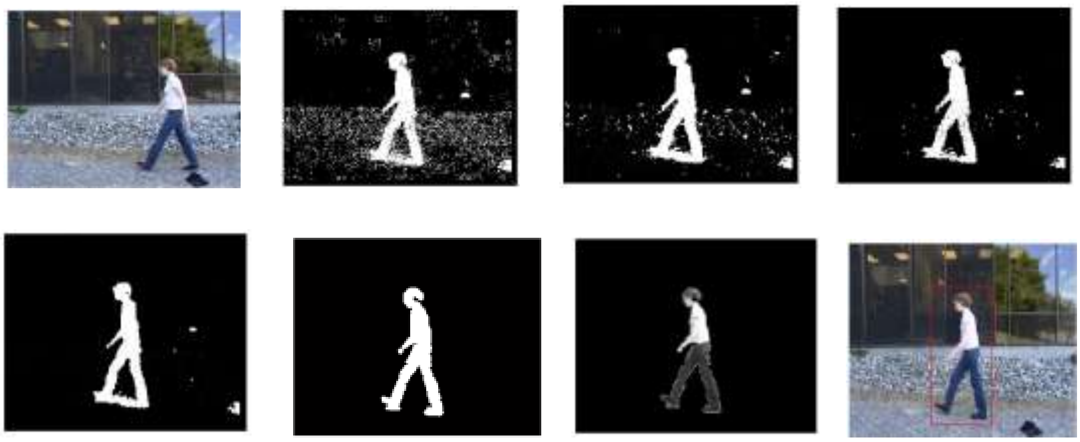
This definition ends up in the boundary issue of CCH such the bar chart might bear abrupt changes albeit color variations are literally little. This reveals the explanation why the CCH is sensitive to hissing interference like illumination changes and division errors. The projected FCH primarily modifies chance Pi|j as follows. rather than victimisation the chance Pi|j, we tend to think about every of the N components in image I being associated with all the colour bins via fuzzy-set membership operate such the degree of "belongingness" or "association" of the th component to the ith color bin is decided by distributing the membership worth of the jth pixel, µij to the ith color bin.

1.1 Definition (Fuzzy Color Histogram)

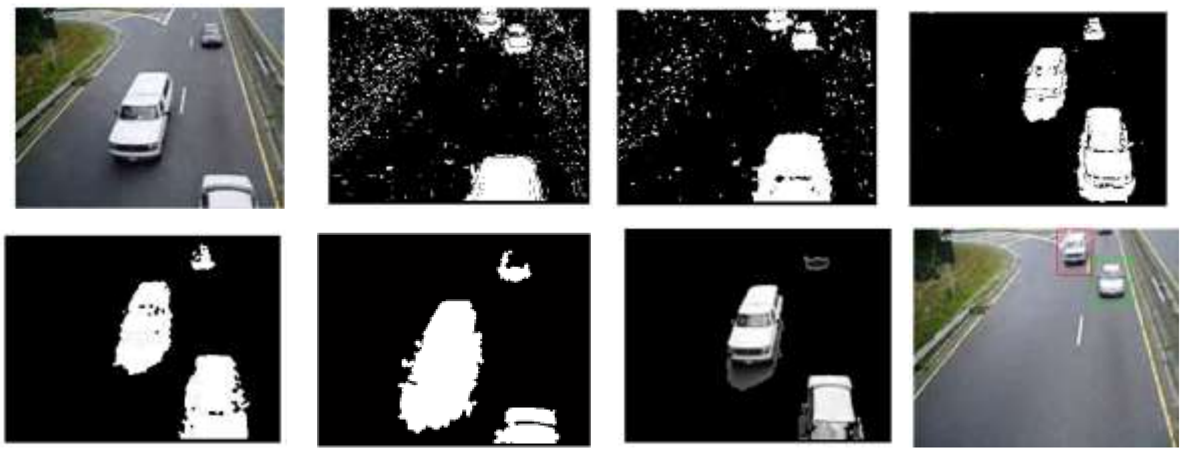
The fuzzy color bar chart (FCH) of image I may be expressed asF(I)=[f1,f2, f3,...... fn], where

$$f_i=\sum_{j=1}^{N} \mu ijPj = \frac{1}{N}\sum_{j=1}^{N} \mu ij$$

has been outlined in (1), and is that the membership worth of fifteenth element within the th color bin. In distinction with CCH, our FCH considers not solely the similarity totally different|of various} colours from different bins however conjointly the unsimilarity of these colours assigned to constant bin. Therefore, FCH effectively alleviates the sensitivity to the clamant interference.



Fuzzy Membership primarily based native bar chart options the thought of mistreatment FCH in a very native manner to get the reliable background model in dynamic texture scenes is impelled by the observation that background motions don't build severe alterations of the scene structure despite the fact that they're cosmopolitan or occur suddenly within the spatiotemporal domain, and color variations yielded by such unsuitable motions will so be with efficiency attenuated by considering native statistics outlined in a very fuzzy manner, i.e., relating to the result of every component price to all or any the colour attributes instead of only 1 matched change the native region (see Fig. 1). Therefore, it's thought that fuzzy membership primarily based native histograms pave the way for sturdy background subtraction in dynamic texture scenes. during this section, we tend to summarize the FCH model [12] and analyze the properties associated with background subtraction in dynamic texture scenes.



II. BACKGROUND SUBTRACTION WITH LOCAL FCH FEATURES

In this subdivision, we tend to describe the procedure of background subtraction supported our native FCH options. To classify a given picture element into either background or moving objects within the current frame, we tend to initial compare the ascertained FCH vector with the model FCH vector revived by the web update as expressed in (6):

$$\mathbf{Bj(k)} = \begin{cases} \mathbf{1,\ if\ S(Fj(k), F\hat{}j(k))} \\ \mathbf{0,\ otherwise} \end{cases} > \tau$$

Where Bj(k)=1 denotes that the th element within the th video frame is set because the background whereas the corresponding element belongs to moving objects if.B(j,k)= 0. τ may be a thresholding price starting from zero to one. The similarity live employed in (6), that adopts normalized bar graph intersection for easy computation, is outlined as follows:

$$s(Fj(K), F^{\wedge}j(K)) = \frac{\sum_{i=1}^{c} \min[fk, f^{\wedge}k]}{\max[\sum_{i=1}^{c} fk, \sum_{i=1}^{c} f^{\wedge}k]}$$

Where denotes the background model of the th constituent position within the th video frame, outlined in (8). Note that the other metric (e.g., trigonometric function similarity, Chi-square, etc.) may be used for this similarity live while not important performance drop. so as to take care of the reliable background model in dynamic texture scenes, we want to update it at every constituent position in an internet manner as follows:

$$F^{\wedge}_j(k) = (1-\alpha).F^{\wedge}_j(k-1) + \alpha . F_j(k) , k \geq 1$$

Where $F^{\wedge}_j(0) = F_j(0)$. α $\mathcal{E}[0 ,1]$ is the learning rate. Note that the larger denotes that native FCH options presently discovered powerfully have an effect on to make the background model. By doing this, the background model is adaptively updated. For the sake of completeness, the most steps of the planned technique square measure summarized in formula one.

III. ALGORITHM 1: BACKGROUND SUBTRACTION USING LOCAL FCH FEATURES

Step-1: Construct a membership matrix exploitation fuzzy c-means clustring supported (3) and (4) (conducted offline solely once).

Step-2: Quantize RGB colours of every constituent at the kth video frame into one in every of m bar chart bins(e.g., rth bin wherever r = one,2,.....m).

Step-3: notice the membership worth uir at every constituent position (i=1,2,...c).

Step-4: work out native FCH options exploitation (5) at every constituent position of the kth video frame.

Step-5: Classify every constituent into background or not supported (6).

Step-6: Update the background model using(8).

Step-7: return to step a pair of till the input is terminated (k=k+1).

IV. CONCLUSION

In this paper, we introduce a novel descriptor on representing Background subtraction for dynamic texture using fuzzy c -means clustering algorithm, called fuzzy colour histogram (FCH).Based on extensive experimental results, our FCH is less sensitive and more robust than CCH (Conventional colour histogram) on dealing with illumination changes such as lighting intensity changes, region-of-interest background subtraction, and possibly other uncovered aspects in new applications. 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

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BIOGRAPHICAL NOTES

Mr. M. Venkata Ravi Teja is presently pursuing M. Tech. final year in Electronics and Communication Engineering Department (Specialization in Digital Electronics Communication Systems) from A.I.T.S Rajampet, Andhra Pradesh, India.

Mr. K. Riyazuddin is working as a Assistant Professor in Electronics and Communication Engineering Department, A.I.T.S Rajampet, Andhra Pradesh, India.