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# **Object -Based Forgery Detection in Video by Motion Estimation Algorithm**

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**ABSTRACT**: In the current times the extent of video forgery has inflated on the online with the increase in the role of malware that has created it achievable for any user to transfer, transfer and share objects on-line in conjunction with audio, images and video. With the wide availability of powerful media editing tools, it becomes much easier to manipulate or even tamper digital media without leaving any perceptible traces. This leads to an increasing concern about the trustworthiness of digital media contents and there is a pressing need to develop effective forensic techniques to verify the authenticity, originality, and integrity of media contents. Digital media production and writing technologies have junction rectifier to widespread forgeries and unauthorized sharing of digital video. Gaussian Mixture Model (GMM) is a well-known algorithm that is robust against repetitive motions, illumination changes and long-term scene changes. Adaptive Noise Cancellation (ANC) is another algorithm that has significant robustness against shadow, noise, lighting changes, etc. In this paper, a background is made for each frame by GMM method that is used instead of previous frame in ANC algorithm. This background is much similar to the real background than previous frame is used by ANC. Simulation results show that proposed algorithm detects motions much efficiently than other algorithms This paper presents a method to find forgery by motion estimation algorithm

**KEYWORDS: Forgery**, motion detection, background subtraction, adaptive noise cancellation, gaussian mixture model

### I. INTRODUCTION

Motion detection from video sequences is a main task in computer vision applications that is used for video surveillance, human detection, vehicle detection, traffic monitoring, gesture recognition and tracking. Motion detection algorithms maybe categorized in two distinct groups. First group's algorithms use visual features of objects such as colour, shape, texture, etc. Other algorithms are based on motion features that background subtraction and optical flow are two prevalent approaches to motion detection using motion features. In background subtraction, algorithms model a background with using statistical methods and subtract current frame from background to detect the motions. Background modelling is the main part of algorithms that use background subtraction.

The accurate modelling of background will enable algorithms to detect motions better and will increase the efficiency of algorithm dramatically. Background modellers must be robust against environmental changes such as illumination changes and shadow and also be sensitive enough to detect all objects that move. Algorithms that use background subtraction are categorized into recursive and non-recursive. Non-recursive algorithms use only N previous frames of current frame that have stored in a buffer for modelling background. Non-recursive algorithms use various techniques. Median filtering uses the median of pixels that located at the current pixel of the frames that are in the buffer. Linear predictive filtering applies a linear predictive filter to the pixels in the buffer whereas non parametric model uses all of the stored frames in the buffer for estimating background but not a single background PCA, brightness and chromaticity are the other non-recursive techniques that are used to background subtraction. On the other hand, algorithms that use recursive technique consider a single background model that updates itself based on each input frame. Therefore, all the frames from the beginning until the current on apply their effect on the single background model.



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### II. ANC-MAP ALGORITHM

In this paper, Adaptive Noise Cancelation is considered as an efficient algorithm for motion detection. Instead of previous frame that is used as reference input of ANC method, GMM method is used to model the background in ANC that increases the accuracy of detecting motions.

Adaptive filter is used for the cancellation of the noise component which is overlap with unrelated signal in the same frequency range. As shown in Fig. 2, there is a primary input that consists of main signal (s[n]) and noise (N<sub>0</sub>(n)) that corrupts the main signal. The reference input (N<sub>1</sub>(n)) tries to model the N<sub>0</sub>(n). In ANC, the reference input is adaptively filtered and subtracted from the primary input to extract the main signal. The output (differences between d[n] and y[n]) is used to adjust the adaptive filter, in order to minimize the energy of the error signal. For minimizing the energy of error signal, there are different methods such as least mean square (LMS) and recursive least square (RMS). In ANC, the LMS is used due to its simplicity and fast convergence. The LMS updates filter coefficient as follow: w (n + 1) = w(n) + \mu.e(n)x(n)

whe31,34,42,re, w is vector of adaptive filter coefficient, x is input of adaptive filter,  $\mu$  is step size and n is iteration number. For using ANC to motion detection purpose, two successive frames are used as ANC inputs. As shown in Fig. 3, normalized gray levels of two successive frames are changed to X and Y vectors and represent primary and references signals. The main signal s (n) will be changed by motions, it is subtracted the reference and primary input and s(n) is obtained as an output signal. ANC algorithm detects inner parts of moving objects as a background due to use of two successive frames. To reconstruct the moving object, ANC algorithm is followed by a Bayesian stage to detect the omitted inner parts of moving objects.

### **III. PROPOSED ALGORITHM**

In spite of using Bayesian, ANC cannot detect foreground and remove background completely. Figs (a), (b) show that ANC detects foreground partially and figs (c),(d) show that ANC cannot remove repetitive motions well. Also figs. (e), (f) show that ANC detects following of moving objects wrongly. All of the errors are appeared internal using successive frames in ANC method's inputs.



(a)

(b)

(c)

(d)



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Fig 1: Different cases of ANC. Figs (a), (b) show that ANC detects foreground partially and figs (c),(d) show that ANC cannot remove repetitive motions well. Also figs. (e), (f) show that ANC detects following of moving objects wrongly.

In this paper, in order to solve these problems a background for each frame is constructed and is used instead of previous frame in the reference input of ANC block. Because of the high ability of GMM method in constructing multimodel backgrounds we used it for constructing it. Stauffer and Grimson proposed modelling each channel of a pixel as a mixture of K Gaussians. GMM maintains a density function for each pixel. Thus, it is capable of handling multimodal background distributions. On the other hand, since GMM is parametric, the model parameters can be adaptively updated without keeping a large buffer of video frames. The pixel distribution F(It = u) is modelled as a mixture of K Gaussians:

 $F (It = u) = \sum_{i=1}^{k} w_i, t. n(u; \mu_i, t, \sigma_i, t)$ 

where  $(u; \mu i, t, \sigma i, t)$  is the i-th Gaussian component with intensity mean  $\mu i, t$  and standard deviation w<sub>i,t</sub>.  $\sigma i, t$  is the portion of the data accounted for by the i-th component.



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Fig 2. Proposed Algorithm

The value of K ranges from three to five, depending on the available storage. For each input pixel It, the first step is to identify the component i whose mean is closest to I<sub>t</sub>. Component i is declared as the matched component if  $|I_{t-\mu,t-1}| < D.\sigma_{i,t}$ , where D defines a small positive deviation threshold. The parameters of the matched component are then updated as follows:

$$\mathbf{W}_{i,t} = (1 - \alpha)\mathbf{w}_{0,t-1} + \alpha$$

$$\mu_{i,t} = (1-\rho) \mu_{i,t+\rho} I_t$$

where  $\alpha$  is a user-defined learning rate with  $0 < 1 < \alpha$ .  $\rho$  is the learning rate for the parameters If no matched component can be found, the component with the least weight is replaced by a new component with mean It, a large initial variance  $\sigma 0$  and a small weight w0.Finally, all the weights are renormalized to sum up to one. To determine whether It is a foreground pixel, we first rank all components by their values of w(i,t)/ $\sigma$ (i,t). Higher-rank components thus have low variances and high probabilities, which are typical characteristics of background. If  $i_1, i_2, \dots, i_k$  is the component order after sorting, the first M components that satisfy the following criterion are declared to be the background components:

 $\sum_{k=i1}^{im} wk$ ,  $t \ge \tau$ 

Where  $\tau$  is the weight threshold. It is declared as a foreground pixel if it is within D times the standard deviation from the mean of any one of the background components. Note that the above formulation can be easily extended to handle color data. The computational complexity and storage requirement of GMM is linear in terms of the number of



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components K In this paper, by using GMM method for each frame the background is constructed. This background contained many changes that related to the real background. The normalized gray level of constructed background is placed in column vector Y. This vector is used as reference input of ANC block. Also the normalized gray level of original frame is placed in column vector X and used as main input of ANC block. There is great similarity between constructed background and the real background for frame t. On the other hand, ANC algorithm omitted every correlation between its inputs. So the proposed algorithm can efficiently eliminate the background and shows moving objects' changes in its output. By a simple thresholding on the absolute error and reshaping the vector, the output signal can be realized as an image including only moving objects.

#### **IV. COMPARISON**

Detection results of proposed algorithm compared with other algorithms.



Fig 3.Comparison of different algorithms

### **V. SIMULATION RESULTS**

In order to validate the proposed algorithm, it has been tested on a variety of indoor and outdoor environments such long-term changes, repetitive motions, shadows etc. An assessment on the performance of the existing methods on mention scenes is shown in Fig. We compare the improved algorithm with the original algorithm and the GMM method with fixed number of components M = 5.In all experiments, the parameters are set as follows: the step size is chosen as  $10\Box 6$ , filter length is equal to 8, the learning rate is chosen as  $10\Box 3$  and the parameter B is set to0.5ts. it is a fixed threshold which is selected experimentally and has a value between 0 and 1.Regarding each motion detection challenges, some video shave been selected to evaluate algorithms. In Fig., tennis sequence is an example of indoor test with existence of shadow



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Fig 4: Stimulation results of proposed algorithm, ANC & GMM

### VI. CONCLUSION

In this paper, we have proposed the improved ANC motion detection algorithm for forgery detection in video surveillance applications. The experiments showed that the algorithm can successfully segment the foreground objects even if their motions is very slow during the time, and it can remove the background impressively even in the existence of repetitive motions and lighting changes. In spite of effective improvement in the segmentation, the processing time doesn't change much.

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