International Journal of Scientific Research in Computer Science, Engineering and Information Technology
© 2017 IJSRCSEIT | Volume 2 | Issue 2 | ISSN : 2456-3307

Optimizing and Background Learning in a Single Process of Moving Object Detection

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ABSTRACT

Video surveillance systems have long been in use to monitor security sensitive areas. The making of video surveillance systems "smart" requires fast, reliable and robust algorithms for moving object detection, classification, tracking and activity analysis. Moving object detection is the basic step for further analysis of video. It handles segmentation of moving objects from stationary background objects. Object classification step categorizes detected objects into preened classes such as human, vehicle, animal, clutter, etc. It is necessary to distinguish objects from each other in order to track and analyse their actions reliably. In previous system performed background subtraction by using Canny Edge Detection. In Canny Edge Detection process we are taking two images for comparison those are background image and foreground image.

Keywords : Object Detection, GDSM, DP-GMM

I. INTRODUCTION

Background subtraction can be defined as a binary segmentation of a video stream, into the foreground, which is unique to a particular moment in time, and the background, which is always present [1]. It is typically used as an interest detector for higher level problems, such as automated surveillance, action recognition, intelligent environnements and motion analysis. Dynamic background, where objects such as trees blow in the wind, escalators move and traffic lights change colour. [2],[3]. These objects, whilst moving, still belong to the background as they are of no interest to further analysis. Noise, as caused by the image capturing process. It can vary over the image due to photon noise and varying brightness. In some cases, such as low light/thermal, it can dominate. Camouflage, where a foreground object looks very much like the background, e.g., a sniper in a ghillie suit. [3],[4].

Camera shake often exists, a symptom of mount points that are subject to wind or vibrations. This can be considered to be a type of highly correlated global noise.[1] we propose to use a Dirichlet process Gaussian mixture model (DP-GMM) to provide a per-pixel density estimate (DE)[6]. This is a non-parametric Bayesian method that automatically estimates the number of mixture components required to model the pixels background colour distribution, e.g., a tree waving backwards and forward in front of the sky will generate single mode pixels at the trunk and in the sky, but two mode pixels in the area where the branches wave, such that the pixels transition between leaf and sky regularly

II. METHODS AND MATERIAL

RELATED WORK

The methods of moving object detection can be divided into four categories detecting followed by tracking,subtracting [1] frames modeling background by density function modeling background by subspace and modeling background by low-rank matrix . The last two categories dominate the state-of-the-art methods and are closely relatedto our work. Note that moving object detection methods and batch methods. methods can also be divided into incremental Our method belongs to incremental one.[7]

Subtracting frames This kind of methods detects moving objects based on the differences between adjacent frames But these methods were proved not robust against illumination variations, changing background, camera motion,[8][9]and noise.

Modeling background by density function This strategy assumes that the background is stationary and can be modeled by Gaussian, Mixture of Gaussians, or Dirichlet Process MixtureModels[5] . The foreground (moving regions) can then be obtained by subtracting the current frame with the background model.

Modeling background by subspace Instead of using a density function, subspace based methods model the background as a linear combination of the bases of a subspace Because the subspace can be updated in an incremental (online) manner, its efficiency is much higher. [6],[3]. This kind of subspace based algorithms needs to impose constraints on the foreground in order to obtain valid solutions. Foreground sparsity is one of the widely used constraints which implies that the area of moving objects is small relative to the background. Principal Component Pursuit (PCP)[5]. is a classical subspace method for background modeling. Because of its close relationship to our method, we briefly describe it. Mathematically, let O Rn×m be the observation matrix containing m frames. Each column of O corresponds to a vectorized frame that has n pixels. Generally, O can be decomposed as O = B + F where B Rn×m is the low rank matrix (background) and F Rn×m is the sparse matrix (foreground). The PCP method can be formulated as the following minimization problem:

min kBk + _ kFk1 , s.t. B + F = O, (1)

where the nuclear norm kBk is used to estimate the rank of B and the l1 norm of F is used to measure the sparsity of the foreground F. The constraint B + F = O makes that the minimization of rank of the background and the sparsity of[10],[11],[12].the foreground is meaningful in the sense of the sum of the background and the foreground approaches to the observation. Without this constraint, traditional robust subspace methods can only deal with noise and outliers . The method improves PCP by taking the foreground connectivity(i.e., foreground structure) into account. RFDSA takes smoothness and arbitrariness constraints into account. But PCP, RFDSA , and the method are batch algorithms. Its detection speed cannot arrive at real-time level. Therefore, incremental (online) subspace methods are crucial for real-time detection . He et al proposed an online subspace tracking algorithm called GRASTA (Grassmannian Robust Adaptive Subspace Tracking Algorithm). Similar toPCP, GRASTA also explores norm for imposing sparsity on foreground. But the GRASTA algorithm does not utilize any connectivity (a.k.a., smoothness) property of foreground. The GOSUS (Grassmannian Online Subspace Updates with Structured-sparsity) algorithm imposes a connectivity constraint on the objective function by grouping the pixels with a superpixel method and encouraging sparsity of the groups. Because of the large computational cost of the superpixel algorithm , GOSUS is not as efficient as GRASTA.[10]

Modeling background by low-rank matrix Low rank modeling is effective in video representation. [7]A sequence of vectorized images is represented as a matrix and the matrix is approximated by the sum of matrices of vectorized foreground, background, and noise . It is rational to assume that the background matrix is low-rank. DECOLOR (Detecting Contiguous Outliers in the LOw-rank Representation) is considered as one of the most successful low-rank based algorithms. In DECOLOR, both foreground sparsity and contiguity (connectivity) are taken into account. It can be interpreted as a penalty regularized RPCA. But the matrix computation can be started only if all of the predefined number of successive images are available. Obviously, such a batch method is not suitable for real-time video analysis due to its low efficiency. ISC blue('I', 'S', and 'C' standing for "Incremental", "Sparsity", and "Connectivity", respectively) and COROLA are incremental versions of DECOLOR ISC and COROLA transforms low-rank method to subspace.

PROPOSED METHOD

In proposed system presenting a Moving Object Detection by Detecting Contiguous Outliers in the generic algorithm which is used for efficient object detection. In proposed system using GDSM Technique taking video as input The proposed method is based on a multi-scale local contrast and global rarity quantification to compute bottom-up saliency maps. The algorithm only uses motion features (direction and speed) but can be easily generalized to other dynamic or static features. Video surveillance, social signal processing and, in general, higher level scene understanding can benefit from this method. [11]GDSM minimizes a low rank image comparison techniques and detection process is done with interrupted action. In proposed system totally discard the false alarm and missed alarm. The effect of the embodiment of attentive visual selection in a pan-tilt camera system. The constrained physical system is unable to follow the important fluctuations characterizing the maxima of a saliency map. In Proposed system extends to detect human-like motion patterns instead of appearance patterns, making the detection more robust to difference in appearance due to environment. The proposed method recovers both pose, orientation and position in the image but is computationally heavier.[13],[14].

Basic Low Ranking Approximation:

$$\text{minimize} \quad \text{over } \widehat{D} \quad \|D - \widehat{D}\|_F \quad \text{subject to} \quad \text{rank}\big(\widehat{D}\big) \leq r$$

Has analytic solution in terms of the singular value decompositionof the data matrix. The result is referred to as the matrix approximation lemma or Eckart–Young–Mirsky theorem. [11],[15].Let

$$D = U\Sigma V^\top \in \mathbb{R}^{m\times n}, \quad m \leq n$$

be the singular value decomposition of D and partition U, $\Sigma =: \operatorname{diag}(\sigma_1, \ldots, \sigma_m)$, and V as follows:

$$U =: \begin{bmatrix} U_1 & U_2 \end{bmatrix}, \quad \Sigma =: \begin{bmatrix} \Sigma_1 & 0 \\ 0 & \Sigma_2 \end{bmatrix}, \quad \text{and} \quad V =: \begin{bmatrix} V_1 & V_2 \end{bmatrix},$$

where Σ_1 is $r \times r$, U_1 is $m \times r$, and V_1 is $n \times r$. Then the rank-r matrix, obtained from the truncated singular value decomposition

$\widehat{D}^* = U_1\Sigma_1 V_1^\top$, is such that

$$\|D - \widehat{D}^*\|_F = \min_{\text{rank}(\widehat{D})\leq r} \|D - \widehat{D}\|_F = \sqrt{\sigma_{r+1}^2 + \cdots + \sigma_m^2}.$$

The minimizer $\widehat{D}^*$ is unique if and only if $\sigma_{r+1} \neq \sigma_r$.

The Frobenius norm weights uniformly all elements of the approximation error $D - \widehat{D}$. Prior knowledge about distribution of the errors can be taken into account by considering the weighted low-rank approximation problem

$$\text{minimize} \quad \text{over } \widehat{D} \quad \text{vec}^\top\big(D - \widehat{D}\big) W \,\text{vec}\big(D - \widehat{D}\big) \quad \text{subject to} \quad \text{rank}\big(\widehat{D}\big) \leq r,$$

where $vec(A)$ victories the matrix A column wise and W is a given positive (semi)definite weight matrix. The general weighted low-rank approximation problem does not admit an analytic solution in terms of the singular value decomposition and is solved by local optimization methods[6],[9],[14].

The proposed method is based on a multi-scale local contrast and global rarity quantification to compute bottom-up saliency maps. The algorithm only uses motion features (direction and speed) but can be easily generalized to other dynamic or static features. Video surveillance, social signal processing and, in general, higher level scene understanding can benefit from this method.

Secondly, we investigate the effect of the embodiment of attentive visual selection in a pan-tilt camera system. The constrained physical system is unable to follow the important fluctuations characterizing the maxima of a saliency map. The proposed method recovers both pose, orientation and position in the image but is computationally heavier.

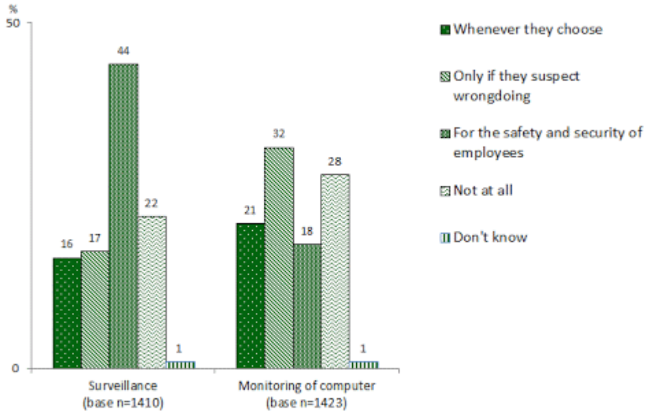
Algorithm: Genetic Dynamic Saliency Map

S = **IMG**(I)
1: A= fg
2: for each color channel map f_k(I) : k = 1; 2; 3g in Lab space
3: for _ = 0 : _ : 255
4: B = **THRESH**(_k(I); _)
5: e B = **INVERT**(A)
6: add **OPENING**(A; !o) and **OPENING**(e B; !o) to B
7: for each Bk 2 B
8: Ak = **ZEROS**(Bk:size())
9: set Ak(i; j) = 1 if Bk(i; j) belongs to a surrounded region
10: Ak = **COMPARE**(Ak; !d1)
11: Ak = **NORMALIZE**(A)
12: A_ = 1n Pn k=1 Ak
13: S = **INTERRUPT**(A_)
14: return s;

The algorithm only uses motion features (direction and speed) but can be easily generalized to other dynamic or static features.

III. RESULTS AND DISCUSSION

The GDSM (Genetic Dynamic Saliency Map) algorithm technique used in this system has the selection of relevant motion from multi-object movement. This method based on a multi-scale local contrast and global rarity quantification to compute bottom-up saliency maps. The algorithm only uses motion features (direction and speed) but can be easily generalized to other dynamic or static features. Video surveillance, social signal processing and, in general, higher level scene understanding can benefit from this method.



IV.CONCLUSION

In this paper, we propose a novel framework named GDSM to segment moving objects from image sequences into frames. It avoids complicated motion computation by formulating the problem as outlier detection and makes use of the low-rank modelling to deal with complex background. We established the link between Foreground and background images with mapping pixels values. Compared with server, Dynamic pixels changes in motion detection process. Which is greedier to detect outlier regions that are relatively dense and contiguous. Despite its satisfactory performance in our experiments, GDSM also has some disadvantages. Since GDSM minimizes a low rank image comparison techniques and detection process is done with interrupted action.

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