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THRONG PERSPECTIVENESS TO FERRETOUT BUZZYWORTHY INCIDENCE IN FLOCK AMBIENCE

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***Abstract*: The continual development of technology in digital era has huge impact in human life. Thus deal of surveillance system is significant. While this work focused the detection of anomalous events in crowded atmosphere through video (i.e. both motion and motionless) information. This is effectively approached by the concept based on swarm theory. A movement concept mainly works on detection theory namely Histogram of oriented swarms (HOS) and Histogram of oriented gradients (HOG). HOS and HOG are together combined to form pattern theories which recognize each frame. Thus HOS and HOG are preferably used to capture the outlook of human body and objects (eg:car) in accordance to variable posture. These visible and movable factors with relative time and space of moving pixels are extracted including noise, dispersion, velocity and accuracy. Thus also achieving low computation cost. Thus resultant experiments determine the high accuracy and pixel level detection comparing to high level technique.**

I. INTRODUCTION

In the upcoming world the surveillance system plays a vital role in terms of safety. It is clear that anomalies should be detected automatically once it occurs. Even though the technology is getting revamped, it is a hard nut to crack even for the trained professionals to monitor the unusual events which is taking place in the video. To handle this situation a various techniques is proposed. Analyzing the motion and behavioral characteristics is quite complicated in the traditional methods, for this purpose the state of art technique is used. Furthermore, the anomaly may vary significantly based on the various aspects. The anomaly might be an interesting event or an unusual incident, that is in one video sequence it may be an anomaly pattern and in either case it might be a normal pattern of another video. The spatiotemporal changes have emerged in appearance and motion features. For instance if the car passes through the crowded environment it is detected as an anomaly pattern of appearance and the anomaly based on motion includes the changes in the density and the magnitude of an individual which is abnormal. To look up these challenging tasks, the two descriptor has been introduced which is HOG and HOS. In case of HOG (histogram of orientated gradients) is used to ferret out the appearance based anomaly and HOS (histogram of orientated swarm) used in order to capture the movements which seems to be not as usual with a low noise. Previously PSO (particle swarm optimization) and SFM (social force model) has been used based on swarm intelligence. To detect the anomaly which is appeared in the frame the region of interest and the temporal information alone is considered. Using the values of optical flow the prey is generated and agents determine the location and motion of the swarm. Applying our proposed technique RANSAC (random sample consensus) we achieve apparent video scenes with

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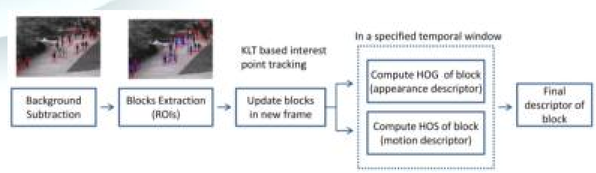
more accuracy than the state of art and pixel level event- detection method.

II. STATE OF THE ART

Using the traditional methods, the huge crowd cannot be detected so a various approaches have made to aide this situation. This work is effective only in the low density crowd. Using tracking methods further the computational cost is increased simultaneously. The normal behavioral characteristics of human is determined using SFM and two main function is being performed that is only motion information is considered if the abnormalities is noticed. Whereas in cases, the both motion and appearance characteristics is considered. This method focuses on detecting the motion information. It ferrets out the anomaly in huge crowded scenes but fails to consider the small frames in the video, which is not easily noticeable. The min cut/max flow algorithm is applied to capture the direction and the motion of each individual. In this method the appearance information is ignored completely. Initially the anomaly is detected only nearby distances then low level features with preset threshold values is used to deliver an alert message and also based on the optical flow textures the anomaly is detected. Using the joint modeling the normal and abnormal pattern is calculated. Christo Ananth et al. [1] discussed about Improved Particle Swarm Optimization. The fuzzy filter based on particle swarm optimization is used to remove the high density image impulse noise, which occur during the transmission, data acquisition and processing. The proposed system has a fuzzy filter which has the parallel fuzzy inference mechanism, fuzzy mean process, and a fuzzy composition process. In particular, by using no-reference Q metric, the particle swarm optimization learning is sufficient to optimize the parameter necessitated by the particle swarm optimization based fuzzy filter, therefore the proposed fuzzy filter can cope with particle situation where the assumption of existence of "ground-truth" reference does not hold. The merging of the particle swarm optimization with the fuzzy filter helps to build an auto tuning mechanism for the fuzzy filter without any prior knowledge regarding the noise and the true image. Thus the reference measures are not need for removing the noise and in restoring the image. The final output image (Restored image) confirm that the fuzzy filter based on particle swarm optimization attain the excellent quality of restored images in term of peak signal-to-noise ratio, mean absolute error and mean square error even when the noise rate is above 0.5 and without having any reference measures.The UCSD dataset is used to provide more accuracy and for effective results. The interaction forces are calculated both internally and externally.

III. OVERALL ARCHITECTURE OF THIS PAPER

This paper focuses on detecting dynamically varying abnormalities in videos with throngs of fluctuating densities. To characterize each scene effectively at low computational cost, better accuracy, less fabricated agitations and effective spatiotemporal localization of irregularities, we incorporate both motion and appearance features by using RANSAC algorithm. Random sample consensus (RANSAC) is an iterative method to estimate parameters of a mathematical model from a set of observed data which contains outliers. Depending on the camera perspective for each dataset, the scope of the region of interest (ROI) is determined by applying background subtraction using weighted moving mean [28]. Background subtraction attempts to identify moving articles from the difference between the current frame and the reference frame in a pixel-by-pixel approach. For a given data



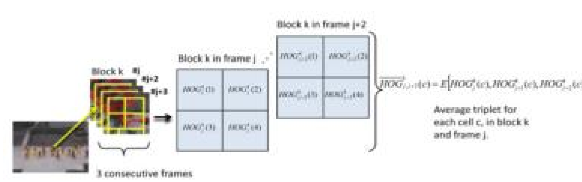


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Fig.1.Problem formulation. (a) Overview of final motion-appearance descriptor calculation. (b) Extraction of appearance descriptor (HOG). Each block is divided into 4 cells and HOG histograms are calculated for each of them. The block is tracked over time and the final HOG descriptor results from the average of consecutive triplets after a normalization step. The HOGk j (c) symbol represents the HOG histogram, calculated from the cth cell of block k, at frame j.

set, a ROI of 20x20 pixels is more than enough to capture the information, too large information can cause noise in the descriptor. Once ROIs are extracted, the interest points in them are tracked until the next frames using the KLT tracker, while the foreground grid is continuously updated, with new interest points defined in each new frame's foreground area. The resulting ROIs are considered as informative only if it contains at least 60% moving pixels otherwise the ROI is considered as a noise and are ignored. Fig.1 (a) illustrates an outline method for extracting the descriptor. The stages for appearance and motion descriptors are discussed in more detail in the outcome.

A. APPEARANCE DESCRIPTORS

The Histogram of Oriented Gradients (HOG) proposed in [7], used to extract the appearance characteristics of a video sequence. It uses grey scale images, since it is invariant to color, illumination and local geometric transformations which results in standardization. Simultaneously, it can differentiate deviations even in small parts of the image. In some cases, Gaussian windowing technique is used over the block during voting in order to reduce aliasing, spatial and angular linear interpolation. Votes are gathered over the pixels of each cell. The procedure for this computation is given as follows: each block (k) from the input video sequence is divided into 2 2 cells, as it was described by Dalal et al. [29] in order to provide strong radiance invariance on each block. The HOG in block (k) of frame (j) contains c^{th}cell is $(1 < c < 4)$and it is represented by $HOG_j^k(c)$, of dimension1 9. Each histogram is standardized and the 4 resulting cell histograms are concatenated, forming a 1 36 block descriptor, which is also normalized for noise elimination. Once HOGs for each block are calculated, they are averaged over 3 consecutive frames so as to include comfortable progressive information and at the same time achieve temporally local noise reduction. The final appearance descriptor is thus a concatenation of a 3 frame average for each cell c in block k:

$$\overline{HOG}_{j,j+2}^{k}=\mathrm{E}\left[HOG_j^k(c), HOG_{j+1}^k(c), HOG_{j+2}^k(c)\right] \quad (1)$$

This means that a 15 frame time window will result in 5 concatenated triplets of 136 descriptors, resulting in a 1180 final spatiotemporal appearance descriptor. The entire process for extracting HOG descriptor is depicted in Fig.1 (b). For simplicity of notation, in the sequel, the HOG descriptor of Eq. (1) for block k, averaged over frames j to j+2 will be represented as $HOG_{j,j+2}$including the average over all 4 cells.

B. MOTION DESCRIPTORS

Histogram of Oriented Swarm (HOS) is used to arrest the ROIs principal gesture and spot abnormal events in a video sequence. In order to reduce noise and image filtering, we use Swarm based methods in [31]. The motion features are extracted by the attraction and repulsion forces 'to facilitate crowd collection. The main idea is to observe actions in crowded scenes by a swarm of agents "hovering" above them, to arresttheirdynamics in a mutual manner and also taking motion history into account. Swarms are organized and the proxies' locations are taken out from their accelerated motion, derived from the forces acting on the swarm as described in Sec. IV. For human subjects, 3D depth boundaries overlap with member and figure ends, so movement variances are good signs for the outline of an individual. The foremost models of our flock descriptor are presented in the subsequent division.

IV. SWARM MODELLING FOR CROWDS DYNAMICS

The major work of swarm modeling is to filter the noise in images and also to better diagnosis of

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Fig.2. Input for background.

prey which is highly complex. The basic that is used to capture the dynamics of crowd is the physics-based modeling which is the general theory to interconnect the swarm dynamics in nature. The agents are used to track the prey. The agents are used for dual work that is tracking and also to interact with each other. The forces between the agents are discussed below they are interaction force, friction force and inertia force. The swarm modeling is also used to extract the motion features of swarm. Comparing to OF value swarm modeling is to take the crowd behavior accurately under any circumstance.

A. PREY GENERATION

Each prey is observed by scheming the OF magnitude value of the pixels from the ROI. Each region of interest (ROI) is represented by rectangular block. In previous papers luminance value is used for calculating prey position but now OF magnitude value is used for surpassed result. In general, the number of prey is equal to number of ROI in particular frame. For every instance there will be variation in the prey count. Preys are tracked by the agents using their dynamics. The number of pixels in each ROI is represented as n and frames of video sequence as m. each pixels in ROI is represented as i and each frame as j. the prey position is determined by

$$x_p(\mathrm{t}) = O_{ij} \qquad (2)$$

Sequence of pixels are selected to form a prey thus obtain a meaningful information; we know that $1 \le \mathrm{t} \le$ n.m. The final prey position is calculated be

$$[x_p(1),\ldots,x_p(\mathrm{nm})] = [O_{11},\ldots,O_{1m},\ldots,O_{n1},\ldots,O_{nm}] \qquad (3)$$

The trajectory of each prey is exacted by agents to characterize the motion, behavior and accuracy for prey the OF orientation also taken into account. The movement and behavior of prey is extracted over a period of time.

The main work of background subtraction is to filter the foreground objects from the background. For this subtraction we use Contour-based technique where one background model is maintained as a static. This technique consists of two parts i.e. thermal and visible. Here, the input it is converted into Contour saliency graph. From this graph, binary contour is combined into thermal and visible domain to examine the corners of ROI, color and intensity information.

$$tCSM_b = tCSM_b^T \cup tCSM_b^V \qquad (4)$$

A ROI is a procedure of gloss, frequently associated with definite or computable data (e.g., dimensions like mean or volume concentration), conveyed as structural or in text form. In computer revelation and visual character recognition, the ROI explains the margins of an entity under deliberation. In several applications, symbolic (textual) markers are added to a ROI, to designate its content in a close way. Inside a ROI may lie distinct points of interest (POIs).

In KLT, a local area is considered a worthy feature to track when both the eigenvalues of the gradient (∇) medium were larger than a threshold then the problem is formulated as,

$$\nabla d = e \qquad (5)$$

An affine conversion is inserted between the image of the currently traced feature and its image from a non-consecutive previous frame. If the affine compensated image is too dissimilar the feature is dropped. The reasoning is that between consecutive frames a translation is a sufficient model for tracking but due to more complex motion, perspective effects, etc. a more complex model is required when frames are further apart.

$$T_z = \mathrm{a} \qquad (6)$$

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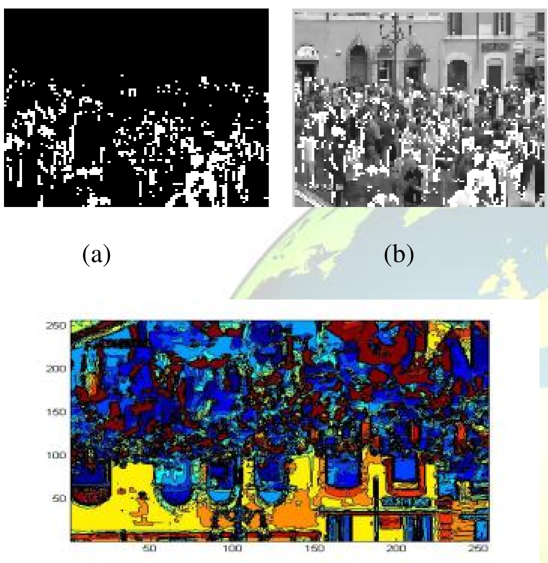
Where T a matrix of gradients is, z is a vector of affine coefficient and a is an error vector. Compare this to Support Vector Data Description is an information portrayal method that can provide the target data set a spherically shaped description and be used to outlier detection or classification. In the real world, the target data set frequentlyholds morethan one class of



(a) (b)

(c)

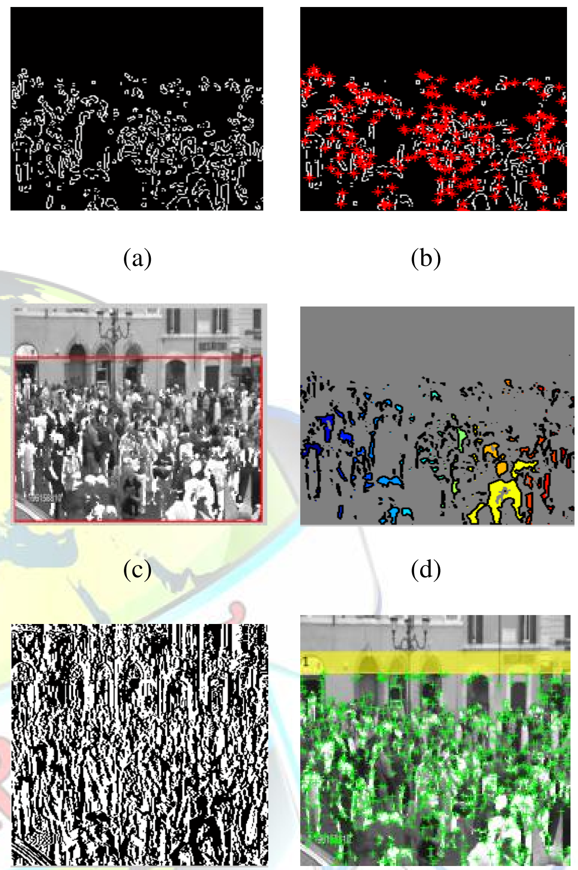
Fig.2. (a) Binary moving object, (b) Moving object (c) Contour of crowd

Substances and each class of substances need to be defined and distinguished instantaneously. In this case, traditional SVDD can give aexplanation for the target data set, regardless of the differences between different targets classes in the target data set. If the target data set contains two classes of objects then the two-class SVDD can provide hyper sphere shaped description

C. ANOMALY DETECTION AND LOCALIZATION

By combining the appearance and motion descriptor, we can able to find the final descriptor for anomaly descriptor. The resulting feature of HOG and HOS are combined and averaged over 3 Consecutive in a time space of m frames which is given in equation (7).

$$\{\overline{HOG}_{1,3}^{k}(c), \overline{HOS}_{1,3}^{k}(c), \dots, \overline{HOG}_{m-2,m}^{k}(c), \overline{HOS}_{m-2,m}^{k}(c)\} \qquad (7)$$



(a) (b)

(c) (d)

(e) (f)

Fig.3. (a) Edge detected image, (b) Corner detected image, (c) Bounding box of detected image, (d) Tracking of whole frame, (e) Vertical gradient and (f) Detected KLT point feature.

Where, $HOG_{m-2,m}$represents the average to a block for frames m-2 to m in appearance modeling and $HOS_{m-2,m}$ represents the average to a block for m-2 to m. Fig.4. shows the entire process takes place in each ROI. A standardization phase takes place to form the absolute descriptor so as to accomplish gauge invariance. Afterwards, Random Sample Consensus (RANSAC) is used to determine each region's normality and also to crack the Location Determination Prob-

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lem (LDP), which canregulate the facts in the cosmos that project onto an image into a set of benchmarks with notoriousssituations. By using this, we can able to evaluate the constraints of a mathematical model from a set of detected records which contains outliers.

Let us consider a dataset whose data comprises of "inliers Assuming that the n points are selected independently for the estimation of model, w^n is the probability that all n points are inliers, 1-w^n is the probability that at least one of the n points is an outlier and k is the probability that the algorithm never selects a set of n points which all are inliers and this must be the same as 1-p. Consequently,

$$1\text{-p} = (1 - w^n)^k \quad (8)$$

By taking logarithm on both sides,

$$K = \frac{\log(1-p)}{\log(1-w^n)} \quad (9)$$

The RANSAC processusuallycalculates the stroke from the selected points and it is then critical that the two points are distinct. To gain additional confidence, the Standard deviation can be added to k and it is given by,

$$SD(k) = \frac{\sqrt{1-w^n}}{w^n} \quad (10)$$

V. EXPERIMENT

In this section we introduced a RANSAC method with the SVDD to increase the accuracy of previous approach. In order to compare the variation we used a new set of data for detecting the anomaly in that crowded atmosphere.

We know that video is a sequence of frames. To simplify the work videos are transformed to frames. To achieve this splitting the video to frames conversion is used.

This is a process of comparing the two frames for eliminating the background leaving the foreground to detect the objects. For this permanent background model for the frames is maintained .It may be static or dynamic. According to our BG subtraction contour-based approach is used. In this technique object detection is done by thermal and visible imagery. The initial region of interest is identified by thermal domain and color and intensity information is examined from visible domain. In this work background subtraction is a basic process before entering into robust detection. In figure 3 a density of motion using contour is revealed.

The ROI is for bounding exact content by using the rectangular box. The ROI is to for a particular purpose determined from selected frames of input i.e. datasets.

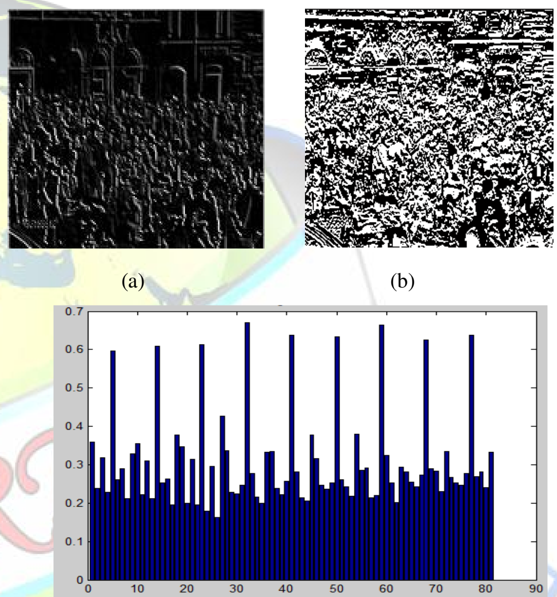

Fig.5. (a) Combined Gradient Image, (b) Horizontal gradient and (c) Histogram of Features

The main work is to show the corner and edge of the prey. A ROI is always associated with measure dimensions like volume or mean intensity.

The kanade-lucas-tomasi (KLT) feature tracker is a simple feature based tracking algorithm in computer vision. The traditional technique for the image registration seems to be costly that is main reason to propose KLT at the same means it is too fast in performance comparing to older in matching the matches. The KLT tracking which eliminates the effect motion prediction in object like features (e.g. Tree motion).When we track the features using KLT those content are segmented and data's are extracted. Classi-

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fying an image is impossible so extraction of important part in image is done in KLT. Observation of gradient is plays a major role. In figure 5(b) calculation of gradient as horizontal wise i.e. row wise is done. In figure 5(c) calculation of gradient in both combined means (row and column) is done.

VI. CONCLUSION

In this paper, we addressed the problem of detecting anomalous events in different situations, recorded from fixed surveillance cameras. Throng intellect is exploited for the removal of strong gesture appearances and organized, with arrival features, form a descriptor which describes each scene effectively. Its significant concert in 4 absolutely various categories of datasets demonstrate the technique's applications and its overview in real life situations. Our procedure can be meritoriously used for stimulating throng videos with several constrictions, local noise and local gauge dissimilarities. The output of both motion and appearance is descripted and the final outcome is obtained with greater accuracy and at less computational price by using RANSAC algorithm which is suitable for a variety of investigation method.

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