A Literature Study on Crowd (People) Counting With the Help of Surveillance Videos

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Abstract: **The categories of crowd counting in video falls in two broad categories: (a) ROI counting which estimates the total number of people in some regions at certain time instance (b) LOI counting which counts people who crosses a detecting line in certain time duration. The LOI counting can be developed using feature tracking techniques where the features are either tracked into trajectories and these trajectories are clustered into object tracks or based on extracting and counting crowd blobs from a temporal slice of the video. And the ROI counting can be developed using two techniques: Detection Based and Feature Based and Pixel Regression Techniques. Detection based methods detect people individually and count them. It utilizes any of the following methods:- Background Differencing, Motion and Appearance joint segmentation, Silhouette or shape matching and Standard object recognition method. Regression approaches extract the features such as foreground pixels and interest points, and vectors are formed with those features and it uses machine learning algorithms to subside the number of pedestrians or people. Some of the common features according to recent survey are edges, wavelet coefficients, and combination of large set of features. Some of the common Regressions are Linear Regression, Neural Networks, Gaussian Process Regression and Discrete Classifiers. This paper aims at presenting a decade survey on people (crowd) counting in surveillance videos.**

Keywords: **ROI counting, LOI counting, Head-detection, Regression, Features.**

I. INTRODUCTION

Current population of the world is approximately 7.7 billion according to recent statistical report. Today all regions in the world are connected with some form of transport systems; cities in all countries are filled with luxury multi-purpose malls, stadiums and so on. Where-ever we go all over the world we are facing one or other problems with the crowd due to increasing population and more modern development in technology. So there is a need for some responsible technology to overcome the problems created by increasing population; like automated systems for finding Tourists flow estimation in-order to provide proper resources to them which in-turn attracts many Tourists who will again increase the countries revenue; for actively managing city services for public comfort; Crowd behavior modeling, disaster prevention and crowd control for public safety; some statistical applications like allocation of resources for public events, usage statistics to public transport systems, finding occupancy limit of a building and crowd behavior can help architects and town-planners to design safer buildings and real-time estimation of people in a shopping mall can provide valuable information for managers.

II. CATEGORIES OF PEOPLE / CROWD COUNTING SYSTEM

Ma, Zheng et al, 2013 and Li, Jingwen, et al, 2011 have categorized the crowd counting in video as two broad categories.

Estimating the number of people using

- Region of interest (ROI counting)

This is a process of estimating the total number of people in some regions at certain time instance.

- Line of interest (LOI counting)

This is the method of counting people who crosses a detecting line in certain time duration.

A. LOI COUNTING:

The LOI counting can be developed using feature tracking techniques:

- ***Feature Tracking Counting:***

Cong, Yang, et al, 2009 highlighted that in this technique the features are either tracked into trajectories and these trajectories are clustered into object tracks or based on extracting and counting crowd blobs from a temporal slice of the video.

B. ALGORITHMS BASED ON FEATURE TRACKING COUNTING:

(a) Based on Feature Trajectories:

Rabaud, Vincent, et al, 2006 have developed a methodology based on a highly parallelized version of the KLT tracker in order to process the video into a set of feature trajectories. These will provide a substrate for motion analysis, their unequal lengths and fragmented nature present difficulties for subsequent processing. This will be addressed by a simple means of spatially and temporally conditioning the trajectories. Then they have integrated it with a learned object descriptor to achieve a segmentation of the constituent motions. This framework will face problems while identifying a more complex model (in appearance and motion) of the objects. Antonini, Gianluca,et al, 2006 have introduced an approach that uses the lustering methods for automatic counting of pedestrians in video sequences. Clustering techniques are applied to the resulting trajectories from tracking system in order to reduce the bias between the number of tracks and the real number of targets. The main hypothesis will be those trajectories belonging to the same human body are more similar than trajectories belonging to different individuals. The assumptions made by this system result in a limitation when the focus is on the tracking problem.

(b) Block-Based/Motion Feature:

Park, Hyun Hee, et al, 2006 have introduced a method that involves robust background subtraction uses a mixture of K Gaussian, the block-based decision method and a processing which analyze various actions that can occur with moving people in real world environments. The accuracy rate is 100% if the number of people is lesser and this rate decreases with the increase in number of people. Chen, Chao-Ho, et al, 2008 have exploited for classifying each block according to its motion vector and are collected to form a passenger object for counting. The inherent problems of camera shaking and variation of illumination in the bus can be rectified. If the passenger flow is so crowded that some person may stay on the stair for longer time will be counted twice.

(c) Using moving direction:

Chen, Thou-Ho, et al, 2006 have framed a bi-directional people counter model based on area and color analyses. The passing people are roughly counted with the area of people projected on an image captured by a zenithal video camera and then the moving direction of the pedestrian can be recognized by tracking each people-pattern with an analysis of its HSI histogram. There are some factors which influence the counting accuracy, such as a crowded situation that the segmented people-pattern is composed of more than five persons, abrupt moving and some intentional actions.

(d) Based on Feature tracking:

Brostow, Gabriel, et al, 2006 have proposed a framework that uses probabilistic clustering of low level image features which is good at finding a first approximation of the number and location of individual entities in crowded video sequences. Footage of animals, insects, and complex pedestrian traffic containing significant occlusions is processed in a one-shot fashion, without the benefit of training data or any notion of an appearance model. This has the effect that the complexity of non-temporally smoothed entity detection is primarily limited by the scene complexity, and less by the number of individuals.

(e) K-means based segmentation for real-time people counting:

Antić, Borislav,et al, 2009 have developed an efficient and reliable approach to automatic people segmentation that uses k-means clustering to enable the segmentation of single persons in the scene; tracking and counting. The Block-wise background subtraction used in this model will be more resilient to shadows.

(f) Fuzzy-based Approach:

Sivabalakrishnan, M.,K. Shanthi, 2015 have discussed that for handling object extraction challenges in dynamic environments, the approach have fused high-level knowledge and low-level features and developed a fuzzy logic inference system for people tracking. This algorithm is not computationally intensive and not robust in a dynamic environment.

(g) Based on Ellipse Detection and Forward/Backward Tracing:

Huang, Chung-Lin, et al, 2011 have introduced a new approach which will extract the foreground object silhouettes as blobs. And then it generates the blob linkage based on the one-to-one or one-to-many correspondence between the blobs in every two consecutive frames. Later it labels the number of objects in each blob by applying the ellipse detection technique. Forward/Backward tracing is done to re-label the number of objects in the occluded blob. Occlusion problem jeopardizes the efficiency when the crowd is high.

(h) Based on blob analysis/tracking:

Lee, Gwang-Gook, et al, 2008 have introduced an approach that involves counting the number of pedestrians using simple blob analysis and their moving directions are obtained from slopes of the blobs. There is a possibility of miss detections occurrence when multiple people passed around the border of the system. Velipasalar, Senem,et al, 2006 have developed an approach that involves two-level hierarchical tracking for counting multiple people by using only one camera. For cases not involving merges or splits, a fast blob tracking method is used and for interactions among people the system uses the mean shift tracking algorithm. This approach results may be erroneous when people wears clothes with similar color to the floor.

(i) Using Multiple Lines:

Barandiaran, Javier, et al, 2008 have performed counting is performed by analyzing an image zone composed by a set of virtual counting lines. The system runs on a commercial PC, does not need a special background and is easily adjustable to different camera height requirements. The approach fails to handle problem of shadows in the scene; children or people carrying things and people moving very slowly.

(j) Background Modeling and Subtraction Based People Counting:

Kumar, Rakesh, et al, 2012 have implemented Sigma-Delta background modeling and subtraction to segment the people from region which provides blobs as a result with connected component. Blobs were used to track and count the entry and exit of people. It also counts two or more people based on blob size and distance between floor and camera. People will be counted if and only if they passed through the three regions (ROI) consecutively. The accuracy rate decreases rapidly if there is a small change in the lighting conditions.

C. ROI Counting:

Cong, Yang, et al, 2009 and Riachi, Shirine, et al, 2014 have highlighted that the ROI counting can be developed using two techniques:

- ***Detection Based Techniques:***

These approaches detect people individually and count them. It utilizes any of the following process Background Differencing, Motion and Appearance joint segmentation, Silhouette or shape matching and Standard object recognition method.

- ***Feature Based and Pixel Regression Techniques:***

These approaches extract the features such as foreground pixels and interest points. And vectors are formed with those features and it uses machine learning algorithms to subside the number of pedestrians or people. Some of the common features according to recent survey are edges, wavelet coefficients, and combination of large set of features. Some of the common Regressions are Linear Regression, Neural Networks, Gaussian Process Regression and Discrete Classifiers.

D. DETECTION BASED TECHNIQUES:

(a) Detection/ Tracking based on head/shoulder regions :

Sidla, Oliver, et al, 2006 have proposed a system that uses motion to compute ROI and prediction of movements, extracts shape information from the video frames to detect individuals, and applies texture features to recognize people. A search strategy will create trajectories and new pedestrian hypotheses and then filters and combines those into accurate counting events. Computation time of the proposed system is high. Li, Min, et al, 2008 have combined a MID (Mosaic Image Difference) based foreground segmentation algorithm and a HOG (Histograms of Oriented Gradients) based head-shoulder detection algorithm to provide an accurate people counts in the observed area. Merad, Djamel, et al, 2010 have implemented a new head detection based on skeleton graph processing which will extract the head of each person crowded with other persons in the same blob. Then, the head pose estimation was estimated by finding the rigid transformation between the reference system of the model head and the reference system of the camera. This method can be made robust only with an integration of the tracking process. Xu, Huazhong, et al, 2010 introduced a counting system which consists of four modules: foreground extraction (an adaptive components number selection strategy for mixture of Gaussians model is used), head-shoulder component detection, tracking (Kalman filter techniques and cost function is used) and trajectory analysis. Mutual occlusion has not been taken cared. Hu, Yaowu, et al, 2011 have initiated a novel body descriptor used for finding people's head which is defined as Body Feature Rectangle (BFR). This method can divide the multiple-people image into individuals whatever people merge with each other or not. The passing people can be counted accurately even under the influence of wearing hats. This method will be imprecise when the number of people is more than six.

(b) Based on fusion of shape and motion information:

Pätzold, Michael, et al, 2010 have presented a direct, counting by detection, method based on fusing spatial information received from an adapted Histogram of Oriented Gradients algorithm (HOG) with temporal information by exploiting distinctive motion characteristics of different human body parts. Processing with high density crowds revealed a limitation: if the person density exceeds a certain threshold and heads occlude each other, the system is not able to detect and thus the person count is underestimated.

(c) Based on detection flow:

Xing, Junliang, et al, 2011 have proposed a counting framework based on detection flow provides a better way to estimate the crowd size with following merits: 1) it can greatly alleviate the common weakness of an object detector including miss detection; 2) it is robust to temporal object occlusions; 3) it is more competent to give specific descriptions of the crowd, e.g. crowd moving directions and target locations. This framework cannot be used with the scene with serious occlusions.

(d) Based on Combination of New Static Detection and Dynamic Detection:

Zhou, Xuan, et al, 2012 have developed an approach which will divide the monitoring area into blocks at first, and then recognize people in each block and combine both the static detection and the dynamic detection. In the static detection part, covariance algorithm is used to avoid factitious adjustment of threshold. Next some interference of non-human objects can be excluded effectively by using the dynamic detection. The algorithm requires fixed indoor environments and it won't compromise with the other environments.

(e) Fast Crowd Segmentation Using Shape Indexing:

Dong, Lan, et al, 2007 have created a framework based on background differencing. This novel example-based algorithm which maps the global shape feature by Fourier descriptors to various configurations of humans directly. They have used locally weighted averaging to interpolate for the best possible candidate configuration. The inherent ambiguity resulting from the lack of depth and layer information in the background difference images is mitigated by the use of dynamic programming that finds the trajectory in state space that best explains the evolution of the projected shapes. This algorithm will work very efficiently only when there is low to moderate number of people in the scene.

E. FEATURE BASED AND PIXEL REGRESSION TECHNIQUES:

(i) FEATURE BASED LEARNING TECHNIQUES:

(a) Based on Multiple Local Features:

Ryan, David, et al, 2009 have introduced an approach uses local features to count the number of people in each foreground blob segment. It can easily be used to estimate crowd density throughout different regions of the scene and be used in a multi-camera environment. This approach reduces the required training data. Due to imperfect foreground segmentation, some blobs are prone to errors such as splitting, fading and noise which reduce overall perfection in counting.

(b) Counting People in Groups:

Fehr, Duc, et al, 2009 have proposed a model in which the first step is foreground–segmentation and then the different blobs get projected onto the head and ground planes. Later projections are used to estimate the number of people in a group. The count estimates is combined with tracking information to get a smooth count estimate. This is not desirable in public places like airports or railway stations it is highly likely that there will be people who remain stationary for extended periods of time.

(c) Based on Group Tracking and Local Features:

Ryan, David, et al, 2010 have implemented an algorithm that uses tracking and local features to count the number of people in each group as represented by a fore-ground blob segment. Tracking is implemented to improve the robustness of the estimate. The system is limited by the simple least-squares linear model which is used for group size estimation.

(d) A robust method for counting people:

Ye, Qing, 2010 have developed a method that has counted the number of people through four modules: image pre-processing module, morphology processing module that uses improved erosion operation and the improved dilation operation to extract target feature, image marking module uses connected component detection algorithm and people counting module. This method should not overcome the problems such as illumination, rapidly changing weather conditions, people head which are covered completely.

(e) Based on Self-learning:

Li, Jingwen, et al, 2011 have introduced a method based on the bag-of-features model and real-time updates the classifier to make it more suitable for the characteristics of the pedestrians in current scene. It can effectively detect the pedestrians especially the slowly moving or static ones. Partial occlusion in crowded scenes and the effect of poor illumination are the main drawbacks.

(f) Based on Amid (Accumulated Mosaic Image Difference) And Pdc (Perspective Distortion Correctness):

Hani, C. Jerlin Sheela, et al, 2014 have proposed a system that estimates the number of people in crowded scenes using amid and pdc for wide-area surveillance. The accumulated mosaic image difference (amid) method is applied to extract crowd areas having irregular motion. The specific number of persons and velocity of a crowd can be adequately estimated by the algorithm from the density of crowded areas.

(g) Texture Analysis Based on Gabor Filter:

Qing WEN, Chengcheng JIA, et al, 2011 have developed a method for estimating the number of people using a mathematical relationship between the global texture features of crowded scene and number of people in the scene. A set of well-established 2-D Gabor filters are used to extract the global texture features and LS-SVM method is utilized to learn the mathematical relationship. The computational cost is very high.

(h) Viewpoint Invariant Approach:

Kong, Dan, et al, 2006 have introduced a method method that takes into account feature normalization to deal with perspective projection. The training features include edge orientation and blob size histograms. A density map is used for feature normalization. The relationship between the feature histograms and the number of pedeszz

trians in the crowds is learned from labeled training data. For better results offline training based on neural network is needed.

(i) Statistical method:

Celik, Hasan, et al, 2006 have discussed an effective method is implemented which is based on a reliable foreground object extraction, a perspective correction and a confidence rate that steers a weighted median filter to refine the counts. Smaller persons are likely to account less than adults. Hou, Ya-Li, et al, 2011 have proposed an effective method for estimating the number of people and locate each individual in a low resolution image with complicated scenes. Expectation Maximization (EM)-based method has been developed to locate individuals in a low resolution scene. In this method, a new cluster model is used to represent each person in the scene. This method is not suitable for a low-resolution video for handling a denser crowd and to accurately distinguish human and non-human objects.

(j) Learning-based Method:

Ye, Weizhong, et al, 2007 have introduced a method that adopts separated blobs as the input of the people number estimator. Then, the blobs are selected according to their features after background estimation and calibration by tracking. And then, each selected Blob in the scene is trained to predict the number of persons in the blob. Later, the people number estimator is formed by combining trained sub-estimators according to a predefined rule. This method will count a part of a person as a whole person which is decreasing the efficiency of the system. And it does not handle even a moderate crowd effectively.

(k) Based on Edge detection:

Yu, Shengsheng, et al, 2008 have discussed a method that includes three steps: (i). A new Foreground/Background Edge Model for detecting moving people based on edge detection.(ii). Two effective methods are used for moving people tracking. (iii). Counting process. The algorithm cannot handle the situation when the person wears clothes with similar color to the floor, and when the detected foreground edge is divided into smaller curves.

(l) Complex network-based algorithm:

Yueguo Zhang, Lili Dong, et al, 2013 have introduced an approach that will count moving people by establishing a mapping between the feature of moving interest points and the number of people of a crowd scene. Human motion behavior and high occlusion scenarios are not considered.

(m) Automated People Counting System for a Mass Site:

Hou, Ya-li, et al, 2008 have discussed that several people counting methods based on crowd density are considered to find the relationship between the foreground pixels and the number of people in the huge crowd .The best estimation result is from this method that considers two types of foreground pixels: those that come from relatively stationary crowd, and those that come from moving people. Non-human objects are not properly discarded means Non-human objects will also be counted in case of huge crowd. Error rate is little higher.

(n) Cross Camera People Counting:

Lin, Tsung-Yi, et al, 2011 developed a novel approach which is a cross camera people counting that can adapt itself to a new environment without the need of manual inspection. It composed of a pair of collaborative Gaussian processes (GP). It establishes a cross camera people counting system that can facilitate forensics investigation and security preservation and a principled way to estimate the degree of occlusions. If the degree of occlusions increases the efficiency of the approach may decrease.

(o) Automatic bi-directional people-counting method:

Chen, Chao-Ho, et al, 2012 have proposed aa approach involves two-stage segmentation for extracting each person from a crowd. Crowd segmentation is done by frame-difference technique, followed by morphological processing and region growing. People-image features, such as the area, height, and width of each people-pattern, are analyzed in order to correctly segment each person from each individual people-pattern. The abrupt change of people movement and intentional actions will disturb the system performance.

(p) Using multiple cameras:

Dittrich, F., A. L. Koerich, et al, 2012 created a novel method for people counting in crowded scenes that combine the information gathered by multiple cameras to mitigate the problem of occlusion. This proposed method detects the corner points associated to the people present in the scene and computes their motion vector. During the training step the mean number of points per person is estimated and the image plane is transformed to the ground plane using homography and weights are assigned to each corner point according to its distance to the camera. The occurrence of occlusions will decrease the efficiency of the system.

(q) People Counting across Multiple Cameras/ Online Adaptive Learning for Multi-camera People Counting:

Li, Jingwen, et al, 2012 have developed a multi-object tracking method by means of synthesizing the local-feature-level information into object-level based on an electing and weighting mechanism (EWM) and also introduces a scheme to integrate the counting results from multiple cameras. They have also developed an online adaptive learning people counting system across multiple cameras with partial overlapping Fields Of Views (FOVs). This system uses similarity measurement combined with homography transformation to find the corresponding people in overlapping FOVs and integrates the counting results of multiple cameras. The challenges that are not faced are that the people with low motion are treated as background; the human whose clothes is very similar to the background; the change of illumination and occlusion.

(r) Scene Invariant Crowd Counting:

Ryan, David, et al, 2008 have introduced a framework which uses the global scaling factor which allows the system to be used in multiple scenes without re-training the neural network. A median filter is applied to the network's output, which increases stability and accuracy of the estimate.

(s) Spatio-Temporal Optical Flow Analysis:

Benabbas, Yassine, et al, 2010 have proposed a new approach to count the number of people who cross a counting line from monocular video images. The proposed framework accumulates image slices and estimates the optical flow on them. And then, it performs online blob detection on these slices in order to extract the crossing persons. The number of persons associated to each blob will be determined using a linear regression model applied to blob features which are the position, velocity, orientation and size.

(ii). PIXEL and REGRESSION TECHNIQUES:

(a) Based on Regression Technique/ on Low-Level Features:

Chan, Antoni B, et al, 2008 have discussed a privacy-preserving system for estimating the size of inhomogeneous crowds, composed of pedestrians that travel in different directions. The crowd is segmented into components of homogeneous motion, using the mixture of dynamic textures motion model and a set of simple holistic features is extracted from each segmented region, and the correspondence between features and the number of people per segment is learned with Gaussian Process regression. The techniques fails when there are very few people (less than two) in the scene. Chan, Antoni B, et al, 2012 have also discussed an approach that estimates the size of the crowd, which travels in different directions. Here, the crowd is segmented into components of homogeneous motion, using the mixture of dynamic-texture motion model. A set of holistic low-level features is extracted from each segmented region, and a function that maps features into estimates of the number of people per segment is learned with Bayesian regression. Later Gaussian process regression and Poisson regression are used. One limitation, for crowd counting using Bayesian regression is that it requires training for each particular viewpoint.

(b) Based on Bayesian Poisson Regression:

Chan, Antoni B, et al, 2009 have also introduced an algorithm that derives a closed-form approximation to the predictive distribution of the model and can be kernelized, enabling the representation of non-linear log-mean functions. And later an approximate marginal likelihood can be optimized to learn the hyper-parameters of the kernel. Thus they have related the proposed approximate Bayesian Poisson regression to Gaussian processes. The appearance of non-human objects like bicycles affects the overall working of the algorithm.

(c) Based on feature regression:

Fradi, Hajer, et al, 2012 have developed a counting system based on measurements of interest points, where perspective normalization and crowd measure-informed density estimation are introduced into a single feature, where the correspondence between this feature and the number of persons is learned by Gaussian Process regression. Here the accuracy of the people count is less.

(ii) COMBINATION OF BOTH DETECTION-BASED AND FEATURE-BASED SYSTEM:

(a) Based on PCA-Based Multilevel HOG-LBP Detector :

Zeng, Chengbin, et al, 2010 have developed a framework by combining the multilevel HOG (Histograms of Oriented Gradients) with the multilevel LBP (Local Binary Pattern) as the feature set, detection of the head-shoulders of people can be done. To improve the detection performance, Principal Components Analysis (PCA) is used to reduce the dimension of the multilevel HOG-LBP feature set.

(iii) COMBINATION OF BOTH LOI COUNTING AND ROI COUNTING:

(a) Statistical Model:

Chan, Antoni B, et al, 2008 have modeled an approach that shows the mixture of dynamic textures, a statistical model for an ensemble of video sequences that is sampled from a finite collection of visual processes, each of which is a dynamic texture. An expectation-maximization (EM) algorithm is used for learning the parameters of the model, and the model is used with implement computer vision applications. It is a time consuming process.

(b) Counting by Integer Programming with Local Features:

Ma, Zheng,et al, 2013 have discussed an integer programming method for estimating the instantaneous count of pedestrians. Through a line sampling process, the video is first converted into a temporal slice image and from that the number of people is estimated using a regression function that maps from local features to a count. An integer programming method is included to recover the number of pedestrians crossing the line of interest in each frame. This method causes localization errors in certain cases.

III. CONCLUSIONS AND FUTURE WORK

This survey note highlights that though there is a lot of methodologies, algorithms, approaches or framework works available in the field of crowd (people) counting systems is still required for the robust system which should handle the following scenarios with a single framework: heavy occlusion, massive crowd, both static and dynamic crowd counting, all kind of environments, less computational cost and time. Therefore efficient people count extractions are useful in many ways; one such example is resource allocation for public events and so on. In order to overcome the issues like the ambiguous appearance of body parts, occlusion, we need a robust method for extracting the people count. The future work will involve the following procedure for creating a novel people counting system. The first step is to use best approaches like adaptive Gaussian mixture model for extracting background information from moving images. The second step is to describe the local/global features such as Crowd density, relative height/width; foreground pixels, horizontal/vertical mean kinetic energy and crowd distribution are extracted for People Count. The feature descriptor like SIFT can be used for calculating the histogram and represented in a vector. After sampling , the features the learning approaches like classifiers can be used for the extraction of the people count.

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