AN ENHANCED CLOUD BASED FRAME WORK FOR MILITARY REAL-TIME SECURITY: SURVEILLANCE NETWORK APPROACH

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Abstract

Technology today is bringing newer versions of systems for all capacity and capability. An enhanced cloud based frame work will collate and refashioned all the new surveillance camera, videos and process all to give us what we call an enhanced system. The facilities in terms of hardware and software will be cloud based. Unlike the existing surveillance systems, the cloud based frame work is embedded with enhance facilities that can collect, processed analysed and interpret data on real time basis, highly scalable and has no storage limit. A prototype framework is been designed to validate the proposed approach that will be cloud based. The proposed cloud Based framework is more reliable and much more efficient.

Key words: Cloud, Framework, Real – time – Security, Network

Introduction

Before now the security apparatus have their surveillance equipment install around places usually termed as flash point. This days there is what is called modern video surveillance systems composed of lots of heterogeneous cameras distributed over variety of sites. The systems collect, process, and analyze different video streams to detect objects of potential security threats. Despite of significant benefit, there are important problems concerned in systems which are scalability, resource utilization, ubiquitous access, searching, processing, and storage to support large – scale surveillance. These all have their series of limitations ranging from infrastructural limitations to man management deficiencies. The only way out from these problems was to come up with and enhanced and cloud-based surveillance that respond in real time online speed with an improved real time online security processes Karimaa (2011) and Raty (2010).

The existing work studies design and implement of the cloud – based surveillance system, for example, dependability characteristics, resource allocation, video system , for example, dependability characteristics,, resources allocation, video recording, cloud storage mechanism, and cloud computing suitability for video surveillance. However, there are also some significant research challenges to develop a cloud-based video surveillance system. For instance, the strategy for video acquisition and storage over the cloud, the technique for effective processing of video data and its manifold structure. Therefore, a whole cloud- based video surveillance framework is in need to address two above mentioned challenges. Hussain (2013) Karimaa (2011) and Lin et all. (2012).

Some researchers have attempted potential directions for clould-based video surveillance systems. But cost [and security [8] make some organizations difficulty to choose cloud-based solutions. Even some may argue that a cloud approach may seem not needed on account of strong local control in surveillance solutions and Nevertheless, with the availability of cloud-based video surveillance solutions and strong research on cloud technology. The sign of its potential growth become obvious. In this paper, the framework of a cloud-based video surveillance system is designed and deployed, and a novel approach is proposed for object detection in video processing Hussien (2013) and Lin et all (2012).

Guassian Mixture Model (GMM) was widely applied in background model and video processing. However, it have some weakness of reqdetect false target. Inspired by the edge information with efficient noise suppression, an improved algorithm based on Edge frame Difference and GMM (EFD-GMM) is proposed to model the background and detect the moving object. The paper validates it on a deployed prototype surveillance system, and further discuss the detecting performance on two public datasets.

Related Work

Video surveillance over cloud is an emerging research area. Literature review shows that there is a growing interest in adopting the cloud technology in this new area. A cloud-based video surveillance system is first proposed in with emphasis on storage. The paper analyzed the storage requirements of a cloud-based surveillance system different with the traditional one, and also investigated a secure cloud storage system and a video transmission optimization. Karimaa studied the dependability of video surveillance technologies over cloud, such as the authority, security, maintainability and reliability characteristics of the cloud-based video surveillance solutions.

Recently, Neal explored whether cloud computing is suitable for high – resolution video surveillance management system, and cloud computing is considered a suitable application for video surveillance management system. However, there are issues of cost and other threats to study. Next, Hossain discussed the solutions of cloud-based video surveillance with some reservation to security and privacy aspects. In the paper, beside designing a Hadoop distributed file system for recording system, Lin also provided store backup and monitoring features for video processing tasks.

Real attention was put on the deployment of a software to realize video service platform and object detection in multi camera surveillance system Lin (2012). Hossain proposed a dynamic resource allocation mechanism for service composition in cloud afterwards, and suggested that a number virtual machines need to be optimally utilized for multiple surveillance services. All the above works demonstrate different aspects of system, and some especially focus on the strategy for video acquisition and storage to the cloud.

As for video processing in the cloud-based surveillance system, the result of objective detection play important roles in providing information for better video processing. From the multiple cameras, images quality in video are always impacted even being corrupted by noise. There is a challenging work in object detection. Several previous works have been carried out on object detection, in particular like clustering approach, mean shift-based method, graph-based method, Bayesian –based method. Guassian Mixture Model (GMM) is well known, but the main drawback of GMM is that the prior distribution does not depend on the pixel index and not on the spatial relationship between the labels of neighboring pixels. Thus, the object detection is extremely noise prone and illumination dependent, even prone to detect false target.

To overcome these disadvantages, Liu employed K-means clustering for GMM initialization to increase the function convergence rate, there is still the problems of poor anti-interference ability and easily noise prone when modeling background when copping with video in complicated environment. Wei introduced three frame difference into GMM to restrain error detection rate of moving object. However, this approach is difficult to adapt the light change and easily get incomplete object because of the three frame different. Similarly, Mahnood applied the frame difference in edge detection. Although it eliminate the influence of illumination change, the approach has low accuracy of detecting moving object for it is hard to get a complete object in the foreground. Overall, the above works improve the technique video processing from different aspect, so this paper concentrate to develop a distinctive algorithm which is contribute to dealing with issues of noise prone, illumination depending and false target detection.

Approach and Methodology

The challenge of scheduling camera resources to the real time appearance of targets, with imperfect knowledge of future resource requests, led this tema to apply on-line scheduling algorithms to the management of the surveillance system. Here we explore our framework for comparing the performance of such algorithms.

The decision – making environment of our surveillance airship demonstrates several unique aspects of on-line scheduling problems. Our system does not permit preemption, meaning that once a camera is tasked to a particular target it cannot begin a new task until it has completed the user-specified duration for filming. Although we do not refer to our on-line scheduling algorithm as a clairvoyant herein, the nature of our on-line scheduling algorithm resembles this concept in that all pertinent information, such as duration of processing and deadline for scheduling, is known by the system when targets appear. Furthermore, our on-line algorithm optimizes the user defined utility of targets captured, which is determined by the priority scores associated with the AOIs in which the targets appear. Even though there is rich literature concerning on-line scheduling problems, the utility – maximizing objective of our algorithm represents a unique adaptation of the on-line scheduling problem Hossein (2013).

To analyze the performance of our on –line scheduling algorithm, the team established a framework for algorithm comparison, which begins with setting an upper-bound for optimal achievable performance using an off-line version of the scheduling problem, which includes the release time of each target as a constraint. The off-line formation of the scheduling algorithm is NP-hard [1]. Table 11 defines the terms for the off-line binary integer program (BIP):

The off-line formulation of this problem represents an upper-bound on optimal achievable performance of our greedy algorithm in an overloaded system. To measure the performance of our greedy algorithm, our team utilized a performance ratio, defined as the ratio between the cumulative priority score of the greedy algorithm and the cumulative priority score of the off-line clairvoyant. Similarly, our greedy algorithm acts as a benchmark for comparison of more robust on-line algorithms that could be implemented in the future.

When comparing the greedy algorithm's performance to the off-line clairvoyant formulation of the problem, the team identified two variables of interest for future design considerations regarding automated video surveillance. First, the team examined how the greedy algorithm's performance varied is the overloaded, if its loading factor is greater than one, implying that there are more resource requests than can be feasibly met by the system. The results presented in this paper examine the on-line scheduling algorithm's performance under the following measurement of loading factor: second, each set of experiments conducted under a particular loading factor varied the presence of user subjectively, which is a measurement of the proportion of total field-of-view the user designates as an AOI. The team ran two forms of AIO allocation. First, it allocate the entire proportion of AOI covered area to one level of AOI for each user- define AOI level. Second, the team distributed the total area of AOI variation is to analyze how the under-or over-confidence of a human – user can bias the results of the heuristic algorithm. Table 111 outline our experimentation.

Proposed Method for Object Detection in Video Processing

As mentioned above, object detection is one of the key task for video processing service in the system, During Video processing, GMM has been widely applied in background model and object detection. However, it have some weakness of convergence, sensitive to ambient noise and sudden light change, and prone to detect false target therefore, to overcome the disadvantages, we improve traditional GMM in open CV library and propose a novel EFD-GMM approach for B.

The flowchart of method is described in Fig.4. firstly, frame difference is introduced into GMM background model, which quickly distinguishes the background and moving region to extract the foreground. Then, the background model is mixed with the edge frame difference, and different updating rates are adopted during modeling to accelerate speed of convergence for noise suppression and illumination independent. Finally, image and operation is performed among the foreground information detected by background model, the blob information calculated by frame difference and contour information gotten from edge frame difference. The approach has improvements on noise suppression, shadow removal and false target elimination, because of the processes of adding frame difference to GMM and integrating edge frame difference.

Framework for a Cloud-Based Video Surveillance System

In view of a cloud-based video surveillance system, there are several issues to explore for framework deployment. System requirements analysis, system architecture design, score system modules and system prototype deployment are described as follows.

System Requirements Analysis

By analyzing the cloud-based video surveillance system, four main function requirements are listed in Fig1, user manager, system setting, cloud-based video manager and video surveillance service. User manager module is composed of the operations of creating, updating, retrieval, and deleting system users. The users usually access to the system by heterogeneous video providers, so the system setting module is necessary to include the providers, networks and devices. Cloud-bridges between users and video surveillance service. Besides, the functions in video surveillance services include object detection, event analysis and abnormal warning.

Discussion of Results

From the experimentation with the greedy algorithm under the aforementioned environmental settings, the team has formed three preliminary conclusion from the results. Three factors contribute to the decrease in performance ratio; loading factor, proportion of AOI assignment, and the disparity between target deadline and duration.

Loading factor, a measurement of traffic intensity within the system, exacerbated the shortcomings of the greedy algorithm as it was increased during experimentation. Under a loading factor of one, the greedy algorithm performed just as well as the off-line clairvoyant algorithm performed just as well as the off-line clairvoyant algorithm. Fig,2,3,and 4 display the average cumulative differences between the clairvoyant algorithm and the greedy algorithm. In these graphs, the experiments are ordered from most difficult to least difficult to demonstrate the effect certain experimental factors on the degradation on the performance ratios. Notice that as loading factor is increased, the different in performance widens. This is especially true for experiments where there is a high proportion of AOI assignment, and the disparity between target deadline and duration.

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Adding Frame Difference to GMM

GMM uses several frames to model background at the beginning. In the complicated scene, the background could hardly be modeled, for the background is shaded by the moving objects in most of the time. Thus, we consider the frame different method [22] as the compensation for foreground extraction, and then rectify it using the blob information dilated from the frame difference image.

We first calculate the difference image among successive frames, using a threshold T to get a binary image to distinguish background n foreground coarsely. The process is described as follows. A count value C for each pixel ($0 \leq C \geq M$) is initialized as m/2 (is the upper limit of C), two frame f_1 and f_{1-1} are used to detect the foreground in

$$C = \sum C - 1/B \quad f_1 \ (i,j) - f_{1-1}\ (i,j) \leq T$$

$C + 1 \quad f_1 \ (i,j) - f_{1-1} \ (i,j) \leq T$

$X = - 2C/M \ X \ \alpha \ \ (0 \leq C \leq M)$

When B is a coefficient determined by camera parameters. The pixel is identified as the background and the count C increases if the difference between two frames are not more than T, and vice versa. The updating rate α will increase. The threshold T consists T_c and T_r T_r is a fixed empirical value 30, and T_c is an optimum factor with the change of frame.

$T = T_c + T_r, \quad T_c = 1/n \sum_{ij} f_1 \ (i,j) - f_{1-1} \ (i,j)$

Moreover, if the pixels changes rapidly in the video frame, GMM will be updated sooner with the updating rate α for background modeling. To construct GMM, each pixel is modeled by a mixture of k Gaussain distributions. The sample value of a certain pixel point P (x,y) I $\{X_1 X_{2.....}, X_1\}$, the probability of the present observed pixel value X_1 in t^{th} time is

$P(X_t) = \sum C - 1/B \quad f_1 \ (i,j) - f_{1-1} \ (i,j) \leq T$

Where, K is the quantity of model components, and i,t w i,t and $\sum_{I,t}$ are the of the model in t^{th} respectively. If the difference value between the present pixel and the background model is within a certain range, it can be considered as the background. That is, if it meet the condition / Xt – i,t / 2.5 w i,t – I, the model will be updated by.

The updating speed of GMM mainly depends on lean rate α $M_{K,t}$ is 1 for the matched model or 0 for the remaining distributions. If none of them match the current pixel, the least probable distribution will be replaced by a new with the current mean, the initialized high variance, an a low prior weigh. α is determined by the frame difference process, the learning rate p, u and updated. Finally, for background estimation [24], we can sort order of K Gaussain distributions according to w/0, and suppose the first B distributions as the background models.

B = arg min ($\sum_{k=1}$ w k,t >T) Although the combination of frame difference and GMM make the convergence of model better, the updating and estimation of model is still vulnerable to the sudden light change. We adopt the method of Canny edge detection on frame difference image, then integrate the contour information from edge frame difference (EFD) to the foreground mask for sake of removing the false target. The basic idea is that the edge frame difference in false area is robust to the moving object in foreground contour has some inner cavity. Therefore, we perform the image AND operation among the blob, foreground and contour information, then flood fill the foreground to get a complete object. In fact, the experimental result in the next section validate that the EFD and GMM are really mutual reinforcing to suppress noise, remove shadow and eliminate false target.

Moreover, the performance of EFD – GMM can pave the basis fro the next steps of event analysis and abnormal warning.

In our system, a LIB linear SVM [23] classifier is learned to determine whether the event of object is abnormal or not.

Experimental Result and Analysis

To verify the proposed algorithm, the comparison experiments are made in video sequences from different scenes. They are carried out on the client of the developed system prototype. We run the experiments on Pentinum (R) E700 @3.2 GHz CPU unit, dual CPU core, 2 GB memory, drive with 64 – bit windows file system in Microsoft server. Two datasets belongs to Kyushu University and Institute of Automation of Chinese Academy of Science are used to test various situations, such as sudden light changes, a pedestrian comes into the scenery and stay for a while, and ambient noise. Besides, we set the parameters of our algorithm K, α and T to 5,0.03 and 0.85 in trials.

In Fig. 6, we compare the original GMM [19] EFD [27] and the proposed EFD-GMM methods to validate the performance on an indoor video with quick lighting changes. The example from the 25th frame, 541th frame 857^{the} frame in the original video are located in the first column ()corresponding to Fig. 6(a1,(b1) and (c1), respectively). The results of object detection by original GMM re in second column in Fig. 6, the results of EFD are in the third column (corresponding to (a1, (b1) and (c1), respectively). The results of object Detection by original GMM are in second column in Fig. 6, the results of EFD are in the third column, and the EFD-GMM results are in fourth column. It obvious that the method of EFD-GMM gets the best performance in the extracted foreground and object detection, for we exclude lots of unnecessary moving points in background updating. Moreover, by comparison between the second and third column, EFD can indeed perform better than GMM when light is changing.

In Fig. 7 we also compare the GMM, EFD and EFD-GMM to validate the performance on an outdoor video while a pedestrian starts walking instead of squatting. The example from the 100th frame in the original video are Fig. 7 (a) and the results of object detection by GMM EFD and EFD-GMM are in Fig 7(7), (c) and (d), respectively. It shows that there is q false target around the object detected by GMM, because pixels of the long-time stationary target are gradually recognized as the background, and part of them is left in the foreground once the timely to remove the false target.

In Fig. 8, the results in a complicated outdoor situation with weaving leaves are compared. The example from the 331th frame in the video are Fig. 8(a), and he result of object detection by GMM, EFD and EFD – GMM are in Fig.8(b), (c) and (d), respectively. In Fig 8(b) and (c), the leaves are detected as the object, but they are ambient noise in fact. EFD-GMM is robust on this situation and has the ability of noise suppression in Fig. 8 (d) compared with the other methods. In total, 3338 frame videos

Conclusions

From the development of our simulation environment and the resulting experimentation, the team has drawn several conclusions concerning both the design considerations for the development of the surveillance airship and motivation for future research. Furthermore, the team feels the applications and definition of the requirements of the surveillance system justify the extension of on – line scheduling algorithms for governing the control and management of resources within an overloaded surveillance system.

Further study will suggested on how to also examine the disparity between deadline and duration settings assigned to targets can affect the system's performance. The prevalence of high priority AOIs in our system degraded the performance of the greedy algorithm. Examining the difference in performance ratios between experiments 2 A 50% (942) and 4A 50% (894)

Under a loading factor of five, we observe a 5.1 percent decrease in performance ratio. Similarly, we observed a 4.9 percent decrease in the performance ratio these experiments under a loading factors of three. This trend implies that an individual with a tendency toward over confidence in their allocation of high priority AOIs may impede the performance of the system.

We would like to expand our research and simulation from our greedy method to include analysis of more robust on-line scheduling algorithms. Specifically, we would focus on dynamic algorithms that use predictive control methods. These algorithms, such as the receding horizon algorithm, provide a blend of methods that compute the upper-bound of optimal achievable performance at any given state and use these approximations to determine mixed integer program solutions [5]. These results would construct suboptimal policies for there is a more optimal method for scheduling.

The team would also examine the algorithm's performance with the presence of a human operator. For instance, we would allow the operator to create and update AOIs as well as set their duration. Deadline and priority. We would expand control by allowing the operator to influence the system in ways other than assigning AOIs. Finally, we would compare the results from human experiments to the preliminary results presented in this paper.

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guidance in directing us toward a practical environment in which we could analyze the effects of scheduling algorithms.

Conclusion

To integrate lots of heterogeneous cameras and analyze numerous video for detecting the objects of potential security threats, this paper develop a new cloud – based video surveillance system. Based on the system requirements analysis, the architecture framework is designed with two core system modules. In the video surveillance services, to fulfill the key task of video processing, a novel EFD-GMM approach is proposed for object detection. A prototype system is developed on the designed could architecture to validate the proposed approach. The experimental results show that the approach is effective and robust than GMM in complicate scenes from various video providers. However, the classifier for abnormal analysis needs improvement, and the cost remains a decisive factor to embrace the cloud-based surveillance. Therefore, future works may be directed to these issues for video surveillance application.

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