IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

LIVE SURVEILLANCE - DETECTING ABNORMAL EVENTS IN REAL TIME FOR ENHANCED SECURITY

[1]Kalaiarasi [2]Kiruthika, [3] Nivetha [4]Siva Sabarishwari
[1]Assistant Professor, [2,3,4] Students
Department of Computer Science and Engineering,
PERI Institute of Technology, Chennai, India

***ABSTRACT*:** Abnormal event detection, human behavior detection, as well as object recognition plays a vital role in the creation of a smart CCTV system. These systems make it possible to detect abnormal events in an environment, abnormal behaviors by humans and the state of alert in the environment. Machine Vision property along with Machine Learning are used in these systems to detect as well as identify the particular anomalies that arise in the video feed from the CCTV. Frame by frame processing is commonly used and Supervised Learning is the commonly used training method for these systems. However, since the anomalies are of many different kinds and also because it is not feasible to pre-detect and train all types of anomalies, supervised learning is being replaced by unsupervised learning and semi - supervised learning for training the system. This system provides a means of minimising or removing the human workload that has to be put on to manually detect and create an alert on detection of an abnormality in the live feed provided by the CCTV. Also the system increases the storage efficiency by storing only the abnormal events in original quality and storing the normal scenarios in low quality for archiving. Also this system provides an extension of creating a distributed abnormality classification system, where only the abnormal events are sent on to different dedicated systems to classify the abnormality

I INTRODUCTION

In the present day world, CCTV cameras are seen in every nook and corners of our surroundings. The primary objective of a CCTV camera is in the post scenario analysis as the CCTV records everything and these recordings are used only after an event has occurred in order to determine its aspects. As the world today demands the system to be more active than passive, technologies such as machine vision along with sophisticated machine learning algorithms are being incorporated to develop new systems and thereby send alerts to the respective authorities as soon as the anomalies are detected.

The analysis of crowd behavior and object detection can be deployed in many applications such as theft detection in crowded environments. As it is quite likely for people to be positioned at varying locations in the crowd and may move in diverse directions, it becomes a challenging task to find the effective features of the crowd and as a result, the higher level analysis of crowd behavior becomes a tedious task

SYSTEM ANALYSISEXISTING SYSTEM

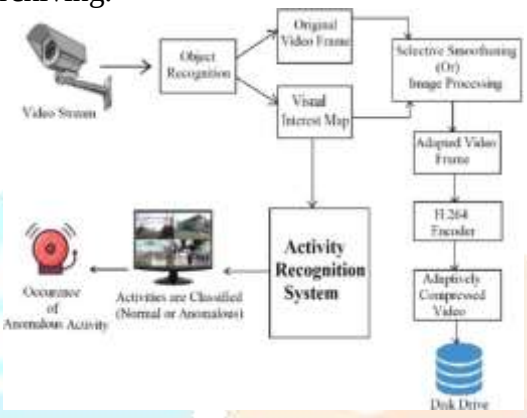
In this project, proposed an unsupervised method for detecting anomalies and changes in RS images by means of a multivariate Gaussianization methodology that allows to estimate multivariate densities accurately, a long-standing problem in statistics, and machine learning. The methodology transforms arbitrarily complex multivariate data into a multivariate Gaussian distribution. Since the transformation is differentiable, by applying the change of variables formula, one can estimate the probability at any point of the original domain.

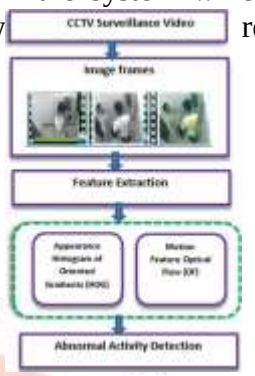
EXISTING SYSTEM

This system is useful for reducing human workload and is also able to accept multiple video streams from a centralized storage location. Also,it was possible to perform the data collection of crowd density and movement with lower consistency and accuracy.

PROPOSED SYSTEM

With our system, we can automate the process of detecting abnormal events from CCTV camera feeds. CNN and LSTM technologies are used to detect anomalies in both supervised and unsupervised manner. Alert messages can be sent to authorities on detection of events. Original Quality video snippets of the abnormal event can be stored in high quality and low quality recordings for events which are considered as normal are stored separately. By implementing this system, we reduce the time taken and human workload for detecting anomalies and also the system becomes more storage efficient. The design of this system consists of various modules or parts that have to be integrated together to complete the system. This involves the creation of Video Compressor, Anomaly Detector, Storage Management and Alert Management modules. Video Compressor is the first module in the system which is used to compress the original video in order to store it as low quality, low resolution video for archiving.





Anomaly Detector detects the presence of any kind of anomalies in the live feed from the CCTV system. This module is trained by Unsupervised learning method so that the system can detect all kinds of anomalies (both predetermined and undetermined). Also the video snippet where the anomaly is occurring is stored in the original video quality and resolution. Storage Management module is used to manage the storage of both the low quality archived video and original quality anomalous video snippets. These are stored separately for future reference. Alert Management module is used to manage and send the alert to respective personnel on identification of the anomaly

FEASIBILITY STUDY

In the present day world, CCTV cameras are seen in every nook and corners of our surroundings. The primary objective of a CCTV camera is in the post scenario analysis as the CCTV records everything and these recordings are used only after an event has occurred in order to determine its aspects. As the world today demands the system to be more active than passive, technologies such as machine vision along with sophisticated machine learning algorithms are being incorporated to develop new systems and thereby send alerts to the respective authorities as soon as the anomalies are detected. The analysis of crowd behavior and object detection can be deployed in many applications such as theft detection in crowded environments. As it is quite likely for people to be positioned at varying locations in the crowd and may move in diverse directions, it becomes a challenging task to find the effective features of the crowd and as a result, the higher level analysis of crowd behavior becomes a tedious task.

SYSTEM IMPLEMENTATION

- **MODULE LIST**
  - ✓ Data Collection
  - ✓ Pre-Processing
  - ✓ Segmentation
  - ✓ Classifications

MODULE DESCRIPTION

- **Data Collection :** We are using the UCSD anomaly detection dataset and Avenue dataset, of which UCSD dataset contains videos acquired with a camera mounted at height overlooking a pedestrian walkway. These videos mainly contain pedestrians. Abnormal events are mainly non-pedestrian entities in the walkway which are bikers, skaters, and small carts and also include unusual pedestrian motion patterns like people walking across a walkway or at the grass surrounding it. The two parts of UCSD dataset are ped1 and ped2. We are using Ped1 Ped2 and Avenue dataset for training and Testing.

- **Pre-Processing :** The training set consists of sequences of normal video frames. The model will be trained to reconstruct these sequences. Initially we are taking only the 5th alternate frame from the video sequence. This is done to reduce the processing time and memory usage

- **Segmentation :** We use Adam Optimizer with the learning rate set to 0.0001, It is reduced when training loss stops decreasing by using a decay of 0.00001, and sets the epsilon value to 0.000001. For initialization Xavier algorithm is employed , which prevents the signal from becoming too tiny or too massive to be useful because it goes through each layer.

- **Classifications :** Each video is tested individually. UCSD Ped1 dataset provides 36 testing videos and each of these videos contains 200 frames. Since we are taking only 5th alternative frames, we get a total of 40 frames from each video in UCSD Ped1 dataset. In UCSD Ped2, we have 12 testing videos of varying numbers of frames. In Avenue Dataset, we have 21 testing videos with varying duration. Here we are only selecting 5- Alternate frames. This is done to reduce the processing time taken and memory usage. Even though we might get a much better result if we select all the frames, it is not recommended to do so as it takes a lot of time to produce the required outputs. Sliding window technique is used to get all the sequences of the 4 consecutive frames (after selecting 5- Alternating Frames). This means that for each t between 0 and 36 in UCSD Ped1 dataset, the regularity score, Sr(t) of the sequence that starts at frame(t) and ends at frame (t+3) is calculated. hen we are getting a reconstruction error value that is greater than the threshold, our system sends the alert signal. Also the system starts to store the frames of original quality and resolution from a predefined number of frames before the occurrence of the abnormality to a predefined number of frames after the occurrence of the abnormality in a video format for future reference. We find it acceptable to store 10 to 20 frames from before the occurrence of the abnormality to 100 to 120 frames after the occurrence of the abnormality, to get a clear idea of what the abnormality is, and how it is occurring.

CONCLUSION

Abnormal event detection is a prominent feature in the creation of a smart CCTV system where it is possible to automatically detect abnormalities and create the necessary alerts. Supervised learning models are commonly used in the existing systems to detect the various anomalies along with reasonable computational resources. However, since the anomalies are of various kinds, it won't be feasible to train the system to detect all types of anomalies. For this reason, supervised learning is replaced by unsupervised learning to effectively train the system. By implementing this system, we also make a system that is storage efficient by saving only the abnormal frames in high quality while he recordings would be saved in lower quality. In the future, both supervised as well as unsupervised learning methods can be combined together to improve the system. Also anomaly identification methods could be added in the future to identify various types of anomalies as well as object detection.

REFERENCES

[1].Wang, T., Chen, J., & Snoussi, H. Online detection of abnormal events in video streams. Journal of Electrical And Computer Engineering, 2013.

[2].Lee, S. C., & Nevatia, R, Hierarchical abnormal event detection by real time and semi-real time multi-tasking video surveillance system. Machine Vision and Applications, 25(1), 133-143, 2014.

[3].Gu, X., Cui, J., & Zhu, Q, Abnormal crowd behaviour detection by using the particle entropy. Optik-International Journal for Light and Electron Optics, 125(14), 3428-3433, 2014.

[4]. Varol, G., & Salah, A. A, Efficient large-scale action recognition in videos using extreme learning machines. Expert Systems with Applications, 42(21), 8274-8282, 2015.

[5]. Yuan, Y., Qi, L., & Lu, X, Action recognition by joint learning. Image and Vision Computing, 55, 77-85, 2016.

[6]. Ravanbakhsh, M., Nabi, M., Sangineto, E., Marcenaro, L., Regazzoni, C., & Sebe, N, Abnormal event detection in videos using generative adversarial nets. In IEEE International Conference on Image Processing, pp. 1577-1581, 2017.

[7]. Xue, L., Xiandong, S., Lanshun, N., Jiazhen, L., Renjie, D., Dechen, Z., & Dianhui, C, Understanding and improving deep neural network for activity recognition, arXiv preprint arXiv:1805.07020, 2018.

[8]. Wang, T., Qiao, M., Deng, Y., Zhou, Y., Wang, H., Lyu, Q., & Snoussi, H, Abnormal event detection based on analysis of movement information of video sequence. Optik, 152, 50-60, 2018.

[9]. Hu, X., Huang, Y., Duan, Q., Ci, W., Dai, J., & Yang, H, Abnormal event detection in crowdedscenes using histogram of oriented contextual gradient descriptor. EURASIP Journal on Advances in Signal Processing (1), 54, 2018.