Real-time Scalable Video Stream Analysis with Object, Event and Anomaly Detection.

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Abstract

Computer vision has been a large area of research in recent years, devising methodologies to understand and act on events seen within video streams. A major application of computer vision is to detect anomalies autonomously, and alert users to when they occur. Although industrial technologies exist that are able to do this to a basic standard, they often rely on expensive and exclusive hardware.

This paper proposes an extendable and scalable framework that is able to provide accurate anomaly detection, in real-time, without complex hardware requirements. The framework will show how the adoption of distributed computing and machine learning enable real-time anomaly detections, without requiring specialized hardware. My design approach is to allow extensibility at every opportunity, so the framework can be adapted for a multitude of use cases, some of which I propose within this paper. Furthermore, the framework will allow horizontal scaling enabling it to handle large volumes of data, while keeping its real-time requirements intact. Finally, the framework will be hosted publicly allowing new avenues to be explored by the community, with avenues of exploration suggested at the end of this paper.

Declaration

“I declare that this dissertation represents my own work, except where otherwise stated.”

Acknowledgments

This is my acknowledgments.

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# Introduction

## Motivation

In the United Kingdom, an estimated 4.2 million surveillance cameras watch us every day (Norris and McCahill, 2006). CCTV is deployed to businesses, homes, shops and on high streets making us one of the most watched nations in the world. This mass deployment of surveillance equipment is meant to deter criminals and, if a crime is committed, track the perpetrator. This can be seen through its 96% availability in homicide investigations (Yard, 2010). However, for it to be used someone must watch all relevant footage highlighting points of interest, which can be considered as anomalies in the footage. If these anomalies could be detected in real-time a more pro-active approach to policing could be evolved.

This is the key problem with current CCTV, it does not provide real-time analysis or understanding of what is happening within the video stream. This means CCTV can only be adopted in a post-event capacity, with a large time input from users. It also means, due to its simple nature, all video footage must be stored for long periods of time, when a user may only be interested in the anomalous periods within the video stream. To solve this a system needs to be developed that can work on existing CCTV systems and is able to understand events occurring within a video, detecting and storing anomalies.

Systems in the market that could contribute to providing this functionality, either only provide sub-parts of the desired system, or require specialized hardware to be used which means current deployed CCTV cameras would have to be replaced during adoption (Table 2).

Therefore, there is a demand for an extendable video processing framework, which is able to add intelligence to video streams. A proposed framework should be configurable to many use cases through configuration and extendibility. Furthermore, it must be easy to scale, allowing it to meet the demands of any user.

## Aim

Propose an extendable framework for object detection and tracking, behavior and activity analysis and anomaly detection, making use of distributed computing and machine learning.

## Objectives

1. To research existing video processing techniques and available software packages in order to detect objects and events within a video stream.
2. To research machine learning techniques for detecting anomalies in time series data produced from objective one.
3. Develop testing scenarios that will allow the evaluation of machine learning models in their ability to detect anomalies in real-time.
4. Develop a framework that provides a minimum viable product of object, event and anomaly detection, while being scalable and extensible.
5. Using the test scenarios defined in objective three, evaluate the applications ability to detect anomalies and alert users in real-time.
6. Compare and contrast the performance and storage requirements of the proposed framework against existing CCTV technologies and approaches.

## Paper Structure

I will describe my paper structure here.

# Background and Literature Review

## Video Processing Methodologies and their Adoption

In order to develop an effective video processing framework, we must be able to understand what is within each frame of a video to a level that we can perform any desired actions, such as detecting anomalies. Architecture designs for this have been presented in the past (Figure 1), that show theoretically the different stages you must build upon to enable successful video processing.

The adoption of a framework following this structure allows for accurate information to be captured at different levels of processing, enabling complex behavior and identification of objects to be accomplished.



Figure 1: Adaptation of video processing within a general framework for automated visual surveillance system (Ko, 2008).

### Object Detection Techniques

Detecting objects in images relies on being able to interpret the combinations of pixels correctly to identify the particular object you are looking for. The most common method of doing this is using a Haar feature-based cascade classifier (P. Viola and Jones, 2001). This machine learning approach works by showing a classifier a multitude of images, with some containing the object you wish to detect. The classifier then attempts to apply features to the image that allow it to accurately detect the desired object. Once the classifier is trained, we extract the Haar features from the images, where each feature is a single value obtained by subtracting the sum of pixels under the white rectangle from the sum of pixels under the black rectangle (Figure 2).

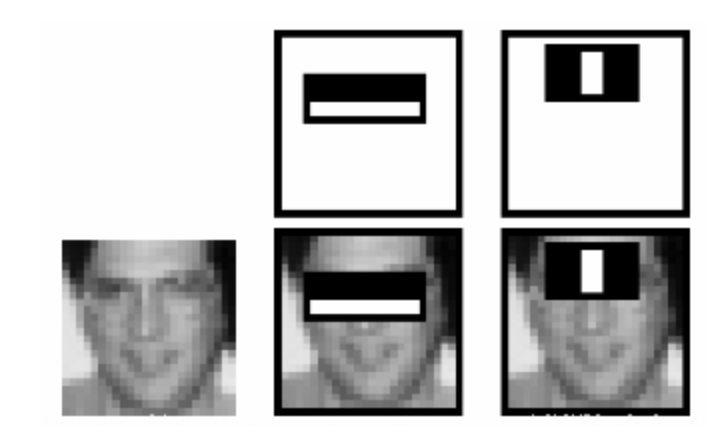
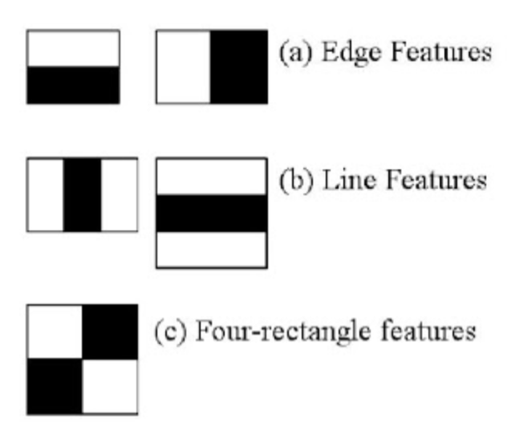


Figure 2: Left, an example of Haar cascade features. Right, the adoption of Haar cascade features in detecting a face (OpenCV, 2018).

From this point we are able to improve the performance of detections using an algorithm called Adaboost (P. a Viola and Jones, 2001), which allows ranking of features based on their error rate when attempting to successfully identify the object.

Further work has been proposed in this field using a deep learning based approach (Lecun, Bengio and Hinton, 2015). However, to make this approach feasible within real-time constraints specialized GPU (Graphics Processing Unit) hardware must be used, which would limit the extensibility of any proposed framework making use of these techniques.

### Object Tracking Techniques

Provided an objects location is correctly calculated, the next phase of a proposed framework is to give the object persistent identity between frames, which employs tracking techniques. Tracking works on an online basis, meaning as new sequential data becomes available to the model, it can adapt at runtime to provide improved predictions on future data. Usually, this incorporates identifying an objects appearance and motion pattern allowing the accurate predictions of an objects location as it moves. When providing object tracking capabilities a variety of algorithms have been developed and made available (Table 1).

|  |  |  |  |
| --- | --- | --- | --- |
| Approach | Overview | Pros | Cons |
| Multiple Instance Learning | Tracks an object by treating its location as a set of positions (‘bags’) that each could contain the objects location based on its previous location. This gives the learning algorithm the responsibility of removing the ambiguity of the exact object location and predicting which instance in each bag is most correct (Baben and Belongie, 2009). | Works well when object partially occluded due to its bag representation. | The tracker cannot handle full occlusion of objects well. |
| Median Flow | Tracks an object by selecting a variety of points within the object space and then computes the trajectory for this object, both forwards and backwards in time. This means the tracker is able to compare both trajectories and make accurate predictions of the objects final location (Kalal, Mikolajczyk and Matas, 2010). | Works well when an objects trajectory is predictable. | The tracker becomes less reliable under fast or unpredictable motion. |
| Tracking-Learning-Detection | Breaks the tracking problem up into: Tracking, learning and detection. The tracker then follows an object between frames with the detector correcting the tracker based on all observed appearances. The learning estimates the error of the detector and updates it to avoid these errors in future (Kalal, Mikolajczyk and Matas, 2012). | Works well under long periods of occlusion. | The tracker does not perform well under large full rotations and can create lots of false positives. |

Table 1: A comparison of three common approaches to object tracking.

### Behavior and Activity Analysis

Detection techniques.

## Anomaly Detection with Machine Learning

This will be a talk on anomaly detection and machine learning.

### Anomaly Detection Models

Talk about the models specifically and research done into them.

### The Impact of Human Behavior

Talk about how humans may affect ability to detect anomalies.

## Distributed Computing and the Cloud

This will be a talk on distributed computing and the cloud.

### Cloud Providers

Talk about cloud providers and their benefit.

### Distributed Computing

Apache Storm, talk about the key technologies.

### Distributed Messaging

Apache Kafka, talk about the key technologies.

## Existing Technologies and Approaches

|  |  |  |  |
| --- | --- | --- | --- |
| Product | Overview | Functionality | Limitations |
| Nest (Nest, 2017) | Gives event and motion detection allowing you to be alerted through an app in real-time if something happens within your home out of the ordinary. | Provides event and anomaly detection and real-time alerts when these occur. | Requires specialized hardware, is not extendable for development and is marketed for home use only. |
| A Video Analysis Framework for Surveillance System (Suvonvorn, 2008) | Gives a novel framework approach to online video analysis using .NET 2.0. | Provides object detection, event detection and extendibility to insert new functionality within the application. | Does not make use of distributed computing so will be unable to scale to all user requirements. It is also written in a language that requires a Microsoft workstation to run. |
| DiVA (SanMiguel *et al.*, 2008) | Gives a distributed video processing framework that uses a database as a message source allowing components to communicate agnostic of technologies adopted. | Provides object detection with the goal of detecting object abandonment and removal. This can be extended by implementing modules/algorithms that communicate through the integrated database. | Uses a singular database to communicate, rather than a distributed messaging system. It also requires fixed hardware meaning it currently does not make use of Cloud Computing. |

Table 2: A list of current technologies in the market that aim to provide smart CCTV.

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Footnotes

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Tables

Table 1

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