Movement Classification Technique for Video Forensic Investigation

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ABSTRACT
Movement classification or activity analysis is one of the most important areas in video surveillance. However, manually detecting, classifying and analyzing interesting moving objects by humans does not guarantee absolute correctness. When considering thereal environment and trying to relate the way objects interact in a surveillance covered area, it is not so easy interpreting every activity correctly. These challenges posed by defining and classifying objects' behaviours as normal or abnormalmovements. These challengescan be tackled using video analytic technologies. The objective of video analytic technologies is to detect the presence of objects that are moving in its field of view and to classify their movements for security, traffic monitoring and safety applications. There are a lot of hurdles faced by video analytic systems that impede their ability to perform accurately. This study presents a review of movement classification techniques and algorithms, which can tackle the challenges of realistic and practical outdoor surveillance scenarios.

Keywords
movement classification; video forensic; cortical learning algorithms; post incidence analysis; video analytic

1. INTRODUCTION
Despite significant and growing investment in CCTV surveillance systems, today more than 98% of footage goes unseen due to the high cost of skilled monitored staff [1]. Even when a videois monitored, there might be operator fatigue, which might lead to an important security events being overlooked. The lack of efficient monitoring often leads to a poor return on investment and sub-optimal security outcomes.

Video analytic is very important due to a lot of devices capable of producing videos ranging from hand-held phones to video cameras. As the world is turning digitised, human beings are becoming less sensitive even to the videos they upload on social media such as Facebook, Instagram, etc.

Police officers, most times, manually analyse videos from surveillance cameras to detect anomalies. The manual analysis of such videos may pose challenges such as missing a very important event by the investigator because, he/she getting bored or being distracted. The process of investigating video footages usually involves a lot of man power. At each point in time, at least, one investigator is supposed to be physically viewing such video footage on screen and manually analyzing it if the need arises. This is a time-consuming operation, and it is very costly, because, the staff involved in the investigation needs to be paid for the services rendered. Also, human beings are easily distracted and sometimes inefficient.

Considering an investigator who is manually viewing one screen showing two video footages, after 10 minutes, the investigator may miss 45% of the events, and after 22 minutes, the investigator may miss 95% of the events [1]. The big challenge comes in when during the miss that occurs due to the inefficiency of the investigator leads to an event that goes unnoticed.

Thus, there exists a need for proper consideration of research in the direction of automated video forensic investigation and a proper development of a framework to handle such sensitive issues.

The use of video analytic tools for post-incident analysis dictates the application of well-established digital forensics rules into the new video forensic framework. Steps of forensics include Preparation, Collection, Examination, Analysis, and Reporting.

A video analytic system consists of many modules; one key module is the movement classification module. In this module, the movements of detected objects are recorded and compared to infer anomaly. State-of-the-art movement classifications rely mainly on rule-based classification techniques, where the abnormalities in the video are traced and reported to the user. Such techniques attempt to learn normal movements to identify abnormal movements.

Artificial Intelligence (AI) and Neural Networks (NN) have been heavily used to solve the problem of movement classification. However, they still suffer from various limitations such as their limited scope of operations. In the attempt of mimicking the function of a human brain, learning models inspired from the neocortex have been proposed which offer better understating of how our brains function. Recently, new bio-inspired learning techniques have been proposed and have shown evidence of superior performance over traditional techniques. In this regard, Cortical Learning Algorithms (CLA) inspired from the neocortex are more favored.The CLA processes streams of information, classify them, learning to spot differences, and using time-based patterns to make predictions. In humans, these capabilities are largely performed by the neocortex. Hierarchical Temporal Memory (HTM) is a technology modeled on how the neocortex performs these functions. HTM offers the promise of building machines that approach or exceed human level performance for many cognitive tasks [2].

Hence, this paper aims to study the application of cortical learning algorithms to movement classification and review an HTM-based technique developed for the efficient automation of post-incident analysis and video forensic.

2. MOVEMENT CLASSIFICATION CHALLENGES
In recent years, the development of outdoor surveillance technologies has captured the interest of both researchers and practitioners across the globe. The objective of these technologies is to detect the presence of objectsthat are moving in its field of view for a Closed Circuit TeleVision

(CCTV) camera(s) for national security, traffic monitoring in big cities, homes, banks and market safety applications. However, detecting, classifying and analysingof moving interesting objectswas traditionally a manual job performed by humans in which the guaranty of absolute attention overtime by ahuman on duty remain small, especially in practical scenarios.

In general, in an attempt to develop a video analyticsystem that can detect and classify the presence of objects moving in its field of view, that system must be able to:

a) Classify detected objects into various categories

b) Track the detected objects over time

c) Classify their movements.

It is also interesting to note that, each of the above tasks poses its challenges in term of design and implementations.

2.1 Movement Classification Challenges of Outdoor Surveillance

There are lots of hurdles faced by outdoor surveillance system designers and implementers. The first step toward automated activity detection is monitoring, detection and classification of moving objects in the field of view of CCTV cameras; another challengeis that, sensor resolution is finite, and it is impractical for a single camera to observe the complete area of interest. Therefore multiple cameras need to be deployed.Also, the detected objects are context-dependent, but for general surveillance system any independently moving objects such as a vehicle, animal or a personare deemed to be interesting, but detecting and classifying of these objects is a difficult problem because of the dynamic nature of object appearances and viewing conditions in practical scenarios.

Other challenges are that appearance of objects can vary considerably over time depending on the camera view, like front view or side view; dynamic nature of lighting condition to relative distance to cameras can also affect the true appearance of an object over time. After tracking objects, it is important to record their movements over time, and the problems arise as a result of the need to estimate the trajectory of an object as the object moves around a scene, in modeling this kind scenario that requires where the object is in the image at each instant in time. The whole idea is to keep tracking and continuously observing an object concerning their size, motion and shapes that vary over time.

In a realistic environment such as shopping centres, busy street or ports, some objects are likely to change shape and size while moving. Another scenarios challenge in outdoor surveillance is the issue of occlusion, in real life situation,an object may be blocked by another object or structure or even shadow of another object that leads to a discontinuity in real time observation, detecting and classifying moving objects toward effective and automatic video forensic analysis. Detecting and classification of a moving object under occlusion is very difficult because accurate position, shape, size and motion or velocity of an occluded object cannot be determined which could affect the result of forensic video analysis.

3. VIDEO ANALYTIC

The use of video analytic technologies has gained much attention in the research community and the global security around the world [3]. The purpose of intelligent visual surveillance in most cases is to detect, recognize, or learn interesting events that seem to constitute some challenge to the community or area of the target [4]. These challenges posed by defining and classifying events as unusual behaviour [5], abnormal behaviour [6], anomaly [7] or irregular behaviour [8].

When considering thereal environment and trying to relate the way objects interact in surveillance covered area, it is not so easy interpreting every activity correctly. However, much effort has been done in respect to smart video surveillance server. Video processing and computer vision technologies are usually carried out by the smart surveillance server to automatically segmentmoving objects (blobs), localize the segmented blobs, classify them, identify them, track their positions, and automatically classify their movements [9]. This process is based on what the user requests and these activities are inserted into an active scene, as Figure 1 shows.

The majority of automatic video analysis methods are based on background analysis that aims at segmenting moving objects by distinguishing between foreground and background areas in video sequences, based on a background model [10].

Cluttered environments that contain so many moving objects pose a challenge for many anomaly-detection algorithms. But in real life cases, these are the kind of scenarios we meet when considering movement classification in video surveillance [3].

There have been several proposed methods to tackle issues relating to surveillance cameras/videos to include the work carried out by [11] which is targeted at locating interesting bodies by using uni-modal background model.

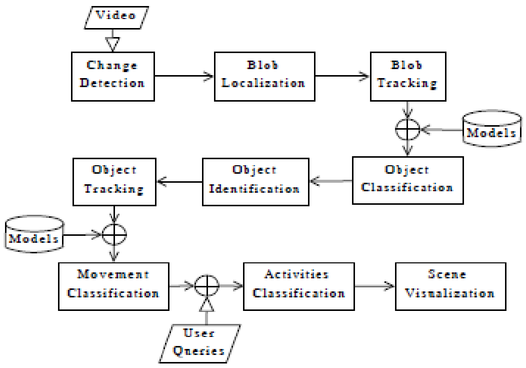

Figure 1. The internal structure of smart video surveillance server

An adaptive multi-modal background subtraction method was proposed by [12] which handles slow changes in illumination, repeated motion from background clutter and long term scenes. Temporal Templates are important when considering movement classification problems. Researchers in [13] proposed the motion history and motion energy which is all forms of temporal templates. There have been several researchers studying Recurrent Motion Images (RMIs) which could detect repeated motion and hence it has been successful in object detection and classification [14]. Researchers in [15] recently carried out an exhaustive literature concerning surveillance videos. They pointed out that, classification could be done using shape-based, texture-based or motion-based features. They also noted that shape-based methods are moderately accurate, computationally low and operate as a simple pattern-matching approach that can be appliedwith appropriate templates. This kind of technique, however, does not work well in dynamic situations and finds it difficult locating internal movements. Considering motion-based techniques, the accuracy is also moderate, computationally high, and does not require predefined pattern templates. The challenges with these techniques are that they find it difficult identifying a non-moving human. When considering texture-based methods, they noted that, the accuracy is high, computation is high, and these kinds of techniques provide improved quality, even though there is an additional computational time [15].

4. RELATED LITERATURE FOR MOVEMENT CLASSIFICATION TECHNIQUES

Many researchers have suggested over the years that, activity analysis in video surveillance will be the most important area of research when considering video analyticresearch [3] [16]. Even though there are a lot of CCTV cameras to capture abnormalities or unusual behaviors, resources to monitor and analyse such captured video footage are fairly limited [3].

The majority of existing movement classification algorithms use simple rule-basedtechniques [17].

Some researches on video analyticare focused on action recognition, body parts recognition and body configuration estimation [18]. There has been arecent advancement in researching about semantic descriptions of humans in challenging unconstrained environments [19].

Our focus in this research is however on movement classification and when considering movement classification techniques, the question “what is going on in a scene” is considered [3]. In this sense, there must be a clear definition of what is considered normal/usual and abnormal/un-usual. Abnormalities are defined as actions that are fundamentally different in appearance or an action done at an unusual location, or/and at an unusual time [20]. When considering anomaly-detection algorithm, detecting the spot and where anomalies occur with little to no false alarm is of great emphasis [3].

When considering modeling scene behaviour, statistically based methods are currently used instead of rule-based methods, which use already defined rules to classify normal behaviour from abnormal behaviour that were previously used [21]. Statistically-based methods are believed to achieve a more robust framework to get useful information in behaviours of a considered scenario [3]. This kind of method is based on either learning from normal behaviour and then using such criteria to differentiate between normal behaviour and abnormal behaviour, or the process of learning and detecting normal and abnormal behaviours is done automatically (in an unsupervised way). The challenge with this kind of approach is that, human beings behave abnormally in different ways, and as such systems may trigger wrongly, hence a false alarm. Much work has been done on using machine learning techniques to train some algorithms on normal behaviour and abnormal behaviour so that such algorithms could effectively differentiate these two cases. Unfortunately, it is a hard task to exhaust all the abnormal behaviours to be carried out in real life scenarios [3].

Several attempts have been in place for movement classification, using different techniques such as pattern recognition [22] [23], artificial intelligence [23] [24], and neural network techniques [25].

4.1 Cortical Learning Algorithm

The Cortical Learning algorithm (CLA) is a result of an attempt to model the complex and structural nature of neocortex, and capture the algorithmic properties and characteristics of theneocortex. It is biologically proven that neocortex is the seat of intelligent thought in the human or mammalian brain. Intelligent properties such as vision, movement, hearing, touchingetc are all performed by this intelligentseat, this cognitive tasks that arelargelyperformed by the neocortex of humans arevery difficult to design in real life scenarios.

There are many things humans find easy to do that computers are currently unable to do. This task includes vision, hearing, touching, movement, understanding spoken language and planning capabilities that are largely performed by the human neocortex. Despite extensive research carried out previously, only a few results were achieved in modeling higher-level cognitive functions like Hierarchical Temporal Memory (HTM) with Cortical Learning Algorithm. Human capabilities are largely dependent on their behavior that influences what they perceive. Almost all humans actions change what they sense [26]. Sensory input and motor behavior are intimately entwined. For decades, the prevailing view was that a single region in the neocortex, the primary motor region, was where motor commands originated in the neocortex. Over time, it was discovered that most or all regions in the neocortex have a motor output, even low-level sensory regions. It appears that all cortical regions integrate sensory and motor functions.

Cerebral context is part of thehuman brain that constitutes about 85% of thetotalmass and is responsible for higher level cognitive functions [26]. The different parts of the neocortex, whether they are responsible for vision, hearing, touch, or language, all work on the same principles. The cells in a region of cortex can learn and recall sequences of patterns, which is an essential element for forming invariant representations and making predictions [27]. Cortical is derived as a result of function or condition of cerebral cortex in the human brain

It is very clear that Artificial Intelligence (AI) techniques are very important and have several applications that cut across several important areas of life. However, [28] noticed that in the mid-1980s, AI systems were failing in some applications and hence people started thinking of alternative ways to solve problems and in an effective way that it will not fail. Research in [29] viewed this assessment quite differently by postulating that by aiming to achieve areal human level, AI could imply the swap of operations that humans carry out for payment that could be automated, thus involving the task of building a special purpose system. This lead to the interest in Neural Networks, which were an improvement over AI and was in a way builton architecture to depict real nervous systems [28].

The researchers in [28] however noticed that NN could not meet very three important criterion that the brain had. These were:

a) In real cases, brains process rapidly changing streams of information and not thestatic flow of information.

b) The feedback connections which dominates most connections in the neocortex were not understood

c) Any theory that wishes to imitate the brain should take the physical structure of the brain into consideration and as such neocortex is never a simple structure [28].

The whole process of neural networks was concerned with a static input pattern being converted to a static output patternthat is far from what the actual brain processes. As time has evolved, NN has evolved too, but none of the techniques associated with neural networks has cared to incorporate the architecture of neocortex into NN.

AI and NN have so much focused on the fact that, intelligence lies in the behavior that a program or neural network produces a given input is processed. However, intelligence is not all about acting or behaving intelligently but is also about knowing exactly what goes on in your head. Thus understanding what goes on in one's head will greatly assist in developing machines that are more intelligent [28]. To be able to extract the real intelligence, to build intelligent machines, we will need to extract intelligence from nature's engine of intelligencethat is neocortex [28]. The research in [29] argued for the development of ageneral purpose educable system that can learn and be taught to perform any of the high volume jobs that humans perform.

In general, [28] noted that, to build a system that behave like the brain, there should be an intake of thestream of changing information, recognition of patterns in such a way that, there is no prior knowledge about the input source, make accurate predictions and react correctly.

This could only be achieved with the help of understanding how the neocortex works, which is the part of the brain that handles higher functions in human beings such as conscious thoughts and language processing. This approach will be based on modeling the structure of the neocortex and how it works. But approaches like AI are built upon the idea of a neural network, which in essence, NN does not behave in the same way as the brain thinks, and this is not what is considered intelligence. More importantly, NNs can never produce systems that can have behaviour [30]. This approach is thought to be implemented using the Cortical Learning Algorithm (CLA). This approach is usually made up of six very important components that include: online learning from streaming data, thehierarchy of memory regions, sequence memory, sparse distributed representations, all regions are sensory and motor, and attention. The CLA processes streams of information, classify them, learning to spot differences, and using time-based patterns to make predictions.

In humans, these capabilities are primarily performed by theneocortex. Hierarchical Temporal Memory (HTM) is a technology modeled on how the neocortex performs these functions. HTM offers the promise of building machines that approach or exceed human level performance for many cognitive tasks.

Almost all the most important activities carried out by mammals are controlled by the neocortex such as vision, hearing, touch, movement, language, and planning [27].

HTM models neurons thatare arranged in columns, in layers, in regions, and in thehierarchy. HTM works on the basis of a user specifying the size of a hierarchy and what to train the system on, but how the information is stored is controlled by HTM. In general, the HTM is a hierarchical organization and is basicallytime-based. The HTM consists of theregionthat is the main unit of memory and it also comprises of feedback connections which makes the hierarchy diverges as one descends the hierarchy.

In all of these, thetime has a major role as it plays a very important role in learning, inference and prediction. An HTM algorithm learns the temporal sequence from thestream of input data; even though it is difficult to predict what patterns may likely follow the next. This HTM algorithm is very important because, it covers what is believed to be the building block of the neural organization in the neocortex [27].

5. REVIEW OF AN HTM-BASED MOVEMENT CLASSIFICATION TECHNIQUE

Hierarchical Temporal Memory is a technology that model on how higher level capabilities of humans neocortex brain perform atask such as visual pattern recognition, understanding language recognizing objects movement, etc. This paper proposes an object's movement classification technique based on the concept of this technology. However, HTM provides a type of neural network in a memory based network which fundamentally trained on a lot of time varying data and rely on storing alarge set of patterns and sequences. Information follow is always in a distributed fashion.HTM consist of regions that represent a level of hierarchy in the network, as you ascend in the hierarchy there is always convergence of information due to feedback, while as you descend, the information diverges in the hierarchy [27] [30].

5.1 ProcessingObject Movement Classification Information in an HTM Network

Traveling up and down in the hierarchy, spatial and temporal resolution diverges and converges. At the lowest level of an HTM network, the input patterns of object identification and movement classification are constantly changing, much like the incoming sensory stimuli we humans receive. Cell activation patterns are more stable because information is transferred up and down in the hierarchy in predictable sequences. The brain constantly compares incoming sensory patterns and stores a model of the world that is largely independent of how it is perceived under changing conditions.

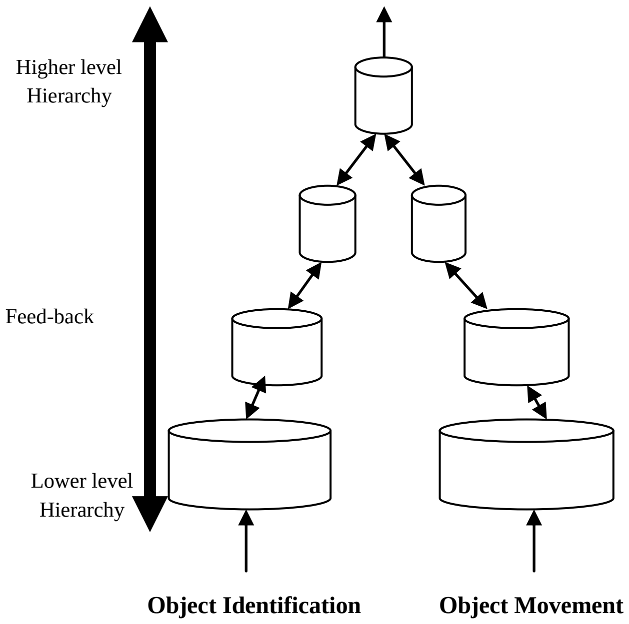

Figure 2. Converging networks from two different sensors [31]

One network might be processing object identification information and another network might be processing object movement information as both networksascend to ahigher level in the hierarchy it significantly reduces training time and memory usage because patterns learned at each level of the hierarchyare reused when combined at higher levels [31].

For illustration in the framework, it is interesting to note the movement classification patterns. At the lowest level of thehierarchy, brain stores information about thetiny section of object movements such as zero “0” anda tinysection of object identification of point. The “0” and “point” are afundamental component of movement and identification and classification of an object. Later these lower level patterns are recombined at mid levels intoa complex pattern that, it further recombined again to ahigher level to form object movement, as well as theobject itself. In an input vector that described the movement of theobject (can be animateotherwise) in a particular direction of a cell movement that are activated. The first phase calculates each column movement. The overlap of each column is simply the number of connected synapses. With active inputs when this value is less than the minimum movement (lower level), the score is zero (0) [31].

5.1.1 Spatial Pooler in HTM

The spatial pooler:

- Learns about connections between synapses and inputs.
- Determines how many synapses are connected to valid inputs.
- Multiplies the number of active synapses by the boosting factor.
- Columns with stronger activation inhibit columns with weaker activation in the neighbourhood.
- Permanence values of all potential synapses are updated.
- Permanence values of synapses connected to active inputs to be increased

The most important role of the spatial pooler is converting the input of a region into a sparse pattern. This role is important because the technique used to learn sequences and make predictions entails beginning with sparse distributed patterns. The following functions can be used to ascertain how a spatial pooler learns and operates: [31]

(a) Ensure all columns are used: an HTM region has a set number of columns that learn to represent common patterns in the input. The goal is to ensure that all columns learn to represent something useful irrespective of how many columns they are.

(b) Ensure desired density is maintained: it is essential for a region to form a sparse representation of its inputs and the column with the majority of input inhibits their neighbours. Inside the radius of inhibition, only the column with the most active input are enabled and the rest are disabled.

(c) Avoid trivial patterns: trivial patterns must be avoided by setting a minimum threshold of input for the column to be active

(d) Extra connections must be avoided to avoid different subsets of the synapses responding to different patterns

(e) Self adjusting: just like real brains and the neocortex, the HTM regions must have receptive fields that are self adjusting [31].

5.1.2 Temporal Pooler

Temporal pooler learns sequences and makes predictions. In temporal pooler:

- Cells activated by feed forward input become active.
- Cells activated by lateral input enter predictive state.
- Synapses are updated for learning

The basic method is that when a cell becomes active it forms connections to other cells that were active just prior. Cells can then predict when they will become active by looking at their connections. If all the cells do this, collectively they can store and recall sequences, and they can predict what is likely to happen next. There is no central storage for a sequence of patterns; instead, memory is distributed among the individual cells. Because the memory is distributed, the system is robust to noise and error. Individual cells can fail, usually with little or no discernible effect [2][31].

Hierarchical temporal memory (HTM) is memory based systems that model the architectural details of neuron that, as such is one of the category of neural network (NN). These HTM model neurons which are arrange in columns, layers as well as regions of hierarchy. HTM as a network are trained on lots of time varying data, and rely on storing large set of objects patterns and sequence. The benefit of hierarchy in neocortext is efficiency; it perhaps significantly reduces training time for the system and memory usage because patterns learned at each level of the hierarchy are reused when combined in novel ways at higher levels. These characteristics makes it ideal for use in efficiently classifying movements for analytic and investigation purposes.

6. CONCLUSION

Automatic analysis of videos for forensic purposes has been subject to technology evolution. There have been various developments over the subject that has compromised human error in post-incident analysis. The concept of video analytics is of more significance due to the increased number of devices that are capable of recording and producing videos, increasing the probability of video evidence that can be used for a trial. Previously video analytics was subject to investigator viewing but this has been subject to human error. The legal system has also been investing heavily in this area to develop a framework and technology improvement. Therefore, there is a need for an automated video forensic investigation tool and a proper development of a framework that can address the sensitive issues associated with this application.

This research studied the requirements of video forensic investigation, surveyed previous works done and investigated the use of neocortex inspired learning techniques in developing movement classification tools. The paper also reviewed a movement classification technique,based on HTM, which is able to tackle the challenges of realistic/practical outdoor surveillance scenarios.This paper has identified HTM as a suitable technology to propose a novel movement classification technique.

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