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The Need for Marker-Less Computer Vision Techniques for Human Gait Analysis on Video Surveillance to Detect Concealed Firearms

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Abstract

Crimes involving the use of firearms have been on the increase in the past few years. One of the measures adopted to prevent these crimes is the use of CCTV operators at video surveillance centers to detect persons carrying concealed firearms on their bodies by monitoring their behavior. This paper has found that this technique has challenges associated with human weaknesses and errors. A review of the current attempts to automate video surveillance for concealed firearm detection has found that they have the limitation that the techniques can only be employed on stationary and cooperative persons. This makes them inappropriate for real-life surveillance. This paper highlights the need for automated video surveillance solutions that can detect persons carrying concealed firearms when they are not stationary and aware of the scanning process. We further explore automated behavioral analysis and specifically gait analysis as a possible technique for concealed firearm detection on video surveillance. Lastly, the paper highlights the possibility and viability of human gait analysis using marker-less computer vision techniques for detecting persons carrying firearms on their waist line.

Key Words: Computer Vision; Concealed Firearm Detection; Human Gait Analysis; Video Surveillance.

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1. Introduction

1.1. Background of the Study

The increase in crime and risk of terrorist attacks has seen governments and organizations increase their security alertness [1]. References [2, 3] in their studies indicate that one of the security threats is the increase in crimes involving the use of firearms carried and concealed underneath a persons' clothes as illustrated in figure 1. Various security measures have been put in place in an attempt to counter this threat. References [4, 5, 6, 7] identify these measures as 1) Visual inspection and pat down by security guards 2) The use of hand-held and/or walk-through metal detectors 3) The use of CCTV operators in video surveillance centers to monitor people 4) Smart video Surveillance using image sensor technologies such as infrared and passive millimeter wave imagers.

Figure 1: A Person Carrying a concealed firearm *[8]*

A common challenge with pat downs and the use of metal detector technologies is that they are invasive to persons being searched and they require the security personnel to be very close to the persons being searched, hence posing a security challenge to them [9]. The use of CCTV operators at video surveillance centers is able to address this challenge since the operators are able to monitor persons from a distance and detect those carrying concealed firearms [10, 11]. References [12, 13] indicate that CCTV operators can accurately identify persons carrying concealed firearms by analysing their behaviour. However, this paper found that their efficiency is affected by visual overload, ability to remain alert over a long period of time and task interruptions [14, 15]. Figure 2 illustrates a CCTV operator monitoring over 20 screens simultaneously and additionally responding and manning several phones.

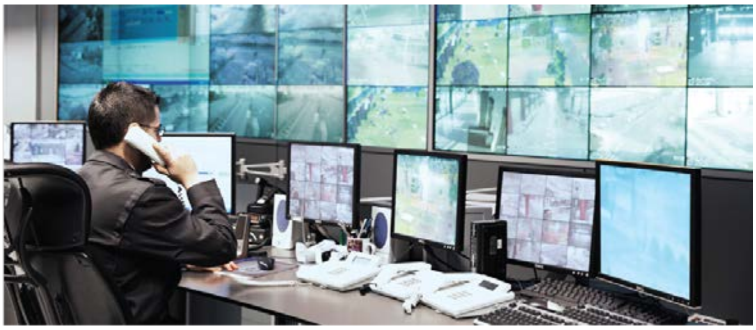

Figure 2: CCTV Operator at work *[16]*

There is therefore a need for automated solutions to manage the surveillance process [17]. These solutions would reduce these inefficiencies and errors associated with monitoring using human operators [18]. Attempts to have automated video Surveillance systems to detect persons carrying firearms concealed underneath their clothing have been made. This has been achieved using image sensor technologies such as Infrared and Passive Millimeter wave imagers [19]. The use of these technologies can detect concealed firearms from a distance [10]. However, they require that the person being scanned is stationary and cooperative as illustrated in figure 3 [11]. In addition, [11] points out that this is not beneficial in real life surveillance where people are moving and not stationary. Reference [9] concurs and further indicates that it would be more practical and beneficial to have techniques that are able to identify persons carrying concealed firearms from a distance, when they are not aware and not stationary.

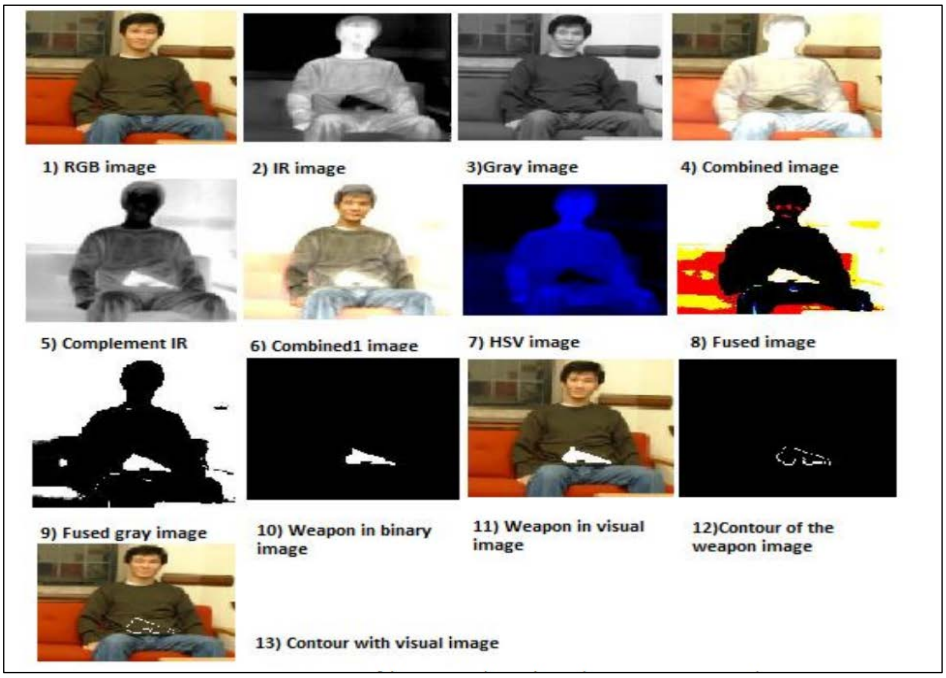

Figure 3: Concealed weapon detection algorithm using infrared *[20]*

1.2. Statement of the Problem

Current attempts to have smart video surveillance systems for concealed firearm detection using Infrared and Passive Millimeter wave imagers has been found to be impractical in real life scenarios [11]. This is because the persons being scanned must be stationary and cooperative [10, 11]. Real life surveillance requires a solution that can detect persons carrying concealed firearms without their knowledge and when they are moving about their business and not in a stationary state [9].

2. Literature Review

2.1. Detection of Firearms using computer vision techniques

Reference [7] defines a firearm as a portable gun. Firearms can generally be carried either in a concealed/hidden manner as illustrated in figure 1 or visibly/uncovered as shown in figure 4. Computer vision is the process of modelling and replicating human vision using computers [21]. Computer vision techniques for the detection of persons carrying uncovered /visible weapons on video surveillance have been developed.

Reference [22] proposed an algorithm that analyses the shape and size of a visual firearm using MPEG-7 visual descriptors. Reference [7] proposed an algorithm that uses color-based segmentation to eliminate objects from an image that are not of interest using k-mean clustering algorithm. After this, Harris interest point detector and Fast Retina Key point (FREAK) are used to locate the object (firearm) in the segmented images. Reference [22] proposed an algorithm based on a Neural Network and an MPEG-7 descriptor to classify frames from video surveillance. The neural network was trained to raise an alarm when an uncovered firearm is detected. Reference [23] developed a computer vision model that uses convolutional neural network classifier to detect uncovered firearms. The output from their model is illustrated in figure 4. Not much research has been done on the detection of concealed firearms on video surveillance using computer vision techniques. Most of the existing methods are based on imaging techniques like infra-red imaging and millimeter wave imaging which have certain challenges highlighted earlier [7].

Figure 4: Detection of Visible Firearms *[23]*

2.2. Behavioural Indicators of Persons carrying concealed firearm

Previous studies have pointed out that people carrying concealed firearms normally exhibit certain behavioural characteristics that CCTV operators are able to use to accurately identify them [12, 13] . Behavioural or nonverbal communication is the use of visual cues such as facial and eye expressions, hand and arm gestures, postures, positions, use of space between individuals and objects, gait (Walking). [12] indicates that the intentions of people can be inferred based on their behaviour with high levels of accuracy.

[12, 24, 25] in their studies identified various behavioral indicators of persons carrying concealed firearms. These are;

a. Asymmetrical Gait

Gait is defined as the repetitive manner of walking, arm swing, stepping or running [26, 27]. Carrying a concealed weapon normally influences the gait of a person [12]. Most illegal firearms are carried un-holstered and are at the front right side of a person's waistline, tucked into a belt [25, 28]. When a firearm therefore is tucked into the pants pocket or the front waistband, it may hinder leg movements on that side of the body resulting in having the right stride being shorter than the left [24]. Consequently, this may also result in a disrupted stride and shortened arm swing as the individual attempts to either conceal the weapon or limit its movement so as not to drop it [25].

b. Security Feel

Security feel is the repeated touching of an item of value [28]. This is normally associated with persons carrying valuable items for example firearms. This repeated touching may be conscious or unconscious and is aimed at ensuring that the item is still in procession and in the case of a concealed firearm to ensure that the firearm is concealed by clothing [25]. Security feel can involve touching the firearm with any part of the body, depending on its location. When a person is performing a security feel with the hand, one can see the person's finger tips tapping the area or the palm of the hand touching the concealed weapon [25].

c. Blading

Blading is a whereby when a person carrying a concealed firearm is approached from the front, he will turn the firearm side of his body away from the person approaching [24]. This is normally a nervous reaction to the presence of law enforcement. For example if a person has a concealed weapon on the right hip and is approached by someone from whom they would want to conceal the firearm, he will instinctively turn their body to the right and walk on the left side of the oncoming person blocking the view of his hip where the firearm is located [25].

d. Repositioning of firearm

Whenever a firearm is carried loosely, it will inevitably move around with the heaviest portion facing down and this will require some type of repositioning [29]. This is normally depicted by an offender performing a circular or lifting movement outside of the clothing to adjust the firearm's position [24, 25].

e. Adjusting of Pants

Most concealed and illegal firearms are carried on the waistline, without a holster [25, 28]. When a person sits or stands up, and has a concealed firearm on his waistline, he will often adjust the belt and the firearm on it to account for the change in position.

2.3. Human Gait Analysis as a Promising Technique for Concealed Firearm Detection

[12] did a study to explore whether the recognition of offenders with a concealed firearm by a CCTV operator might be based on the recognition of non-verbal behaviour that is accessible from CCTV images. The study conducted experiements whereby CCTV operators were presented with video clips of persons carrying concealed firearms and others not carrying concealed firearms. They were then asked to fill in a cue- detection questionnare in order to describe the overall movement of surveillance targets using a number of characteristics of the targets movement pattern and indicate how they arrived at the decision of either armed or unarmed.

Pearson correlations were performed to investigate the possible relationship between the CCTV operators performance in identifying a concealed firearm and the visual cues. There was a significant positive correlation between the gait and posture of the target and the ability of the CCTV operators to determine that the target was carrying a concealed firearm. In addition, a significant negative correlation was found with the use of facial expressions. To confirm these findings, the study further used eye tracking glasses to determine the areas on a targets body where CCTV operators spent more time looking at. They found that in cases where a target had a concealed firearm, the operators spent a significant amount of time looking at their legs. In a debriefing interview after the study, the operators indicated that they focused on the lower body (legs) since they noticed differences in speed and stride lengths of the walking targets.

2.4. Gait Capture Systems

Human motion analysis is the study of human motion by observation, augmented by instrumentation for measuring body movements, body mechanics and the activity of the muscles with an aim to produce information based on the motion [30, 31]. Human gait analysis is a branch of human motion analysis which is specific to the study of human walking [30]. The basic gait parameters most frequently used to obtain information on spatial and temporal gait variables as well as walking patterns are step length, stride length, cadence and walking velocity [32, 33]. Reference [34] indicate that the data obtained from these analysis is quantifiable and hence provides baseline data to aid in decision making.

There are two broad categories of gait capture systems used to capture human motion. These are Non-Optical (non visual) and Optical Motion (visual) capture systems as illustrated in figure 5 [35]. Non Optical systems are human motion capture systems that do not utilize video cameras as their primary sensor. These systems include Inertial devices, Electromechanical and Electromagnetic systems [35].

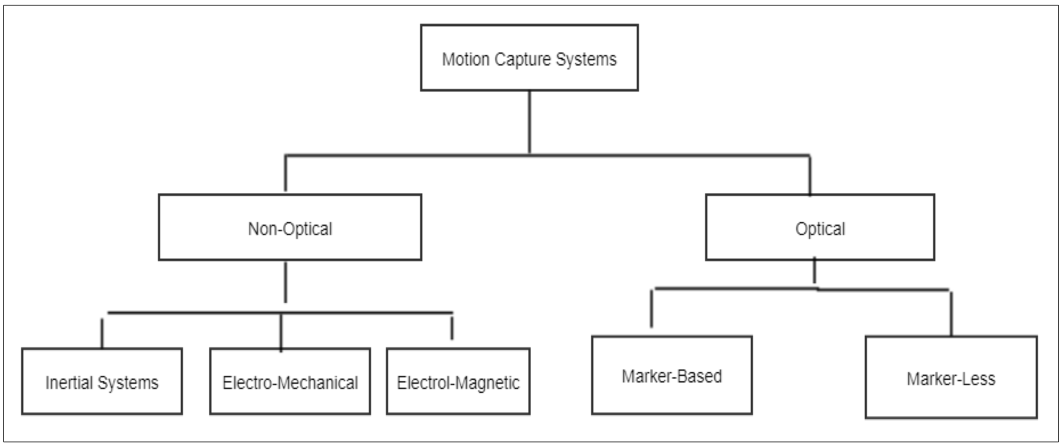

Figure 5: Categories of Motion Capture systems [35]

Optical sensor systems on the other hand make use of video cameras as their primary sensor [35]. Optical Human Motion capture systems can be grouped into two; 1) Marker based 2) Marker-Less systems. Marker-based systems rely on sensors attached to key locations of the human body, whilst marker-less systems rely on computer vision techniques to extract motion features from the video stream [36, 35]. Optical Marker-less Capture Systems can extract the gait parameters of a subject without placing any markers/sensors on the human body. This is achieved by use of video cameras fitted with computer vision-based software [35]. [37] argues that Marker-Less systems are suited for visual surveillance applications where mounting markers or sensors on the subject may not be an option.

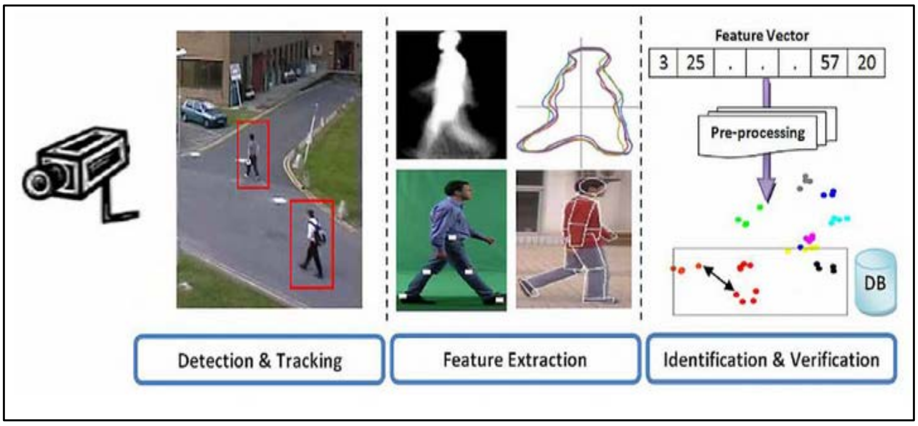

Figure 6: Architecture of a marker-less system for human motion analysis *[38]*

Figure 6 illustrates the architecture of a marker-less system for human motion analysis. This architecture consists of the following subsystems as outlined by [39, 38].

Step #1: Detection of the human subject.

The first step for an automated marker-less motion capture system is to detect moving objects such as people or vehicles in the scene.

This is achieved by various motion segmentation methods such as 1) Background subtraction 2) Optical flow 3) Temporal differencing and 4) Statistical Background Modeling [38].

Step #2: Tracking of the human subject

Tracking is the process of locating the positions of the person of interest in a video scene [40, 38]. This is achieved using the various attributes of an object such as velocity, color and texture [38]. There are three object tracking techniques as identified by [40, 38] 1) Point tracking, 2) Kernel tracking, 3) Silhouette based tracking.

Step #3: High-Level Feature Extraction

The next phase after tracking is feature extraction which is a process of estimating the set of measurements of high level features in this case the configuration of the whole body or the different body parts in a given scene and tracking them over a sequence of consecutive frames [39]. There are two approaches commonly used to extract features for human motion analysis, namely handcrafted representation-based approaches and Learning-based representation approach [41]. Handcrafted representation-based approaches are based on expert designed feature detectors and descriptors. Learning based approaches is a recently developed approach whereby the machine has the capability of learning features automatically from the raw data. This learning encompasses a set of methods that enable the machine to process the data in raw form. This eliminates the need of handcrafted feature detectors and descriptors [42].

Step #4: Classification Techniques

Classification is the final phase in a smart video processing model also referred to as identification or verification stage [39]. It is mainly a pattern classification problem which involves matching a test sequence with an unknown label against a group of labelled training set. Various pattern recognition methods can be employed in computer vision field; 1) Support Vector Machines (SVM) 2) K-Nearest Neighbor method (KNN) 3) Decision Tree 4) Artificial Neural Networks [43, 39].

2.5. Applications of Computer Vision Techniques in the field of Gait Analysis

Reference [37] indicates that the use of computer vision techniques is most suited for video surveillance applications where mounting markers or sensors on the subject may not be an option. Recent studies have proposed various applications of computer vision techniques in gait analysis which have achieved great success.

Reference [44] developed a computer vision and machine learning model to uniquely identify people (gait biometrics) . This model achieved over 99% correct recognition rate. Reference [45] developed a gait-Based Gender Classification for Video Surveillance Applications. The model achieved 91.6% female recall rate and 97.3 male recall rate with 94.5% overall accuracy rate. Reference [46] developed a model for age estimation using computer vision and gait analysis between young and elderly people. The model was able to achieve a 74.47% recognition rate with a good recall and precession for both young and elderly classes. In the medical field, computer vision has been used to detect normal vs abnormal patient gait and to detect Parkinson’s disease.

Reference [47] utilized computer vision techniques to detect gait abnormalities. Based on gait features, the system classified between the normal and abnormal test subjects with a classification rate of 85%. [48] Developed a computer vision-based system for the classification between 5 types of gait: normal, diplegic, hemiplegic, neuropathic and Parkinson’s. The model achieved 80% correct classification rate.

3. Conclusions

The use of Human CCTV operators to monitor video cameras has been shown to have certain limitations. Different authors reviewed concur that there is need for automated surveillance solutions to mitigate these challenges. This paper focused on the automated video surveillance for firearms concealed underneath a person’s clothing. Various authors have proposed the use of infrared and passive millimetre wave imagers. However, this paper found that the use of these techniques has the challenge that persons being scanned must be stationary and cooperative. This was viewed not to be ideal for real life surveillance. An effective system would be one where the persons being scanned would be unaware and not necessarily stationary.

Previous studies reviewed indicate that CCTV operators can accurately identify persons carrying firearms on their lower body and concealed underneath their clothing by the changes in their gait. This paper therefore finds that the automated analysis of gait is a promising technique for concealed firearm detection. The automated analysis of gait can be achieved by either using optical or non-optical techniques. This paper found that optical techniques are marker-less and therefore would be most ideal in real life surveillance. Marker-less techniques require the use of computer vision procedures.

4. Recommendations

Various authors reviewed in this paper have proposed applications of marker-less computer vision techniques for gait analysis. These applications have been found to have great success with over 85% classification and recognition rates. None was found in the area of concealed firearm detection. The detection of concealed firearms using computer vision and gait analysis would be a viable option since as discovered in the literature review, the use of these techniques in other applications have shown tremendous success and also that gait can be captured from a distance, without prior consent of the subject and gait also has the advantage that it is difficult to hide or fake as compared to other body languages such as facial expressions.

5. Limitations

Previous studies by [44] indicate that gait is a unique biometric. This creates an impact limitation since the computer vision models to be developed for concealed firearm detection will be specific to the study-population and may not be generalizable.

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