ANOMALY ACTIVITY CLASSIFICATION IN THE GROCERY STORES

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To my beloved father and mother

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ABSTRACT

Nowadays, because of the growing number of robberies in shopping malls and grocery stores, automatic camera's applications are vital necessities to detect anomalous actions. These events usually happen quickly and unexpectedly. Therefore, having a robust system which can classify anomalies in a real-time with minimum false alarms is required. Due to this needs, the main objective of this project is to classify anomalies which may happen in grocery stores. This objective is acquired by considering properties, such as; using one fixed camera in the store and the presence of at least one person in the camera view. The actions of human upper body are used to determine the anomalies. Articulated motion model is used as the basis of the anomalies classification design. In the design, the process starts with feature extraction and followed by target model establishment, tracking and action classification. The features such as color and image gradient built the template as the target model. Then, the models of different upper body parts are tracked during consecutive frames by the tracking method which is sum of square differences (SSD) combined with the Kalman filter as the predictor. The spatio-temporal information as the trajectory of limbs gained by tracking part is sent to proposed classification part. For classification, three different scenarios are studied: attacking cash machine, cashier's attacking and making the store messy. In implementing these scenarios, some events were introduced. These events are; basic (static) events which are the static objects in the scene, spatial events which are those actions depend on coordinates of body parts and spatio-temporal events in which these actions are tracked in consecutive frames. At last, if one of the scenarios happens, an anomalous action will be detected. The results show the robustness of the proposed methods which have the minimum false positive error of 7% for the cash machine attack and minimum false negative error of 19% for the cashier's attacking scenario.

ABSTRAK

Kini disebabkan peningkatan gejala kecurian di pusat-pusat membeli-belah dan pasaraya, aplikasi kamera automatik menjadi keperluan penting bagi mengesan aksi ganjil. Aksi-aksi tersebut sering berlaku dengan cepat dan tanpa diduga. Maka perlu diwujudkan satu sistem yang mantap yang berupaya mengklasifikasikan perkara yang mencurigakan dalam masa sebenar dengan kesilapan isyarat kecemasan minimum. Berpandukan isu ini, objektif utama projek ialah mengelaskan perbuatan pelik yang mungkin berlaku di pusat membeli-belah. Objektif dapat dicapai dengan mempertimbangkan beberapa perkara seperti menggunakan satu kamera tetap di pasaraya dan menempatkan sekurang-kurangnya seorang petugas pada paparan kamera. Disamping itu, aksi-aksi bahagian atas tubuh manusia digunakan untuk menentukan keganjilan. Model pergerakan yang jelas digunakan sebagai asas kepada reka bentuk klasifikasi keganjilan. Proses di dalam reka bentuk ini bermula dengan ekstrak ciri diikuti dengan penubuhan model sasaran, pengesanan dan pengelasan aksi. Beberapa ciri seperti warna dan kecerunan imej membina templat sebagai model sasaran. Kemudian, model-model anggota berlainan pada tubuh bahagian atas dikesan semasa kerangka yang diambil secara berturutan melalui kaedah pengesanan iaitu jumlah berlainan persegi (SSD) yang digabungkan dengan penapis Kalman sebagai peramal. Informasi *spatiotemporal* sebagai trajektori anggota yang didapati melalui pengesanan dihantar ke bahagian klasifikasi yang dicadangkan. Tiga senario berbeza dikaji untuk tujuan pengelasan: serangan pada mesin tunai, serangan pada juruwang dan perbuatan menyelerakkan pasaraya. Bagi melaksanakan kesemua senario, beberapa peristiwa diperkenalkan. Peristiwa-peristiwa ini ialah: peristiwa (statik) asas iaitu objek statik di tempat kejadian, peristiwa berkaitan ruang yang mana aksi-aksi berkaitan dengan koordinasi anggota badan dan peristiwa-peristiwa *spatiotemporal* iaitu kejadian yang dikesan pada kerangka berturutan. Akhirnya, jika mana-mana senario berlaku, satu perlakuan ganjil akan dikesan. Pelaksanaan senario tersebut dilaksanakan, diklasifikasikan keganjilan dan hasilnya menunjukkan kemantapan kaedah yang dicadangkan dengan kesilapan positif minimum 7% bagi serangan pada mesin tunai dan kesilapan negatif minimum 19% bagi senario serangan pada juruwang.

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CHAPTER 1

INTRODUCTION

1.1 Background of the study

Recently, it has been a crucial situation for law enforcement and security guard to recognize and monitor the suspicious activities (surveillance) due to increasing crimes (anomalies), especially in the shopping mall, grocery stores. Thus, the usage of surveillance cameras begun and human personnel are hired to monitor camera footage. But it is not reliable enough due to the human subjective nature where issues such as fatigue and careless happened. The analysis of footage is made easier by arriving automated video methods which automatically recognize human activity.

Recognizing human actions for classification anomalies from video is one of the most promising applications of computer vision [1]. For approaching to identify human actions, several methods are proposed by researchers which can be categorized as model-based [2, 3, 4, 5] and model-free [6, 7] approaches. In model-based (generative model) approaches, an initial human model is constructed for matching with the features extracted from consecutive frames to find pose estimation. On the other hand, model-free (discriminative model) approaches, investigate a direct relation between image observations and the pose estimation.

1.2 Problem statement

According to the uprising number of crimes (anomalies), the usage of security camera in variety areas, such as banks, airports, shopping malls, grocery stores, is increasing. Moreover, these anomalous actions usually happen quickly and unexpectedly, hence, surveillance needs a robust automated system which classifies suspicious action in a short period of time with considering the minimum false alarms. In this thesis the problems of classifying the anomalies in small stores like grocery stores are investigated. According to the size of stores and existence of cash machine the problems of classification need to be solved based on upper body parts, because the lower body parts are not visible in the scene.

1.3 Objective

The work in this thesis aims to address two important problems confronted in the anomaly classification. Furthermore, the algorithms are designed to achieve real-time performance.

- Tracking different upper body parts. The goal of tracking part is to find the trajectory of the interest states in which those states represent the location of different upper body parts like, wrists, elbows and shoulders in the consecutive frames.

- Anomaly classification. The second objective of this project is to classify anomalies which happen in the grocery stores. Variety actions may be done by customers when looking for some stuff in the grocery stores. These actions are classified as normal actions and abnormal actions (anomalies)

1.4 Scope

This research is about classifying actions happened inside the grocery stores; therefore the location is indoor place. As this work is contributed to small groceries, the usage of camera is limited to one fixed camera located behind of the cashier. Data gathering is performed by SLR Camera and the size of datasets is 240×320 pixels with the length of 30 to 100 seconds.

The number of people in the camera vision is restricted to presence of either cashier and customer or just customer. Because this project is focused on suspicious actions that occurred around counter and existence of the counter desk, the actions of upper body are investigated to classify anomalies.

In the case of actions, most of actions are normal, hence, finding the pattern for normal actions is impossible, however, anomalies can easily be defined by breaking normal conditions. Here, the scope of study is restricted to three common actions that can be classified as an anomaly. These actions are attacking to the cash machine; making the store messy and threatening cashier with gun.

1.5 Contributions

This research contributes a real-time monocular upper body method for classifying anomaly in the grocery stores and can be developed for anomalies happen far from cash machine. Also, different contributions on the tracking and classification part can be drawn:

- One of the contribution of this study is to solve the problems of upper body tracking challenges such as cluttered background, occlusion, different object pose (translation, rotation and deformation) while proposing a method which fulfill the real-time aspect of the study.

- The second contribution aims to propose the classification methods based on tracked parts of upper body which classify the most common anomalies happen in the grocery stores such as attacking cash machine; cashier’s attacking and making the store messy. Moreover, this classification method gains the minimum false alarm.

1.6 Thesis outline

The rest of this thesis is organized as follows: Chapter 2 reviews various methods and approaches in the field of anomaly classification and tracking of moving objects in the computer vision applications, while the existing methods in the case of object detection is also provided. Chapter 3 describes the proposed framework which contains of target model establishment techniques, articulated motion model SSD Tracking and Kalman filter for the tracking part and implementation of classification method to fulfill the aim of classifying three different anomalies which are attacking cash machine, cashier threatened by gun and making messy, Chapter 4 describes the qualitative and quantitative results of proposed methods for the tracking and classification approaches and finally, conclusion and future work are presented in chapter 5.

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