THREE DIMENSIONAL INFORMATION ESTIMATION AND TRACKING FOR MOVING OBJECTS DETECTION USING TWO CAMERAS FRAMEWORK

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A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy (Electrical Engineering)

Faculty of Electrical Engineering
Universiti Teknologi Malaysia

MARCH 2015

Specially dedicated to *Mum and Dad*

I love you both.

ACKNOWLEDGEMENT

First and foremost, I would like to express my deepest gratitude to my supervisor Assoc. Prof. Syed Abdul Rahman for his continuous and immense support, financial aid, supervision, and encouragement for the entire duration of my study. I would also like to express my gratitude to Dr Musa for his constructive comments and suggestions during this research work.

Special indebtedness goes to my friends in Universiti Teknologi Malaysia (UTM), especially my colleagues at the CVVIP lab for their assistance, understanding, and moral support.

I wish to thank Ministry of Science, Technology and Environment (MOSTI), Ministry of Higher Education (MOHE), Research Management Centre (RMC) and UTM for financial supports and facilities.

Last but not least, I am also grateful to my family members for their support, patience, and continuous helps.

ABSTRACT

Calibration, matching and tracking are major concerns to obtain 3D information consisting of depth, direction and velocity. In finding depth, camera parameters and matched points are two necessary inputs. Depth, direction and matched points can be achieved accurately if cameras are well calibrated using manual traditional calibration. However, most of the manual traditional calibration methods are inconvenient to use because markers or real size of an object in the real world must be provided or known. Self-calibration can solve the traditional calibration limitation, but not on depth and matched points. Other approaches attempted to match corresponding object using 2D visual information without calibration, but they suffer low matching accuracy under huge perspective distortion. This research focuses on achieving 3D information using self-calibrated tracking system. In this system, matching and tracking are done under self-calibrated condition. There are three contributions introduced in this research to achieve the objectives. Firstly, orientation correction is introduced to obtain better relationship matrices for matching purpose during tracking. Secondly, after having relationship matrices another post-processing method, which is status based matching, is introduced for improving object matching result. This proposed matching algorithm is able to achieve almost 90% of matching rate. Depth is estimated after the status based matching. Thirdly, tracking is done based on x-y coordinates and the estimated depth under self-calibrated condition. Results show that the proposed self-calibrated tracking system successfully differentiates the location of objects even under occlusion in the field of view, and is able to determine the direction and the velocity of multiple moving objects.

ABSTRAK

Penentukuran, pemadanan dan pengesanan adalah faktor utama untuk mendapatkan maklumat 3D yang terdiri daripada kedalaman, arah dan halaju. Untuk mendapatkan kedalaman, parameter kamera dan pemadanan objek adalah dua input yang diperlukan. Kedalaman, arahan dan objek berpadan boleh dicapai dengan tepat jika kamera ditentukur dengan baik menggunakan penentukuran tradisional manual. Walau bagaimanapun, kebanyakan kaedah penentukuran tradisional manual adalah sukar untuk digunakan kerana penanda atau saiz sebenar sesuatu objek dalam dunia sebenar mesti disediakan atau dikenali. Penentukuran diri boleh menyelesaikan had penentukuran tradisional, tetapi tidak sesuai untuk memadankan objek. Cara-cara yang lain telah cuba untuk memadankan objek menggunakan maklumat visual 2D tanpa penentukuran, tetapi cara-cara itu mengalami ketepatan padanan yang rendah di bawah herotan perspektif yang besar. Kajian ini memberi tumpuan kepada pencapaian maklumat 3D di bawah penentukuran diri. Dalam sistem ini, pemadanan objek dan pengesanan dijalankan di bawah keadaan penentukuran diri. Tiga sumbangan diperkenalkan dalam kajian ini untuk mencapai objektif. Pertama, pembetulan orientasi diperkenalkan untuk mendapatkan matriks hubungan yang lebih baik untuk pemadanan objek semasa pengesanan. Kedua, selepas matriks hubungan satu lagi kaedah pasca-pemprosesan, pemadanan objek menggunakan status, diperkenalkan untuk meningkatkan pencapaian ketepatan. Algoritma yang dicadangkan mampu mencapai kadar sepadan hampir 90%. Kedalaman dianggarkan selepas pemadanan objek menggunakan status. Ketiga, pengesanan dilakukan berdasarkan koordinat *xy* dan kedalaman dianggarkan di bawah keadaan penentukuran diri. Keputusan menunjukkan bahawa sistem pengesanan yang dicadangkan berjaya membezakan lokasi objek walaupun dalam keadaan halangan dalam bidang pandangan, dan mampu untuk menentukan arah dan halaju objek bergerak.

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LIST OF ABBREVIATIONS

3D	-	3 Dimension
2D	-	2 Dimension
SURF	-	Speeded-Up Robust Feature
SIFT	-	Scale-Invariant Feature Transform
ASIFT	-	Affine Scale-Invariant Feature Transform
ASURF	-	Affine Speeded-Up Robust Feature
MSER	-	Maximal Stable Extremal Regions
IBR	-	Intensity extrema-based detector
EBR	-	Edge based detector
MM-SIFT	-	Multi-resolution MSERs and SIFT
SUSAN	-	Smallest Univalue Segment Assimilating Nucleus
FAST	-	Features from accelerated segment test
FAST-ER	-	Features from accelerated segment test-Enhanced repeatability
RANSAC	-	Random Sample Consensus
LMedS	-	Least Median of Squares
LTS	-	Least Trimmed Squares
MLESAC	-	Maximum Likelihood Estimation SAmple Consensus
EMD	-	Earth Movers Distance
MAP	-	Maximum A Posterior
HT	-	Hough Transform
OC	-	Orientation Correction

LIST OF SYMBOLS

π	-	Pi
$\leq$	-	Less-than or equal to
$\geq$	-	Greater than or equal to
$^{\circ}$	-	Degree

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Surveillance systems have been widely used especially in the security fields such as access control in restricted areas, person-specific identification, anomaly detection, and for alarm systems [1]. This system can detect, monitor, and also analyse moving object behaviour in the field of view even under occlusive conditions. In addition, the object's velocity and direction can also be estimated easily for applications such as crime prevention and traffic incident detection. Today's surveillance system can be found everywhere in the cities, either in indoors or outdoors such as shopping centres, banks, outdoor car park areas, airports, or even in the streets. Since early 1980s, surveillance systems have been installed widely in public spaces for crime prevention in developed countries such as UK, USA and Australia. In Malaysia, the first surveillance camera was installed in 1966 [2]. In 1993, a directive was issued by the government to install surveillance cameras in all the car parks of public buildings [2]. In following years, the Ministry of Housing and Local Government initiated a Safe City Programme to install CCTV cameras for crime prevention in Kuala Lumpur (KL) under Strategy 2 of Target Hardening[2]. According to Malaysian Communications and Multimedia Commission (MCMC) report, snatch-theft cases dropped by 50% in Kuala Lumpur after the installation [2]. In 2012, Automatic Enforcement System (AES) was introduced to detect speeding vehicles and record traffic offenders [3].

1.2 Problem Statement

Generally, surveillance systems are used in recognizing objects, tracking objects from different views, and identifying 3D information of objects. Surveillance systems may come with a single camera or more. The multiple camera systems normally involve several cameras positioned at different angles looking at certain overlapping areas. Some systems can only provide 2D space information (x-y coordinates) and thus not capable to provide 3D information of an object. The system is further upgraded during research growth in these years. For many surveillance applications, 3D information, i.e. depth, direction, and velocity are important parameters [4] (such as location detection or crowd behaviour detection). As a consequence, much recent research has been focused on tracking using the 3D location of the targeted objects [5-8]. By using 3D information, more accurate results can be obtained and at the same time occlusion problems can be solved. In order to extract 3D information, calibration, matching and tracking are the major concern in the surveillance system and much research have been conducted to improve the traditional system.

The key to the acquiring 3D information is calibration. 3D information can only be estimated accurately if all cameras are calibrated (i.e. Intrinsic and extrinsic parameters of the camera are extracted) from which the 3D space or world coordinates can be computed. Some methods use single camera calibration, while others use multi camera calibration. Calibration techniques can be grouped into either traditional calibration or self-calibration. In traditional calibration, both intrinsic and extrinsic parameters are extracted. The relationship between world coordinates and pixel coordinates is established from the parameters. The corresponding object can then be matched easily even under large perspective distortion since in the traditional calibration, all cameras are connected with a single world coordinate system. Likewise, spatial matching using alignment can be done easily under the traditional calibration. However, most of the traditional calibration techniques are very inconvenient to use because manual labelling and the size of the object in the real world are needed as inputs. To overcome this limitation, a self-

calibration technique has been developed. This process depends only on images captured by the camera using image 2D space *x-y* coordinates. However, the currently available self-calibration is only able to estimate the intrinsic parameters such as the focal length and the performance can still be improved. Since the extrinsic parameters cannot be extracted, 3D information cannot be found and the spatio-temporal feature between cameras cannot be matched.

There are several methods commonly used in matching corresponding objects in 2D space based on visual information without using any calibration or self-calibration [9-12]. However, these state-of-the-art techniques lack matching accuracy under large perspective distortion. Some researchers introduced a method to match the object in 2D space with large perspective distortion, but this requires longitude and latitude values as input, which can only be determined experimentally and inconveniently [13, 14]. Some other methods have been introduced using spatial information for matching. However, these methods require traditional calibration or manually selected matched points as input [15, 16]. Overall, corresponding identified objects from different views and intrinsic parameters are necessary inputs to estimate the depth of the object. In estimating the depth of the objects based on multiple images only from different views with large perspective distortion without using complex calibration, feature matching between cameras is essentially important

A more accurate tracking can be performed higher with the presence of 3D information [5-8]. Previous work shows that 3D tracker can yield 50% less error compared to 2D tracker [6]. However, most current surveillance systems are not able to estimate the 3D information of the moving object without traditional calibration. Thus, a 3D surveillance tracking method that estimates the depth, direction and velocity of the moving object based on self-calibration approach is equally important. Additionally, such a system requires a good matching method under large perspective distortion to determine the depth, direction and velocity.

Therefore, a system that is able to estimate distances of moving objects from the camera using self-calibration and feature matching should be addressed. This system should be able to find the corresponding objects from multiple scenes without any traditional calibration. Also, this system should be able to estimate directions and velocities of the moving objects based on videos.

1.3 Research Objectives

Based on the problem statement, the aims of this research are given as follows:

i. To estimate 3D information which is the depth of moving object based on 2D matching and self-calibration.
ii. To track and to estimate directions and velocities of multiple moving objects based on the estimated 3D information.

1.4 Research Scopes and Assumptions

Many researchers focus on different aspects of surveillance. In this thesis, the focus is in calibration, matching and tracking. Therefore, several scopes and assumptions have been established for this research.

1.4.1 Scopes

- The focus is on the tracking of multiple moving objects (human and vehicles)
- Two static cameras are used.

- At least 50% overlapping region of images in multiple cameras are considered.
- The 3D information considered are depth, direction and velocity.

1.4.2 Assumptions

- All the cameras are assumed to be located vertically above the moving objects.
- Baseline of cameras is assumed to be known.
- The system should be based only on the video frame without knowing any real world information such as the real size of the objects.

1.5 Research Contributions

To extract 3D information, focal length and corresponding points are needed. Based on these two key points, the contributions of this research are as follows:

i. The tracking system is established based on the *x-y* coordinates and estimated depth using linear prediction that can solve the occlusion problem. In this, the locations of multiple moving objects can be distinguished even if there is occlusion. Directions of the moving objects are estimated by comparing the ratio of left and right depth value while the velocity is estimated based on 2D *x-y* coordinates and estimated depths.

ii. A depth estimation system is developed based on a new corresponding points matching algorithm and an object matching process during tracking. The new algorithm is established by combining rectification, speeded-up robust feature (SURF),

orientation correction, epipolar geometry, and also status based matching so that the matched objects can be found even under large perspective distortion. Depth is estimated from the matched objects with self-calibration.

iii. An orientation correction method is proposed to increase the number of correct matched points between two images during interest point matching. This algorithm is established based on the relative rotational angle between two images.

1.6 Research Methodology

To find the depth in the uncalibrated or self-calibrated condition, this research assumes that all cameras are on the same baseline, i.e. the distance between two cameras at the same level of position. Before the depth can be estimated, the relationship between each camera must also be established for the purpose of finding a corresponding object. To find the corresponding objects, the system must be able to overcome the affine transformation problem. The following is the flow of proposed system of this research:

- Images from different views must be rectified to become undistorted images. If the affine transform no longer exists in the image, the matching between images can be obtained.

- SURF is used to find the corresponding points between images. Since better matched points can produce a better fundamental matrix, orientation correction is introduced in this thesis to increase the number of correctly matched points. The orientation correction is computed based on the hypothesis that all features are rotated at the same angle.

- With a set of correctly matched points which is evenly distributed on the entire image, fundamental matrix can be generated for computing depth.

Since the depth can only be estimated if all cameras are on the same baseline, both images must be aligned so that they are on the same view plane.

- After the fundamental matrix is established and the images are aligned, the 3D information depth can be estimated with the presence of focal length from self-calibration using vanishing points.
- The object is tracked using 2D + depth linear prediction along with the estimated 3D information, and in this way the direction and velocity can be estimated.

1.7 Structure of Thesis

This thesis is organized as follows: Chapter One presents the introduction. Chapter Two discusses all the literature reviews related to the surveillance system. State-of-the-art techniques for all stages in the surveillance are discussed in this chapter. Chapter Three highlights the details of all the stages of the proposed technique. The experimental results based on the matching and tracking on the standard datasets are presented in Chapter Four. Last but not least, Chapter Five concludes the thesis along with suggestions for future work.

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