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I hereby declare that I have checked this thesis and in my opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Doctor of Philosophy (Electrical Engineering).

____

(Supervisor's Signature)

Full Name : Ir. Dr. Kamarul Hawari bin Ghazali

Position : Professor

Date : 3 July 2017

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____

(Student's Signature)

Full Name : Wan Nur Azhani bt. W.Samsudin

ID Number : PEE 11007

Date : 3 July 2017

IMPROVED ABNORMAL DETECTION USING SELF-ADAPTIVE SOCIAL FORCE MODEL FOR VISUAL SURVEILLANCE

WAN NUR AZHANI BT. W.SAMSUDIN

Thesis submitted in fulfillment of the requirements
for the award of the degree of
Doctor of Philosophy (Electrical Engineering)

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To Mohd Harizan Zul, Muhammad Imran Danial, Nur Sarah Safiyya, beloved parents, and family.

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TABLE OF CONTENTS

DECLARATION		
TITLE PAGE		
ACKNOWLEDGEMENTS		**iii**
ABSTRAK		**iv**
ABSTRACT		**v**
TABLE OF CONTENTS		**vi**
LIST OF TABLES		**ix**
LIST OF FIGURES		**x**
LIST OF SYMBOLS		**xiii**
LIST OF ABBREVIATIONS		**xvii**
CHAPTER 1 INTRODUCTION		**1**
1.1	Background of Study	1
1.2	Problem Statements	4
1.3	Objectives	6
1.4	Scope of Works	6
1.5	Thesis Overview	10
CHAPTER 2 LITERATURE REVIEW		**11**
2.1	Introduction	11
2.2	Crowd Understanding	11
2.3	Crowd Analysis	12
2.4	Applications of Crowd Analysis	16
2.5	Abnormal Behavior Detection in Visual Surveillance	19
	2.5.1 Global Anomaly Detection	20

	2.5.2	Local Anomaly Detection	21
2.6	Data Acquisition for Surveillance		23
2.7	Image Pre-Processing in Visual Surveillance		24
	2.7.1	Motion Detection using Optical Flow	25
	2.7.2	Particle Advection	32
2.8	Image Processing in Visual Surveillance		33
	2.8.1	Social Force Model	34
	2.8.2	Classification Methods in Past Research	40
2.9	Summary		41
CHAPTER 3 METHODOLOGY			**43**
3.1	Introduction		43
3.2	Data Acquisition		46
	3.2.1	UMN Dataset	46
	3.2.2	PETS2009 Dataset	46
	3.2.3	Malaysia Crime Dataset	47
3.3	Image Pre-Processing		49
	3.3.1	Optical Flow-based Motion Detector	50
	3.3.2	Particle Advection based on Linear Interpolation	54
3.4	Image Processing		58
	3.4.1	Feature Extraction using SFM	59
	3.4.2	Feature Extraction using Self-Adaptive SFM	64
	3.4.3	Decision	67
3.5	Summary		72

CHAPTER 4 RESULT AND DISCUSSION **73**

4.1 Introduction 73

4.2 Comparison between Different Methods in Abnormal Detection 76

4.2.1 Abnormal Detection using Optical Flow 76

4.2.2 Abnormal Detection using Social Force Model 83

4.2.3 Abnormal Detection using Self-Adaptive SFM 90

4.3 Performance Evaluation on Benchmarking Datasets 102

4.3.1 Performance Evaluation on UMN Dataset 102

4.3.2 Performance Evaluation on PETS2009 Dataset 105

4.3.3 Performance Evaluation on Malaysia Crime Dataset 109

4.4 Abnormality Localization in Crowd Scene 114

4.5 Summary 116

CHAPTER 5 CONCLUSION **117**

5.1 Review of Findings 117

5.2 Summary of Contributions 119

5.2.1 An algorithm based on SFM theory 119

5.2.2 A New Framework for Surveillance Application 119

5.3 Future Research Enhancement 119

REFERENCES **121**

APPENDICES **134**

A LIST OF PUBLICATIONS **134**

B GRID SIZE OPTIMIZATION **135**

C VALIDATION RESULTS FOR EACH DATASET **136**

LIST OF TABLES

Table 2.1	Some of the crimes occurred in Malaysia.	13
Table 2.3	The gaps between past researches.	42
Table 3.1	Particles' coordinates before and after particle advection.	58
Table 4.1	Confusion matrix.	75
Table 4.2	Quantitative result of abnormal detection for indoor scene using Horn-Schunck optical flow.	78
Table 4.3	Quantitative result of detection using Horn Schunck optical flow on outdoor scene.	81
Table 4.4	Quantitative result of detection using SFM for an indoor scene.	85
Table 4.5	Quantitative result of abnormal detection using SFM on outdoor scene.	88
Table 4.6	Quantitative result of detection using proposed algorithm on indoor scene.	94
Table 4.7	Quantitative result of abnormal detection using proposed algorithm on outdoor scene.	100
Table 4.8	Performance of proposed method on UMN dataset.	105
Table 4.9	Performance of proposed method on the PETS2009 dataset.	108
Table 4.10	Performance of proposed method on Malaysia Crime dataset.	111
Table 4.11	Accuracy of detection using proposed framework.	112
Table 4.12	Result of comparison for different methods using random dataset.	112

LIST OF FIGURES

Figure 1.1	Visual surveillance system.	2
Figure 1.2	Area of study.	9
Figure 2.1	(a) Structured scene. (b) Unstructured scene.	12
Figure 2.2	Framework for crowd analysis.	16
Figure 2.3	Applications of crowd analysis.	17
Figure 2.4	General framework of visual surveillance.	19
Figure 2.5	CCTV control room in Malaysia; where the ratio of the camera to the operator is low.	24
Figure 2.6	The optical flow at the point is the 2D-velocity vector.	26
Figure 2.7	The motion constraint line.	28
Figure 2.8	The aperture problem: We cannot tell in which way the line is moving with only those 2 frames.	29
Figure 3.1	Flow of research methodology.	43
Figure 3.2	Research framework.	45
Figure 3.3	Some of videos used in performance evaluations.	48
Figure 3.4	Optimization of data acquisition.	49
Figure 3.5	Comparison of optical flow performances for Malaysia Crime dataset.	51
Figure 3.6	Comparison of optical flow performances for UMN dataset.	52
Figure 3.7	Comparison of optical flow performances for PETS2009 dataset.	52
Figure 3.8	(a) Weighted flow field using a Gaussian filter. (b) Flow field without a filter. (c) Field vectors after filtered. (d) Field vectors before filter.	54
Figure 3.9	Grid size calibration for proposed research framework.	55
Figure 3.10	(a) Initialized particles (b) Particles being advected to new locations.	56
Figure 3.11	Particles advected to a new location. (a) Six particles in the current location. (b) Six particles moved to new location.	58
Figure 3.12	A particle is described by a velocity vector $\vec{V_i}$, a vector pointing towards the target (desired direction) $\vec{e_i}$ and a radius R_i .	60

Figure 3.13	The forces acting on a particle *i*, is the interaction force from particle *j*, $j(\overrightarrow{f_{ij}})$, the repulsive force from the wall $w(\overrightarrow{f_{iW}})$ and the force towards the target $\overrightarrow{f_i^d}$.	60
Figure 3.14	Flowchart for adaptive thresholding.	69
Figure 3.15	Accuracy of using fixed thresholding and adaptive thresholding method.	70
Figure 3.16	Significant interaction forces limit by adaptive thresholding.	71
Figure 4.1	ROC curve.	74
Figure 4.2	Plot of abnormal detection using optical flow for an indoor scene.	77
Figure 4.3	Detection results using Horn-Schunck optical flow for indoor scene.	78
Figure 4.4	Plot of abnormal detection using optical flow for an outdoor scene.	80
Figure 4.5	(a) Detection results using Horn-Schunck optical flow for outdoor scene. (b) Results after compared with ground truth.	81
Figure 4.6	Plot of interaction force using SFM on the indoor scene.	84
Figure 4.7	Plot of velocity similarity problem for an indoor scene.	86
Figure 4.8	Plot of interaction force using SFM on outdoor scene.	87
Figure 4.9	(a) Detection results using SFM. (b) Results after compared with ground truth.	88
Figure 4.10	Plot of velocity similarity problem for an outdoor scene.	90
Figure 4.11	Particles with its respective interaction forces.	91
Figure 4.12	Significant interaction force for each frame on the indoor scene.	92
Figure 4.13	Detection results using adaptive thresholding for an indoor scene. (a) and (b): Detection for normal frames. (c) and (d): Abnormality detected in the scene.	93
Figure 4.14	Qualitative result for abnormality detection for an indoor scene.	94
Figure 4.15	Comparison of optical flow, SFM and Self-adaptive SFM for an indoor scene.	96
Figure 4.16	Interaction forces for the corresponding particles.	97
Figure 4.17	Significant interaction forces for each frame in an outdoor scene.	97
Figure 4.18	Detection results using adaptive thresholding for an outdoor scene. (a) and (b): Detection for normal frames. (c) and (d): Abnormality detected in the scene.	98
Figure 4.19	Qualitative result of abnormal detection for an outdoor scene.	99

Figure 4.20	(a) Detection results using proposed algorithm. (b) Results after compared with ground truth.	100
Figure 4.21	Comparison of optical flow, SFM and Self-Adaptive SFM for an outdoor scene.	102
Figure 4.22	Experiment on UMN dataset Clip 1.	103
Figure 4.23	Experiment on UMN dataset Clip 2.	104
Figure 4.24	ROC curve of abnormal detection of UMN dataset.	104
Figure 4.25	Experiment on PETS2009 dataset Clip 1.	106
Figure 4.26	Experiment on PETS2009 dataset Clip 2.	107
Figure 4.27	ROC curve of abnormal detection of the PETS2009 dataset.	108
Figure 4.28	Experiment on Malaysia Crime dataset Clip 1.	109
Figure 4.29	Experiment on Malaysia Crime dataset Clip 2.	110
Figure 4.30	ROC curve of abnormal detection on Malaysia Crime dataset.	111
Figure 4.31	Accuracy percentage for all three methods.	113
Figure 4.32	Accuracy, recall and precision for detection using proposed algorithm.	114
Figure 4.33	(a) Region with high magnitude of interaction forces in the indoor scene. (b) Plot of interaction forces for an indoor scene.	114
Figure 4.34	(a) Region with high magnitude of interaction forces in an outdoor scene. (b) Plot of interaction forces of an outdoor scene.	115

LIST OF SYMBOLS

v_i^q	replaced personal desire velocity
v_i^p	desire velocity
v_i^c	average velocity of neighboring individual
τ	relaxation time
$\overrightarrow{f_i^d}$	desired movement force
f_{ij}^{body}	body force
v_i	actual velocity of particle i
κ	large constant determines strength of normal and tangential elastic
k	large constant determines strength of normal and tangential elastic
v_i^0	initial desired velocity of particle i
∂I	image intensity derivatives
Δv_{ji}^t	tangential velocity difference
t_{ij}	tangential direction
d_{ij}	distance between particle i and j
F_{sig}	significant interaction force
∂x	image intensity derivatives of component x at $I(x,y,t)$
∂y	image intensity derivatives of component y at $I(x,y,t)$
∂t	image intensity derivatives of component t at $I(x,y,t)$
$v_{F_{\mathrm{int}}}$	variance of interaction force
t_{iW}	direction tangential to wall
η_{iW}	direction perpendicular to wall
$>$	greater than
d	data measurement
$<$	smaller than
Δt	change of time
Δx	change of x
Δy	change of y

$\sqrt{\ }$	square root
$\int$	integral
$\sum$	sum
A_i	control parameter for interaction strength
B_i	control parameter for the range of repulsive interaction
dI	derivative of gradient intensity
dt	derivative of time
dv_i	derivative of actual velocity
dx	derivative of x
dy	derivative of y
e_i	desired direction
F_a	actual force
F_{int}	interaction force
F_p	personal desire force
F_{ped}	repulsive force
f_{ij}^{slid}	sliding friction force
ρ	estimator
θ	theta
σ	scale parameter
D	image domain
f_α	resulting force
f_{ij}	interaction force between particle i and j
f_{iW}	repulsive force from wall w
d_{iW}	distance to wall
I	gradient intensity
I_x	gradient intensity respects to x
I_y	gradient intensity respects to y
I_t	gradient intensity respects to t
i	individual i

j	individual j
m_1	mean of class 1
m_2	mean of class 2
m_i	mass of individual
$O(x_i, y_i)$	optical flow at coordinate (x_i, y_i)
O_{ave}	spatio-temporal average of optical flow
p_i	panic weight
r_i	radius of particle i
r_j	radius of particle j
t	time
$\overrightarrow{\nabla I}$	intensity spatial gradient
u, v	flow velocity in optical flow
$u_{current}$	current value of u
$v_{current}$	current value of v
Ω	neighborhood of pixels
v_1	variance for class 1
v_2	variance for class 2
v_i	velocity of individual
λ	magnitude that reflects relative influence of smoothness term
x	horizontal value in a pair of coordinates
X_{new}	current value of x
$X_{previous}$	former value of x
y	vertical value in a pair of coordinates
Y_{new}	current value of y
$Y_{previous}$	former value of y
$\overline{F_{\text{int}}}$	mean of interaction force
$W(x, y)$	weights allocated to individual pixels in Ω
ρ_{HS}	minimization error
$(d_s - u(s;a))$	residual errors

dr_i	the change of position
η_{ij}	normalized vector pointing from j to i
R_{ij}	sum of radii i and j
v_i	velocity of i
v_j	velocity of j
n	number of frames
$\vec{v}$	velocity field

LIST OF ABBREVIATIONS

.avi	video file format
2D	two-dimensional
3D	three-dimensional
ACC	accuracy
AUC	area under curve
AUV	Autonomous underwater vehicle
BOW	bag of words
CCTV	closed-circuit television
Eq.	equation
FN	false negative
FNR	false negative rate
FP	false positive
FPR	false positive rate
FTLE	Finite-time Lyapunov Exponent
GMM	Gaussian mixture models
HMM	Hidden Markov Model
HOF	Histogram of Optical Flow
HOG	Histogram of Oriented Gradients
HOP	Histogram of Oriented Pressure
HOSF	Histogram of Oriented Social Force
KLT	Kanade-Lucas tracker
LBP	Local Binary Pattern
LDA	Latent Dirichlet Allocation
LRT	light rail transit
LTA	Linear Trajectory Avoidance
MBH	Motion Boundary Histogram
MLM	Manifold Learning Model
MRF	Markov Random Fields
MRI	magnetic resonance imaging
OF	optical flow
OFCE	optical flow constraint equation

PCA	Principal Component Analysis
PCA	Principal Component Analysis
Prx	proximity
PSO	Particle Swarm Optimization
PSO-SFM	Particle Swarm Optimization-Social Force Model
RANSAC	RANdom SAmple Consensus
ROC	receiver operating characteristics
SAFM	Social-attribute Aware Force Model
SFM	Social Force Model
SFSO	Social Force Swarm Optimization
SIFT	Scale Invariant Feature Transform
STC	Sparse Topical Coding
STCOG	Spatial Temporal Co-occurrence Gaussian Mixture Model
SVM	Support Vector Machine
TN	true negative
TNR	true negative rate
TP	true positive
TPR	true positive rate
UMN	University of Minnesota
UMP	Universiti Malaysia Pahang

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ABSTRAK

Perkembangan teknologi di dalam bidang visi komputer menyebabkan permintaan yang tinggi terhadap sistem pengawasan automatik bagi menggantikan pengawasan visual secara tradisional. Sistem pengawasan automatik merupakan salah satu sistem yang digunakan untuk memantau tingkah laku dan aktiviti orang awam sama ada normal ataupun tidak. Pengesanan tingkah laku yang tidak normal di khalayak ramai secara automatik adalah satu topik penyelidikan yang perlu diberikan perhatian, terutamanya di tempat-tempat awam. Sistem ini sangat penting untuk mengesan aktiviti yang tidak normal secepat mungkin dan mengambil tindakan yang sewajarnya bagi memastikan keselamatan orang awam dan seterusnya dapat mengurangkan kerugian yang dialami. Tujuan utama penyelidikan ini dijalankan adalah untuk mencari daya interaksi yang sangat penting dalam mengesan ketidaknormalan di khalayak ramai dengan menggunakan kaedah '*Self-Adaptive Social Force Model*'. Untuk menjayakan kerja penyelidikan ini, kaedah aliran optik '*Horn-Schunck*' diguna untuk mendapatkan vektor bagi aliran optik tersebut bagi setiap piksel di dalam imej. Untuk mengelakkan masalah dalam menjejaki setiap individu, alir zarah secara lintang dilakukan untuk menjejaki kesinambungan aliran orang ramai dan trajektori itu. Zarah-zarah ini kemudiannya digerakkan ke lokasi baru berpandukan vektor aliran optik bagi setiap zarah tersebut di kedudukan terkini. Dengan menggunakan vektor aliran yang diperolehi pada peringkat ini, daya interaksi dianggarkan berdasarkan teori '*Social Force Model (SFM)*'. Eksperimen ini dijalankan dengan hipotesis bahawa daya interaksi yang bermagnitud tinggi menggambarkan tingkah laku yang tidak normal di khalayak ramai. Walau bagaimanapun, terdapat satu masalah dengan kaedah '*SFM*' yang dijalankan oleh pengkaji terdahulu, iaitu masalah persamaaan antara halaju sebenar dan halaju yang dikehendaki yang disebabkan oleh pengesanan yang tidak tepat. Anggaran daya interaksi yang berkualiti adalah sangat penting di dalam kes ini dan masih belum diterokai lagi. '*Self-Adaptive Social Force Model*' dibangunkan untuk mencari daya interaksi yang terbaik kerana ia adalah penting untuk mengesan ketidaknormalan dengan lebih tepat menggambarkan tingkah laku orang ramai. Daripada eksperimen yang dijalankan, lokasi berlakunya ketidaknormalan di dalam imej boleh dikenalpasti berdasarkan magnitud daya interaksi yang tinggi bagi zarah tersebut. Algoritma yang diusulkan diuji dengan tiga set data yang mencabar dan mengandungi video yang tidak normal termasuk video jenayah yang berlaku di Malaysia. Algoritma ini juga diuji dengan dua persekitaran yang berbeza, iaitu dalaman dan luaran. Prestasi algoritma ini adalah tertinggi berbanding dengan kaedah lain, iaitu dengan peratus 97 dan 100. Selain itu, set data penanda aras juga digunakan untuk menilai prestasi algoritma yang diusul. Untuk set data yang pertama iaitu *UMN*, nilai di bawah graf, '*AUC*' dikira dan keputusan menunjukkan nilai untuk '*Self-Adaptive Social Force Model*' agak setanding dengan kerja penyelidikan yang sebelumnya dengan skor 0.9916.Untuk set data *PETS2009*, skor '*AUC*' adalah 0.9026 dan 0.9940 untuk set data jenayah Malaysia. Kesimpulannya, daya interaksi yang tinggi menggambarkan ketidaknormalan di suatu tempat kejadian dan algoritma '*Self-Adaptive Social Force Model*' adalah sesuai untuk diimplementasikan di tempat yang mempunyai kebarangkalian yang tinggi untuk berlakunya jenayah agresif.

ABSTRACT

With the growth of technology in computer vision, there is a great demand for an automated surveillance system in replaced to the traditional visual surveillance. The automated surveillance system is a system that monitors the behavior and activities of the crowd whether it is normal or not. The abnormal detection in a crowd is a noteworthy research topic in automated surveillance system in public places. It is emergent to detect the abnormal events as quickly as possible and take appropriate actions to minimize the loss and ensure the public safety. In this work, we aim to find the significant interaction forces and detect the abnormality in the crowd by using Self-Adaptive Social Force Model. For this point, Horn-Schunck optical flow is used to get the flow vector for each pixel in the image frames. Instead of tracking individuals, particle advection is performed to capture continuity of crowd flow and its trajectories. These particles are then advected to a new location according to its underlying optical flow vector at the current location. Using the attained flow vectors from this stage, interaction force estimation is done based on SFM theory. This experiment is done with the hypothesis that high magnitude of interaction force portrayed the abnormal behavior in a crowd. However, there is a problem with the earlier SFM, which is the similarity of actual velocity and desired velocity caused the abnormal detection inaccurate. The estimation of the good quality of interaction forces is critical in this case and has not been explored yet. So, Self-Adaptive SFM is developed in order to estimate a good quality of interaction forces since it is crucial to achieve better abnormal detection, which represents the behavior of the crowd. From the experiment, the highest and least magnitude of interaction force can be localized in the image frame. The proposed algorithm is validated with three challenging datasets contain abnormal videos, including the videos of crime in Malaysia. For both indoor and outdoor scene, the proposed algorithm outperforms the other methods with accuracy 97% and 100%. For the benchmarking datasets, the AUC (Area under Curve) score of the proposed algorithm is quite comparable with previous works with the score of 0.9916. The AUC score provided by the proposed algorithm on PETS2009 datasets is about 0.9026 and 0.9940 for Malaysia Crime dataset. Based on these results, it can conclude that the high magnitudes of interaction forces portray the abnormality in the scene and Self-Adaptive SFM is well-performed on crime scene with the rapid motion characteristic.

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