SINGLE SAMPLE FACE RECOGNITION USING A NETWORK OF SPIKING NEURONS

BY

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A thesis submitted in fulfilment of the requirement for the degree of Doctor of Philosophy (Engineering)

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MAY 2015

ABSTRACT

Conventional face recognition methods usually assume the possession of multiple samples per person (MSPP) available for classification. This assumption however, may not hold in many practical face recognition applications since only single sample per person (SSPP) is available for enrollment. The scarcity in numbers of training sample could deteriorate the reliability of many popular face recognition methods. Thus, in this thesis, a novel semi-supervised face recognition approach is proposed to address the SSPP problem by effectively extracting the inherent information in face image through local ensembles strategy. A Spiking Neural Network (SNN) based classifier called Coincidence Detection SNN (CD SNN) is proposed which identifies the synchronization between input spikes and at the same time employs the psychophysically-relevant feature selection through synaptic time constant prediction (τ_s Prediction) as bias for more accurate face classification. The CD SNN classifier is built on top an improved Zero-Order Spike Response Model (SRM_0), utilizing spike time approximation using the proposed Output Spike Time Prediction (OSTP) approach for faster computation. The classification is then performed on more efficient and compact image representations acquired through SNN Face Descriptor (SNN FD). Comparisons with several state-of-the arts methods using several popular face datasets reveal that the proposed method can achieve equivalent performance under SSPP constraints, and in fact on several occasions, delivers significantly better performance than existing methods. Additionally, through a survey, it is found that proposed method performs better than human in SSPP face recognition. Based on the same survey, assessment on the difference of feature selection between human and proposed method is also presented.

ملخّص البحث

طرق التعرف على الوجه التقليدية عادة ما تفترض امتلاك عدة عينات متاحة للتصنيف لكل شخص MSPP. غير أن هذا الافتراض قد لا يستخدم في العديد من التطبيقات العملية للتعرف على الوجوه بما إن عينة واحدة فقط لكل شخص SSPP متاحة للتسجيل. النقص في أعداد نماذج التجارب يمكن أن يؤثر سلبا بدقة العديد من طرق التعرف على الوجه الشائعة. وبالتالي في هذا البحث يُقترح طريقة مبتكرة شبه موجهه للتعرف علي الوجوه لمعالجة مشكلة العينة الواحدة المتاحة لكل شخص عن طريق استخراج فعال للمعومات الكامنة في صورة الوجه من خلال استراتيجية المجموعات المحلية. ويُقترح أيضا شبكة نتوءات عصبية SNN تستند إلي مصنف يسمي كاشف التطابق CD SNN والذي يحدد التزامن بين المدخلات البارزة وفي نفس الوقت يعمل علي إختيار الميزات النفسية الفيزيولوجية ذات الصلة تتعلق باللون والشكل من خلال تنبؤ الوقت المستمر Prediction τ_s لتشابك لخلايا كتحيز لتصنيف الوجه الأكثر دقة. هذا المصنِف CD SNN مبني علي أعلي نموذج مطور لكشف الفوارق الأوَّلي SRM_0، الاستفادة من تقريب الوقت الزمني للفروقات باستخدام طريقة التوقع الزمني للفوارق الناتجة المقترحة OSTP يعطي حسابات أسرع. من ثم يتم إجراء التصنيف علي بيانات صور مدمجة و أكثر كفاءة مكتسبة من خلال فروقات الخلايا العصبية الواصفة للوجه SNN FD. مقارنات مع العديد من أحدثا النظريات باستخدام عدة مجموعات بيانات شئعة للوجوه تكشف عن أن النظرية المقترحة يمكنها تحقيق أداء مكافيء تحت قيود عينة SSPP، وفي الواقع في عدة حالات يوفر أداء أفضل بكثير من النظريات الموجودة. بالإضافة إلى ذلك، من خلال الدراسة، تبين ان النظرية المقترحة تعطي أداء أفضل من الانسان في التعرف علي الوجوه من خلال عينة واحدة لكل شخص. واستنادا إلى نفس المسح، تم تقديم تقييم علي الاختلافات في إختيار الميزات بين البشر والنظرية المقدمة.

APPROVAL PAGE

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DECLARATION

I hereby declare that this thesis is the result of my own investigation, except where otherwise stated. I also declare that it has not been previously or concurrently submitted as a whole for any other degrees at IIUM or other institutions.

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……..……..…… ……..

Signature Date

This thesis is dedicated to my beloved mother, father, and wife for their continuous love, support and prayers

ACKNOWLEDGEMENTS

First of all, I would like to express my utmost heartfelt gratitude to the almighty Allah swt. for granting me the ability to successfully finish my doctoral thesis. My foremost appreciation goes to Assoc. Prof. Dr. Amir Akramin Shafie, my supervisor, for his academic guidance and many other supports throughout my doctoral study. This thesis could not have been successfully completed without his guidance, insightful instructions, and constructive criticism throughout my research. He is a model of teacher and a supervisor besides a perfect academic advisor. Over the years, I have learned from him not only effective research approaches and good study habits, but also academic writing and an optimistic, positive attitude. I also thank another supervisor of my doctoral research, Dr. Yasir M. Mustafah for his invaluable guidance towards completion of my thesis.

Special gratitude goes to respected Deputy Dean, Postgraduate and Research Prof. Erry Yulian Triblas Adesta, and Postgraduate coordinator, Assoc. Prof. Dr. Nahrul Khair Alang Md. Rashid for their comments and guidance from time to time which made me able to finish my thesis on time. Special thanks also go to Universiti Teknologi MARA (UiTM) especially to the Fakulti Kejuruteraan Elektrik (FKE) for awarding me the scholarship throughout my period of study. My doctoral study will not be completed without their assistances.

I would like to thank my doctoral thesis examiners, Prof. Dr. Dino Isa, Assoc. Prof. Dr. Hadzli Hashim, and Assoc. Prof. Dr. Nahrul Khair Alang Md. Rashid for their fruitful feedback and ideas. Their time, thoughts and opinions are instrumental vis-à-vis the accomplishment of my thesis.

I am also heavily indebted to my parents, Kamaru Zaman Bin Asli and Robiah Binti Embong, and my dearest wife, Wan Noraini Binti Wan Razab, as well as my beloved children, Umar Abdul Aziz and ‘Amrul Faateh for their continuous profound support and concern. My graduate studies would not have been possible without their support, and to my colleague Khairul Affendi, I am thankful for his co-operation and lending me helping hands during my study period. I am also deeply grateful to my other family members, friends and colleagues who either directly or indirectly helped me to accomplish my research successfully.

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LIST OF ABBREVIATIONS

2DPCA	Two-Dimensional Principal Component Analysis
ACO	Ant Colony Optimization
AHP	After-Hyperpolarization Potential
AI	Artificial Intelligence
ANN	Artificial Neural Network
APCA	Adaptive Principal Component Analysis
ARG	Attributed Relational Graph
BPDC	Backpropagation Decorrelation
CCA	Curvilinear Component Analysis
CCTV	Closed-Circuit Televisions
CD	Coincidence Detection
CD SNN	Coincidence Detection Spiking Neural Network
CN	Convolutional Network
CPU	Central Processing Unit
DF	Deformation of Face
DLR	Double Linear Regression
DMMA	Discriminative Multimanifold Analysis
DNA	Deoxyribonucleic Acid
DOF	Degree of Freedom
EBGM	Elastic Bunch Graph Matching
ELL	Electrosensory Lobe
EPSP	Excitatory Postsynaptic Potential
ESN	Echo State Network
ESRC	Extended Sparse Representation-Based classifier
FCU	Feature Computation Unit
FERET	Facial Recognition Technology
FG	Firing Region
FLD	Fisher's Linear Discriminant
fMRI	functional Magnetic Resonance Imaging
FPGA	Field-Programmable gate Array
FS	Feature Selection
GPU	Graphics Processing Unit
GW	Gabor Wavelets
ICA	Independent Component Analysis
IP	Intrinsic Plasticity
IPSP	Inhibitory Postsynaptic Potential
ISI	Inter-spike Interval
ISOMAP	Isometric Map
JAFFE	Japanese Female Facial Expression
KPCA	Kernel Principal Component Analysis
LBP	Local Binary Pattern
LDA	Linear Discriminant Analysis
LGBPHS	Local Gabor Binary Pattern Histogram Sequences
LIF	Leaky-Integrate-and-Fire
LLE	Locally Linear Embedding

LLS	Locally Lateral Subspace
LLV	Locally Lateral Vector
LMS	Least Mean Square
LP	Local Patch
LPP	Locality Preserving Projection
LR	Linear Regression
LSM	Liquid State Machine
LTD	Long-Term Depression
LTP	Long-Term Potentiation
MB	Megabytes
MDS	Multidimensional Scaling
MLP	Multilayer Perceptrons
MSE	Mean Squared Error
MSPP	Multi Samples per Person
NA	Not Available
NCF	Non-Coincidence Factor
NFG	Non-Firing Region
NMDA	N-methyl-D-aspartate
NN	Nearest Neighbor
ORL	Olivetti Research Laboratory
OSTP	Output Spike Time Prediction
PCA	Principal Component Analysis
PD	Pixel Descriptor
PDM	Partial Distance Measure
PSP	Postsynaptic Potential
PSTH	Peri-Stimulus-Time Histogram
RBF	Radial Basis Function
RC	Resistor-Capacitor
RM	Residual Membrane Potential
RN	Random Noise
RNN	Recurrent Neural Network
RO	Rank-Order
RO	Random Occlusion
SACO	Simple Ant Colony Optimization
SAPR	Synaptic Activity Plasticity Rule
SIFT	Scale-Invariant Feature Transform
SNN	Spiking Neural Network
SNN FD	Spiking Neural Network Face Descriptor
SOM	Self-Organizing Map
SPAN	Spike Pattern Association
SPDA	Sparsity Preserving Discriminant Analysis
SPP	Sparsity Preserving Projection
SRM	Spike Response Model
SRM_0	Zero-Order Spike Response Model
SS	Single Subspace
SSDR	Semi-Supervised Dimensionality Reduction
SSPP	Single Sample per Person
STDP	Spike-Time Dependent Plasticity
SVM	Support Vector Machine

TM	Template Matching
TTFS	Time to First Spike
UAV	Unmanned Autonomous Vehicle
VLSI	Very Large Scale Integration

CHAPTER ONE

INTRODUCTION

1.1 INTRODUCTION

There are several ways to recognize a person from another person. Face, fingerprint, DNA, gait and iris are among biometrics properties that are widely used for person recognition. However, face recognition is the leading approach due the non-expensive implementation and non-obtrusive nature of the image acquisition which is possible without active subject participation (Jain, 2007; Li, 2009). Even more so, the accuracy of face recognition in ideally controlled settings is equivalent to fingerprints and iris recognition (Phillips, Scruggs, O'Toole, Flynn, Bowyer, & Schott, 2006). However, in unconstrained environment, several factors such as illuminations, noise, variation in poses, facial expressions, occlusions and disguises were identified by previous researchers as contributing factors to degradation of face recognition performance (G. B. Huang, Ramesh, Berg, & Learned-Miller, 2007; Ruiz-del-Solar, Verschae, & Correa, 2009). Up until recently, a face recognition that can surpass human visual system ability in dealing with all those constraints is not yet available (Sinha, Balas, Ostrovsky, & Russell, 2006a).

As the recognition of faces in unconstrained settings are being studied and researched currently, the result of recognition is getting better. Even though it is not flawless, there are many real-world applications of face recognition have been developed in many areas such as entertainment, smart cards, information security, surveillance and law enforcement (Zhao, Chellappa, Rosenfeld, & Phillips, 2003). As