

HUMAN-MACHINE INTERACTION BY TRACKING HAND MOVEMENTS

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

School of Mechatronic Engineering UNIVERSITI MALAYSIA PERLIS

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Dedicated to my parents

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TABLE OF CONTENTS

THESIS DECLARATION	PAGE II
ACKNOWLEDGMENT	III
TABLE OF CONTENTS	V
LIST OF TABLES	XIV
LIST OF ABBREVIATIONS	XV
LIST OF SYMBOLS	XVII
ABSTRAK	XIX
ABSTRACT	XV XVII XIX XX
CHAPTER ONE: INTRODUCTION	1
1.1 Introduction to Human-Machine Interaction	1
1.2 Problem Statements	1
1.3 Research Objectives	3
1.4 Overview of The Thesis	5
Xe.	
CHAPTER TWO: LITERATURE REVIEW	6
2.1 Introduction	6
2.2 Video Capturing	6
2.3 Understanding Hand Gesture Recognition Systems	7
2.3.1 What are Hand Gestures?	7
2.3.2 Hand Gesture Recognition	7
2.3.3 Hand Gesture Recognition Systems' Categorie	es 8
2.4 Hand Gesture Recognition by Context	9
2.4.1 Communicational Hand Gestures	10

	2.4.2 Control and Manipulation Hand Gestures	10
	2.4.3 Interactive Hand Gestures	11
2.5	Hand Gesture Recognition by Technology	11
	2.5.1 Non-Vision-Based Hand Gesture Recognition	12
	2.5.1.1 Touch Technology	12
	2.5.1.2 Data-Gloves and Virtual Reality	12
	2.5.2 Vision-Based Hand Gesture Recognition	13
	2.5.2.1 Model-Based Approaches	14
	2.5.2.1 Model-Based Approaches 2.5.2.2 Hybrid-Based Approaches 2.5.2.3 Appearance-Based Approaches Visual Appearance-Based Approaches	15
	2.5.2.3 Appearance-Based Approaches	16
2.6.	Visual Appearance-Based Approaches	16
	2.6.1 Hand Tracking and Segmentation	17
	2.6.2 Feature Extraction and Representation	17
	2.6.2.1 Contour-Based Methods	18
	2.6.2.2 Area-Based Method	20
	2.6.2.3 Spatio-temporal methods	20
	2.6.3 Hand Gesture Detection	20
	2.6.4 Classification and Grammar Role	21
2.7	Hand Posture Recognition	21
2.8	The Hausdorff Distance under Rigid Motion	22
2.9	Summary	24
СН	PTER THREE: INVESTIGATIONS AND DEVELOPMENT OF HYBRID	
	TECHNIQUES FOR 3D OBJECTS RECOGNITION FROM 2D SILHOUETTE PATTERNS	25
3.1	Introduction	25
3.2	Related Works	29
3.3	Feature Extraction by Fourier's Descriptors	32

3.4	Contours of 3D Objects.	35
3.5	Preparation of the Data Sets for the Training of Neural Networks	38
3.6	Learning Procedures	39
3.7	Evaluation of the Learning Phase	42
3.8	Flowcharts Representing Used Algorithms	44
3.9	Proposed Algorithm; its Application and Results	48
	3.9.1 Proposed Algorithm for Recognition of 3D Objects	48
	3.9.2 Experimental Results	51
	3.9.2.1 Objects Recognition of Different Categories	51
	3.9.2.1 Objects Recognition of Same Category	53
	3.9.2.2 Application & Result of Recognition of Different Unknown Models of Air Planes	53
	3.9.2.3 Using BBNN and FD's System for Learning and Recognition of 3D Hand at Different Orientations.	55
3.10	Summary	58
CHA	APTER FOUR: HUMAN SKIN DETECTION, HAND TRACKING AND	
	GESTURE SEGMENTATION FOR HUMAN- MACHINE INTERACTION	61
4.1	Introduction	61
4.2	Hand Segmentation	63
4.3	Hand Tracking	64
4.4	State of Hand Gesture Recognition	64
4.5	Related Work	65
4.6	Hand Segmentation - Method 1	67
	4.6.1 Skin Pixel Classification	69
	4.6.2 Procedure	69
	4.6.3 Procedure Summary	70

	4.6.4 Connectivity Analysis	71
	4.6.5 Skin Detection Algorithm	72
4.7	Hand Segmentation - Method 2	74
	4.7.1 Skin Colour Modelling	75
	4.7.2 Connected Component Operators	77
	4.7.3 Example of a Connected Component Operator	78
4.8	Hand Tracking	80
	4.8.1 Hand tracking - Method 1	80
	Hand Tracking 4.8.1 Hand tracking - Method 1 4.8.2 Hand Tracking - Method 2 4.8.3 Tracking Procedure Application of Hand Segmentation Summary APTER FIVE: NEW MORPHOLOGY TECHNIQUE FOR 3D HAND	82
	4.8.3 Tracking Procedure	85
4.9	Application of Hand Segmentation	88
4.10	Summary	93
	9/07	
CHA	HIER FIVE. NEW MORIHOEOGI TECHNIQUE FOR 3D HAND	
CHA	APTER FIVE: NEW MORPHOLOGY TECHNIQUE FOR 3D HAND TRACKING AND ITS APPLICATION IN MANIPULATOR ROBOT	94
CH A	TRACKING AND ITS APPLICATION IN	94 94
	TRACKING AND ITS APPLICATION IN MANIPULATOR ROBOT	
5.1	TRACKING AND ITS APPLICATION IN MANIPULATOR ROBOT Introduction	94
5.15.2	TRACKING AND ITS APPLICATION IN MANIPULATOR ROBOT Introduction Related Works	94 96
5.15.25.3	TRACKING AND ITS APPLICATION IN MANIPULATOR ROBOT Introduction Related Works Hand Segmentation	94 96 106
5.1 5.2 5.3 5.4	TRACKING AND ITS APPLICATION IN MANIPULATOR ROBOT Introduction Related Works Hand Segmentation Extraction of Hand Features (Based on Morphology)	9496106112
5.1 5.2 5.3 5.4 5.5	TRACKING AND ITS APPLICATION IN MANIPULATOR ROBOT Introduction Related Works Hand Segmentation Extraction of Hand Features (Based on Morphology) Estimation of Hand Position	9496106112115
5.1 5.2 5.3 5.4 5.5 5.6	TRACKING AND ITS APPLICATION IN MANIPULATOR ROBOT Introduction Related Works Hand Segmentation Extraction of Hand Features (Based on Morphology) Estimation of Hand Position Deduction of 3D Hand Orientation	94 96 106 112 115 118
5.1 5.2 5.3 5.4 5.5 5.6 5.7	TRACKING AND ITS APPLICATION IN MANIPULATOR ROBOT Introduction Related Works Hand Segmentation Extraction of Hand Features (Based on Morphology) Estimation of Hand Position Deduction of 3D Hand Orientation Robotic Wrist Manipulation	9496106112115118124
5.1 5.2 5.3 5.4 5.5 5.6 5.7 5.8	TRACKING AND ITS APPLICATION IN MANIPULATOR ROBOT Introduction Related Works Hand Segmentation Extraction of Hand Features (Based on Morphology) Estimation of Hand Position Deduction of 3D Hand Orientation Robotic Wrist Manipulation Applications and Accuracy Graphical Accuracy Representation of Robot Manipulator Movements Related	94 96 106 112 115 118 124 127

5.10 Further Recognition of Hand and Fingers Movements Actions	131
5.9.1 Introduction	131
5.9.2 Mathematical Model Filter for Movements & Direction Detection	133
5.9.3 Hand Gesture Path Detections and Analysis	139
5.9.4 Recognition Method for Fingers and Hand Gestures Activity	142
5.9.5 Applications and Results for Hand and Fingers Movements Direction Detections	142
5.11 Obtained Results Comparison by Morphology and Hybrid FD's & BPNN Techniques	145
5.12 Summary	146
CHAPTER SIX: CONCLUSION & RECOMMENDATION	149
REFERENCES	153
INTERNATIONAL SCOPUS CONFERENCES	170
LIST OF ISI & SCOPUS PAPERS PUBLICATIONS	170
LIST OF AWARDS	172
.xe ^x	

LIST OF FIGURES

NO.		PAGE
2.1	The main three classes of hand gestures according to their context and application	9
2.2	Microsoft surface diagram.	12
2.3	Hand model of real hand scanned using a polhemus laser scanner.	15
2.4	Two examples of manually created models (a) is a 3D model, (b) is a 2D model.	15
2.5	Chain code representation.	19
2.6	Hand posture representation using signature method (a) with regular sampling step, (b) adaptive sampling step.	19
3.1	Views of a 3D object from different viewing angles (24 images are shown out of a total of $46,656 \times 106$).	26
3.2	Modes of 3D patterns in nature.	27
3.3	Reconstruction of "E" from a variable number of coefficients.	35
3.4	Objects used for the extraction of Fourier's coefficients.	36
3.5	The equally spaced extracted points from the contours of the objects.	36
3.6	Prototypes used in the learning set for the neural network.	38
3.7	Protocol for obtaining all the required rotated images with the simulated camera.	39
3.8	Local and global minima of the sse function from an epoch of the 5 HL network.	44
3. 9	Shows the flowchart of the simulated 3d objects algorithm.	45
3. 10	Flowchart of the learning steps algorithm	46
3.11	Flowchart of the generalisation steps algorithm	47
3.12	Block diagram of the complete system for learning, generalization and recognition.	49
3.13	Flowchart diagram of the complete system for learning, generalization and recognition.	50
3.14	Different models and views of cups.	51
3.15	Different models and views of unknown cars.	51

3.16	Different models and views of unknown airplanes.	51
3.17	Different models and partial views of unknown cars.	52
3.18	Different models and partial views of unknown airplanes.	52
3.19	Different models and partial views of unknown airplanes captured with a light intensity that was reduced by 20%.	52
3. 20	Three different prototypes of air planes	53
3. 21	Three models of unknown air planes	54
3.22	Shows the samples of 3D hands been used for learning	55
3.23	Show the learning progress with number of epochs using BPNN & FD's.	56
3.25	The system tested with known and unknown 3D hands.	57
4.1	Show hand gesture transitions that the user can carry out.	65
4.2	Gesture signs and valid gesture transitions.	88
4.3	Shows the blob contours found by the algorithm for different environment conditions where the system has been tested.	90
4.4	Shows a fault of hand segmentation mixed with face, (a) hand is far from face; (b) hand near to face; & (c) hand overlap to face.	90
4.5	Shows faults that detection of hand and face skins as one region when they are overlapped with non-skin regions	91
4. 6	Shows detection of maximum hand skins area indicating non-skin (blue circles) and lighter (yellow circle) colour regions.	91
4.7	Shows a hand been segmented and isolated from the other environments	92
5.1	Image progression of hand segmentation (a) original snapshot, (b) after conversion to grey scale, (c) filtered image, (d) after conversion to black and white, (e) after noise removal, and (f) after thinning.	110
5.2	Flowchart of hand segmentation, classification & recognition algorithm	11
5.3	Block diagram of hand segmentation, classification & recognition algorithm	112
5.4	Proposed reference point for hand tracking.	112
5.5	The image is separated into zones and the vertical position of the reference point lies on only one of these zones.	114

5.6	(a) Normal view of the hand (red spot indicates the reference point) (b) because the rotated hand gives a false premise for the reference point, its rotation is reversed to obtain a more accurate view of the width of the hand.	114
5.7	(a) Many features were extracted from the segmented human hand image, including height, length and position, and width (b) example of width measure.	115
5.8	The different x and y coordinates of the hand can be easily tracked examples are shown of the detection of (a) left hand side movement, (b) right hand up and side movements, (c) left hand backward movement, and (d) left hand side and backward movements.	116
5.9	Comparison of identification features after two successful hand registrations. Because the hand in (b) is half as long the hand in (a), the hand in (b) is twice as far away from the camera than in (a).	117
5.10	(a) Normal hand width, (b) when the maximum hand width increases significantly, the gripper hand state is changed from closed to open.	118
5.11	Rotation of the human hand about the z-axis (a) angle of rotation approximately 90°, (b) angle of rotation less that 90°, and (c) angle of rotation greater than 90°.	120
5.12	Differing hand widths correspond to rotations about the y-axis (a) no rotation (0°), (b) partial rotation, and (c) full rotation (90°).	122
5.13	Rotation about the x-axis, (a) original reference image (b) a reduction in the human hand length corresponds to an increase in the rotation angle.	123
5.14	Effect of a change in the intensity threshold to (a) 75, (b) 10, (c) 125 (default), (d) 15 and (e) 17.	123
5.15	Different human hand configurations (a) in the original registration, the hand width and length are determined and recorded (b) an increase in the y position, a decrease in the x position and a constant hand length and width (after image rotation) mean that there is no rotation about the x and y-axes and an increase in the rotation about the z-axis (c) an increase in the x position, a decrease in the y position, and a decrease in the hand width corresponds to no rotation about the x-axis and increased rotation about the z and y-axes.	123
5.16	Simulation of the configuration of a human hand with a robotic manipulator (a) original registered configuration, (b) rotation about	
	two angles, and (c) rotation and translation.	127
5. 17	Graphical representation of hmi & hand movements (right-left)	128
5. 18	Graphical representation of hmi & hand movements (up-down)	129

5.19	Graphical representation of hmi & hand movements (forwards & backwards) zooming effects.	129
5. 20	Graphical representation of hmi & hand movements (rotation about y & z axes)	129
5.21	Schematic diagram of the experimental setup of the teleguided manipulator robotic system over long distances.	130
5.22	Schematic diagram of the experimental setup of the computerized simulated manipulator system within one system.	131
5.23	Flow chart of the learning and generalization algorithm.	133
5.24	Collective video views showing of detected gesture and its movement directions; (a) shows normal video from the webcam, using standard normal webcam (b) shows detected hand gesture moving to the right, (c) shows detected hand gesture moving upwards, (d) show detected hand gesture moving down wards and opening fingers state);	136
5.25	Detailed views of hand gesture detections, direction and its speed; (a) representing hand gesture movement directions, black arrow direction represents gesture movement's direction (gmd) (colour changing from blue to red) and (b) representing the speed of the moving gesture, the width of the blue line indicating the speed, getting thicker means faster.	137
5.26	Collective gesture views of some hand and fingers states, direction of movement indicated by the arrow direction; (a) no movement; no gesture view, (b) fingers bending with their gestures detection, (c) hand movements with their gestures detection, (d) two fingers movements with their gestures detection, and (e) a hand grip movement with its gestures detection.	138
5.27	Hand gesture classification and recognition system.	143
5.28	Hand gesture detection classification and recognition system; (a) showing two fingers in a closing state with their rate of centre of gravity changes, (b) showing two fingers in a opening state with their rate of centre of gravity changes, (c) showing	144
	men rate of centre of gravity changes, (c) showing	144

LIST OF TABLES

NO. 3.1	Review of previous work on 3D pattern recognition.	PAGE 30
3.2	The influence of geometric transformations on FD's.	33
3.3	Invariant coefficients of the Fourier's descriptors for the airplane.	37
3.4	Invariant coefficients of the Fourier's descriptors for the car.	37
3.5	Invariant coefficients of the Fourier's descriptors for the cup.	37
3.6	Details of the learning phase of the back propagation neural network.	43
3. 7	Recognition results for three unknown airplanes using 4 hidden layers	54
3. 8	Recognition results for three unknown airplanes using 5 hidden layers	54
3. 9	Recognition results for six known and unknown hands using 3 hidden layers	57
4.1	Shows the various thresholds used in the algorithm.	74
5. 1	Literature review of hand gesture recognition.	97
5.2	DH parameters for the proposed simulated robotic manipulator links.	125
5.3	Results comparison by morphology and hybrid FD's & BPNN techniques	145

LIST OF ABBREVIATIONS

HMI Human-Machine Interaction

CNC Computer Numerical Controls

PCA Principal Component Analysis

PDM Point Distribution Model

MRI Magnetic Resonance Image

ID Identification

SIFT Scale Invariant Feature Transform

Centre of Mass CoM

HD Hausdorff Distance

riginal copyright Hausdorff Distance Under Rigid Motion M_{E}

Model-Matching Methods MMM

UPAO Unknown Partially Appeared Objects

LIL Low Intensity of Light

FD's Fourier's Descriptors

Neural Network NN

Back Propagation Neural Network BPNN /

 C_{m} Fourier's Series Coefficients

FFT Fast Fourier Transform

Q Number of Weights in Neural Network

SSE Sum of the Squared Errors

MCMomentum Constant

MER Maximum Error Ratio

LRI Learning Rate Increase

LRD Learning Rate Decrease HCI **Human-Computer Interaction**

HMM Hidden Markov Models

Gibbs Random Field **GRF**

HSV Hue, Saturation and Value

RGB Red, Green, Blue

SE Structuring Element

DH

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GMD

DFT

LIST OF SYMBOLS

V	Vector
T	Translation Factor
S	Scaling Factor
R	Rotational Matrix
b	Biases Matrix
θ	Biases Matrix Phase Angle Probability Density Function Fourier's Coefficient Delay of Time or Distance Covariance New Weight Matrix Old Weight Matrix
P	Probability Density Function
a_n	Fourier's Coefficient
τ	Delay of Time or Distance
C	Covariance
W ^{new}	New Weight Matrix
$\mathbf{W}^{\mathrm{old}}$	Old Weight Matrix
α	Learning Rate
δ	Difference Between Two Vectors / Change in Weight
$\nabla \mathbf{w}$	The Derivative of the Activation Function
μ_{s}	Mean Vector
$\Sigma_{ m s}$	Covariance Matrix
p	Conditional Probability
c	Chrominance Vector
<i>(</i> 0	Skin Probability Image

- R 2D Rotation Matrix
- Gradient Magnitude G
- L_p Distance from position
- Distance to the new position L_N
- ** Convolution Operator
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XVIII

Pergesanan Interaksi Manusia-Mesin Melalui Pergerakan Tangan

ABSTRAK

Pengesanan berasaskan pemerhatian pergerakan dan isyarat tangan merupakan satu masalah yang sangat mencabar kerana sifat rumit gerakan tangan, ini adalah mengapa algorithma pengesanan imej mempunyai pengiraan yang kompleks. Dalam penyelidikan ini satu teknik pengesan dan pengenalan pergerakan dan isyarat tangan dalam bentuk tiga dimensi (3D) diperkenalkan. Ianya boleh digunakan untuk interaksi manusia dan komputer serta dalam lain-lain aplikasi sistem robotik. Teknik yang diperkenalkan bagi menyelesaikan masalah pengesanan dan pengenalan pergerakan dan isyarat tangan adalah berdasarkan keperihalan Fourier, Neural Network dan secara pendekatan morfologi dalam isyarat objek 3D daripada satu imej bayangan. Walaubagaimanapun terdapat banyak halangan dan cabaran untuk mengenalpasti sesuatu objek seperti perubahan saiz, translasi, putaran pada tiga paksi, akulasi separa, kekurangan pengcahayaan dan juga kecacatan bentuk objek yang terlibat. Bagi mengatasi segala masalah ini, dalam kajian kami menggunakan perihalan berubah Fourier dan teknik rambatan balik Neural Network untuk pengesanan objek 3D daripada corak bayang 2D. Pendekatan yang dicadangkan ini adalah menggunakan koefisien keperihalan Fourier dan teknik rembatan balik Neural Network dengan jumlah lapisan tersembunyi yang berbeza untuk membina pengkelasan optimum objek 3D daripada satu imej bayangan. Selain daripada itu, kaedah menggunakan pemprosesan imej dan teknik morfologi yang digabungkan dengan pelbagai kaedah formula matematik bagi mengira kedudukan dan orientasi tangan juga dicadangkan. Objek yang telah dikenalpasti didedahkan kepada keamatan cahaya yang berbeza, disepara aklusikan, diubah saiznya, ditanslasi, diputarkkan pada semua tiga paksi dan juga menggunakan kecacatan struktur bentuk dalam kaedah pengkajian. Teknik yang telah dicadangkan ini diaplikasikan dan diuji ke atas Sistem Simulasi Manipulasi Robotik UniMAP (UniMAP Robot Manipulator Simulation System). Teknik ini membolehkan sistem robotik bertindak sebagai sistem pintar bagi mengesan kedudukan tangan manusia dalam ruang 3D dan menganggarkan pelbagai orientasi dan kedudukan tangan manusia dalam masa sebenar. Matlamat akhir adalah membolehkan algoritma yang dicadangkan ini digunakan dalam dalam sistem pergelangan tangan sfera robotik. Dalam kaedah ujian ini, keperluan untuk kalibrasi kamera yang berterusan tidak diperlukan. Ianya hanya memerlukan sekali sahaja proses kalibrasi pada peringkat awal bagi mengesan kedudukan awal tangan. Dengan menggunakan teknik yang telah dicadangkan ini pelbagai pergerakan dan isyarat tangan dapat dikenalpasti dengan tepat. Keputusan eksperimen ini menunjukkan teknik ini merupakan satu teknik yang mantap, tidak seperti teknik-teknik lain yang menggunakan fungsi pembelajaran atau teknik menyeluruh yang mahal. Pengesanan pergerakan tangan yang tepat dan beban komputasi yang ringan menyebabkan kelajuan pemprosesan yang tinggi dan ini membolehkan kami mencapai kemajuan tinggi dalam eperimentasi ini. Teknik yang diperkenalkan ini boleh digunakan dengan pelbagai jenis teleoperasi manipulator robotik atau lain-lain aplikasi interaksi manusia-komputer yang mengutamakan kelajuan pemprosesan.

Kata Kunci Pengenalan Corak Tiga Dimensi, Manipulator Pintar, Replika Tangan Tiga Dimensi, Interaksi Manusia-Komputer, Morfologi.

Human-Machine Interaction by Tracking Hand Movements

ABSTRACT

The vision-based hand tracking and gesture recognition is an extremely challenging problem due to the intricate nature of hand gestures this is a reason that available computer vision algorithms are computationally complex. In this research work a new methodology for 3D human hand gestures detection and recognition is proposed, which can be used for natural and intuitive human-computer interaction and other robotic systems. The proposed method based on Fourier's descriptors, neural networks and morphology approaches to solve the problem of human hand tracking and gesture recognition of 3D objects from a single silhouette image. There are many constrains and challenges are there for the recognition of an object, like size change, translation, rotation around the three axes, partial occlusion, low intensity of light as well as the deformation of the shape. In this research work we used invariant Fourier's descriptors and back propagation neural networks techniques for 3D objects recognitions from their 2D silhouette pattern to solve above mentioned challenges. The proposed approach used Fourier's descriptors coefficients and back propagation neural network with different numbers of hidden layers to build the optimal classifier of 3D pattern from a single silhouette image. Besides that, another method is proposed using image processing and morphology technique in conjunction with various mathematical formulas to calculate hand position and orientation. The recognised objects are exposed to different intensities of light, are partially occluded, with size change, translation, rotation about all the axes and we used also deformed shapes. This new proposed method was applied and tested on the simulated Manipulated Robotic System (UniMAP Robot Manipulator Simulation System) that allows this robotic system to act as an intelligent system to track a human hand in 3D space and estimate its orientation and position in real time with the goal of ultimately using the algorithm with a robotic spherical wrist system. During experiment, there was no need for continuous camera calibration, and it required only once at the beginning for the registration of the hand and using proposed technique large number of hand movements and orientations are correctly identify. Experimental result shows that proposed method is a robust technique, unlike other approaches that use costly leaning functions or generalization methods. The high performance was achieved during experiments because of the accurate hand movement identification and the low computational load that results in a fast processing time. The proposed method could therefore be used with different types of teleoperated robotic manipulators or in other human-computer interaction applications in which a fast processing time was important.

Keywords 3D Pattern Recognition, Intelligent manipulator, 3D Hand Replication, Human Computer Interaction, Morphology.

CHAPTER ONE

INTRODUCTION

1.1 Introduction to Human-Machine Interaction

Human-machine interaction (HMI) is a field of study of the interaction between humans (applicants or users) and actual machines Ravani, (2011). The purpose of research in this field leads towards better human-machine systems analysis, design and implementation to perform tasks collaboratively with human activities. Modern technologies of manufacturing and assembly lines, devices production, everyday appliances needs, advanced control in such auto pilot and in- railways trains or vehicle systems, and software systems (e.g. computer-aided design software system, CNC (Computer Numerical Controls), etc.) are all the result of the growing interest of both industry needs and academic researchers in the field of HMI. It is an interdisciplinary field of human factors and ergonomics, computer engineering, engineering design, mechatronic engineering, applications in most fields and interface design.

1.2 Problem Statements

Human machine interaction system is getting more and more attractive in the field of robotic and intelligent systems in most of life applications now a days. Recently, the interactions of hand or eye movements are most applicable in some critical applications such as nuclear reactor controls or for purposes of disasters recoveries. The human hand interaction using a simple webcam without any needs of

calibration or extra expensive requirements e.g. specific gloves fitted with sensor or colouring parts for human hands while natural hand or fingers are very preferable. The limitation factors to the system performance are the kind of technique to be used; heavy computational processes, huge looping or iterations are not preferable. Therefore in well-designed ones are the most wanted.

Recently, there are several issues raised by applicants and users across disciplines that need to be focused upon for future advances in HMI in terms of speed, intelligent level and complex issues that can be handled while keeping the cost at normal or even to a cheaper level. One major issue is regarding the fundamental things that need to be considered by designers in the process of development of machines and other automated systems with which humans interaction. For example, currently intelligent teleguided robot manipulator systems for solving configuration, calibration or external support to eliminate the humans decision making Hussain et al. (2013). The process is becoming a totally automated process that essentially eliminates the human out of the loop.

In this process human designers loose an opportunity of exhibiting their creativity. Another problem with the current HMI systems is that communication between the human and the machine is very primitive and primarily is a monologue of information exchange. It is crucial, as a first step towards building better human-machine systems, to understand the core capabilities that are to be expected of machines in interaction with humans. Therefore the question in this thesis study is what are the basic requirements to be addressed when building human interaction systems for better HMI and how to implement such a system for human hand tracking and replication. Within the context of human-machine systems, there is a new paradigm for better interaction, which is to develop adaptive machines that can sense the user's state and act

accordingly. For example, by means of sensors "planted" on the hand or fingers of a human hand to drive an intelligent manipulator robot, an on-board computer could recognize the state of the human hand and take actions to put influence over the manipulator robot to change it properly according to Chiri (2011).

Research reports in literature seem to bring the future closer to reality by the day. However, a major issue remains that the state of the human hand cannot be accurately sensed. The main objective is that if a machine takes action based on an incorrectly identified state of the human hand, it may lead to huge problems. There are several algorithms reported in literature to infer the human hand. All these differ from technique to another of inference and this effect their power of accuracy. The problem is that each of these algorithms gives a so-called "opinion" about the state, which is only an estimate of the actual state. Hence, the other question raised in this thesis are Is there a way to integrate various techniques of inference of the human's activities state for better accuracy of inference? And would representation of human hand state in a 'natural' way significantly affect the user's actions in doing a task done by manipulator robot?

In general, the contemporary literature in HMI has not provided sufficient knowledge to answer the above questions; a detailed review of literature is provided in the next chapter. The motivation of this thesis is to generate knowledge to answer these questions and is to advance technologies for better HMI.

1.3 Research Objectives

There are three challenging objectives defined for the work been presented on this thesis study:

Objective 1 Explore the core capabilities in human-machine systems for good interactions between humans and machines by means of a case study about human hand tracking and replication. However, the outcome can be easily adapted to any so-called intelligent hardware machine system according to Oborski (2004).

Objective 2 Develop a framework that allows the integration of various algorithms / techniques for object recognition based in 3D. An investigation of 3D objects recognition from their 2D patterns based on invariant Fourier's descriptors and using back propagation neural networks. The development of hybrid morphology based algorithm for recognition of hand orientation and position. The hybridization and integration of various types of algorithms on multiple cues should result in a more accurate result than a single algorithm according to Hussain et al. (2005) & Elhachloufi (2011).

Objective 3 Build a simulated test-bed model in which the machine can be guided by a human hand movements that affect the machine's state in a natural way; design and conduct experiments to generate knowledge about the effect of such a natural human hand movements activities, that a machine's state can follow user's actions (all the possible changes in orientations, translation and size of 3D hand about the three axes x, y & z; which leads to millions of hand states) NOT like other applications of recognising few tens of hand signs or states. The experimental procedure and results are also discussed to understand the specific effects in terms of tracking and replication of hand movements by intelligent manipulator robot according to Kosuge (1998), Hussain et al. (2012) & Hussain et al. (2013).