

IMPROVING ROBOTIC GRASPING SYSTEM
USING DEEP LEARNING APPROACH

MOHANNAD K. H. FARAG

DOCTOR OF PHILOSOPHY

UNIVERSITI MALAYSIA PAHANG



SUPERVISOR'S DECLARATION

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 Doctor of Philosophy.

(Supervisor's Signature)

Full Name : ABDUL NASIR ABD GHAFAR

Position : SENIOR LECTURER

Date : 21/8/2020



STUDENT'S DECLARATION

I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

(Student's Signature)

Full Name : MOHANNAD K. H. FARAG

ID Number : PET17003

Date : 21/8/2020

IMPROVING ROBOTIC GRASPING SYSTEM USING DEEP LEARNING
APPROACH

MOHANNAD K. H. FARAG

Thesis submitted in fulfillment of the requirements
for the award of the degree of
Doctor of Philosophy

Faculty of Electrical and Electronic Engineering Technology
UNIVERSITI MALAYSIA PAHANG

August 2020

ACKNOWLEDGEMENTS

My first thanks go to Allah Subhanhu Watala, who created me and gave me the power and the ability to learn and to conduct a work that may benefit my society such as this research study.

My special thanks to Dr. Mohammed Hayyan ALSIBAI and Dr. Abdul Nasir Abd Ghafar for their continuous support, encouragement, and leadership, and for that, I will be forever grateful.

Also, I wish to express my highest appreciation and thanks to the two women who provided their life, effort and support for my PhD work, to my mother, may Allah grant her his infinite mercy, and my wife, thank you for your support and patience.

Finally, I cannot forget and reward those who gave my emotional and financial encouragement to successfully accomplish this goal. To the members of my family, my father, brothers, and sisters and my lifetime teachers Ustaz Ahmed Abdul Nasir and Dr. Basim Hammeed, thank you for sticking with me.

ABSTRAK

Pergerakan robot tradisional bergantung kepada modul pergerakan yang telah diprogramkan, menyebabkan keterbasan fungsi dan operasi robot. Genggaman sistem penglihatan komputer atau visi komputer (computer vision) bagi tujuan pengesanan genggaman robot (grasp detection) telah terbukti sebagai bidang penyelidikan yang aktif dan menjadi tumpuan para penyelidik. Seiring dengan kajian semasa, penghasilan konfigurasi genggaman penuh objek sasaran merupakan dikenalpasti sebagai cabaran utama bagi penghasilan operasi robot di tahap optimum. Pengintegrasian teknologi penglihatan komputer (computer vision) dan penderian taktil (tactile sensing) dijangka menjadi inisiatif yang mampu untuk mengoptimumkan fungsi robot. Walau bagaimanapun, kajian terkini telah menggunakan penderian taktil (tactile sensing) berdasarkan model pengesanan genggaman bagi meningkatkan ketepatan pengesanan, tetapi tidak melaporkan kejayaan genggaman fizikal. Oleh itu, kajian ini menyetengahkan isu gelinciran genggaman (slip event) yang berpunca daripada faktor-faktor tertentu. Kajian ini dijalankan bertujuan untuk membangunkan model pengesanan genggaman Deep Learning dan algoritma pengesanan gelinciran, seterusnya menghasilkan satu sistem genggaman robot yang inovatif. Menerusi teknik empat langkah augmentasi data (four-step data augmentation), ketepatan genggaman yang dicapai adalah 98.2%, melebihi output data terbaik yang dilaporkan di mana 625 contoh baru dihasilkan bagi setiap gambar asal dengan label genggaman yang berbeza. Selain itu, teknik dua langkah pemindahan pembelajaran (two-step transfer learning) telah berjaya meningkatkan output yang diperolehi bagi fasa kedua kajian sebanyak 0.3% berbanding dengan fasa pertama. Manakala bagi genggaman fizikal robot, kaedah perwakilan genggaman tujuh dimensi (seven-dimensional grasp representation) yang dicadangkan membolehkan pengesanan sendiri bagi saiz dan kedalaman genggaman dilakukan. Model yang dibangunkan mencatat 74.8 milisaat sebagai masa pengesanan. Ketepatan pengesanan yang tinggi memungkinkan genggaman model tersebut dilakukan untuk aplikasi robot yang bersifat masa nyata (real-time). Berdasarkan pemerhatian terhadap maklum balas masa nyata (real-time) dari sensor perintang pengesan daya (force sensing resistor sensor), algoritma pengesanan gelinciran yang dicadangkan menunjukkan tindak balas pantas dalam dengan catatan masa secepat 86 milisaat. Penemuan ini membolehkan sistem untuk terus menahan objek sasaran dengan peningkatan kekuatan genggaman dengan kadar segera. Pengintegrasian model Deep Learning dan pengesanan gelinciran telah menunjukkan peningkatan yang signifikan sebanyak 18.4% menerusi hasil penyelidikan genggaman yang dilakukan pada robot SCARA. Selain itu, alat pengesan tepi (edge detector) Zerocross-Canny yang digunakan telah meningkatkan ralat kedudukan robot sebanyak 0.27 mm berbanding dengan kajian terdahulu, seterusnya memperkenalkan sistem genggaman robot yang inovatif dengan menggunakan skema Grasp-NoDrop-Place.

ABSTRACT

Traditional robots can only move according to a pre-planned trajectory which limits the range of applications that they could be engaged in. Despite their long history, the use of computer vision technology for grasp prediction and object detection is still an active research area. However, the generating of a full grasp configuration of a target object is the main challenge to plan a successful robotic operation of the physical robotic grasp. Integrating computer vision technology with tactile sensing feedback has given rise to a new capability of robots that can accomplish various robotic tasks. However, the recently conducted studies had used tactile sensing with grasp detection models to improve prediction accuracy, not physical grasp success. Thus, the problem of detecting the slip event of the grasped objects that have different weights is addressed in this research. This research aimed to develop a Deep Learning grasp detection model and a slip detection algorithm and integrating them into one innovative robotic grasping system. By proposing a four-step data augmentation technique, the achieved grasping accuracy was 98.2 % exceeding the best-reported results by almost 0.5 % where 625 new instances were generated per original image with different grasp labels. Besides, using the two-stage-transfer-learning technique improved the obtained results in the second stage by 0.3 % compared to the first stage results. For the physical robot grasp, the proposed seven-dimensional grasp representations method allows the autonomous prediction of the grasp size and depth. The developed model achieved 74.8 milliseconds as prediction time, which makes it possible to use the model in real-time robotic applications. By observing the real-time feedback of a force sensing resistor sensor, the proposed slip detection algorithm indicated a quick response within 86 milliseconds. These results allowed the system to maintain holding the target objects by an immediate increase of the grasping force. The integration of the Deep Learning and slip detection models has shown a significant improvement of 18.4% in the results of the experimental grasps conducted on a SCARA robot. Besides, the utilized Zerocross-Canny edge detector has improved the robot positioning error by 0.27 mm compared to the related studies. The achieved results introduced an innovative robotic grasping system with a Grasp-NoDrop-Place scheme.

TABLE OF CONTENT

DECLARATION	
TITLE PAGE	
ACKNOWLEDGEMENTS	ii
ABSTRAK	iii
ABSTRACT	iv
TABLE OF CONTENT	v
LIST OF TABLES	x
LIST OF FIGURES	xi
LIST OF SYMBOLS	xvi
LIST OF ABBREVIATIONS	xviii
LIST OF APPENDICES	xix
CHAPTER 1 INTRODUCTION	1
1.1 Background of The Thesis	1
1.1.1 Robotic Grasping Systems	1
1.1.2 Image Processing and Deep Learning	2
1.1.3 Deep Learning Methods in Robotic Grasp Detection	4
1.1.4 Object Slip Detection	5
1.2 Problem Statement	7
1.3 Research Objectives	9
1.4 Research Scope	9
1.5 Research Contribution and Its Significance	10
1.6 Thesis Organization	12

CHAPTER 2 LITERATURE REVIEW	14
2.1 Introduction	14
2.2 Robotic Grasping Systems	15
2.2.1 Vision-Guided Robots	15
2.2.2 Robotic Hand	22
2.3 Image Processing	25
2.3.1 Image Processing Algorithms	25
2.3.2 Edge Detection Techniques	27
2.4 Deep Learning	29
2.4.1 Deep Learning Concept	29
2.4.2 Types of Machine Learning Algorithms	31
2.4.3 Types of DNN Models Implemented in Computer Vision and Robotic Applications	32
2.4.4 Evaluation of DNN Models Implemented in Computer Vision and Robotic Applications	40
2.4.5 Deep Learning-Based Object Detection	42
2.4.6 Transfer Learning Approach	43
2.5 Deep Learning Methods in Robotic Grasp Detection	49
2.5.1 Grasp Representation	49
2.5.2 Grasp Detection	51
2.6 Object Slip Detection	62
2.6.1 Coefficient of Coulomb's Friction	64
2.6.2 Slip Detection Technology	65
2.7 Summary	72

CHAPTER 3 METHODOLOGY	74
3.1 Introduction	74
3.2 Development of Deep Learning Model for Grasp Detection Using Two-Stage-Transfer-Learning Technique	76
3.2.1 The First Stage: Grasp Detection Model Development Using Cornell Dataset	79
3.2.2 The Second Stage: Grasp Detection Model Development Using the New Training Dataset	89
3.3 Simulation Design of SCARA Robot	93
3.3.1 Homogeneous Transformation Matrix and D-H Parameters of SCARA Robot	93
3.3.2 Simulink model of KSS-1500 SCARA robot	95
3.3.3 Simulation Design for Robotic Grasping	97
3.4 Development of Slip Detection Model	100
3.4.1 Measurement Principle of Force Sensing Resistors (FSRs)	100
3.4.2 Object Slip Detection Model	101
3.4.3 Detection Model with The Parallel Gripper of SCARA Robot	104
3.4.4 Design of Initial Test of Slip Detection Model Using Robot Hand	105
3.5 Edge Detection-Based Robot Positioning	108
3.5.1 A comparison of Edge Detection Methods	108
3.6 Integration of Deep Learning and Slip Detection Models in an Innovative Robotic Grasping System	113
3.6.1 Object drop prevention phase	114
3.7 Hardware Experiment Design	116
3.7.1 Robotic Arm	116
3.7.2 Vision System	118
3.7.3 Camera Calibration	118

3.7.4	Experiment Design of Robot Positioning	121
3.7.5	Experiment Design of The Integrated Grasping System (Grasp-NoDrop-Place Scheme)	122
3.8	Evaluation Metrics	125
3.8.1	Grasp Detection and Object Classification	126
3.8.2	Robot Positioning	127
3.8.3	Robot Grasp and Place	127
3.8.4	Object Slip Detection	128
3.9	Summary	128
CHAPTER 4 RESULTS AND DISCUSSIONS		130
4.1	Introduction	130
4.2	Deep Learning Model for Grasp Detection	130
4.2.1	The First Stage: Grasp Detection Model Using Cornell Dataset	131
4.2.2	The Second Stage: Grasp Detection Model Using the New Training Dataset	134
4.3	Simulation Results of Robotic Grasping	137
4.4	Initial Test of Slip Detection Model Using Robot Hand	141
4.5	Experiment Results of Robot Positioning	147
4.6	Experiment Results of The Integrated Grasping System (Grasp-NoDrop-Place Scheme)	151
4.7	Summary	168
CHAPTER 5 CONCLUSION AND RECOMMENDATION		170
5.1	Conclusion	170
5.2	Recommendation	172

REFERENCES	173
LIST OF PUBLICATIONS	188

LIST OF TABLES

Table 2.1	Comparison between direct-driven & wire-driven joint	23
Table 2.2	Comparison of of 25 different robotic grasping systems	24
Table 2.3	Types of Deep Learning Algorithms	33
Table 2.4	Comparison of CNNs, DBMs, DBNs, and SAEs	42
Table 2.5	Comparison between different grasp representations	51
Table 2.6	Direct regression for robotic grasp detection proposed by Redmon & Angelova (2015)	54
Table 2.7	Regression & classification for robotic grasp detection proposed by Redmon & Angelova (2015)	55
Table 2.8	Multi-grasp detection proposed by Redmon & Angelova (2015)	56
Table 2.9	Multi-object & multi-grasp detection proposed by F. J. Chu et al. (2018)	57
Table 2.10	Multi-grasp & default orientation proposed by X. Zhou et al. (2018)	58
Table 2.11	Data augmentation proposed by Ribeiro & Grassi (2019)	59
Table 2.12	Recent contributions in robotic grasp detection reported from tests performed on the Cornell Grasp Dataset	62
Table 3.1	Training algorithm options	89
Table 3.2	Properties of the designed object models	91
Table 3.3	D-H parameters of KSS-1500 SCARA robot	95
Table 3.4	Overall results of Precision, Recall and F-measure for edge detection methods	111
Table 3.5	KSS-1500 robotic arm characteristics	117
Table 3.6	User I/O DSUB-15P pin configurations	117
Table 4.1	Prediction accuracy and time of grasp on the Cornell Grasp Dataset	133
Table 4.2	Grasp detection and object classification results of the Deep Learning model in the two stages	135
Table 4.3	Simulation evaluation of robotic grasping and Object classification on the objects with different geometric shapes	139
Table 4.4	Numeric values of slip detection experiments	142
Table 4.5	Samples of experiment results of robot grasping phase	156
Table 4.6	Two samples of experiment results of robot placing phase	162
Table 4.7	Overall experimental results of the innovative grasping system for grasping objects with different geometric shapes	165

LIST OF FIGURES

Figure 2.1	Schematic drawing of two robot arm types (a) Cartesian robot (b) SCARA robot	16
Figure 2.2	7-DOF robotic manipulator with 2-finger gripper	16
Figure 2.3	Puma manipulator from DENSO Corporation	17
Figure 2.4	STAIR 2 robot	17
Figure 2.5	Universal Robot UR10 robotic arm	18
Figure 2.6	Grasping of objects with different shapes	18
Figure 2.7	Grasping of objects with different shapes	19
Figure 2.8	Position estimation the position unit is in millimeters	19
Figure 2.9	Vision-guided grasping system for grasping and classifying machine parts	20
Figure 2.10	The object drops while assessing the grasp stability	21
Figure 2.11	Using of tactile sensing to complement the use of visual sensors	21
Figure 2.12	Diagram of our visual-tactile multi-modal model system	22
Figure 2.13	Image processing algorithm chain	25
Figure 2.14	Flow chart of Canny edge detection operator	28
Figure 2.15	Visualized comparison of first derivative and second derivative edge detection operators	28
Figure 2.16	Relationship of Deep Learning, Machine Learning and Artificial Intelligence	30
Figure 2.17	The concept of (a) Machine Learning (b) Deep Learning	31
Figure 2.18	Types of Deep Learning Models	33
Figure 2.19	Filtering and pooling transformation with Convolutional Neural Network	35
Figure 2.20	The typical architecture of CNN model	36
Figure 2.21	Architecture of Restricted Boltzmann Machine	37
Figure 2.22	Architecture of (a) Deep Belief Networks and (b) Deep Boltzmann Machines	37
Figure 2.23	Architecture of Stacked Autoencoders	39
Figure 2.24	Recurrent Neural network structure	40
Figure 2.25	Q-network structure	40
Figure 2.26	The three research categories in object detection: (a) Objectness Detection, (b) Salient Object Detection, and (c) Category-Specific Object Detection	44
Figure 2.27	Block diagram of transfer learning process.	45

Figure 2.28	Instances-Based transfer learning technique	46
Figure 2.29	Mapping-Based transfer learning technique	46
Figure 2.30	Network-Based transfer learning technique	48
Figure 2.31	Adversarial-Based transfer learning technique	48
Figure 2.32	An image of textureless /transparent /reflective objects (b) Depths estimated by a stereo system	50
Figure 2.33	The images (top row) with the corresponding labels (shown in red in the bottom row) of the five object classes used for training	50
Figure 2.34	Types of Deep Learning approaches for robotic grasp systems	52
Figure 2.35	Interaction forces at the contact surface during lifting the target object	53
Figure 2.36	An example of rectangular representation $g = \{x, y, \theta, h, w\}$	60
Figure 2.37	Damaged end-effector of SCARA robot	63
Figure 2.38	Measurement of friction Coefficient	65
Figure 2.39	Interaction forces at the contact surface during lifting the target object	65
Figure 2.40	Deformation of the contact area detected by CCD camera	66
Figure 2.41	Carbon Micro Coil (CMC)	67
Figure 2.42	Outputs of CMC sensor and laser displacement meter	67
Figure 2.43	Inductive sensing mechanism (a) sensor assembly in gripper pad (b) relative positions of a pair of inductors	69
Figure 2.44	Schematic of a μ -LDV (a) basic LDV sensor (b) μ -LDV sensor	69
Figure 2.45	Bottlecap unscrewing Experiment (top) Evolution of the gripping force, (middle) images taken with an external camera, (bottom) GelSlim images where points labeled in the plot for the bottle cap unscrewing process	70
Figure 3.1	Research methodology flow chart	75
Figure 3.2	The first stage of of grasp detection model development using Conrell grasp dataset	77
Figure 3.3	The second stage of of grasp detection model development based on the collected training dataset	78
Figure 3.4	Extraction of the grasp rectangles values from dataset points	80
Figure 3.5	Grasp regression and object detection algorithm	81
Figure 3.6	Four-step data augmentation procedure	83
Figure 3.7	Data pre-processing procedure	84
Figure 3.8	Model architecture based on AlexNet CNN (Caldera et al. 2018) with five ouptut nodes for grasp regression and one node for object classification	86
Figure 3.9	Network-Based transfer learning workflow	88

Figure 3.10	Seven-dimensional grasp representation	90
Figure 3.11	Twelve object models designed with different geometric shapes	92
Figure 3.12	Examples of object models with 7-dimensional grasp labeling	92
Figure 3.13	The final model architecture with seven output nodes for grasp regression and one node for object classification	93
Figure 3.14	The coordinate system of SCARA with 4 DOFs and a parallel gripper	94
Figure 3.15	The Simulink model of KSS-1500 SCARA robot	96
Figure 3.16	The simulation procedure for validation of SCARA Simulink model	96
Figure 3.17	Tracking the desired trajectory by robot Simulink model	97
Figure 3.18	Simulation block diagram of for Deep learning-based grasp detection	98
Figure 3.19	The simulation procedure for validation of SCARA Simulink model	99
Figure 3.20	Force-sensing technology (a) FSR structure (b) measurement principle	101
Figure 3.21	Schematic drawing of contact surfaces and force balance on the target object	102
Figure 3.22	The slip detection model for SCARA parallel gripper (a) 3-D drawing of contact surfaces and force balance (b) schematic lock diagram	104
Figure 3.23	Schematic diagram of robot hand controller	105
Figure 3.24	Schematic diagram of robot hand controller with the object slip detector	106
Figure 3.25	Pneumatic robot hand structure	107
Figure 3.26	Example of an input image with designed six holes	110
Figure 3.27	An example of a segmented and filtered image	110
Figure 3.28	Edge detection comparisons (a) Precision, (b) Recall, (c) F-measure	111
Figure 3.29	An example of segmented images with number of detected circular objects	112
Figure 3.30	Robotic grasp detection phase based on the Deep Learning model	113
Figure 3.31	Robotic place detection phase based on the edge detection model	114
Figure 3.32	Robot grasping with three cases of slippage detection feedback (a)& (d) before grasping (b) & (e) after grasping w/ slip (c) & (f) after grasping w/o slip (a)-(c) for a cylindrical object (d)-(f) for a cuboidal object	115
Figure 3.33	The scheme of Grasp-NoDrop-Place system	116

Figure 3.34	Four DOFs GLOBOT KSS-1500 SCARA robot; X, Y, Z and θ axes	116
Figure 3.35	User I/O DSUB-15P por	117
Figure 3.36	Vision-guided KSS-1500 SCARA robot	118
Figure 3.37	One sample of the calibration images	119
Figure 3.38	Detected and reprojected points of the sample calibration image	119
Figure 3.39	The average of reprojection errors for 40 calibration images	120
Figure 3.40	Checkboard image after removing lens distortion	120
Figure 3.41	Design of robot positioning experiment	121
Figure 3.42	The integrated grasping system (Grasp-NoDrop-Place sheme)	123
Figure 3.43	Experiment design for vision-guided robotic Grasp-NoDrop-Place	123
Figure 3.44	Parallel gripper of SCARA robot (a) 3-D drawing of contact surfaces and force balance (b) actual gripper with two FSR sensors	125
Figure 4.1	Samples of training results positive grasp predictions indicated in green-red rectangles, and negative grasp predictions indicated in blue-red rectangles	132
Figure 4.2	Example of the four-step data augmentation, 625 instances were generated per original image with new grasp rectangle labels	133
Figure 4.3	Training progress (a) training accuracy (b) training loss	136
Figure 4.4	Samples of obtained results using the new training dataset, the positive grasp predictions are indicated in green-red rectangles, while the negative grasp predictions are indicated in blue-red rectangles	136
Figure 4.5	An example of a simulated robot grasp (a) the robot is in a home configuration with an input image (b) the robot moved to the detected position successfully	138
Figure 4.6	Some results of the simulated robot grasp	139
Figure 4.7	Slip detection for a cup (a) force command response (b) slip occurs by water filling	143
Figure 4.8	Slip detection for a tube (a) force command response (b) slip occurs by pushing the tube	144
Figure 4.9	Slip detection for a bottle (a) force command response (b) slip occurs by adding a weight	145
Figure 4.10	Slip detection for a chip can (a) force command response (b) slip occurs by adding a metal can	146
Figure 4.11	Slip detection for a metal can (a) force command response (b) slip occurs by adding a weight	147
Figure 4.12	Fifty defined positions in Region B	148

Figure 4.13	An example of edge detection-based robot positioning experiment result, (a) input image, (b) undistorted image, (c) segmented image, (d) detected hole	150
Figure 4.14	An example of generated SCARA place code using edge detection-based robot positioning model to place the cylindrical object on the detected position	151
Figure 4.15	The results of positioning errors for 50 experiments	151
Figure 4.16	Experiment procedure of the Grasp-NoDrop-Place scheme	153
Figure 4.17	Deep learning-based grasp detection model for robot grasping phase	155
Figure 4.18	Example of successful physical robot grasping with the grasp size h_{gr} and depth z_{gr} (a) object model 1 (b) object model 9	157
Figure 4.19	Example of physical robot grasping with the detected slip event, object model 3 (a) the object grasped but not lifted yet (b) the object lifted and the drop prevented by a quick increase of the grasp force	158
Figure 4.20	Example of physical robot grasping with no slip event occurred, object model 11 (a) the object grasped but not lifted yet (b) the object lifted without a slippage	158
Figure 4.21	Deep learning-based grasp detection model with slip detection phase	159
Figure 4.22	Edge detection-based model for robot placing phase	161
Figure 4.23	Overall innovative grasping system (Grasp-NoDrop-Place scheme)	164
Figure 4.24	Examples of unsuccessful physical robot grasping when no-slip detection implemented (a) object model 6 (b) object model 2	165
Figure 4.25	Experiment success rate of the robot grasp for object models 1-6	166
Figure 4.26	Experiment success rate of the robot grasp for object models 7-12	167
Figure 4.27	Example of unsuccessful physical robot grasping due to an incorrect orientation (a) object model 5 (b) object model 8	168

LIST OF SYMBOLS

B_{eff}	effective viscous friction factor (Ns/m)
P_m	actual muscle pressure (MPa)
C_1 & C_2	adaptive backstepping control parameters (second ⁻¹)
e_{av}	average of the positioning error
$u(t)$	control input of adaptive backstepping controller
F_c	coulomb friction force (N)
k	current experiment attempt
F_d	drop prevention force (N)
F_l	FSR sensor feedback (N)
z_{gr}	grasp depth (mm)
F_g	grasp force (N)
(x_{gr}, y_{gr})	grasp position (mm)
h_{gr}	grasp size (mm)
F_i	initial grasp force (N)
a & b	modelling coefficients of robot finger
N_{act}	number of actuators
N_{dof}	number of degrees of freedom
P_a	object's actual position
P_d	object's detected position
z_1	PAM mechanical displacement error
z_2	PAM velocity error
z_{pr}	place depth (mm)
(x_{pr}, y_{pr})	place position (mm)
$e(k)$	positioning error of the k^{th} experiment,
R	pulley radius (m)
t_s	response time (ms)
(x_r, y_r)	robot coordinate system (mm)
l	robot finger length (mm)
K	slip detector coefficient
S	slip detector sensitivity

k_l	spring coefficient (N/m)
n	total experiment attempts
I	total moment of inertia of the finger (Kg.m ²)
x_l	translational position of PAM actuator (m)
(x_w, y_w)	world coordinate system (mm)
μ	friction coefficient
F_t	tangential force
F_n	normal force
θ	orientation of the rectangle
(x, y)	the center of grasp rectangle
h	the height of gripper parallel plates
w	the maximum distance between gripper parallel plates

LIST OF ABBREVIATIONS

μ -LDV	Doppler Velocimeter
AI	Artificial Intelligence
BLDC	Brushless Direct Current
CMC	Carbon Micro-Coil
CNN	Convolutional Neural Network
DAG	Directed Acyclic Graph
DAQ	Data Acquisition
DBM	Deep Boltzmann Machines
DBN	Deep Belief Networks
DL	Deep Learning
DNN	Deep neural networks
DOF	Degree of Freedom
FN	False Negative
FP	False Positive
FSR	Force Sensing Resistor
KSS	Korea Standard SCARA
LC	Inductor and Capacitor
ML	Machine Learning
PAM	Pneumatic Artificial Muscle
RBM	Restricted Boltzmann Machines
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
RPN	Region Proposal Network
SAE	Stacked Autoencoders
Sparse AE	Sparse Auto-Encoder
SCARA	Selective Compliant Assembly Robot Arm
SCTM	Soft Compliant Tactile Microsensor
SGD	Stochastic Gradient Descent
SGDM	Stochastic Gradient Descent with Momentum
TP	True Positive

LIST OF APPENDICES

- Appendix A: Specifications of Camera Model CM3-U3-13S2C-CS-SET
- Appendix B: Camera Calibration Parameters
- Appendix C: Operational Definitions
- Appendix D: Design Procedure of Adaptive Backstepping Controller
- Appendix E: MATLAB Code of Edge Detection Comparison
- Appendix F: MATLAB Code of Edge Detection-Based Robot Positioning
- Appendix G: MATLAB Code of Transfer Learning Process
- Appendix H: MATLAB Code of Vision-Guided Robotic Grasp and Place

REFERENCES

- Abd, Moaed A., Iker J. Gonzalez, Thomas C. Colestock, Benjamin A. Kent, and Erik D. Engeberg. 2018. "Direction of Slip Detection for Adaptive Grasp Force Control with a Dexterous Robotic Hand." *IEEE/ASME International Conference on Advanced Intelligent Mechatronics, AIM 2018*-July:21–27.
- Accoto, Dino, Ranjana Sahai, Francesco Damiani, Domenico Campolo, Eugenio Guglielmelli, and Paolo Dario. 2012. "A Slip Sensor for Biorobotic Applications Using a Hot Wire Anemometry Approach." *Sensors and Actuators A: Physical* 187:201–8.
- Al-Saffar, Ahmed Ali Mohammed, Hai Tao, and Mohammed Ahmed Talab. 2017. "Review of Deep Convolution Neural Network in Image Classification." *2017 International Conference on Radar, Antenna, Microwave, Electronics, and Telecommunications (ICRAMET)* 26–31.
- Alcala, Rony, Zuedmar G. Arceo, Jonathan N. Baterisna, Jimmy O. Morada, and Julius Oliver D. Ramirez. 2018. "Selective Compliance Articulated Robotic Arm (SCARA): Application of Inverse Kinematics on the Control of Pick and Place Using Microsoft Kinect Xbox 360." *Research Gate*.
- Alexe, Bogdan, Thomas Deselaers, and Vittorio Ferrari. 2012. "Measuring the Objectness of Image Windows." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 34(11):2189–2202.
- Amoako-yirenyki, Peter, Justice Kwame Appati, and Isaac Kwame Dontwi. 2016. "Performance Analysis of Image Smoothing Techniques on a New Fractional Convolution Mask for Image Edge Detection." *Open Journal of Applied Sciences* 06(July):478–88.
- Andhare, P., and S. Rawat. 2016. "Pick and Place Industrial Robot Controller with Computer Vision." Pp. 1–4 in *2016 International Conference on Computing Communication Control and automation (ICCUBEA)*.
- Arulkumaran, Kai, Marc Peter Deisenroth, Miles Brundage, and Anil Anthony Bharath. 2017. "Deep Reinforcement Learning: A Brief Survey." *IEEE Signal Processing Magazine* 34(6):26–38.
- Atkeson, C. G., and J. C. Santamaria. 1997. "A Comparison of Direct and Model-Based Reinforcement Learning." *Proceedings of International Conference on Robotics and Automation* 4(April):3557–64.
- Azizpour, Hossein, Ali Sharif Razavian, Josephine Sullivan, Atsuto Maki, and Stefan Carlsson. 2016. "Factors of Transferability for a Generic ConvNet Representation." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 38(9):1790–1802.
- Azlan, Norsinnira Zainul, and Mohannad Farag. 2015. "Adaptive Backstepping Position Control of Pneumatic Anthropomorphic Robotic Hand." *Procedia Computer Science* 76(Iris):161–67.

- Bang-Jensen, Jørgen, and Gregory Z. Gutin. 2009. *Digraphs: Theory, Algorithms and Applications*. London: Springer London.
- Beccai, Lucia, Stefano Roccella, Luca Ascari, Pietro Valdastri, Arne Sieber, M. Chiara Carrozza, and Paolo Dario. 2008. "Development and Experimental Analysis of a Soft Compliant Tactile Microsensor for Anthropomorphic Artificial Hand." *IEEE/ASME Transactions on Mechatronics* 13(2):158–68.
- Beck, Sebastian, Ralf Mikut, Arne Lehmann, and Georg Bretthauer. 2003. "Model-Based Control and Object Contact Detection for a Fluidic Actuated Robotic Hand." *Proceedings of the IEEE Conference on Decision and Control* 6(December):6369–74.
- Ben-Ari, M. 2006. *Principles of Concurrent and Distributed Programming*. 2nd ed. Addison-Wesley.
- Bengio, Y. 2009. "Learning Deep Architectures for AI." *Foundations and Trends in Machine Learning* 2(1):1–127.
- Bernstein, Alexander V., and E. V. Burnaev. 2018. "Reinforcement Learning in Computer Vision." Pp. 58–64 in *Tenth International Conference on Machine Vision (ICMV 2017)*. Vienna, Austria: SPIE.
- Bicchi, A., and V. Kumar. 2000. "Robotic Grasping and Contact: A Review." Pp. 348–53 vol.1 in *Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference on Robotics and Automation. Symposia Proceedings (Cat. No.00CH37065)*. Vol. 1.
- Birglen, Lionel, and Clément M. Gosselin. 2005. "Fuzzy Enhanced Control of an Underactuated Finger Using Tactile and Position Sensors." *Proceedings - IEEE International Conference on Robotics and Automation* 2005(April):2320–25.
- Birglen, Lionel, Thierry Laliberté, and Clément Gosselin. 2008. *Underactuated Robotic Hands*. Vol. 40. Springer-Verlag Berlin Heidelberg.
- Bishop, Chris. 2006. *Pattern Recognition and Machine Learning*. Springer.
- Brejcl, Marek, and Milan Sonka. 2000. "Object Localization and Border Detection Criteria Design in Edge-Based Image Segmentation: Automated Learning from Examples." *IEEE Transactions on Medical Imaging* 19(10):973–85.
- Calandra, R., A. Owens, D. Jayaraman, J. Lin, W. Yuan, J. Malik, E. H. Adelson, and S. Levine. 2018. "More Than a Feeling: Learning to Grasp and Regrasp Using Vision and Touch." *IEEE Robotics and Automation Letters* 3(4):3300–3307.
- Calandra, Roberto, Andrew Owens, Manu Upadhyaya, Wenzhen Yuan, Justin Lin, Edward H. Adelson, and Sergey Levine. 2017. "The Feeling of Success Does Touch Sensing Help Predict Grasp Outcomes." *ArXiv Preprint*.
- Caldera, Shehan, Alexander Rassau, and Douglas Chai. 2018. "Review of Deep Learning Methods in Robotic Grasp Detection." *Multimodal Technologies and Interaction* 2(3):57.

- Canny, John. 1986. "A Computational Approach to Edge Detection." *IEEE Transactions on Pattern Analysis and Machine Intelligence* PAMI-8(6):679–98.
- Chang, Hang, Ju Han, Cheng Zhong, Antoine M. Snijders, and Jian Hua Mao. 2018. "Unsupervised Transfer Learning via Multi-Scale Convolutional Sparse Coding for Biomedical Applications." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 40(5):1182–94.
- Chu, Fu-Jen, and Patricio A. Vela. 2018. "Deep Grasp: Detection and Localization of Grasps with Deep Neural Networks." *ArXiv Preprint* (1).
- Chu, Fu Jen, Ruinian Xu, and Patricio A. Vela. 2018. "Real-World Multiobject, Multigrasp Detection." *IEEE Robotics and Automation Letters* 3(4):3355–62.
- Cornell. 2009. "Cornell University, Robot Learning Lab." Retrieved December 25, 2019 (http://pr.cs.cornell.edu/grasping/rect_data/data.php).
- Cotton, D. P. J., P. H. Chappell, A. Cranny, N. M. White, and S. P. Beeby. 2007. "A Novel Thick-Film Piezoelectric Slip Sensor for a Prosthetic Hand." *IEEE Sensors Journal* 7(5):752–61.
- Cutkosky, M. R. 1989. "On Grasp Choice, Grasp Models, and the Design of Hands for Manufacturing Tasks." *IEEE Transactions on Robotics and Automation* 5(3):269–79.
- Cutkosky, Mark R., and John Ulmen. 2014. "Dynamic Tactile Sensing." Pp. 389–403 in *The Human Hand as an Inspiration for Robot Hand Development*, edited by R. Balasubramanian and V. J. Santos. Cham: Springer International Publishing.
- Dahiya, Ravinder S., Giorgio Metta, Maurizio Valle, and Giulio Sandini. 2009. "Tactile Sensing From Humans to Humanoids." *IEEE Transactions on Robotics* 26(1):1–20.
- Dawood, Hassan, Hussain Dawood, and Ping Guo. 2013a. "Efficient Texture Classification Using Short-Time Fourier Transform with Spatial Pyramid Matching." Pp. 2275–79 in *Proceedings - 2013 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2013*. IEEE.
- Dawood, Hassan, Hussain Dawood, and Ping Guo. 2013b. "Global Matching to Enhance the Strength of Local Intensity Order Pattern Feature Descriptor." Pp. 497–504 in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. Vol. 7951 LNCS. Springer, Berlin, Heidelberg.
- Deselaers, Thomas, Bogdan Alexe, and Vittorio Ferrari. 2012. "Weakly Supervised Localization and Learning with Generic Knowledge." *International Journal of Computer Vision* 100(3):275–93.
- Diftler, M. A., C. J. Culbert, R. O. Ambrose, R. Platt, and W. J. Bluethmann. 2003. "Evolution of the NASA/DARPA Robonaut Control System." Pp. 2543–48 vol.2 in *2003 IEEE International Conference on Robotics and Automation (Cat. No.03CH37422)*. Vol. 2.

- Ding, X., Y. Luo, Q. Yu, Q. Li, Y. Cheng, R. Munnoch, D. Xue, and G. Cai. 2017. "Indoor Object Recognition Using Pre-Trained Convolutional Neural Network." Pp. 1–6 in *2017 23rd International Conference on Automation and Computing (ICAC)*. Huddersfield, UK: IEEE.
- DMBH Co., Ltd. 2018. "DMBH Co., Ltd." Retrieved (<http://www.dmbh.co.kr/?ckattempt=1>).
- Dong, S., D. Ma, E. Donlon, and A. Rodriguez. 2019. "Maintaining Grasps within Slipping Bounds by Monitoring Incipient Slip." Pp. 3818–24 in *2019 International Conference on Robotics and Automation (ICRA)*.
- Druzhkov, P. N., and V. D. Kustikova. 2016. "A Survey of Deep Learning Methods and Software Tools for Image Classification and Object Detection." *Pattern Recognition and Image Analysis* 26(1):9–15.
- Egmont-Petersen, M., D. De Ridder, and H. Handels. 2002. "Image Processing with Neural Networks- A Review." *Pattern Recognition* 35(10):2279–2301.
- Fang, Jian, and Wei Li. 2013. "Four Degrees of Freedom SCARA Robot Kinematics Modeling and Simulation Analysis SCARA Robot Kinematics." *International Journal of Computer, Consumer and Control* 2(4):20–27.
- Fangwei Zhao, and C. J. S. DeSilva. 2002. "Use of the Laplacian of Gaussian Operator in Prostate Ultrasound Image Processing." Pp. 812–15 in *Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. Vol.20 Biomedical Engineering Towards the Year 2000 and Beyond (Cat. No.98CH36286)*. Vol. 2. IEEE.
- Farag, Mohannad, Norsinnira Zainul Azlan, and Salmiah Ahmad. 2017. "Cascade Control of Robotic Fingers with Anthropomorphic Inspiration." *2016 IEEE International Conference on Automatic Control and Intelligent Systems, I2CACIS 2016* (October):168–73.
- Farag, Mohannad, Norsinnira Zainul Azlan, and Mohammed Hayyan Alsibai. 2018. "Development of Anthropomorphic Robotic Hand Driven by Pneumatic Artificial Muscles for Robotic Applications." *IOP Conference Series: Materials Science and Engineering* 342.
- Fawcett, Tom. 2006. "An Introduction to ROC Analysis." *Pattern Recognition Letters* 27(8):861–74.
- Feng, Chenhuan, Guanbin Gao, and Yongli Cao. 2016. "Kinematic Modeling and Verification for a SCARA Robot." in *3rd International Conference on Materials Engineering, Manufacturing Technology and Control (ICMEMTC 2016)*. Atlantis Press.
- Ferrari, Luca Enrico. 2014. "Matlab-Based Control of a SCARA Robot."
- Flanagan, J. Randall, and Alan M. Wing. 1993. "Modulation of Grip Force with Load Force during Point-to-Point Arm Movements." *Experimental Brain Research* 95(1):131–43.

- Francomano, Maria Teresa, Dino Accoto, and Eugenio Guglielmelli. 2012. "Experimental Characterization of a Flexible Thermal Slip Sensor." *Sensors (Switzerland)* 12(11):15267–80.
- Francomano, Maria Teresa, Dino Accoto, and Eugenio Guglielmelli. 2013. "Artificial Sense of Slip - A Review." *IEEE Sensors Journal* 13(7):2489–98.
- Fukushima, Kunihiko. 1980. "Neocognitron: A Self-Organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position." *Biological Cybernetics* 36(4):193–202.
- Gashler, Mike, and Tony Martinez. 2011. "Temporal Nonlinear Dimensionality Reduction." Pp. 1959–66 in *Proceedings of the International Joint Conference on Neural Networks*. IEEE.
- Goodfellow, Ian, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. "Generative Adversarial Nets." Pp. 2672–80 in *Advances in Neural Information Processing Systems 27*, edited by Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger. Curran Associates, Inc.
- Gretton, Arthur, Bharath Sriperumbudur, Dino Sejdinovic, Heiko Strathmann, Sivaraman Balakrishnan, Massimiliano Pontil, and Kenji Fukumizu. 2012. "Optimal Kernel Choice for Large-Scale Two-Sample Tests." Pp. 1205–13 in *Proceedings of the 25th International Conference on Neural Information Processing Systems - Volume 1, NIPS'12*. USA: Curran Associates Inc.
- Guo, Di, Fuchun Sun, Bin Fang, Chao Yang, and Ning Xi. 2017. "Robotic Grasping Using Visual and Tactile Sensing." *Information Sciences* 417:274–86.
- Guo, Hao, Han Xiao, Shijun Wang, Wenhao He, and Kui Yuan. 2015. "Real-Time Detection and Classification of Machine Parts with Embedded System for Industrial Robot Grasping." *2015 IEEE International Conference on Mechatronics and Automation, ICMA 2015* 1691–96.
- Han, Junwei, Dingwen Zhang, Gong Cheng, Nian Liu, and Dong Xu. 2018. "Advanced Deep-Learning Techniques for Salient and Category-Specific Object Detection: A Survey." *IEEE Signal Processing Magazine* 35(1):84–100.
- Hariharan, Bharath, Pablo Arbelaez, Ross Girshick, and Jitendra Malik. 2017. "Object Instance Segmentation and Fine-Grained Localization Using Hypercolumns." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 39(4):627–39.
- Heikkila, J., and O. Silven. 1997. "A Four-Step Camera Calibration Procedure with Implicit Image Correction." Pp. 1106–12 in *Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition*. IEEE Comput. Soc.
- Hinton, G. E., and R. R. Salakhutdinov. 2006. "Reducing the Dimensionality of Data with Neural Networks." *Science* 313(5786):504–7.

- Ho, V. A., D. V Dao, S. Sugiyama, and S. Hirai. 2011. "Development and Analysis of a Sliding Tactile Soft Fingertip Embedded With a Microforce/Moment Sensor." *IEEE Transactions on Robotics* 27(3):411–24.
- Hochreiter, Sepp, and Jürgen Schmidhuber. 1997. "Long Short-Term Memory." *Neural Computation* 9(8):1735–80.
- Hoffman, Judy, Eric Tzeng, Trevor Darrell, and Kate Saenko. 2017. "Simultaneous Deep Transfer across Domains and Tasks." Pp. 173–87 in *Advances in Computer Vision and Pattern Recognition*. IEEE.
- Holz, Dirk, and Sven Behnke. 2016. "Fast Edge-Based Detection and Localization of Transport Boxes and Pallets in RGB-D Images for Mobile Robot Bin Picking." *47th International Symposium on Robotics (ISR) 2016*(June):133–40.
- Hossain, Delowar, and Genci Capi. 2016. "Object Recognition and Robot Grasping : A Deep Learning Based Approach." *The Robotics Society of Japan* (October).
- Huang, Guo-shing, Hsiung-cheng Lin, and Po-cheng Chen. 2011. "Robotic Arm Grasping and Placing Using Edge Visual Detection System." *2011 8th Asian Control Conference (ASCC)* 240:960–64.
- Huang, Jui Ting, Jinyu Li, Dong Yu, Li Deng, and Yifan Gong. 2013. "Cross-Language Knowledge Transfer Using Multilingual Deep Neural Network with Shared Hidden Layers." Pp. 7304–8 in *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*. IEEE.
- Ibrahim, B. S. K. K., and Ahmed M. A. Zargoun. 2014. "Modelling and Control of SCARA Manipulator." Pp. 106–13 in *Procedia Computer Science*. Vol. 42. Elsevier.
- Ikeda, A., Y. Kurita, J. Ueda, Y. Matsumoto, and T. Ogasawara. 2004. "Grip Force Control for an Elastic Finger Using Vision-Based Incipient Slip Feedback." Pp. 810–15 vol.1 in *2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (IEEE Cat. No.04CH37566)*. Vol. 1.
- Ishihara, Hidenori, Naoki Hirose, Shota Funaoka, Kazuo Morita, and Tohru Miyake. 2011. "Proposal of Anthropomorphic Hand with Passive Warped Fingertip." Pp. 1219–24 in *2011 IEEE International Conference on Mechatronics and Automation*. IEEE.
- Issa, A., M. O. A. Aqel, B. Zakout, A. Abu Daqqa, M. Amassi, and N. Naim. 2019. "5-DOF Robot Manipulator Modelling, Development and Automation Using LabVIEW, Vision Assistant and Arduino." Pp. 124–29 in *2019 International Conference on Promising Electronic Technologies (ICPET)*.
- Jabalarneli, Amirhossein, Nabil Etehad, and Aman Behal. 2018. "Edge-Based Recognition of Novel Objects for Robotic Grasping." *ArXiv Preprint*.
- Jadhav, Jagruti, Mehzabeen Attar, Shradha Patil, and Saleem Beg. 2018. "Object Recognition Using CNN." *International Journal of Advance Research, Ideas and Innovations in Technology* 4(2):1987–91.

- Jeon, Myounghoon. 2017. "Robotic Arts: Current Practices, Potentials, and Implications." *Multimodal Technologies and Interaction* 1(2):5.
- Johan, Tegin, and Wikander Jan. 2005. "Tactile Sensing in Intelligent Robotic Manipulation – a Review." *Industrial Robot: An International Journal* 32(1):64–70.
- Jordan, M. I., and T. M. Mitchell. 2015. "Machine Learning: Trends, Perspectives, and Prospects." *Science (New York, N.Y.)* 349(6245):255–60.
- Jouppila, Ville T., S. Andrew Gadsden, Gary M. Bone, Asko U. Ellman, and Saeid R. Habibi. 2014. "Sliding Mode Control of a Pneumatic Muscle Actuator System with a PWM Strategy." *International Journal of Fluid Power* 15(1):19–31.
- Kappassov, Zhanat, Juan Antonio Corrales, and Véronique Perdereau. 2015. "Tactile Sensing in Dexterous Robot Hands - Review." *Robotics and Autonomous Systems* 74:195–220.
- Karpathy, Andrej. 2016. *Deep Learning for Computer Vision*. Vol. 7.
- Kawamura, Takuya, Naoto Inaguma, Ko Nejigane, Kazuo Tani, and Hironao Yamada. 2013. "Measurement of Slip, Force and Deformation Using Hybrid Tactile Sensor System for Robot Hand Gripping an Object." *International Journal of Advanced Robotic Systems* 10.
- Kawamura, Takuya, Ko Nejigane, Kazuo Tani, and Hironao Yamada. 2012. "Hybrid Tactile Sensor System for a Robot Hand and Estimation of Fine Deformation Using the Sensor System." *International Journal of Social Robotics* 4(SUPPL.1):93–100.
- Khan, Salman, Hossein Rahmani, Syed Afaq Ali Shah, and Mohammed Bennamoun. 2018. *A Guide to Convolutional Neural Networks for Computer Vision*. Vol. 8. 1st ed. edited by G. Medioni and S. Dickinson. Morgan & Claypool.
- Kim, Phil. 2017. *MATLAB Deep Learning*. Berkeley, CA: Apress.
- Kornblith, Simon, Jonathon Shlens, and Quoc V. Le. 2018. "Do Better ImageNet Models Transfer Better?" *ArXiv Preprint*.
- Kragic, D., and H. I. Christensen. 2003. "Robust Visual Servoing." *The International Journal of Robotics Research* 22(10–11):923–39.
- Krishna, Manoj, M. Neelima, M. Harshali, and Venu Rao. 2018. "Image Classification Using Deep Learning." *International Journal of Engineering & Technology* 7(2.7):614–17.
- Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. 2012. "ImageNet Classification with Deep Convolutional Neural Networks." *Advances In Neural Information Processing Systems* 1–9.
- Kumar, R., S. Lal, S. Kumar, and P. Chand. 2014. "Object Detection and Recognition for a Pick and Place Robot." Pp. 1–7 in *Asia-Pacific World Congress on Computer Science and Engineering*.

- Kumra, Sulabh, and Christopher Kanan. 2017. “Robotic Grasp Detection Using Deep Convolutional Neural Networks.” *IEEE International Conference on Intelligent Robots and Systems* 2017-Sept:769–76.
- Kyberd, Peter J., and Paul H. Chappell. 1992. “Object-Slip Detection during Manipulation Using a Derived Force Vector.” *Mechatronics* 2(1):1–13.
- De La Rosa, Erick, and Wen Yu. 2016. “Restricted Boltzmann Machine for Nonlinear System Modeling.” Pp. 443–46 in *2015 IEEE 14th International Conference on Machine Learning and Applications, ICMLA 2015*. Miami, FL, USA: IEEE.
- LeCun, Y., B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard, and L. D. Jackel. 2008. “Backpropagation Applied to Handwritten Zip Code Recognition.” *Neural Computation* 1(4):541–51.
- LeCun, Yann, Bengio Yoshua, and Hinton Geoffrey. 2015. “Deep Learning.” *Nature* 521(7553):436–44.
- Lenz, Ian, Honglak Lee, and Ashutosh Saxena. 2015. “Deep Learning for Detecting Robotic Grasps.” *The International Journal of Robotics Research* 34(4–5):705–24.
- Levine, Sergey, Peter Pastor, Alex Krizhevsky, Julian Ibarz, and Deirdre Quillen. 2018. “Learning Hand-Eye Coordination for Robotic Grasping with Deep Learning and Large-Scale Data Collection.” *International Journal of Robotics Research* 37(4–5):421–36.
- Li, J., S. Dong, and E. Adelson. 2018. “Slip Detection with Combined Tactile and Visual Information.” Pp. 7772–77 in *2018 IEEE International Conference on Robotics and Automation (ICRA)*.
- Lin, Chieh Chun, Pablo Gonzalez, Ming Yang Cheng, Guor Yieh Luo, and Tzu Yang Kao. 2017. “Vision Based Object Grasping of Industrial Manipulator.” *2016 International Conference on Advanced Robotics and Intelligent Systems, ARIS 2016* 1–5.
- Liu, Tie, Zejian Yuan, Jian Sun, Jingdong Wang, Nanning Zheng, Xiaoou Tang, and Heung Yeung Shum. 2011. “Learning to Detect a Salient Object.” *IEEE Transactions on Pattern Analysis and Machine Intelligence* 33(2):353–67.
- Liu, Xiaobo, Zhentao Liu, Guangjun Wang, Zhihua Cai, and Harry Zhang. 2017. “Ensemble Transfer Learning Algorithm.” *IEEE Access* 6:2389–96.
- Long, Mingsheng, Yue Cao, Jianmin Wang, and Michael I. Jordan. 2015. “Learning Transferable Features with Deep Adaptation Networks.” Pp. 97–105 in *Proceedings of the 32Nd International Conference on International Conference on Machine Learning - Volume 37, ICML’15*. JMLR.org.
- Long, Mingsheng, Han Zhu, Jianmin Wang, and Michael I. Jordan. 2016. “Deep Transfer Learning with Joint Adaptation Networks.”

- Luo, Ping, Yonglong Tian, Xiaogang Wang, and Xiaoou Tang. 2014. “Switchable Deep Network for Pedestrian Detection.” Pp. 899–905 in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*. IEEE.
- Luo, Zelun, Yuliang Zou, Judy Hoffman, and Li Fei-Fei. 2017. “Label Efficient Learning of Transferable Representations Across Domains and Tasks.” Pp. 164–76 in *Proceedings of the 31st International Conference on Neural Information Processing Systems, NIPS’17*. USA: Curran Associates Inc.
- Maeda, Sho, Nobutaka Tsujiuchi, Takayuki Koizumi, Mitsumasa Sugiura, and Hiroyuki Kojima. 2011. “Development and Control of Pneumatic Robot Arm for Industrial Fields.” *IECON Proceedings (Industrial Electronics Conference)* 9:86–91.
- Mahler, Jeffrey, Jacky Liang, Sherdil Niyaz, Michael Laskey, Richard Doan, Xinyu Liu, Juan Aparicio Ojea, and Ken Goldberg. 2017. “Dex-Net 2.0: Deep Learning to Plan Robust Grasps with Synthetic Point Clouds and Analytic Grasp Metrics.” *ArXiv Preprint*.
- Maini, Raman. 2003. “Study and Comparison of Various Image Edge Detection Techniques.” *International Journal of Image Processing* 147002(3):1–12.
- Mamun, A., and M. Y. Ibrahim. 2010. “New Approach to Detection of Incipient Slip Using Inductive Sensory System.” Pp. 1901–6 in *2010 IEEE International Symposium on Industrial Electronics*.
- Martin, James. 1965. *Programming Real-Time Computer Systems*. edited by Hardcover. Englewood Cliffs: Prentice Hall.
- Al Mashhadany, Yousif I. 2012. “SCARA Robot: Modeled, Simulated, and Virtual-Reality Verified.” Pp. 94–102 in *Trends in Intelligent Robotics, Automation, and Manufacturing*, edited by S. G. Ponnambalam, J. Parkkinen, and K. C. Ramanathan. Berlin, Heidelberg: Springer Berlin Heidelberg.
- MathWorks. 2019a. “Deep Network Designer.” Retrieved February 4, 2019 (<https://www.mathworks.com/help/deeplearning/ref/deepnetworkdesigner-app.html?searchHighlight=Deep>).
- MathWorks. 2019b. “Point Grey Camera Support from Image Acquisition Toolbox.” Retrieved <https://www.mathworks.com/hardware-support/point-grey-camera.html>.
- MathWorks. 2019c. “Set Up Parameters and Train Convolutional Neural Network.” Retrieved February 7, 2019 (<https://www.mathworks.com/help/deeplearning/ug/setting-up-parameters-and-training-of-a-convnet.html>).
- MathWorks. 2019d. “Simulink Real-Time.” Retrieved February 14, 2019 (<https://www.mathworks.com/products/simulink-real-time.html>).
- MathWorks. 2019e. “Transfer Learning Using AlexNet.” Retrieved February 7, 2019 (<https://www.mathworks.com/help/deeplearning/examples/transfer-learning-using-alexnet.html>).

- MathWorks. 2019f. “Transfer Learning with Deep Network Designer.” Retrieved February 7, 2019 (<https://www.mathworks.com/help/deeplearning/ug/transfer-learning-with-deep-network-designer.html>).
- McMorran, Darren, Dwayne Chung Kim Chung, Jonathan Li, Murat Muradoglu, Oi Wah Liew, and Tuck Wah Ng. 2016. “Adapting a Low-Cost Selective Compliant Articulated Robotic Arm for Spillage Avoidance.” *Journal of Laboratory Automation* 21(6):799–805.
- Merriam-Webster Collegiate Dictionary. 2003. *Merriam-Webster Collegiate Dictionary, 11th Edition*.
- Morita, Nobutomo, Hirofumi Nogami, Eiji Higurashi, and Renshi Sawada. 2018. “Grasping Force Control for a Robotic Hand by Slip Detection Using Developed Micro Laser Doppler Velocimeter.” *Sensors (Switzerland)* 18(2):326.
- Murali, Adithyavairavan, Yin Li, Dhiraj Gandhi, and Abhinav Gupta. 2018. “Learning to Grasp Without Seeing.” *ArXiv Preprint*.
- Murphy, Kevin P. 2012. *Machine Learning a Probabilistic Perspective*. MIT Press.
- National Instruments. 2019. “NI PCI-6024E.” Retrieved February 14, 2019 (<http://sine.ni.com/psp/app/doc/p/id/psp-29/lang/en>).
- Nicholls, Howard R. 1992. *Advanced Tactile Sensing for Robotics*. USA: World Scientific Publishing Co., Inc.
- Olson, David L., and Dursun Delen. 2008. *Advanced Data Mining Techniques*. 1st ed. Berlin, Heidelberg: Springer Berlin Heidelberg.
- Ouyang, Wanli, Xiaogang Wang, Xingyu Zeng, Shi Qiu, Ping Luo, Yonglong Tian, Hongsheng Li, Shuo Yang, Zhe Wang, Chen Change Loy, and Xiaoou Tang. 2015. “DeepID-Net: Deformable Deep Convolutional Neural Networks for Object Detection.” Pp. 2403–12 in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*. Vols. 07-12-June. IEEE.
- Park, Dongwon, Yonghyeok Seo, and Se Young Chun. 2018. “Real-Time, Highly Accurate Robotic Grasp Detection Using Fully Convolutional Neural Networks with High-Resolution Images.” *ArXiv Preprint* abs/1809.0.
- Petrovskaya, Anna, Oussama Khatib, Sebastian Thrun, and Andrew Y. Ng. 2006. “Bayesian Estimation for Autonomous Object Manipulation Based on Tactile Sensors.” *Proceedings - IEEE International Conference on Robotics and Automation* 2006:707–14.
- Pierson, Harry A., and Michael S. Gashler. 2017. “Deep Learning in Robotics: A Review of Recent Research.” *ArXiv Preprint* 1–41.
- Pinto, Lerrel, and Abhinav Gupta. 2016. “Supersizing Self-Supervision: Learning to Grasp from 50K Tries and 700 Robot Hours.” *Proceedings - IEEE International Conference on Robotics and Automation* 2016-June:3406–13.

- Poola, Indrasen. 2017. "The Best of the Machine Learning Algorithms Used in Artificial Intelligence." *International Journal of Advanced Research in Computer and Communication Engineering* 6(10):187–94.
- POWERS, and David M.W. 2011. "Evaluation: From Precision, Recall and F-Measure to ROC, Informedness, Markedness and Correlation." *Journal of Machine Learning Technologies* 2(1):37–63.
- Razavian, Ali Sharif, Hossein Azizpour, Josephine Sullivan, and Stefan Carlsson. 2014. "CNN Features Off-the-Shelf: An Astounding Baseline for Recognition." *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops* 512–19.
- Razzaq, Alaa M., Dayang L. Majid, Mohamad R. Ishak, and Uday M. Basheer. 2019. *Effects of Solid Fly Ash on Wear Behaviour of AA6063 Aluminum Alloy*. Elsevier Ltd.
- Redmon, Joseph, and Anelia Angelova. 2015. "Real-Time Grasp Detection Using Convolutional Neural Networks." Pp. 1316–22 in *2015 IEEE International Conference on Robotics and Automation (ICRA)*. Seattle, WA, USA: IEEE.
- Ribeiro, E. G., and V. Grassi. 2019. "Fast Convolutional Neural Network for Real-Time Robotic Grasp Detection." Pp. 49–54 in *2019 19th International Conference on Advanced Robotics (ICAR)*.
- Robert, Bogue. 2017. "Recent Developments in Robotic Tactile Perception." *Industrial Robot: An International Journal* 44(5):565–70.
- Rofalis, Nikolaos, Lazaros Nalpantidis¹, Nils Axel Andersen, and Volker Kruger. 2016. "Vision-Based Robotic System for Object Agnostic Placing Operations." Pp. 467–75 in *Visigrapp 2016. 11th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications*.
- Le Roux, Nicolas, and Yoshua Bengio. 2008. "Representational Power of Restricted Boltzmann Machines and Deep Belief Networks." *Neural Computation* 20(6):1631–49.
- Ruiz-del-solar, Javier, Patricio Loncomilla, and Naiomi Soto. 2018. "A Survey on Deep Learning Methods for Robot Vision." *ArXiv Preprint* 1–43.
- Salakhutdinov, Ruslan, and Geoffrey Hinton. 2009. "Deep Boltzmann Machines." Pp. 448–55 in *Proceedings of the Twelfth International Conference on Artificial Intelligence and Statistics*. Vol. 5, *Proceedings of Machine Learning Research*, edited by D. van Dyk and M. Welling. Hilton Clearwater Beach Resort, Clearwater Beach, Florida USA: PMLR.
- Salakhutdinov, Ruslan, and Hugo Larochelle. 2010. "Efficient Learning of Deep Boltzmann Machines." Pp. 693–700 in *Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics*. Vol. 9, *Proceedings of Machine Learning Research*, edited by Y. W. Teh and M. Titterton. Chia Laguna Resort, Sardinia, Italy: PMLR.

- Sammut, Claude, and Geoffrey I. Webb, eds. 2010. *Encyclopedia of Machine Learning*. Boston, MA: Springer US.
- Saxena, a., J. Driemeyer, and a. Y. Ng. 2008. "Robotic Grasping of Novel Objects Using Vision." *The International Journal of Robotics Research* 27(2):157–73.
- Scaramuzza, Davide, Agostino Martinelli, and Roland Siegwart. 2006. "A Toolbox for Easily Calibrating Omnidirectional Cameras." Pp. 5695–5701 in *IEEE International Conference on Intelligent Robots and Systems*. IEEE.
- Schmidhuber, Jürgen. 2015. "Deep Learning in Neural Networks: An Overview." *Neural Networks* 61:85–117.
- Schneiderman, H., and T. Kanade. 1998. "Probabilistic Modeling of Local Appearance and Spatial Relationships for Object Recognition." *CVPR '98 Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition* 45.
- Serrezuela, Ruthber Rodriguez, Adrian Fernando Chavarro Chavarro, Miguel Angel Tovar Cardoso, Alejandro Leiva Toquica, and Luis Fernando Ortiz Martinez. 2017. "Kinematic Modelling of a Robotic Arm Manipulator Using MATLAB." *ARNP Journal of Engineering and Applied Sciences* 12(7):2037–45.
- Shaw, J., and V. Dubey. 2016. "Design of Servo Actuated Robotic Gripper Using Force Control for Range of Objects." Pp. 1–6 in *2016 International Conference on Advanced Robotics and Intelligent Systems (ARIS)*.
- Shrivastava, Suyash. 2017a. "MATLAB GUIDE Development for SCARA Robot." *IOSR Journal of Mechanical and Civil Engineering (IOSR-JMCE)* 14(5):50–53.
- Shrivastava, Suyash. 2017b. "Matlab Guide for Forward Kinematic Calculation of 3 To 6 Dof Scara Robots." *International Journal of Research in Engineering and Technology* 06(09):46–52.
- Siciliano, Bruno, Lorenzo Sciavicco, Luigi Villani, and Giuseppe Oriolo. 2009. *Robotics: Modelling, Planning and Control*. Springer, London.
- Sinha, Rajat Kumar, Ruchi Pandey, and Rohan Pattnaik. 2017. "Deep Learning For Computer Vision Tasks: A Review." in *2017 International Conference on Intelligent Computing and Control (I2C2)*.
- Song, A., Y. Han, H. Hu, and J. Li. 2014. "A Novel Texture Sensor for Fabric Texture Measurement and Classification." *IEEE Transactions on Instrumentation and Measurement* 63(7):1739–47.
- Srivastava, Nitish, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. 2014. "Dropout: A Simple Way to Prevent Neural Networks from Overfitting." *Journal of Machine Learning Research* 15:1929–58.
- Srivastava, Nitish, and Ruslan Salakhutdinov. 2014. "Multimodal Learning with Deep Boltzmann Machines." *Journal of Machine Learning Research* 15:2949–80.

- Sung, Jaeyong, Seok Hyun Jin, Ian Lenz, and Ashutosh Saxena. 2016. “Robobarista: Learning to Manipulate Novel Objects via Deep Multimodal Embedding.” *ArXiv Preprint*.
- Tan, Chuanqi, Fuchun Sun, Tao Kong, Wenchang Zhang, Chao Yang, and Chunfang Liu. 2018. “A Survey on Deep Transfer Learning.” Pp. 270–79 in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. Vol. 11141 LNCS. Springer, Cham.
- Tatsumi, Masayuki, Kazuhiro Izusawa, and Shinichi Hirai. 2011. “Miniaturized Unconstrained Valves with Pressure Control for Driving a Robot Finger.” *2011 IEEE International Conference on Robotics and Biomimetics, ROBIO 2011* 1528–33.
- Tekscan. 2018. “FlexiForce Load/Force Sensors and Systems.” Retrieved August 6, 2018 (<https://www.tekscan.com/flexiforce-load-force-sensors-and-systems>).
- Teshigawara, Seiichi, Takahiro Tsutsumi, Yosuke Suzuki, and Makoto Shimojo. 2012. “High Speed and High Sensitivity Slip Sensor for Dexterous Grasping.” *Journal of Robotics and Mechatronics* 24(2):298–310.
- Tighe, Joseph, Marc Niethammer, and Svetlana Lazebnik. 2015. “Scene Parsing with Object Instance Inference Using Regions and Per-Exemplar Detectors.” *International Journal of Computer Vision* 112(2):150–71.
- Tobin, Josh, Rachel Fong, Alex Ray, Jonas Schneider, Wojciech Zaremba, and Pieter Abbeel. 2017. “Domain Randomization for Transferring Deep Neural Networks from Simulation to the Real World.” Pp. 23–30 in *IEEE International Conference on Intelligent Robots and Systems*. Vols. 2017-Sept. Vancouver, BC, Canada: IEEE.
- Tsujiiuchi, Nobutaka, Takayuki Koizumi, Shinya Nishino, Hiroyuki Komatsubara, Tatsuwo Kudawara, and Masanori Hirano. 2008. “Development of Pneumatic Robot Hand and Construction of Master-Slave System.” *Journal of System Design and Dynamics* 2(6):1306–15.
- Tzeng, Eric, Judy Hoffman, Kate Saenko, and Trevor Darrell. 2017. “Adversarial Discriminative Domain Adaptation.” Pp. 2962–71 in *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017*. Vols. 2017-Janua. IEEE.
- Urban, Steffen, Jens Leitloff, and Stefan Hinz. 2015. “Improved Wide-Angle, Fisheye and Omnidirectional Camera Calibration.” *ISPRS Journal of Photogrammetry and Remote Sensing* 108:72–79.
- Vincent, Pascal, Hugo Larochelle, Isabelle Lajoie, Yoshua Bengio, and Pierre-Antoine Manzagol. 2010. “Stacked Denoising Autoencoders: Learning Useful Representations in a Deep Network with a Local Denoising Criterion Pierre-Antoine Manzagol.” *Journal of Machine Learning Research* 11:3371–3408.

- Voulodimos, Athanasios, Nikolaos Doulamis, Anastasios Doulamis, and Eftychios Protopapadakis. 2018. “Deep Learning for Computer Vision: A Brief Review.” *Computational Intelligence and Neuroscience* 2018:1–13.
- Wan, Chang, Rong Pan, and Jiefei Li. 2011. “Bi-Weighting Domain Adaptation for Cross-Language Text Classification.” Pp. 1535–40 in *IJCAI International Joint Conference on Artificial Intelligence*. AAAI Press.
- Wang, Song, Feng Ge, and Tiecheng Liu. 2006. “Evaluating Edge Detection through Boundary Detection.” *Eurasip Journal on Applied Signal Processing* 2006(1):1–15.
- Watkins, Christopher J. C. H., and Peter Dayan. 1992. “Q-Learning.” *Machine Learning* 8(3):279–92.
- Watson, Joe, Josie Hughes, and Fumiya Iida. 2017. “Real-World, Real-Time Robotic Grasping with Convolutional Neural Networks.” Pp. 617–26 in *Towards Autonomous Robotic Systems*, edited by Y. Gao, S. Fallah, Y. Jin, and C. Lekakou. Cham: Springer International Publishing.
- Westerlund, Lars. 2000. *The Extended Arm of Man: A History of Industrial Robot*. Informationsförlaget.
- Wilson, D. Randall, and Tony R. Martinez. 2003. “The General Inefficiency of Batch Training for Gradient Descent Learning.” *Neural Networks* 16(10):1429–51.
- Xu, Yonghui, Sinno Jialin Pan, Hui Xiong, Qingyao Wu, Ronghua Luo, Huaqing Min, and Hengjie Song. 2017. “A Unified Framework for Metric Transfer Learning.” *IEEE Transactions on Knowledge and Data Engineering* 29(6):1158–71.
- Yang, Bei, Xiaogang Duan, and Hua Deng. 2015. “A Simple Method for Slip Detection of Prosthetic Hand.” *2015 IEEE International Conference on Information and Automation, ICIA 2015 - In Conjunction with 2015 IEEE International Conference on Automation and Logistics* (August):2159–64.
- Yang, Yezhou, Yi Li, Cornelia Fermuller, and Yiannis Aloimonos. 2015. “Robot Learning Manipulation Action Plans by ‘Watching’ Unconstrained Videos from the World Wide Web.” *Twenty-Ninth AAAI Conference on Artificial Intelligence (AAAI-15)* 3686–92.
- Yaniger, Stuart I. 1991. “Force Sensing Resistor a Review of the Technology.” Pp. 666–68 in *Electro International, ELECTR 1991 - Conference Record*. IEEE.
- Yosinski, Jason, Jeff Clune, Yoshua Bengio, and Hod Lipson. 2014. “How Transferable Are Features in Deep Neural Networks?” Pp. 3320–28 in *Proceedings of the 27th International Conference on Neural Information Processing Systems - Volume 2, NIPS’14*. Cambridge, MA, USA: MIT Press.
- Yousaf, Rehan Mehmood, Hafiz Adnan Habib, Hussain Dawood, and Sidra Shafiq. 2018. “A Comparative Study of Various Edge Detection Methods.” Pp. 96–99 in *2018 14th International Conference on Computational Intelligence and Security (CIS)*. IEEE.

- Zatsiorsky, Vladimir M., and Mark L. Latash. 2004. "The Principle of Superposition in Human Prehension." *Robotica* 22(2):231–34.
- Zeng, Andy, Shuran Song, Kuan-ting Yu, Elliott Donlon, Francois R. Hogan, Maria Bauza, Daolin Ma, Orion Taylor, Melody Liu, Eudald Romo, Nima Fazeli, Ferran Alet, Nikhil Chavan Dafle, Rachel Holladay, Isabella Morona, Prem Qu Nair, Druck Green, Ian Taylor, Weber Liu, Thomas Funkhouser, and Alberto Rodriguez. 2018. "Robotic Pick-and-Place of Novel Objects in Clutter with Multi-Affordance Grasping and Cross-Domain Image Matching." *ArXiv Preprint*.
- Zhang, C., and Z. Zhang. 2019. "Modelling and Simulation of SCARA Robot Using MATLAB/SimMechanics." Pp. 516–19 in *2019 IEEE 3rd Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC)*.
- Zhang, Fangyi, Juergen Leitner, Michael Milford, Ben Upcroft, and Peter Corke. 2015. "Towards Vision-Based Deep Reinforcement Learning for Robotic Motion Control." Pp. 1–8 in *Proceedings of the Australasian Conference on Robotics and Automation 2015, Australasian Conference on Robotics and Automation, ACRA*, edited by H. Li and J. Kim. Australia: Australian Robotics and Automation Association.
- Zhang, H. 2016. *Surface Characterization Techniques for Polyurethane Biomaterials*. Elsevier Ltd.
- Zhang, Xiwu, Lei Wang, Yan Zhao, and Yan Su. 2018. "Graph-Based Place Recognition in Image Sequences with CNN Features." *Journal of Intelligent & Robotic Systems* 1–15.
- Zhang, Y., X. Duan, G. Zhong, and H. Deng. 2016. "Initial Slip Detection and Its Application in Biomimetic Robotic Hands." *IEEE Sensors Journal* 16(19):7073–80.
- Zhang, Zhengyou. 2000. "A Flexible New Technique for Camera Calibration." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 22(11):1330–34.
- Zhaohui, Zheng, Ma Yong, Zheng Hong, Gu Yu, and Lin Mingyu. 2018. "Industrial Part Localization and Grasping Using a Robotic Arm Guided by 2D Monocular Vision." *Industrial Robot: An International Journal* 45(6):794–804.
- Zhou, Jing, and Changyun Wen. 2008. *Adaptive Backstepping Control of Uncertain Systems*. Springer-Verlag Berlin Heidelberg.
- Zhou, X., X. Lan, H. Zhang, Z. Tian, Y. Zhang, and N. Zheng. 2018. "Fully Convolutional Grasp Detection Network with Oriented Anchor Box." Pp. 7223–30 in *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*.
- Zhu, Han, Mingsheng Long, Jianmin Wang, and Yue Cao. 2016. "Deep Hashing Network for Efficient Similarity Retrieval." *Proceedings of the 30th Conference on Artificial Intelligence (AAAI 2016)* (1):2415–21.