

### Tactile Based Active Perception of Structural Members in Truss Structures

#### by Lili Bykerk

Thesis submitted in fulfilment of the requirements for the degree of

#### **Doctor of Philosophy**

under the supervision of Distinguished Professor Dikai Liu and Professor Kenneth Waldron

University of Technology Sydney Faculty of Engineering and Information Technology

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### **Certificate of Original Authorship**

I, Lili Bykerk, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy in the School of Mechanical and Mechatronic Engineering, Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

### Abstract

Complex Three-Dimensional (3D) truss structures such as power transmission towers require regular inspection and maintenance during their service life. Developing a robot to climb and explore such complex structures is challenging. Changing lighting conditions can render vision sensors unreliable; therefore, the robot should be endowed with a complementary sensory modality such as touch for accurate perception of the environment, including recognising a structural beam member and its properties of cross-sectional shape, size and the grasping Angle-of-Approach (AoA).

The research presented in this thesis addresses three questions related to grasping and touch based perception of beam members in truss structures. (1) Methods for designing adaptive grippers for grasping a wide variety of structural beam member cross-sectional shapes and sizes; (2) Sensing for data collection and methods for classifying beam member properties; and (3) Efficient methods for selecting the next best grasping action to confidently recognise a beam member.

A stiffness constrained topology optimisation design method is developed and applied in designing a soft gripper for grasping a variety of cross-sectional shapes of beam members. The gripper design is verified through both simulation and experiments. It is found that the gripper is proficient in grasping different shapes and sizes of beam members, with adequate contact points. A comparative study of commonly used machine learning classifiers is conducted to analyse the effectiveness of recognising a structural beam member and its properties. Using data collected during grasping with a soft gripper, the cross-sectional shape, size and grasping AoA of a beam member are classified. Evaluation of the various classifiers revealed that a Random Forest (RF) classifier with 100 trees achieved high classification accuracies, with short training and classification times.

An information-based method for selecting the next best grasping AoA to confidently recognise a beam member is developed. This method is verified through simulation using grasping data collected with a soft gripper. The results show that this method can correctly recognise a structural beam member and its properties, typically with fewer than four grasping actions. This method can be generally used with many different gripper designs and sensor arrangements.

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### Acronyms & Abbreviations

- 2D Two-Dimensional
- **3D** Three-Dimensional
- **ANN** Artificial Neural Network
- AoA Angle-of-Approach
- AoAs Angles-of-Approach
- **BN** Bayesian Network
- **CAS** Centre for Autonomous Systems
- CAD Computer Aided Design
- **CC** Constant Curvature
- **CCD** Charge-Coupled Device
- **CCW** Counterclockwise
- **COTS** Commercially Available Off-The-Shelf
- CO<sub>2</sub> Carbon Dioxide
- **CPR** Cardiopulmonary Resuscitation
- CW Clockwise
- **DES** Dielectric Elastomer Sensor
- **DOF** Degrees Of Freedom

<b>ECOC</b> Error-Correcting Output Codes	
EGaIn Eutectic Gallium-Indium	
EP	Exploratory Procedure
e-3DP	Embedded 3D Printing
FEA	Finite Element Analysis
FSR	Force Sensitive Resistor
KLD	Kullback Leibler Divergence
k-NN	k-Nearest Neighbours
LDA	Linear Discriminant Analysis
LVDT	Linear Variable Differential Transformer
<b>MEMS</b> Microelectromechanical Systems	
NZ New Zealand	
<b>OC</b> Optimality Criteria	
<b>OOB</b> Out-of-bag	
PAM	Pneumatic Artificial Muscle
PCC	Piecewise Constant Curvature
<b>PDMS</b> Polydimethylsiloxane	
<b>PPE</b> Personal Protective Equipment	
PCB Printed Circuit Board	
<b>RF</b> Random Forest	
<b>RVDT</b> Rotational Variable Differential Transform	
$\mathbf{SA}$	South Australia

- **SIMP** Solid Isotropic Material with Penalisation
- **SVM** Support Vector Machine
- **TEPCO** Tokyo Electric Power Company
- ToMBot Tower Maintenance Robot
- **UK** United Kingdom
- **USA** United States of America
- **UTS** University of Technology Sydney
- **WHS** Workplace Health and Safety

## Nomenclature

#### **General Notations**

$[\cdots]^T$	Transpose
$f(\cdots)$	A scalar valued function
$\mathbf{f}\left(\cdots\right)$	A vector valued function
$max(\cdots)$	Maximum value

$\tilde{\mathbf{x}}_{\mathrm{stiffer}}$	The density of elements in the regions of the design domain to	
	stiffen	
$ ilde{\mathbf{x}}_{\mathrm{rest}}$	The density of elements in the remainder of the design domain	
α	A user defined stiffness multiplier	
$N_i$	The neighbourhood of an element	
$x_i$	An element in the design domain	
$x_e$	The design variable	
$v_i$	Volume of an element in the design domain	
$ar{v}$	The prescribed volume limit of the design domain	
$H_{ij}$	A weight factor	
L	A unit length vector with all zeros at all degrees of freedom exce	
	at the output point where it is one	
n	The number of elements used to discretise the design domain	
F	A vector of nodal forces	
$\mathbf{U}(\tilde{\mathbf{x}})$	A vector of nodal displacements	
$\mathbf{K}( ilde{\mathbf{x}})$	Global stiffness matrix	

	Information-based Method	
Bm	Number of beam members	
N <sub>AoA</sub>	Number of Angles-of-Approach (AoAs)	
$N_{ba}$	Number of beam-angle pairs	
$N_g$	Number of grasps performed for data collection	
$N_{grasps}$	Number of grasps executed for beam member identification	
β	Angle shift increments	
F	Force Sensitive Resistor ( <b>FSR</b> ) data	
$I_a$	Information for a candidate Angle-of-Approach (AoA)	
$N_{FSR}$	Number of individual <b>FSR</b> sensors	
$N_{enc}$	Number of encoder readings	
n	Number of predicted beam member AoAs after a haptic glance	
$\mu_i$	Average of <b>FSR</b> data for a given sensor number and AoA	
$\sigma_i^2$	Variance of <b>FSR</b> data for a given sensor number and AoA	
τ	Threshold value above which to count the Random Forest (RF)	
	classifier votes as valid	

## **Glossary of Terms**

Autonomous	Without human intervention.
Compliance Match	The principle that contacting materials should
	share similar mechanical rigidity in order to evenly
	distribute internal load and minimise interfacial
	stress concentrations.
Effector	An organ or cell that acts in response to a stimulus.
Extensor Digitorum Communis	A muscle of the posterior forearm present in hu-
	mans and other animals. It extends the medial four
	digits of the hand.
Exteroception	By which one perceives the outside world.
Haptic Glance	A brief, spatially constrained contact that involves
	little or no movement of the fingers.
Haptic Perception	The ability to identify something by active explo-
	ration of surfaces by a moving subject.
Interphalangeal Joint	Hinge joints between the phalanges of the fingers
	that provide flexion towards the palm of the hand.
Metacarpophalangeal Joint	Hinge joints between the metacarpal bones and the
	proximal phalanges of the digits.
Modulus of Elasticity	A quantity that measures an object or substance's
	resistance to being deformed elastically when a
	stress is applied to it.

Papillae	A small rounded protuberance on a part or organ
	of the body. Associated with nerve endings, they
	are able to relay sensory information.
Phalanges	Finger or toe bones.
Proprioception	The ability to sense the position, location, orienta-
	tion and movement of the body and its parts.
Tactile Pattern	A distribution of tactile sensor readings collected
	during grasping.