

**HAPTIC BASED SURFACE STIFFNESS
IDENTIFICATION USING MACHINE LEARNING**

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Master of Science

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Thesis submitted in partial fulfillment of the requirements for the degree
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DECLARATION

I declare that this is my own work and this Thesis does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

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The supervisor should certify the Thesis with the following declaration.

The above candidate has carried out research for the Master of Science Thesis under my supervision. I confirm that the declaration made above by the student is true and correct.

Name of Supervisor: Dr A. M Harsha S. Abeykoon

Signature of the Supervisor:

Date: 11/5/2023

DEDICATION

This study is wholeheartedly dedicated to my beloved parents and my spouse. For there endless love, support and encouragement.

ACKNOWLEDGEMENT

This project was made possible by the generosity of several individuals. It gives us immense pleasure to express my sincere gratitude and appreciation to everyone.

Initially, I would want to express my appreciation to my supervisor, Dr. A. M. Harsha S. Abeykoon, for all of his assistance and advice. Two years of my life were spent working under his direction. I praised him for his encouragement, support, and patience. This job could not be performed without this assistance.

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ABSTRACT

Touch is an essential environmental input for all living things, including humans. Most of the objects with which individuals interact are soft and malleable. Humans have inherited the ability to perceive and recognize differences in the deformable features of objects. Robotic systems have been developed to support numerous industries, and in robotics, “haptics” refers to forces and force feedback from the object. In many sectors, robotic devices handle deformable objects. We believe that to improve operational quality, robotic systems must be able to recognize deformable objects. While it is possible to observe the characteristics of items during their manipulation, haptic-based object identification remains a challenging subject due to the complexity of deformable object characteristics.

The discussion of object classification methodology begins with collecting object deformation data and sensors for data collection. Sensor array-based measurement techniques are capable of observing the pressure variation of the deformation area, while single point measurement techniques are capable of observing the force variation and compression depth of the object. The use of force response and compression distance measurements enables the extraction of additional attributes of deforming objects, such as stiffness, hysteresis, velocity, acceleration fluctuation, and energy absorbed during compression.

The use of machine learning to classify objects with features avoids many disadvantages associated with traditional mathematical model-based classification methodologies. The ability to handle time series data and large amounts of data are also key features of machine learning. In this study, we introduce the construction of additional features that may improve classification and use the Time Series Forest Classifier (TSFC) and permutation importance to identify the best performing features for object classification.

Keywords: Haptic, Haptics object modeling, deformable objects, Haptics features for machine learning, disturbance observer, reaction force observer, time series classification

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LIST OF ABBREVIATIONS

Abbreviation	Description
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FC	force cycle
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FDM	Forward deference method
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TSFC	Time Series Forest Classifier
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