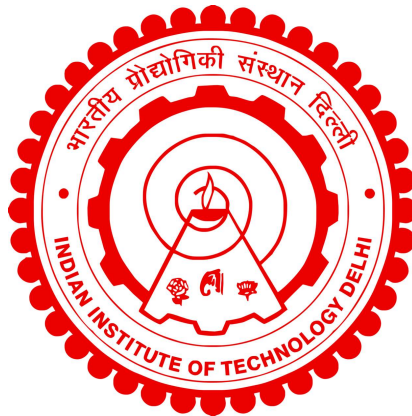


**HAPTICS: A CASE FOR EDGE AI BASED
CONVERGENCE OF COMMUNICATION,
COMPUTE AND CONTROL**

MUNEEB AHMED



**BHARTI SCHOOL OF TELECOMMUNICATION
TECHNOLOGY AND MANAGEMENT**

INDIAN INSTITUTE OF TECHNOLOGY DELHI

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by

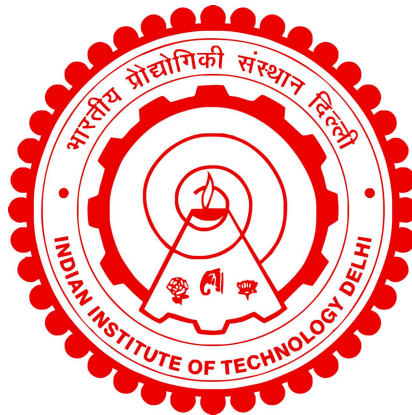
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Bharti School of Telecommunication Technology and
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Submitted

in fulfillment of the requirements of the degree of Doctor of Philosophy

to the



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Say, "My Lord! increase me in knowledge."

*Dedicated to my family and teachers for their unwavering
love, support and guidance.*

Certificate

This is to certify that the thesis entitled “**Haptics: A case for Edge AI based convergence of communication, compute and control**”, submitted by **Muneeb Ahmed** to the Indian Institute of Technology Delhi, for the award of the degree of **Doctor of Philosophy**, is a record of the original, bona fide research work carried out by him under our supervision and guidance. The thesis has reached the standards fulfilling the requirements of the regulations related to the award of the degree.

The results contained in this thesis have not been submitted in part or in full to any other University or Institute for the award of any degree or diploma to the best of our knowledge.



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A handwritten signature in black ink, appearing to read 'Muneeb Ahmed', with a stylized flourish at the end.

Muneeb Ahmed

Indian Institute of Technology Delhi

Abstract

This thesis concerns key aspects of robotic teleoperation, focusing on haptic feedback and edge computing paradigms. Our aim is to analyse the interaction of a remotely operated robot with its environment using haptic data.

We leverage a probabilistic approach to explore the signal-level characteristics of haptic signatures observed during robot-environment interaction to develop insights into the magnitude of information content embedded within haptic signals. The robot’s feedback is modelled as a Markov process to analyse its entropy. Next, mutual information is utilized to understand the degree of correlation in the signals. The set of experiments is performed in two settings, viz., without any robot-object interaction and with robot-object interaction across different 3D objects.

Owing to direct physical interaction with the objects, haptic feedback data is expected to be rich in embedding the object information, prompting inquiries into its potential for discerning the information about the structural type of the objects. In this context, we curate a novel haptic dataset of 58 objects, both in physical and simulated space, varying in shape, size, and material. Leveraging machine learning techniques, we address the problem of estimating the shape of 3D objects using haptic signatures. Next, we present a novel data augmentation technique to synthesize new haptic signatures that bring about variability in the curated dataset. We evaluate the augmentation mechanism and present insights from the results concerning shape detection from haptic data.

Furthermore, it is important to comprehend the essential characteristics of kinaesthetics in order to determine its capability of quantifying the intent of the human user who controls the robot’s state with an exoskeleton glove via a network in the framework of bilateral teleoperation. To mitigate the effect of channel delays, it is desired to synthesize a compact representation of the human input, as its intent, ahead of time. We present an estimation and prediction mechanism that generates a predicted intent within a specified prediction window, leveraging an attention-based convolutional encoder network. In addition, considering the significant advancements in vision-based approaches in recent years, this part of our study aims to compare data obtained through vision and haptic feedback, specifically focusing on quantifying human intent as a usecase.

Finally, this thesis investigates the feasibility and limitations of edge analytics for facilitating bilateral teleoperation. By examining scenarios encompassing both autonomous and non-autonomous robotic systems, the research elucidates the potential benefits of edge computing in enhancing the efficiency and standardization of teleoperation frameworks. Through rigorous experimentation and analysis, it provides a comprehensive understanding of the potential and limitations of haptic-based teleoperation systems, paving the way for advancing the role of edge analytics in teleoperation paradigms.

सार

यह थीसिस रोबोटिक टेलीऑपरेशन के प्रमुख पहलुओं से संबंधित है, जो हैट्रिक फीडबैक और एज कंप्यूटिंग प्रतिमानों पर केंद्रित है। हमारा उद्देश्य हैट्रिक डेटा का उपयोग करके दूर से संचालित रोबोट की उसके पर्यावरण के साथ बातचीत का विश्लेषण करना है।

हम हैट्रिक सिग्नल में अंतर्निहित सूचना सामग्री की मात्रा में अंतर्दृष्टि विकसित करने के लिए रोबोट-पर्यावरण इंटरैक्शन के दौरान देखे गए हैट्रिक सिग्नल की सिग्नल-स्तरीय विशेषताओं का पता लगाने के लिए एक संभाव्य दृष्टिकोण का लाभ उठाते हैं। रोबोट की प्रतिक्रिया को उसके एन्ट्रॉपी का विश्लेषण करने के लिए मार्कोव प्रक्रिया के रूप में मॉडल किया जाता है। इसके बाद, संकेतों में सहसंबंध की डिग्री को समझने के लिए पारस्परिक जानकारी का उपयोग किया जाता है। प्रयोगों का सेट दो सेटिंग्स में किया जाता है, अर्थात्, बिना किसी रोबोट-ऑब्जेक्ट इंटरैक्शन के और विभिन्न 3D ऑब्जेक्ट्स में रोबोट-ऑब्जेक्ट इंटरैक्शन के साथ।

ऑब्जेक्ट्स के साथ प्रत्यक्ष भौतिक इंटरैक्शन के कारण, हैट्रिक फीडबैक डेटा ऑब्जेक्ट की जानकारी को एम्बेड करने में समृद्ध होने की उम्मीद है, जिससे ऑब्जेक्ट्स के संरचनात्मक प्रकार के बारे में जानकारी को समझने की इसकी क्षमता के बारे में पूछताछ की जा सकती है। इस संदर्भ में, हम 58 वस्तुओं का एक नया हैट्रिक डेटासेट तैयार करते हैं, जो भौतिक और नकली दोनों जगहों पर हैं, जो आकार, माप और सामग्री में भिन्न हैं। मशीन लर्निंग तकनीकों का लाभ उठाते हुए, हम हैट्रिक सिग्नल का उपयोग करके 3D ऑब्जेक्ट के आकार का अनुमान लगाने की समस्या का समाधान करते हैं। इसके बाद, हम नए हैट्रिक सिग्नल को संश्लेषित करने के लिए एक नई डेटा वृद्धि तकनीक प्रस्तुत करते हैं जो क्यूरेटेड डेटासेट में परिवर्तनशीलता लाती है। हम वृद्धि तंत्र का मूल्यांकन करते हैं और हैट्रिक डेटा से आकार का पता लगाने से संबंधित परिणामों से अंतर्दृष्टि प्रस्तुत करते हैं।

इसके अलावा, द्विपक्षीय टेलीऑपरेशन के ढांचे में एक नेटवर्क के माध्यम से रोबोट की स्थिति को एक्सोस्केलेटन दस्ताने के साथ नियंत्रित करने वाले मानव उपयोगकर्ता के इरादे को निर्धारित करने की इसकी क्षमता निर्धारित करने के लिए किनेस्थेटिक्स की आवश्यक विशेषताओं को समझना महत्वपूर्ण है। चैनल देरी के प्रभाव को कम करने के लिए, समय से पहले, मानव इनपुट के एक कॉम्पैक्ट प्रतिनिधित्व को उसके इरादे के रूप में संश्लेषित करना वांछित है। हम एक अनुमान और भविष्यवाणी तंत्र प्रस्तुत करते हैं जो एक निर्दिष्ट भविष्यवाणी विंडो के भीतर एक अनुमानित इरादे को उत्पन्न करता है, एक ध्यान-आधारित कन्वोल्यूशनल एनकोडर नेटवर्क का लाभ उठाता है। इसके अलावा, हाल के वर्षों में दृष्टि-आधारित दृष्टिकोणों में महत्वपूर्ण प्रगति को ध्यान में रखते हुए, हमारे अध्ययन के इस भाग का उद्देश्य दृष्टि और हैट्रिक फीडबैक के माध्यम से प्राप्त डेटा की तुलना करना है, विशेष रूप से उपयोग के मामले के रूप में मानव इरादे को निर्धारित करने पर ध्यान केंद्रित करना।

अंत में, यह थीसिस द्विपक्षीय टेलीऑपरेशन की सुविधा के लिए एज एनालिटिक्स की व्यवहार्यता और सीमाओं की जांच करती है। स्वायत्त और गैर-स्वायत्त रोबोटिक प्रणालियों को शामिल करने वाले परिदृश्यों की जांच करके, शोध टेलीऑपरेशन फ्रेमवर्क की दक्षता और मानकीकरण को बढ़ाने में एज कंप्यूटिंग के

संभावित लाभों को स्पष्ट करता है। कठोर प्रयोग और विश्लेषण के माध्यम से, यह हैट्रिक-आधारित टेलीऑपरेशन सिस्टम की क्षमता और सीमाओं की व्यापक समझ प्रदान करता है, जो टेलीऑपरेशन प्रतिमानों में एज एनालिटिक्स की भूमिका को आगे बढ़ाने का मार्ग प्रशस्त करता है।

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Abbreviations

AI	Artificial Intelligence
AR	Augmented Reality
ARH	Allegro Robotic Hand
CLE	Compact/Latent Encoding
CNN	Convolution Neural Network
CWL	Condition With Load
DHG	Dexmo Haptic Glove
DL	Deep Learning
DOF	Degree Of Freedom
DTree	Decision Tree
EPS	Entropy Per Sample
ETSI	European Telecommunications Standards Institute
GRU	Gated Recurrent Unit
HG	Haptic Glove
iCLAP	Iterative Closest Labeled Point
IMU	Inertial Measurement Unit
K-NN	K-Nearest Neighbour
LSTM	Long Short Term Memory
MAE	Mean Absolute Error
MEC	Mobile Edge Computing
MECH	Mobile Edge Computing Host
MECO	Mobile Edge Computing Orchestrator
MECP	Mobile Edge Computing Platform
ML	Machine Learning
MLP	Multiple Layer Perceptron
MSE	Mean Squared Error

<i>n</i> D	<i>n</i> dimensional
NLD	No Load Condition
NN	Neural Network
OROS	Orchestrating Robotic Operating System
PC	Principal Component
PCA	Principal Component Analysis
RBF	Radial Basis Function
RH	Robotic Hand
RNN	Recurrent Neural Network
ROS	Robot Operating System
RTNP	Real-Time Messaging Protocol
SD	Standard Deviation
SDG	Synthetic Data Generation
SLAM	Simultaneous Localization And Mapping
SVM	Support Vector Machine
UALCM	User Application Life-cycle Management
UE	User Equipment
URLLC	Ultra-reliable Low Latency Communications
VR	Virtual Reality

Symbols

\mathcal{O}_i	denotes i^{th} object in physical space
$\hat{\mathcal{O}}_i$	denotes i^{th} object in simulated space
\mathbf{Q}_{DHG}	denotes joint space configuration of Dexmo Haptic Glove
\mathbf{Q}_{ARH}	denotes joint space configuration of Allegro Robotic Hand
\mathbb{R}	denotes set of Real numbers
\mathbb{Z}^+	denotes set of positive Integers
\mathcal{L}	denotes cross-entropy loss function
f_r	denotes retargeting algorithm
$\ \mathbf{x}\ , \mathbf{x} $	denote L1 norm of \mathbf{x}
$\ \mathbf{x}\ _2$	denotes L2 norm of \mathbf{x}
\mathbb{F}_n	denotes n dimensional vector