MACHINE LEARNING OF HAPTIC OBJECTS AND REPRODUCTION FOR VIRTUAL REALITY

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Degree of Master of Science

Department of Electrical Engineering

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

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ABSTRACT

Humans interact with machines extensively through our auditory and visual senses, but they frequently ignore their most trusted sense: touch. However, the sense of touch has tremendous potential in almost all fields, including medicine, exploration, industrial robots, and gaming. Haptics, or the science of touch, enables humans to not only remove the barriers to achieve realization in virtual world, but also to perform a wide range of real-world manipulation tasks.

Unlike visual and auditory senses, sense of touch is bilateral. Thus, realistic haptic feedback takes utmost importance to achieve realization in the virtual world and to enhance human performance in the real world. Prior studies have used an environment model to reproduce the haptics sensation from the environment as if it's from the real environment. Most studies have employed conventional spring damper model to model the environment model and motion parameters were considered as the factors affecting for force response. However, the traditional spring damper model doesn't reflect the actual object. Furthermore, the influence of learned force on reproduction requires special consideration, but haptics studies mostly consider motion data. However, there can be several factors affecting the recreation of haptic feedback. Thus, it is essential to analyze these factors to precisely reproduce an object in haptic dimension. Most studies have utilized force/torque sensors despite their shortcomings such as narrow bandwidth, signal noise, complicity, non-collocation, and instability. However, robust sensorless force/torque control over a wide bandwidth can be achieved using observer techniques and Disturbance Observer (DOB) and Reaction Force Observer (RFOB) are primarily used to get force measurements. AI enables computers to utilize vast quantities of data and employ their acquired intelligence to arrive at optimal conclusions and uncover insights in mere fractions of the time it would take for humans to do the same. Thus, recent technological studies have focused on using AI techniques to analyze larger and more complex data sets to achieve accurate and faster results. Thus, incorporating AI with haptics allows seamless integration with virtual reality and tune this technology to achieve precise responses.

Thus, this study focused on introducing machine learning and deep learning based vivid force sensation reproduction through a virtual model which replicates the actual environment. The information needed is abstracted through Disturbance Observer (DOB) and Reaction Force Observer (RFOB) based sensorless approach. Furthermore, statistical analysis was conducted on data to identify important features affecting the target value of force response.

Keywords *— Haptic interaction, Force response, Disturbance Observer, Virtual reality, force response, motion parameters, Artificial Intelligence, correlation, Principal Components Analysis (PCA), Random Forest, Haptic object Reproduction, RMSE.*

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LIST OF ABBREVIATIONS

Abbreviation	Description
AI	Artificial Intelligence
ANN	Artificial Neural Network
API	Application program interface
BP	Back Propagation
DNN	Deep Neural Network
DOB	Disturbance Observer
I/O	Input / Output
LSI	Large-Scale Integration
LSTM	Long short-term memory networks
MAE	Mean Absolute Error
MCS	Motion copying system.
ML	Machine Learning
MSE	Mean Squared Error
NN	Neural Network
PC	Principal component
PCA	Principal Component Analysis
PMML	Predictive Model Markup Language
RFOB	Reaction Force Observer
RMSE	Root Mean Squared Error

RNN	Recurrent Neural Network
SDK	Software Development Kits
SGD	Stochastic gradient descent
SVR	Support Vector Regression
XML	Extensible markup language

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NOMENCLATURE

M	Motor mass
M_n	The nominal value of motor mass
K_f	Motor force constant
K_{fn}	The nominal value of force constant
I_a^{ref}	Motor current
B	Viscosity coefficient
g_{dis}	Cut off frequency of DOB
g_{rec}	Cut off frequency of RFOB
x	Compression depth
$\dot{x}$	Velocity
F_m	Generated motor force
F_{dis}	Disturbance force
F_{ext}	Reaction force
F_{int}	Interactive force
F_f	Static friction
K_p	Proportional gain of the controller
g_v	Velocity filter constant
g_a	Acceleration filter constant
F_{cmd}	Force command

F_{res}	Force response
$\hat{F}_{dis}$	Estimated disturbance force
$\hat{F}_{ext}$	Estimated reaction force
$\ddot{x}$	Acceleration
c	Cycle No.
d	Permanent Deformation
$A^{F_{res}.x}$	Area F_{res} vs x curve
k	Stiffness coefficient
b	Damping coefficient
F_e	Reaction force from environment
C_p	Proportional gain of the position controller
C_d	Derivative gain of the position controller
C_i	Integral gain of the position controller
x_{ref}	Position reference command by operator
x_{err}	Compression depth error
dx_{err}	Change in compression depth error
$\int x_{err}$	Sum of compression depth errors
x_{err}^{pre}	Previous compression depth error
$\left(\int x_{err}\right)^{pre}$	Previous sum of compression depth errors