Data-Driven Modeling, Rendering, and Quantifying User Perception of Textured Surfaces and Automotive Systems

Presenter: Mudassir Ibrahim Awan
Advisor: Prof. Seokhee Jeon

Work Scope

Haptic Perception

Tactile Perception
Through skin

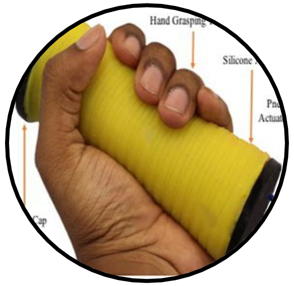
Thermal

Air Flow

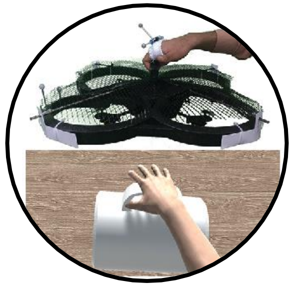
Texture

Kinesthetic Perception
Through Joints

Stiffness



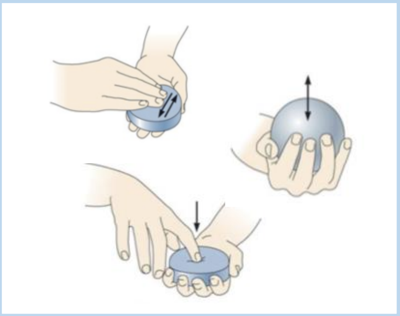
Weight



Force/Torque

Motivation

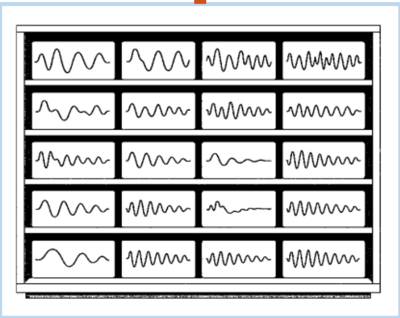
Perception Attribute Prediction
without users ?



Haptic Properties

Modeling

Recorded



Haptic Signal Library

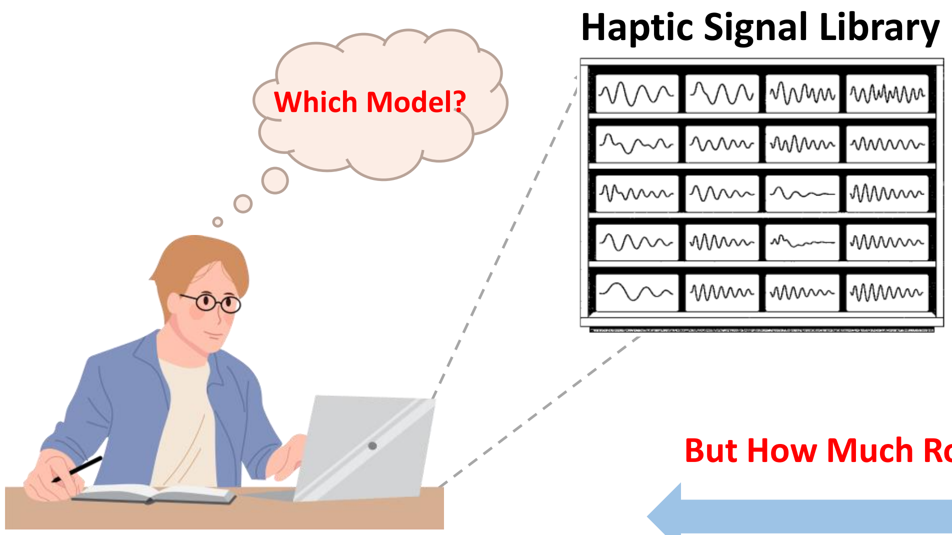
Haptic Interface

- Rough
- Slippery
- Soft

User Perception

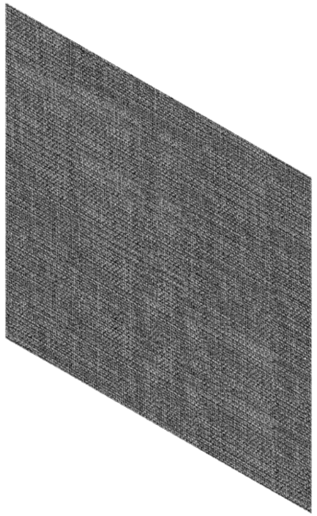
Signal generation form Perception ?

Motivation

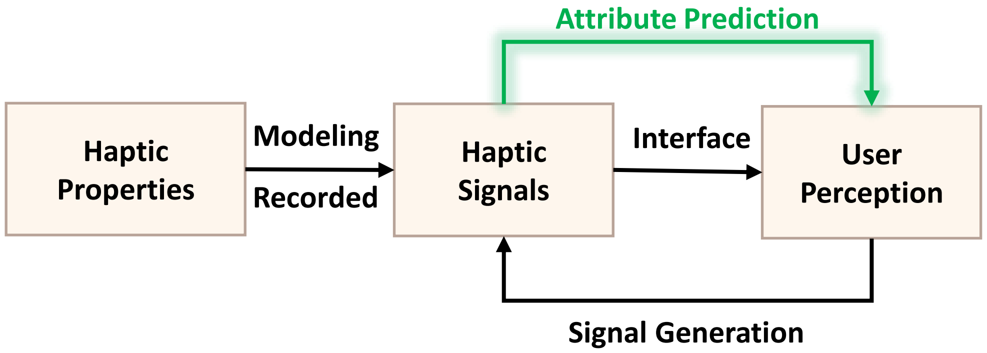


Haptic Content Designer

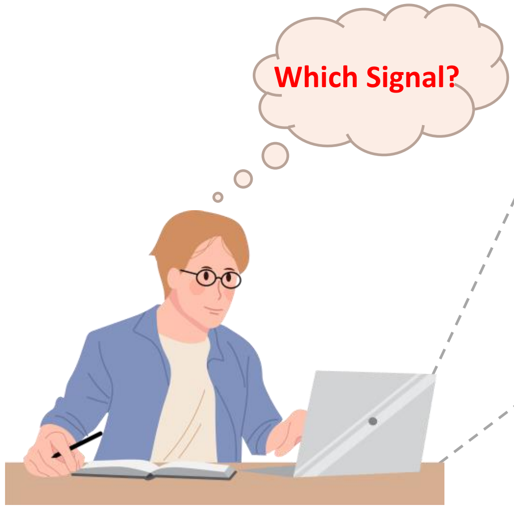
But How Much Rough This Texture Is?



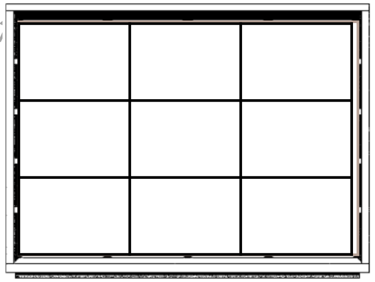
Want to Play This Texture in VR



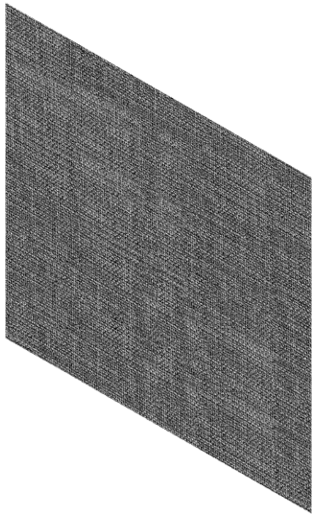
Motivation



No Signal Library

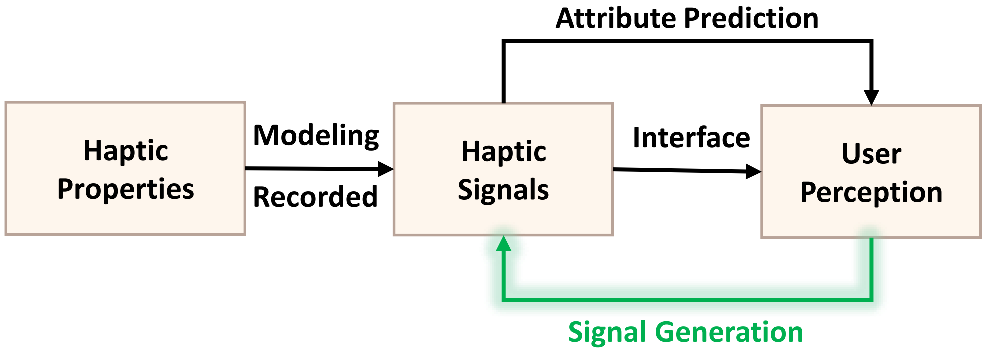


Know the Perception But Signal Not Available

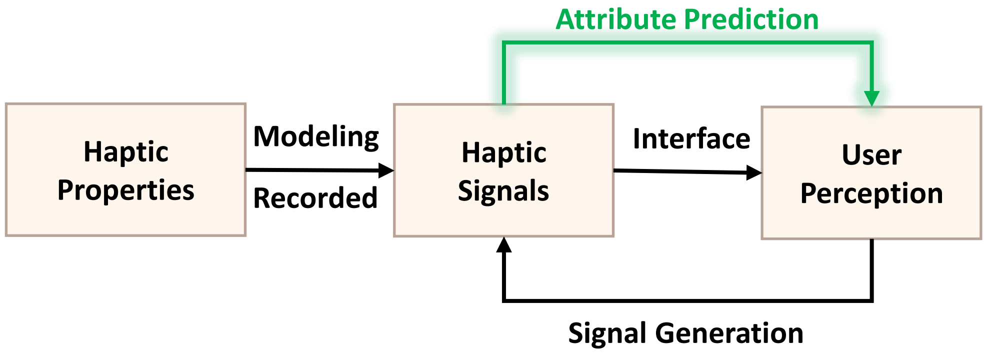


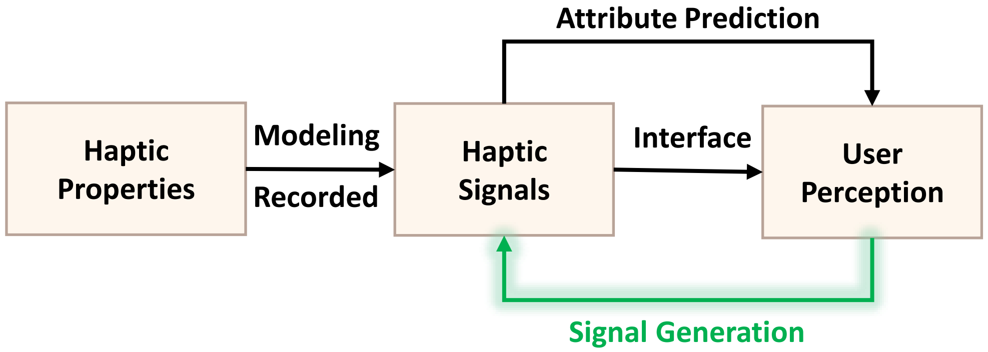
Render a Rough Texture in VR

Haptic Content Designer



Why Do We Need This?





Use Cases (User Perception Prediction)

- ✓ **Quantify perceptual differences in feel and performance.**
- ✓ **Compare user perception across various signals.**
- ✓ **Detect deviations from expected perceptual results.**
- ✓ **Recreate realistic door feel in VR/AR environments.**

Use Cases (Signal Generation from Perception)

- ✓ **Support for countless perception-driven profiles.**
- ✓ **Generate signals tailored to user-defined attributes.**
- ✓ **Data Augmentation**

How People Are Doing?

Physics Based

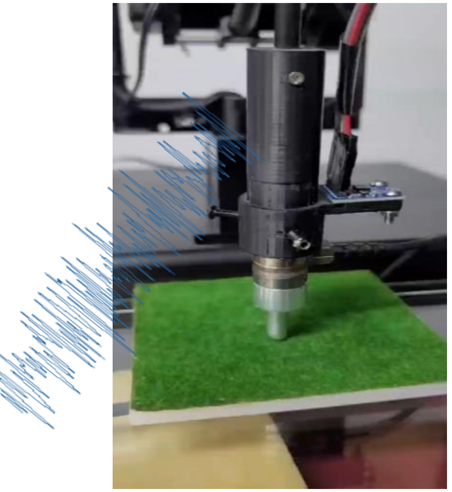
$$Q = 2\left[1 + \left\{\frac{1.348}{\boxed{a/R} + \boxed{b/R}} + \frac{0.01583}{\boxed{a/R}}\right\}\boxed{(P/E)}^{1/2}\right]$$

$$\frac{df_D}{dx} = \kappa\left(1 - \frac{f_D}{f_C}\mathrm{sgn}(v)\right)^{\boxed{\alpha}}$$

$$f_v = f_c(1 + \boxed{d}(\| p_{c+1} - p_{t+1} \|))$$

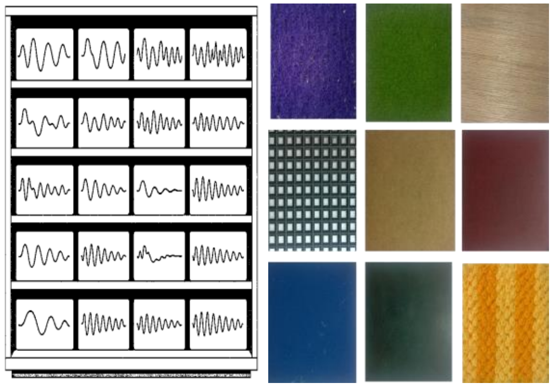
$$\vec{F}_t = \left(\boxed{K_t d_t^{n_t}} + \boxed{B_t d_t^{n_t}}\dot{d}_t\right)\vec{N}(\vec{x}),$$

Data-Driven Based



Data Recording
(sensnorized tool)

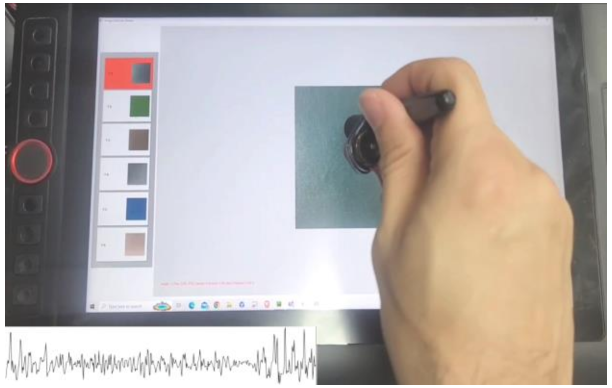
Modeling



Haptic Library
(Physical Signal Space)

Rendering

Replaying Virtual Copy

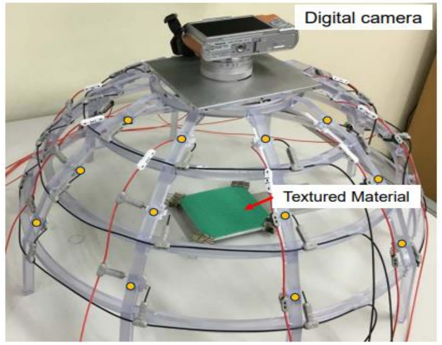


Virtual Copy

How People Are Doing?

Physics Based

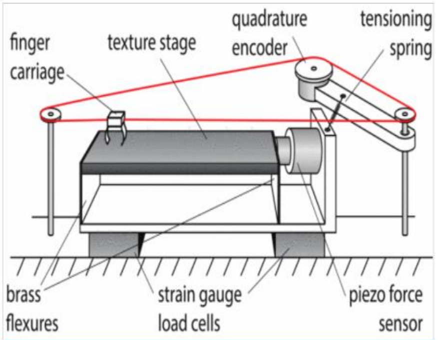
Shin, et al. (2018)



Photometric Stereo For Texture

$$(a(x,y),\mathbf{n}(x,y)) = \operatorname{argmin}\sum_{i=1}^{N}\left|I_i(x,y) - a(x,y)\mathbf{n}(x,y)^T\mathbf{l}_i(x,y)L(x,y)\right|^2$$

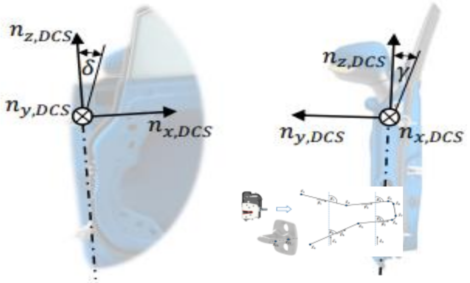
Meyer et al. (2016)



Weibull Distribution For Texture

$$f(x;\lambda,k) = \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1}e^{-(x/\lambda)^k},\ x \geq 0$$

Husing, et al. (2016)



Car Door Hinge Design Model

$$\gamma_{tors,i} = arccos\left(\frac{\vec{n}_H\cdot\vec{n}_{i,proj,xz}}{\|\vec{n}_H\|\cdot\|\vec{n}_{i,proj,xz}\|}\right) \quad \text{with } i = [LH; UH]$$

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Shin, Sunghwan, and Seungmoon Choi. "Geometry-based haptic texture modeling and rendering using photometric stereo." In 2018 IEEE Haptics Symposium (HAPTICS), pp. 262-269. IEEE, 2018.
Meyer, David J., Michael A. Peshkin, and J. Edward Colgate. "Tactile paintbrush: A procedural method for generating spatial haptic texture." In 2016 IEEE Haptics Symposium (HAPTICS), pp. 259-264. IEEE, 2016.
Cousin, Andreas, et al. Holistic kinematic design of automotive door systems. No. RWTH-2023-12283. Lehrstuhl und Institut für Getriebetechnik, Maschinendynamik und Robotik, 2024.

How People Are Doing?

Physics Based

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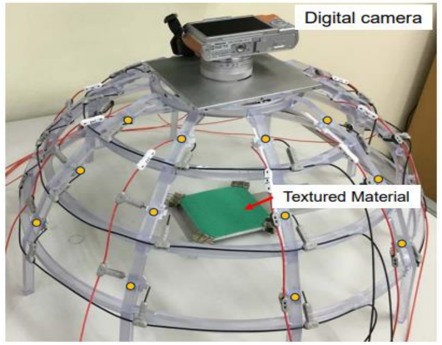

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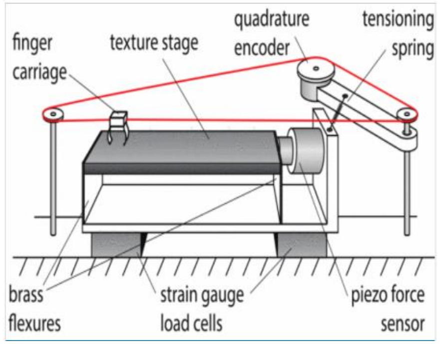

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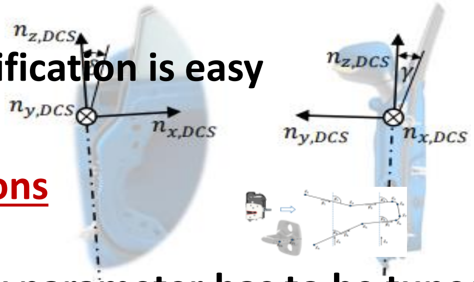

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Advantages

- ✓ **Design control by parameters**
- ✓ **Modification is easy**

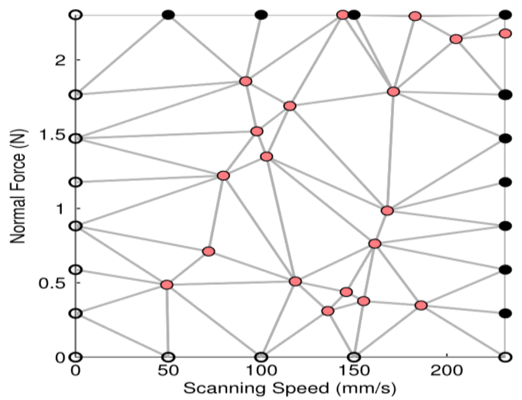
Limitations

- ✓ **Every parameter has to be tuned (manual or auto)**
- ✓ **Relatively difficult to make realistic**
- ✓ **Very difficult to make new haptic signals**

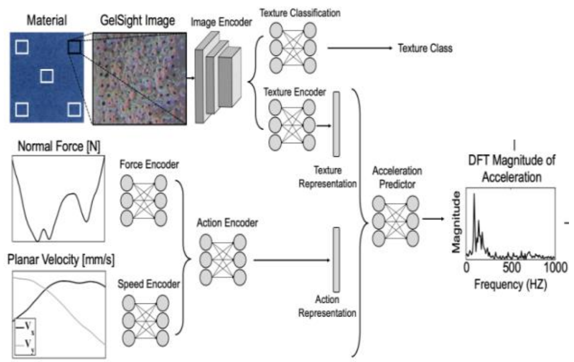
How People Are Doing?

Data-Driven Based

Culbertson, et al. (2014)



Heravi, et al. (2024)



Interpolation-Based Methods

- **Data:** Acceleration based modeling
- **Approach:** Interpolation based approach with Auto Regressive (AR models)

Deep-Learning -Based Methods

- **Data:** Acceleration + GelSight Images based modeling
- **Approach:** AlexNet Based Encoder for images; NN for Tactile processing

Advantages

- ✓ **Highly Realistic**
- ✓ **Better Generalizability**
- ✓ **Highly Scalable**

Limitations

- ✓ **Need special hardware to collect data**
- ✓ **Physical object/surface is required**
- ✓ **Deep learning based are computationally expensive**

- Culbertson, Heather, J. Unwin, and Katherine J. Kuchenbecker. "Modeling and rendering realistic textures from unconstrained tool-surface interactions." *IEEE transactions on haptics* 7.3 (2014): 381-393.
- Heravi, Negin, et al. "Development and evaluation of a learning-based model for real-time haptic texture rendering." *IEEE Transactions on Haptics* (2024).

Literature Review – Research Gap

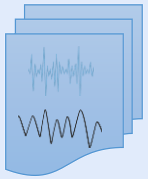
Objects Properties

- Friction
- Stiffness
- Roughness
- Force/Torque

Modeling/ Encoding

Haptic Signal Library

Haptic Models



Haptic Interface

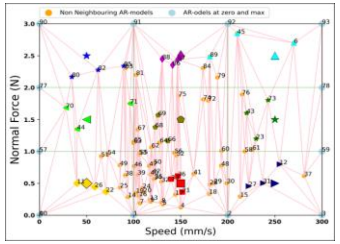
Haptic Perception

- Rough = 80%
- Sticky = 30 %
- Bumpy = 90%
- Soft = 50%

Modeling

Mapping

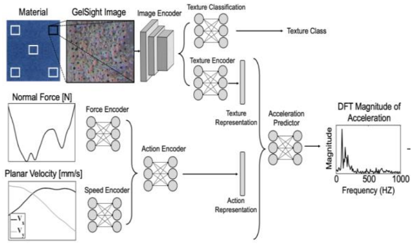
Interpolation



Advantages
- Realistic Feedback

Limitations
- **Requires manual Tuning**
- **Interpolation may not cover all interactions**
- **Input Scalability issue**

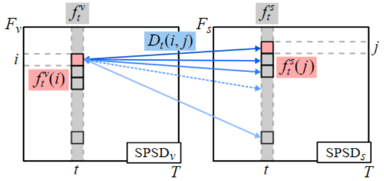
Deep-Learning



Advantages
- Highly Realistic Feedback
- Input Scalability

Limitations
- **Requires Segmented Data**
- **Computational Expensive**

Parametric

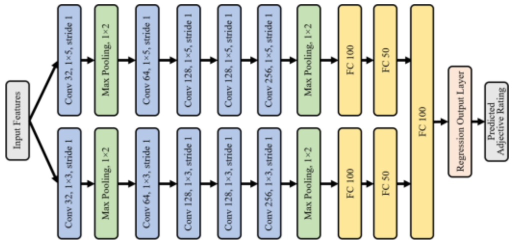


(b) Crossmodal inter-band spectral mapping

Advantages
- Easy to implement

Limitations
- **Does not provide actual human rating of attributes**
- **Generalizability and robustness**

Deep-Learning



Advantages
- Can estimate human-assigned rating
- Input dimension is scalable

Limitations
- **Prior studies utilized either vision or tactile for physical signal space.**
- **Limited prior Studies**

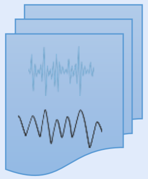
Literature Review – Research Gap

Objects Properties
- Friction
- Stiffness
- Roughness
- Force/Torque

Modeling/ Encoding

Haptic Signal Library

Haptic Models



Haptic Interface

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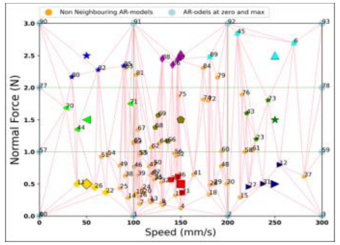
Modeling

Mapping

Interpolation



Advantages
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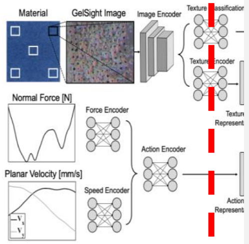
Deep-Lea



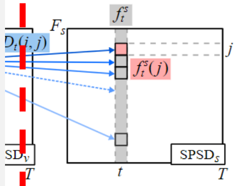
Advantages
- Highly Realistic
- Input Scalability

Limitations
- Requires Segme
- Computational

Modeling:
- ✓ DL-Based Model
- ✓ Computationally Efficient
- ✓ Easier Preprocessing

Mapping:
- ✓ Multimodal DL-Based Technique
- ✓ Estimate Adjective Ratings
- ✓ Better Generalization And Robustness

metric



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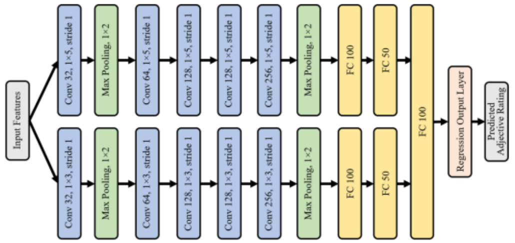


Advantages
- Can estimate human-assigned rating
- Input dimension is scalable

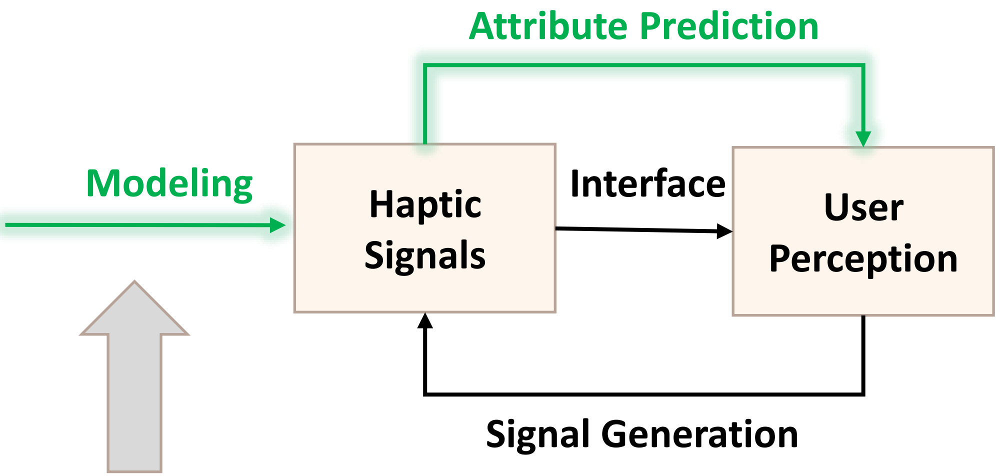
Limitations
- Prior studies utilized either vision or tactile for physical signal space.
- Limited prior Studies

What we are doing?

Tactile (Texture)

Limited work to Predict perception

- ✓ Multimodal technique is introduced
- ✓ Predict Perception
- ✓ Robust and High Generalizability



Lack Of Efficient Modeling Techniques

- ✓ DL-Based Computationally Efficient Model
- ✓ Easier Preprocessing

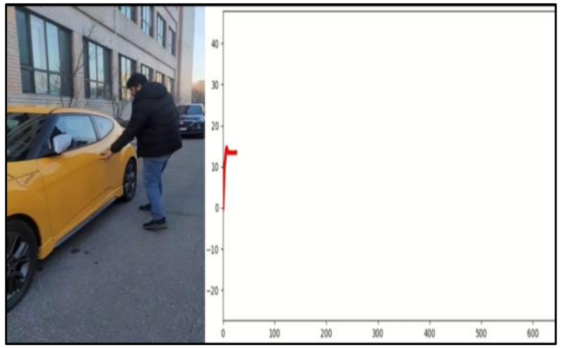
What we are doing?

Kinesthetic (Opening of Car Door)

Limited work to Predict perception

- ✓ First ever attempt to quantify haptic attributes for car door
- ✓ Introduce an end-to end framework

Attribute Prediction



Modeling

Haptic Signals — **Interface** → **User Perception**

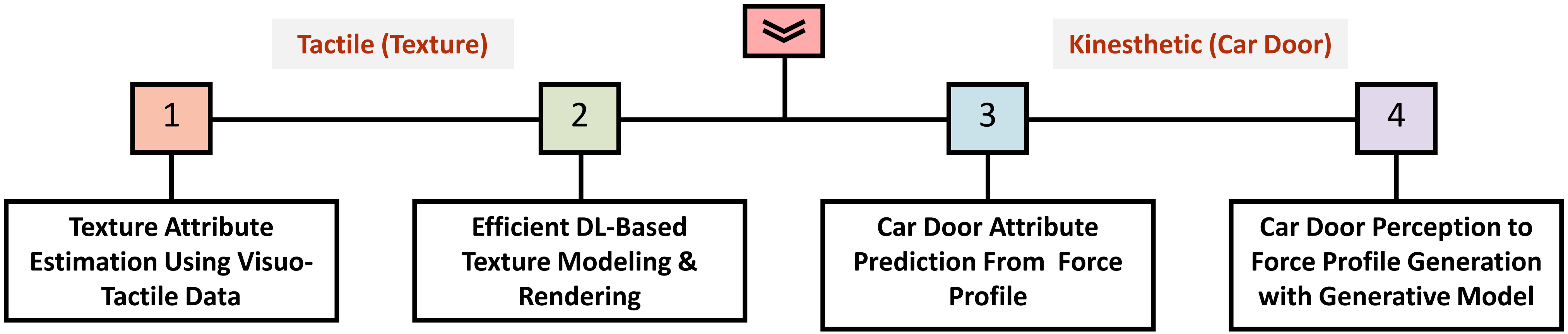
Signal Generation

- ✓ Support for countless perception-driven profiles.

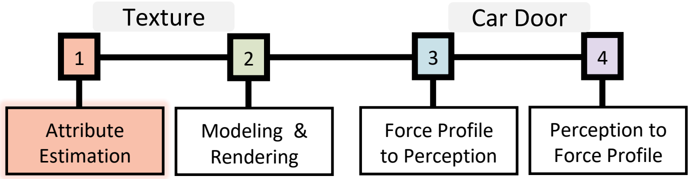
Currently no Signal Library exist

Contributions

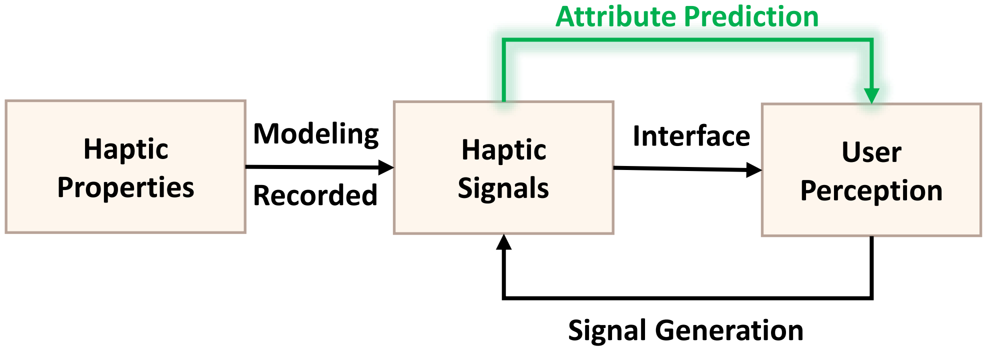
Modeling/Rendering Haptic Signals and Quantifying Haptic Attributes

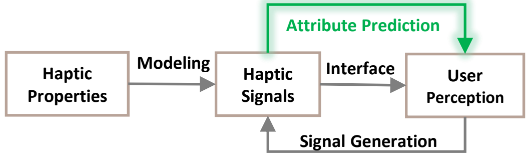


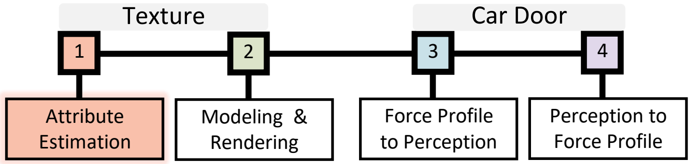
1. **Awan, Mudassir Ibrahim,** Myrah Naeem, and Seokhee Jeon “Text-Driven Generative Framework for Multimodal Visual and Haptic Texture Synthesis ”,In IEEE World Haptics Conference, 2025, (**Accepted).**
2. **Awan, Mudassir Ibrahim,** Sungjoo Kang, Dongbeom Ko, Waseem Hassan, Seong Tae Kim, and Seokhee Jeon. “Fourier-enhanced Transformer Encoder Network for Efficient Haptic Texture Modeling/Rendering." IEEE Transactions on Industrial Informatics (Under Review).
3. **Awan, Mudassir Ibrahim,** and Seokhee Jeon." Estimation of Haptic Texture Attributes using visuo-tactile data” IEEE Access (Under Review).
4. **Awan, Mudassir Ibrahim,** Ahsan Raza, Waseem Hassan, Ki-Uk Kyung, and Seokhee Jeon." Quantifying Haptic Affection of Car Door through Data-Driven Analysis of Force Profile” Nature Scientific Reports (Under Review).
5. **Awan, Mudassir Ibrahim,** Waseem Hassan, and Seokhee Jeon. "Predicting perceptual haptic attributes of textured surface from tactile data based on deep CNN-LSTM network." In Proceedings of the 29th ACM Symposium on Virtual Reality Software and Technology, pp. 1-9. 2023.
6. **Awan, Mudassir Ibrahim,** Tatyana Ogay, Waseem Hassan, Dongbeom Ko, Sungjoo Kang, and Seokhee Jeon. "Model-Mediated Teleoperation for Remote Haptic Texture Sharing: Initial Study of Online Texture Modeling and Rendering." In 2023 IEEE International Conference on Robotics and Automation (ICRA), pp. 12457-12463. IEEE, 2023.



Texture Attribute Estimation Using Visuo-Tactile Data

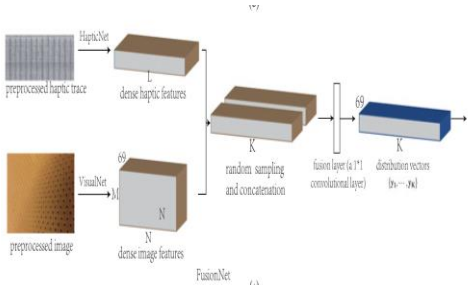






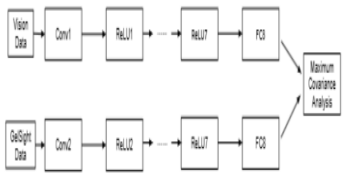
Literature Review

Haitian, et al. (2016)



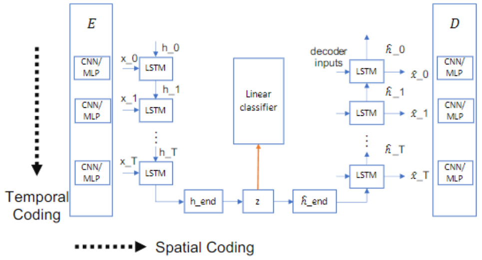
- **Input:** Vision Data & Tactile Data
- **Output:** Texture label Prediction/Classification

Shan, et al. (2018)



- **Input:** GelSight Images & Vision Data
- **Output:** Texture label Prediction/Classification

Ruihan, et al. (2020)



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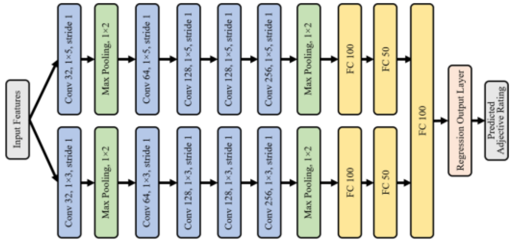
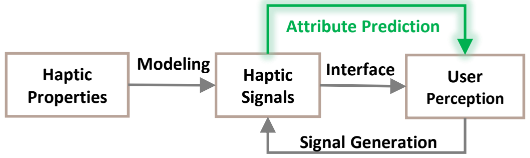
Hassan, et al. (2023)

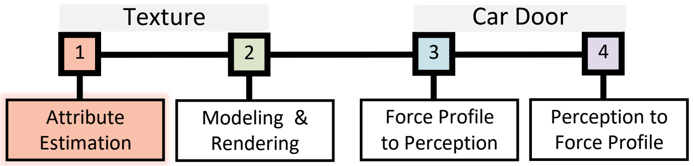


- **Input:** Vision Data
- **Output:** Texture Attribute Prediction

- Zheng, Haitian, et al. "Deep learning for surface material classification using haptic and visual information." *IEEE Transactions on Multimedia* 18.12 (2016): 2407-2416.
- Luo, Shan, et al. "Vitac: Feature sharing between vision and tactile sensing for cloth texture recognition." 2018 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2018.
- Gao, Ruihan, et al. "Supervised autoencoder joint learning on heterogeneous tactile sensory data: Improving material classification performance." *2020 IEEE/RSJ International Conference on Intelligent (IROS), 2020.*
- Hassan, Waseem, Joolekha Bibi Joolee, and Seokhee Jeon. "Establishing haptic texture attribute space and predicting haptic attributes from image features using 1D-CNN." Scientific Reports 13.1 (2023): 11684.

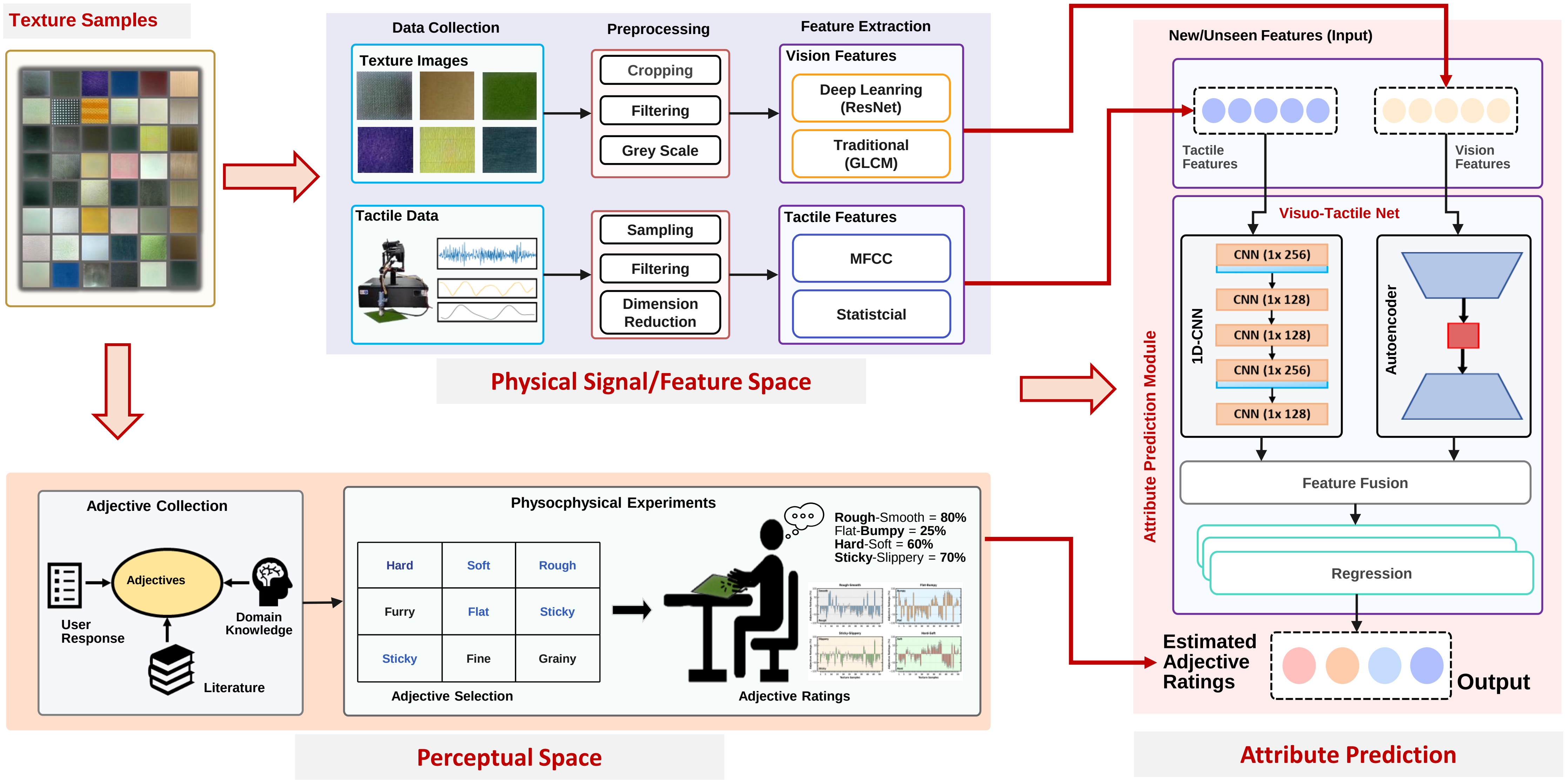


Attribute Prediction
Haptic Properties
Modeling
Haptic Signals
Interface
User Perception
Signal Generation



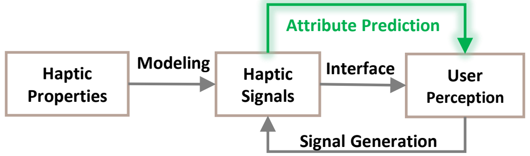
Texture
Car Door
1
2
3
4
Attribute Estimation
Modeling & Rendering
Force Profile to Perception
Perception to Force Profile

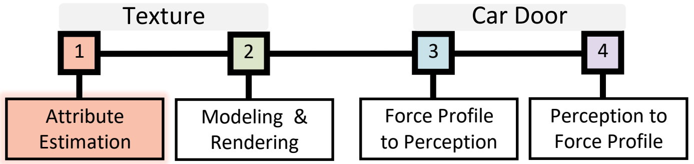
Overview



Texture Samples
Data Collection
Preprocessing
Feature Extraction
Texture Images
Cropping
Filtering
Grey Scale
Vision Features
Deep Leanring (ResNet)
Traditional (GLCM)
Tactile Data
Sampling
Filtering
Dimension Reduction
Tactile Features
MFCC
Statistcial
Physical Signal/Feature Space
Adjective Collection
Adjectives
User Response
Domain Knowledge
Literature
Physocphyical Experiments
Hard
Soft
Rough
Furry
Flat
Sticky
Sticky
Fine
Grainy
Adjective Selection
Rough-Smooth = 80%
Flat-Bumpy = 25%
Hard-Soft = 60%
Sticky-Slippery = 70%
Adjective Ratings
Perceptual Space
New/Unseen Features (Input)
Tactile Features
Vision Features
Visuo-Tactile Net
1D-CNN
CNN (1x 256)
CNN (1x 128)
CNN (1x 128)
CNN (1x 256)
CNN (1x 128)
Autoencoder
Feature Fusion
Regression
Attribute Prediction Module
Estimated Adjective Ratings
Output
Attribute Prediction

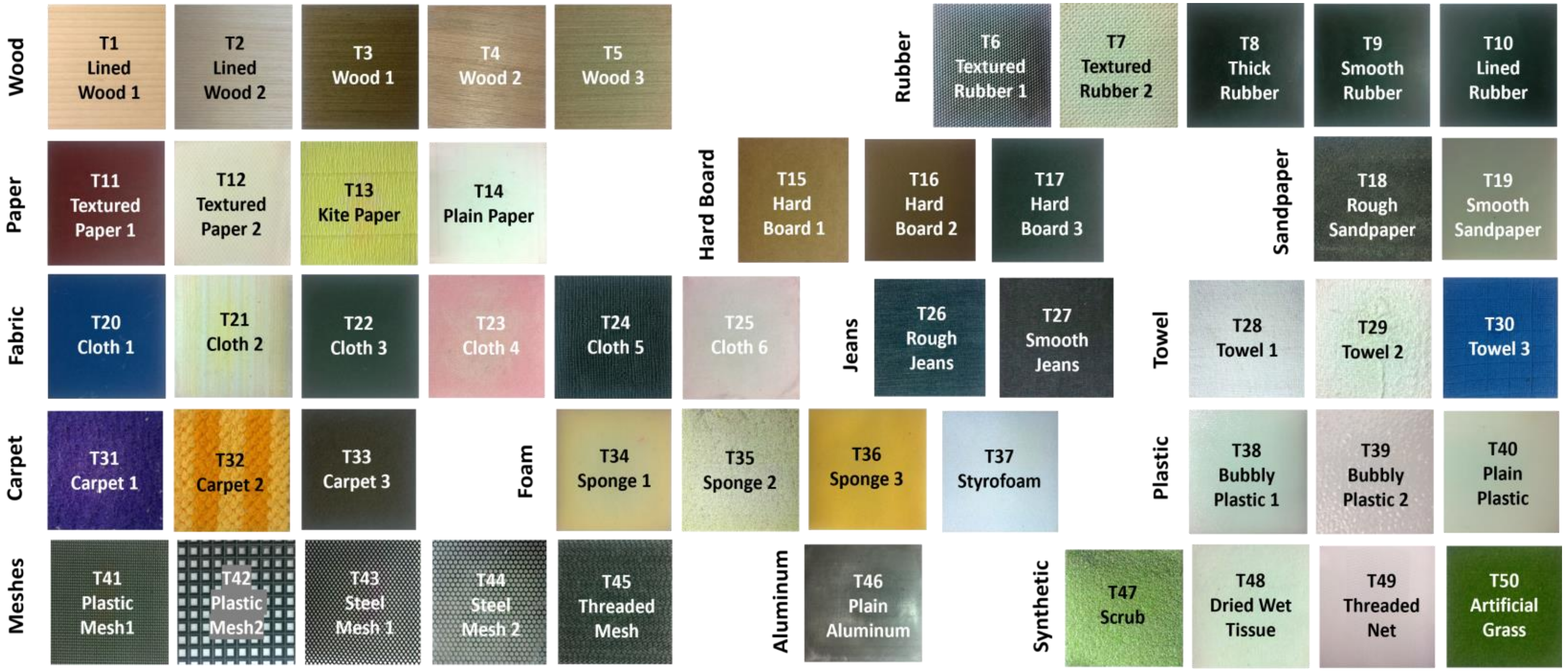
Dataset

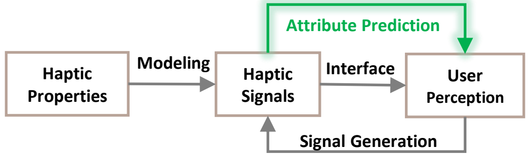


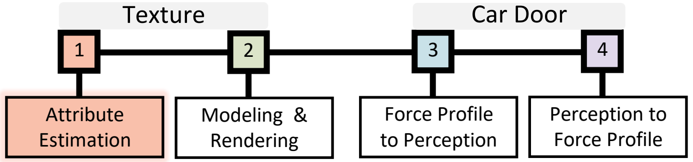


Vision Data

- Collected Data for **50 textures** from diverse categories
- **HD Images** were captured for each texture
- **10 images** for each texture was captured

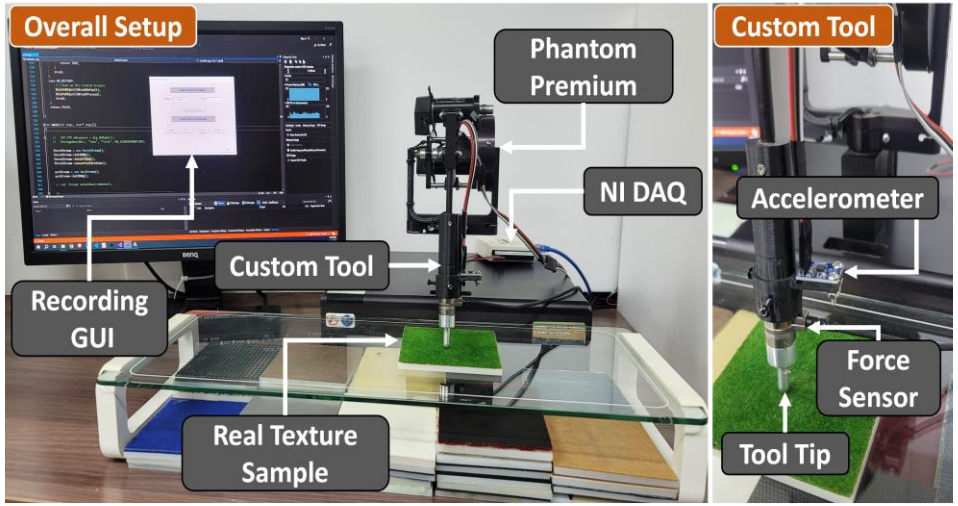






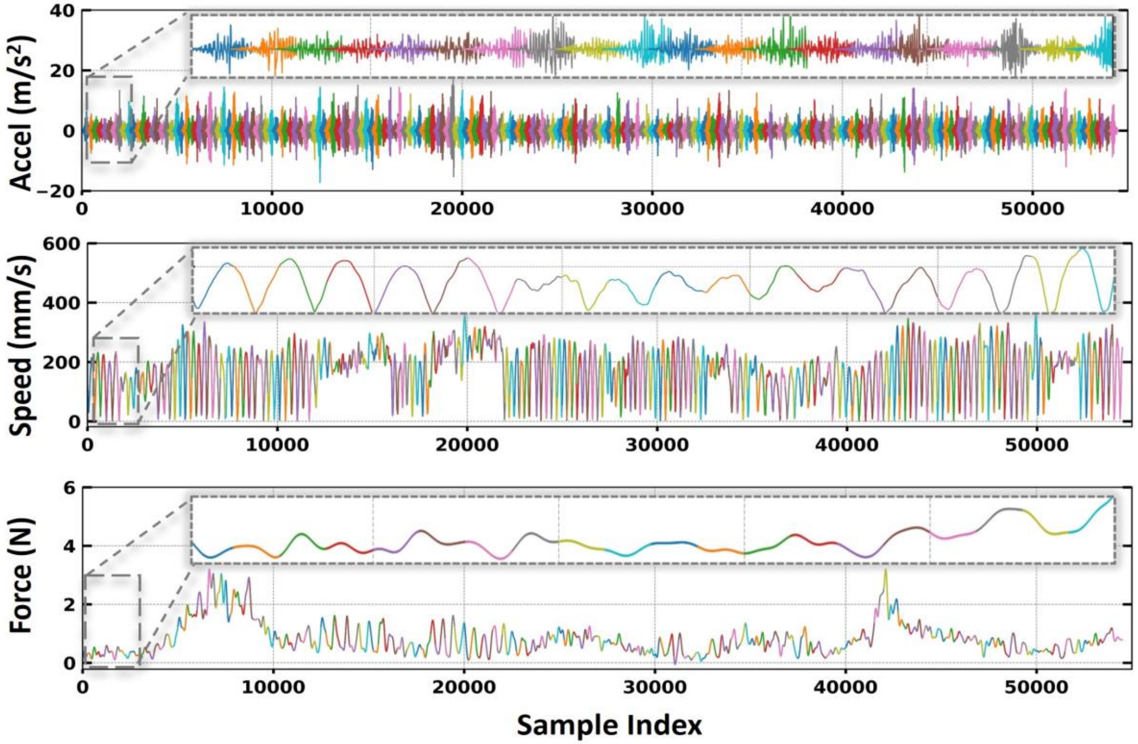
Creating Physical Signal Space

Tactile Data

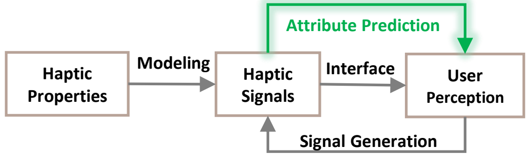


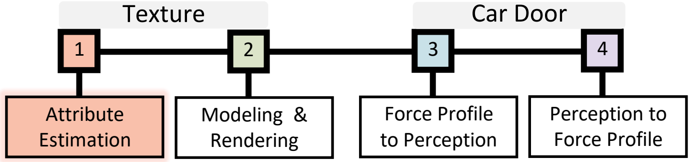
Hardware Setup

Tactile Signals



Processed Tactile Data





Creating Perceptual Space

Experiment 1 (Identify Adjectives)

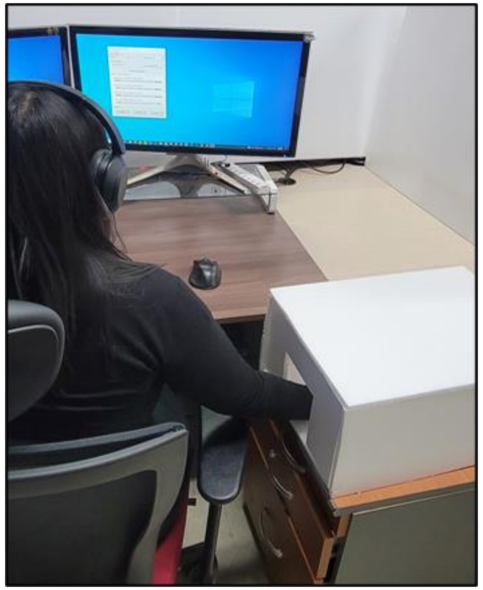


TABLE 1: Attributes presented to participants for the attribute selection experiment. The four selected attribute pairs, highlighted in bold dark blue, were subsequently used for the rating experiment.

Refined	Jarred	Bald	Mushy	**Flat**	Vague
Furry	Grating	Silky	Warm	Thick	**Smooth**
Hard	Bouncy	Pleasant	Glassy	Pointy	Blur
Sticky	Sharp	Dense	Angular	Hatched	Even
Jagged	Spongy	**Bumpy**	Cold	Slow	Dark
Grainy	Patterned	**Slippery**	Light	Slick	Granular
Distinct	Irritating	Wooden	Mild	Bright	**Rough**
Prickly	Metallic	Bubbly	Deep	Fast	Heavy
Solid	Fine	Blur	Shallow	Rigid	**Soft**
Glassy	Thin	Hatched	Sparse	Blunt	Fizzy

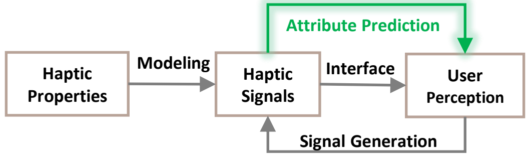
Identified Attributes/Adjectives

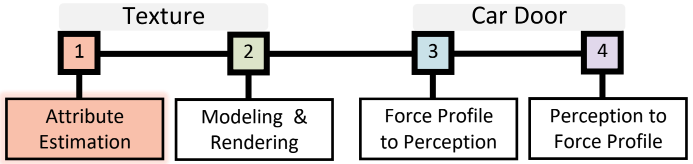
1. **Rough - Smooth**
2. **Sticky - Slippery**
3. **Hard - Soft**
4. **Flat – Bumpy**

Experiment Setup

List Of Adjectives

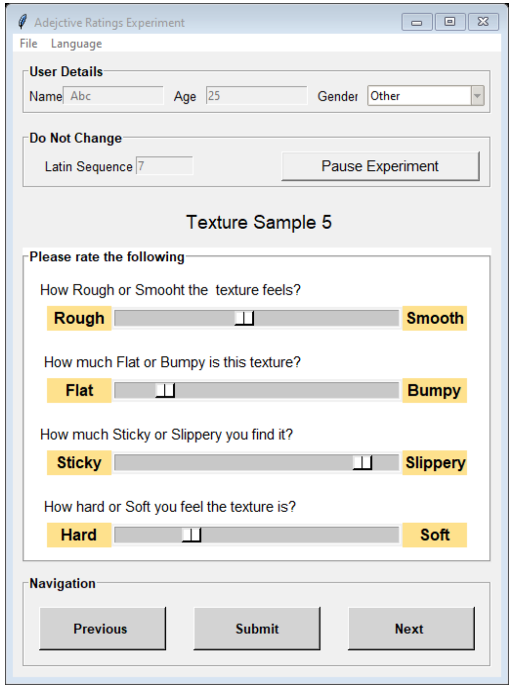
Bi-polar Adjective Pairs

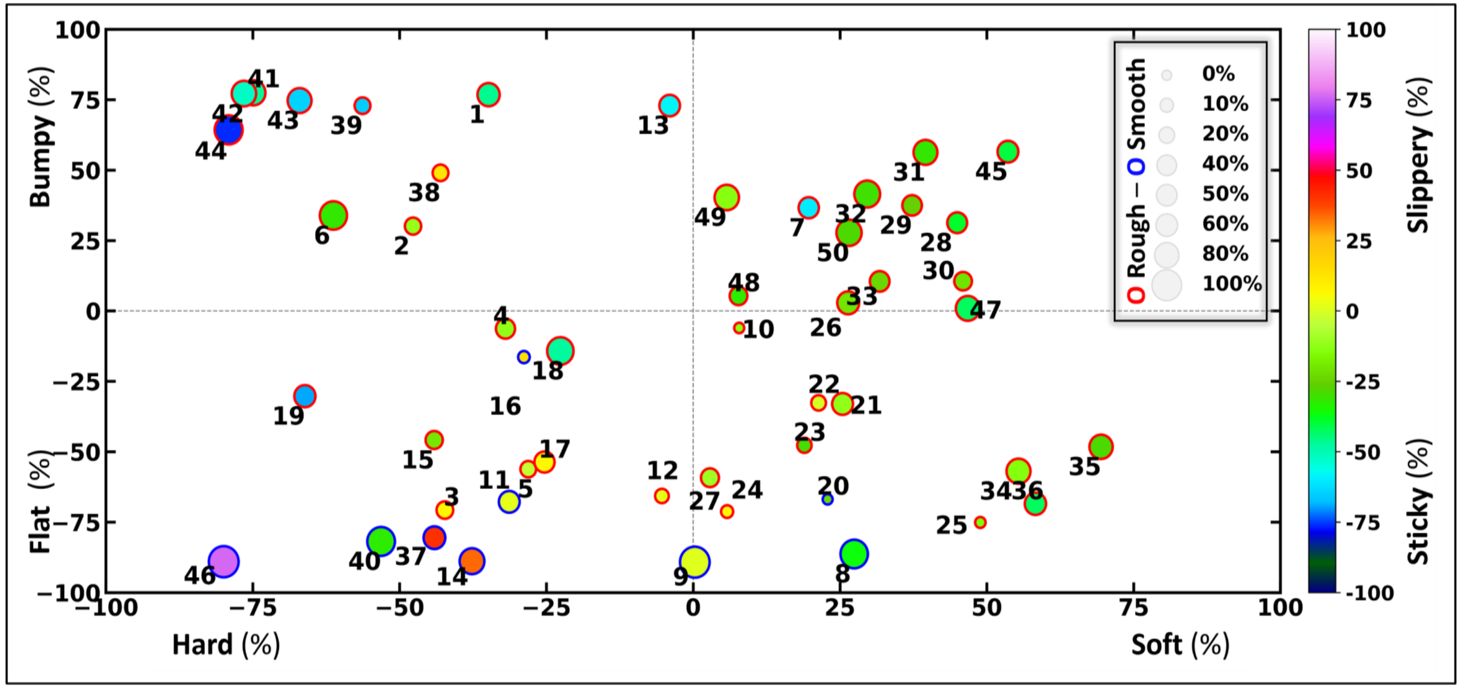




Creating Perceptual Space

Experiment 2 (Adjective Ratings)

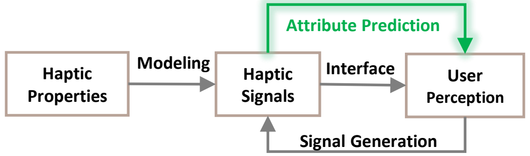


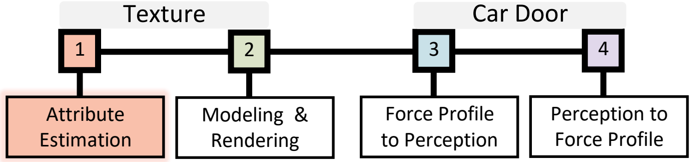


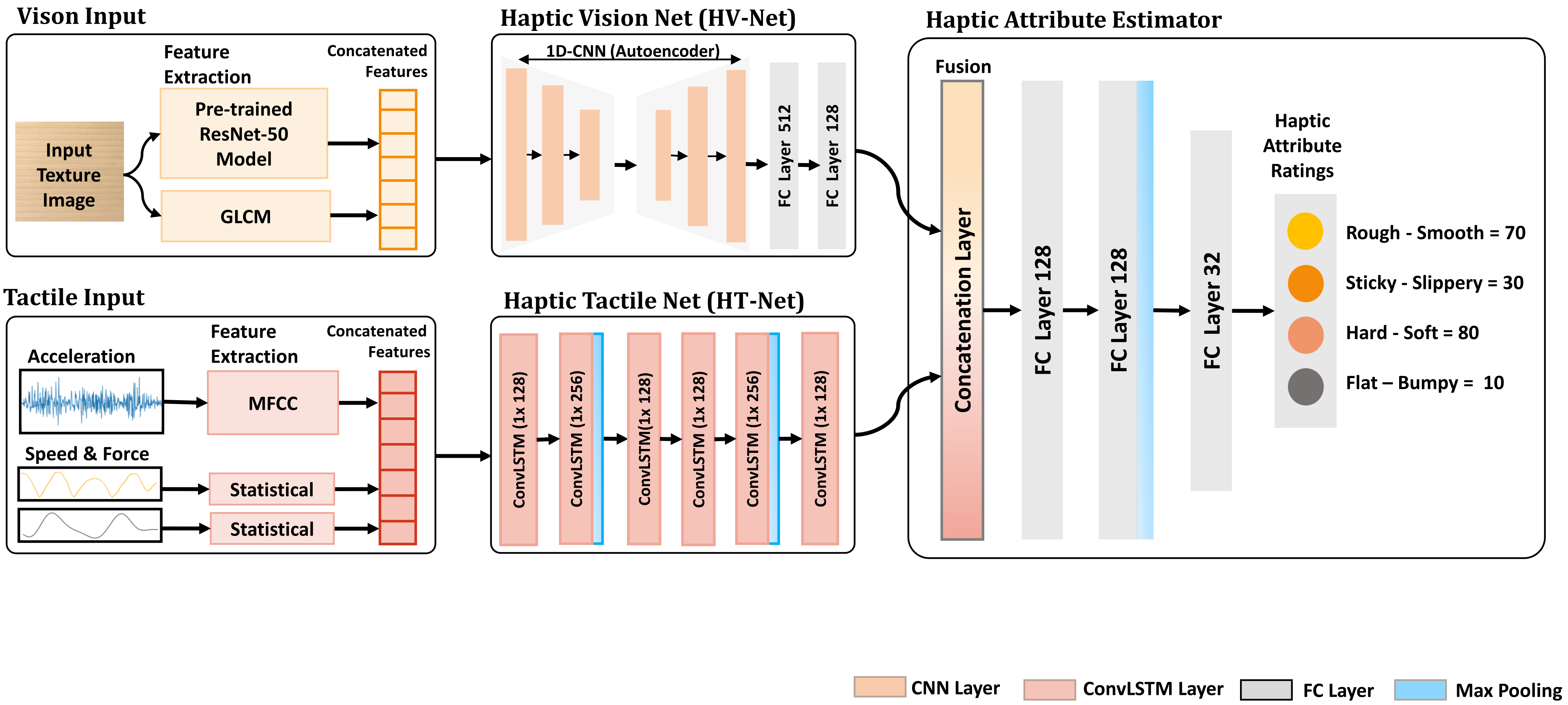
Attribute Ratings GUI

Perceptual Space

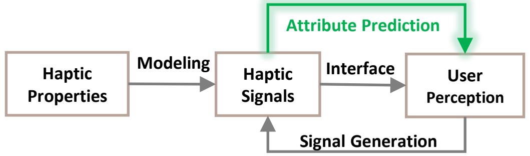
Attribute Prediction Model (Visuo-Tactile Net)

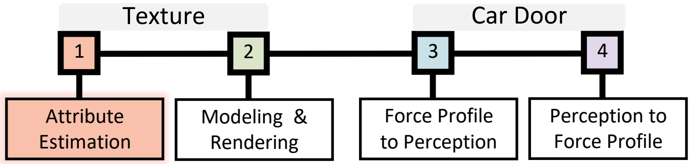






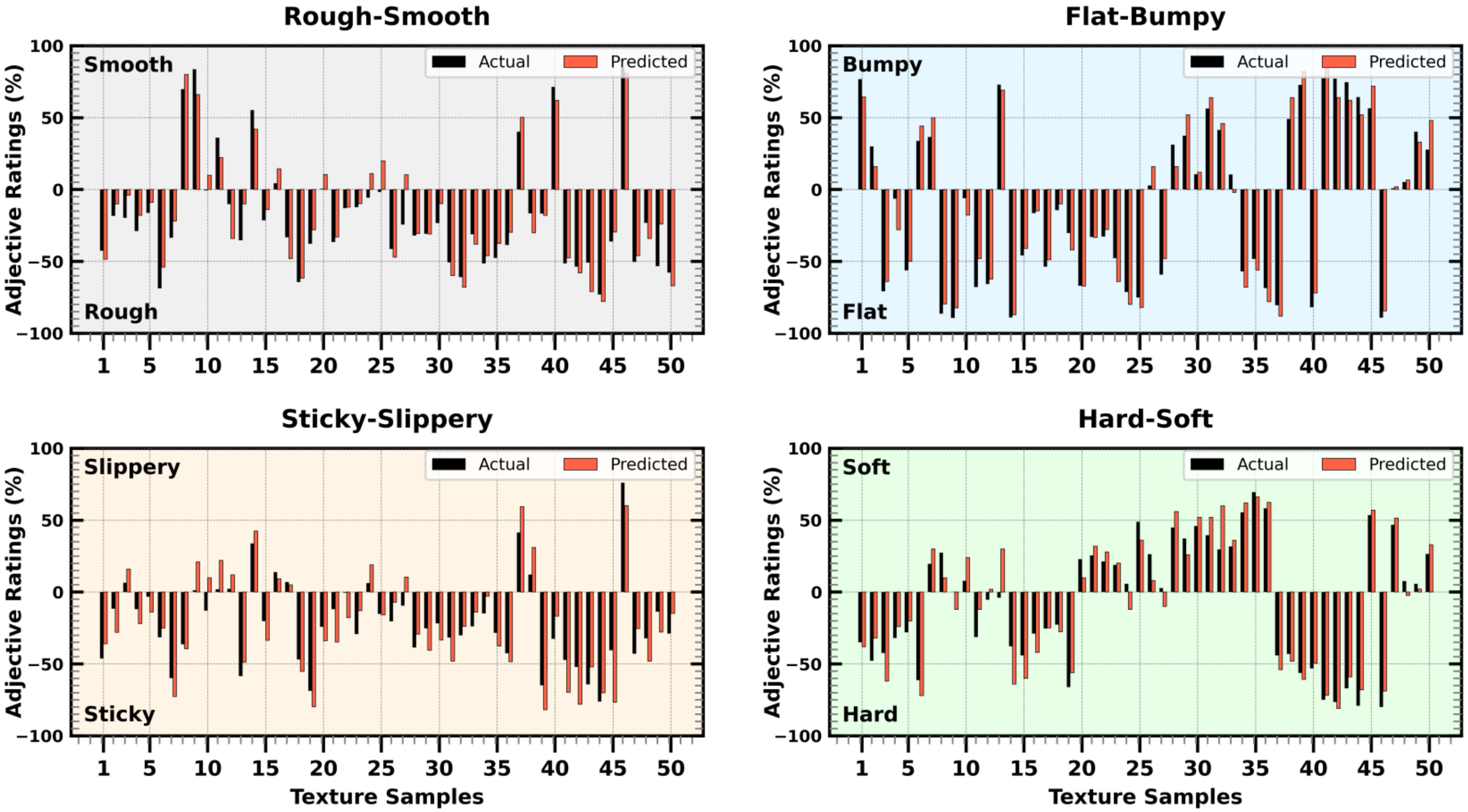
Evaluation - Attribute Prediction Results



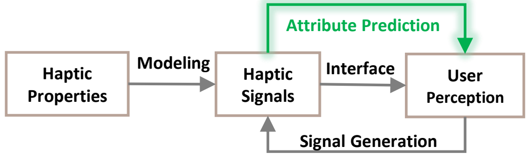


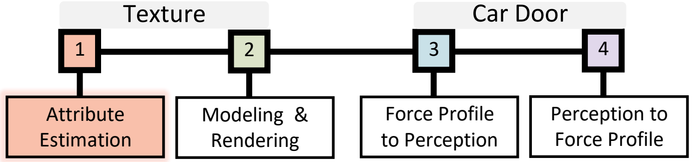
Actual Vs Predicted

- A total of 50 textures (n =50) were used in this study.
- For **evaluation Leave One Out Cross Validation (LOOCV)** technique was used.
- Results indicate that in most cases, the predicted attribute values aligned well with the actual values.



Evaluation - Attribute Prediction Results





Comparison with Existing Approaches (MAE)

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \tilde{y}_i|$$

Methods	R-S	F-B	S-S	H-S
Artificial Neural Network	21.13	26.12	22.85	25.44
Vision 1D-CNN [50]	18.55	19.63	17.89	17.24
Haptic CNN [14]	13.17	11.32	12.01	8.38
Tactile CNN-LSTM [13]	10.58	8.98	13.76	11.92
Tactile SVM [51]	9.40	14.89	15.35	10.54
Proposed Method	**5.23**	**4.48**	**6.67**	**5.21**

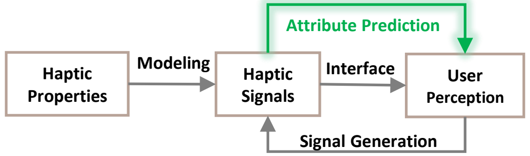
Comparison with Existing Approaches (RMSE)

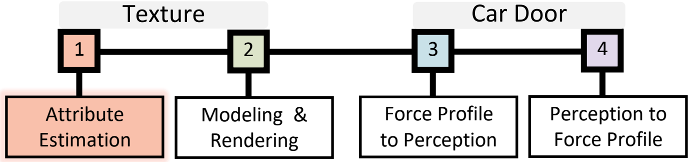
$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \tilde{y}_i)^2}$$

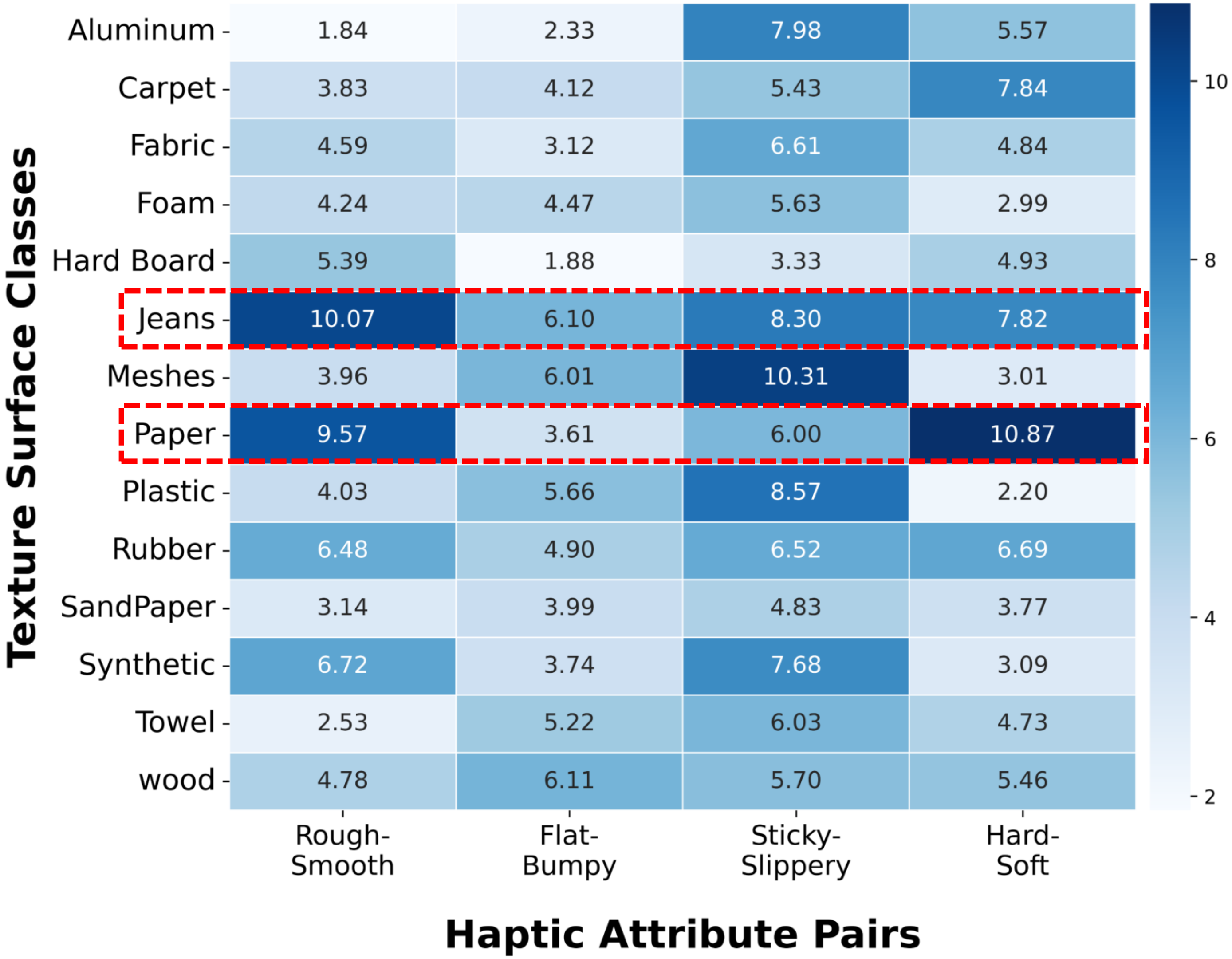
Methods	R-S	F-B	S-S	H-S
Artificial Neural Network	24.41	31.62	25.73	32.19
Vision 1D-CNN [50]	22.35	24.88	19.61	20.59
Haptic CNN [14]	18.21	12.15	14.19	12.65
Tactile CNN-LSTM [13]	13.45	10.65	15.20	13.78
Tactile SVM [51]	11.26	16.37	20.81	11.93
Proposed Method	**6.81**	**5.67**	**7.52**	**6.13**

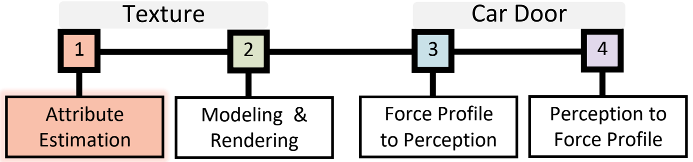
- The Model was **compared against other existing approaches**.
- The mean MAE for **Flat-Bumpy** was recorded as **4.48 out of 100** as the lowest.

Evaluation - Attribute Prediction Results

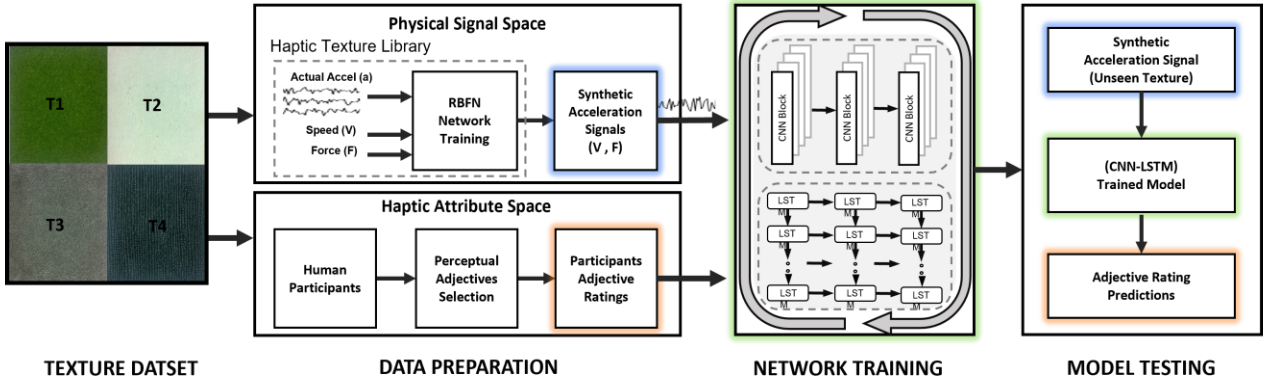




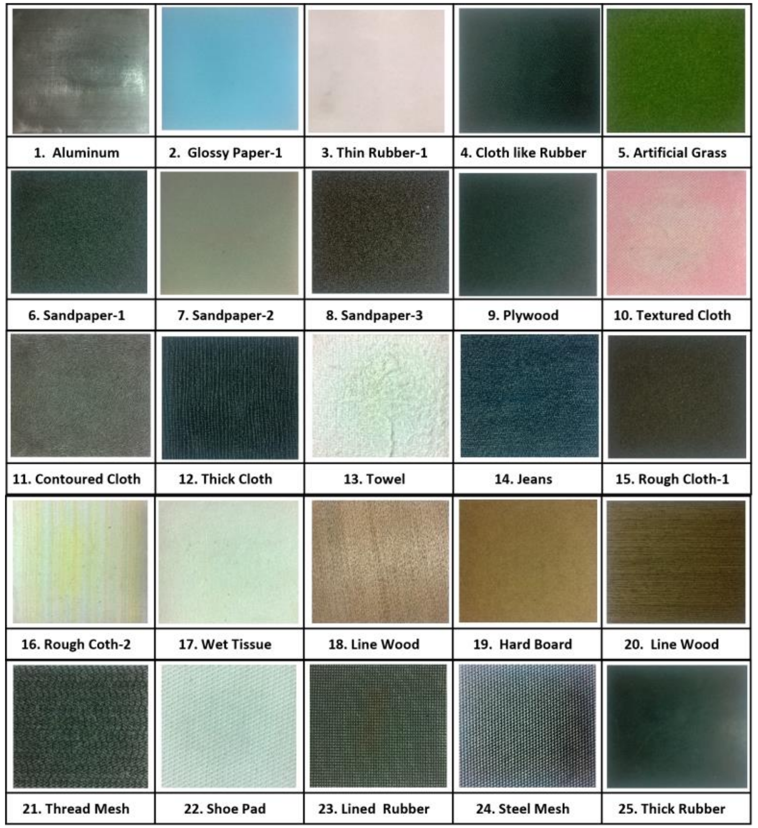




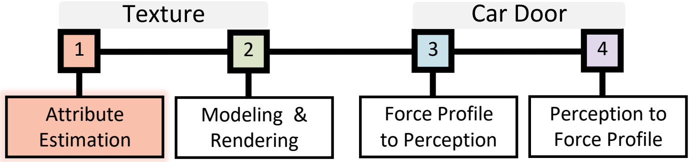
Case Study: Attribute Prediction for Synthesized Signals



- Used **Haptic Texture Library** to **Synthesize haptic Signals**
- A total of **25 texture data was gathered** form the Haptic Texture Library.
- Acceleration Profiles was created by using different speed and force combinations:
  - ✓ **Speed : (50, 100, 150, 200, 250)**
  - ✓ **Force : (0.1, 0.2, 0.3, 0.4, 0.5)**

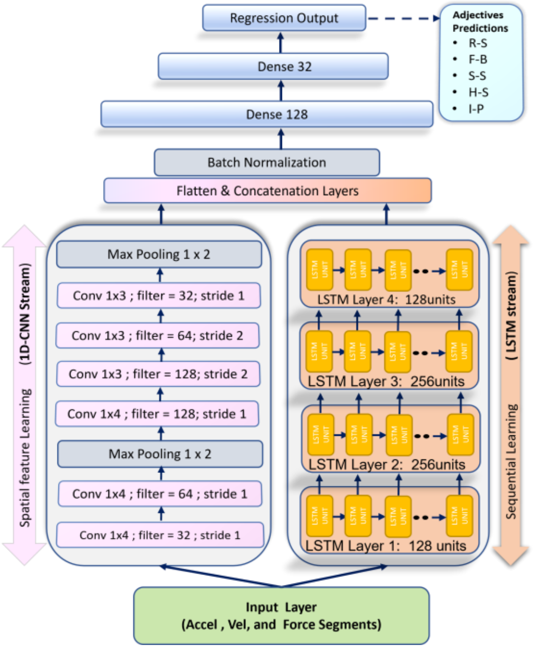


Texture Samples

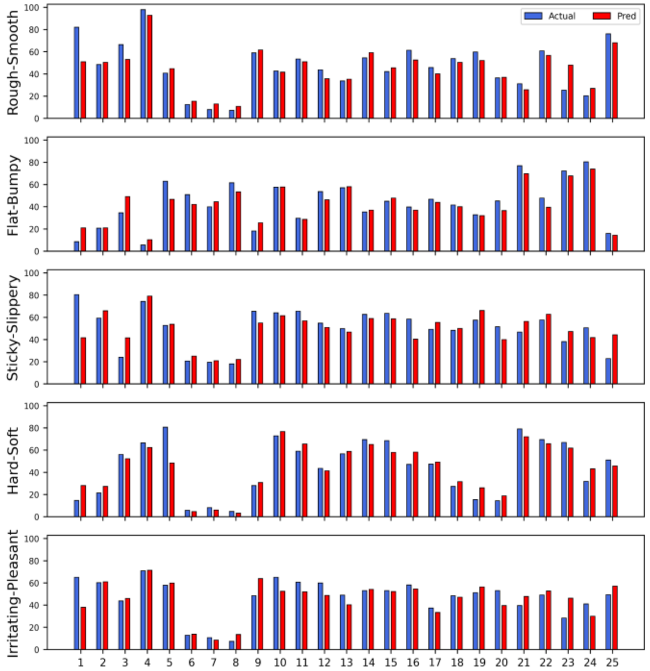


Case Study: Attribute Prediction for Synthesized Signals

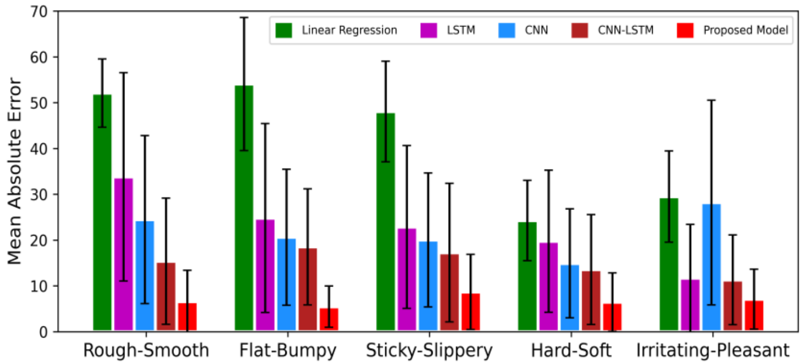
- ✓ A **CNN-LSTM based model** was proposed.
- ✓ Evaluation is done using **Leave one cross validation technique (LOOCV).**



CNN-LSTM Model



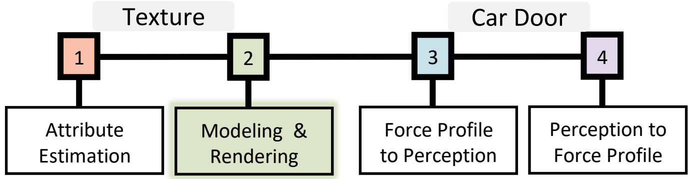
Actual Vs Predicted



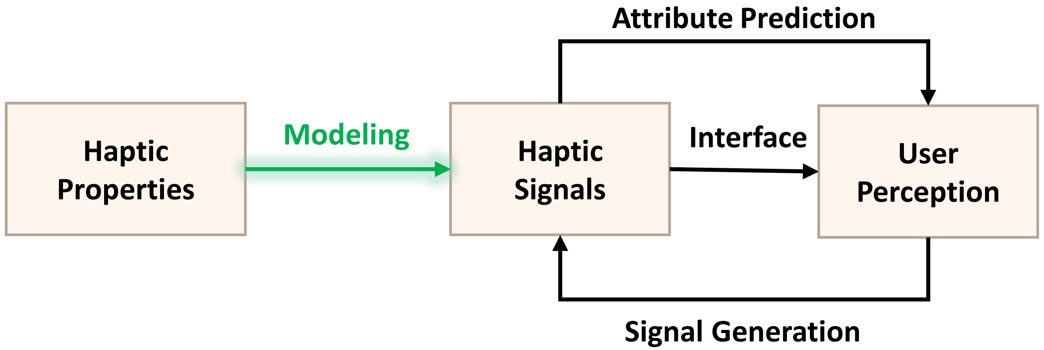
Comparison with Other Approaches

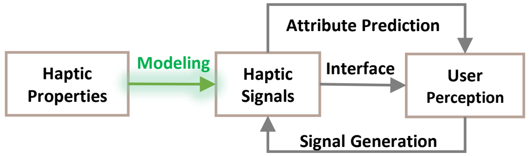
Adjective Pair	MAE	RMSE
Rough-Smooth	6.552	9.371
Flat-Bumpy	5.451	7.008
Sticky-Slippery	8.683	11.813
Hard-Soft	6.452	8.992
Irritating-Pleasant	7.082	9.555

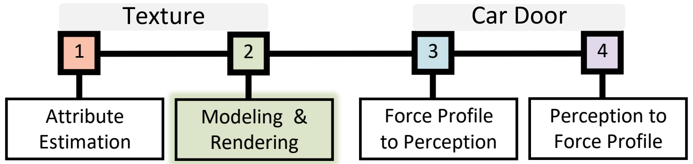
Attribute Based Comparison



Efficient DL-Based Haptic Texture Modeling & Rendering



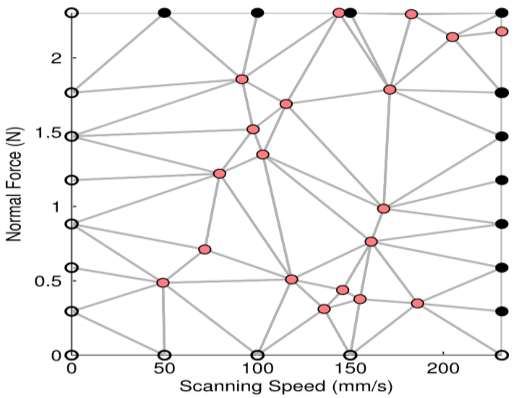




Literature Review

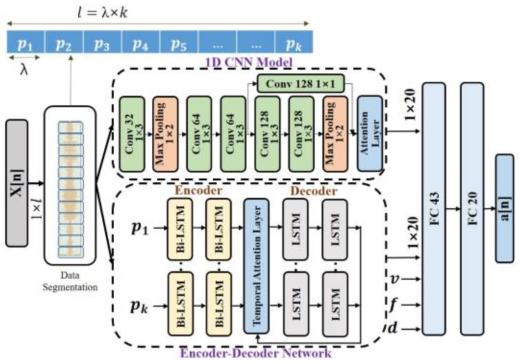
Texture Modeling and Rendering

Culbertson, et al. (2014)



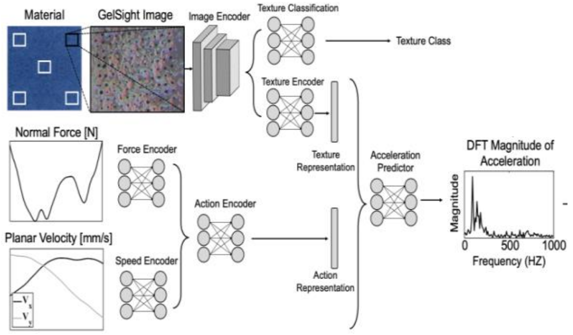
- **Data:** Acceleration based modeling
- **Approach:** Interpolation based approach with Auto Regressive (AR models)
- Requires Segmentation Algorithms

Joolee, et al. (2021)



- **Data:** Acceleration based modeling
- **Approach:** CNN and Bidirectional-LSTM based encoder- decoder network
- Computationally Expensive

Heravi, et al. (2024)

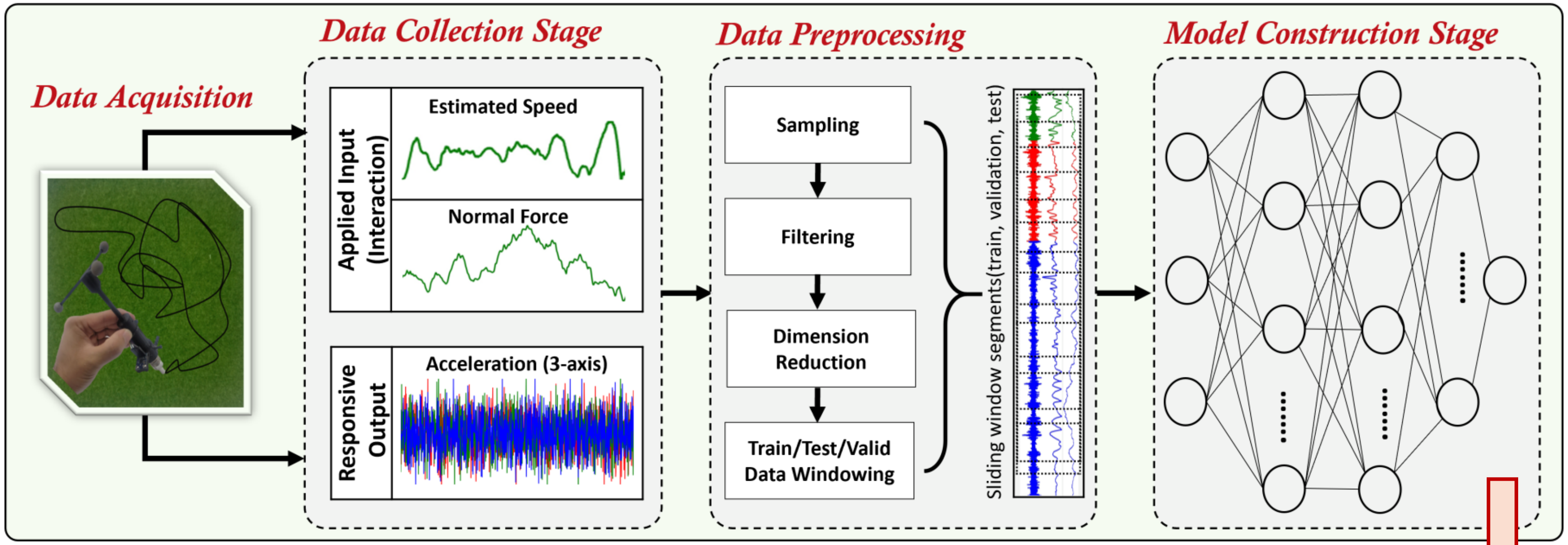


- **Data:** Acceleration + GelSight Images based modeling
- **Approach:** AlexNet Based Encoder for images; NN for Tactile processing
- Computationally Expensive

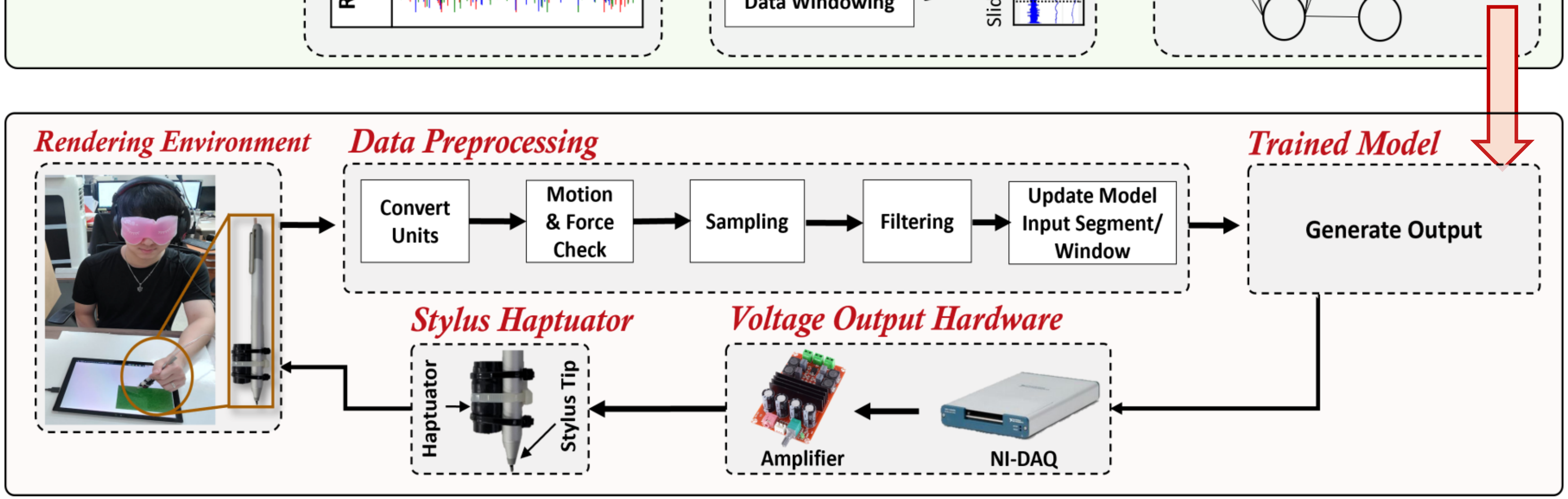
- Culbertson, Heather, J. Unwin, and Katherine J. Kuchenbecker. "Modeling and rendering realistic textures from unconstrained tool-surface interactions." *IEEE transactions on haptics* 7.3 (2014): 381-393.
- Joolee, Joolekha Bibi, and Seokhee Jeon. "Data-driven haptic texture modeling and rendering based on deep spatio-temporal networks." *IEEE Transactions on Haptics* 15.1 (2021): 62-67.
- Heravi, Negin, et al. "Development and evaluation of a learning-based model for real-time haptic texture rendering." *IEEE Transactions on Haptics* (2024).

Overview

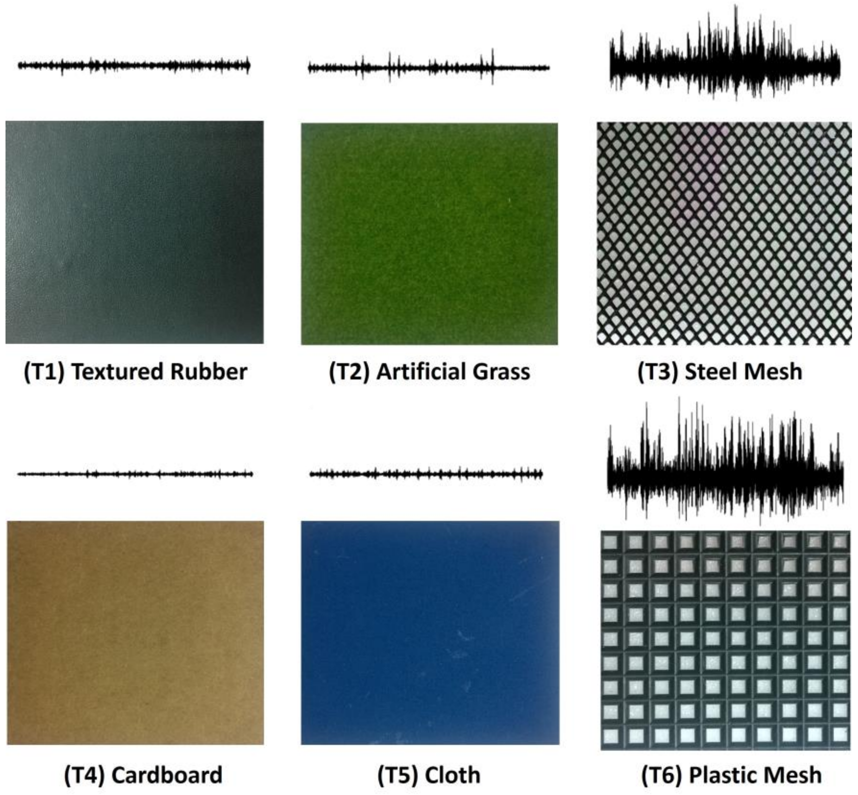
Texture Modeling



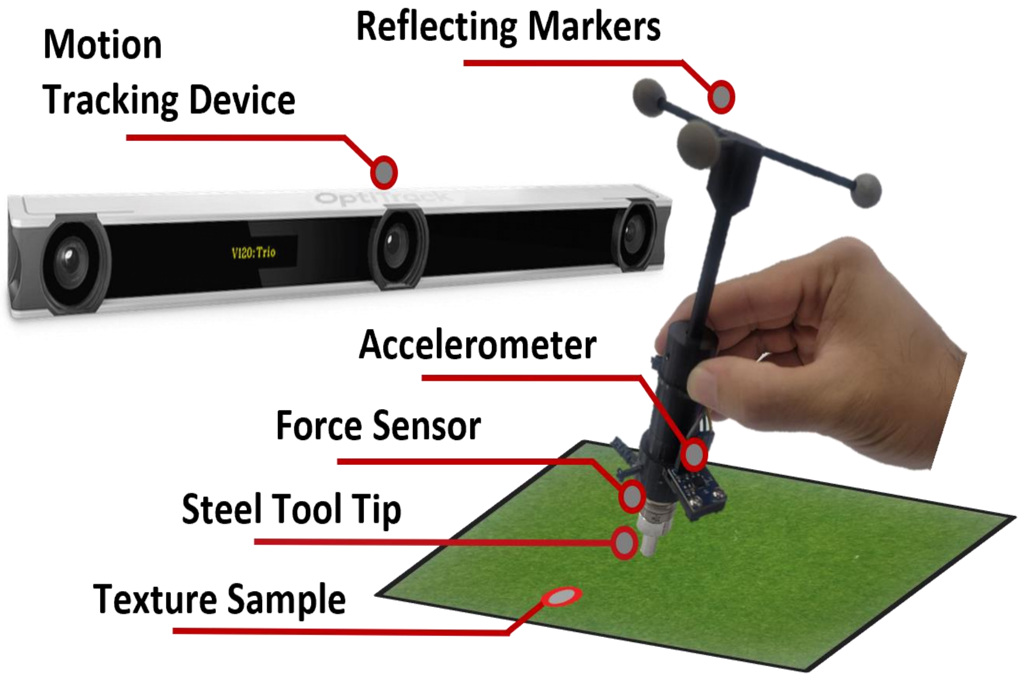
Texture Rendering



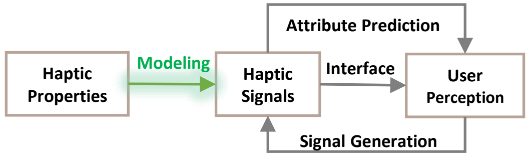
Dataset

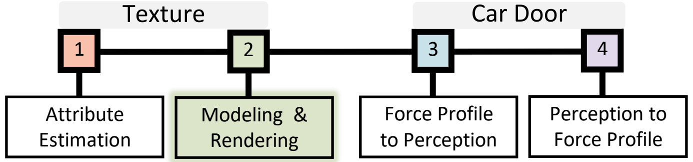


Real Texture Samples



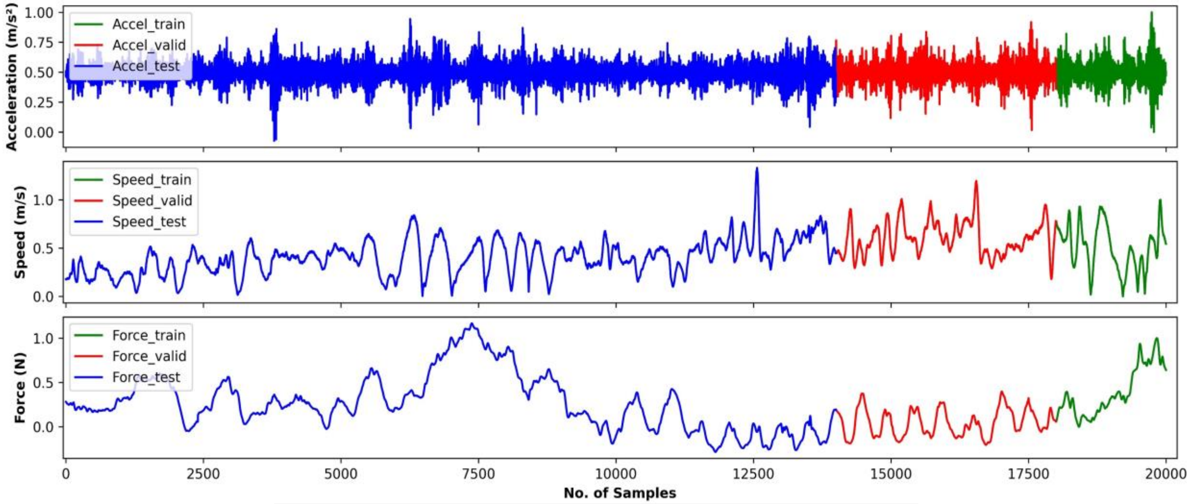
Tactile Signal Recording





Dataset - Preprocessing

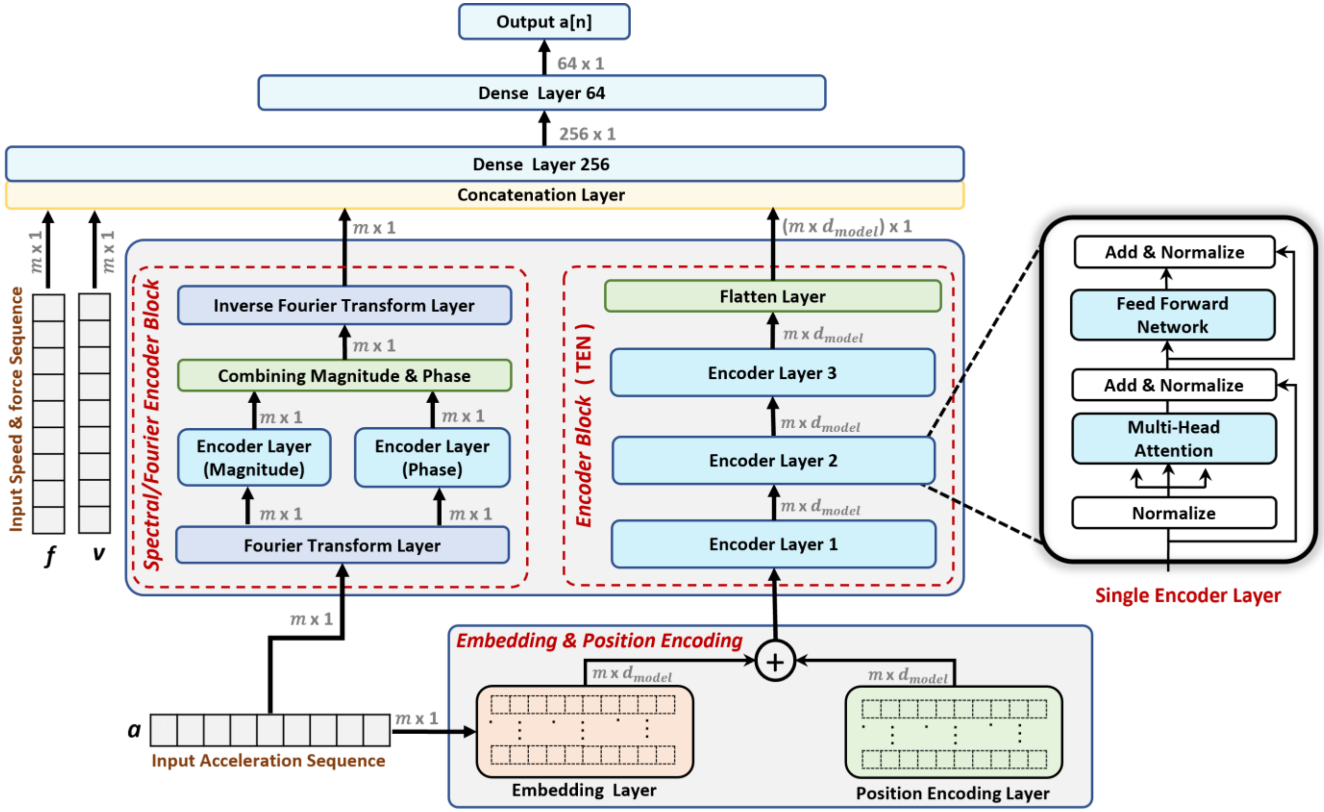
- The dataset was captured for **six textured surfaces**.
- The data includes interaction signals such as **scanning speed and applied force**, along with **vibrations recorded as acceleration** signals for **20 seconds**.
- The collected data was **split into training, validation, and test** sets.
- The **test set** was used for **evaluation**.



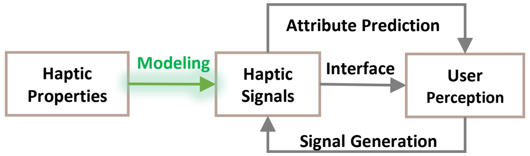
Processed Data (Train, Valid, Test)

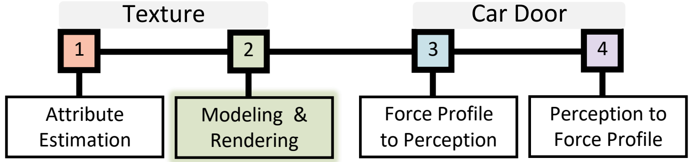
Modeling - Fourier Enhanced Transformer Network (FoTEN)

- A Transformer typically consists of an Encoder and Decoder network .
- In this study, **only the encoder component of transformer network is utilized** which is **responsible for feature extraction.**
- Proposed Transformer Model consist **of four encoder layers**, **one Fourier and one inverse Fourier layer** to capture information along the spectral content of signals.
- The features form **encoder stream and Fourier stream are concatenated** before passing to the dense layer followed by a final regression layer in order to make final predictions.



Transformer Based Architecture





Evaluation - Numerical

Comparison with Existing Approaches

Time Domain Error Metric

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|a_i - \tilde{a}_i|$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(a_i - \tilde{a}_i)^2}$$

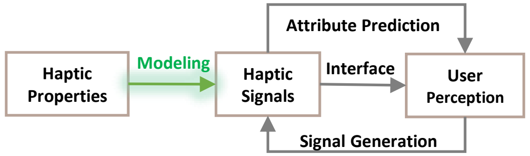
Spectral Domain Error Metric

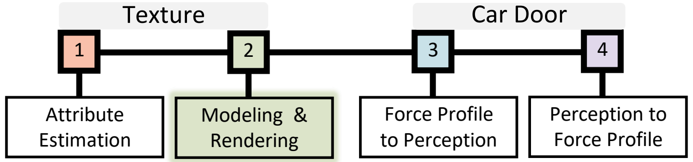
$$GFC = \frac{\left\|\sum_i A_d(f_i)\,A_m(f_i)\right\|}{\sqrt{\left\|\sum_j \left[A_d(f_j)\right]^2\right\|}\sqrt{\left\|\sum_k \left[A_m(f_k)\right]^2\right\|}}$$

Table 5.1: Comparison of error metrics (MAE and GFC) across existing methods and textures, with modeling types and features.

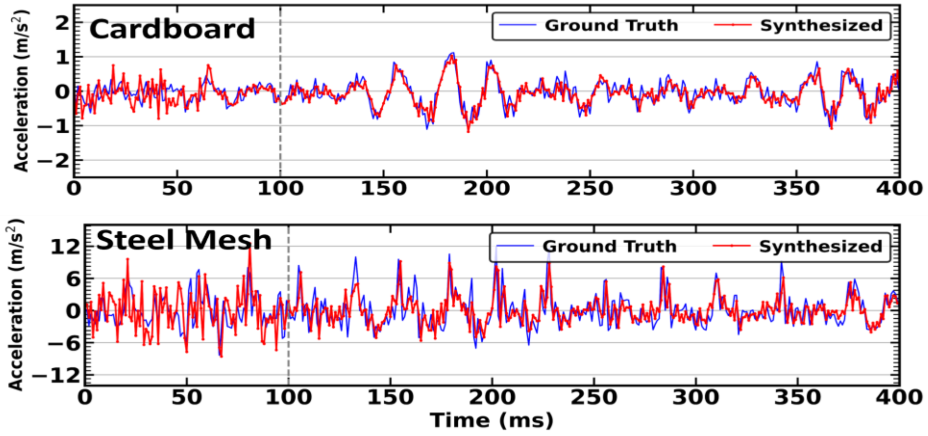
Study	Modeling Type	Segmentation Technique	Modeling Features	Metric	Textures T1	T2	T3	T4	T5	T6	Mean
Piece-wise AR [11] (2014)	Stochastic	AutoParm	Raw Acceleration	MAE	0.48	0.36	0.39	0.41	0.27	0.53	0.406
				GFC	87.56	80.58	86.58	85.16	91.18	88.79	86.64%
FNN [39] (2015)	NN	Constant Speed & Force	Raw Acceleration + Frequency Decomposition	MAE	0.41	0.28	0.46	0.29	0.39	0.47	0.384
				GFC	89.31	90.88	86.37	86.14	85.08	89.92	87.94%
GAN-based [38] (2018)	DL	Constant Speed & Force	Raw Acceleration + Spectrogram	MAE	0.23	0.28	0.27	0.29	0.32	0.37	0.292
				GFC	90.85	89.39	88.50	90.54	83.21	90.71	88.86%
DSTN [40] (2021)	DL	Constant Speed & Force	Raw Acceleration	MAE	0.15	0.18	0.27	0.17	0.15	0.27	0.195
				GFC	91.83	89.96	90.54	88.18	90.22	90.71	90.24%
HapInf [83] (2023)	DL	Sliding Window	Raw Acceleration	MAE	0.18	0.16	**0.12**	0.15	0.17	0.29	0.176
				GFC	89.14	92.02	**91.48**	92.01	91.36	89.38	90.89%
FoTEN (ours)	DL	Sliding Window	Raw Acceleration + Fourier Transform	MAE	**0.13**	**0.11**	0.16	**0.13**	**0.14**	**0.19**	**0.148**
				GFC	**90.83**	**93.82**	91.17	**93.83**	**92.17**	**91.84**	**92.28%**

[7] S. Shin, R. H. Osgouei, K.-D. Kim, and S. Choi, "Data-driven mod- eling of isotropic haptic textures using frequency-decomposed neural networks," in 2015 IEEE World Haptics Conference (WHC)
[8] J. B. Joolee and S. Jeon, "Data-driven haptic texture modeling and rendering based on deep spatio-temporal networks," IEEE Transactions on Haptics, vol. 15, no. 1, pp. 62–67, 2021.
[13] H. Culbertson, J. Unwin, and K. J. Kuchenbecker, "Modeling and rendering realistic textures from unconstrained tool-surface interactions," IEEE transactions on haptics, vol. 7, no. 3, pp. 381–393, 2014.
[17] A. Abdulali and S. Jeon, "Data-driven modeling of anisotropic hap- tic textures: Data segmentation and interpolation," in International Conference on Human Haptic Sensing and Touch Enabled Computer Applications. Springer, 2016.

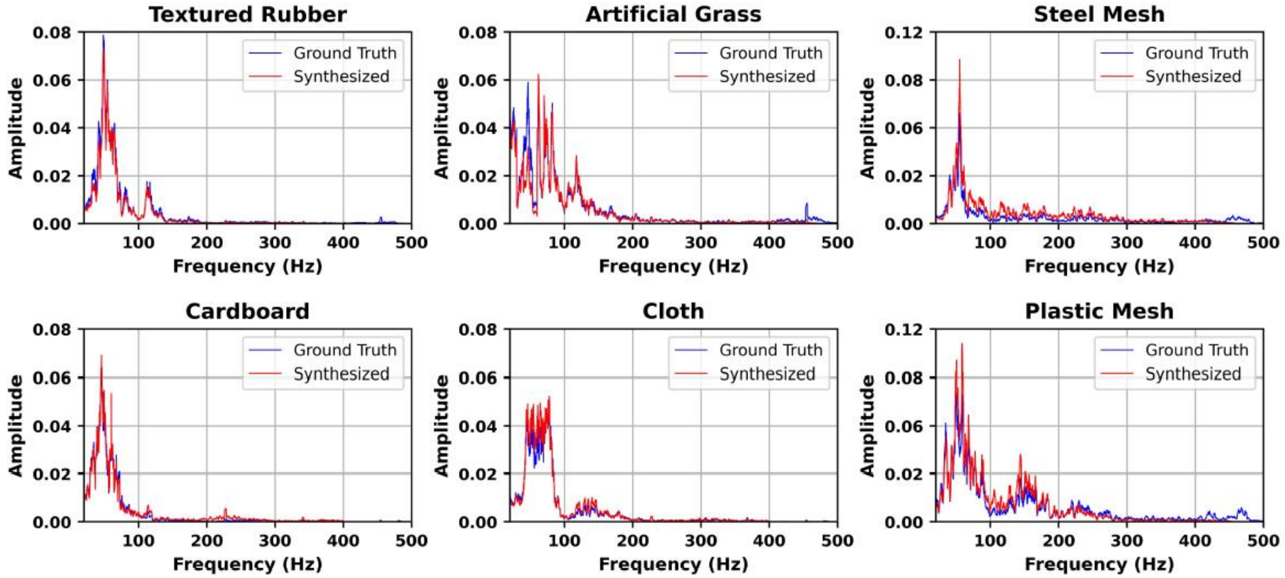




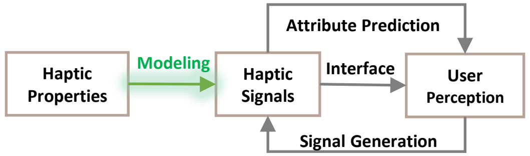
Evaluation - Numerical

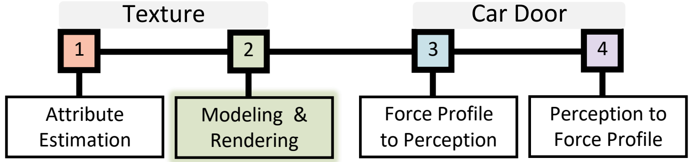


Actual Vs Predicted (Time Domain)



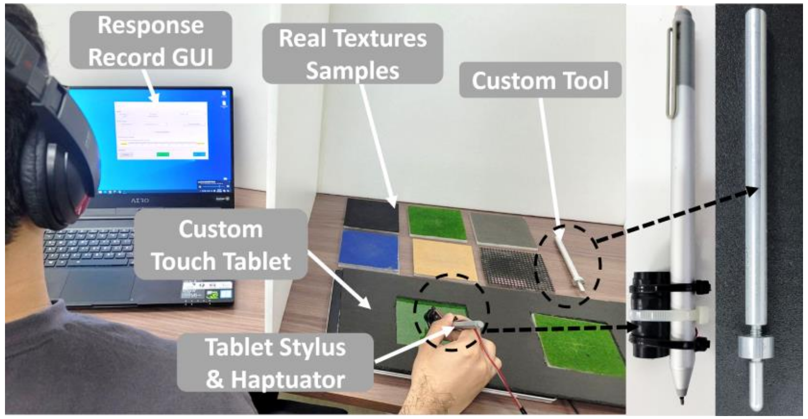
Actual Vs Predicted (Frequency Domain)



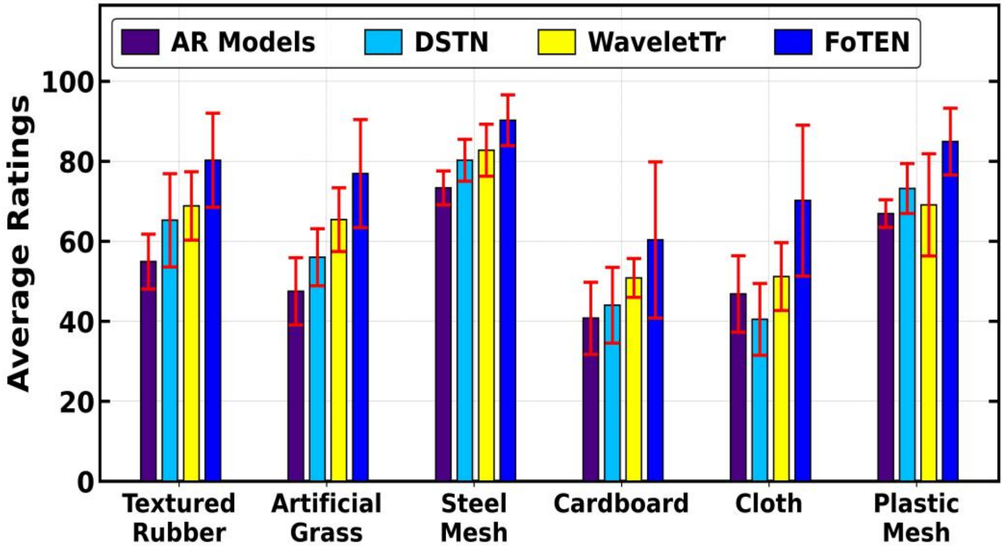


Evaluation – Perceptual Study

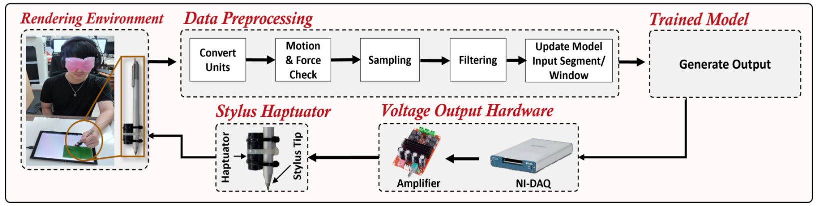
- A **similarity rating experiment** was compared to gauge the quality of proposed framework where participants compared real textures and their virtual copies
- The perceptual experiment results shows that the **proposed approach** was **preferred by participants** across all textures.

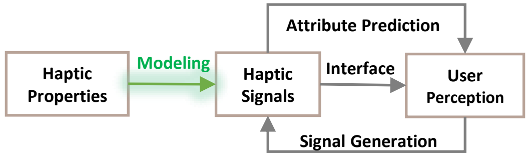


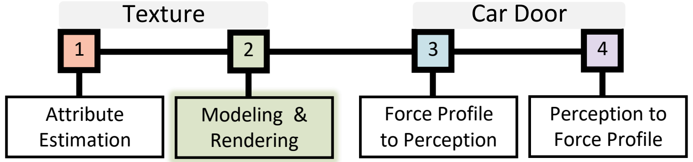
Perceptual Experiment Setup



Perceptual Experiment Results



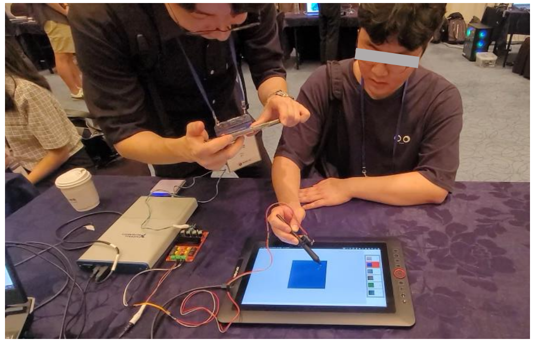


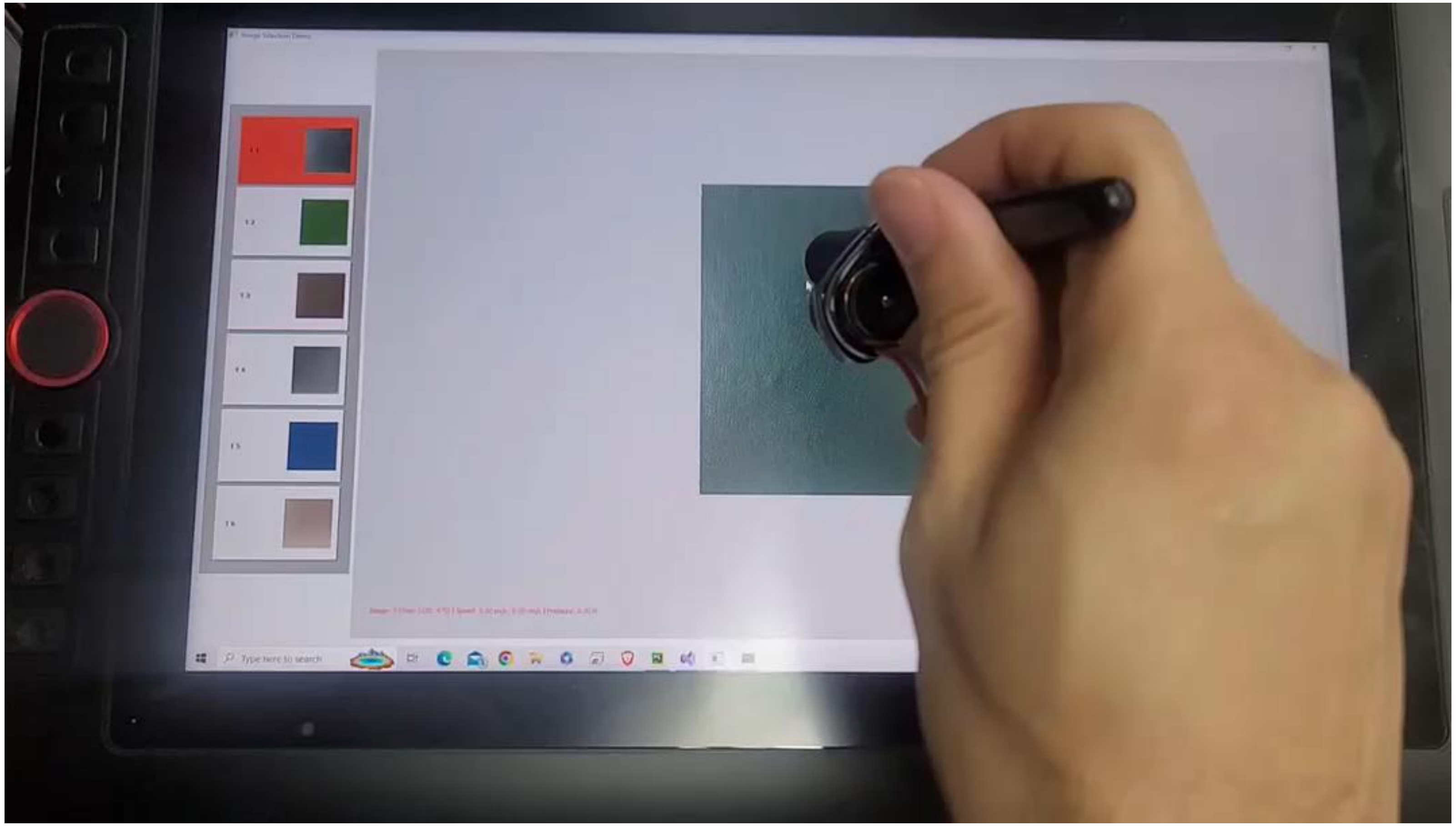


Demonstration – Texture Rendering

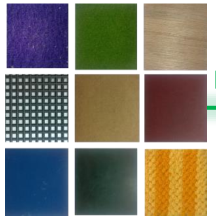
- For each texture, vibrations can be heard.
- Fine textures have lower vibrations, resulting in a lower sound.
- For grid-like textures, the vibration amplitudes are higher, producing a grated vibration sound.

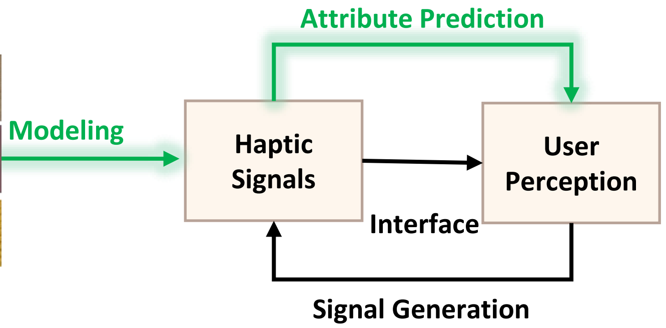
Demo presented at Korea Haptic Conference, 2024.

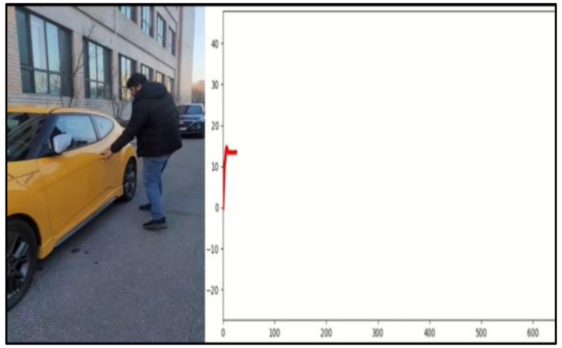


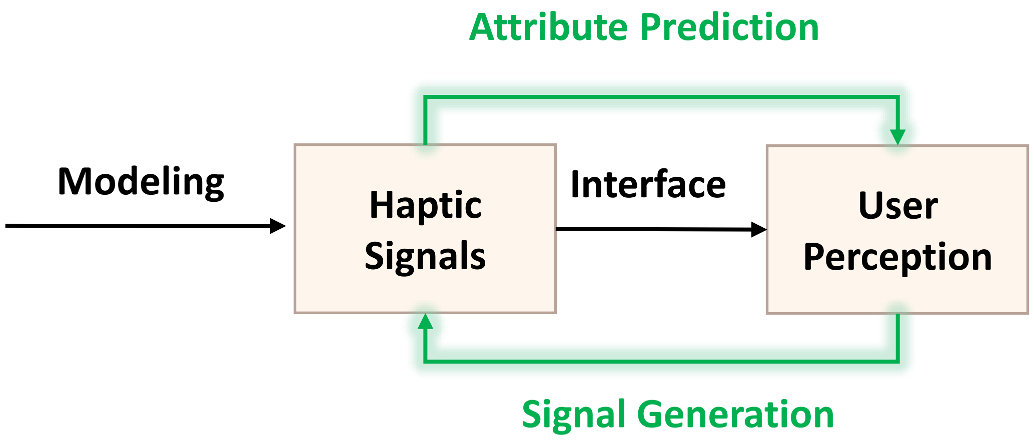


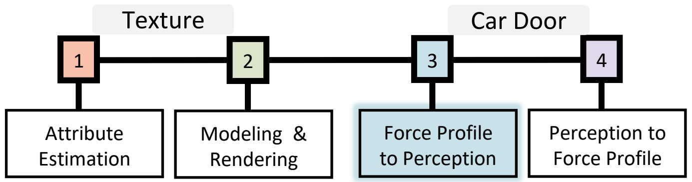
Kinesthetic (Car Door System)



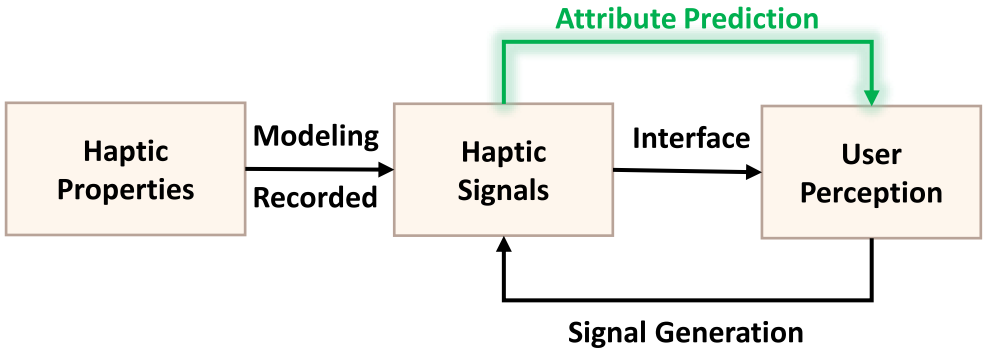




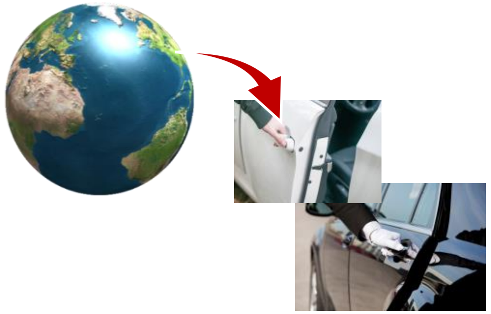




Car Door Perceptual Attribute Estimation and Force Profile Generation

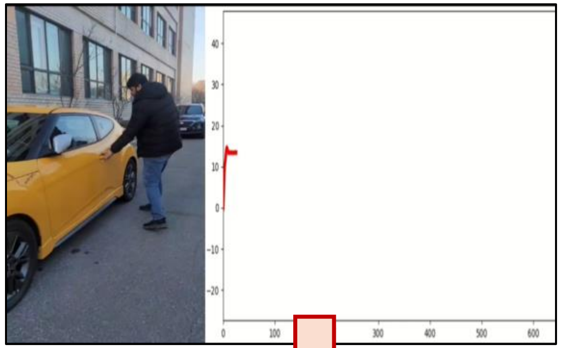


Motivation



Infinite Car Doors

User Preferences



Haptic Attributes

- **Easy-to-Pull = 90 %**
- **Damped = 50%**
- **Expensive = 90%**
- **Classy = 60%**

Car Door Designer

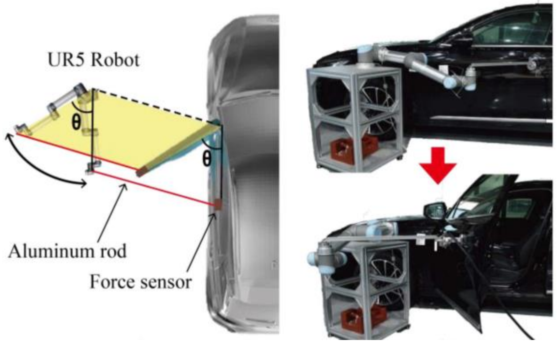
No framework to estimate the door car profile from perceptual ratings

Literature Review

Michael, et al. (2010)

- Designed a car door simulator
- Can replicated door torque/force

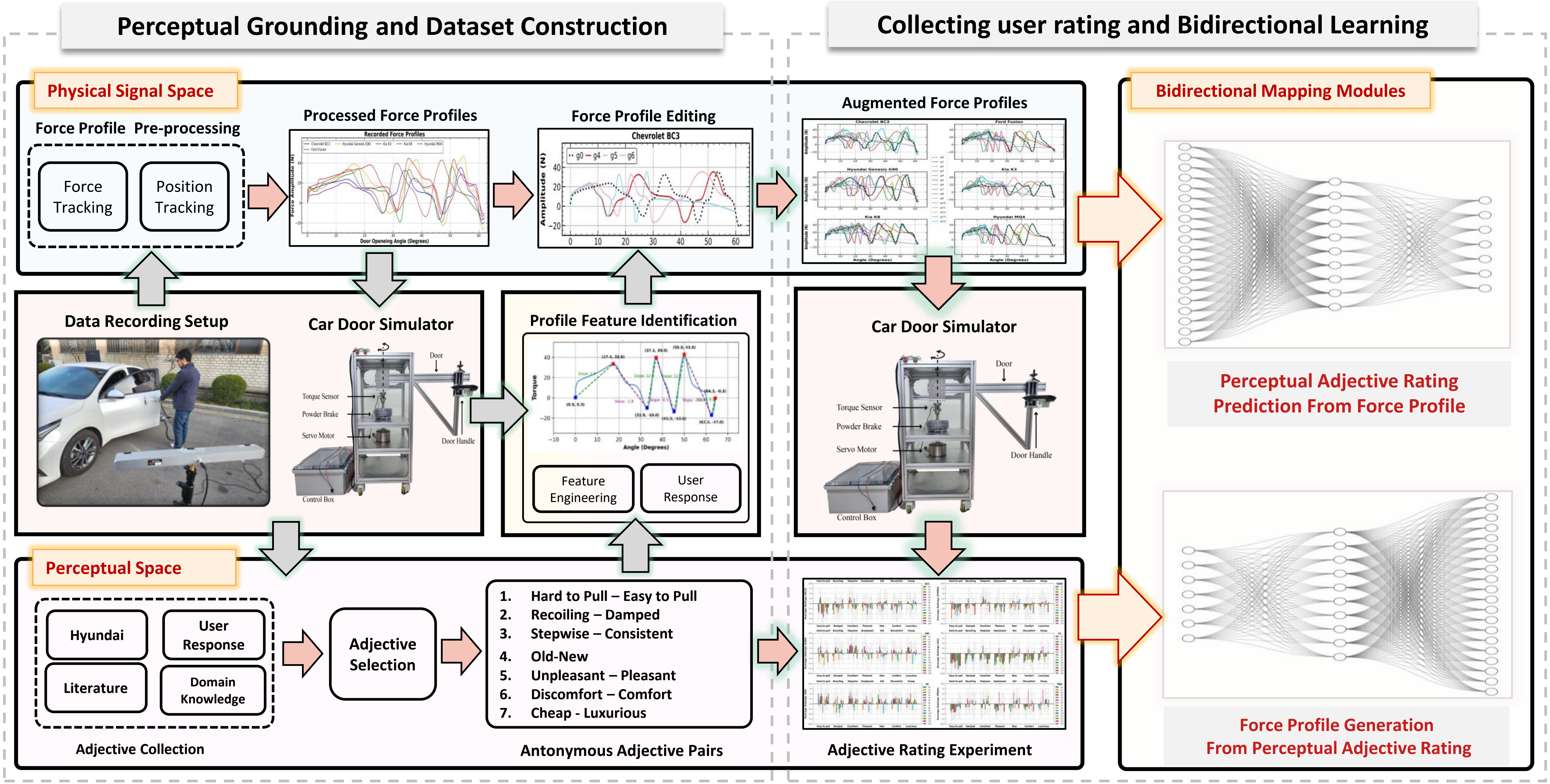
Ma, et al. (2024)



- Designed a car door simulator
- Can replicated door torque/force, inertia and weight.

Strolz, Michael, et al. "Development and evaluation of a device for the haptic rendering of rotatory car doors." *IEEE Transactions on Industrial Electronics* 58.8 (2010): 3133-3140.
Ma, Jihyeong, Ji-Sung Kim, and Ki-Uk Kyung. "A hybrid haptic device for virtual car door interactions: Design and implementation." *IEEE Robotics and Automation Letters* (2024).

Overview



Perceptual Grounding and Dataset Construction
Collecting user rating and Bidirectional Learning
Physical Signal Space
Force Profile Pre-processing
Force Tracking
Position Tracking
Processed Force Profiles
Recorded Force Profiles
Force Profile Editing
Chevrolet BC3
Augmented Force Profiles
Data Recording Setup
Car Door Simulator
Door
Torque Sensor
Powder Brake
Servo Motor
Door Handle
Control Box
Profile Feature Identification
Feature Engineering
User Response
Car Door Simulator
Perceptual Space
Hyundai
User Response
Literature
Domain Knowledge
Adjective Collection
Adjective Selection
1. Hard to Pull – Easy to Pull
2. Recoiling – Damped
3. Stepwise – Consistent
4. Old-New
5. Unpleasant – Pleasant
6. Discomfort – Comfort
7. Cheap - Luxurious
Antonymous Adjective Pairs
Adjective Rating Experiment
Bidirectional Mapping Modules
Perceptual Adjective Rating Prediction From Force Profile
Force Profile Generation From Perceptual Adjective Rating

Framework Pipeline

Perceptual Space | Perceptual Space

Physical Signal Space | Physical Signal Space | Bi-directional Modeling

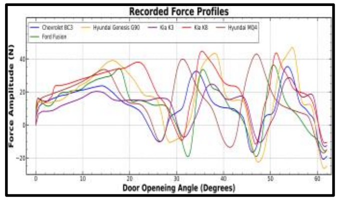
Texture: 1 Attribute Estimation — 2 Modeling & Rendering

Car Door: 3 Force Profile to Perception — 4 Perception to Force Profile

- ✓ Collecting Force Data from real cars.
- ✓ Preprocess & replay on Car Door Simulator

Physical Signal Space

Phase 1



1. **Recoiling – Damped**
2. **Stepwise – Consistent**
3. **Old-New**

Perceptual Space

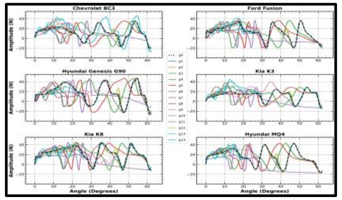
Experiment 1 & 2

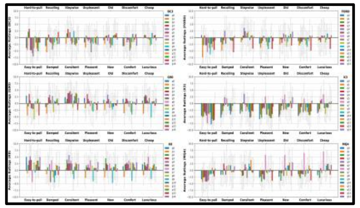
- ✓ **Exp. 1:** Create a lexicon of adjectives
- ✓ **Exp. 2:** Adjectives selection from the compiled list.
- ✓ User response for feature engineering

- ✓ Do feature Engineering on Force Profiles
- ✓ Create new/augmented Profiles
- ✓ 14 new profiles created for each car (total 15)

Physical Signal Space

Phase 2





Perceptual Space

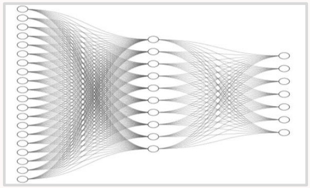
Experiment 3

- ✓ Adjective Rating Experiment with Car Door simulator
- ✓ Using adjectives from Experiment 1 & Profiles from Phase 2

- ✓ **Modeling 1:** Force Profile to Perception
- ✓ **Modeling 2:** Perception to force profile

Bi-directional Modeling

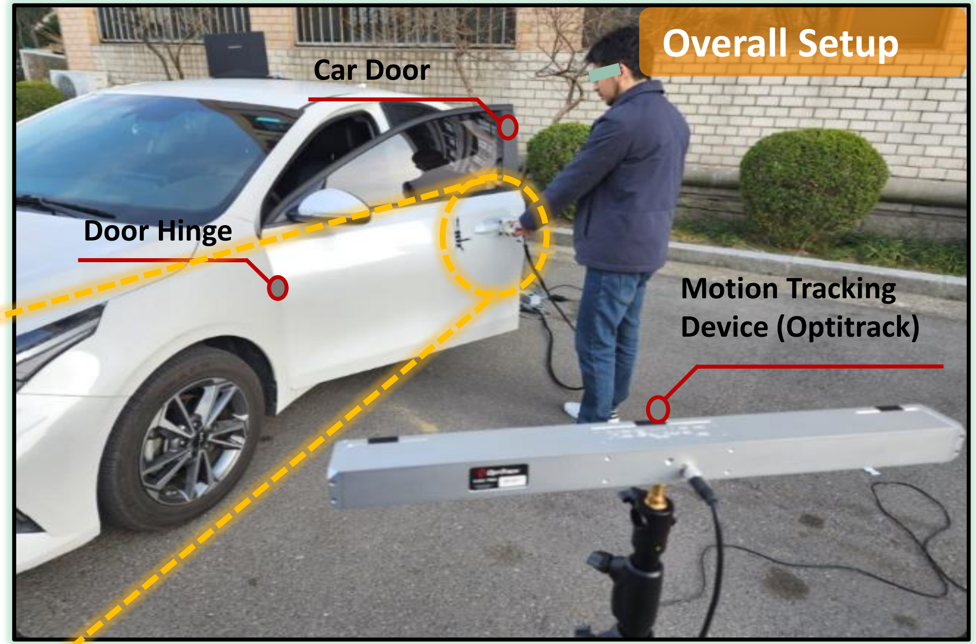
Perception & Force



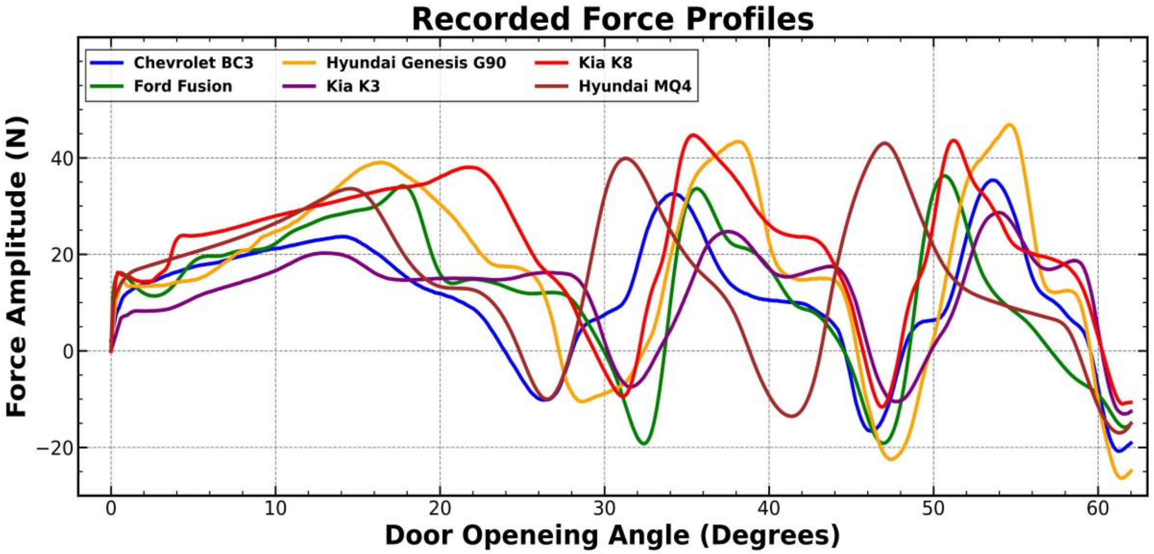
Phase 1: Collecting Data - Real Cars

The Data was recorded for 6 real cars:

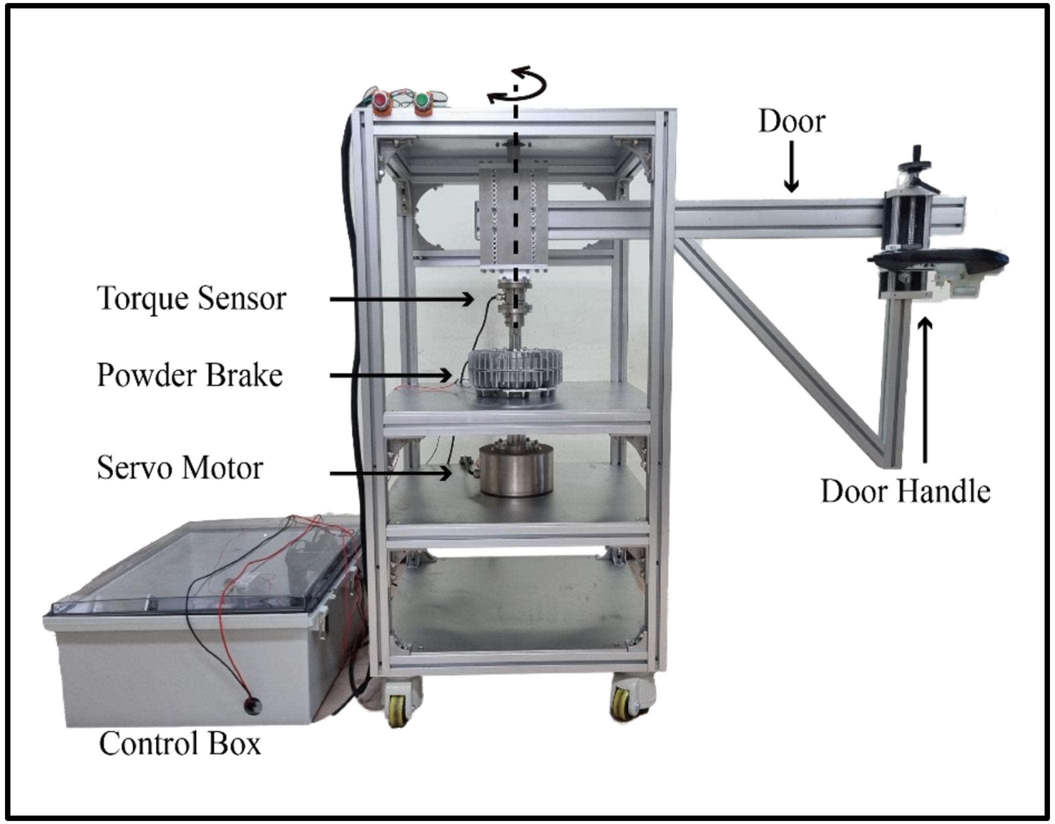
- ✓ Chevrolet BC3
- ✓ FORD Fusion
- ✓ Genesis G90
- ✓ KIA K3
- ✓ KIA K8
- ✓ Hyundai MQ4



Phase 1 : Force Profile Preprocessing



Preprocessed Force Profiles from 6 Cras



Car Door Simulator

Experiment 1: Adjective Lexicon

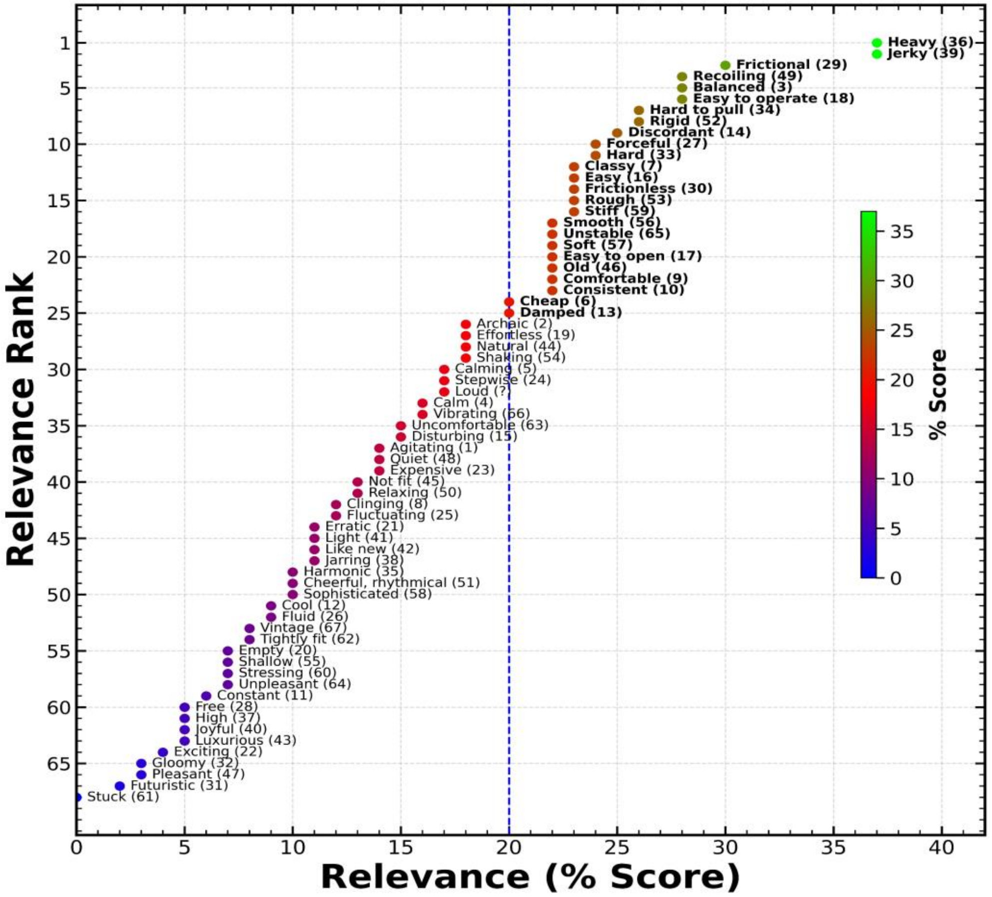
The lexicon of adjectives built from four sources :

- ✓ Hyundai research
- ✓ Literature
- ✓ Domain expert
- ✓ Experiment

1 Agitating	18 Easy to operate	35 Harmonic	52 Cheerful, rhythmical
2 Archaic	19 Effortless	36 Heavy	53 Rigid
3 Balanced	20 Empty	37 High	54 Rough
4 Calm	21 Erratic	38 Jarring	55 Shaking
5 Calming	22 Exciting	39 Jerky	56 Shallow
6 Cheap	23 Expensive	40 Joyful	57 Smooth
7 Classy	24 Stepwise	41 Light	58 Soft
8 Clinging	25 Fluctuating	42 Like new	59 Sophisticated
9 Comfortable	26 Fluid	43 Loud	60 Stiff
10 Consistent	27 Forceful	44 Luxurious	61 Stressing
11 Constant	28 Free	45 Natural	62 Stuck
12 Cool	29 Frictional	46 Not fit	63 Tightly fit
13 Damped	30 Frictionless	47 Old	64 Uncomfortable
14 Discordant	31 Futuristic	48 Pleasant	65 Unpleasant
15 Disturbing	32 Gloomy	49 Quiet	66 Unstable
16 Easy	33 Hard	50 Recoiling	67 Vibrating
17 Easy to open	34 Hard to pull	51 Relaxing	68 Vintage

Constructed perceptual adjective/attributes list

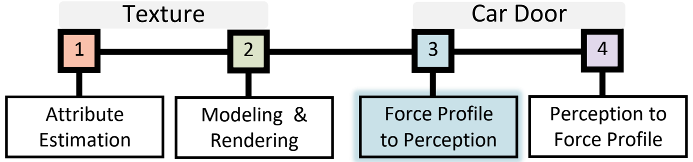
Experiment2: Adjective Selection



Relevance Percentage Score by Users

#	Attribute	Antonym
1	Easy-to-pull	Hard-to-pull
2	Damped	Recoiling
3	Consistent	Stepwise
4	Pleasant	Unpleasant
5	New	Old
6	Comfort	Discomfort
7	Luxurious	Cheap

Created Antonymous Pairs

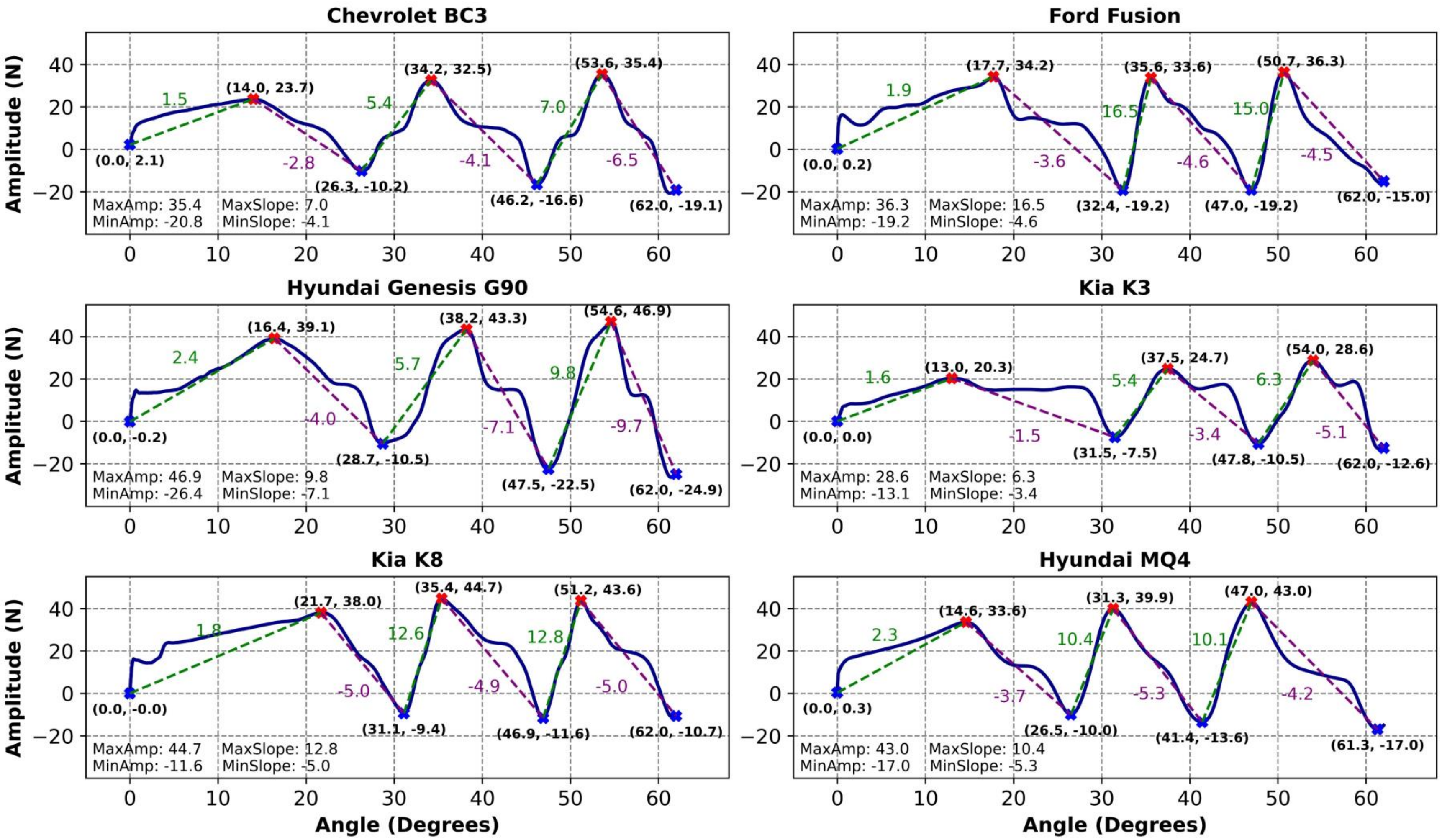


Phase 2: Force Profiles Augmentation

Post Experiment 2 user interview suggested:

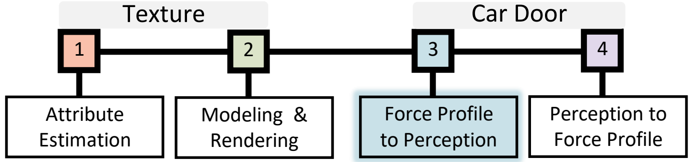
- ✓ ***First Peak Amplitude***
- ✓ ***Peak Positions***
- ✓ ***Peak Slope***
- ✓ ***Number of Bumps***

could be the salient features.



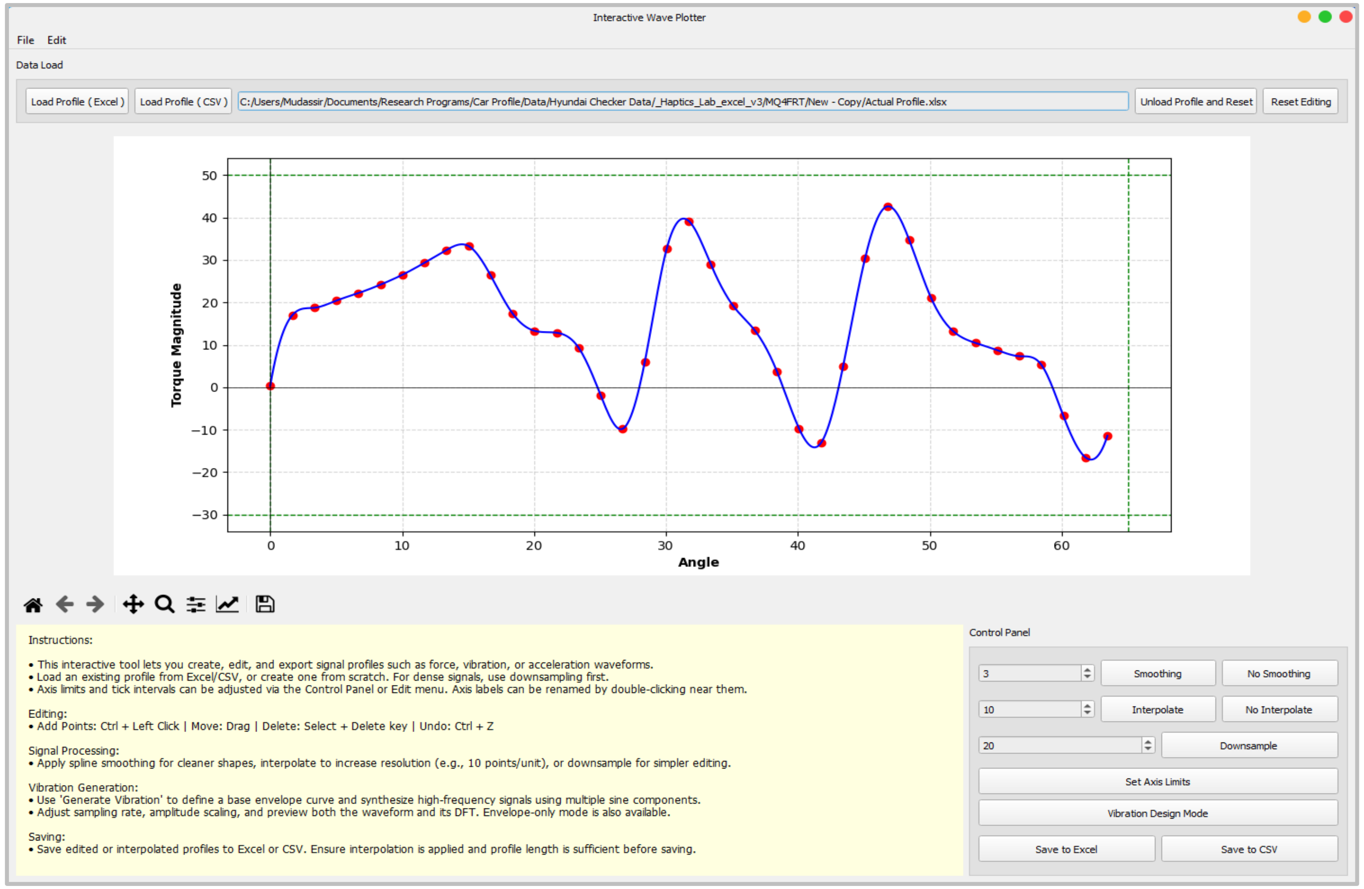
Feature Engineering on Real Force Profiles

Phase 2: Force Profiles Augmentation



A total of **14 new Profiles** were created from **each real force profile** with a **custom developed Profile Editor**:

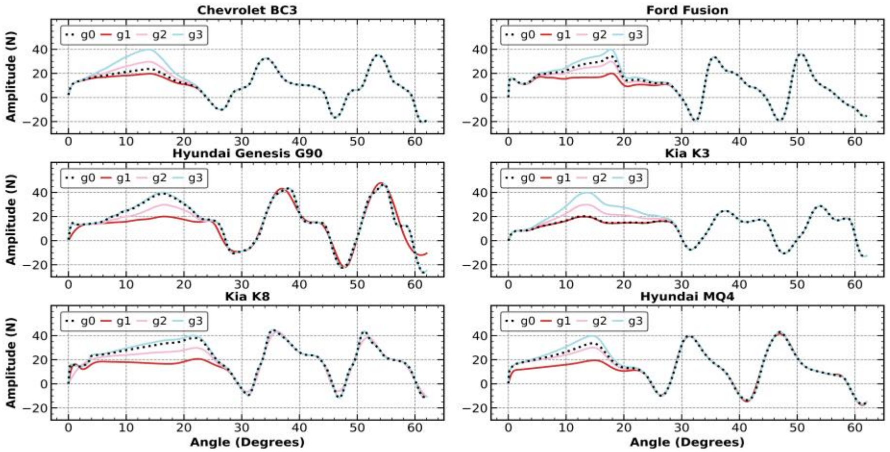
- ✓ **Amplitude Adjustment (g1–g3):** First peak amplitude set to 20 N, 30 N, and 40 N
- ✓ **Peak Position Shift (g4–g6):** First three cycles compressed to complete before 15°, 30°, and 45°, respectively.
- ✓ **Random Alterations (g7–g9):** Introduced localized changes such as early peaks, flattened segments, and added minor cycles.
- ✓ **Plateau Modifications (g10–g12):** Adjusted the post 2^{nd} peak plateau; unaltered (g10), stretched (g11), or stretched and raised (g12).
- ✓ **Pre-Peak Bumps (g13–g14):** Small oscillations added before the first peak using g2 and g3 as bases.



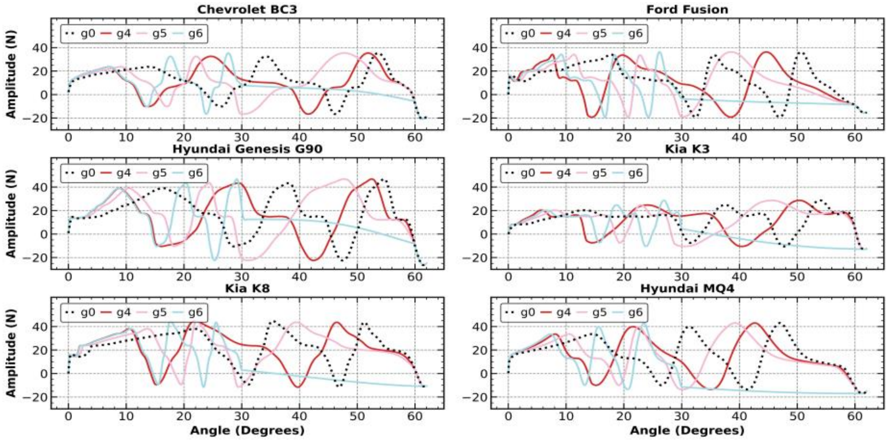
Developed Profile Editor Software

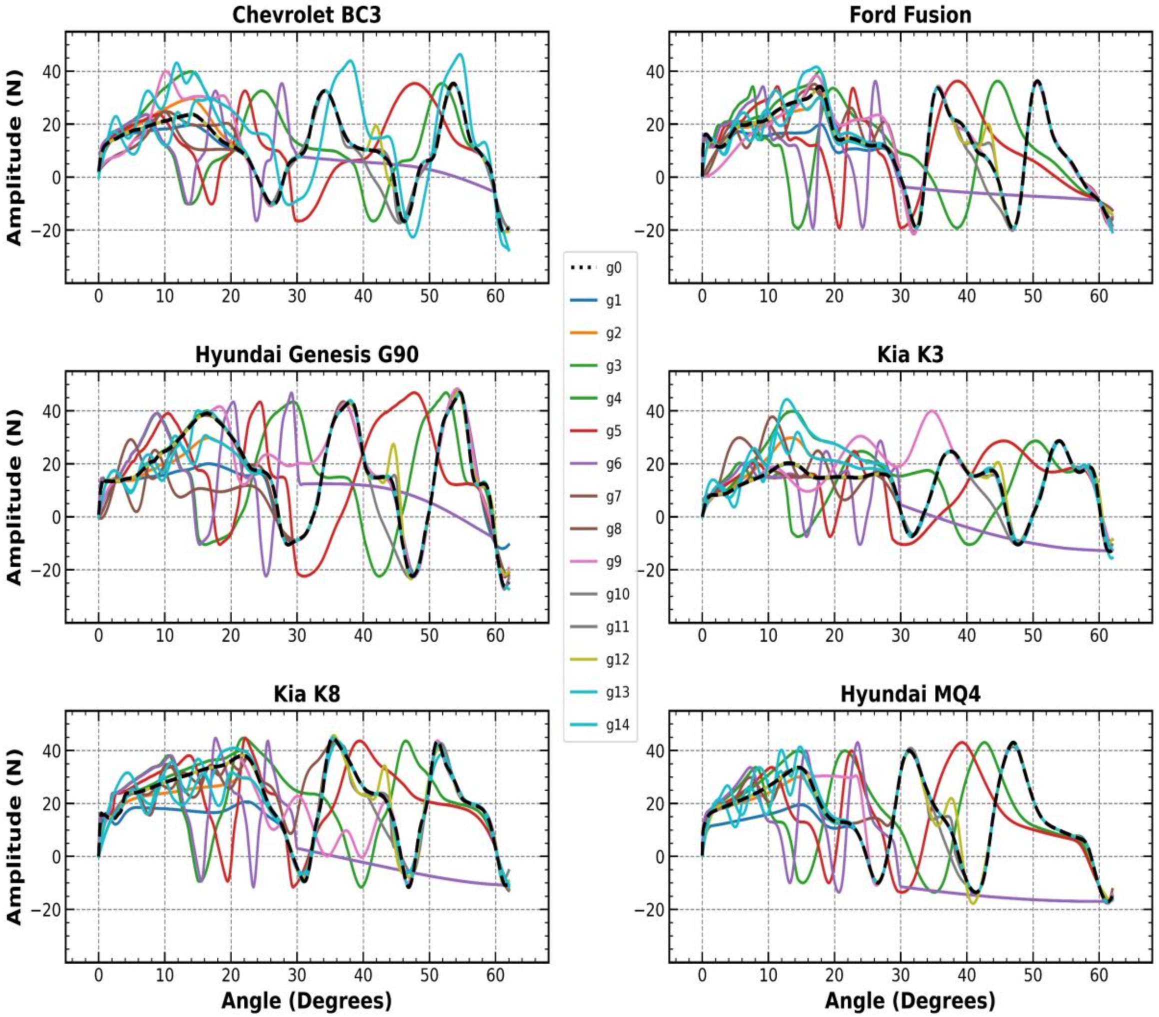
Phase 2: Force Profiles Augmentation

Amplitude Adjustment (g1–g3):



Peak Position Shift (g4–g6):

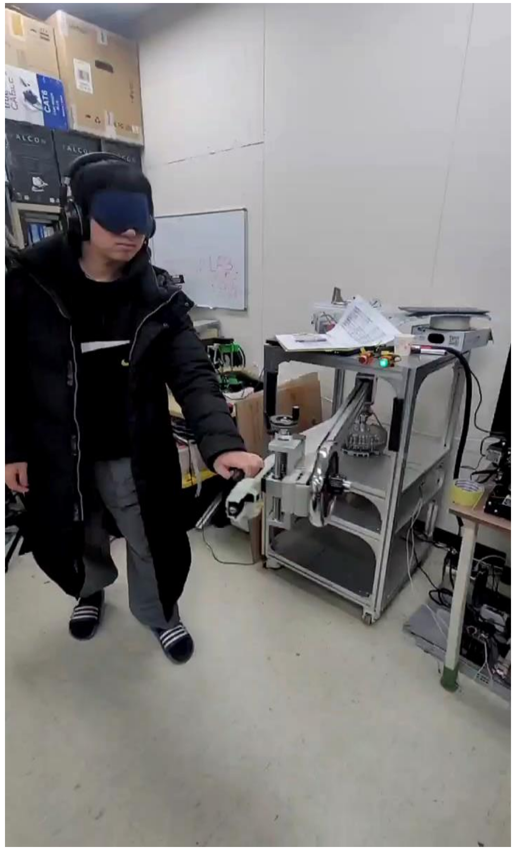




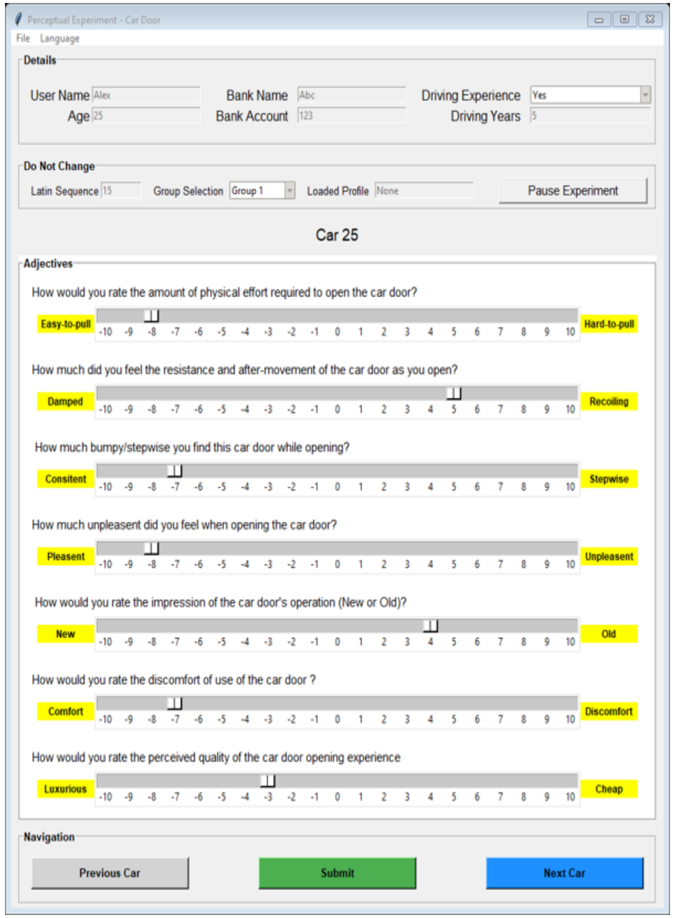
All Augmented Profiles
(Physical Signal Space)

Experiment 3: Adjective Rating

- ✓ A total of 90 Force profiles were used (14 augmented + 1 original x 6cars)
- ✓ A total of 40 Participants took part in the experiment.
- ✓ Users rated 7 antonymous adjective pairs from scale -10 to +10

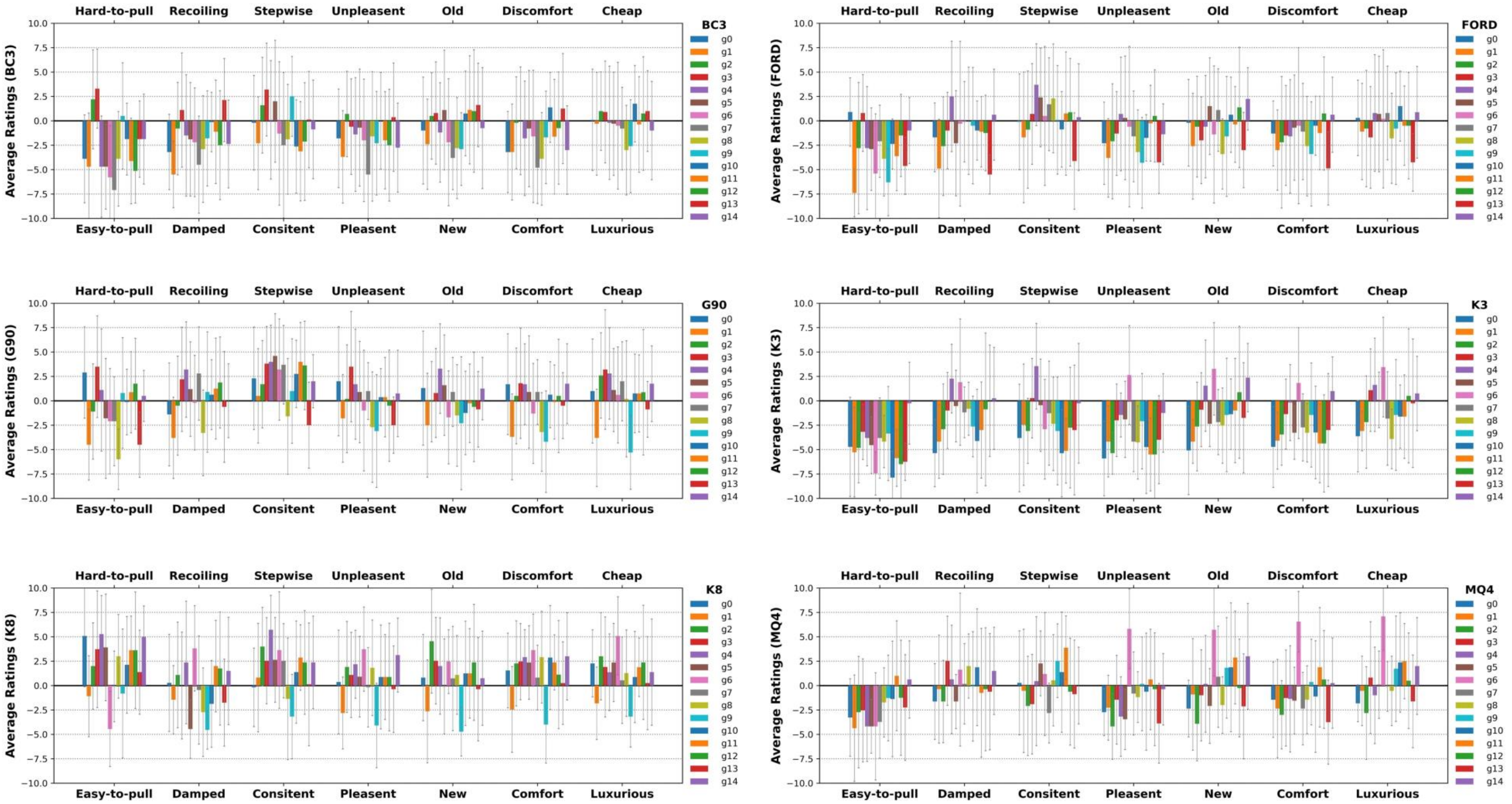


Experiment Setup



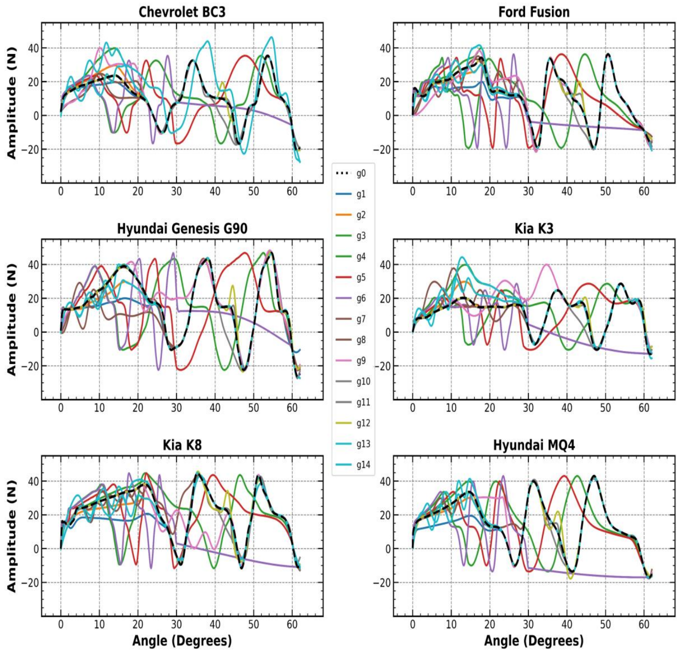
Adjective Rating Experiment GUI

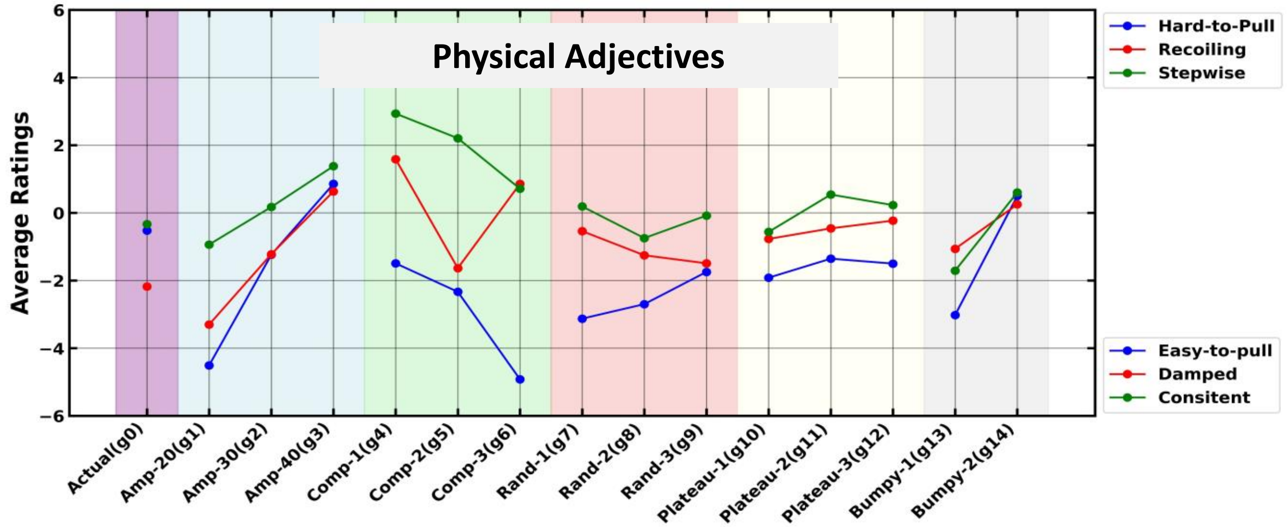
Adjective Rating Experiment Results

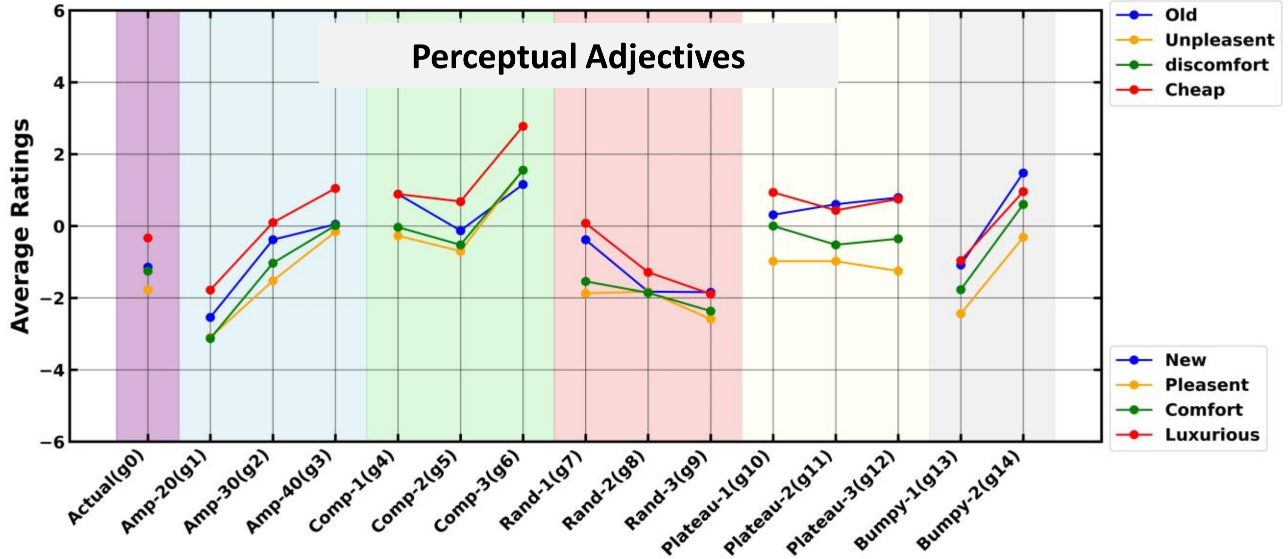


Adjective Ratings
(Perceptual Space)

Adjective Rating Experiment Results



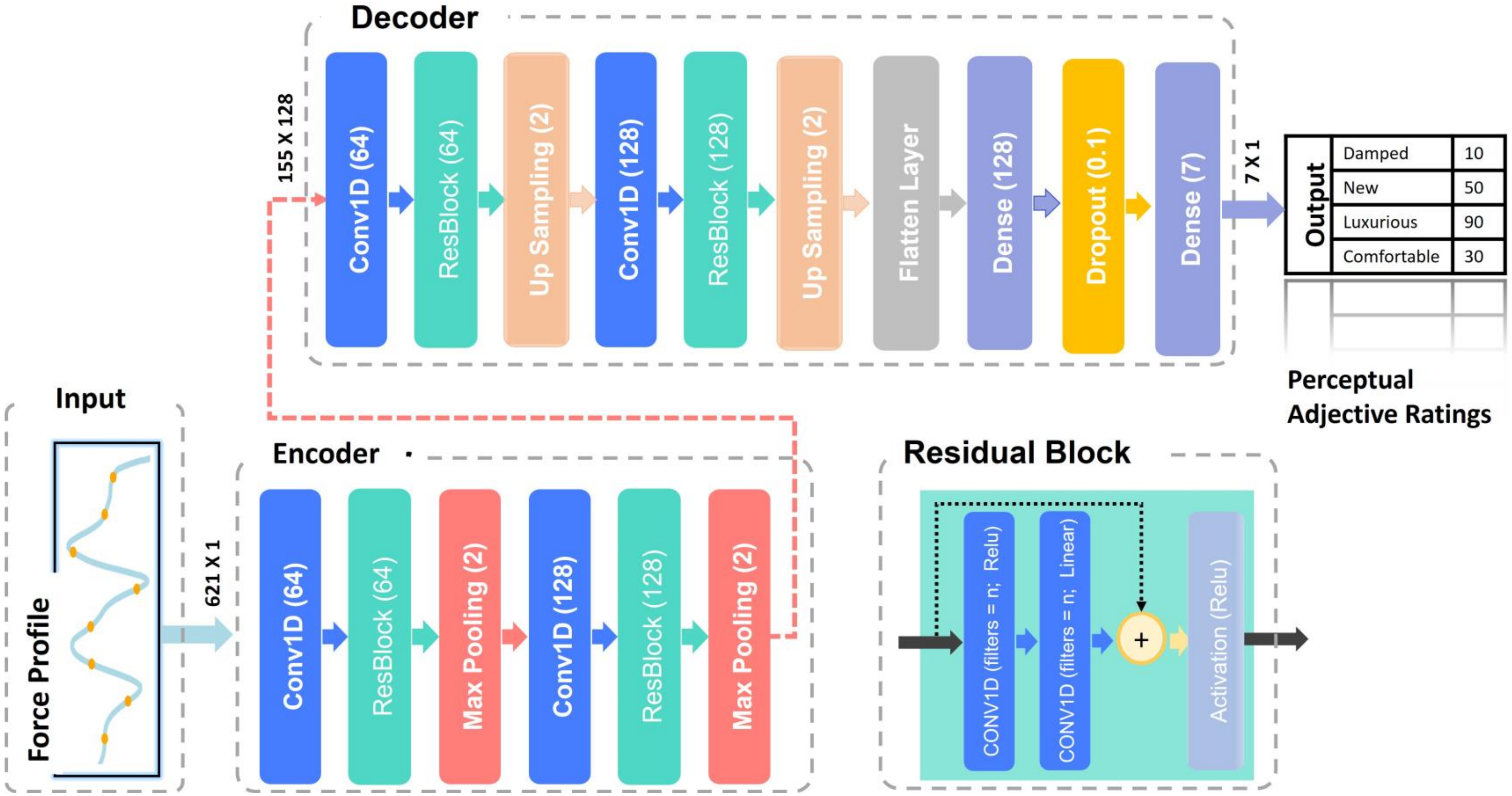




- ✓ The trends are visible across all the augmented variations except from (g7 to g9) the random variations.
- ✓ The analysis suggested the augmentation were useful in both Physical and Emotional Attributes .

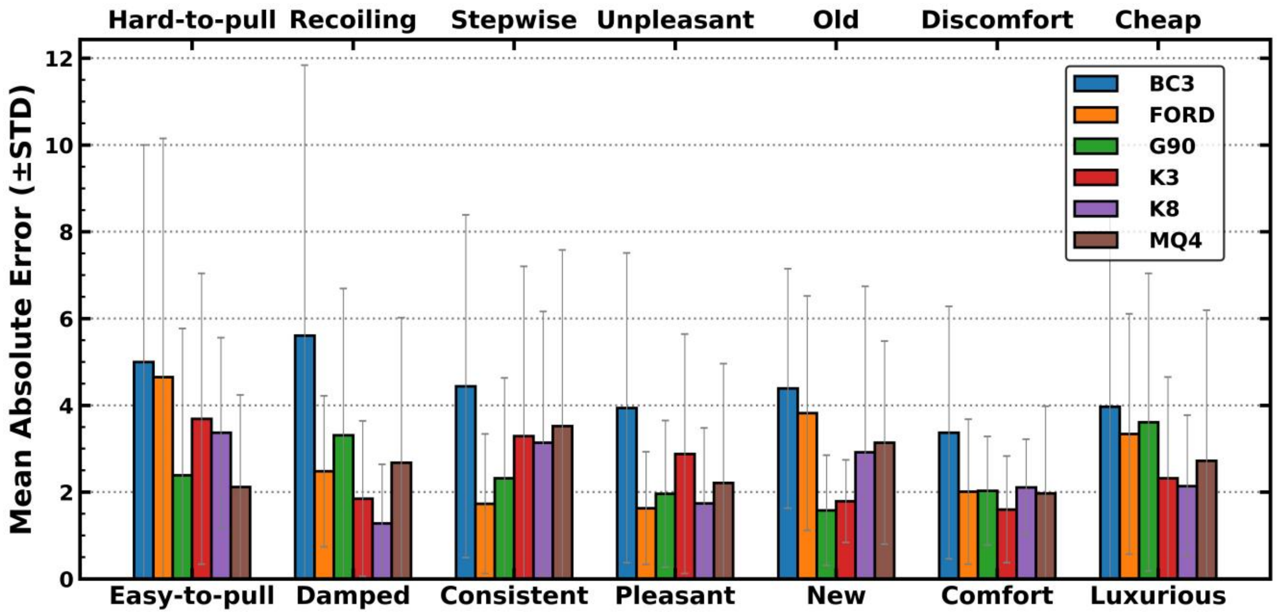
Force Profile to Perception Model

- ✓ Model **takes force profile as input** while **predicts haptic perceptual attributes**
- ✓ The model is based on **encoder-decoder** architecture with **residual blocks.**
- ✓ Model is **trained** in a way so its encoder and decoder **could be used separately** for **repurpose.**

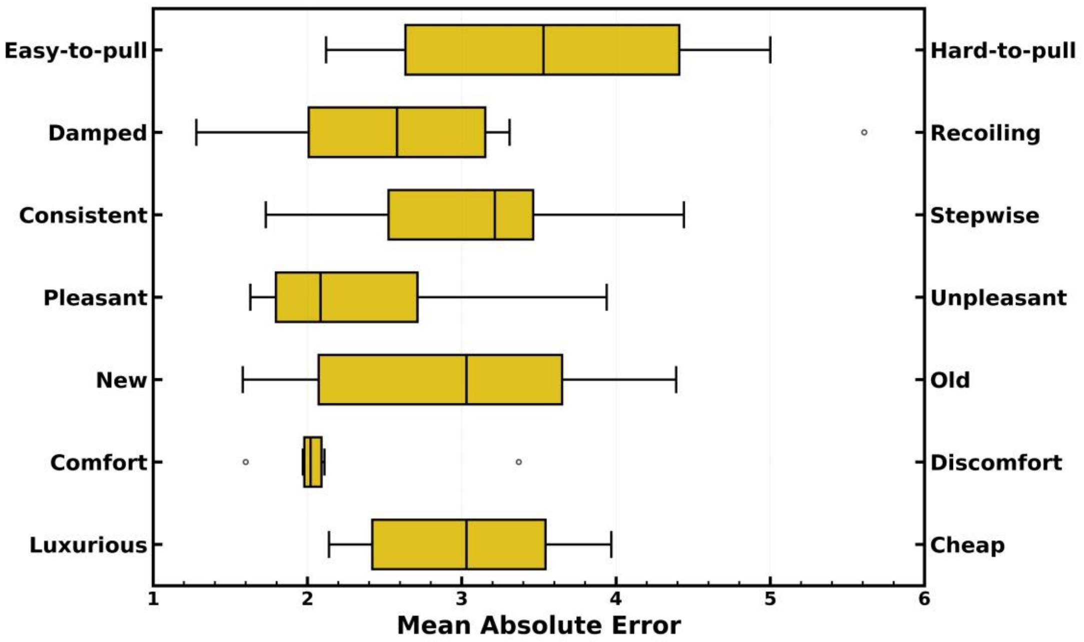


Encoder - Decoder Based Network with Residual Block

Evaluation

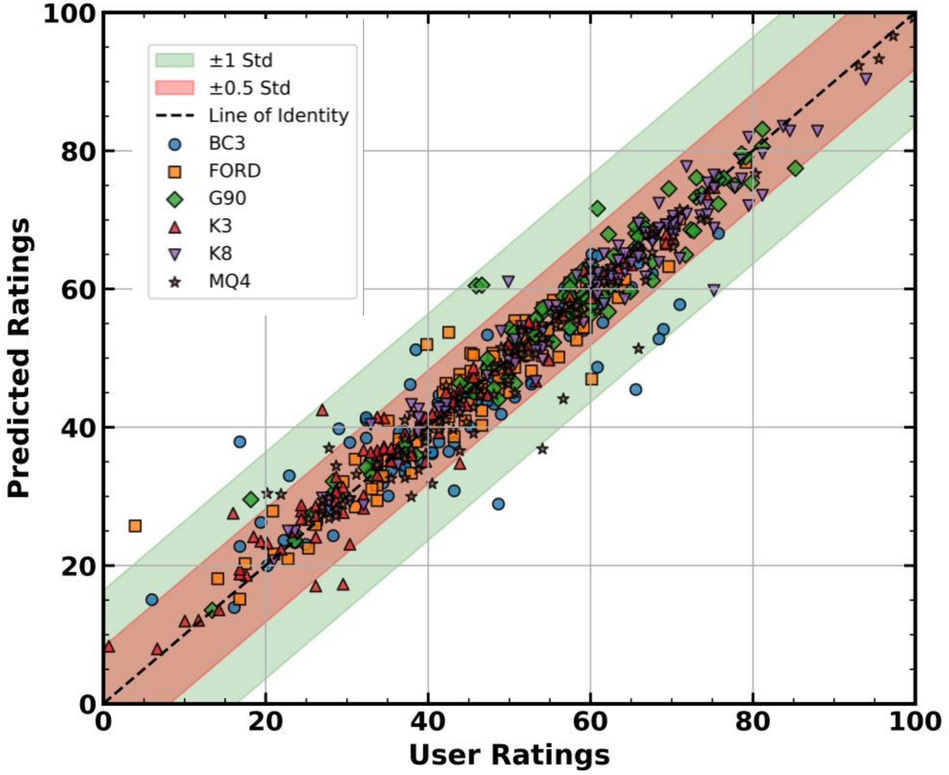


Mean Absolute Error (MAE) by Cars and Attributes

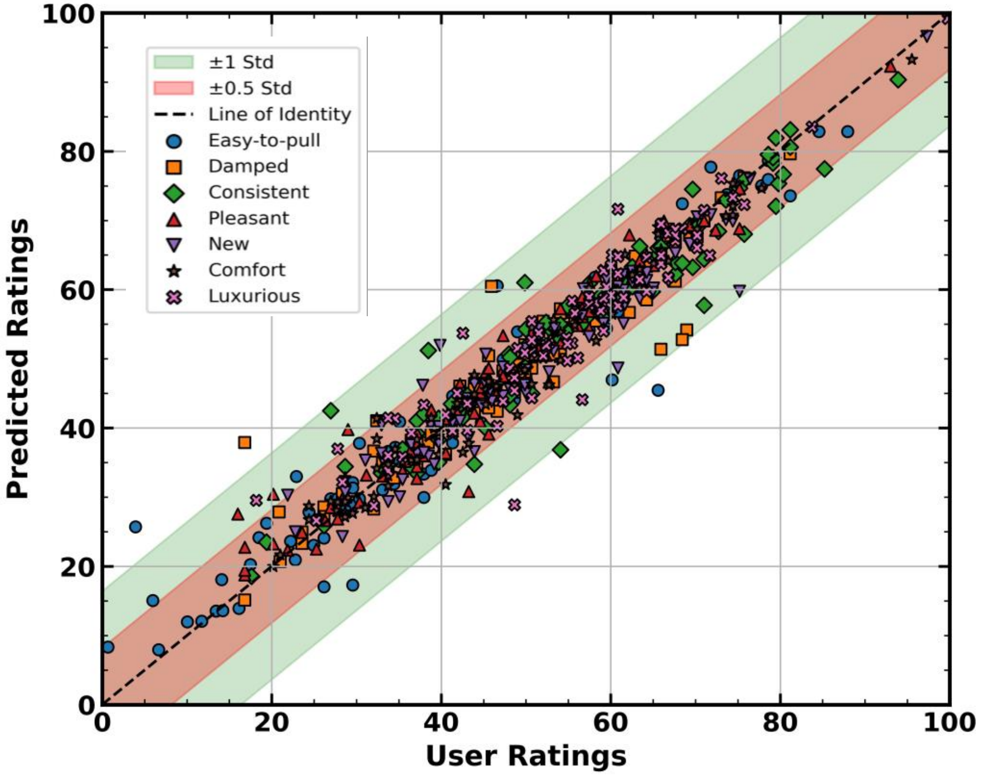


Overall Mean for Attributes

Evaluation

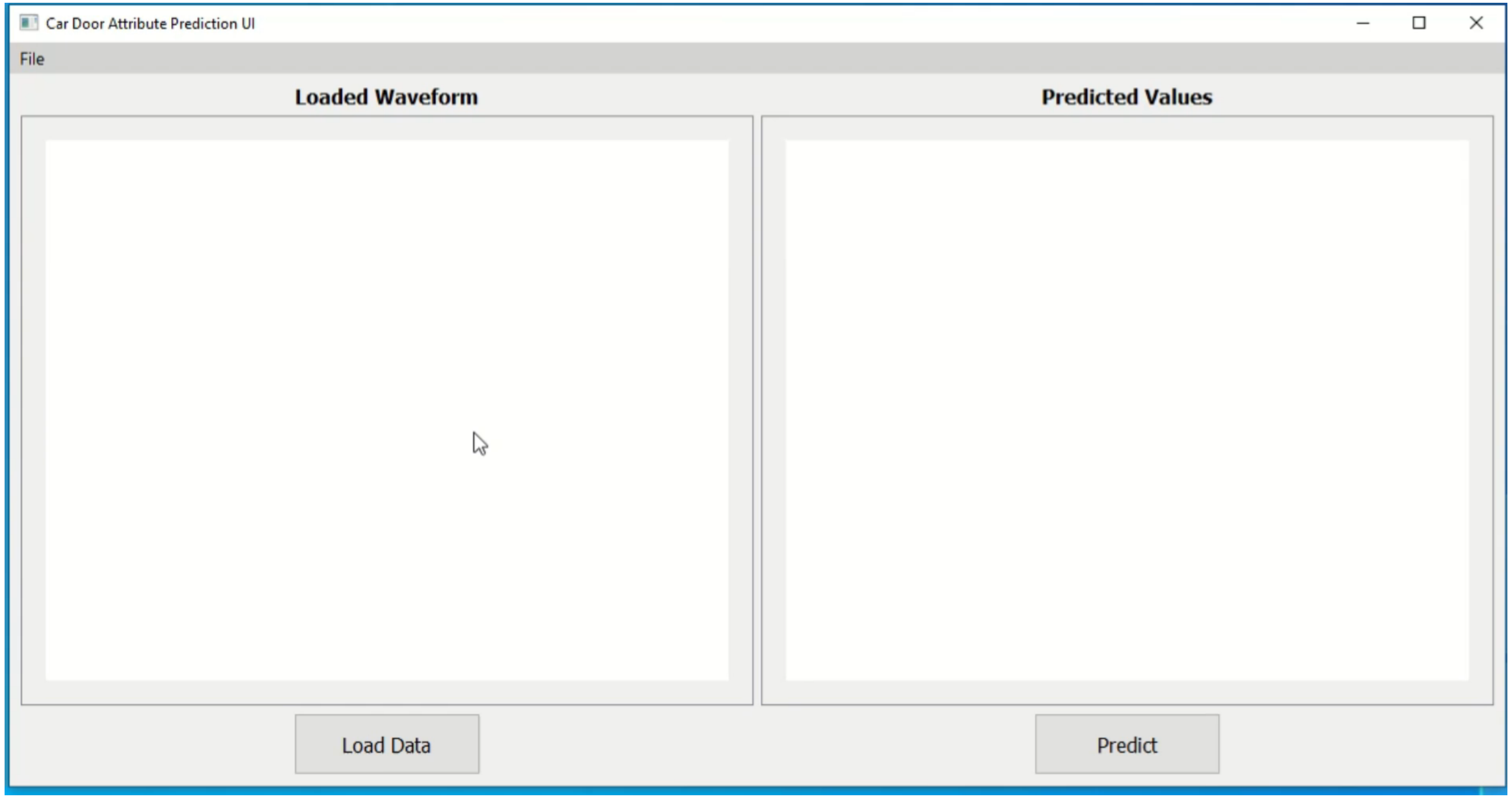


Error Divergence by Cars

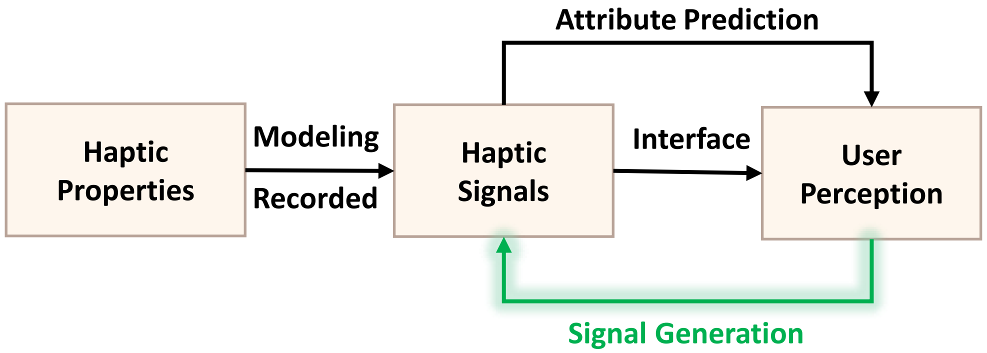


Error Divergence by Attributes

Demonstration: Perceptual Attribute Prediction

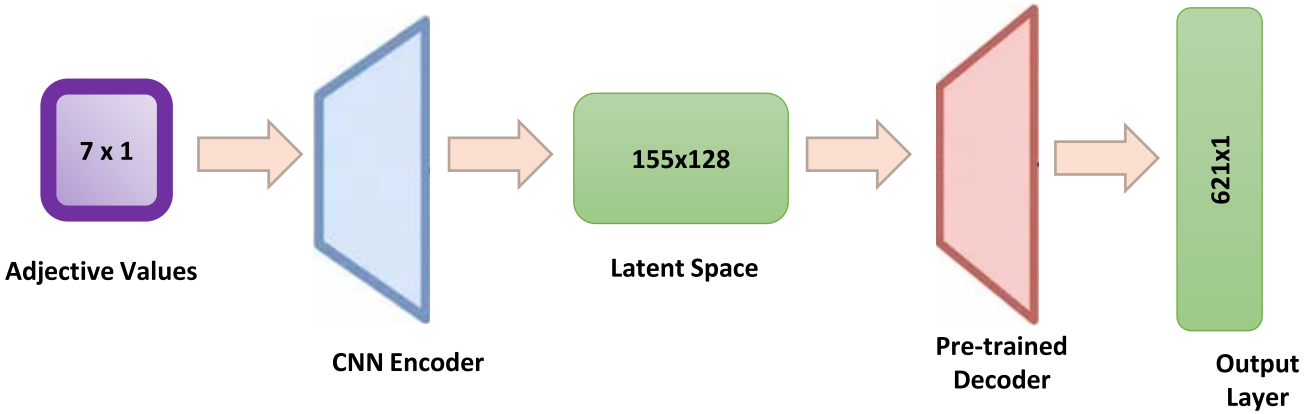


Perception to Force Profile Generation



Perception to Force Model

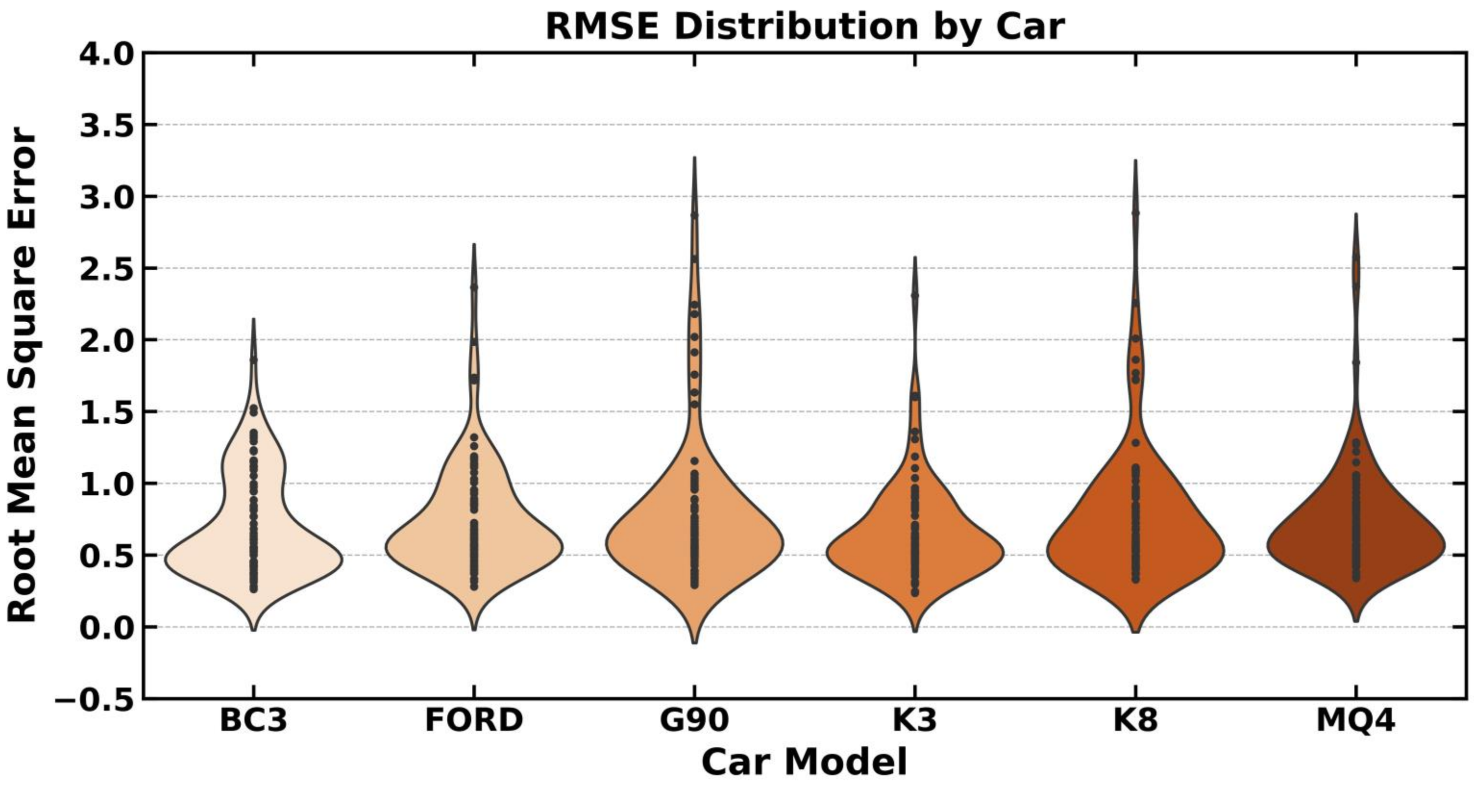
- The model uses an encoder–decoder design, where a 7-dimensional perceptual rating vector is reshaped and passed through 1D convolutional layers to form a latent representation.
- The encoder includes 4 Conv1D layers (64→128→256→512 filters), max pooling, and a dense projection reshaped to match the decoder's latent shape of (155, 128).
- The decoder, pretrained from the signal-to-rating model, is repurposed to reconstruct a 621-point force profile using residual blocks and up-sampling layers.
- Decoder weights remain frozen to preserve the learned signal structure, while the encoder and final dense output layer are retrained for perceptual-to-force mapping.
- This architecture enables accurate force waveform generation from perceptual inputs with reduced trainable complexity.



Pre-trained Decoder

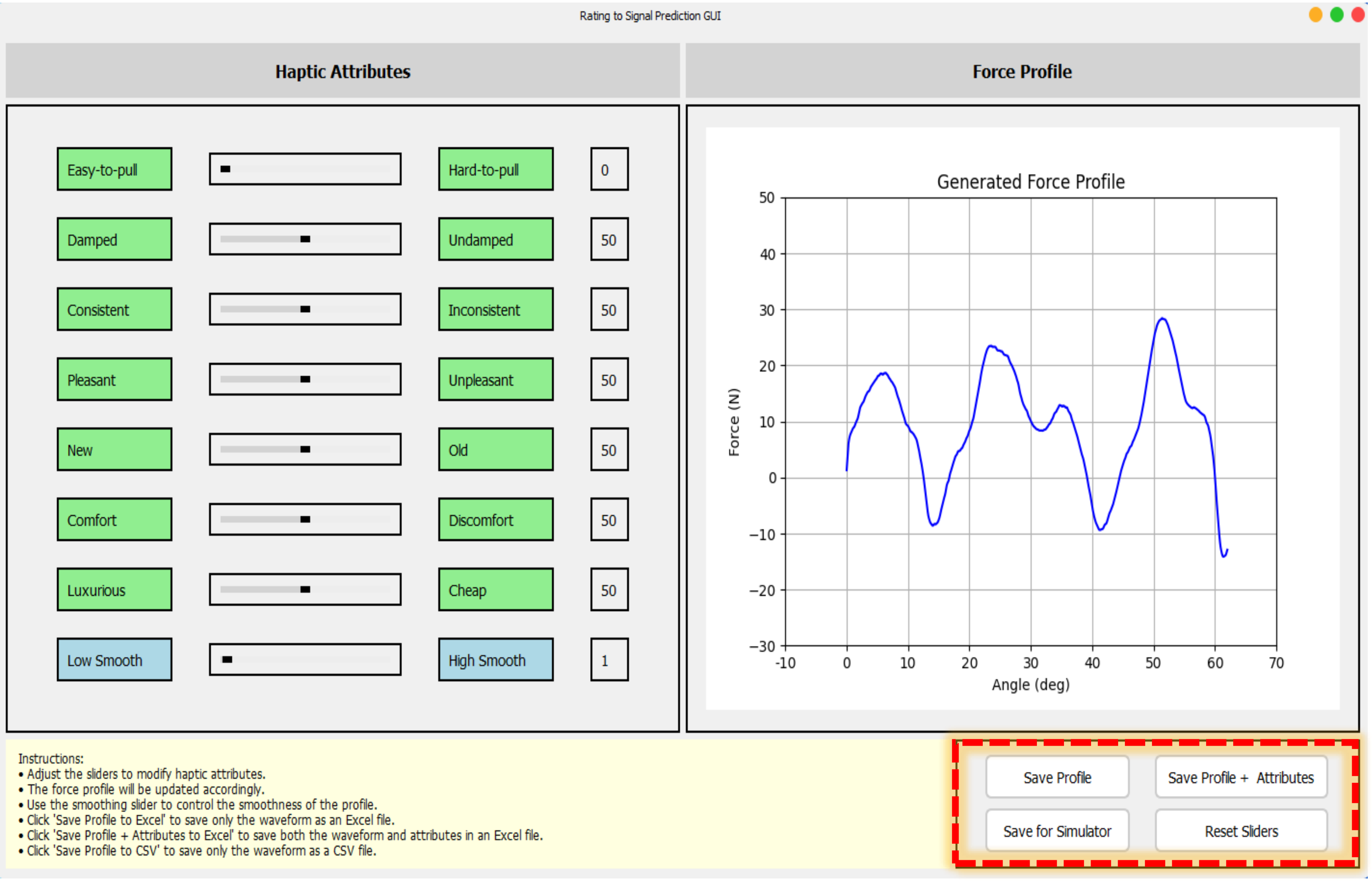
Evaluation - Numerical

Overall **Mean MAE is 0.578**
while **RMSE is 0.727**



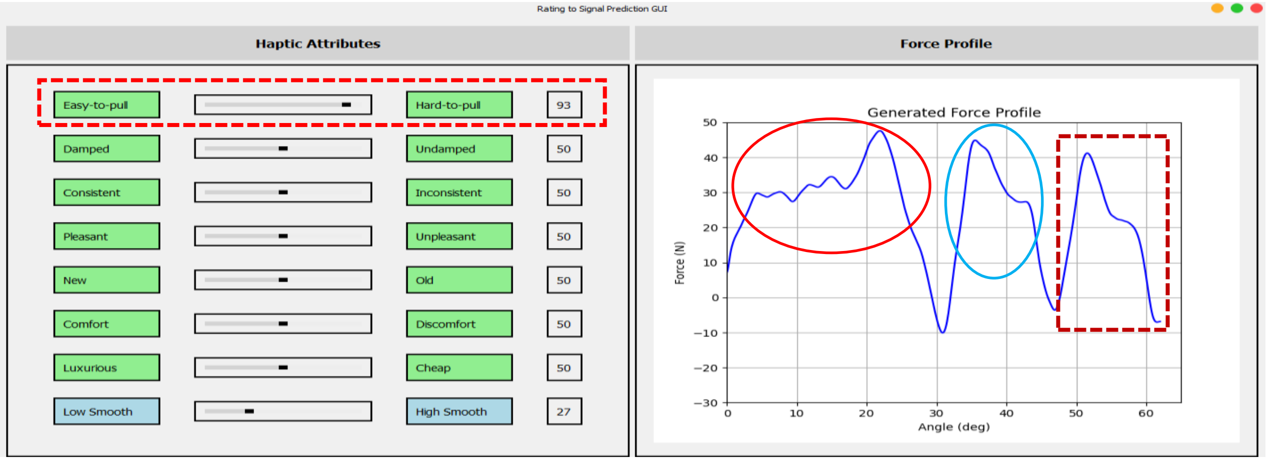
RMSE for Actual Vs Generated Force Profiles by the Model

Perception to Force User Interface



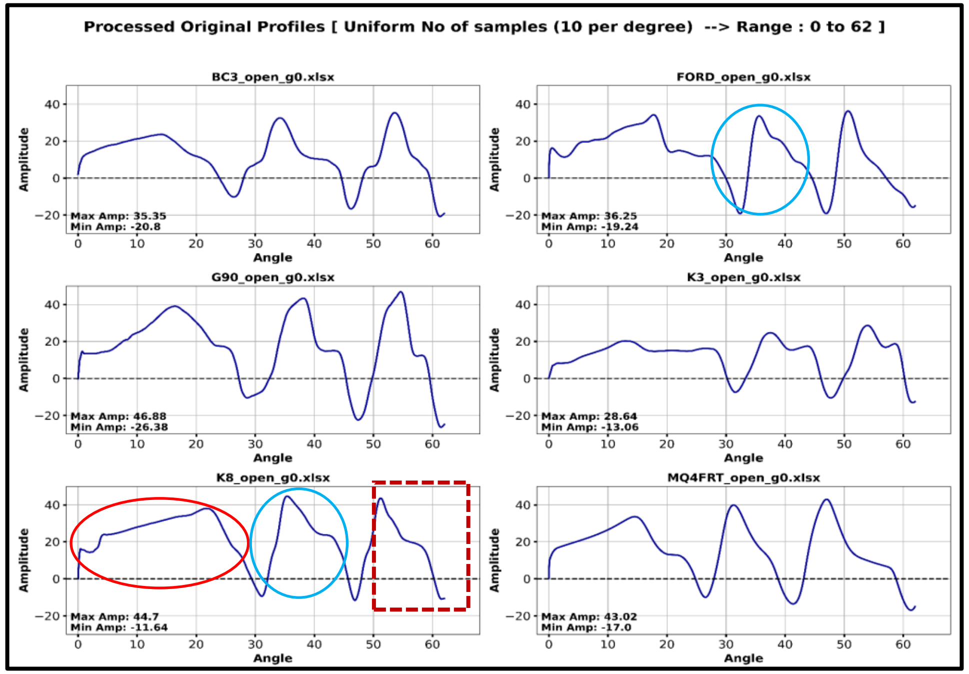
- The **User Interface (UI)** is designed to **facilitate users/designers** to create force profile.
- It **includes slider to adjust adjective values**.
- User can reset all slider values at any time using **reset button.**
- The generated profiles can be saved directly in the format required by Car Door Simulator Program.

Analysis: **Perception to Force**



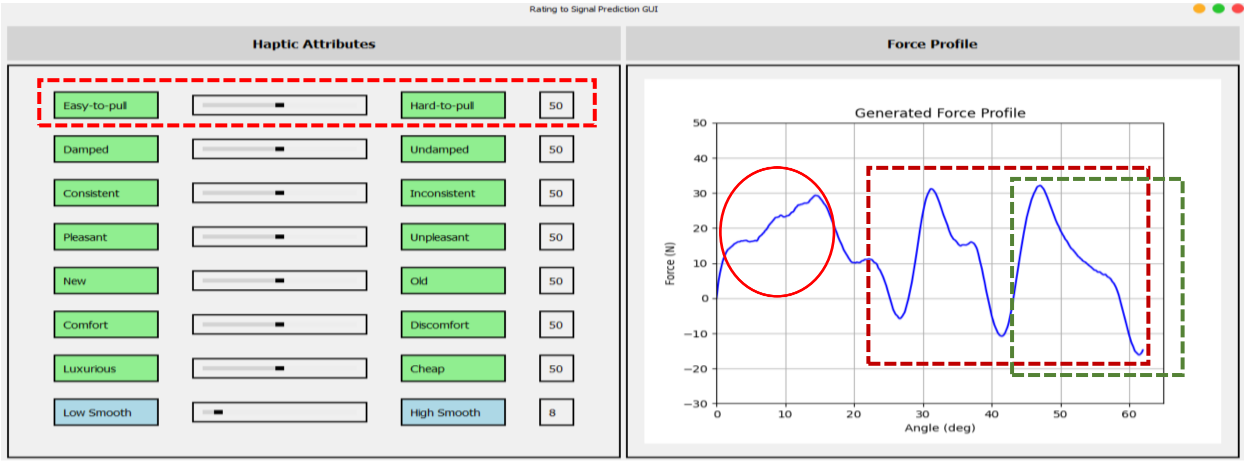
Easy To Pull : 10 %
Others : 50 %

Hypothesis: Profile should be hard to pull and should be close to G90, K8 or FORD



Observation: New Profile share features mostly from K8 variant with small bumps and slightly form FORD (2nd Peak)

Analysis: Perception to Force

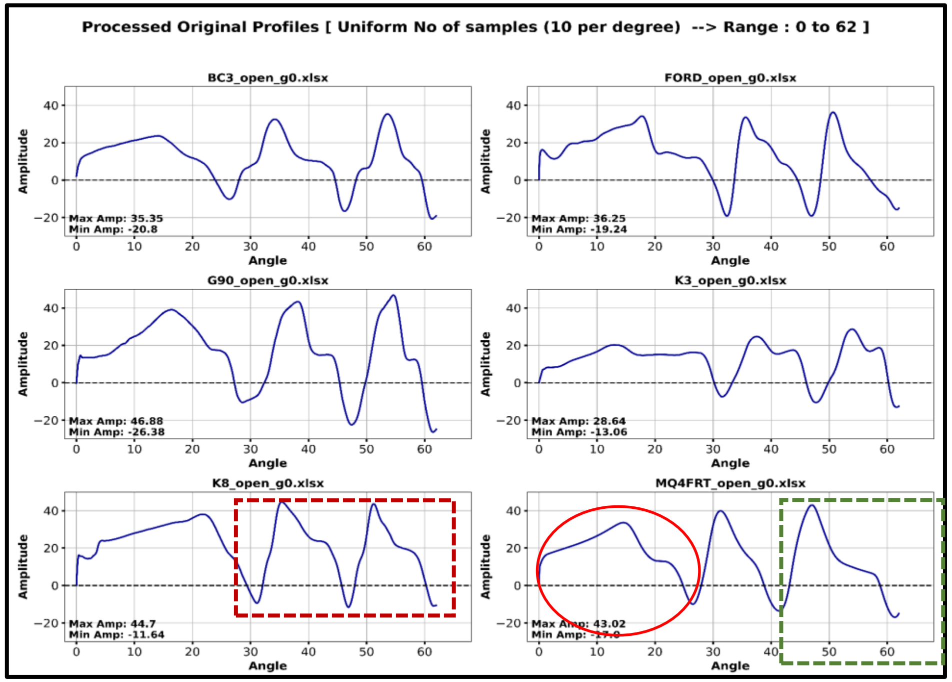


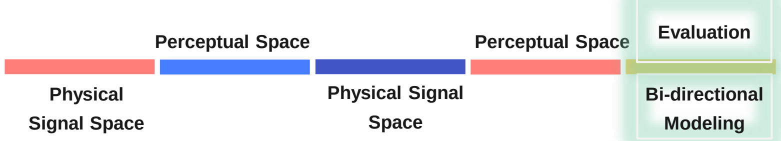
Easy To Pull : 50 %
Others : 50 %

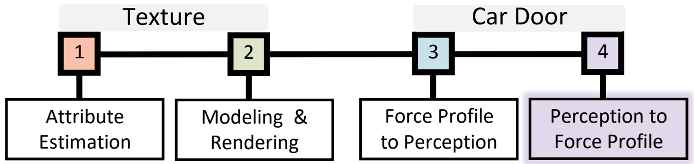
Hypothesis: Profile should be moderate to pull and should be close to MQ4 or Ford.

Observation: New Profile share features mostly form MQ4 and slightly from K8 (2nd peak and plateau shape).

K8 might appear because of other adjectives.

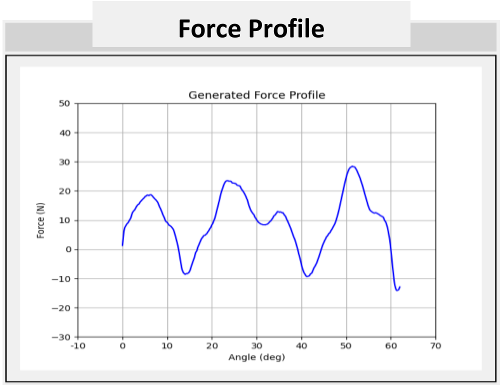




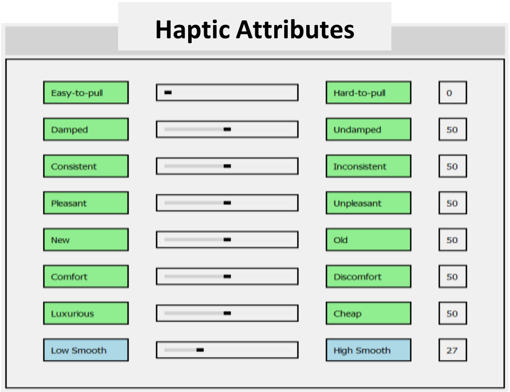


Evaluation: **Perceptual**

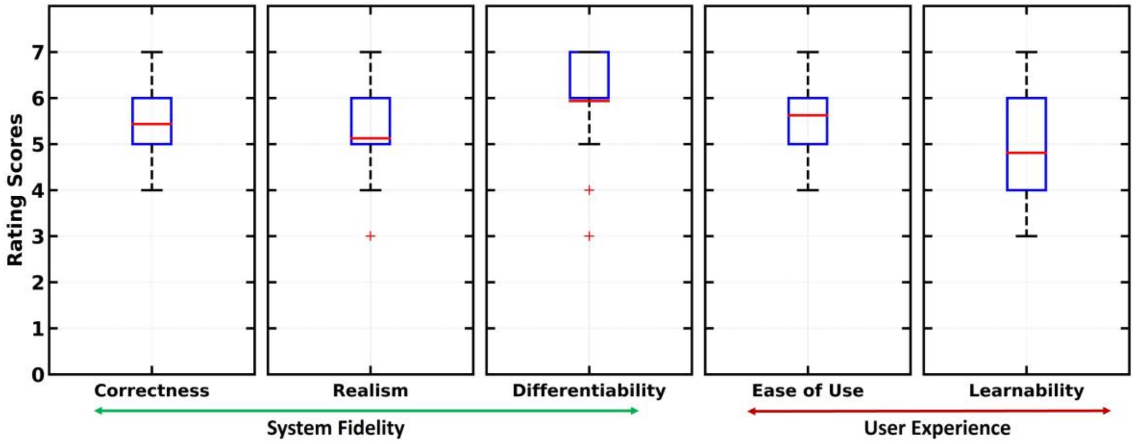
- A total of **16 participants** took part in this experiment.
- The participants includes those from:
  - ✓ **Haptic Experts**
  - ✓ **Car Door Designer**
  - ✓ **Haptic Content Designer**
  - ✓ **Participants from adjective rating Study**



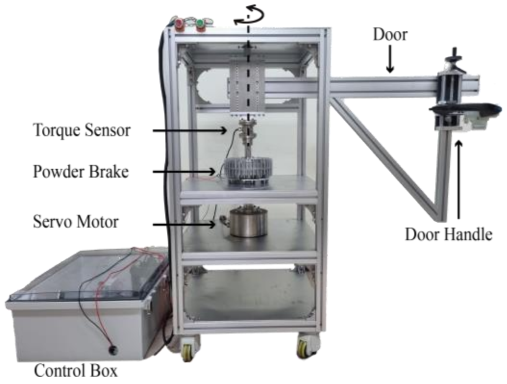
Generated Force Profile



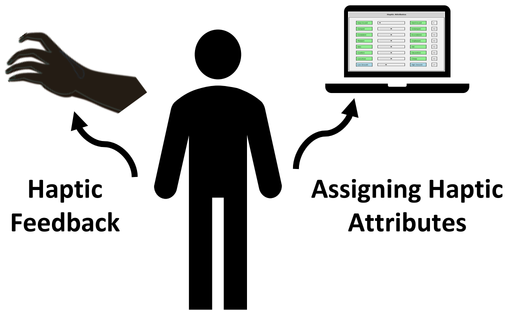
User Interface



User Experiment Results



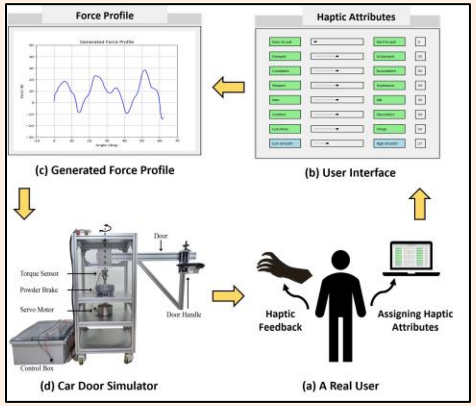
Car Door Simulator

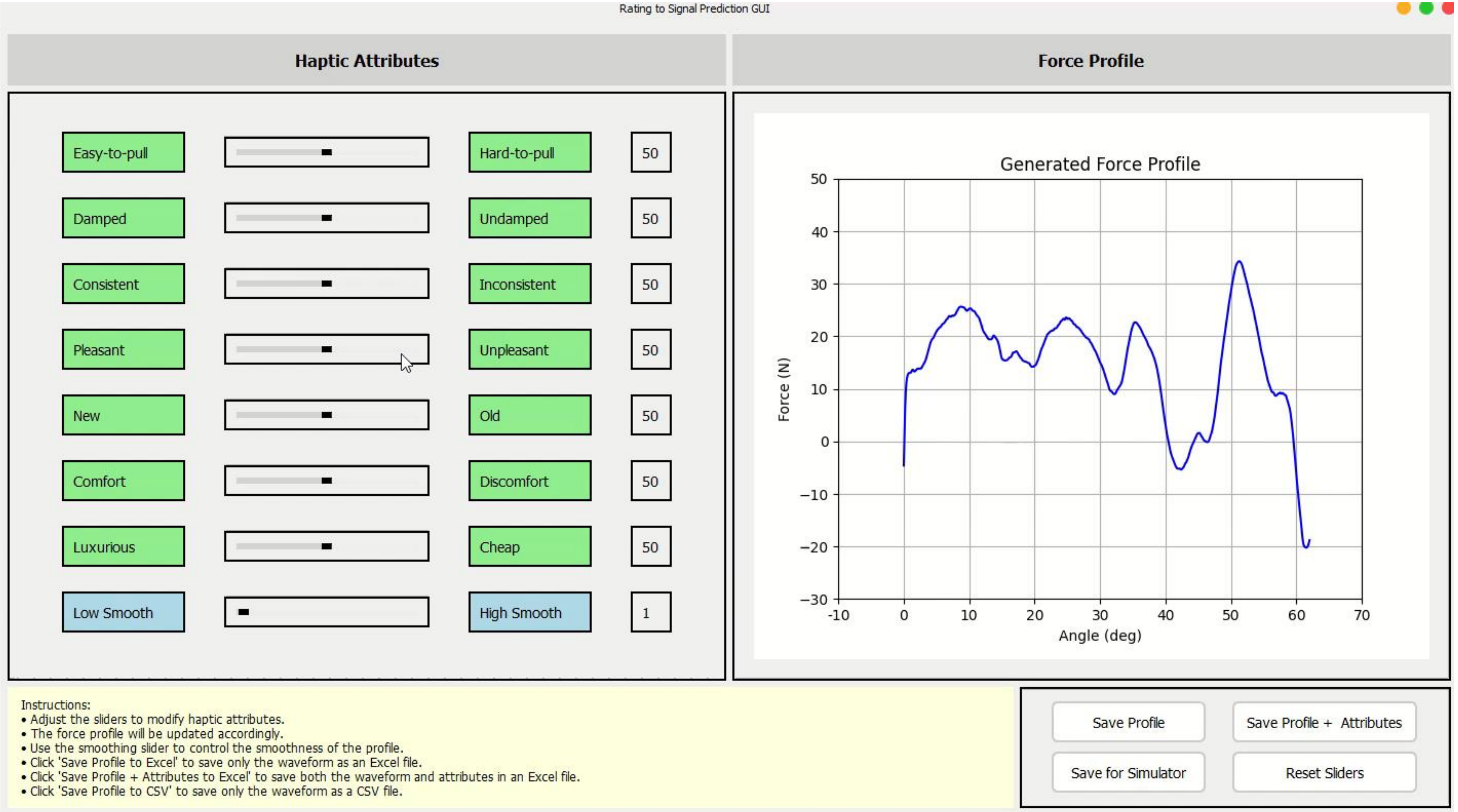


A Real User

Demonstration: Perception to Force Profile Generation

Demo presented at World Haptic Conference, 2025.





Conclusions

Tactile (Texture)

Haptic Texture Attribute Estimation

- Rough - Smooth = 70
- Sticky - Slippery = 30
- Hard - Soft = 80
- Flat – Bumpy = 10

Modeling

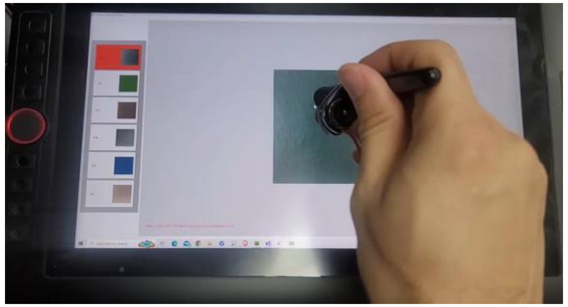
Attribute Prediction

Haptic Signals

Interface

User Perception

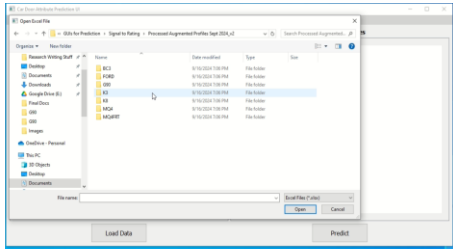
Signal Generation



Haptic Texture Modeling And Rendering

Kinesthetic (Car Door)

Car Door Attribute Estimation



Modeling

Attribute Prediction

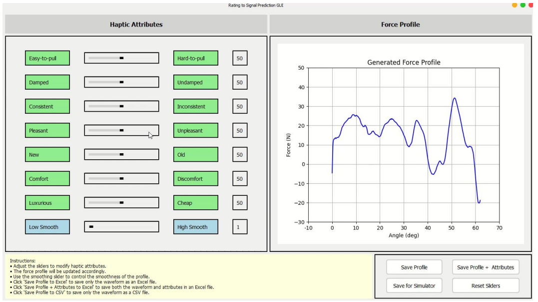
Haptic Signals

Interface

User Perception

Signal Generation

Car Door Profile Generation



Future Directions

- Establish a **teleoperation setup** that **integrates attribute estimation, model selection, and texture rendering.**

- Enhance the **car door GUI to dynamically adjust the influence of one attribute on others** based on their correlation.

- Develop a **text-to-haptics** system that can **generate** haptic signals for **multiple properties** using only **text descriptions**

- Extend the deep learning-based **haptic feedback generation system** from the car door application to other real-world product design scenarios, such as:

  - **Baseball simulators**
  - **Vintage vehicle vibration emulation**
  - Other physically interactive systems

Thank You

1. **Awan, Mudassir Ibrahim,** Myrah Naeem, and Seokhee Jeon “Text-Driven Generative Framework for Multimodal Visual and Haptic Texture Synthesis ”,In IEEE World Haptics Conference, 2025, (**Accepted).**

2. **Awan, Mudassir Ibrahim,** Jae-Ik Kim, Tae-Heon Yang and Seokhee Jeon “Modular Haptic Texture Rendering System Using a Wearable Piezoelectric Ring ”, In IEEE World Haptics Conference, 2025, (**Accepted).**

3. **Awan, Mudassir Ibrahim,** Sungjoo Kang, Dongbeom Ko, Waseem Hassan, Seong Tae Kim, and Seokhee Jeon. “Fourier-enhanced Transformer Encoder Network for Efficient Haptic Texture Modeling/Rendering." IEEE Transactions on Industrial Informatics (Under Review).

4. **Awan, Mudassir Ibrahim,** and Seokhee Jeon." Estimation of Haptic Texture Attributes using visuo-tactile data” IEEE Access (Under Review).

5. **Awan, Mudassir Ibrahim,** Ahsan Raza, Waseem Hassan, Ki-Uk Kyung, and Seokhee Jeon." Quantifying Haptic Affection of Car Door through Data-Driven Analysis of Force Profile” (Under Review).

6. **Awan, Mudassir Ibrahim,** Waseem Hassan, and Seokhee Jeon. "Predicting perceptual haptic attributes of textured surface from tactile data based on deep CNN-LSTM network." In Proceedings of the 29th ACM Symposium on Virtual Reality Software and Technology, pp. 1-9. 2023.

7. **Awan, Mudassir Ibrahim,** Tatyana Ogay, Waseem Hassan, Dongbeom Ko, Sungjoo Kang, and Seokhee Jeon. "Model-Mediated Teleoperation for Remote Haptic Texture Sharing: Initial Study of Online Texture Modeling and Rendering." In 2023 IEEE International Conference on Robotics and Automation (ICRA), pp. 12457-12463. IEEE, 2023.

8. **Awan, Mudassir Ibrahim,** Raza, Ahsan and Seokhee Jeon. "DroneHaptics: Encountered-Type Haptic Interface Using Dome-Shaped Drone for 3-DoF Force Feedback." In 2023 20th International Conference on Ubiquitous Robots (UR), pp. 195-200. IEEE, 2023

9. **Awan, Mudassir Ibrahim**, and Seokhee Joen. "Surface texture classification based on transformer network." 한국 HCI 학회 학술대회 (2023): 762-764.

10. **Awan, Mudassir Ibrahim**, Seungchae Kim, Seokhee Jeon. (2024-12-18). Haptic Feedback Chair for Simulating Heartbeat Sensations. 한국정보과학회 학술발표논문집, 전남.

11. Hashem, Mohammad Shadman, Ahsan Raza, **Mudassir Ibrahim Awan**, and Seokhee Jeon. "Pulsating Feedback: Render Human wrist Pulse via soft pneumatic actuator." 한국정보과학회 학술발표논문집 (2023): 1439-1441.

12. Joolekha Bibi Joolee, Waseem Hassan, **Mudassir Ibrahim Awan**, Seokhee Jeon. (2019-06-26). Haptic Texture Mapping on Real world 3D Object using Surface Texture and Haptic Model. 한국정보과학회 학술발표논문집, 제주.

Thank you for your attention.