INTUITIVE

INnovative Network for **T**raining in To**U**ch **I**nterac**TIVE** Interfaces

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Description:

Characterization of neuromimetic sensorimotor processing.

Identification of tactile interaction invariants.

Implement learning classifier system for high-dimensional data.

Neuromimetic sensorimotor processing

INTUITIVE Deliverable Report

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Learning classifier system for high dimensional sensorimotor data

Objective:

The aim of this deliverable is the identification of tactile interaction invariants and to build a classifier system based on these invariants for a high dimensional dataset.

Dataset description:

The dataset chosen for this problem is the LMT Haptic texture database recorded by the technical university of Munich [1]. A phantom Omni SensAble device is used to scan over 108 textures for recording acceleration signals. These texture signals are available in the form of text files stored during the recording sessions of 10 different people. There is other data (like images, audio) recorded during this process, but the texture signals (in the form of acceleration signals) suffice the purpose of my thesis.

There are two types of datasets used in this classification problem. One is the acceleration data obtained from the accelerometers and the other is the frictional force obtained from a FSR sensor attached to the setup.

Relative performance of Machine learning classifiers:

Table 1 shows the performances of different machine learning (ML) classifiers for the classification of raw frictional force dataset. It can be observed that every classifier has a low performance and is not suitable for classifying this kind of haptic dataset. Similarly, it can be observed from Table 2 that the classifiers performed badly for a dataset which contains all three axes of raw acceleration signals. This is an indication that ML classifiers (Support vector, decision tree, random forest) are unable to perform separation of categories of textures with the help of raw data.

Choice of classifiers:

Several machine learning classifiers and neural network models were applied on the haptic dataset in consideration. Support vector, decision tree and random forest classifiers showed better performances in comparison to others.

Table1: Classifier performance for raw frictional force data

Frictional force- Raw data				
Classifiers	Accuracy (%)	Precision	Recall	F1 score
Support vector	9.56	0.01	0.09	0.09
Decision Tree	8.74	0.08	0.09	0.08
Random Forest	14.10	0.13	0.14	0.13

Table2: Classifier performance for 3 axis raw acceleration data

Acceleration: 3axes - Raw data				
Classifiers	Accuracy (%)	Precision	Recall	F1 score
Support vector	10.01	0.10	0.10	0.09
Decision Tree	11.27	0.12	0.11	0.11
Random Forest	20.03	0.19	0.20	0.19

Classification on raw data showed poor performance on both frictional force and acceleration data. The raw data is insufficient for the classification of haptic data to identify texture labels.

Feature extraction:

There is a lack of domain-knowledge features for haptic signals. This motivates the use of audio-domain features since the signal source is a vibrating object in the two cases. The data is in the form of time-dependent signals which means audio features can be applied for the classification of haptic signals as well. Features most frequently used in audio processing are: Mel frequency cepstral coefficients (MFCC) which is quantification technique for time dependent signals, spectral roll-off which is a measure of right skewness of a spectrum, zero crossing rate which captures rhythmic features of a signal, spectral flux which is the rate of change of spectrum, chromograms, and pitch.

Table 3: Full form for feature set

f1	f2	f3	f4	f5	f6	f7	f8	f9	f10	f11
Mean RMSE	Std. RMSE	Mean energy	Std. energy	Mean Zero crossing	Mean centroids	Mean band-width	Maxi pitch	MFCC 0	MFCC1	MFCC2

f12	f13	f14	f15	f16	f17	f18	f19	f20	f21	f22
MFCC3	MFCC4	MFCC5	MFCC6	MFCC7	MFCC8	MFCC9	MFCC10	MFCC11	MFCC12	Roll-off

Importance of feature extraction:

Table 4 shows the classification performance of different classifiers on frictional force data but after feature extraction. The performance of the ML classifiers increased significantly, and it can be seen that the random forest classifier performs the best with an accuracy of 72.31%. On the other hand, it is interesting to note from Table 5 that random forest classifiers performed best with a 92.50% accuracy, precision, recall, and F1 score. Also, the other classifiers had an above average accuracy for the classification of textures based on acceleration data with all three axes.

This is an interesting observation because the discrimination process becomes better when the classification is based upon the acceleration data than frictional force data. So, we can conclude that acceleration signals contain better discriminatory characteristics when compared to the frictional force.

It is also noted that random forest classifier consistently performed well for the discrimination of ten different textures.

Table 4: Classifier performance for features of frictional force data

Frictional force- Features				
Classifiers	Accuracy (%)	Precision	Recall	F1 score
Support vector	65.38	0.65	0.65	0.64
Decision Tree	56.92	0.57	0.57	0.57
Random Forest	72.31	0.72	0.72	0.72

Table 5: Classifier performance for features of 3 axis acceleration data

Acceleration: 3 axis - features				
Classifiers	Accuracy (%)	Precision	Recall	F1 score
Support vector	85	0.86	0.85	0.84
Decision Tree	87.50	0.89	0.87	0.86
Random Forest	92.50	0.93	0.92	0.92

Table 6, 7 and 8 are performance tables for classification of acceleration data along the x, y, and z axis respectively. Acceleration recorded along the x, y, and z axes during scanning textures were sufficient for the discrimination of different textures and identification of texture category. Classification along the z axis acceleration data performed better than the other two axes with accuracies above 80%. In short, random forest classifiers also work well also in the classification of haptic data of x, y, and z axes separately.

Table 6: Classifier performance for features of x-axis acceleration data

Acceleration: x-axis - Features				
Classifiers	Accuracy (%)	Precision	Recall	F1 score
Support vector	85	0.91	0.85	0.85
Decision Tree	67.50	0.67	0.675	0.64
Random Forest	87	0.92	0.87	0.88

Table 7: Classifier performance for features of y-axis acceleration data

Acceleration: y-axis - Features				
Classifiers	Accuracy (%)	Precision	Recall	F1 score
Support vector	75	0.71	0.75	0.75
Decision Tree	65	0.73	0.65	0.63
Random Forest	80	0.82	0.8	0.81

Table 8: Classifier performance for features of z-axis acceleration data

Acceleration: z-axis - Features				
Classifiers	Accuracy (%)	Precision	Recall	F1 score
Support vector	85	0.88	0.85	0.84
Decision Tree	67.50	0.74	0.67	0.68
Random Forest	92.50	0.98	0.92	0.94

Table 4-8 shows that the performance of classifiers was boosted when features were given as input instead of the raw data itself. This clearly suggests the importance of features in the classification of haptic data from scanning over texture surfaces.

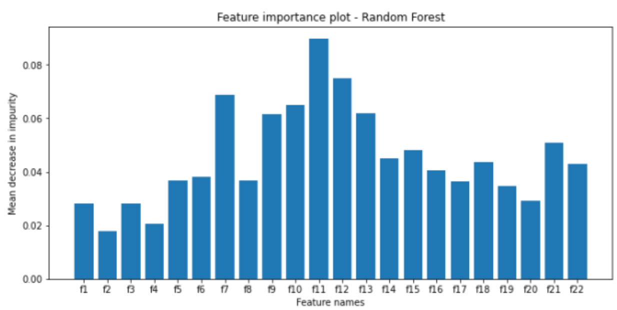

Figure 1: Feature plot of Random Forest on x, y, z axes (acceleration)

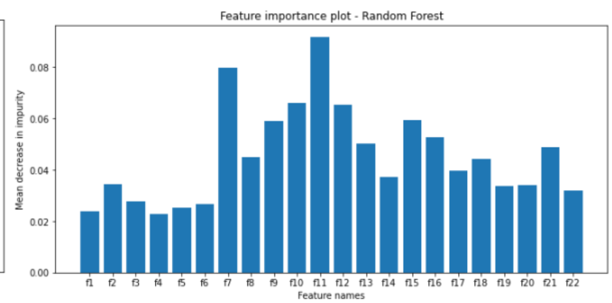

Figure 2: Feature plot of Random Forest `on x-axis (acceleration)

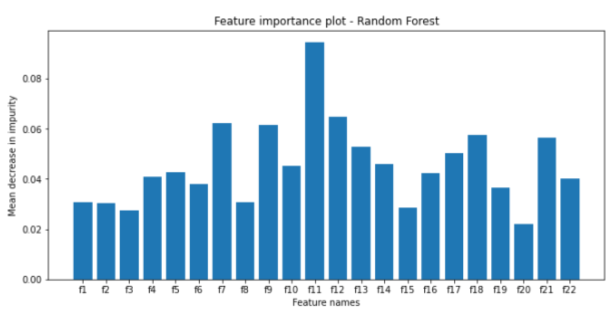

Figure 3: Feature plot of Random Forest

on y-axis (acceleration)

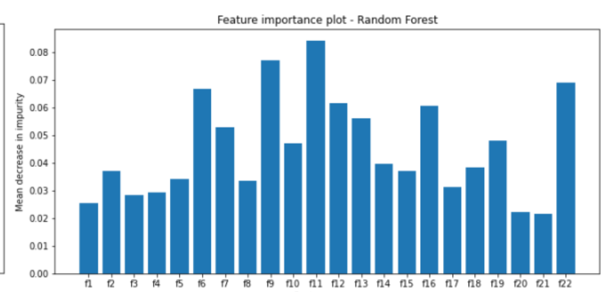

Figure 4: Feature plot of Random Forest

on z-axis (acceleration)

Invariance in classification:

The significance of features can be assessed with the help of classification accuracy decreased with the removal of a feature. The GINI importance or mean decrease in impurity is used to evaluate the feature importance in a classification process. This will give the feature with the decrease of which the classification performance will drop.

From Figure 1, it can be observed that if the classification process drops the feature 11 (which is MFCC2, the 2nd coefficient in Mel frequency cepstrum), the accuracy of the classifier also drops. In other words, the feature 11 has the highest feature importance and helps in the classification of acceleration signals obtained from textures. This can be observed in every case of classifications as seen in Figures 1-4.

Table 9 shows how the absence of a feature (which is MFCC2) drastically reduces the performance of random forest classifiers from 97.50% to 67.50%. Figure 5 suggests that the MFCCs were sufficient for the classification of texture signals as the classifier gave a good performance even after other audio-domain features like pitch, energy were removed. Table 9 also suggests the possible removal of MFCCs.

In the end, better performing classifiers portray better feature importance plots. It is safer to say that there is a constant feature which is assisting in the discrimination of different texture surfaces. This is the invariant which consistently helps in the classification of haptic data.

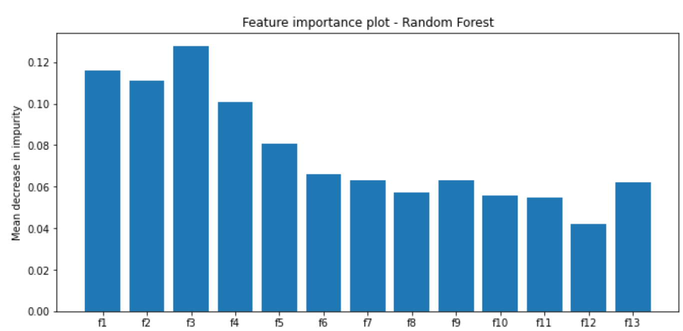

Figure 5: Feature plot of Random Forest on 3 axes (acceleration) with all 13 MFCCs

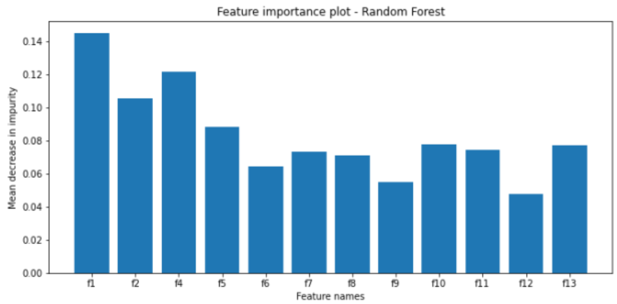

Figure 6: Feature plot of Random Forest on 3 axes axes(acceleration with MFCC-2 dropped

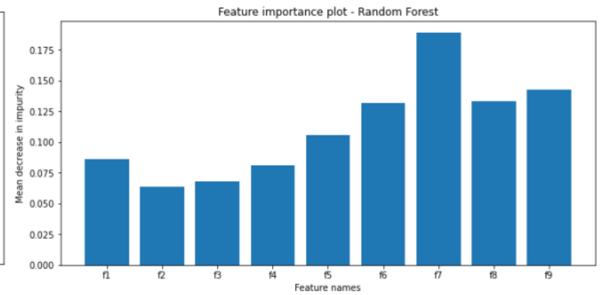

Figure 7: Feature plot of Random forest on 3 axes(acceleration) with no MFCCs

Table 9: Classifier performance for different feature set of 3-axis acceleration data

Classifiers	Feature set	Accuracy (%)	Precision	Recall	F1 score
Random Forest	MFCC 1-13	97.50	0.98	0.97	0.97
Random Forest	MFCC2 dropped	84.50	0.87	0.83	0.83
Random Forest	Without MFCCs	77.50	0.88	0.77	0.78

Table 10: Full form of feature set in table 5 and 6

f1	f2	f3	f4	f5	f6	f7	f8	f9	f10	f11	f12	f13
MFCC 0	MFCC 1	MFCC 2	MFCC 3	MFCC 4	MFCC 5	MFCC 6	MFCC 7	MFCC 8	MFCC 9	MFCC 10	MFCC 11	MFCC 12

Table 11: Full form of feature set in table 7

f1	f2	f3	f4	f5	f6	f7	f8	f9
Mean RMSE	Std. RMSE	Mean energy	Std. energy	Mean Zero crossing	Mean centroids	Mean band-width	Maxi pitch	Roll-off

However, this invariance might be limited to this category of haptic data. That is, texture surfaces can possess Mel frequency cepstral coefficient 2 as the most important feature of discrimination and other MFCCs to support the classification process for an appreciable performance.

Shortcomings of the dataset:

The dataset selected for the classification is from the LMT database which was recorded by scanning over the texture surface. This is not sufficient enough to train a classifier if a prediction model has to be developed in future. The classification model needs to see a larger number of training data with many trials for a single texture surface. Hence, the next step will be to record texture surface information (acceleration signals) with different texture surfaces and a larger number of trials on a single texture surface. This data collection process is already in progress and is developed along with another ESR Alexis Devillard from Imperial College London. The data collection will include videos of texture surfaces with varying illumination, acceleration data and audio in later stages if useful for further processing.

Further investigation:

The Machine learning classifiers performed well for the classification of haptic data and give a feature which efficiently classifies acceleration signals. However, this remains to be verified and cross-checked with another method. Currently, I am working on autoencoders. Raw data fed into autoencoders will be able to generate encoded data. When feature extraction is applied over encoded data and original data for comparison, the invariancy/constancy in the dataset appears during this comparison. The encoded and original features are comparable and share similar features which indicates the preservation of constant characteristics before and after encoding.

References:

1. https://zeus.lmt.ei.tum.de/downloads/texture/