Tactile Sensing
Building a Tactile Sensor
Human Receptors

- Two major layers
- Two main types
  - Fast Adapting: Pacinian and Meissner corpuscles
  - Slow Adapting: Merkel disk, Ruffini organ
Artificial Finger

Randomly placed sensors
Strain Gauges
Polyvinylidene Fluoride
Two Layers

Hard outer core (Epidermis)
Soft inner layer (Dermis)
Hard Back (Bone)
Designed In-house
Distinguishing Natural Textures

- Natural Surfaces
- Classify based on frequency components
- Accuracy of 95±4%
Experimental Setup
Training

• Multidimensional time-series data
• Pre-processed to generate attributes for machine learning
• Use Weka implementation of decision trees with naive Bayes classifier in leaf nodes
Typical Frequency Response

Frequency Spectrum (Carpet I)

Normalized Magnitude

0 10 20 30 40 50 60 70 80 90 100

0.2 0.4 0.6 0.8 1

Frequency (Hz)

Filtered Signal
Actual Signal

FC1
FC4
FC3
FC2
FC5
Sample Classifier Output

(PVDF\textsubscript{1}, PVDF\textsubscript{2}, PVDF\textsubscript{3}, PVDF\textsubscript{1}, PVDF\textsubscript{2}, PVDF\textsubscript{3}, PVDF\textsubscript{1}, PVDF\textsubscript{2}, PVDF\textsubscript{3}, PVDF\textsubscript{1}, PVDF\textsubscript{2}, PVDF\textsubscript{3}, SG\_AVG\textsubscript{1}, SG\_AVG\textsubscript{2}, SG\_AVG\textsubscript{3}, SG\_AVG\textsubscript{4}, SPEED, Material Class)

\begin{align*}
\text{SPEED} = 20: & \text{ NB 1} \\
\text{SPEED} = 25: & \text{ NB 2} \\
\text{SPEED} = 30: & \\
\text{PVDF}_1^2 \leq 58.89: & \\
\text{PVDF}_1^1 \leq 50.96: & \\
\text{PVDF}_1^1 \leq 14.34: & \text{ NB 3} \\
\text{PVDF}_1^1 > 14.34: & \\
\text{PVDF}_2^2 \leq 51.57: & \text{ NB 4} \\
\text{PVDF}_2^1 > 51.57: & \text{ NB 5} \\
\text{PVDF}_1^1 > 50.96: & \\
\text{PVDF}_1^1 \leq 62.25: & \text{ NB 6} \\
\text{PVDF}_1^1 > 62.25: & \text{ NB 7} \\
\text{PVDF}_1^2 > 58.89: & \text{ NB 13} \\
\text{PVDF} \text{ Fourier components} \\
\text{Strain Gauge average}
\end{align*}
Texture Classification Results

Boosted NBTree classifier accuracy

Accuracy(%) vs. Number of Fourier Components

- Voting
- Standard
Slip Prediction

- Perform time-domain analysis to predict slip
- Seven objects
- Predict slip at least 100ms before it happens with 96% accuracy
Methodology

Training Data

Principal Component Analysis (PCA)

Clustering

Temporal Pattern Learning

Preprocessing

PCA Model

Mixture Model

Contact-Pattern Model

Prediction

Test Data

We deal with the "curse of dimensionality" by dividing the problem into two stages: dimensionality reduction using clustering and temporal pattern extraction. Figure 5 shows an overview of the learning methods. The data are preprocessed before any analysis is performed. The clustering method used in this thesis assumes that all variables are independent. In the first stage of training, the data are projected onto a new basis using principal component analysis (PCA), which will be described in Section 5. The model coefficients from the training data are saved and later used to transform the test data into the new coordinate systems. Clustering is performed on the output of the PCAs. Clustering serves two purposes: First, the aim of clustering is to find intrinsic structure within the data. Second, it reduces the high-dimensional time.
Preprocessing

Sequences are labelled using high resolution linear variable differential transformer (LVDT), which is a linear distance sensor.
Build Gaussian mixture models using minimum message length as the optimisation criterion.
Learning Patterns

\[ V_{\text{original}} = \{BCCDDC\ldots\} \]

(a) Example of a feature vector.

(b) Three state hidden Markov model.

The letters \(T\) and \(S\) represent contact states: stationary and slip, respectively.

A, B, C, and D: membership of a particular cluster
Experimental Setup