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Material Classification by Tactile Sensing using Surface Textures

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Abstract— **In this paper we describe an application of machine learning to distinguish between seven different materials, based on their surface texture. Applications of such a system includes quality assurance and estimating surface friction during manipulation tasks. A naive Bayes classifier is used to distinguish textures sensed by a bio-inspired artificial finger. The finger has randomly distributed strain gauges and Polyvinylidene Fluoride (PVDF) films embedded in silicone. Different textures induce different intensity of vibrations in the silicone. Textures can be distinguished by the presence of different frequencies in the signal. The data from the finger is pre-processed and the Fourier coefficients of the sensor outputs are used to learn a classifier for different textures. The performance of the classifier is evaluated against a naive time domain based learner. Preliminary results show that our classifier performs better.**

I. INTRODUCTION

There is increasing interest in humanoid robots that are intended to work alongside humans in unstructured, "human-centric" environments. To be able to operate in such environments, the humanoids need to be able to dextrously manipulate objects[1]. Humans have sophisticated tactile perception. They can perform complex tasks such as distinguishing between different textures, grasping objects of different shapes and sizes, and avoiding slip while applying minimal force to the grasped object. The capability for such a diverse skill-set can be attributed to the well developed tactile perception at the finger-object contact[2].

We learn much of our tactile perception by interacting with the environment. Observing the tactile exploration of children, they carefully interact with the objects in the world, repeatedly trying to pick up an object, learning to perceive the world through their tactile sensors. If robots are to develop similar perception, they must also be able to learn. Most of the research in tactile sensing has focused on building and characterising transducers. Very little work has been done on learning. The major contribution of this paper is a learning system for an artificial finger to differentiate between different textures. A bio-inspired robotic finger is developed to provide the sensory information for the learner. The finger is made of silicone with randomly distributed strain gauges and PVDFs. The sensory output from the finger is used to learn to distinguish between different textures. Texture classification is based on the Fourier coefficients of the sensor's signals.

Results from a preliminary experiment, where the finger successfully classifies eight different textures is presented. The textured surfaces include carpet, two flooring vinyls with different textures, a tile with smooth surface, a tile with textured surface, a sponge and piece of wood.

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II. BACKGROUND

Our research is comprised of two equally important components, the development of artificial tactile sensors and the design and application of machine learning algorithms to interpret the sensory information. The following sections provide an overview of existing work in these two areas.

A. Artificial Tactile Sensors

In an attempt to equip robots with dexterity to match that of humans, the past three decades has seen increased research in the development of an artificial sense of touch. A great deal of effort has been devoted to developing tactile sensors that can provide sufficient information for dexterous manipulation. Many physical phenomena have been used to create tactile sensors. These include capacitive[3], piezo-resistive[1][4], optical[5], [6], [7] and magnetic[8]. Knowledge of all three components of force plays a crucial role in acquiring tactile perception. Attempts have been made to build sensors which can provide all three components of force[6], [8]. However the resultant sensors are hard to replicate or are too bulky to acquire acceptable spatial resolutions.

Commercial sensors provide good spatial resolution but they have two major disadvantages. Firstly, they only react to stimuli normal to the surface of the sensor. Secondly, to decrease the wiring complexity of the sensors, commercial sensors apply scanning techniques to acquire data. Hence increase in spatial resolution is achieved at the expense of temporal resolution.

Some researchers have taken advantage of Micorelectromechanical Systems (MEMS) to manufacture tactile sensors with capability to provide force and temperature information[9]. MEMS based sensors are very attractive for use in robotics because of their small size and capability to provide multiple modes of transduction. However, their development is in the early stages and require a lot of resources to replicate.

The sensors discussed so far are surface sensors i.e. they are attached to the surface of the robot fingers. Human hands use multiple sensors at different depths. Using human fingers as an inspiration, soft fingers with randomly distributed receptors at different depths have been developed[10]. The novelty of this approach lies in the absence of any need for calibration, the robot has to learn how to acquire meaningful information such as slip conditions and object texture

[1]Pressure Profile Systems

through the interaction with the environment. These qualities make this sensor of particular interest for machine learning experiments.

B. Artificial Tactile Perception

Application of machine learning to tactile sensors is in its infancy. Some researchers have developed models of the sensor's response to physical stimuli and show that the signals from the actual sensors match that of the model [11]. Others have demonstrated that in principle, the signals produced by the transducers can differentiate between different materials[12]. This work has not found its way into robotics. These sensors can be integrated with machine learning to provide far superior performance and equip robots with tactile perception comparable to that of humans.

The past decade has seen a slow move from pure transducer manufacturing. Machine learning has been applied to various physical phenomena such as detection of slip condition and differentiating between different surface textures. Artificial Neural Networks (ANN) have been used to fuse vision and tactile sensory information to improve the accuracy of 3D object recognition[13], differentiate between different objects found commonly in a shopping bag[14], and to detect slip [15], [16].

III. Sensor Design

A bio-inspired tactile sensor, which mimics human mechanoreceptors has been developed. In this section we provide an overview of the human tactile sensors and justify our choice of artificial finger which will be described later.

A. Biological Tactile Sensors

Human tactile sensors can be divided into two broad categories namely, slowly adapting, and fast adapting receptors. Slowly adapting receptors respond to low frequency stimuli. In other words they provide static properties of a stimulus. On the other hand fast adapting receptors provide transient properties of the stimulus. The sensors are spread in two layers and respond to frequencies ranging from DC to 400Hz[17].

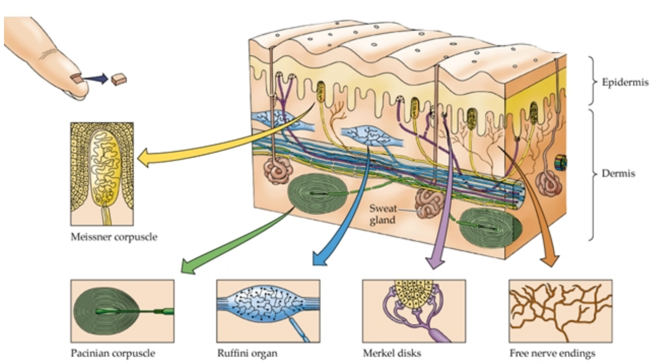


Fig. 1. Human mechanorecpetors[2]

[2]Courtesy of `http://grants.hhp.coe.uh.edu/clayne/6397/Unit4_files/image019.jpg`

From the biology of human fingers, we learn that a robotic finger needs two types of sensors, one that responds to stretch and another one that can respond to vibrations. The frequency response of these sensors can be limited to a maximum of 400Hz.

B. Artificial Tactile sensors

Our artificial finger is based on original work by Hosoda, Tada and Asada[18]. The finger consists of strain gauges and PVDFs embedded in a silicone finger. The strain gauges are equivalent to slow adapting mechanoreceptors. These sensors provide a change of resistance proportional to the strain applied to them i.e. they respond to lateral stretch. The PVDFs are equivalent to fast adapting mechanoreceptors. These sensors provide an electrical charge in response to the applied pressure. PVDFs are piezoelectric in nature, and are stimulated by vibrations. Fig. 2 is an illustration of the artificial finger.

The sensors are randomly distributed in two layers. The outer layer is harder than the inner layer. The harder outer layer allows the finger to have a less tacky surface while the soft inner layer allows the finger to conform to the object in contact. The back of the finger is made from hard material to provide structural support. Fig. 3 shows the artificial finger mounted on a gripper. The prototype finger has two PVDF sensors and two strain gauges in each layer. The final design will include sixteen strain gauges and PVDFs.

Placing sensors randomly in the finger has several advantages. Random placement in the silicone allows the finger to sense forces in multiple direction. While the basic sensing elements of the finger respond to stimuli only in one direction, as a whole the finger can respond to forces in multiple directions. This is similar to human fingers, where some afferents respond strongly to a preferred direction of force[19]. Another advantage of random placement is ease of manufacture. One may argue particular arrangements might be more favourable. However precise placement and modelling of such arrangements may be very difficult and costly. Random arrangement, which relies on machine learning algorithms to map the signals to meaningful data provide rich and robust tactile perception.

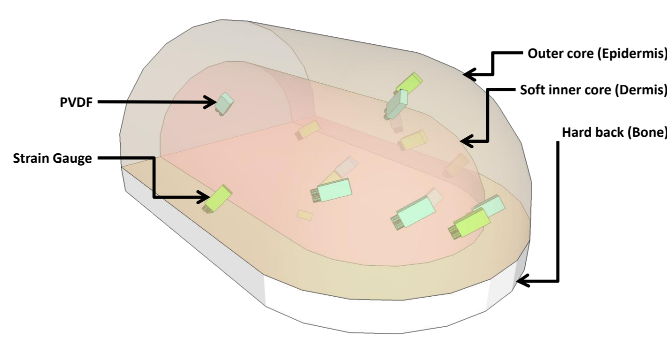


Fig. 2. Finger with embedded strain gauges and and PVDFs in two layers

IV. LEARNING ALGORITHM

The proposed algorithm uses frequency domain analysis to distinguish between different textures. A surface with fine textures will stimulate the sensors at a higher frequency than a surface with coarse textures. In humans, the mechanoreceptors thought to be responsible for texture classification are Meissner's corpuscles[17]. These receptors respond to the rate of change of the stimulus. This makes frequency domain analysis a natural choice.

A. Feature Extraction

The first step in the feature extraction process is to segment the signals from the sensors into the regions where the sensor is in contact with the surface. In these experiments, this step is carried out manually. Each segment, the entire interval when the sensor is in contact with the object, is transferred to the frequency domain using Fast Fourier Transform. The Fourier coefficients are used as features for the classification.

The classification algorithm works by looking at the major components of the Fourier coefficents. Fig. 4 shows a typical frequency response for a PVDF sensor, when stimulated by a particular textured surface. If the algorithm is to pick three major components from the raw data, all points will lie in the vicinity of the first peak. It will be more meaningful to pick the high level peaks as features. An algorithm has been devised to extract these peaks.

Algorithm 1 is a procedure to detect the peaks in the frequency domain. The peak detection algorithm divides the frequency spectrum into n equal regions. The choice of n depends on the resolution of the frequencies of interest. The algorithm goes into a loop until it finds the desired number of peaks. In each iteration of the loop, the algorithm extracts the region with the highest energy, then it checks if the current region is contiguous with any existing peaks. If any such peak is found, the algorithm extends the boundaries of that peak to include the current peak. If the region is not contiguous with any peak, a new peak is created. At the end of the loop, the current region is removed from the list of regions to be considered and the loop is repeated. Fig. 4 shows five peaks being detected by the algorithm. The peak frequencies are marked in red.

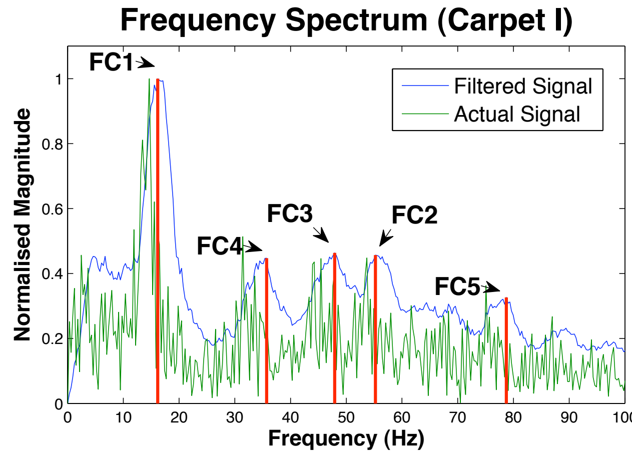


Fig. 4. Frequency response of a PVDF sensor when rubbed across a textured surface. The detected frequency components are marked FC1-FC5.

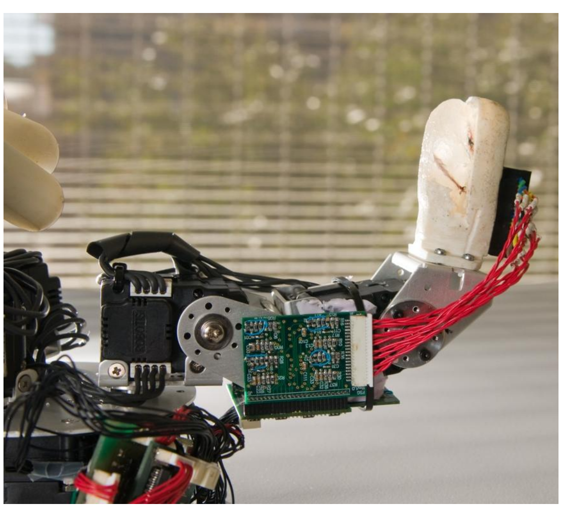


Fig. 3. The artificial finger mounted on a Robotis 9 degree of freedom gripper

B. Naive Bayes Learner

All robots are prone to wear and tear. Hence it is crucial to choose an algorithm that can be trained with a small number of training data. The naive Bayes classifier is one algorithm which meets this criterion. In particular, the assumption of independence between class features means that the model parameters for each feature can be treated as a one dimensional distribution.

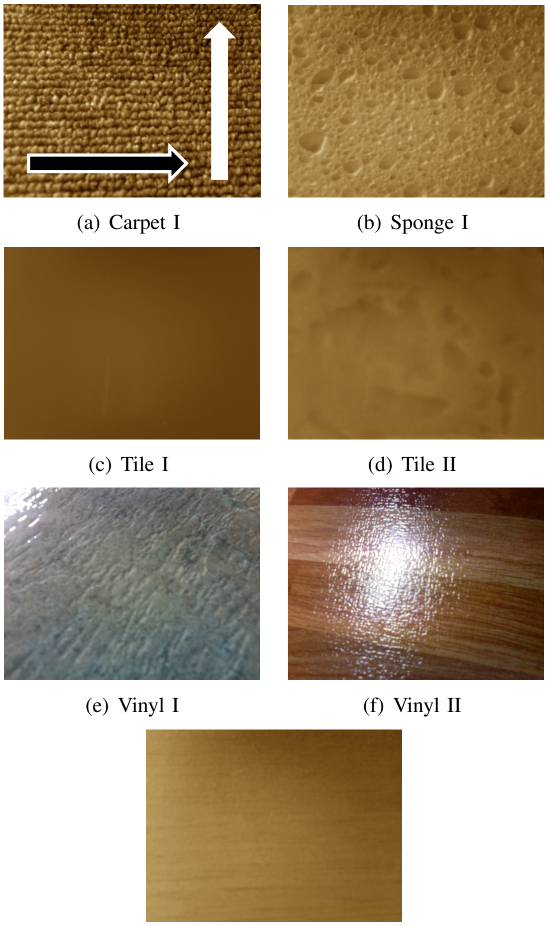
The naive Bayes learner takes as input three frequencies for each sensor i.e. one frequency for each peak detected. The value of frequency for each peak is determined by the Fourier coefficient with the highest magnitude which is contained in that peak's region.

V. EXPERIMENTAL SETUP

Seven natural surfaces with different textures were used to test the learning method. The experimental set up consists of a Denso robotic arm, an ATI force torque sensor, a Robotis

Algorithm 1 Peak Detection Algorithm

$peaks \leftarrow []$
$regions \leftarrow n$ equal divisions of frequency spectrum
$currentRegion \leftarrow []$
repeat
  $currentRegion \leftarrow$ region with the highest energy
  if $isContiguous(currentRegion)$ **then**
    $peaks \leftarrow updatePeak(currentRegion)$
  else
    $peaks \leftarrow$ create $newPeak(currentRegion)$
  end if
  $regions \leftarrow$ remove $currentRegion$
until desired number of peaks found



(a) Carpet I (b) Sponge I

(c) Tile I (d) Tile II

(e) Vinyl I (f) Vinyl II

(g) Wood I

Fig. 5. Test Surfaces

9 degree of freedom gripper, the robotic finger and a data acquisition unit.

A. Textures

The selection of textures deliberately included surfaces which were made of same material but different textures. The selected textures include carpet, dishwashing sponge, a tile with smooth surface, a tile with textured surface, two flooring vinyls with different surface textures and a piece of wood(Fig. 5).

The same carpet was used to provide two types of textures. The threads of most fabrics have a preferred direction. Humans are capable of making a distinction between the preferred direction and the non-preferred direction. Dragging your fingers along the non-preferred direction shows more resistance than dragging it along the preferred direction. The robotic finger was dragged in both these direction. Fig. 5(a) shows in black marking the preferred direction (Carpet I) and the non-preferred direction (carpet II) in white.

The two tiles selected have a very subtle difference between them. Tile I has a smooth surface, Tile II has small indentations. Vinyl I has fine textures compared to Vinyl II. Sponge I represents a soft surface with a rich texture. Wood I represents a non sticky, yet smooth surface.

B. Data Acquisition

Acquisition of the data involves conditioning of the transducer's signals to a format that can be digitised. The signals produced by the strain gauges and the PVDFs have very small magnitudes. The sensors are mounted on a robotic arm, which produces a significant amount of electromagnetic interference. These factors make it necessary to design and implement signal conditioning units that can amplify the small signals with a high signal to noise ratio.

Differential amplifiers are used to convert charges produced by the PVDFs into a voltage (Fig. 6(a)). This helps in reducing noise of the system by common mode rejection. A buffer is used to isolate the signals from the rest of the system, such as analog to digital converters.

An Anderson loop [20] was realised to acquire signals from the strain gauges (Fig. 6(b)). The Anderson loop works by sending a fixed current through the strain gauge, which also passes through a reference resistor. The difference between the voltage across the strain gauge, and the voltage across the sense resistor is proportional to the value of strain on the gauge. The signals provided by Anderson loop show much lower drift rate than traditionally used methods such as Weatstone bridge. The analog signals are digitised at a sampling frequency at 2.5KHz. The final stage of both amplifiers employ a low pass filter, which has a 3dB point of 500Hz, to avoid aliasing during the digitisation process.

C. The Learning Task

The learning task is to differentiate between different textures using signals from the developed finger. Fig. 7 illustrates the setup for data collection. The finger is attached to a Robotis 9 degree of freedom gripper, which in turn is attached to a Denso arm. The textured surface is mounted on the force torque sensor. The force torque sensor is used to monitor the total force applied to the surface.

The robot drags the finger across each material at a constant speed. Each run starts with the finger being positioned above starting point. The finger does not make any contact with the surface. Then the finger is moved to make contact with the surface and reach a total force of approximately 1N.

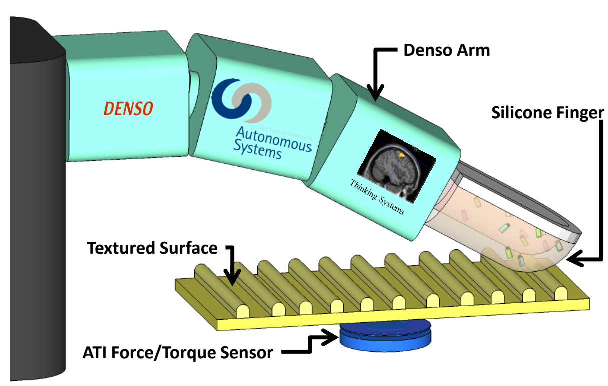
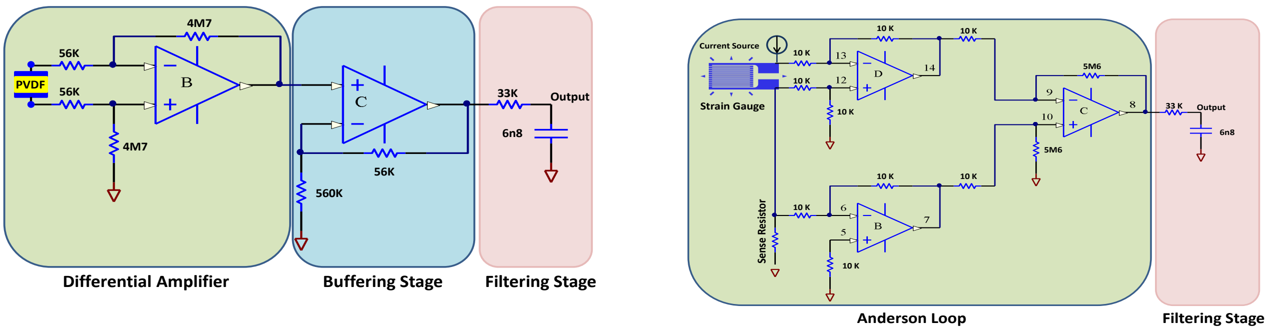


Fig. 7. Experimental Setup



(a) PVDF Amplifier

(b) Anderson Loop

Fig. 6. Data Acquisition Unit

With the force being kept constant, the finger moves towards the end point. The traversed path is a straight line. Once at the end point, the finger is lifted and moved to the starting position. There is a slight delay between two runs to make sure all of the sensors have reached their idle state.

Throughout the experiment, the total force applied to the surface of each material and the distance between the starting point and the end point across all materials is kept constant. This procedure is repeated fifty times for each material.

VI. Results

A naive Bayes classifier was trained using Weka[21], with fifty samples for each texture. The features for the classifier were the first three major Fourier components of each sensor. These features were extracted using the algorithm described in Section IV. The classifier was capable of predicting textures with an accuracy of 78% using 10-fold cross-validation.

Table I shows the confusion matrix for the classifier. A careful study of the confusion matrix reveals some interesting points. The majority of the misclassifications are between materials which share common properties. Carpet I is misclassified as Carpet II and vice versa. These objects are made of the same material. The only difference between them is the direction in which the artificial finger was dragged. Similarly the classifier is confused between Tile I and Tile II. Textures that are common between the two materials is overwhelming the difference between them. This is reflected in the frequency domain by having a large magnitude for the Fourier coefficients of those frequencies. Since the algorithm picks only the first three major components to differentiate, more subtle features will not be noticed unless the number of Fourier coefficients used to classify are increased. Table II shows the results from a naive Bayes learner where five Fourier coefficients were used to build a classifier. The prediction accuracy of the learner is increased from 78% to 83.5%. This is a good result, even human subjects will find it hard to classify between these materials with 100% accuracy. Human studies will be carried out in future.

It is intriguing that the rate of confusion between Vinyl I and Vinyl II is very low. A closer inspection of the surfaces reveals that while these two objects are made of same material, the surface textures are significantly different, which are present throughout the material.

To provide a baseline for measuring performance of this classifier, a simple learner was built. The richer the texture, the higher is the rate of vibration in the signal. This information can be encapsulated in the average amplitude of the signal over a fixed window. Each trial run is divided into three equal parts - initial contact, middle and lift off region. The fixed window was taken from the middle region. This ensures that the feature is not affected by the variations induced by the initial contact and lift off. The width of the the window was chosen to be the average length of the middle region of all trials. A feature vector is generated by averaging the signals of each sensor over the selected

TABLE I
Confusion matrix for naive Bayes learner with three Fourier coefficients. Classification Accuracy 78%.

C1	C2	S1	T1	T2	V1	V2	W1	Class
38	7	4	0	0	0	1	0	C1 = Carpet I
3	46	1	0	0	0	0	0	C2 = Carpet II
7	9	33	0	0	0	0	1	S1 = Sponge I
0	0	0	42	7	0	1	0	T1 = Tile I
0	0	0	11	37	0	2	0	T2 = Tile II
0	0	1	0	0	40	1	8	V1 = Vinyl I
0	0	1	0	1	1	39	8	V2 = Vinyl II
0	0	4	0	0	7	2	37	W1 = Wood I

TABLE II
Confusion matrix for naive Bayes learner with five Fourier coefficients. Classification Accuracy 83.5%.

C1	C2	S1	T1	T2	V1	V2	W1	Class
41	4	2	0	0	0	0	3	C1 = Carpet I
6	42	1	0	0	0	0	1	C2 = Carpet II
2	0	39	0	0	4	0	5	S1 = Sponge I
0	0	0	42	6	0	2	0	T1 = Tile I
1	0	0	4	44	0	0	1	T2 = Tile II
0	1	1	0	0	47	1	0	V1 = Vinyl I
2	0	0	0	0	1	40	7	V2 = Vinyl II
1	0	1	0	0	9	0	39	W1 = Wood I

TABLE III

CONFUSION MATRIX FOR NAIVE BAYES LEARNER WITH AVERAGE AMPLITUDE IN A FIXED WINDOW. CLASSIFICATION ACCURACY 65.75%.

C1	C2	S1	T1	T2	V1	V2	W1	Class
34	14	0	0	2	0	0	0	C1 = Carpet I
4	42	0	0	0	4	0	0	C2 = Carpet II
0	0	41	0	0	1	1	7	S1 = Sponge I
1	0	2	32	8	4	1	2	T1 = Tile I
2	2	4	15	17	5	0	5	T2 = Tile II
0	1	1	2	2	35	6	3	V1 = Vinyl I
0	0	3	0	0	7	33	7	V2 = Vinyl II
0	1	8	0	2	6	4	29	W1 = Wood I

window, resulting in an eight dimensional vector. A naive Bayes learner produced predictions with an accuracy of 65.75% with 10-fold cross-validation.

The method based on the frequency features provides much better predictive power than the naive time domain based classifier. Table III shows the confusion matrix for the naive classier. There is no evidence that the classification is based on the textures. For example Tile II is misclassified as Carpet II and Sponge I and Title I Vinyl I and Wood II.

VII. CONCLUSION AND FUTURE WORK

We have presented a successful application of machine learning to classify surface textures based on the Fourier coefficients. The main contribution of this work is a learning method that can classify different textures without making any prior assumptions about the materials. It has been demonstrated that with only fifty training samples, a learning algorithm can be trained to make reasonable predictions. We have presented a comparison with a simpler time domain method and shown that our method produces predictions with higher success rate.

Future experiments will investigate the elimination of the external force/torque sensor and the effect of different speeds on the prediction accuracy.

The Fourier transform does not provide information on how the frequency content changes over time. The change of textures over time is an important distinguishing factor between surfaces with irregular texture. To this end, application of Short Term Fourier Transform and Wavelet transform may be studied.

The number of Fourier components needed for classification is dependent on the complexity of the surface texture. Complex surfaces, with subtle differences will require more Fourier components to capture the differences. This is not preferred as the number of training data required to train the learning algorithm has to be increased. Another interesting avenue to explore is the use of symbolic approaches. If the time series is converted in to a series of symbols, one might look for symbol patterns which represent different textures. In our view, these methods should provide more robust classifiers with higher prediction capability.

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