A Bio-Mimetic Fingertip that can Detect Force and Vibration Modalities
Investigation of Bio-mimetic Fingertip's Ability to Discriminate Textures

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For humanoid robots which interact with objects in unstructured environments, tactile sensing is important. It helps the robot to evaluate surface properties of the objects it interacts with. Texture identification and discrimination is an ability of such kinds of robots. In this paper, the development of a bio-mimetic fingertip that has accelerometers and force sensors to detect micro-vibration and force modalities is introduced. Furthermore, the ability of the fingertip in discriminating materials using textures is investigated. An artificial intelligence based approach is proposed with four parameters as classifiers for the ANN. The classifiers are the mean, standard deviation, and energy of detailed and approximate values of discreet transformation of the convoluted signal of accelerometer sensor signals. The method shows promising results as it was able to discriminate seven materials, six fabrics and one metal surface with 55% accuracy.

Key Words**:** Tactile sensing, Texture discrimination, Robot hand

1. Introduction

The ability to discriminate materials or objects based on surface texture is an important characteristic of the human tactile system. Likewise, in service robots, medical robots and exploration robots etc. where the robot interacts autonomously with the unstructured environment, similar capability is required.

In recent years several artificial fingertips were developed with tactile perception. These had different methods of sensing. Among them, few were designed to mimic a biological finger. Most of the fingertips used sensors which used MEMS based technologies. Ho *et al*. [1] developed a MEMS based soft fingertip and conducted texture recognition experiments using the power spectrum density of the obtained signal. Boissieu *et al.* [2], Oddo *et al.* [3] developed similar MEMS based fingertips and conducted research on surface textures identification. Jamali *et al.* [4], and Takamuku *et al.* [5] developed anthropomorphic fingertips where randomly distributed strain gauges and Polyvinylidene Fluoride (PVDF) films embedded in silicon. Jamali *et al.* conducted material classification experiments with the fingertip using a naive bayes classifier. Liu *et al.* [6] developed a robot finger that can detect contact location, normal and tangential forces and vibrations generated when the fingertip contacts with a surface. This finger was used to recognize materials by gently sliding along the material with varying velocities and applying a dynamic friction model to evaluate contact parameters and used a naive bayes function for classification.

Discrimination of surface textures has been studied by using various methods. Converting the time domain sensor signal in to frequency domain and analyzing was a common method. Sukhoy *et al.* [7], and Howe *et al.* [8] used accelerometer based systems to identify textures. Sukhoy *et al.* used Fast Fourier Transform (FFT) data for a support vector machine learning algorithm to obtain a accuracy of 80%. Tanaka *et al.* [9] developed a PVDF based system incorporating piezoresistive effect and pyroelectric effect of a PVDF film. Ho *et al.* [10]- [11] used a fabric sensor and discreet wavelet transform of the signal to discriminate three types of textures. Discriminating textures by various types of sensors are presented in [12] - [15]. These sensor systems have varying degrees of success rates.

Uses of machine intelligence based classification methods are becoming more popular. Jeremy *et al.* [16] proposed a bayesian exploration method for identifying textures with BioTac fingertip. It yielded a 95.4% success rate. Cuevas *et al.* [17] developed a fingertip with a piezoelectric microphone and used a learning vector quantization technique and obtained an over 93% success rate.

The authors of this paper have developed a bio-mimetic fingertip [18] that can detect force and vibration modalities. The aim of this paper is to evaluate its ability to discriminate fabrics based on the surface textures. Six fabrics and one metal surface were used in the experiment. The fingertip moved in an exploratory motion similar to that of a human finger. The accelerometer signals were processed and three magnitude acceleration values were calculated. Then the fabrics were classified using features generated by the above magnitude acceleration values. The signals of two adjacent accelerometers were convoluted and this convoluted signal was used to generate feature vectors for the ANN. The success rate of the method was calculated.

2. Bio Mimetic Finger

2.1 Design of fingertip

The proposed bio-mimetic fingertip is designed to mimic the functions of a human fingertip. It has the ability to detect force and vibration modalities from embedded force sensors and MEMS accelerometers. The fingertip has a bone to determine shape, a tissue layer and a skin layer. It has a frequency response up to 500 Hz similar to a human fingertip [19].

The fingertip is designed to be two and a half times the size of an average thumb of an adult. This was necessary to allow commercially available sensors to be used in the construction of the fingertip. It is cylindrical in shape with half hemispherical at the end. The diameter of the cylinder and the hemisphere is 34 mm. Fingertip is designed with a nail made of plastic connected to the bone and tissue. The nail acts as a sensing surface as well as a boundary (hard surface) to stop the extensive deformations of the tissue. The fingertip has two tissue layers. The inner layer is made from polyurethane rubber (Hitohada human skin gel,

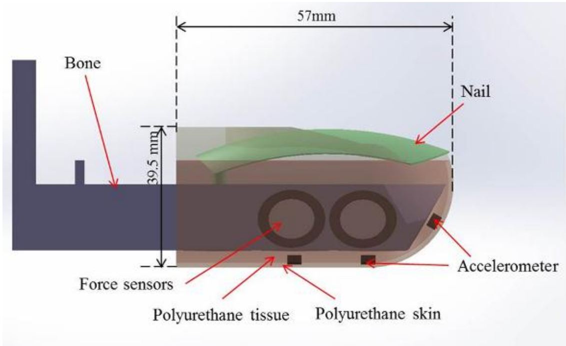

Fig. 1: Bio–mimetic fingertip with five accelerometers and eight force sensors

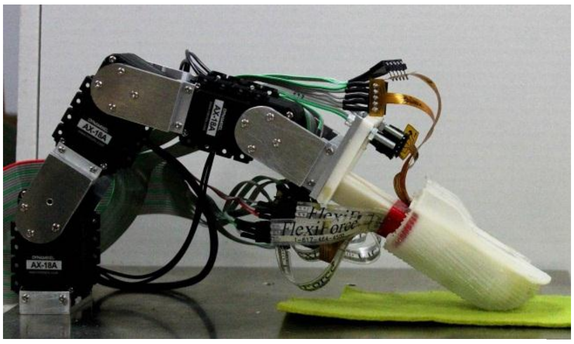

Fig. 2: The robot finger

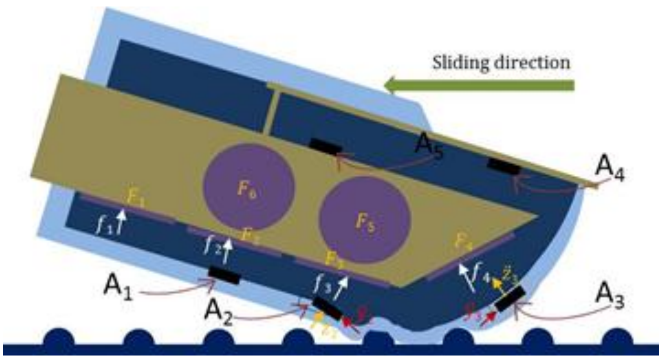

Fig. 3: When the fingertip moves on a rough surface the skin layer and the tissue layer deforms. Because of the deformation, Vertical force fi is applied to the i-th force sensors F_i. Acceleration components y_i and z_i are detected by A_i

www.exseal.co.jp) having hardness 5 and the outer layer is made from Sylgard 184 (www.dowcorning.com) which is comparatively harder than the polyurethane rubber tissue layer. The outer skin layer is similar to the skin of the human fingertip. The outer rubber layer has friction ridges similar to the human fingertip.

In the flat surfaces of the bone "Flexiforce" A201 force sensors are bonded. The three long surfaces of the bone are fixed with seven force sensors, two for the side surfaces and three for the underside. Front surface of the bone is covered by a single force sensor. These eight force sensors change resistance proportional to the applied vertical force.

The fingertip consists of five Analog Devices ADXL327BCPZ three-axis accelerometers. The accelerometers are bonded on to a flexible printed circuit board. Three accelerometers are suspended between the two tissue layers and 1mm away from the skin outer boundary. They are placed at the middle of the sensing surface of the force sensors. From the other two accelerometers, one is on the fingertip bone and the other is on the inside surface of the nail, (Fig. 1).

The bio-mimetic fingertip is connected to three servo motors (Fig. 2). This setup is similar to the distal, intermediate, and proximal phalanx of a human finger. It has three rotational joints thus, three degrees of freedom in a vertical plane. It can move similar to a human finger. The finger system is controlled via a LabView program. From here onwards the total system is introduces as a robot finger.

2.2 Sensing of vibrations and forces

The biomimetic fingertip is capable of picking up micro-vibrations that occur on the surface of the skin layer similar to the fast adapting mechanoreceptors (FA1 and FA2) in the biological skin. The force sensors are capable of adapting to static vertical loads and are correspond to slow adapting mechanoreceptors (SA1 and SA2) in human skin. When the finger is subjected to external vibrations or vibrations generated by the rubbing of a finger on an external surface (Fig.3), the vibrations causes deformations in the skin layer of the fingertip. These deformations propagate along the skin. Propagated deformations cause the accelerometer to move in x, y, and z directions. These movements are captured by the accelerometer as accelerations. Above accelerations are then converted into proportional voltage signals. When a force is applied to the fingertip, it is transmitted to the force sensors through the skin and tissue layers. The sensors detect vertical loads applied to its surface and change its resistance accordingly. Let F_i denotes the i-th force sensors while f_i denotes the vertical force applied to that sensor. Similarly, A_i denotes the i-th accelerometer, and x_i, y_i, and z_i represents its acceleration components.

2.3 Data acquisition and digital signal processing.

The force sensors of the robot finger are connected to a signal amplifier. These amplified force sensor signals and accelerometer signals are converted to digital data by using a National Instruments NI9205 AD converter and stored in a computer. The data is read and analyzed by Labview software. The signals are sampled at a rate of 1.2 kHz for each input. A 500 Hz center frequency low pass filter is applied to the obtained sensor signals. The filter and the sampling rate are adequate as human dynamic sensor field is susceptible only to the micro vibrations having frequency in the range of 50-500 Hz. The obtained signals are saved and analyzed later using MatLab software.

For each accelerometer, the system records three vector components x_i,y_i, and z_i corresponding to the accelerations detected in the x, y, and z directions. To reduce computational cost by reducing the amount of data to be processed, a magnitude a_i of an acceleration vector is computed as:

$$a_i = \sqrt{x_i^{\ 2} + y_i^{\ 2} + z_i^{\ 2}} \tag{1}$$

3. Test setup

The test materials were fixed underneath the fingertip. The fingertip

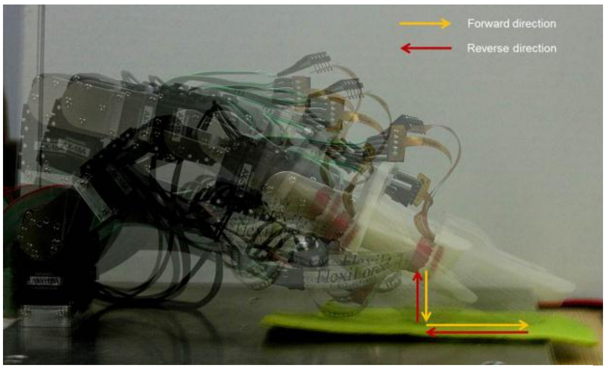

Fig. 4: exploratory motion of finger

was moved in an exploratory motion called the active touch. It is similar to a human moving his/her finger to explore a texture. Fig. 4 shows the trajectory of the fingertip. The applied vertical force was not measured as the exploratory motion conducted by a programmed path while applying a minimal force (light touch). The velocity profile of the different phases of the exploration task was kept constant with all the test samples. This velocity profile was selected after testing different velocity profiles and the relevant sensor signals. It provides the best output signal having a high signal to noise ratio. Higher velocities along with the inertia of the robot finger tend to vibrate the robot finger causing higher noise. From the obtained signal, data relevant to the robot finger's reverse directional motion is separated and used in the following classification methods.

4. Discrimination of Fabrics by Texture

In previous work [18], the fingertip's ability to detect surface profiles is presented by evaluating the pitch of a periodic surface with the help from the special frequency of the surface. The above method has limitations such as it can only be used if the velocity of the fingertip is constant and known. Furthermore, tests have revealed that the fingertip has sensitivity to distinguish only surfaces with spatial period p above 1 mm. But for material discrimination using textures, the fingertip should have the ability to senses textures with spatial period less than 1 mm. Therefore, the ability of the fingertip to discriminate textures needed to be investigated.

For this investigation, seven types of materials were used. Among the materials, six were fabrics because they had very fine textures and varying surface roughness. Polished aluminum surface was chosen as a standard surface (Fig.5). The ability of the fingertip to discriminate fabrics using textures was evaluated by using a neural network. For this method, the sample space was fifteen samples of data per each texture. These 105 test samples were taken in a random order, thus neglecting the effects of wear and tear of skin layer in the acquired sample signals.

Sample #	Material
1	Aluminum
2	Denim
3	Acrylic
4	Meshed Polyester
5	Nylon
6	Felt
7	Polyester

Fig. 5: Test materials

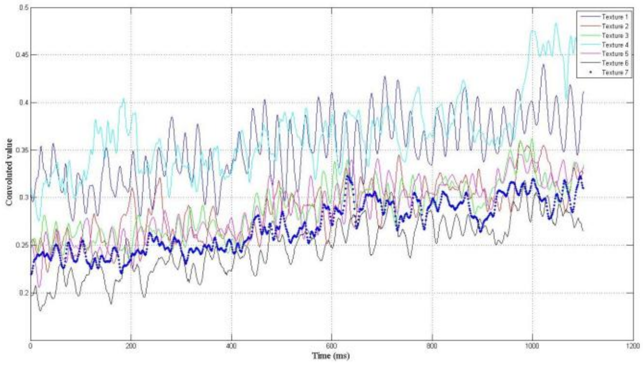

Fig. 6: Convoluted signal of the seven samples

4.1 Convolution of accelerometer signals

It has been noted that when the finger moves on the fabric surface, the contact surface of the fingertip changes with time. Therefore, the intensity of the vibrations detected by the two accelerometers A2 and A3 changed with time. Additionally, as the velocity of the contact surface changes with time, the obtained sensor signal is not a stationary signal and use of FFT to convert it into frequency domain is erroneous. In order to overcome this, the convolution signal of the two accelerometer signals A2 and A3 was calculated. Convolution of the signals *a2* and *a3* is calculated as:

$$(a_2 * a_3) = \sum_{m=-s}^{s} a_2[n].a_3[m-n] \qquad (2)$$

where s is the number of samples of the signal. Additionally, observing the convoluted signals (Fig. 6) of the seven materials, it was observed that the signals were different from one another compared to the raw signal of those materials that seemed similar. This is because the convolution of the two accelerometer signals rectifies for the change of intensity of the two accelerometer signals and it identified periodicities in the signals, which could not be identified by the FFT due to the non-stationary raw signals.

4.2 Feature generation for the ANN

By using the convoluted signal, the following four features were

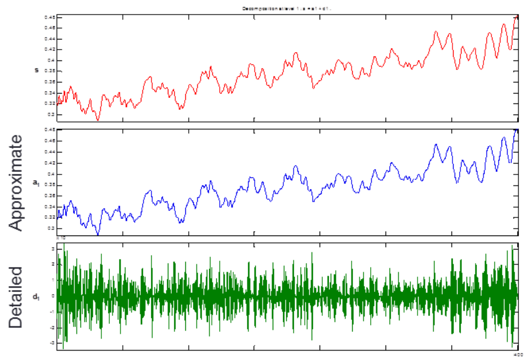

Fig. 7: DWT of convoluted signal of one sample

Table 1 : Confusion matrix of ANN

Output Class \ Target Class	1	2	3	4	5	6	7	
1	**14** 13.3%	**1** 1.0%	**0** 0.0%	**1** 1.0%	**1** 1.0%	**0** 0.0%	**2** 1.9%	73.7% 26.3%
2	**1** 1.0%	**12** 11.4%	**4** 3.8%	**0** 0.0%	**5** 4.8%	**1** 1.0%	**8** 7.6%	38.7% 61.3%
3	**0** 0.0%	**2** 1.9%	**8** 7.6%	**0** 0.0%	**4** 3.8%	**4** 3.8%	**2** 1.9%	40.0% 60.0%
4	**0** 0.0%	**0** 0.0%	**0** 0.0%	**14** 13.3%	**0** 0.0%	**0** 0.0%	**0** 0.0%	100% 0.0%
5	**0** 0.0%	**0** 0.0%	**0** 0.0%	**0** 0.0%	**0** 0.0%	**0** 0.0%	**0** 0.0%	NaN% NaN%
6	**0** 0.0%	**0** 0.0%	**3** 2.9%	**0** 0.0%	**5** 4.8%	**10** 9.5%	**3** 2.9%	47.6% 52.4%
7	**0** 0.0%	**0** 0.0%	**0** 0.0%	**0** 0.0%	**0** 0.0%	**0** 0.0%	**0** 0.0%	NaN% NaN%
	93.3% 6.7%	80.0% 20.0%	53.3% 46.7%	93.3% 6.7%	0.0% 100%	66.7% 33.3%	0.0% 100%	**55.2% 44.8%**

calculated an input into the ANN.

Mean, standard deviation and energy of detailed and approximate values of DWT of convoluted signal (Fig. 7) calculated as follows:

$$\text{Energy, } E_j = \sum_k |d_{j,k}|^2,\ j = 1,2,\ldots N\ , \tag{3}$$

$d_{j,k}$ are wavelet coefficients and N is the level of de-composition. These feature vectors are then input to a single hidden layer ANN with 10 nodes.

5. Results and Discussion

The feature vector of 105 samples was input to the ANN. The ANN had 10 nodes in a single hidden layer. The ANN was trained with 73 training samples and verified with 16 samples. Remaining samples were used as test samples. Table 1 gives the confusion matrix of the total 105 samples. The identification accuracy was 55%. This result was better than chance.

By analyzing the confusion matrix, it was noted that metal and meshed polyester had 93% accuracy in identifying correctly. Denim and felt had a success rate of 80% and 67% respectively. Acrylic was identified 53% of the time. Nylon and polyester was misclassified. Polyester had almost similar texture as denim and even for a human it was difficult to identify with a single exploratory motion. The low rates of success in identifying acrylic, nylon, and polyester may be due to the fine textures and low friction between the fingertip and the fabric.

Furthermore, from the above observations, it was evident that with only single movement, it was difficult to correctly discriminate textures.

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