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Soft Finger-tip Sensing Probe Based on Haptic Primary Colors

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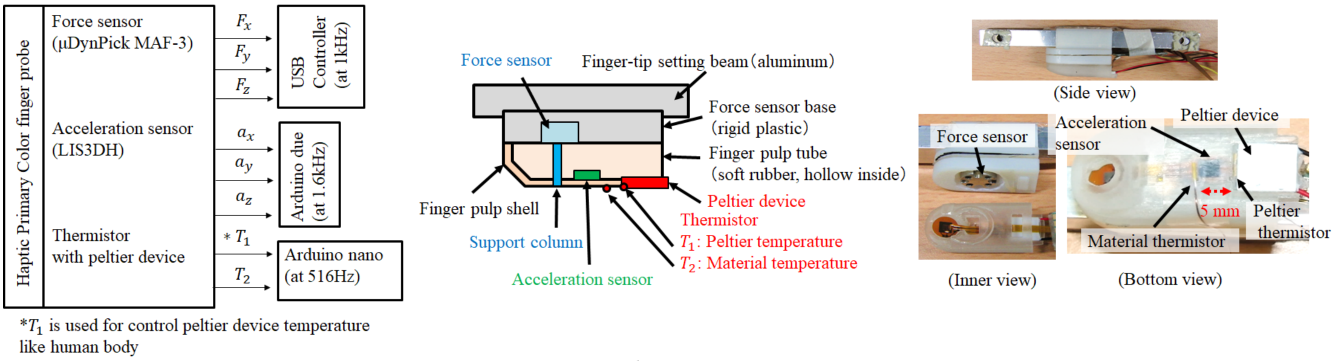

Figure 1: *(a) acquisition signal from force, acceleration, temperature sensor, (b) construction design of tactile probe,(c) developed probe*

Abstract

This paper describes a novel tactile sensing probe based on haptic primary colors (HPCs) and a tactile classifying system. We developed a finger-type soft tactile probe incorporating a sensor to measure three physical quantities: force, vibration, and temperature. We also constructed a tactile probe sliding system on the surface of the material repeatedly. The tactile fluctuation obtained from the tactile probe was recorded, and a frequency analyzed image was generated. In the evaluation experiments, the tactile images were generated by sliding the tactile probe on seven materials (ray fish skin, aluminum plate, rusting hemp fabric, MDF board, tatami mat fabric, acrylic board and rubber sheet). A convolutional neural network (CNN) was constructed and its classification performance was evaluated. In addition, we used tactile images to clarify the classification performance through TLAlexnet (transfer learned Alexnet). Pre-trained TLAlexnet was generated by domain adaptation using the tactile images. The results of TLAlexnet showed the great performance to be 85.0%, 91.7%, and 85.7% with respect to single primary colors of force, vibration, and temperature, respectively, and it improved to 96.4% when using three HPCs. In addition, the classification performance of the proposed seven-layered another CNN that was trained with the obtained tactile images was 98.2% of the CNN constructed using common filtering parameters. Thus, highly accurate classification was realized by using three HPCs elements.

CCS Concepts

• ***Human-centered computing*** → ***Virtual reality;*** *Haptic devices;* • ***Hardware*** → *Haptic devices;* • ***Computing methodologies*** → *Neural networks;*

1. Introduction

Many applications for virtual reality (VR) technology have been developed rapidly in recent years. High-fidelity transmission of sensory information and somatic sensation such as tactile sense, in addition to audiovisual sensation, will provide work flexibility and efficiency. The presentation of tactile information is considered necessary for remote working systems, because of its effec-

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tiveness for the efficient VR operation [FTB*00, KH13]. Our goal is to develop a telexistence [Tac15] robot system with soft finger hands. The robot transmits material information through material sensing and classification results with tactile finger-tip probe. To achieve the material classification, we developed a proposed system to classify the tactile information, to extract features with certain tactile characteristics based on haptic primary colors (HPCs) theory [TMFF15], and also to present tactile features classification results by using machine-learning methods. In order to acquire the required amount of tactile infromation for the machine learning, a soft tactile sensing probe and a recording system were constructed.

1.1. Haptic Primary Colors

Tactile sensation is based on information obtained from human tactile sensors and is a type of human somatosensory sensation. The HPCs is a theory that tactile sensing is composed by elements of tactile stimulus. It is the same as the three elements of light. In the HPCs theory, vibration, force, and temperature correspond to tactile sensation receptors and thermal sensation receptors. Tactile receptors that accept mechanical stimulation include Meissner corpuscles, Pacinian corpuscles, Merkel's cell, and Ruffini ending. Experiments have been conducted to measure the vibration detection area by sinusoidal vibration stimulation ranging from about 1-500 Hz for the measurement of the skin-vibration detection area. As tactile information, it is necessary to measure mechanical vibrations of about 1 kHz stimulus. The force is sensed on muscle, tendon, and joints as a deep sensation. The force is sensed on muscle, tendon, and joints as a deep sensation. The vibration is like the alternating-current component, the force is like the direct current component, thus both vibration and force sensor is needed. The frequent neural firing of temperature receptors at 40 - 45°C in warm sensation and at about 30°C in cold sensation. In this case, temperature sensing is required in the temperature range between 0-50°C.

1.2. Related Works

The tactile signal acquisition methods with finger or hand shape probe has been proposed by several reports. In our previous study [KFIT17], we determined the vibration component of a tactile sensation when sliding an object of materials by using fingertip-like acceleration probe. There are many reports [AS95, BHH*17, CLK14, MPC16, PR03] using a rigid metal-tip stylus. Some reports used gel state tactile sensor [HNNH12, VMK*05, YZO*17], while the other reports using thermal sensor hand [BWK15]. To the contrary we aim to realize soft finger-tip tactile sensing probe like Biotac [WSJL08]. A study [GHKD16] reported the use of for two fingers mounted on a robot hand; the authors classified tactile feel through hand gestures such as squeezing and holding. The Biotac has functions for sensing pressure, vibration through fluid, and core temperature; however, its sampling rate is not high enough to reproduce human sensation; the sampling rate of vibration and thermal capacity are 100 Hz, except for fluid vibration (2.2 kHz). The authors also reported that the classification performance of results by using only haptic is not very high. Moreover, the sensor's sensitivity of Biotac might not be high because the pressure vibration sensor is separated by fluids, and the stimulus transmitting through fluids might have high impedance. Several studies have conducted classified tactile signals with machine learning method like convolutional neural networks (CNNs) constructed from one or multiple physical quantities and multimodal sensations. A few of these studies [HMN16, KFIT17, SSS15] classified various material surfaces through tactile signals acquired from acceleration probe by constructing neural networks/CNN, while the others developed CNNs based on acceleration and by using visual images [ZFJ*16]. In addition, force sensor and microphone devices are included on a report [SSIS17], IR sensor metal detector is on a report [SBS17]. In the former study, its scanning system extracts acceleration, hardness, roughness, friction, sound and image features. The latter one defines tactile features of reflectance from IR led and metal detection, in addition. Both of them conducted the evaluation using some supervised machine learning approaches which are not the deep neural network. Another study [SBS17] proposed a classification method which focused on the velocity of normal force changes while the probe slides the material. On the other hand, in the this study, we aimed to classify signals about three axes of both force and vibration, material surface temperature, directly. A classifying system using CNN classifier was also exploited. In our system, the feature is not extracted explicitly because human finger just senses the force, vibration, temperature. Proposed sensing formula is based on haptic primary colors theory [TMFF15].

A tactile information recording system with a finger slides linearly on a material surface is also proposed [MPC16]. It scans friction coefficients, both lateral and normal force using an external force sensor. In our proposed system, all sensors are embedded in a fingertip to measure the very surface vibration and force well.

Thus, in the current study, we propose the tactile probe that senses force, vibration, and temperature similar to a human finger. It enables high-frequency sampling rate similar to that of the human tactile receptor. The tactile sensors of our probe are distributed on the probe surface for high sensitivity. We also developed a tactile signal recording system that slides the tactile probe linearly and automatically on the surface of materials. This type of automatic system enables us to easily gather a large amount of material textures. After recording a signal, our system produces a tactile spectrogram through a fast Fourier transform (FFT), which is frequently used in audio analysis research [SK03], in which acquired time series audio signal are produced to process frequencies.

1.3. Contribution

We proposed the tactile probe that acquires tactile information of three HPCs (force, vibration, and temperature). In addition, we developed a tactile recording system to conduct the tactile probe sliding on materials. The acquired tactile information was classified by using CNN. The result of cross-validation by using the proposed system classifies seven specific materials with an accuracy of 98.2%. The result also confirmed that combining force, acceleration, and temperature image improves the classification accuracy. Our proposed system enables distinguish between different types of materials according to their surface texture.

2. Tactile Probe, Tactile Feeling Recording System, and Classification System Construction

In this paper, we describe the recording system and classification system of tactile sensation that satisfies the above requirements. In order to obtain tactile information about tactile sensations and temperature sensations, we developed a system that is based on the HPCs to record the force, vibration, and temperature. The force is like the direct current component of the tactile sense, and the vibration is the alternating current component. We propose the tactile probe (Figure 1(b) and (c)) that acquires a tactile signal using three sensors of force, acceleration, and temperature. The probe imitates the fingertip of a human, and it is assumed that tactile signals are obtained by sliding the surface of material samples.

2.1. Tactile probe with built-in three HPCs sensors

We acquired the three-axis of force, which consists of one vertical force axis against a material and a horizontal biaxial moment force using μDynPick MAF-3 piezoresistive force sensor, (1 kHz, three axes, manufactured by Wako Tech). To obtain the vibration, we employed LIS3DH acceleration sensor (1.6 kHz, tri-axial, manufactured by ST Microelectronics). We employed an infrared thermopile TMP-007 (manufactured by Texas Instruments, Inc.) for non-contact temperature sensors that are connected by an FPC connection cable. To acquire the contact temperature, we employed a 56 A 1002 - C 3 thermistor (manufactured by Alpha Technics Co., Ltd.), and both are connected to the embedded controller Arduino Due (32 bit, equipped with Arm Cortex - M 3, 84 MHz). We established a connection from the embedded controller and force sensor by serial USB communication to the PC to record tactile sensing signals (Figure 1(a)) and preserve time-series fluctuations.

The configuration of the tactile probe is shown in Figure 1(b). The tactile probe shape was designed with 3D CAD (Autodesk Inventor), and it was a three-dimensional design modeled by a stereoscopic image printer (Figure 1(c)). The finger pad of the tactile probe was made hollow with a thickness of 1 mm to facilitate vibrating, and it was molded using a flexible but hard material (FLX 9995). We assumed that it is mounted on the robot's fingertips or extremities for remote work. The ease of grasping of objects is important owing to their softness, but the vibration and force that can be acquired become dull in the finger pulp, which is too soft. The base of the force sensor (Figure 1(b)) is made of hard plastic (ABS resin). This is because a base with hardness is better for obtaining the force. The arm of the force sensor is on the opposite side from the base, and touches the back and outside of the finger pulp tube (Figure 1(b)). In Figure 1, the force sensor can measure the vertical force and the horizontal biaxial moment on the bottom of the finger pulp tube. In order to obtain the force from the finger pulp surface to the force sensor, the support column (Figure 1(b)) was extended from the finger pulp bottom surface to the arm of the force sensor. In addition, it is thought that the vibration is more easily measured at the part closer to the contact surface, with the object on the ventral side of the finger pad, where vibrations are generated. Therefore, the acceleration sensor is disposed inside the ventral side of the finger pulp tube (Figure 1(c); the acceleration sensor is transparent).

2.2. Temperature Sensor and Peltier Heater

The contact temperature sensor is attached to the front/outside of the ventral side of the finger pulp tube. The non-contact temperature sensor is mounted in a direction such that it can measure the temperature of the surface of the substance to be contacted from the measurement hole, which is opened on the ventral side of the finger pulp tube (Figure 1(b)). For the contact temperature sensor, we used a thermistor that has a small measurement volume and good reactivity. The non-contact temperature sensor can measure the temperature of the cone-shaped bottom surface region with the sensor surface as the apex, and the finger can measure the temperature immediately before contact with the object, but the effect of the thermal emissivity of the object to be measured and the environment. It is difficult to measure the temperature accurately, easily, and stable. Therefore, we used only thermistors as contact temperature sensors to measure the temperature.

On the ventral surface of the finger pulp tube, we placed a Peltier element to maintain the temperature of the finger pad (Figures 1(b), (c)). We aim to identify materials from temperature fluctuations of the contact object. In order to identify an object's material, the human acquires the temperature fluctuation of the surface of the finger at the time of contact with the object. This is because the thermos receptor resides in the skin surface. In order to discriminate an object on the temperature axis, if the tactile probe has a body temperature, as is the case with humans, heat exchange is caused by the temperature difference with an object, which is usually at room temperature. Therefore, it is easier to measure the characteristics of object temperature change. Figure 2 shows the temperature change example of our proposed tactile probe was pressed against both an aluminum plate and a ray fish skin plate. The tactile probe was pressed against the surface of the sample using a tapping operation, after which it was heated, and the temperature change was recorded. The Peltier element with the built-in tactile probe was maintained at 42°C, which is the upper limit of human skin, which is controlled using a voltage of 5V and a current of 0.5A. Two thermistors are located on finger pulp. One thermistor (T_1) measures the Peltier device temperature for thermal control. The other thermistor (T_2) is located 5 mm forward from Peltier device on the finger pad. Figure 2 shows when the T_2 became 28.9 °C (higher than room temperature), the fingertip pulp was brought into contact with the material for 5 min. In the aluminum sample, the temperature rose after the temperature decreased by 1.5 °C toward the room temperature. After the fingertip pulp contacts the ray fish skin, whereas the fingertip pulp temperature nearly monotonically increased. Because aluminum has a higher thermal conductivity than ray fish skin. Because the thermal conductivity of the ray fish skin is low and the heat conduction to the surroundings of the fingertip pulp is slow, it is believed that the magnitude of the temperature decrease was small. From the above, by touching the object with the heated tactile probe on the human skin, it is possible to determine the tendency of the thermal conductivity of the material. Because the temperature fluctuation is a variable that is unique to each substance that is neither concave nor convex on the surface of the specimen, it can be used independently of the force and vibration as an indicator to determine the material using the temperature for the classification of tactile sensation. The reports [BWK15] also proposed material classification using a heating element and a surface thermistor. It sensing temperature decreasing with 200Hz. In our method, the heating element is as one roll of HPCs sensors which slides material surface.

2.3. Tactile Feeling Recording System

Using the proposed tactile probe, we constructed a recording system (Figure 3) to obtain the texture of the surface material of the object. We built a system for sliding a tactile probe by coupling a linear actuator and a servomotor. The linear actuator, which uses a high-precision ball screw SG2605-A300P-A3CS-NN-PSR(Kuroda Seiko Co., Ltd.) and the servomotor MSMF5AZL1A2 (both of which are manufactured by Panasonic Corporation) are connected by a coupling SCIW-19-5-8 (Misumi Corporation). They are operated by sending command values from the servo amplifier MADLT01SF. A specimen material used to acquire the tactile sensation to be recorded is attached to the work of the actuator, and it moves iteratively. We do not move the tactile probe using the linear actuator. This is because there is no acceleration due to sliding. Two pillars that are located on the sides of the linear actuator support the tactile probe above the linear actuator. Then, the tactile probe has extra freedom along the vertical axis force (blue text in Figure 3). The tactile probe weighed 0.1 kg, and it was pressed with a force of 1 N. The cylinder position was constantly measured by the optical encoder of the motor. In the recording system used in the report [CLK14], the vibration was excited by the reciprocating movement. However, in the proposed recording system, the noisy vibration can be reduced by the cylinder using the high-precision ball screw.

2.4. Imaging of Tactile Information

In the recording system, waveforms of force, acceleration and temperature are obtained as tactile information. The obtained tactile information undergoes the Fast Fourier Transform (FFT) within a unit time delimited in the time direction to generate an image in which the intensity of force, acceleration or temperature frequency varies over time. Image acquisition parameter shows on the Table 1. In the imaging after the FFT, the intensity distribution of frequencies included in the signal is generated.

2.5. Tactile Information Classification System

For the classification of imaged tactile information, we employed a machine-learning method using a CNN, which is well used in the field of computer vision. Alexnet [MPC16] is also frequently used as the benchmark. In this study, we developed a transfer-learning CNN by using Alexnet (which we call TLAlexNet) with tactile images. Alexnet is a pre-trained network through one million general images of thousand categories database [KSG12, Ima12]. But it is not specialized in tactile images, therefore another seven-layered CNN was also constructed for evaluation. The tactile image enters the input layer, and the convolution layer is the second layer. Next, the ReLU layer is configured to become the entire binding layer, then the soft-max layer and the output layer are used for the classification via the two-dimensional max-pooling layer. It will be determined at the section of experiments; convolution filter size, stride size and size of the max-pooling layer. The tactile image is generated using single HPCs or a combination of two or three HPCs.

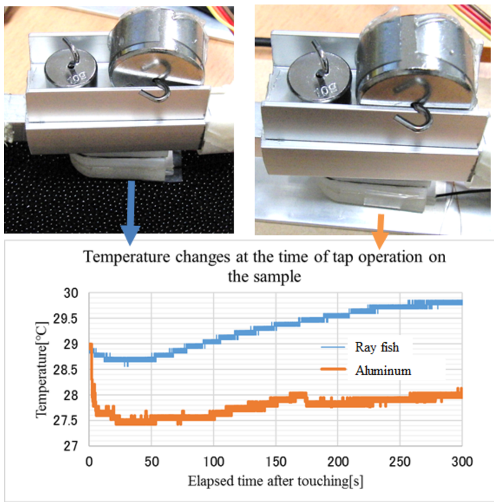

Figure 2: *Example of temperature change when tactile probe pressed against both an aluminum plate and a ray fish skin plate.*

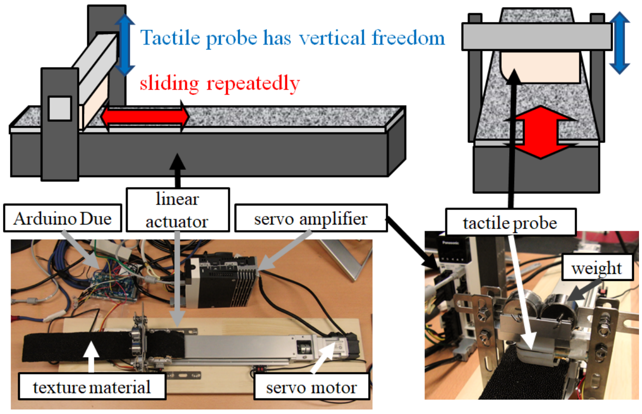

Figure 3: *Recording system of surface material using tactile probe.*

3. Experiments

Using the tactile probe and tactile information recording system, we acquired HPCs tactile information from the sliding operation of seven material surfaces (Figure 5 and 6).

3.1. Acquisition of Force, Acceleration, and Temperature Information

The sampling frequency of the force and acceleration of the tactile information are 1 kHz for the force sensor and 1.6 kHz for the acceleration sensor. Tactile information was acquired by repeatedly sliding a tactile probe, which is pressed 1 N on a material sample, and it is operated at a stroke distance of 20 cm (Table 1). A time for one-way slide takes in 2 - 3 seconds. Figures 5 and 6 show

Table 1: *HPCs Images Acquisition Parameter(left), Parameters of generating images, Images Amount Used for TLAlexnet/Proposed CNN and Classification Accuracy of TLAlexnet/Proposed CNN(right)*

	Acquisition parameter		Generating images		Image amount			Classification performance	
	Sampling frequency [Hz]	Sliding length [cm]	Image width [s]	Size w×h [pixels]	Train images (TLAlexnet /Proposed CNN)	Evaluation	Total	TLAlexnet	Proposed CNN
Force (F)	1k		8		91	39	130	85.0%	85.0%
Acceleration (A) only y-axis	1.6k	20	5	15×501	83	36	119	91.7%	95.6%
Temperature (T)	516		15		55	24	79	85.7%	83.3%
F + A								91.7%	97.0%
F + T				30×501	56	24	80	87.5%	95.2%
A + T								93.5%	98.2%
F + A + T				45×501				96.4%	98.2%

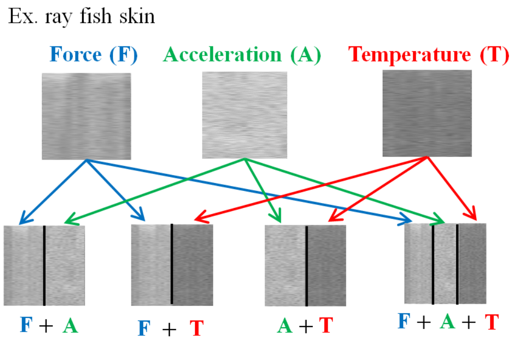

Figure 4: *Combination of HPCs images. Example of ray fish skin.*

the waveforms of the recorded force, acceleration, and temperature as well as the frequency analysis results. For the material sample, we used a ray fish skin, which is rugged but has little friction, a tatami mat fabric, which is smooth, a rusting hemp fabric, an MDF boards, which are dry and rustic, an aluminum plate and an acrylic plate, which presents cool tactile and smoothness, and rubber sheet which has also smoothness. It is shown that the frequency component included in the forces recorded in our proposed system is concentrated mainly in the low-frequency range of 50 Hz or less. The frequency components included in the acceleration, which are set to 800 Hz, especially in the sliding direction. By focusing on a specific frequency, it is possible to confirm the band-like features. Because the frequency components that can be acquired differ for the force and acceleration, it is considered that indicators regarding the discrimination of materials can be independently obtained by a combination of obtained frequency components. We obtained the temperature change during sliding in the same way as the acceleration and force. We measured the temperature of the Peltier device (T_1) and the surface temperature (T_2) of the finger pulp tube 5 [mm] from the Peltier element while controlling the ON/OFF switching of the power supply; as a result, the Peltier device of the tactile probe became 42°C. The temperature sampling rate was about 516 Hz. The temperature waveform (Figure 6, right column) was imaged as well as the force and acceleration.

3.2. Classification using TLAlexnet

Pre-trained Alexnet randomly selected 70% of the images generated from the tactile signals of force, acceleration, and temperature as shown in Table 1, and the domain adaptation was performed through transfer learning. The classification performance was then evaluated with the remaining 30% of the images. Transfer learning was conducted on each contact image of force, acceleration, and temperature (15 × 501 pixels), a combination of two tactile images (15 × 501 pixels) for the $force+acceleration(F+A)$, $theforce+temperature(F+T)$, $theacceleration+temperature(A+T)$, and a combination of three tactile images (15 × 501 pixels) for $theforce+acceleration+temperature(F+A+T)$. For combining several HPCs images, we compound a temperature image next to a force image for $theforce+temperature(F+T)$. We constructed a learning system using MATLAB. The size of the mini batch was [28,28]. Figure 4 shows the combination images of HPCs.

3.3. Classification using Proposed CNN

Similar to the classification using Alexnet, CNN was constructed using each touch image and evaluated. In the construction of CNN, the filter size of the convolution layer was set to a width and height of 8 and 33, respectively. In the pooling layer, the pool size was set to 2 × 2, and the stride was set at 2 × 2. In addition, the output of the total coupling layer was configured to be 5. The CNN that achieves the best performance by changing the classification performance through parameters for each touch was evaluated.

4. Classification Results and Discussion

Compared both situations, 1) The performance classified by independently imaging the tactile information of force, acceleration, and temperature, and 2) The performance in the case of simultaneously categorizing the two and three sets of tactile information into one image, with respect to TLALexnet, the proposed CNN. Table 1 shows the evaluation result by using TLAlexnet / proposed CNN respectively. We used just y-axis of accelerometer because the accuracy was not high when using 3 axes.

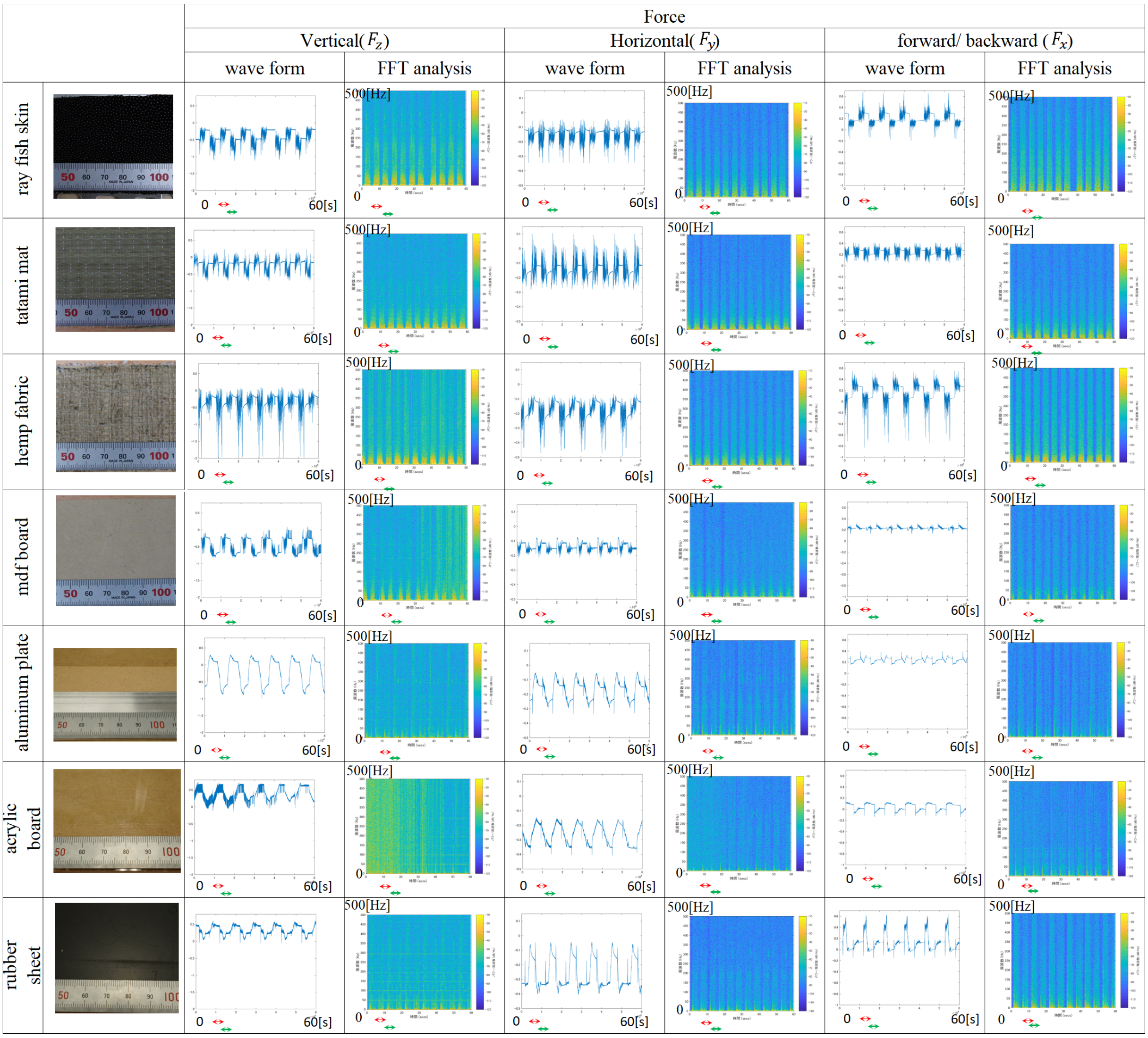

Figure 5: *Waveform of force and image after frequency analysis. Waveform (left) and frequency analysis (∼500 Hz) results (right) obtained in the vertical direction and sliding direction of the force when sliding by reciprocating the skin of ray fish, tatami mat, hemp cloth, and MDF plate.*

4.1. Classification Performance using TLAlexnet

By comparing the classification accuracy of the TLAlexnet, the accuracy was found to be good in the order of $temperature(T) \simeq force(F) < acceleration(A)$ for single HPCs images (Table 1 (right)). In combination, the order was $F+T < F+A < A+T$, which is higher than for a single HPCs. Even with the combinations of tactile images with low classification performance, higher classification performance can be realized. The combinations of the $force + acceleration$, the $force + temperature$, and the $acceleration + temperature$ were complemented, and are thought to be similar to the robust joint Haar-like feature quantity [MKSH08] with a combination of weak classifiers used in the recognition of facial images. This kind of features are called weak classifier, it is known that these combinations of weak classifiers become robust strong classifiers. High classification performance was obtained even with the combination of temperature images with low classification accuracy. Moreover, by combining three tactile combinations, it was possible to obtain maximum classification performance. It contains images of accelerations that can be classified with high accuracy and these seem to have become strong feature extraction entities.

4.2. Classification Performance using Proposed CNN

Table 1 shows the results by using proposed CNN, which is produced by using only tactile images, the classification accuracy of all of HPCs image set increased (it shows right edge column of Table 1). Middle column at Table 1 (right) shows the accuracy of

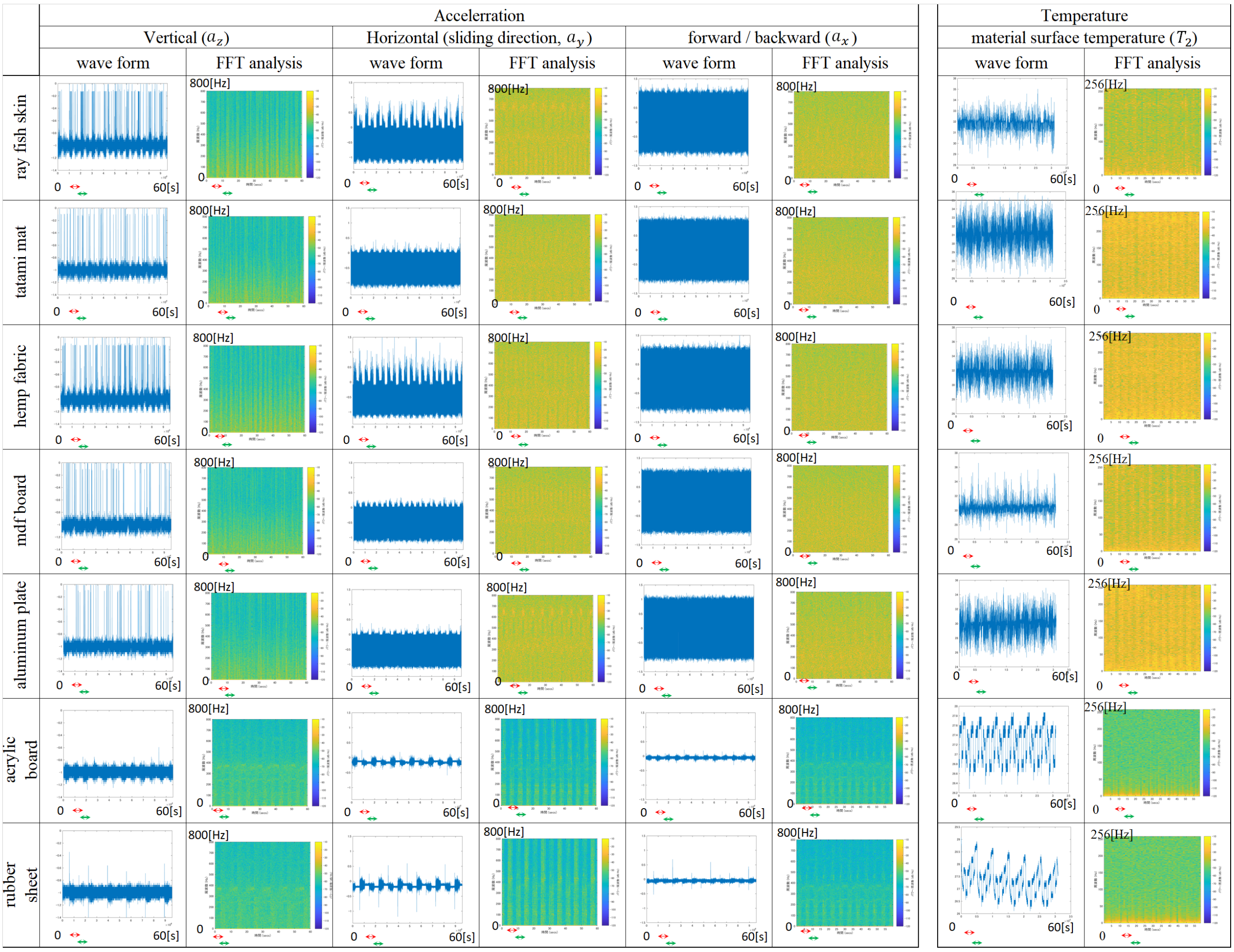

Figure 6: *Left table (Acceleration) shows waveform of acceleration and image after frequency analysis. Waveform (left) and frequency analysis (∼500 Hz) result (right) in the vertical direction and sliding direction of the acceleration. Right table (Temperature) showsT_2 waveform (left) and frequency analysis (∼258 Hz) result (right) when sliding. Both tables are results by reciprocating the skin of ray fish skin, tatami mat, hemp fabric, MDF plate, aluminum plate, acrylic board and rubber sheet.*

proposed CNN of which is made from both filter size [13,13] and 35 filters by using HPCs images, F, A, $F+A$, $F+T$, $A+T$ and $F+A+T$, respectively. The accuracy by using single T image set is almost the same but has a little decreased. It is because that temperature images amount is small as well as low sampling rate, and it is also considered that thermal conduction phenomena changes slowly than the other HPCs, frequency analyze images of temperature has small features. However it seems by combining different HPCs images could increase the classification accuracy even with temperature, temperature image could cover the pair HPCs images. Classification accuracy by using three HPCs images scored 98.2% by using a common filter parameter. From the above, proposed CNN also shows the highest classification accuracy by using three combinations of HPCs images.

4.3. Limitations

Tapping and grasping operation is out of scope in this study, though the robot hand is required such operation. Tactile sensing pattern depends on pressure. Adapting to the pressure changes during such operation is a future work. Our proposed system will be useful when the robot hand touches a object, with normalized velocity. The velocity of robot finger will be acquired because a robot hand should be equipped motion sensing/calculating system to control of it. In this study seven materials are featured, in order to achieve various tactile transmits, more materials need to be analyzed for more tactile information.

5. Conclusion

In this study, we proposed a tactile probe that acquires tactile information of three haptic primary colors. We also developed the recording system which slides material repeatedly. Tactile information was acquired automatically by the tactile probe pressed against the material surface. The sampling rate of the force/acceleration/temperature is 1 k / 1.6 k / 500 Hz, respectively, and it is sufficiently fast to be sensed by the skin receptors. The evaluation was conducted by using both pre-trained TLAlexnet and another trained CNN with seven sets of single HPC image or the combinations of two or three HPC images. The high accuracy of classification was guaranteed by using three combinations of HPC images, and even the combination of low accuracy HPCs provided a sufficient accuracy of classification.

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