Proceedings of the 2006 IEEE/RSJ
International Conference on Intelligent Robots and Systems
October 9 - 15, 2006, Beijing, China

Real-time Estimation of Touch Feeling Factors Using Human Finger Mimetic Tactile Sensors

Shogo Okamoto*, Masashi Konyo*, Yuka Mukaibo**, Takashi Maeno**, and Satoshi Tadokoro*

* Graduate School of Information Sciences, Tohoku University
6-6-01 Aramaki Aza Aoba, Aoba-ku, Sendai, 980-8579, Japan
{okamoto,konyo,tadokoro}@rm.is.tohoku.ac.jp

**Department of Science and Technology, Keio University
3-14-1 Hiyoshi, Kohoku-ku, Yokohama 223-8522, Japan
mukabo@mmm-keio.net, maeno@mech.keio.ac.jp

***Abstract*— To realize a telepresence system with tactile feedback and force feedback, real-time estimation of various tactile sensation must be conducted. Because several types of tactile sensation consist in touch and human tactile feeling has high time resolution. A man feels active touch extraordinary with time delayed transmission of tactile information. Our proposing human finger mimetic sensor covers three tactile factors, which are roughness, softness and friction of objects to touch. Current tactile telepresence systems represent just one tactile sensation in addition to kinesthetic information. For augmented reality, wider tactile factors must be sensed at a tactile sensor system and transferred to a tactile display system with small time delay. We realized quick estimation of vibrational frequencies of the sensor and softness of objects to regenerate touch feelings to human skin by tactile displays, which usually need time-consuming samples and make it hard to address tactile telepresence system. Quick estimation of vibrational frequency was conducted by emulating impulse emission of Meissner's corpuscles. Quick estimation of Young's modulus of objects was solved by computing strain distribution in a sensor.**

I. Introduction

Tactile telepresence system is expected to realize the palpation in minimally invasive diagnosing, training from experts of fine art by sharing tactile sensation and robotic manipulation like grasp with small grip force and automation of the other industries which needs human tactile perceptions and handling.

Studies of tactile telepresence systems which include all of sensing, transmission and representation of tactile sensation have been seen for some purposes. Tactile telepresence system consists of a tactile display and a tactile sensor. In addition to conventional telepresence systems with kinesthetic feedback, tactile telepresence system regenerates tactile information like roughness, friction sensation and softness of objects by tactile displays based on estimated tactile factors by a tactile sensor. Robotic palpation systems [1] [2] were aimed at locating nodules on organs and able to represent a pressure distribution to a fingertip. A master-slave system to transmit roughness sensation in rubbing motion was reported [3]. Control of a contact area between a fingertip and a tactile display to distinguish objects of different Young's modulus based on a sensed or estimated contact area were reported [4] [5]. All of these telepresence system sensed tactile factors of objects and installed tactile displays to present transferred factors, neither in a virtual way nor just force representation. But existing telepresence systems cover only one tactile sensations, like a pressure distribution, roughness or softness of objects to touch and objects' properties must be identified beforehand because their estimation requires time, which complicates practical use.

There are no tactile sensors to cover the whole various human tactile perceptions. So far have reported studies of sensing of pressure distributions in a fingertip-size area, detection of incipient slippage [6] and widely distributable pressure sensors for robots' skin [7] and so on. Because they can be considered most important tactile information for robotic assembly, grasp, handling of the objects or home robots as partners of humans. Contemporary tactile sensors are far from adequate for human to obtain objects' texture which is classified into four factors on material determination as roughness, temperature, friction and softness of objects [8]. In this paper physical parameters that could cause these four types of sensation are named tactile factors. The tactile factors are sensed or estimated individually at a tactile sensor system and transfered to a tactile display system.

High time resolution of human tactile sensation must be contemplated. Human recognition of tactile information have quick time response of less than 1[msec]. Quick estimation and transmission of tactile factors are also required to implement tactile telepresence systems. If not for quick response when a man rubbed objects, it would lack reality and unnatural feeling would be sensed to him.

Hence, necessary conditions of tactile telepresence system are listed as;

1. tactile display to present various tactile factors,
2. tactile sensor to obtain various tactile factors and
3. quick estimation of tactile factors.

We have already overcome condition 1. via ICPF tactile display [9] and condition 2. and 3. are achieved by human finger mimetic tactile sensor [10] using methods described in this paper.

ICPF tactile display is formed by array of ICPF actuators, which can stimulate man finger skin and cause internal deformation to the skin. ICPF actuators can be performed

1-4244-0259-X/06/$20.00 ©2006 IEEE

in enough of broad frequency (0 – 200[Hz]) to correspond to three kinds of tactile mechanoreceptors, Merkel's discs, Meissner's Corpuscles, Pacinian Corpuscles. We proposed the method to synthesize three tactile factors, softness, roughness and friction by ICPF tactile display [9].

Human finger mimetic tactile sensor emulates the physical structure of a man finger. This sensor covers three tactile sensations, roughness, softness and friction of objects. Roughness sensation can be thought to compose of the vibratory frequency and intensity of applied stimulus to the skin. Especially vibrational frequencies take time to be computed by Fourier transformation and identification of Young's modulus usulally needs time series relationships between reaction force and normal displacement. New methods for real-time estimation of vibrational frequency and softness are needed to satisfy the condition 3.

In this paper, firstly the basic specifications of human finger mimetic tactile sensor is described, followed by real-time estimation of vibrational frequency of the sensor by emulating Meissner's ccorpuscles' impulse emission, followed by real-time estimation of Young's modulus using strain distribution in a sensor are described.

II. Human Finger Mimetic Tactile Sensor [10]

Human finger mimetic tactile sensor emulates physical structure of a man finger. The idea of this sensor is that human mimetic sensor may be able to sense various tactile factors quick like humans although its precision may not be accurate. Fig.1 illustrates a schema of the sensor. The sensor is made up of a hard silicon rubber outer layer, a soft inner layer and an acrylic base as a bone of a human finger. The surface of a sensor is covered with lots of small lumps emulating dermal ridges of a man finger. Five strain gauges are embedded and each of them is placed on the bound between an outer layer and an inner layer, just as Meissner's Corpuscles are found on the bound between soft fat tissue and a hard outer epidermis of a man finger. It is also known that when force is applied to the surface of a sensor stress distribution is concentrated around this boundary region most likely.

So far we verified that the frequency of sensor tissue's vibration could be computed by Fourier transformation when a sensor is rubbed against a rough object at a fixed speed, and a variance of the five gauges' output reflects softness of the object to touch. And also static and dynamic friction can be obtained by a torque sensor installed on the base of a sensor [10].

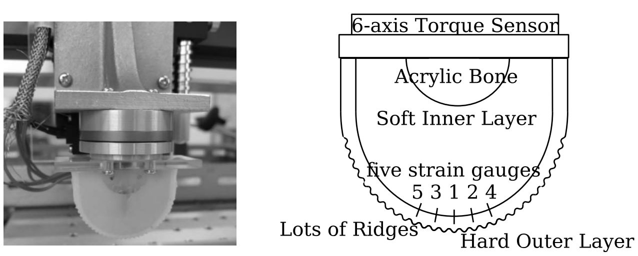


Fig. 1. Human finger mimetic sensor [10]

III. Real-time Estimation of Vibrational Frequency Using Human Finger Mimetic Sensor

Most of the existing tactile displays generate vibratory stimulus to the skin of a finger to represent roughness sensation [12]. Therefore tactile sensor must determine the frequency of vibration to transfer. But generally computing frequency elements by Fourier transformation takes so long time that it makes tactile telepresence system lack the reality. Short-time Fourier transformation (STFT) is a promising approach concerning this purpose, but we confirmed that STFT can not deal with active touch because of some problems (elaborated later). The vibrational frequency corresponding to roughness sensation (0–100[Hz]) must be estimated as quick as possible in other ways. Human finger mimetic tactile sensor may have the capability of estimating vibrational frequency quickly by using biomimetic algorithm.

Ohka's method successfully detected a step of tens of micrometer using a tactile sensor for robots, which implied that the methods of mimicking human mechanism for roughness recognition is also effective for robotic tactile sensors [11]. Ohka's method did not mean to estimate the vibrational frequency of stimulus. This section describes real-time estimation of vibrational frequency by the method of mimicking impulse emission of Meissner's corpuscles.

A. Real-time Vibrational Frequency Estimation by the method of Mimicking Impulse Emission of Meissner's Corpuscles

Some physiological aspects are taken into account for real-time vibrational frequency estimation by our methods. Meissner's corpuscles is said to affect on roughness recognition of humans. Meissner's corpuscles responds to first-order differential of mechanical stimulus given to the skin. Impulse is emitted by a neuron connected to Meissner's corpuscles with temporal stimulus change bigger than a certain threshold. If another impulse is emitted before preceding one attenuates completely, membrane potential is superimposed onto an old signal. This effect is called $time\ summation$ [11].

Next phenomena caused when a human finger mimetic tactile sensor rubs a roughness sample are elaborated. Fig.2 (a) shows output of a strain gauge, when the sensor horizontally rubbed a roughness sample at a speed of 60[mm/sec]. There were two grooves with width 1.5[mm] on a roughness sample. The interval between two grooves was 1.5[mm]. In Fig.2 (a) when the sensor touched the first groove its output abruptly increased and dropped down on contacting a ridge. On passing the second groove sensor's output changes as well as on passing the first groove.

Fig.2 (b) shows first-order differential value of sensor's output (a). There were four spikes in Fig.2 (b) and each of them was caused by begining of a groove or contact with a ridge. Fig.2 (c) shows the emitted impulses when the first-order differential values crosses over a threshold. The time interval between impulses tells vibrational frequency. The time interval between two impulses caused by two grooves was 0.050[sec]. A sensor moved at the speed of 60[mm/sec], 60 [mm/sec] $\times$ 0.050[sec]$=$ 3.0[mm], which equals a distance of

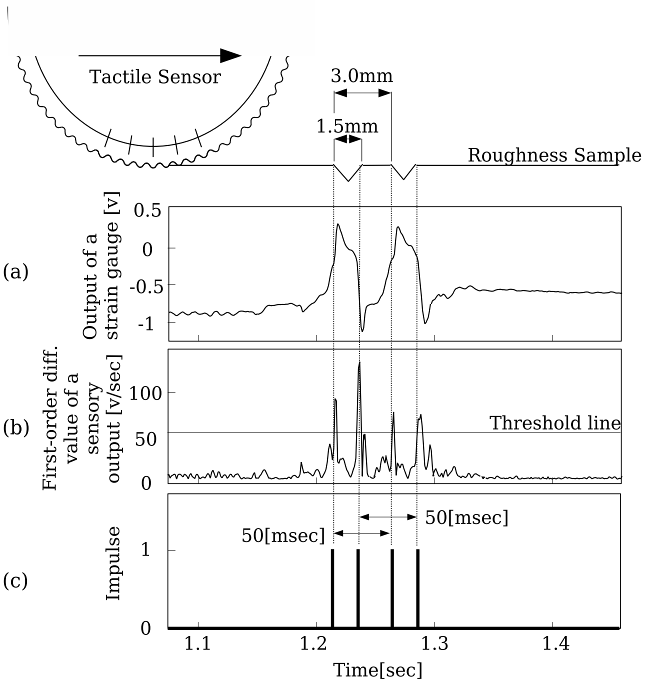


Fig. 2. Output of a strain gauge and first-order differential value of it when the human finger mimetic tactile sensor rubbed a roughness sample

two grooves. In this case the vibrational frequency of a sensor is computed as $1/0.050$=20[Hz]. Same story made sense when using impulses resuled from contacts with ridges. This is the basic principle to instantly estimate the vibrational frequency of the sensor.

Real-time estimation of vibrational frequency is formulated next. When $\epsilon(t)$ is the output of a strain gauge, $x(t)$ denotes absolute value of the first-order differential value of $\epsilon(t)$ as (1).

$$x(t) = \left|\frac{d\epsilon(t)}{dt}\right| \tag{1}$$

$p(t)$ denotes pulse emission at t. When $x(t)$ crosses over a threshold h, $p(t)$ is set to $p(t) = 1$, which means impulse is emitted, in other cases $p(t) = 0$. The condition of $p(t) = 1$ is not $x(t) > h$. Only if $x(t)$ crosses h upward then $p(t) = 1$. This is slightly different from the firing pattern of Meissner's corpuscles. But roughness recognition of humans is affected by both of intensity and vibrational frequency of stimulus. How much and how long $x(t)$ exceeds h are ignored deliberately to extract vibrational frequency in no regard to intensity of perceived roughness.

Threshold value h is determined to be 1.5 times of a mean value of $x(t)$ of a certain period. This period is determined to be 200[msec] in a heuristic way.

$c(t)$ expresses a number of impulse emissions for $a[sec]$ from t as (2). a is 200[msec]. $c(t)$ is pulse density.

$$c(t) = \int_{t-a}^{t} p(\tau)d\tau \tag{2}$$

In an ideal condition impulse emission happens two times for each groove on a sample, one emission should be emitted when a sensor enters a groove, the other one should be emitted when a sensor contacts a ridge. The vibrational frequency of a sensor $f(t)$ is (3).

$$f(t) = \frac{c(t)}{2a} \tag{3}$$

Spatial wavelength of the object's surface to touch at t, $\lambda(t)$, is estimated as (4) where $v(t)$ is velocity of sensor's rubbing motion. This estimation of $\lambda(t)$ is important to realize tactile telepresence systems cause communication band width between a slave side and a master side is not always insured in a real environment. Even when $f(t)$ is not transmitted from a slave side in a certain instant, a tactile displya system can determine the vibrational frequency to represent to an operator based on $\lambda(t)$ and the velocity of touch motions.

$$\lambda(t) = \frac{|v(t)|}{f(t)} = \frac{|v(t)|2a}{c(t)} \tag{4}$$

B. Preliminary Evaluation of Wavelength Estimation

Here proposed method for real-time estimation of vibrational frequency is evaluated. In these experiments roughness samples [13] characterized by groove width and ridge width were used (Fig.3).

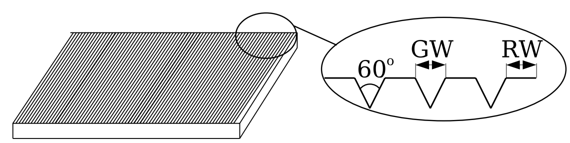


Fig. 3. Roughness sample characterized by groove width and ridge width

All of these experiments were conducted with equipment in Fig.4. A sensor was mounted on a vertical slide table. They were fastened to a single-axis arm.

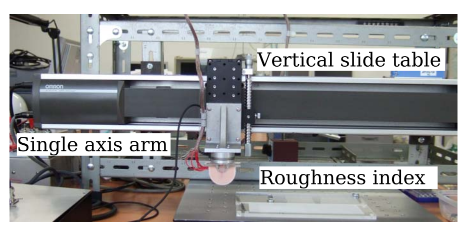


Fig. 4. Experimental equipment

1) Wavelength Discrimination: $\lambda(t)$ are shown in Fig.5 when a sensor rubbed the samples of spatial wavelength 3.0[mm], 2.4[mm], 1.8[mm], 1.2[mm] and 0.6[mm] at a fixed speed of 100[mm/sec] which is a natural speed of human touch. $\lambda(t)$ were estimated based on a vibrational frequency of a tactile sensor $f(t)$ at t. In Fig.5 sampless of different wavelength were discriminated and each of wavelengths was identified unique to some extent. For instance, looking at $\lambda(t)$ of a roughness sample (GW,RW)=(1.5mm,1.5mm) , its wavelength was 3.0[mm] then wavelength of it was not estimated precisely but it is important that different objects can be judged to be different when being touched in a same condition.

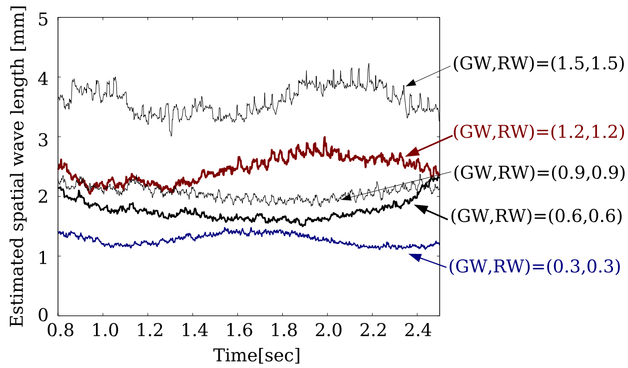


Fig. 5. Estimated spatial wavelengths of roughness samples $\lambda(t)$ when a sensor rubbed them at a fixed speed of 100[mm/sec]

2) Robustness evaluation against vertical displacement: A tactile sensor for a tactile telepresence system has to be robust against the vertical displacement changes to objects to touch or should not be under the influence of reaction force from objects. Fig.6 shows $\lambda(t)$ of roughness samples when the sensor pressed itself to the sampless with vertical displacement d from 0.20[mm] up to 0.80[mm]. As a sensor was just in contact with the object, d was 0[mm]. Reaction force from the object toward the sensor was 0.70[g] when d was 0.2 and when d was 0.8 reaction force was 38.37[g]. Two roughness samples used in this experiment were (GW,RW)=(1.5mm,1.5mm) and (GW,RW)=(0.3mm,0.3mm). In Fig.6 these two samples were judged completely different with different vertical displacements.

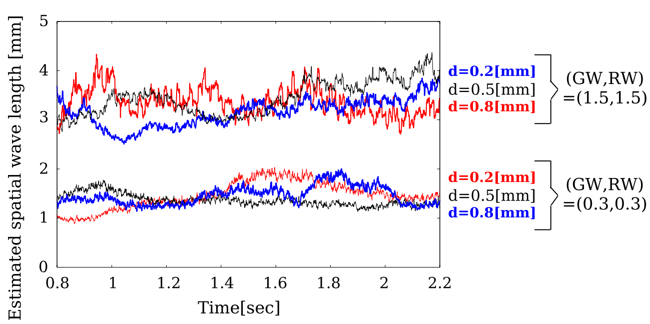


Fig. 6. Estimated spatial wavelength $\lambda(t)$ of two roughness samples with different vertical displacements d

3) Robustness evaluation against velocity change: Tactile sensors for telepresence system must work under active touch, which is natural touch for humans. Changing velocity of touch motion and high time resolution of humans' tactile recognition make it hard to reserve long sampling time for the estimation of $f(t)$. The velocity of a human's natural touch motion is about 1[Hz] and sinusoidal with the max speed of about 100[mm/sec]. $\lambda(t)$ of a roughness sample (GW,RW)=(0.9mm,0.9mm) is shown in Fig.7 where the velocity of rubbing motion was natural one as shown in Fig.7 (a). Fig.7 (b) indicates that $f(t)$ was estimated with time delay of about 100[msec], no matter whether a touch motion was quick or slow. Fig.7 (c) shows $\lambda(t)$ derived by $\lambda(t) = v(t)/f(t)$. $\lambda(t)$ was estimated more precisely when $v(t)$ is quick than slow as well as humans' roughness recognition works.

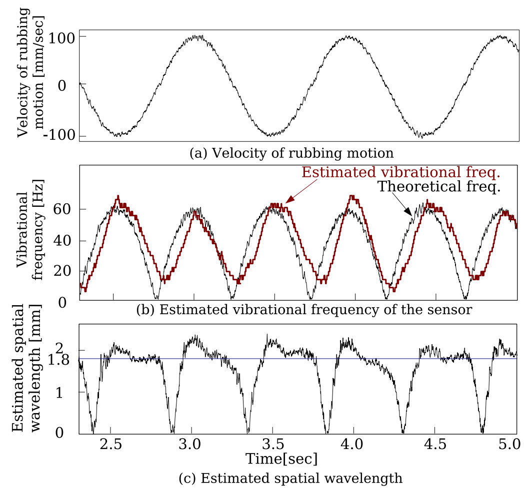


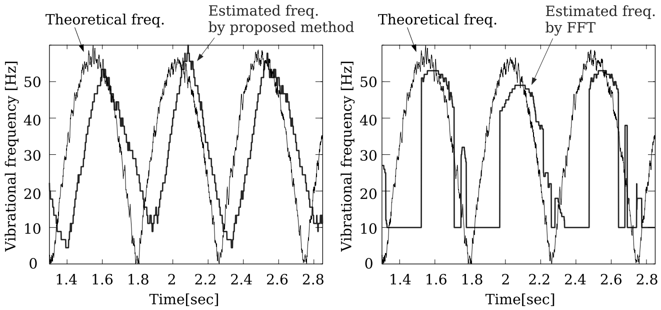
Fig. 7. Wavelength and vibrational frequency estimation under natural touch motion

C. Comparison With STFT for Vibrational Frequency Estimation

STFT is typical of the real-time frequency estimation methods. We also considered to employ STFT but from some experimental results some flaws became clear. Fig.8 shows the estimated frequency of the sensory vibration when a sensor rubbed the sample (GW,RW)=(0.9mm,0.9mm) at a sinusoidal velocity with max speed of 100[mm/sec]. Fig.8 (a) is the estimated frequency by the proposed method, Fig.8 (b) is estimated main frequencies by STFT with the window size of 200[msec]. Both methods could estimate the vibrational frequencies with time delay of about 100[msec]. But the shape of the estimated frequency by the proposed method was more similar to the theoretical vibrational frequency than STFT. Three problems about STFT were found, firstly STFT took time to be computed and estimated frequency could be refreshed about every 10[msec] as the proposed methods could finish the estimation within 1[msec]. Secondly STFT could not successfully extract the main frequencies while the vibrational frequency changed drastically or the rubbing motion was accelerated. Thirdly when a sensory vibrational frequency was low the main frequency was hidden in a lower lobe and could not be separated. STFT has the capability of specifying the set of composed signals though, there is the more preference in the proposed method for reasons above.

D. Vibrational Frequency Estimation by Time Interval Between Impulse Emissions

Fig.9 shows the estimated vibrational frequency, $f_t(t)$, based on the time interval between two impulse emissions.



(a) Estimated freq. by proposed method (b) Estimated freq. by FFT

Fig. 8. Comparison between the proposed method and STFT for vibrational frequency estimation

$f_t(t)$ is computed as (5) where the time interval between two impulse emissions at t is t_v[sec].

$$f_t(t) = \frac{1}{t_v} \tag{5}$$

In Fig.9, there was a flicker in the estimated values, it was noisy. This tells the algorithm from physiological aspects is effective to make estimated vibrational frequency robust.

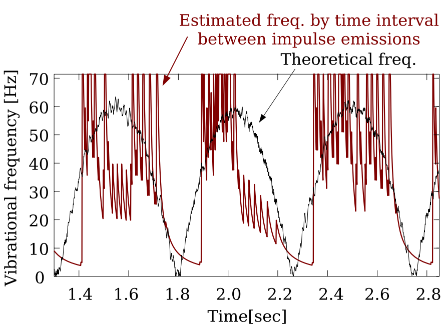


Fig. 9. Estimated vibrational frequency based on the time interval between impulse emissions

IV. Real-time Estimation of Young's Modulus of the Object Using Strain Distribution in a Sensor

In robotics to obtain the Young's modulus of an unknown object, a set of time-series information of relative displacement between a sensor and an object and reaction force from an object is usually required. This method has a few flaws. One is that this method is time-consuming, and another is that this method requires a tactile sensor system to have a sensor apparatus to sense fine relative displacement. It is said that a man recognizes softness of the objects from both of kinesthetic and contact information. Some tactile displays successfully represented softness of objects by changing the contact area between a finger and a display [4] [5]. As the contact area changes, the stress distribution in a finger also changes and a man may utilize it to know softness of objects quickly without time delay. The human finger mimetic tactile sensor employs this way to estimate Young's modulus of objects.

Standard deviation of the five strain gauges' output changes when pressing it onto objects with different Young's modulus [10].

A. Hertz Contact Theory Underlying Real-time Softness Estimation Using Strain Distribution in the Sensor

According to Hertz contact theory, a contact of two spheres of Young's modulus E_f and E_o generates a circular contact area A. Relative displacement of the two spheres are w_f and w_o, a radius of two spheres is R, then (6) describes A.

$$A = \pi R(w_f + w_o) \tag{6}$$

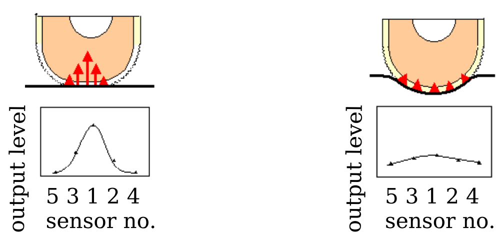
The relationship between relative displacements and Young's modulus is (7).

$$w_o = w_f \frac{E_f}{E_o} \tag{7}$$

By combining (6) and (7), we get (8).

$$\frac{A}{w_f} = \pi R\left(1 + \frac{E_f}{E_o}\right) \tag{8}$$

Human finger mimetic tactile sensor cannot obtain the contact area A and relative displacement w_f directly, but the numerical trend of w_f/A resembles it of the standard deviation of the output of five strain gauges. Fig.10 illustrates the contact between a sensor and a soft object and a hard object. As the Young's modulus of an object to touch E_o is larger, the contact area A is smaller and the standard deviation becomes larger. As E_o is smaller, A is large and the standard deviation becomes smaller. Thus the standard deviation of sensory output can be used to estimate the Young's modulus of objects.



(a) Contact with a hard object (b) Contact with a soft object

Fig. 10. Distribution of reaction force and contact area of the sensor on contacting with a hard and a soft object

B. Experimental Data Underlying Real-time Softness Estimation and Formulation

Fig.11 (a) is the plots of the standard deviation of five strain gauges' output and the reaction force applied to the sensor when a sensor pressed three softness samples, and Fig.11 (b) is a replot of (a) and it shows a relationship between the standard deviation and Young's modulus. Three silicon rubber objects with different Young's modulus were 0.72[MPa], 0.51[MPa] and 0.089[MPa] softness samples. Fig.11 (a) shows the softness of three samples were discriminated by the standard deviation in a reaction force range up to about 100[gf]. Fig.11

(a)(b) implies that the standard deviation of the five strain gauges' output ,S_d, were primarily affected by the reaction force from the object ,f, and Young's modulus of the objects ,E. A regression curve of S_d involving f and E is (9). Young's modulus of the object is estimated by (10).

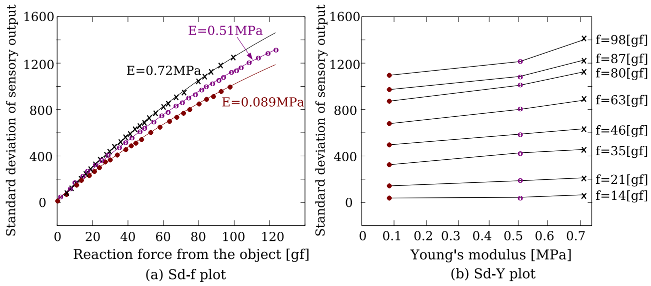


Fig. 11. Experimental results plots between standard deviation of the five strain gauges' output, reaction force from the object and Young's modulus of the objects

$$S_d = -0.0314f^2 + 14.5f + 87.2E^2 + 104.5E - 81.9 \quad (9)$$

$$E = \sqrt{0.0115S_d + 0.00036f^2 - 0.166f + 1.3} - 0.6 \quad (10)$$

V. Conclusion

We could successfully estimated the three tactile factors which are needed to regenerate tactile sensation using tactile display for a tactile telepresence system, just by one sensor apparatus. The vibrational frequency of stimulus was estimated by mimicking Meissner's corpuscles' firing and other related physiological aspects. This proposed methods performed real-time estimation of the object's spatial wavelength. Young's modulus of the objects were estimated instantly by the method considering human's softness recognition using strain distribution in a sensor. Friction occurring with touch can be sensed by a torque sensor as a conventional robotic solution. We are going to work on the realization of a tactile telepresence system with various tactile sensation feedback.

References

[1] R. D. Howe, W. J. Peine, D. A. kontarinis and J. S. Son, "Remote Palpation Technology", IEEE Engineering in Medicine and Biology, 1995

[2] P.Dario and M.Bergmasco, "An advanced robot system for automated diagnostic tasks through palpation", IEEE Trans. on Biomedical Engineering, Vol.35, Issue 2, Feb. 1988, 118-126

[3] Akio Yamamoto, Shuichi Nagasawa, Hiroaki Yamamoto, and Toshiro Higuchi, "Electrostatic Tactile Display with Thin Film Slider and Its Application to Tactile Tele-Presentation Systems", IEEE Transactions on Visualization & Computer Graphics, Vol. 12, No. 2, pp.168-177, 2006

[4] Antonio Bicchi, Enzo P. Schilingo and Danilo De Rossi, "Haptic Discrimination of Softness in Teleoperation: The Role of the Contact Area Spread Rate", IEEE Trans. on Robotics And Automation, Vol.16, No.5, 2000

[5] Kinya Fujita and Yoshiaki Ikeda, "Remote haptic sharing of elastic soft objects", The First Joint Eurohaptics Conference and Symposium on Haptic Interface for Virtual Environment and Teleoperator Systems, 2005

[6] Marc R. Tremblay and Mark R. Cutkosky, "Estimating Friction Using Incipient Slip Sensing During a Manipulation Task", Proceedings of the IEEE International Conference on Robotics and Automation, pp. 363-368, 1993

[7] H. Kawaguchi, T. Someya, T. Sekitani and T. Sakurai, "Cut-and-Paste Customization of Organic FET Integrated Circuit and Its Application to Electronic Artificial Skin", IEEE Journal of Solid-State Circuits, Vol.40, No.1, 2005

[8] Hirokazu Shirado, Takashi Maeno, "Modeling of Texture Perception for Tactile Displays and Sensors", The First Joint Eurohaptics Conference and Symposium on Haptic Interface for Virtual Environment and Teleoperator Systems, 2005

[9] M. Konyo, A. Yoshida, S. Tadokoro and N. Saiwaki, "A Tactile Synthesis Method Using Multiple Frequency Vibrations for Representing Virtual Touch", IEEE/RSJ International Conference on Intelligent Robots and Systems, 2005

[10] Y. Mukaibo, H. Shirado, M. Konyo and T. Maeno, "Development of a Texture Sensor Emulating the Tissue Structure and Perceptual Mechanism of Human Fingers", Proceedings of the 2005 IEEE International Conference on Robotics and Automation, 2005

[11] M.Ohka, T.Kawahara, T.Itahashi, J.Takayanagi, T.Miyaoka and Y.Mitsuya, "A Tactile Recognition System Mimicking Human Mechanism for Recognizing Surface Roughness", JSME international Journal, Series C, Vol. 48, No.2, 2005

[12] Mohamed Benali-Khoudja, Moustapha Hafez, Jean-Marc Alexandre and Abderrahmane Kheddar, "Tactile interfaces: a state-of-the-art survey", 35th International Symposium on Robotics, 2004

[13] Takashi Yoshioka, Barbara Gibb, Andrew K. Dorsch, Steven S. Hsiao and Kenneth O. Johnson, "Neural Coding Mechanisms Underlying Perceived Roughness of Finely Textured Surfaces", The Journal of Neuroscience, 21(17):6905-6916, 2001