35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Smart Sensing of Tool/Tissue Interaction by Resistive Coupling

Shunsuke Yoshimoto[1] Yoshihiro Kuroda[1] Masataka Imura[1] Osamu Oshiro[1] and Kosuke Sato[1]

***Abstract*— A smart sensing of tool-tissue interaction is required to monitor the surgical task without disturbing the tool manipulation. We proposed a new tactile sensing method that enables us to detect the tool-tissue interaction with a simple hardware by resistive coupling. The system consists of two electrodes, a bridge circuit and a differential amplifier for the robust sensing of the contact resistance between the tool and tissue. In order to evaluate the sensing method, we investigated the relationship between the sensor output and the deformation of a wet sponge sample by retraction task. According to the model fitting of the deformation-output profile, we concluded that the proposed sensor provide enough reproducibility in the simple situation. Furthermore, we confirmed that the developed sensor works with a biological sample.**

I. Introduction

Sensing interaction between the tool and tissue is one of the fundamental topics for tactile navigation in a surgical operation. Still, there are a lot of challenging issues in the tactile sensing for a surgical condition because the condition imposes many constraints of the sensor, e.g. size, endurance and sensitivity. In generally, the force, stress and deformation stored in the tool or tissue are considered to capture important information about the surgical state for the design of feedback stimulus. Since these physical quantities come from two objects, tool and tissue, it is difficult to monitor the signals without any mechanical limitations of manipulation.

A lot of tactile sensors have been developed in order to overcome these difficulties. Most common approach to detect the interaction without hindering operation is to mount a miniaturized sensor on the instrument [1], [2], [3]. For example, load cells, strain gauges and piezoresistive sensors are utilized for the sensing of the tool/tissue interaction [4], [5]. Optical sensing is also an effective method to detect a small force [6]. Although these technologies are effective in terms of robust sensing, the fabrication and attaching process are complicated. Camera based sensing is a good solution for these problems, however we need any spatial assumptions to detect information about tool/tissue interaction.

In order to monitor the manipulation of the various tools during an operation, a demountable and generalized sensor is useful. Furthermore, the sensor should not impose any mechanical constraints. The purpose of this research is to achieve such a "smart" sensing of the tool/tissue interaction. To this end, we propose a new sensing technology based on the measurement of electrical contact impedance. With the proposed sensing technology, we only have to connect the sensor electrically to the instrument and tissue to build a sensing system. The future monitoring apparatus of the surgery that is provided with our sensing technology is illustrated in Fig. 1.

[1]S. Yoshimoto, Y. Kuroda, M. Imura, O. Oshiro and K. Sato are with the Graduate School of Engineering Science, Osaka University, {yoshimoto|sato}@sys.es.osaka-u.ac.jp, {ykuroda|imura|oshiro}@bpe.es.osaka-u.ac.jp

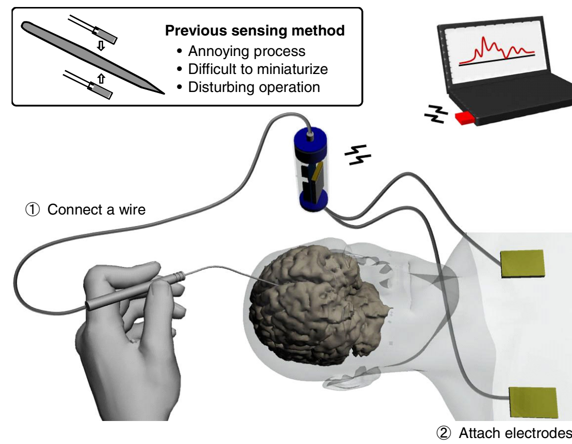


Fig. 1. The goal of this research: We can detect the tool/tissue interaction by connecting wires. The sensor can be attached to various surgical tools.

The proposed sensing method is inspired by our previous work about touch sensing [7]. According to the contact mechanics, contact area is related to the applied force. On the other hand, electrical impedance is inversely proportional to the contact area. Therefore, if the contact impedance is obtained, we can estimate the tool/tissue interaction. Since biological tissue and metal tool are conductors, we can detect the contact impedance by designing a measurement circuit. In this paper, we assume a simple situation of the tool/tissue interaction as a preliminary implementation.

II. Detecting Tool/Tissue Interaction

Our goal is to estimate tissue's behaviors or user's actions by using touch information. The electrical contact impedance between tool and tissue will be sensed and processed for the estimation. In this section, we explain the relationships between the contact impedance and tissue's behavior based on electromechanical property of the tissue. Furthermore we propose a robust sensing circuit of the contact impedance.

A. Electromechanical Property of Tissue

Tissue has two important material property, the elasticity and the conductivity. As for the elasticity, the contact area between rigid body and elastic body is related to the deformation of the elastic object or applied force to the object. According to contact mechanics, the deformation can be represented by a power function of the contact area.

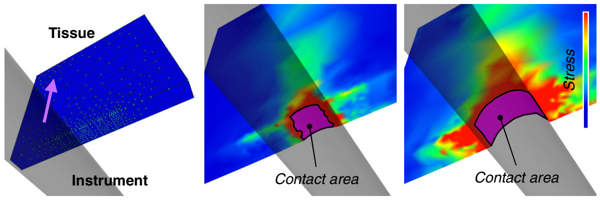


Fig. 2. Analytical understandings: The contact area changes according to the initial contact orientation and the applied force.

However, it is very difficult to build a theoretical model for these phenomenon because the contact state depends on a lot of mechanical conditions, e.g. object shape, contact form and surrounding material. In order to explain the relationship between contact area and applied force, we assume simple shapes of tool and tissue. Fig. 2 shows the analytical diagrams of the interaction between a rectangle tissue and a cylindrical instrument. The contact area increases rapidly when the collision is occurred. Then, the area increases according to the applied force. Briefly, the response of the area shows two characteristic phases, initial contact and force application phase. Therefore, we presume that monitoring contact area enables us to estimate not only the applied force but also the contact orientation.

When the instrument collides with the tissue, an electrical connection will be formed between them. The contact area can be calculated by using the contact impedance because the impedance is inversely proportional to sectional area. Thanks for its low impedance, the electricity flows inside of the tissue. For example, the resistance of the skin surface is $\sim$ 1 MΩ, while the resistance of the internal tissue is $\sim$ 100 Ω [8]. Therefore, we can measure the contact impedance by connecting a signal source to the tissue, i.e. resistive or capacitive coupling [9], [10]. Although the capacitance changes according the contact area, the change is relatively small compare to the resistance. Therefore, we focus on the resistive coupling rather than traditional capacitive coupling.

B. Contact Resistance Measurement

The contact resistance can be measured by forming a closed loop circuit which consists of tissue resistance, contact resistance and a DC power source. However the objective signal is affected easily by the environmental noise. To solve this problem, we utilize a Wheatstone bridge including external 2 MΩ resistances with DC power source and a differential circuit. The most part of the environmental noise can be canceled out by taking difference of the outputs from the bridge circuit. Fig. 3 shows the architecture of the proposed sensing system.

When a grounded instrument collides with the tissue, a closed circuit will be formed. Then, the voltage dividing of the bridge circuit changes according to the contact impedance. As previously mentioned, the contact impedance is related to the applied force. Therefore, we can know how much strongly user is applying the force to the tissue by using the proposed circuit. Note that the circuit works when

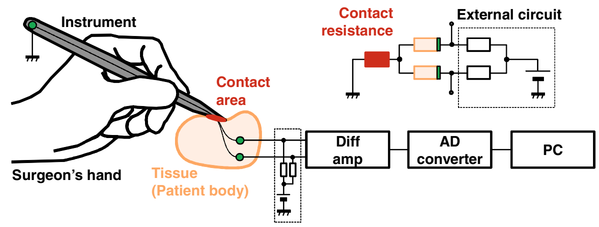


Fig. 3. System overview: The system consists of electrodes, an external bridge circuit, a deferential amplifier and an AD converter. The sensing circuit is considered to work as a Wheatstone bridge by assuming an equivalent circuit of tissue.

the bridge is not in the equilibrium condition. Namely, the amount of perturbation is utilized to control the sensitivity.

The proposed system seems to offer great flexibility of the attaching process. Users only have to connect two electrodes to the tissue (patient's body) and one ground wire to the instrument. Since most surgical tool is a conductor, we can utilize the system for the various instruments. Additionally, a surgeon can bend the instrument to accomplish a complicated operation even though the sensor is mounted on.

III. Assessing Sensor Performance

In order to evaluate the proposed sensing method, three simple experiments are conducted. First, the accuracy and reproducibility are tested by using a phantom material. Next, possible classification of the manipulation are investigated based on the sensor output. Finally, the sensor performance for the tissue sample is confirmed.

A. Experimental Setup

We investigate the relationship between sensor output and object deformation instead of the applied force because the deformation can be detected easily by using a camera based sensing. The experimental setup is shown in Fig. 4. We assumed manipulation by using a suction tube and utilized a stainless tube of 2.5 mm in diameter. In order to measure the deformation of the object, a retro-reflective marker was

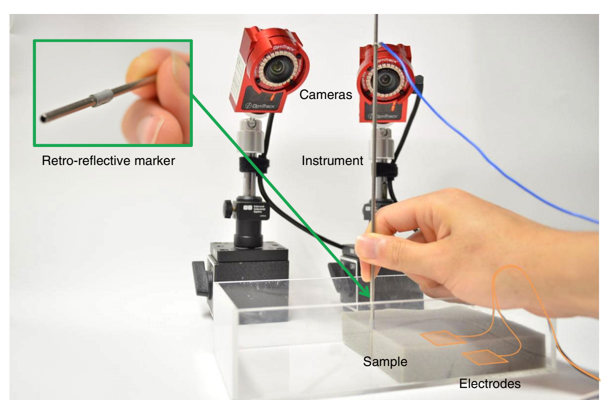


Fig. 4. Experimental setup: One grounding electrode is connected to the tube while two sensing electrodes are connected to the object. The two camera are utilized to detect the deformation of the object.

pasted around the tip of the tool. We constructed a three-dimensional tracking system to estimate the deformation by using two infrared camera (FLEX V100R2, OptiTrack). The camera resolution was 640×480, while the sampling rate was 100 Hz. The tracker accuracy was around 0.1 mm. As for the sensor output, we collected data by using an AD module (Interface Co., LPC-361316). The sampling frequency of the AD input was 10 kHz. The sample material located on 20×20 mm^2 electrodes was fixed by using a plastic tray.

B. Accuracy and Reproducibility

The purpose of this experiment is to know how precisely and reproducibly can we estimate the deformation by using the proposed sensor. To the end, we recorded the deformation of the object and sensor output during the manipulation. The accuracy and reproducibility of the sensing are investigated by a model fitting. We collected data during the retraction task of a sponge material. Some water were transfused to the sample in order to mimic a simple surgical situation. Although the distribution of the fluid changes slightly according to the manipulation, the condition is similar to the surgical situation. Therefore, it is worth to know the performance with this challenging condition. A user pulled and released carefully one side of the material with the tube in 1 second. This task was repeated 10 times.

The response of the sensor output and deformation are shown in Fig. 5. The sensor output increases rapidly when the tool collides to the object. After the initial contact phase, the output changes gradually according to the applied force (manipulation phase). Since the deformation of the retracted tissue is less than several centimeters in such a neurosurgery, the proposed sensor provides enough maximum range. The relationship between the deformation and the sensor output is shown in Fig. 6. We define the accuracy and reproducibility of the sensor as root-mean-square error of the obtained profile and its variance respectively. According to the model fitting, a correlation between the deformation and sensor output was confirmed above 3 mm deformation. The data in the manipulation phase were utilized for the data analysis to evaluate the sensor performance. In this experiment, the fitting error was 0.57 mm while the variance was 0.032 mm. These results seem to show a sufficient good performance for the surgical task in terms of output fluctuation.

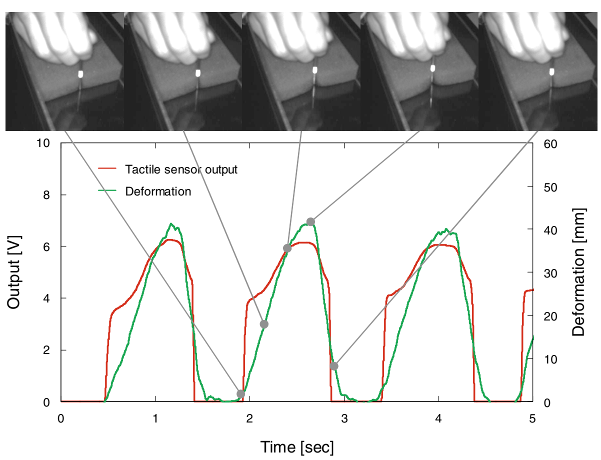


Fig. 5. Recorded sensor output and deformation: One can see the output value changes according to the deformation.

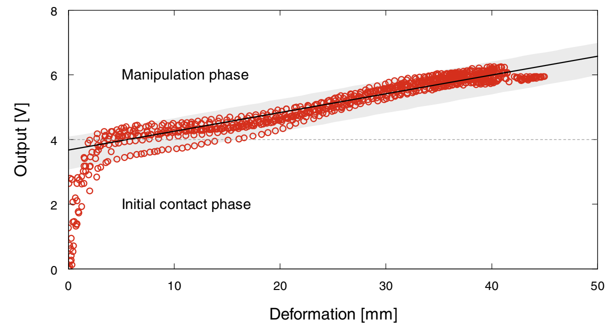
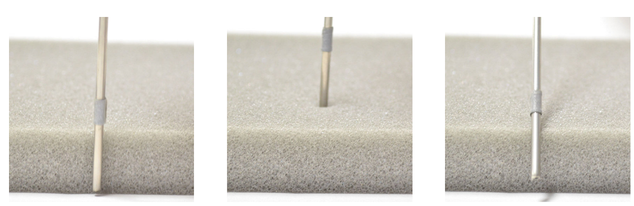


Fig. 6. Deformation-output profile: Down sampled data and fitted line and maximum error range are shown in this graph. A good correlation was confirmed between the deformation and the output.

C. Contact Orientation Effect

As we described above, the deformation-output profile is determined according to the contact conditions, i.e. user's actions. In order to investigate the effect of user's action, we compare the profiles in three different actions. If the differences of the model parameters are indicated, we can utilize the parameters to recognize the user's actions. In this experiment, three types of contact conditions were selected as shown in Fig. 7. Each tasks were executed 10 times in the same manner as the previous experiment.

The deformation-output profiles with fitting curves are illustrated in Fig. 8. In order to obtain the initial contact amount and sensor gain, i.e. intercept and gradient coefficients, we utilized the data in the manipulation phase for the fitting analysis. The manipulation phase was detected by a thresholding operation. The resulting intercept and gradient coefficients are shown in Fig. 9. According to one-way ANOVA , the intercept and gradient coefficients were significantly different ($F(1, 28) = 12$, $p < 0.01$ and $F(1, 28) = 192$, $p < 0.01$ respectively). Therefore, the result indicates that we can categorize these user's actions by using the sensor output. Furthermore, a Tukey test revealed that the two parameters were significantly different between the user's actions, except the intercept coefficients between pushing and pressing ($p < 0.05$).



(a) (b) (c)

Fig. 7. Contact conditions: (a) Retracting. (b) Pushing. (c) Pressing.

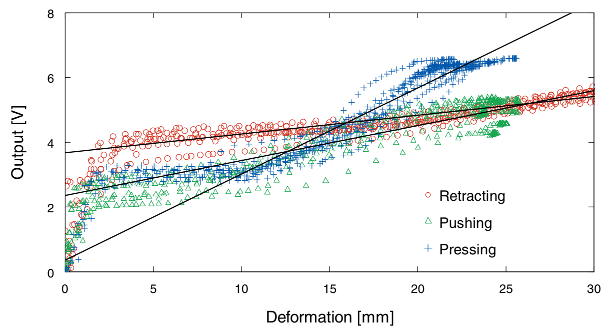
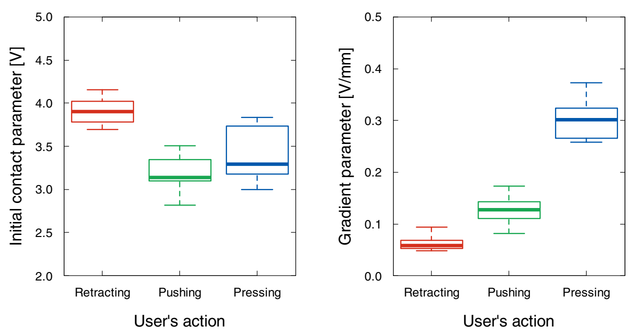


Fig. 8. Deformation-output profiles of the three different contact conditions: The sensor outputs increase rapidly in the initial contact phase while the outputs increase gradually in the manipulation phase.



(a) (b)

Fig. 9. Parameter comparisons: (a) Initial contact parameters, (b) Gradient parameters. The box marks the IQR, the center line marks the median and the whiskers mark the range up to 1.5 times the IQR.

D. Performance with Tissue Sample

Our goal is to apply the proposed sensing technology for the tool-tissue interaction during a surgery. As a simple evaluation, we recorded the sensor output and the tool position during the retraction of a biological sample. A pork tissue whose resistance is similar to the human tissue was utilized as a biological sample in this experiment. Fig. 10 shows the resulting tool position with the sensor output during the manipulation. One can see the sensor output changes according to the tool position, i.e. object deformation. However, the output saturates rapidly because the contact resistance between a tool and a tissue is considerably smaller than that of tool-sponge interaction. To improve the sensor performance on the tissue manipulation, we need to select carefully the bridge resistances according to the conductivity of the object.

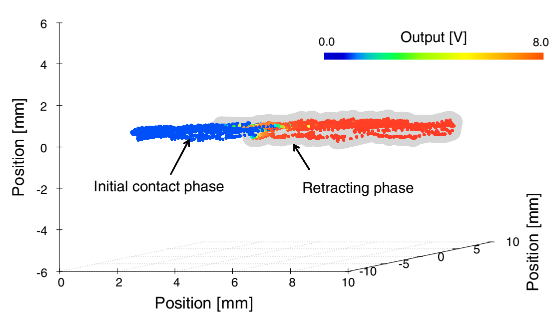


Fig. 10. Result of the tissue manipulation: The tool position is plotted in the three dimensional space. The color of the points represents sensor output.

IV. Conclusion

We proposed a new sensing technology to detect tool-tissue interaction with a simple hardware setup. The strategy of the sensing is based on the resistive coupling between the tool and tissue. We tested the proposed sensing method with retraction tasks of a sponge material. The observed deformation-output profile indicated that the proposed sensor has good accuracy and reproducibility. Furthermore, we confirmed the possibility of task recognition by comparing the sensor profiles of three different conditions. Although we need to optimize the bridge resistance according to object's conductivity, we concluded that the proposed sensing method has a potential to detect the tool-tissue interaction. As the future work, the sensor will be tested in more complicated surgical situation including bloods, biological fluids and other electrical devices with various surgical tools.

Acknowledgment

This work was supported in part by Grant-in-Aid for JSPS Fellows (23-2192) in Japan.

References

[1] J. Rosen, B. Hannaford, C.G. Richards, and M.N. Sinanan: Markov Modeling of Minimally Invasive Surgery based on Tool/Tissue Interaction and Force/Torque Signatures for Evaluating Surgical Skills. *IEEE Transactions on Biomedical Engineering*, Vol.48, No.5, pp.579-591, 2001.

[2] M.I. Tiwana, S.J. Redmond, and N.H. Lovell: A Review of Tactile Sensing Technologies with Applications in Biomedical Engineering. *Sensors and Actuators A: Physical*, Vol.179, pp.17-31, 2012.

[3] P. Puangmali, K. Althoefer, L.D. Seneviratne, D. Murphy, and P. Dasgupta: State-of-the-Art in Force and Tactile Sensing for Minimally Invasive Surgery. *IEEE Sensor Journal*, Vol.8, No.4, pp.371-381, 2008.

[4] I. Brouwer, J. Ustin, L. Bentley, A. Sherman, N. Dhruv, and F. Tendick, Measuring In Vivo Animal Soft Tissue Properties for Haptic Modeling in Surgical Simulation. *Medicine Meets Virtual Reality*, Vol.9, pp.69-74, 2001.

[5] M.C. Yip, S.G. Yuen, and R.D. Howe: A Robust Uniaxial Force Sensor for Minimally Invasive Surgery. *IEEE Transactions on Biomedical Engineering*, Vol.57, No.5, pp.1008-1011, 2010.

[6] J. Peirs, J. Clijnen, D. Reynaerts, H.V. Brussel, P. Herijgers, B. Corteville, and S. Boone: A Micro Optical Force Sensor for Force Feedback during Minimally Invasive Robotic Surgery. *Sensors and Actuators A: Physical*, Vol.115, No. 2, pp.447-455, 2004.

[7] S. Yoshimoto, Y. Kuroda, M. Imura, O. Oshiro: Spatially Transparent Tactile Sensor by using Electromechanical Property of Skin. *Advanced Biomedical Engineering*, Vol.1, 2013 (to appear).

[8] K.R. Foster, and H.P. Schwan: Dielectric Properties of Tissues and Biological Materials: a Critical Review. *Critical Reviews in Biomedical Engineering*, Vol.17, No.1, pp. 25-104, 1989.

[9] T. Baba, T. Ushiama, and K. Tomimatsu: Freqtric Drums: A Musical Instrument that uses Skin Contact as an Interface. In *Proceedings of the 7th international Conference on New Interfaces for Musical Expression*, pp.386-387, 2007.

[10] M. Sato, I. Poupyrev, C. Harrison: Touché: Enhancing Touch Interaction on Humans, Screens, Liquids, and Everyday Objects. In *Proceedings of the 2012 ACM annual conference on human factors in computing systems*, Austin, pp.483-492, 2012.