2014 IEEE International Conference on Robotics & Automation (ICRA)
Hong Kong Convention and Exhibition Center
May 31 - June 7, 2014. Hong Kong, China

Autonomous Penetration Detection for Bone Cutting Tool Using Demonstration-based Learning

Takayuki Osa[1], Christian Farid Abawi[2], Naohiko Sugita[1],
Hirotaka Chikuda[3], Shurei Sugita[3], Hideya Ito[3], Toru Moro[3], Yoshio Takatori[3], Sakae Tanaka[3]
and Mamoru Mitsuishi[1]

***Abstract*— In orthopedic surgery, bone-cutting procedures are frequently performed. However, bone-cutting procedures are very risky in cases where vital organs or nerves exist beneath the target bones. In such cases, surgeons are required to determine the depth of the penetration into the bone by using only their haptic senses. Thus, we developed a hand-held bone-cutting-tool system that detects the penetration of the cutting material. The developed system autonomously detects the penetration before total penetration and stops the actuation of the cutting tool, leaving a very thin remnant of work material. The developed system estimates the cutting resistance by using its motor's current and rotational speed. On the basis of data collected preoperatively, the system estimates the cutting state by using a support vector machine (SVM). According to the SVM outputs, the system detects the penetration of the work material and autonomously stops the actuation of the cutting tool. The proposed method was verified through experiments, and the results showed that the developed system successfully detected the penetrations of work materials and stopped autonomously immediately before total penetration. This study showed that the autonomous detection of bone penetration with a hand-held bone-cutting tool is feasible by using the proposed scheme.**

I. INTRODUCTION

Cutting and drilling bones are very common procedures in orthopedic surgery. However, bone-cutting procedures can be very risky in some cases where vital organs or nerves exist beneath the target bones. In such cases, surgeons are required to determine the depth of the penetration into the bone by using only their haptic senses. For example, in spine surgery, some parts of the spine are eliminated to release the pressure on spinal cord nerves. In this procedure, a surgeon needs to make holes in the spine by using bone-cutting tools to break off the target bones (see Fig. 1). When penetrating the bone using a cutting tool, the surgeon is required to recognize the extent of total penetration (Fig. 2). This recognition requires that a surgeon have skill and experience, and the procedure can be time-consuming and fatiguing. Therefore, if the bone-cutting tool could autonomously detect the penetration of the bone and stop autonomously, the system would improve the safety of bone-cutting procedures and reduce the physical and mental fatigue to surgeons.

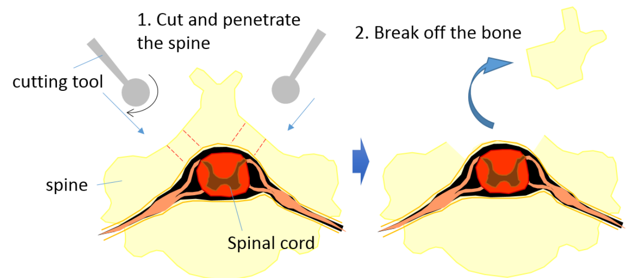


Fig. 1. Example of procedure for spinal surgery. Surgeons cut and penetrate the spine, and the target part of the spine is broken off.

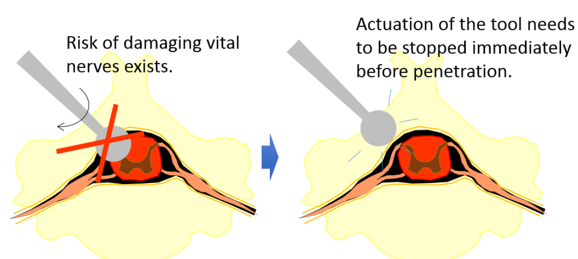


Fig. 2. In spinal surgery, surgeons need to recognize bone penetration and stop cutting immediately afterward. Otherwise, vital nerves under the spine would be damaged.

To improve the safety of cutting and drilling bones in orthopedic surgery, several schemes to detect the penetration of bones have been proposed [1], [2], [3], [4]. These studies proposed penetration detection schemes for robotic surgery using a robotic manipulator. However, at present, most orthopedic surgery operations are performed by surgeons using a hand-held tool system. Therefore, a penetration detection scheme for a hand-held bone-cutting tool could be more practical and useful in actual clinical use.

In this study, we developed a hand-held bone-cutting-tool system that detects the penetration of a work material and autonomously stops its actuation (Fig. 3). The developed system estimates the cutting resistance online by using the

*This work was supported in part by the Global COE Program, Global Center of Excellence for Mechanical Systems Innovation by the Ministry of Education, Culture, Sports, Science and Technology, Grant-in-Aid for Scientific Research(S) 23226006, Grant-in-Aid for JSPS fellows Number 25-7106, and Japan Ministry Internal Affairs and Communications, Strategic Information and Communication R&D Promotion Programme 121803005.

[1]T. Osa, N. Sugita and M. Mitsuishi are with Department of Mechanical Engineering, The University of Tokyo, 113-8656 Tokyo, Japan osa|sugi|mamoru@nml.t.u-tokyo.ac.jp
[2]C. F. Abawi is with Fraunhofer Institute for Manufacturing Engineering and Automation, Stuttgart, Germany christian.abawi@gmail.com
[3]H. Chikuda, H. Itou, T. Moro, S. Sugita, Y. Takatori and S. Tanaka are with The University of Tokyo Hospital, Tokyo, Japan

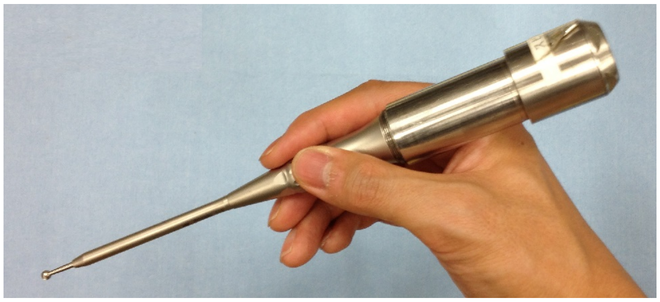


Fig. 3. Bone-cutting tool (Nakanishi Inc., Japan). The autonomous penetration detection was implemented on its controller.

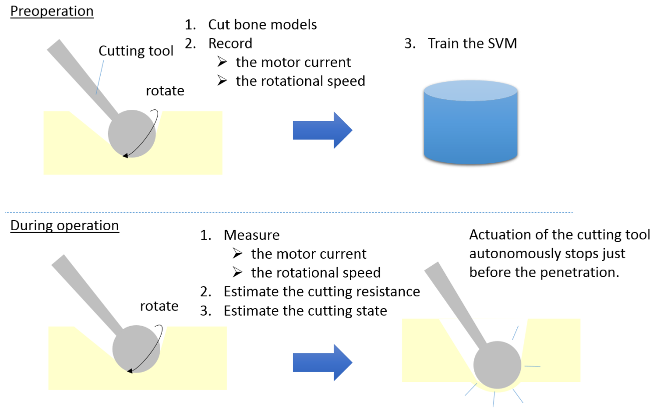


Fig. 4. Procedure of developed system.

motor current and rotational speed of the cutting tool. To detect the penetration of the work material, a demonstration-based learning approach was employed. Specifically, the developed system estimates the cutting resistance online by using a recursive least square (RLS) method; it estimates the cutting states by using a support vector machine (SVM). According to the SVM outputs, the system detects the penetration of the work material online. The proposed control scheme was implemented on a bone-cutting-tool system that is in clinical use. By exploiting the elasticity of bones, the developed system detects their penetration immediately before total penetration. Although we used a round fluted bur in this study, the proposed scheme can be easily applied to bone-cutting tools with other shapes, such as drills and saws. In addition, the proposed scheme can be applied to cutting processes other than orthopedic surgery.

This paper is structured as follows. The next section describes the related studies. Section III gives an overview of the proposed method and the details of the proposed algorithm. Section IV describes experiments that were conducted to evaluate the developed system. Finally, the last section describes the conclusions of this study and outlines the future work.

II. Related Studies

Several studies have been reported on detecting the penetration of bones in orthopedic surgery. Allotta et al. proposed a scheme to detect the bone penetration in robotic orthopedic surgery [1]. They acquired a profile of the thrust force and used the thrust force and its derivative for penetration detection. Ong et al. proposed a method to detect the penetration of bones in drilling performed by using the thrust force [2]. They employed a Kalman filter to make the system robust against the fluctuation of the measured force, and the method was verified using a motorized setup. Ping-Liang et al. developed a system to detect that a cutting tool had finished cutting through a bone for robotic artificial knee joint replacement [3]. Their scheme was developed for bilateral force control by using a master-slave system. Hu et al. developed a robotic spinal surgical system with drilling state recognition [4]. Their system recognized the drilling state on the basis of the measured force and detected the penetration of bones.

In these studies, the use of the thrust force for detecting the bone penetration was very common. However, the thrust force fluctuates according to the motion of the cutting tool. Thus, it was expected that using the thrust force of the cutting tool would be inefficient for detecting the penetration with a hand-held cutting tool. Therefore, we used the motor current and rotational speed of the cutting tool to estimate the cutting state.

In addition, previous studies used some thresholds to detect the change in the state. However, the determination of these thresholds can be heuristic and time-consuming. Therefore, we employed a demonstration-based learning approach to detect the penetration. The developed system estimates the cutting state by using an SVM that can be trained without excessive effort by using recorded data.

III. Method

A. Overview of Proposed Method

The procedure of the developed system is summerized in Fig. 4. Preoperatively, it is necessary to collect data for training an SVM to estimate the cutting state. The motor current and rotational speed of the cutting tool and the cutting resistance have to be recorded in this step. The developed system estimates the cutting resistance online by using RLS. By using the recorded data, the SVM are trained to estimate the cutting states. The system intraoperatively measures the motor current and rotational speed of the cutting tool and estimates the cutting resistance. We use these values as the input feature vector of the SVM. Thereafter, the state of the bone cutting is estimated by using the SVM, and the actuation of the bone-cutting tool is controlled accordingly.

In this framework, it was not necessary to attach additional sensors to the cutting tool, which made the developed system as simple as possible. However, this framework can easily be extended for a multisensor system by expanding the input of the SVM. By using this demonstration-based learning approach, the system can easily learn a nonlinear decision boundary for detecting the penetration of a work material.

Fig. 5. Round fluted bur PDS-2CM-40 (Nakanishi Inc.). The diameter of the cutting edge is 4 mm.

B. System Setup

We developed a bone-cutting-tool system based on a bone-cutting-tool system provided by Nakanishi Inc., Japan. In this study, we used a round fluted bur PDS-2CM-40 (Nakanishi Inc., Japan) as a cutting tool (Fig. 5). We employed this cutting tool because it is widely used clinically. The control unit of the cutting tool, Primado NE151 (Nakanishi Inc., Japan), was customized to achieve remote control from an externally connected computer. The control unit communicates with an externally connected computer using serial communication and sends the motor current and rotational speed of the cutting tool to the computer every 50 ms. The algorithm to estimate the cutting resistance and cutting state is implemented in the externally connected computer. When the computer detects the penetration, it sends a signal to the control unit to stop the cutting tool.

C. Estimation of Cutting Resistance

The following linear expression was used to estimate the cutting resistance:

$$I = k \cdot N \tag{1}$$

where I is the motor current of the cutting tool, k is the cutting resistance and N is the rotational speed of the cutting tool. To estimate the cutting resistance, we employed RLS. Although the measured raw data of the motor current and the rotational speed of the cutting tool are noisy, using RLS for the estimation enabled us to estimate the cutting resistance robustly against white noises.

In the literature dealing with haptic exploration, methods to estimate contact impedance have been extensively investigated [5], [6], [7], [8]. In these studies, the use of RLS is very common. The problem of estimating the coefficients can be expressed in the following equation:

$$d = W^T u \tag{2}$$

where d is the output value, u is the input vector, and W is the vector of the coefficients that need to be estimated In RLS, the following equations are computed recursively.

$$\begin{aligned} K_n &= \frac{P_{n-1} u_n}{\lambda + u_n^T P_{n-1} u_n} \\ W_n &= W_{n-1} + K_n \left(d_n - u_n^T W_{n-1} \right) \\ P_n &= \frac{1}{\lambda} \left(I - K_n u_n^T \right) P_{n-1} \end{aligned} \tag{3}$$

where u_n is the nth measurement of the input vector, d_n is the nth measurement of the output value, and W_n represents the coefficients estimated at the nth step. In our system, we set the following:

$$\begin{aligned} d &= I \\ u &= N \end{aligned} \tag{4}$$

With this setting, W_n is regarded as the estimated cutting resistance. Therefore, we obtain the estimated cutting resistance as:

$$\hat{k} = W_n \tag{5}$$

where K_n and P_n are intervening variables, and P_1 is initialized as an identity matrix. In (3), λ is a forgetting factor. If we set the forgetting factor lower, we can use larger weights for a newer measurement. In our system, we set the forgetting factor to $\lambda = 0.9$.

D. Recognition of Penetration

We employed an SVM to estimate the cutting state [9], [10]. The SVM was trained to output one of two labels, namely, “cutting” and “not cutting”. The SVM outputs “cutting” when the cutting tool cuts materials, and the SVM outputs “not cutting” when the cutting tool is actuated but nothing is being cut. To allow an inseparable training data set, we employed a C-SVM for our system [10]. The nonlinear decision boundaries can be learned using the SVM with a kernel trick [11]. In the developed system, we employed a radial basis function $k(x_i, x_j)$ as a kernel function. This radial basis function is expressed as follows:

$$k\left(x_i, x_j\right) = exp\left(-\gamma \left\| x_i - x_j \right\|^2\right) \tag{6}$$

To estimate whether or not the cutting tool is cutting a material, we used the motor current and rotational speed of the cutting tool, along with the estimated cutting resistance. Therefore, we set the input feature vector of the SVM as $x = [I, N, \hat{k}]^T$, where I is the motor current, N is the rotational speed, and $\hat{k}$ is the estimated cutting resistance.

The proposed scheme to detect the bone penetration and control the cutting tool is summarized in Algorithm 1. The SVM estimates the cutting state at every sampling time. The system counts the cutting duration for the work material, and when the SVM outputs “not cutting” after a certain period of cutting, the system determines that the cutting tool has penetrated the work material. In this scheme, the SVM needs to estimate only whether or not the cutting tool is cutting something. Therefore, the stiffness of the work material used for the training data does not significantly affect the performance of the SVM.

Although the SVM does not directly recognize the moment of the penetration of the work material, the system is expected to detect the penetration and stop the actuation of the cutting tool immediately before the total penetration. The mechanism of detecting the penetration immediately before total penetration is shown in Fig. 6. When the residual thickness of the work material is large, the work material is stiff enough to be cut by the cutting tool. However, when the residual thickness is small, the work material deflects under the load imposed by the cutting tool, and the cutting

Algorithm 1 Algorithm for Penetration Detection

While Actuation of the bone cutting tool is on
Do {
1. Measure the motor current and the rotational speed of the cutting tool
2. Estimate the cutting resistance
3. Estimate the cutting state
  if SVM outputs *"cutting"* **then**
    $count_{cut}++$
  else
    if $count_{cut} > c_{stop}$ **then**
      Actuation of the bone cutting tool stops.
    else
      $count_{cut} = 0$
    end if
  end if
}

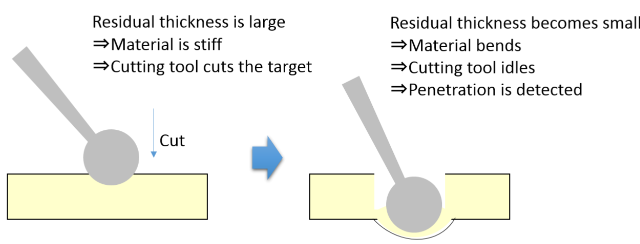


Fig. 6. Mechanism to detect penetration. When the work material became thin, it deflected under the load from the cutting tool, and the cutting tool could not cut the work material.

tool spins without cutting the material. Thereafter, the system recognizes the penetration of the work material and stops the actuation of the cutting tool. Thus, the system is expected to detect the penetration of the work material before total penetration and stop actuation of the cutting tool, leaving a very thin remnant of work material. However, the timing of the penetration detection depends on the stiffness of the work material because it relies on the timing of the deflection of the work material. Therefore, the performance of the penetration detection method must be tested using a material with stiffness that is comparable to that of human bones.

IV. Experiments

To examine the performance of the developed system, we performed two experiments. In the first experiment, the cutting tool was fixed, and the cutting material was moved horizontally by using an XY stage, as shown in Fig. 7. In the second experiment, the cutting tool was held by a human operator, and the performance was examined in a practical setup.

A. Experiments in Motorized Setup

1) Experimental Setup: To evaluate the penetration-detection performance, we performed experiments by using the experimental setup shown in Fig. 7. To evaluate the developed system in a reproducible manner, the cutting tool was fixed on the stage, and the work material was moved horizontally by using the XY stage. In this experiment, plastic plates from Sawbones Inc. (USA) were used. These plates are produced as an alternative test material to human cortical bone. The parameters of this experiment are listed in Table I. In this experiment, the thickness of the work material was changed to investigate the effect of its stiffness. In addition, the cutting angle α, which is shown in Fig. 7, was changed to investigate the effect of the angle between the feed direction of the cutting tool and the surface of the work material.

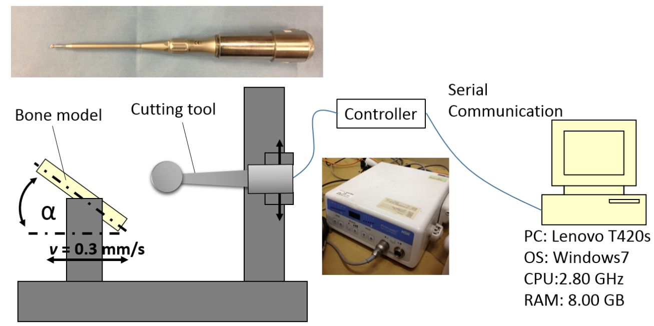


Fig. 7. Experimental setup for motorized experiment.

TABLE I
PARAMETERS OF EXPERIMENT FOR PENETRATION DETECTION PERFORMANCE EVALUATION.

Rotational speed	1000 [rev/min]
Feed speed	0.3 [mm/s]
Plate thickness	2, 3, 4, 5 [mm]
Cutting angle	20, 40, 60, 80 [deg]

The procedure for this experiment was as follows. First, to acquire training data for the SVM, work materials were cut and penetrated without the proposed penetration detection under all the conditions listed in Table I, and the motor current and rotational speed of the cutting tool and the estimated cutting resistance were recorded. Second, the SVM was trained using all of the recorded data. Third, the work material was cut with penetration detection under the conditions listed in Table I. Under each condition, the work material was cut three times.

2) Experiment Results: An example of the recorded data for training the SVM is shown in Fig. 8. The labels of each time step were set manually on the basis of observation. At the time of penetration, the estimated cutting resistance decreased remarkably.

To evaluate the performance of the SVM, we performed a four-fold cross validation. The results are listed in Table II. As listed in Table II, the SVM successfully classified the two classes, namely, "cutting" and "not cutting."

The recorded data when the penetration was detected are shown in Fig. 9. The system detected the penetration successfully when the residual thickness of the work material became small and the estimated cutting resistance decreased.

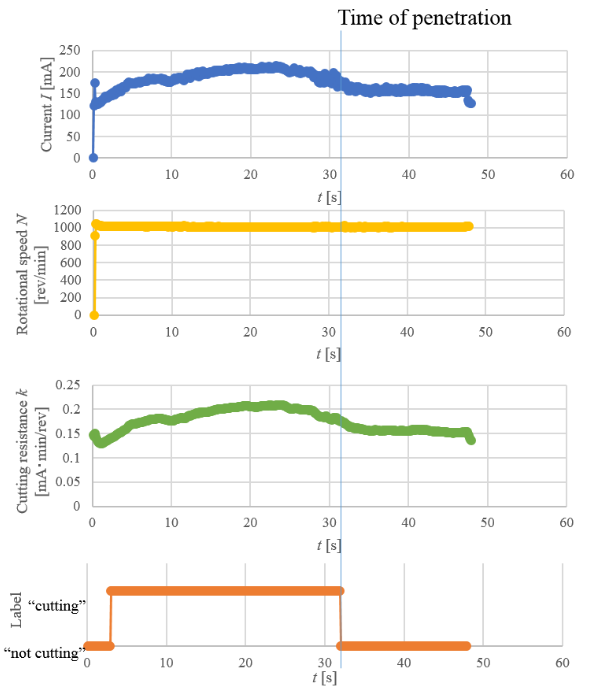


Fig. 8. Example of recorded data for training SVM: plate thickness: 4 mm and cutting angle: 40 °.

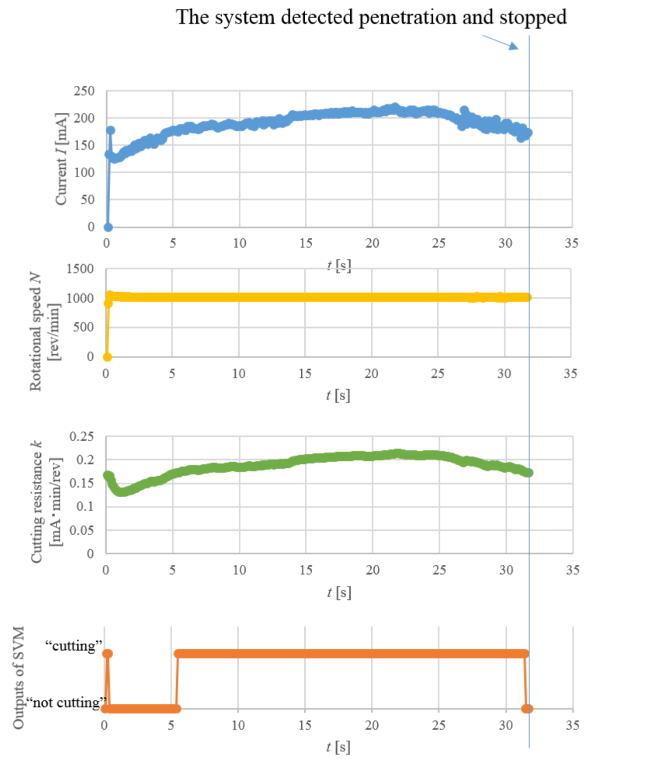


Fig. 9. Recorded data when penetration was detected in experiment. The system detected the penetration and stopped autonomously when the estimated cutting resistance decreased. The experiment conditions: plate thickness: 4 mm and cutting angle: 40 °.

TABLE II

RESULTS OF CROSS VALIDATION.

No.	"cutting"	"not cutting"
1	100.0%	93.8%
2	100.0%	93.4%
3	97.7%	96.5%
4	96.0%	81.8%
Ave.	98.4%	91.4%

The penetration-detection performance in this experiment is shown in Fig. 10 and 11, where we regard the detection as successful in a case where the work material was left under the cutting tool, as shown in Fig. 12. Figure 10 shows the ratio of accurate penetration detection. The results show that the developed system successfully detected the penetration under most conditions. However, when the work material was 2 mm and the cutting angle was 20°, the system occasionally failed to detect the penetration.

Figure 11 shows the residual thickness of the work material when the system detected the penetration. As shown in Fig. 11, the residual thickness of the material was smaller under the condition of a thinner work material. In addition, the residual thickness of the work material was smaller under the condition of a smaller cutting angle.

3) Discussion: As we expected, the developed system detected the penetration of the work material immediately before its total penetration. This feature is very suitable for orthopedic surgery such as spine surgery and neurosurgery. In such surgery, surgeons do not need to penetrate the target bone if it is possible to break off the bone by hand. In addition, if the system detects the penetration before

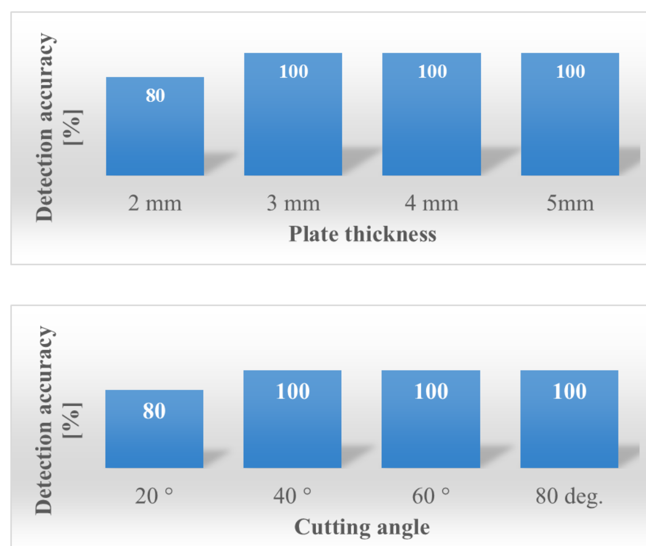


Fig. 10. Accuracy of penetration detection.

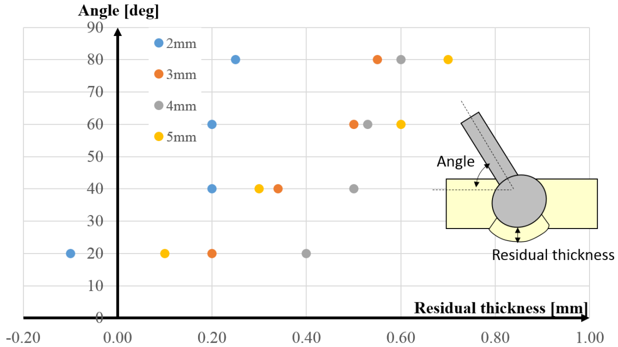


Fig. 11. Residual thickness of work material when system detects its penetration. Negative numbers represent penetration detection failures, and the norm of the negative number means the distance between the edge of the cutting tool and the back side of the work material.

Fig. 12. Example of successful penetration detection. The actuation of the cutting tool autonomously stopped, leaving a thin remnant of work material.

total penetration, surgeons do not have to run the risk of damaging vital organs. Therefore, the feature of detecting the penetration immediately before total penetration is fairly desirable for clinical use.

The effect of the cutting angle is summarized in Fig. 13. The round fluted bur cut the work material in every direction. Consequently, even if the work material was penetrated in one direction, the system detected that the tool was cutting the work material in another direction in some cases. In these cases, the system could not properly detect the penetration. This kind of penetration detection failure can occur when the cutting angle is small.

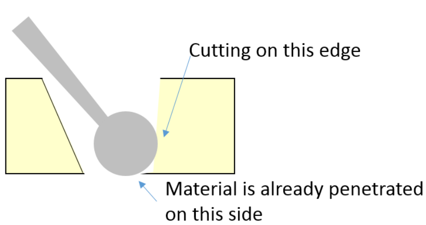


Fig. 13. Cause of penetration detection failure. Even when the work material was penetrated in one direction, the system occasionally failed to detect this penetration if the cutting tool was still cutting the work material in another direction.

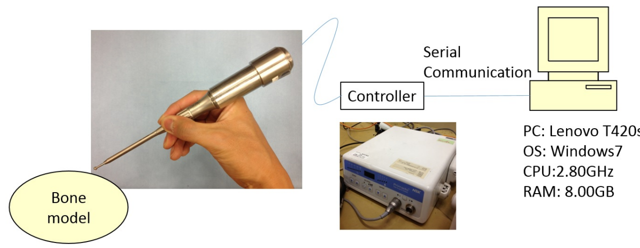
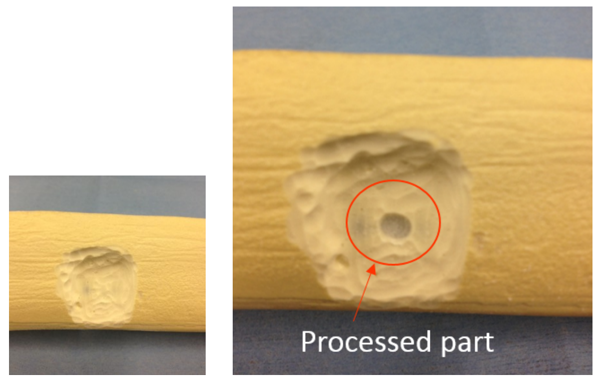


Fig. 14. Experimental setup for hand-held experiment.



(a) (b)

Fig. 15. Results of experiment with the hand-held setup. (a) The state of the cutting material before the experiment. (b) The state of the cutting material after the experiment. The thickness of the processed part was approximately 0.2 mm.

B. Experiment with Hand-held Setup

1) Experimental Setup: To demonstrate the performance of the developed system in a practical setup, we performed an experiment. In this experiment, the bone-cutting tool was held by a human operator instead of being fixed on a table, as shown in Fig. 14. As a work material, a plastic bone model of a tibia (Sawbones, USA) was used.

The procedure for this experiment was as follows. First, to acquire training data for the SVM, the operator cut the work material as he/she liked, and the motor current and rotational speed of the cutting tool, along with the estimated cutting resistance, were recorded. Second, the SVM was trained using the recorded data. Third, the operator cut the work material with the penetration detector.

2) Experiment Results: Figure 15 shows pictures of the work material before and after the experiment. In this experiment, the developed system detected the penetration and stopped the actuation of the cutting tool, leaving a very thin remnant of work material. The residual thickness was about 0.2 mm. This very thin remnant of work material could easily be broken by hand. Thus, we conclude that the system properly detected the penetration.

3) Discussion: With the hand-held setup, the system successfully detected the penetration of the work material as well as in the setup in which the cutting tool was fixed on a stage. However, occasionally, the system mistakenly detected penetration when the cutting tool had not penetrated

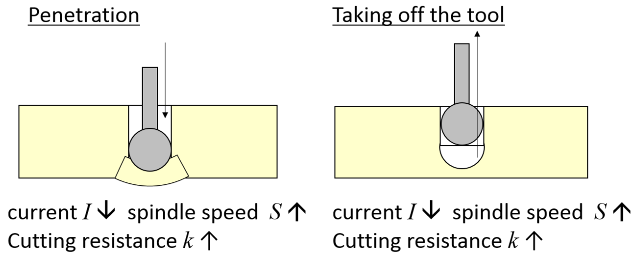


Fig. 16. Cause of false detection of penetration. When the operator took the cutting tool off the bone, the cutting resistance also decreased, similar to the case where the cutting tool penetrated the work material.

the work material. The developed system detected a decrease in the cutting resistance by measuring the motor current and rotational speed of the cutting tool. Therefore, even if the operator took the cutting tool off the bone, the system mistakenly detected the penetration of the bone and stopped the actuation of the cutting tool (Fig. 16). Thus, the motion of the cutting tool must be taken into account to avoid this kind of false detection. The proposed system can be easily extended to take the tool motion into account during penetration detection, by attaching a motion sensor to the instrument and modifying the input of the SVM. This modification will be investigated in future work.

V. CONCLUSIONS

We developed a hand-held bone-cutting-tool system with autonomous penetration detection to improve the safety of orthopedic surgery. The developed system estimates the cutting resistance and cutting states online by using RLS and SVM. The performance of the developed system was verified through experiments. Thanks to the elasticity of bones, the developed system successfully detected the penetration immediately before total penetration in the experiments. The experimental results showed that the accuracy of the penetration detection was greater than 90 % in the fixed experimental setup, and the developed system successfully detected the penetration in the hand-held setup. This study showed that the autonomous detection of bone penetration for a hand-held bone-cutting tool is feasible by using the proposed scheme.

In future work, we will attach sensors (e.g., acceleration sensor) to the cutting tool to measure its motion to improve the penetration detection performance. In addition, the proposed scheme will be extended to take into account the motion and orientation of the cutting tool, and further evaluations of the developed system will be conducted. Furthermore, the proposed scheme needs to be examined using work materials with various stiffness in future work.

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