Trajectory Data Mining for Surgical Workflow Analysis

A. Nara[1], K. Izumi[1], H. Iseki[2], T. Suzuki[2], K. Nambu[3], Y. Sakurai[2]

[1]Digital Human Research Center, National Institute of Advanced Industrial Science and Technology.
Address: 2-41-6, Aomi, Koto-ku, Tokyo, Japan, 135-0064
Telephone: +81-3-3599-8563
Fax: +81-3-5530-2066
Email: {a.nara, kiyoshi}@aist.go.jp

[2]Institute of Advanced Biomedical Engineering & Science, Tokyo Women's Medical University.
Address: 8-1, Kawadacho, Shinjuku-ku, Tokyo, Japan, 162-8666
Telephone: +81-3-5367-9945
Fax: +81-3-5312-1844
Email: {hiseki, takashi_suzuki, yasuo.sakurai}@abmes.twmu.ac.jp

[3]Department of Radiology, Tokyo Women's Medical University.
Address: 8-1, Kawadacho, Shinjuku-ku, Tokyo, Japan, 162-8666
Email: nambu@mel.nasu.toshiba.co.jp

1. Introduction

Surgical workflow monitoring and analysis in the operating room (OR) are an emergent topic for better designing and management of surgical operations (Cleary et al. 2005). These promotes safe and efficient operations through developing context aware ORs, evaluating and training surgical staffs, optimizing surgeries and generating automatic reports. A key research issue for the surgical workflow analysis is workflow segmentation. The surgical workflow has different levels of granularity, and existing studies presented various monitoring methodologies and workflow analyses mostly focusing at a scale of either OR (coarse-scale) or operative field (fine-scale). A coarse-scale approach identifies the broad surgical phases such as the start and end of an operation by monitoring when a patient enters and leaves the OR using patient's vital signs (Xiao et al. 2005) and video imageries (Bhatia et al. 2007). On the other hand, a fine-scale approach detects surgical procedures based on detail actions at the operative field; for example, dissecting, clipping, and detaching a diseased site using instrument signals (Padoly et al. 2007) and exchanging surgical instruments between a surgeon and a scrub nurse from video imageries (Ohnuma et al. 2006).

For better understanding of the surgical workflow, this paper presents a new approach that fills the gap between two scales. Our approach is based on the analysis of staff's trajectories since movement behaviors differ from staff's roles as well as surgical phases. The research objective is to identify distinct surgical events from the trajectory database, which helps the middle-scale surgical workflow segmentation. As a data collection, we developed an ultrasonic location aware system that continuously tracks 3D positions on multiple surgical staffs in the OR environment. For identifying distinct surgical events, we employed the trajectory partitioning algorithm from TRACLS (Lee et al. 2007) and the k-means clustering technique.

2. Methodology

2.1 Data Collection

We installed the ultrasonic 3D location aware system in the OR (5.8m (width) x 4.8m (depth) x 2.9m (height)) at the Tokyo Women's Medical University (TWMU), Japan (Fig.1). It consists of control units (Fig.1a), receivers (Fig.1b), and tags (transmitters) (Fig.1c). The receivers receive ultrasonic pulses emitted from multiple tags. The control units identify each tag's identification and detect associated 3D positions. Because of delicate tasks during a surgical operation, a single tag is hooked on surgical clothes around the nape of surgical staff's neck for the purpose of minimum disturbance (Fig.1c). For 3D position estimation, the system records the time-of-flight, which is the travel time of the signal from transmission to reception. Based on more than three time-of-flight results, the system computes 3D position using the trilateration method using the robust estimation algorithm known as random sample consensus (RANSAC) (Fischler and Bolles, 1981).

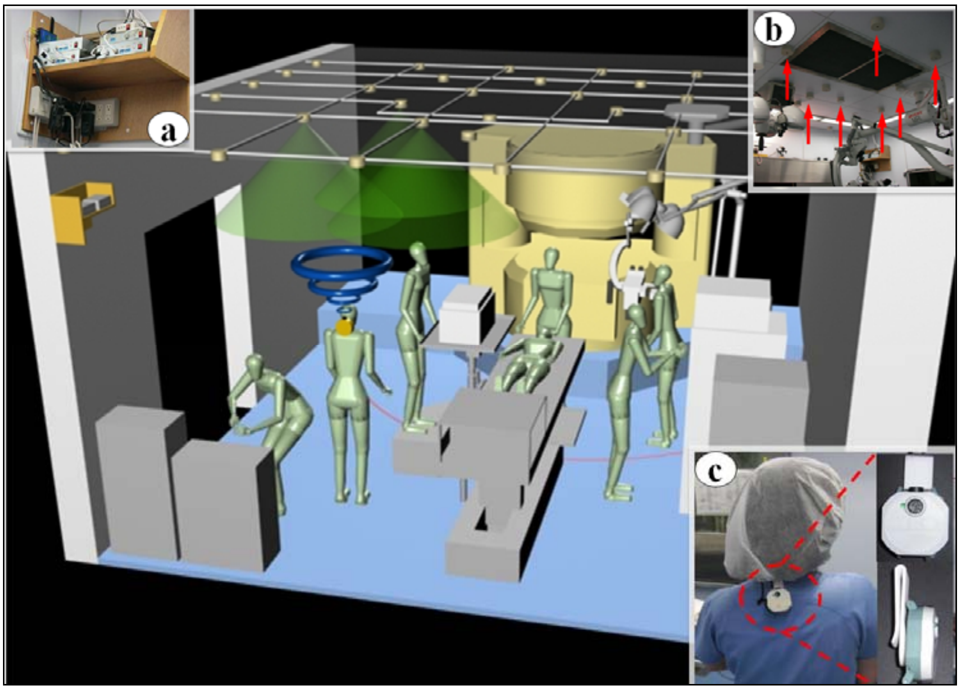

Figure 1. The ultrasonic 3D location aware system.

Ultrasound frequency	40KHz
Position estimation error	≤ 80mm
Sampling frequency	Up to 50 Hz (1 tag), 50/n Hz (n tags)
Measurement range (distance)	Vertical distance from a reader ≈7m
Measurement range (angle)	Vertical angle from a reader ≈100°
Tag size (mm)	44 (w)×75 (h)×24 (d)
Tag weight (g)	30 (tag) + 10 (battery)

Table 1. Specification of the ultrasonic 3D location aware system.

2.2 Trajectory Data Mining

The ultrasonic location aware system collects a set of trajectories from multiple surgical staffs {Trajectory Set: TR_{set} = TR_1,TR_2, TR_3, …, TR_i, where i denotes the number of surgical staffs} during a surgical operation. Each trajectory is composed of a sequence of 4-dimensional points {{TR_i = p_1, p_2, p_3, …, p_j, where j denotes the number of points in the trajectory i}, {p_j = x, y, z, t}}. To extract distinct surgical events for the surgical workflow segmentation, we employed the trajectory data mining technique, which includes two procedures, trajectory partitioning and trajectory clustering (Fig.2). The trajectory partitioning process partitioned an entire trajectory of a surgical staff during a surgery into trajectory partitions (sub-trajectories). By grouping trajectory partitions, the clustering process describes surgical events that have similar trajectory patterns.

In this research, we have adopted a formal partitioning algorithm from TRACLS (Lee et al. 2007). The algorithm finds the points where the behaviour of a trajectory changes rapidly, called as characteristic points (p_c). Each characteristic point partitions a trajectory into trajectory partitions and each partition is represented by a set of line segments between two consecutive characteristic points {TR_i = $TRpar_{(1)}${$p_{c(1)}$ $p_{c(2)}$}, $TRpar_{(1)}${$p_{c(2)}$ $p_{c(3)}$}, ..., $TRpar_{(m)}${$p_{c(n-1)}$ $p_{c(n)}$}, where m denotes the number of trajectory partitions and n denotes the number of characteristic points (m = n-1)}. The optimal partitioning of a trajectory is achieved by two contradictory properties, preciseness and conciseness. Preciseness refers to the minimization of the difference between a trajectory and a set of its trajectory partitions, whereas conciseness refers to the minimization of the number of trajectory partitions. The optimal trade-off between preciseness and conciseness is approximated based on the minimum description length (MDL) principle.

For each trajectory partition, we obtain multi-dimensional vectors to characterize the partition trajectory. The vector values include total distance (x-y axes), distance between start and end nodes (x-y axes), total distance (z axis), and time duration. Based on normalized values of these vectors, we run the k-mean cluster analysis (k=10, group average method).

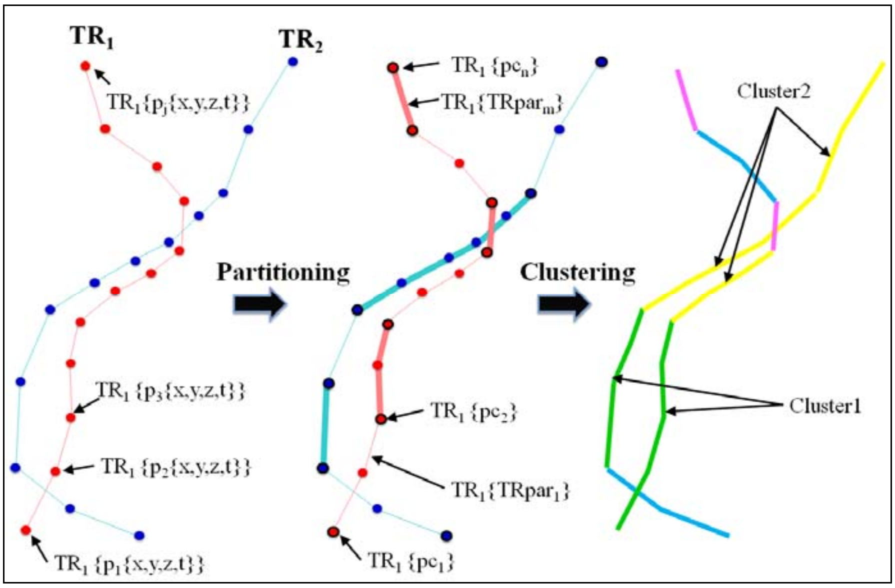

Figure 2. Trajectory data mining; partitioning and clustering.

3. Operation Environment and Preliminary Result

3.1 Operation Environment

The OR, where the ultrasonic location aware system was installed, is used only for neurosurgical operations. As a distinct feature of the room, an operation is performed under the open MRI to increase the tumour resection rate. During an operation, several intraoperative MR images are taken using the open-MRI scanner to confirm brain deformation caused by surgical procedures and tumour situation. A surgery is completed by repeating these processes. A typical middle-scale workflow in the OR is shown in Fig 3.

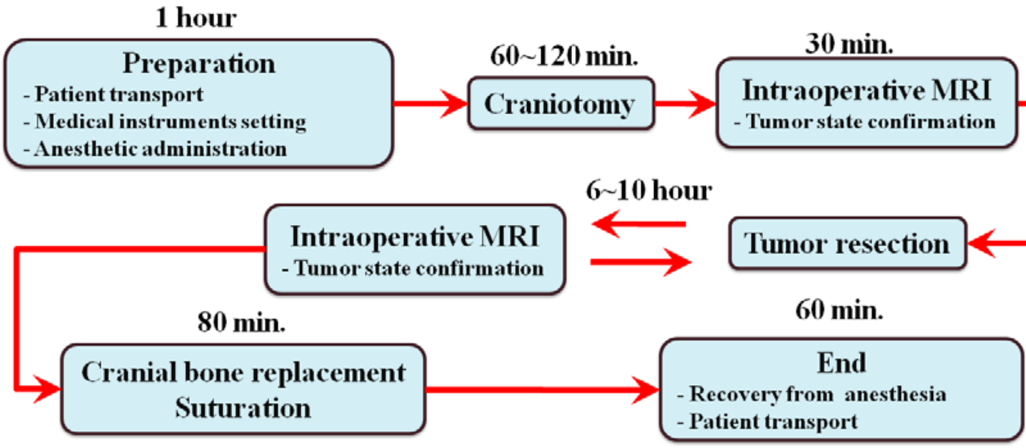

Figure 3. A typical middle-scale workflow of a neurosurgical operation with the intraoperative MRI process.

3.2 Preliminary Result

In our experiment, we have obtained trajectories on circulating nurses, scrub nurses, and a junior-surgeon during an 11-hours-long neurosurgery with two intraoperative MR imaging processes. For each surgical role, we conducted our trajectory data mining analysis. Fig.4 shows the occurrence of 10 clusters through time for each role. The bar chart on top of the figure is the reference of surgical workflow segmentation based on the direct observation. Images on right-bottom of the figure exhibits trajectories associated with their cluster ID. The result shows that some trajectory clusters often appear before and after the workflow shift (images: b, d, f). We confirm that these trajectory clusters represent particular surgical events by comparing trajectories and video imageries. For example, the trajectory cluster “b” represents the circulating nurse behaviour to bring surgical instruments for MRI process stored in a shelf in the OR. Our analytical result is preliminary exploration; however, further exploration on trajectory data mining can identify key surgical events for workflow segmentation. Moreover, it can reveal normal/abnormal trajectory patterns for different surgical workflows as well as staff roles.

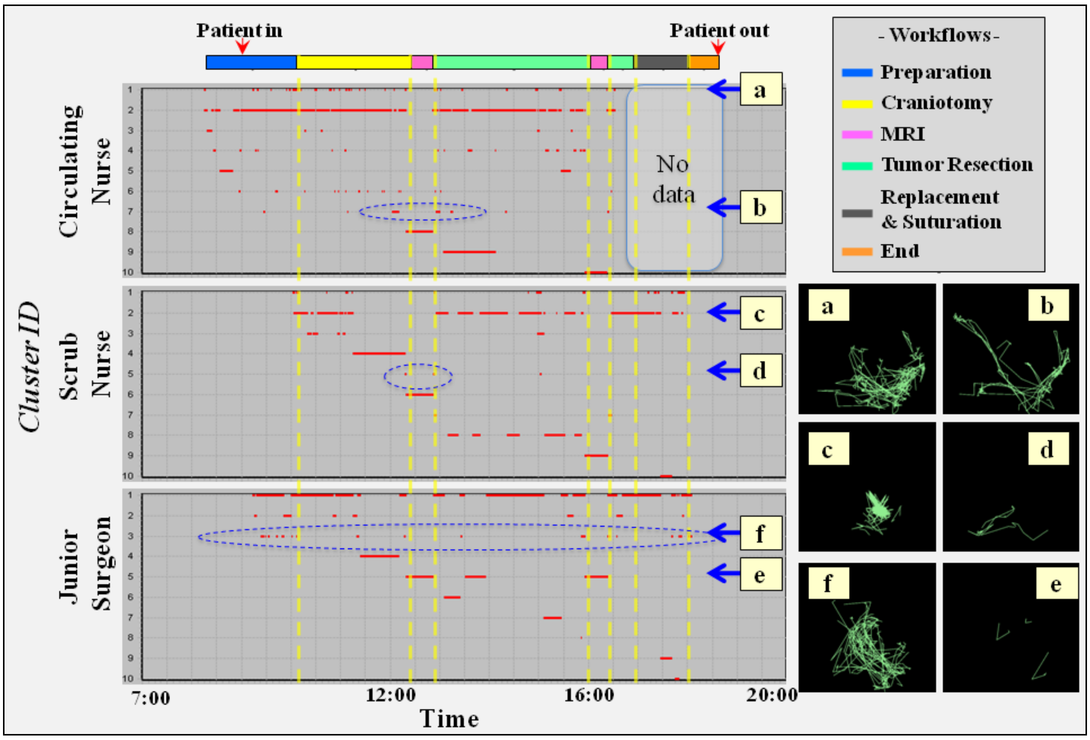

Figure 4. Results of trajectory data mining.

4. Acknowledgment

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