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Data Article

A multichannel electromyography dataset for continuous intraoperative neurophysiological monitoring of cranial nerve

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A B S T R A C T

Continuous Intraoperative Neurophysiologic Monitoring (cIONM) is a widely used technology to improve surgical outcomes and prevent cranial nerve injury during skull base surgery. Monitoring of free-running electromyogram (EMG) plays an important role in cIONM, which can be used to identify different discharge patterns, alert the surgeon to potential nerve damage promptly, etc. In this dataset, we collected clinical multichannel EMG signals from 11 independent patients' data using a Neuromaster G1 MEE-2000 system (Nihon Kohden, Inc., Tokyo, Japan). Through innovative classification methods, these signals were categorized into seven different categories. Remarkably, channel 1 and channel 2 captured continuous EMG signals from the facial nerve (VII cranial nerve), while channel 3 to channel 6 focused on V, XI, X, and XII cranial nerves. This is the first time that intraoperative EMG signals have been collated and presented as a dataset and labelled by professional neurophysiologists. These data can be utilized to develop the architecture of neural networks in deep learning, machine learning, pattern recognition, and other commonly employed biomedical engineering research methods, thereby providing valuable information to enhance the safety and efficacy of surgical procedures.

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Specifications Table

Subject	Neurosurgery / Neurophysiology
Specific subject area	Biomedical Signal Processing, Clinical Electromyography, Intraoperative monitoring, Electrophysiology, EMG Classification
Data format	Raw
Type of data	Tables
Data collection	We collected raw data utilizing the Neuromaster G1 MEE-2000 (Nihon Kohden, Inc., Tokyo, Japan) using free-running EMG, TcMEP from 11 participants. Paired subdermal needle electrodes (1500/13/0.4 mm) were inserted in the special areas. A filter was set between 5 and 2 kHz. After the surgery, we exported EMG data and an event list (labels) via the Neuromaster Review Mode V05-11 (Nihon Kohden, Inc., Tokyo, Japan) software. Due to the specificity of the clinical data, no special filtering or preprocessing was performed on the data so as to avoid distorting special categories of signals and to preserve their authenticity.
Data source location	Operating Room, department of neurosurgery, West China Hospital of Sichuan University, No.37, Guoxue Lane, Wuhou District, Chengdu, Sichuan, China.
Data accessibility	Repository name: Mendeley Data identification number: 10.17632/7hyptcbkkd.2 Direct URL to data: https://data.mendeley.com/datasets/7hyptcbkkd/2

1. Value of the Data

- It's the first dataset that contains six-channel continuous clinical EMG data and also classifies and labels a-train, b-train and other classic cranial nerve injury patterns, which is valuable in neurophysiology, intraoperative cranial nerve preservation, biomedical engineering, pattern recognition, deep learning, etc.
- These data were collected from real neurosurgical surgeries, which are often very difficult to obtain and require a great deal of time and effort to collate.
- We collected a large amount of intraoperative continuous EMG data and spent a lot of time on expert annotation by neurophysiologists. The data are more generalizable and clinically meaningful compared to the previous guided, fixed-posture EMG data performed in the laboratory.
- This dataset is valuable for researchers engaged in the field of EMG classifications, pattern recognition, the recognition of specific EMG signals corresponding to cranial nerve injury and developing new automatic warning methods of intraoperative monitoring.
- In the field of intraoperative cranial nerve preservation, manual identification of monitoring signals is required during surgeries. It leads to a high degree of subjectivity in intraoperative monitoring and alarm criteria, making it difficult to have a more uniform standard. This dataset is proposed to help solve this problem. In addition, it can also provide useful information for medical practices to improve the preservation of cranial nerves and the safety of surgeries.
- In the field of biomedical engineering, it can help to solve the problem of transient abnormal signals that may be missed by insufficient manpower. This dataset has the potential to inspire researchers to develop real-time alarm systems for clinical surgeries. This dataset can be used to develop more deep-learning-based or machine-learning-based algorithms, models, or tools for monitoring neurological function related to surgeries and to study the mechanisms and effects of nerve injury or repair during surgery. Other applications in biomedical engineering are also valuable such as explore the relationship between A-train

Table 1
The average profile of patients participating in the dataset.

Gender		Age (Mean±SD)	Tumor site	
Male ($n = 5$)	Female ($n = 6$)	49.73 ± 16.65	Left ($n = 5$)	Right ($n = 6$)

discharge pattern and postoperative facial paralysis or automated elimination of interference from similar signals that are not easily distinguishable.

2. Background

Cranial nerve injury is a common complication following skull base surgery [1], and can lead to various adverse effects. Nowadays, continuous Intraoperative Neurophysiologic Monitoring (cIONM) has been introduced to minimize the risk of such injuries and aid in the protection of nerves during surgery by continuously monitoring and recording the functional status of specific nerves [2]. It has become one of the most commonly used methods in neurosurgery to enhance surgical outcomes and prevent cranial nerve injuries [3]. However, there are some limitations associated with the use of cIONM to monitor free-running electromyography (EMG) activity in real-time, making it difficult to establish consistent monitoring and alarm standards. The robustness of the signal recognition and the subjectivity of the alarms are yet to be solved. Although relevant studies [4,5] found that some special EMG discharge patterns are highly correlated with postoperative cranial nerve palsy [6], further research is still needed. To help more researchers solve these problems, we compiled this six-channel EMG dataset with the technology of cIONM, aiming to recognize EMG discharge patterns and predict postoperative outcomes.

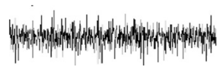
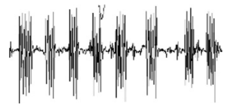
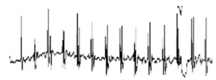
3. Data Description

This dataset was collected from West China Hospital of Sichuan University, Chengdu, Sichuan, China. Cerebellopontine Angle Tumor Surgery (CPA) is one of the most common types of neurosurgical procedures and accounts for approximately 10% of all intracranial tumors [7]. To capture typical discharge patterns, we chose CPA as a representative type of skull base surgery. We collected intraoperative EMG data from 11 patients. These signals were produced during their surgeries. All the patients underwent the same type of surgery.

Compared to previous studies focusing on single-channel EMG signals, we gathered six-channel EMG data simultaneously. We continuously monitored EMG produced by five cranial nerves during the whole surgery. In the six channels monitored, channels 1 and 2 monitored continuous EMG signals from the VII cranial nerve (i.e., the facial nerve). Channel 3 to channel 6 monitored continuous EMG from the V, XI, X, and XII cranial nerves respectively. Table 1 shows the baseline information of these 11 patients. The detailed structure of this dataset is shown in Fig. 1, where “readme.pdf” describes in detail how to understand the label and how each segment of EMG data should correspond to the label. The general folder for the dataset contains two subfolders, “raw” and “process”. In the “raw” folder, the label folder keeps the label files labelled by the neurophysiologists, in which the meanings represented by each label and the EMG signal waveform are shown in Table 2.

The EMG data of patients 1–11 are stored in the “data” folder, respectively. Due to various unavoidable factors such as dormancy of the monitoring machine during the operation, the data of the whole operation is divided into a number of segments. In this dataset, the EMG data of the patients are divided into 2 to 6 segments, respectively. For example, in the EMG data folder of patient 1, there are four EMG files, namely, 1_1.txt, 1_2.txt, 1_3.txt, 1_4.txt. The data of other patients are stored in segments according to this method. However, this is usually not caused by pathological or meaningful factors, and it does not affect the continuity of the EMG data. Please note that in order to protect the patient’s privacy, we anonymized the data. Specifically,

Table 2
Classes of EMG signal content.

Event class	Activity name	Description	EMG Signal Waveform
0	A-train	A sinusoidal, symmetrical sequence of high-frequency and low-amplitude signals, indicates permanent injury	
1	A-train salvo	A typical pattern of A-trains, as salvos of very short trains	
2	B-train with spike	Single spikes that may be regularly or irregular occurring	
3	B-train with burst	Single bursts that may be regularly or irregular occurring	
4	Evoke	Electric evoked compound muscle action potential of muscles innervated by the cranial nerve	
5	Artifact	Interference signals caused by grinding drills, static from equipment, etc.	
6	Quiet	The usual healthy EMG baseline activity	

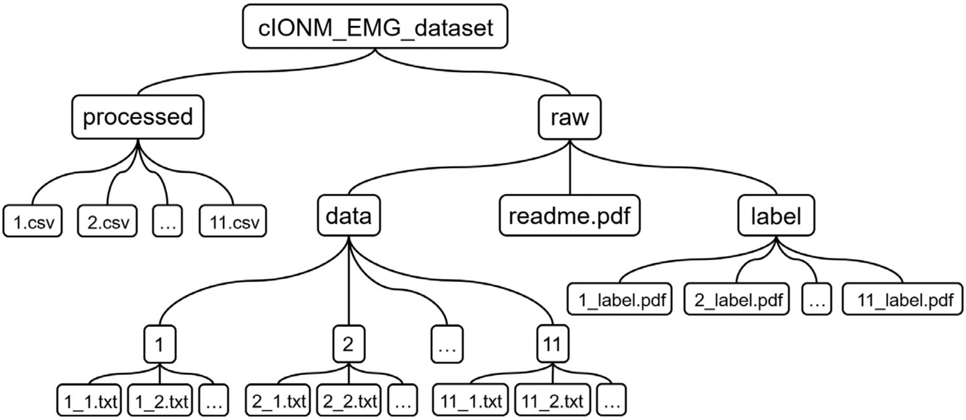


Fig. 1. The record structure of the dataset.

we removed sensitive information such as patient's name, ID, etc. from the files and replaced the patient's name with a serial number.

In each individual EMG data file, such as “1_1.txt”, the first line contains certain configuration values for the segment of electromyographic signal. “TimePoints” indicates the number of sampling points in the file. “Channels=6” signifies that we collected data from six channels. “SamplingInterval[ms]=1.000” denotes a sampling interval of 1.000ms, which corresponds to a sampling frequency of 1 KHz. "Time" refers to the start time. The sampling points and the sampling interval can be used to calculate the duration of the continuous EMG signal collected in the file. Apart from the first line, the remaining data consists of TimePoints rows with 6 columns, where each column represents the electromyographic signal collected from a specific channel. Specifically, both channel 1 and channel 2 capture the EMG signals of the facial nerve, i.e., the VII cranial nerve. Meanwhile, Channel 3 to channel 6 capture the electromyographic signals of the V, XI, X, and XII cranial nerves, respectively.

Next, we'll give an example of how to temporally map a data file to its corresponding label file. In the first line of “1_1.txt”, we can find that the onset of this segment of EMG signal as “Time = 10:31:28”. We can also know the number of sampling point is 4,447,200 and the sampling rate is 1000, from which we can calculate that the signal lasted for 4447.2 s, which means that the EMG is collected from 10:31:28 to 11:45:07. After the calculation we can look for the events that occurred during the corresponding time period from the corresponding label file (1_label.pdf). For example, from 11:24:43 to 11:25:27, the events of the six channels are shown as 6,6,6,6,2,6.

In addition, to make it easier for researchers to understand and apply this dataset, we also provided csv files which are more commonly used in deep learning fields in the “process” folder. Each csv file contains all information of one patient, including six channels of EMG data and corresponding labels. Researchers are usually more familiar with csv files and can easily utilize this dataset for their studies.

3.1. Label Description

In this dataset, in order to facilitate subsequent research such as training neural networks with continuous and complex electromyographic signals collected during surgery for classification or prediction tasks, we proposed an innovative data annotation method after extensive discussions and explorations with clinical physicians. As shown in Table 2, we classified electromyographic signals into seven categories according to previous studies [5,6], where

Event “6” represents the usual healthy EMG baseline activity which we defined as "quiet". We focused more on the six signal categories with special clinical significances, labelled as Event “0” to “5”. The EMG signal waveform of Event 3 comes from patient 2, and the others are come from patient 1 in this dataset [8]. The descriptions of the events are derived from discussions with neurophysiologists and previous research [6,9,10]. Additionally, to simplify the recording of event start and end times, we established markers for the start and end of each event, with 0 indicating the start and 1 indicating the end. The signal category of each channel is represented by a corresponding number in Table 2. Each label is a string of seven digits. Thus, every label generated by the physician’s annotation follows the format: start/end, channel1, channel2, ..., channel6. During the surgical procedure, if meaningful EMG signals occur, neurophysiologists mark the event start and end in the MEE-2000 monitoring software before and after the event. For example, a corresponding label showing “0, 6, 6, 6, 6, 6, 2”means that the EMG signal in channel 6 shows “B-train with spike” while other channels are “quiet”. Through this innovative labelling method, we obtained continuous and authentic electromyographic data during surgery, which assisted the organization of the data.

4. Experimental Design, Materials and Methods

4.1. Patient population

We monitored a consecutive series of 11 patients undergoing Cerebellopontine Angle Tumor (CPA) Surgery. All of the included patients underwent an acoustic neuroma surgery, which is a type of the CPA surgery. The mean age of the patients was 49.73 years (range 26–78 years).

4.2. Data collection

Unlike conventional myoelectric acquisition methods [11] used for gesture recognition or physiological signal acquisition, the intraoperative EMG acquisition process in cIONM is more continuous and specific. Surgery was performed through a standard retrosigmoid approach. Total intravenous anaesthesia was administered using propofol and opioids. The cranial nerve (CN) V, VII, X, XI, XII was monitored with Neuromaster G1 MEE-2000 (Nihon Kohden, Inc., Tokyo, Japan) as shown in Fig. 2, using free-running EMG, TcMEP during the whole surgery. Paired subdermal needle electrodes (1500/13/0.4mm) were inserted in the orbicularis oculi, orbicularis oris, masseter, upper trapezius, cricothyroid, genioglossus muscle. The specific positions of the electrodes are shown in Fig. 3. The numbers in the figure represents the number of channels, and the positions of the channels also show the positions of electrodes. The Roman numerals in the legend represent which cranial nerve the channel monitors, and the legend also indicates the muscle to which the electrode corresponds. The filter was set between 5 and 2 kHz. All data were acquired using a standard methodology consistent with latest international guidelines. [12–14] Study data were collected and managed using REDCap electronic data capture tools hosted at West China Hospital, Sichuan University- Dept. Neurosurgery. [15,16] REDCap (Research Electronic Data Capture) is a secure, web-based software platform designed to support data capture for research studies, providing 1) an intuitive interface for validated data capture; 2) audit trails for tracking data manipulation and export procedures; 3) automated export procedures for seamless data downloads to common statistical packages; and 4) procedures for data integration and interoperability with external sources.

4.3. Data export

The software we used for data visualization and data export is Neuromaster Review Mode V05-11 (Nihon Kohden, Inc., Tokyo, Japan). To export data of a selected patient, we clicked on

Fig. 2. The device and interface for intraoperative EMG collection.

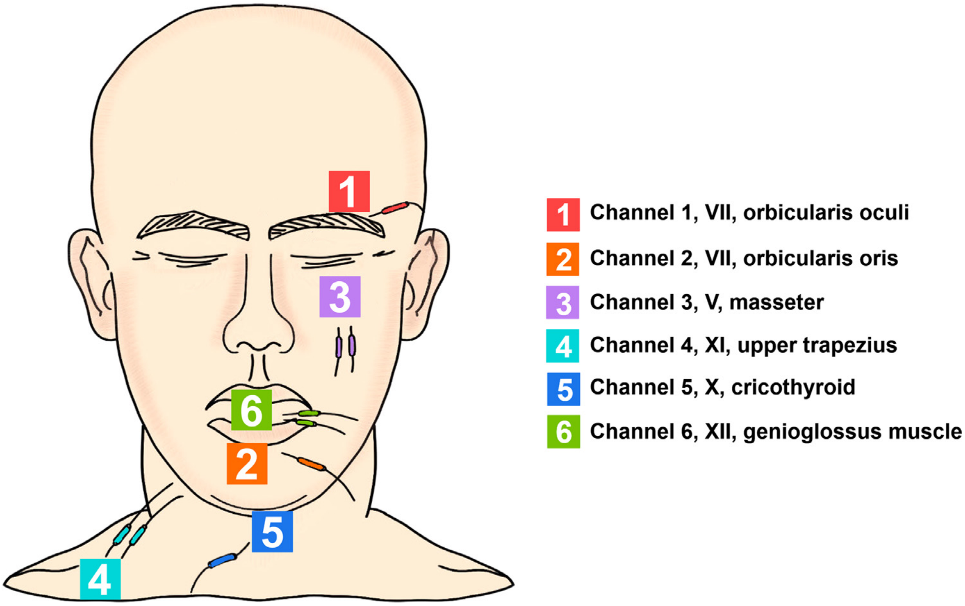


Fig. 3. The positions of subdermal needle electrodes.

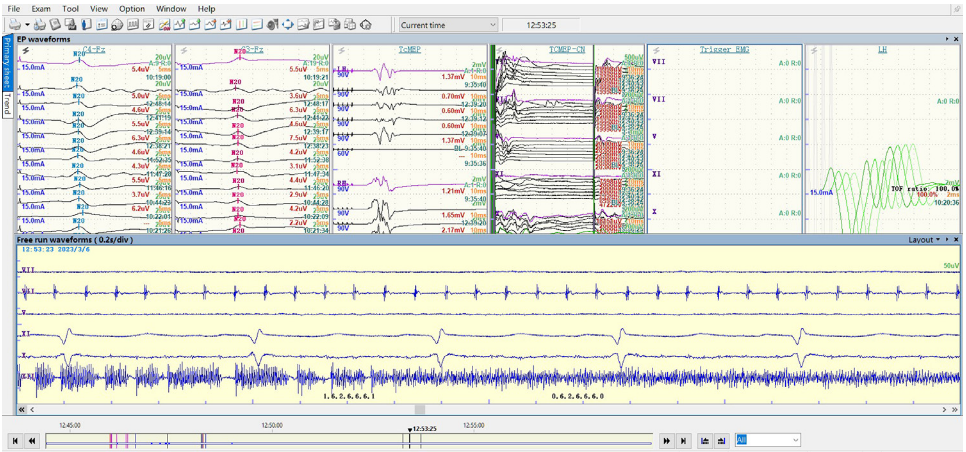


Fig. 4. The software interface when exporting data.

the “review” button and then entered the software page. By selecting the "free run" option under the “exam” tab, the “Free run waveforms (0.1s/div)” window appeared, as shown in Fig. 4. This window displays continuous EMG signals collected from the first to the sixth channels, with the date and time of surgery displayed in the upper left corner. The time axis window below the EMG waveform window provides an intuitive way to observe whether continuous EMG signals are being collected during this time period. Continuous EMG signals are presented as horizontally continuous blue lines in this window.

To export the continuous EMG data, we right-clicked on the “Free run waveforms (0.1s/div)” window and selected the “Export data to ASCII/BINARY file” option. For convenient data processing after export, in the options tab that appeared, we selected the “ASCII” option for the format and the "Continuous" option for the mode, and kept the range as the default "Current waveforms" option. Finally, we clicked on the "OK" button to export the selected phase of six-channel continuous EMG signals. It should be noted that due to various reasons mentioned in the "DATA DESCRIPTOR" part, it's necessary to ensure that each segment of the EMG data for the entire surgery has been exported without omission.

After exporting the EMG data and event list of every participant, we preprocessed the data and generated csv files containing the labels and EMG data. It should be noted that to protect the patients' privacy, the uploaded event lists have been manually processed to remove sensitive information such as names and IDs.

Limitations

Not applicable

Ethics Statement

All subjects gave written informed consent in accordance with the Declaration of Helsinki. The study was approved by the Ethics Committee on Biomedical Research, West China Hospital of Sichuan University, with the Ethics Code: 2020 132. The decision to anonymize the data was made as part of the ethics approval process.

Credit Author Statement

Wanting Ma: Conceptualization, Methodology, Software, Data curation, Writing - original draft, Writing - review and editing. **Lin Chen**: Data curation, Writing - review and editing. **Xiaofan Pang**: Data collection, Data curation, Expert Annotation. **Yuanwen Zou:** Supervision, Writing - review and editing.

Data Availability

A Multichannel Continuous Clinical Electromyography Dataset from Neurosurgery (Original data) (Mendeley Data).

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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