

Rapid Visualization Tool for Intraoperative Dorsal Column Mapping Triggered by Spinal Cord Stimulation in Chronic Pain Patients*

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Abstract— Spinal cord stimulation (SCS) is a widely accepted effective treatment for managing chronic pain. SCS outcomes depend highly on accurate placement of SCS electrodes at the appropriate spine level for a desired pain relief. Intraoperative neurophysiological monitoring (IONM) under general anesthesia provides an objective real-time mapping of the dorsal columns, and has been shown to be a safe and effective tool. IONM applies stimulation to multiple electrode contacts at various intensities and monitors the triggered electromyography (EMG) responses in several muscle groups simultaneously. Therefore, it requires dynamic communication between neurosurgeon and neurophysiologist and continuous real-time annotations of the responses, which makes the procedure complex and experience-based. Here, we describe an automated data visualization tool that generates patient specific activity maps using intraoperatively collected signals. Responses were collected using a High-resolution (HR)-SCS lead with 8 columns of electrodes spanning the dorsal columns. Our JavaScript/Python based graphical user interface (GUI) provides a fast and robust visualization of EMG activity via denoising, feature extraction, normalization, and overlaying of the activity maps on body images in selected colormaps. In contrast to reviewing series of EMG signals, our user-friendly tool provides a rapid and robust analysis of stimulation effects on various muscle groups and direct comparison across subjects and/or stimulation settings. Future work includes expanding analytics capabilities and operating room implementation as a real-time processing tool that can be used in conjunction with the current IONM techniques.

Clinical Relevance— An automated data analysis and visualization tool can provide rapid assessment of myotomes and SCS electrode position based on EMG measures in operating room, thus can help improve clinical SCS outcomes.

I. INTRODUCTION

Spinal cord stimulation (SCS) is an advanced, invasive pain therapy that is widely used for chronic pain syndromes such as medically refractory back and extremity pain [1].

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Clinically, SCS effectiveness depends on optimal electrode placement over the dorsal column (DC). Patient-specific SCS is expected to benefit from high-resolution DC mapping. The ideal electrode stimulating position is application-specific and must consider several neuroanatomical, physiological, and geometric factors. Several clinical rules of thumb for targeted placement have emerged that are informed by spatially normalized dermatomal and myotomal maps linking vertebral levels to distributed patterns of peripheral cutaneous innervation and motor function. Such rules of thumb include electrode placement at T8/T9 for lower back coverage, T9/T10 for buttock and leg coverage, and foot coverage below T10 [2]. However, normalized probabilistic maps fail to account for interindividual variability in the location of spinal segments, left-right asymmetries, or in cutaneous innervation and spinal cord termination patterns, and do not provide guidance for electrode placement in the medial-lateral direction. A discrepancy between the anatomic and physiologic midline within the spinal canal also exists and has been observed in up to 40% of SCS patients [3-4], which further complicates proper electrode placement.

Intraoperative neurophysiological monitoring (IONM) under general anesthesia provides objective real-time mapping of DC as an alternative to awake SCS surgery where electrode placement is assessed based on patient feedback on stimulation-induced paresthesia (sensations of tingling or numbness) [5]. Monitoring of evoked electromyography (EMG) signals during SCS electrode placement has shown high rates of appropriate lateralization or determination of physiologic midline of spinal cord, which can deviate from the anatomic midline, lower revision rates in retrospective studies, and equivocal or superior clinical outcomes in comparative studies [5-8]. IONM is performed by stimulating multiple contacts of the surgical lead using various current levels and assessment of the corresponding responses in muscles by a multidisciplinary team. IONM therefore requires dynamic communication between teams aided by visual assessment and continuous real-time annotations of the responses. An automated feature extraction and mapping approach is expected to aid in rapid success of IONM leading to improved clinical outcomes.

The aim of the present study is to develop an automated JavaScript/Python tool called DCMAP (dorsal column mapping) that generates activity maps of the intraoperatively recorded EMGs triggered by SCS. To visualize patient myotomal maps, we applied this tool to SCS studies with high-resolution 64 electrode (8-column) DC stimulating arrays. Given that the widely used IONM approach includes assessment of 18-20 muscle groups at variable stimulation

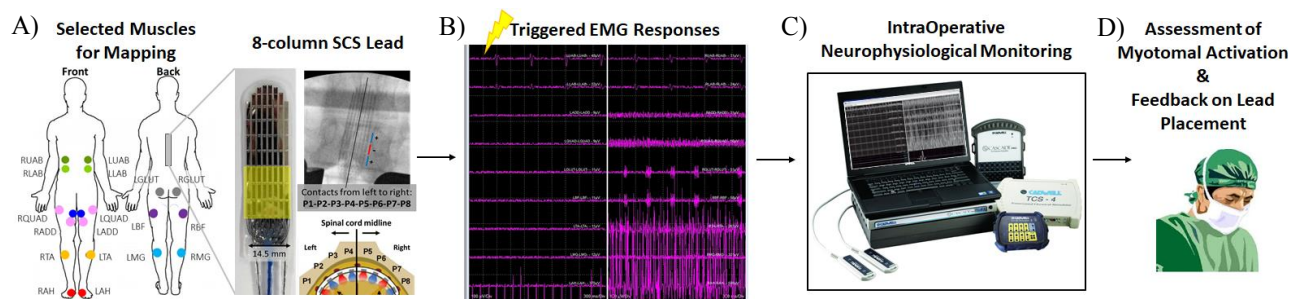


Fig. 1. Intraoperative neuromonitoring (IONM) setup to assess SCS lead placement. A) EMGs evoked by stimulating of the selected contacts over the thoracic area are mapped based on response magnitudes. The color-coded circles represent the muscles used in the protocol. R-/L- indicating right and left side. UAB: upper abdominals. LAB: lower abdominals. QUAD: quadriceps. ADD: adductor magnus. TA: tibialis anterior. AH: adductor hallucis. GLUT: gluteus maximus. BF: bicep femoris. MG: medial gastrocnemius. The contacts of an 8-column High-Resolution SCS electrode (A) is used for testing and highlighted in yellow. B) Ipsilateral EMG Responses. C) IONM System. D) User-in-the loop.

settings, this system might be useful to clinical neuroscience community. The ultimate goal of the study is to implement this tool into an IONM protocol to return a robust, rapid feedback to the neurosurgeon as a strategic feedback modality on lead placement and DC mapping in the operating room.

II. METHODOLOGY

The current study can be partitioned into four stages: surgical implantation of HR-SCS lead, intraoperative collection of stimulation induced EMG responses, offline data analysis/feature extraction, and implementation of a graphical user interface (GUI) for rapid data visualization. Each stage will be explained in detail below. The experimental protocol was approved by the Institutional Review Board of Albany Medical College. All patients provided written informed consent to participate in the study.

A. Patients and Surgery

Intraoperative EMGs were recorded from 4 chronic pain patients who were diagnosed with failed back surgery syndrome and undergoing permanent SCS paddle lead placement. Per our routine protocol, all surgeries were performed under general anesthesia with C-arm fluoroscopic guidance. The 8-column HR-SCS leads (Micro-Leads Inc., Somerville, MA, USA) were placed by laminectomy using the standard techniques [4,8]. Electrode position and myotomal mapping were further assessed by a neurophysiology team with the help of Nuvasive Clinical Services using Cadwell Cascade Pro IONM systems (Cadwell Inc., Kennewick, Wash., USA).

B. Intraoperative Recordings

EMG activity was recorded from legs, extremities, and abdominal muscles using stainless-steel subdermal electrodes (Rhythmlink, Columbia, SC, USA). After the HR-SCS lead was placed over the target, the stimulation protocol was initiated (Fig.1A). The bottom three rows of the lead immediately rostral to the laminectomy site were tested in an anode-cathode-anode configuration by delivering biphasic pulses at 60Hz/300 μ s. Current was gradually increased from 0 to 10mA and corresponding EMG responses per contact set were monitored (Fig.1B). The physiological response thresholds per contact were intraoperatively assessed by the team (Fig.1C-D). At the end of the surgery, signals were

extracted from Cadwell Cascade Pro Neuromonitoring system to ASCII for offline analysis.

C. Signal Processing

De-identified data in ASCII format with predefined fields were converted to .mat files in MATLAB v.2019b using custom MATLAB scripts. Our IONM decision criterion for selective physiological response is 2x larger EMGs on the ipsilateral versus contralateral side. Based on that, three time-domain features were initially implemented into the signal processing pipeline: peak-to-peak amplitude, maximum amplitude, and root-mean-square (RMS). To eliminate the effect of any instantaneous noise or muscle contraction, feature extraction started with denoising, where envelopes of the band-passed filtered signals were computed to mark the peaks in the trace. Then, the peaks exceeding the 10% threshold were removed (Fig. 2). In order to compare EMG activity in the same muscle on different stimulation settings or between muscles on the same stimulation setting, EMG features were normalized using baseline normalization (changes with respect to stimulation OFF condition in logarithmic scale (dB) or percentage (%)), min-max normalization, or group normalization (or common average referencing) [9-10]. Then, an image of the body schematic was overlaid with the smoothed distribution of features using a Gaussian filter. Although data construction and signal processing were initially implemented in MATLAB, all scripts were converted into Python in order to provide a more accessible, freely distributable, open-source platform. This also provides more flexibility for front-end applications.

D. Implementation of Graphical User Interface

Main Window: DCMAP was designed as a visualization tool to provide a quick review of a multi-component, intraoperatively recorded EMG activity in response to SCS. As shown in Fig. 3, it has three main tabs: “Application information” tab that explains the purpose of the tool and details of the workflow. The middle tab, “Search Past Jobs and Examples”, shows sample maps and provides a search option to the user for previously generated heatmaps without entering all parameters again and generating a new map. User must enter the job IDs of the previous maps for the search. Finally, “New Job Submissions” tab renders the user’s inputs and generates the corresponding heatmap with a new job ID. Here, the user selects various parameters such as a specific case based on case number, electrode contact (1 to 8), feature,

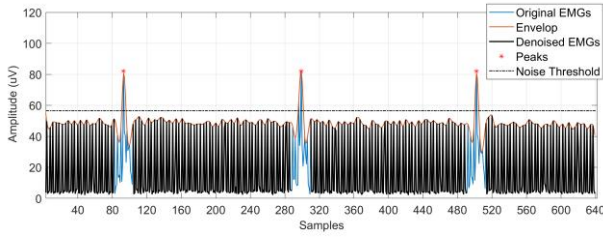


Fig. 2. Example of denoising approach. Noisy EMGs (blue) obtained from LUAB at 3.9mA in patient 2. Denoised EMGs (black) after removal of peaks passing the noise threshold (black dashed line).

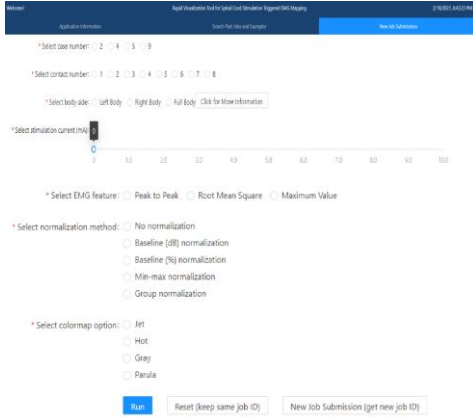


Fig. 3. A screenshot of the DCMAP GUI main window.

normalization approach, and color map (jet, hot, parula, and gray). User can further explore selected muscles, representative x-ray image of the lead over spinal cord, and cross-sectional schematic of the lead on this tab. If the user submits an invalid parameter or skips to submit one, a warning message appears and guides the user on correct selection.

Architecture: Inspired by applications such Stanford's ENCODE Portal [11] and MIMIC-II [12], DCMAP was developed using multiple programming languages (Fig. 4). The front-end of the DCMAP uses HTML/CSS/JavaScript (JS) and back-end of the tool uses Python Django server. The Javascript library Axios handles REST APIs for the front-end and posts the link to the back-end. The Python library Django handles REST APIs for the back-end and gets the link. Python scripts are called to compute features and generate heatmaps under the user's submitted parameters. The parameters and the generated heatmaps in base64 format are stored in the Postgres database. Django posts the base64 SVG data to the front-end to be rendered. Axios receives the image data and the JavaScript library React renders the image accordingly.

III. RESULTS

Fig. 5 demonstrates the heatmaps generated with different input parameters for each patient using DCMAP GUI. Fig. 5A shows the 2-D activity map of peak-to-peak amplitude of EMG signals at 6.3mA in patient 1. Signals were normalized using min-max normalization and shown in parula colormap. The heatmap indicates high activity in upper and lower abdominal muscles as well as relatively high activity on the right side of the body. Fig. 5B shows changes in RMS values from 0mA to 6.2mA in patient 2 when contact-8 was stimulated. Features shown in jet colormap indicates 100%

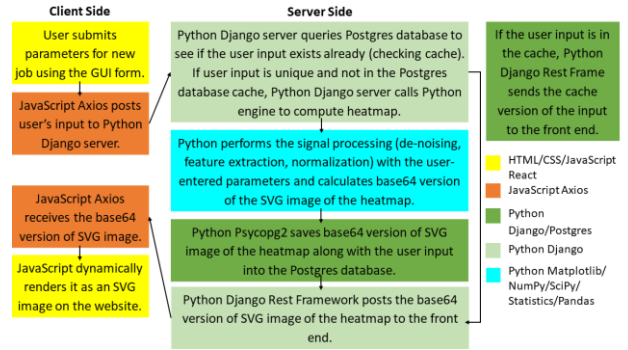


Fig. 4. GUI front-end & back-end architecture. The sequence of steps is indicated by arrows. Color-code represents the programming language.

increase in upper abdominal muscles and ~50% increase in right gluts. Fig. 5C demonstrates RMS values normalized by the group mean in patient 3. The distribution shown in hot colormap indicates that 3.4mA stimulation at contact-5 triggers wider activation across all muscles. Finally, Fig. 5D shows changes in peak amplitude from 0mA to 9mA in patient 4 in response to contact-6 stimulation. Gray colormap indicates stronger muscle activity on the right side of the body. Overall, heatmaps of EMGs in response to thoracic SCS showed stronger ipsilateral activation matching with the clinical decision criterion for accurate lead placement.

IV. CONCLUSION

Accurate placement of the SCS lead over the spinal cord is crucial for optimal pain management. Even though surgical procedures vary somewhat between medical centers, IONM has been shown highly effective in electrode placement resulting in postoperative pain reduction. The approach includes monitoring of EMG activity in muscle groups that correspond to spinal cord level in response to SCS stimulation. Testing of multiple electrode contacts and various stimulation parameters makes the procedure complex. It is also experience-based and depends on neurosurgeon's and neurophysiologist's ability to recognize activated muscles. Given that monitored signals do not undergo any signal processing, it is not possible to directly compare different parameters or contact selections in the OR. Therefore, a rapid visualization tool returning EMG activity maps can provide robust analysis of stimulation effects and help the clinical team aid with decision making.

To the best of our knowledge, this is the first attempt at developing such a tool that analyzes intraoperatively recorded EMG activity evoked by SCS in chronic pain patients. The goal of the present study is to expand the capacity of feature extraction and analytic methods, include additional visualization tools (e.g., raw EMG traces), and to implement a real-time intraoperative processing tool that can serve as an additional guidance in conjunction to the current IONM techniques. Furthermore, the computational architecture behind DCMAP with Python Django server and Postgres database can provide a powerful platform for visualization of larger datasets (e.g., different electrode configurations, multi-center studies, or concurrent requests). The caching feature Postgres database can be useful even after such studies are completed as meta-analyses can be

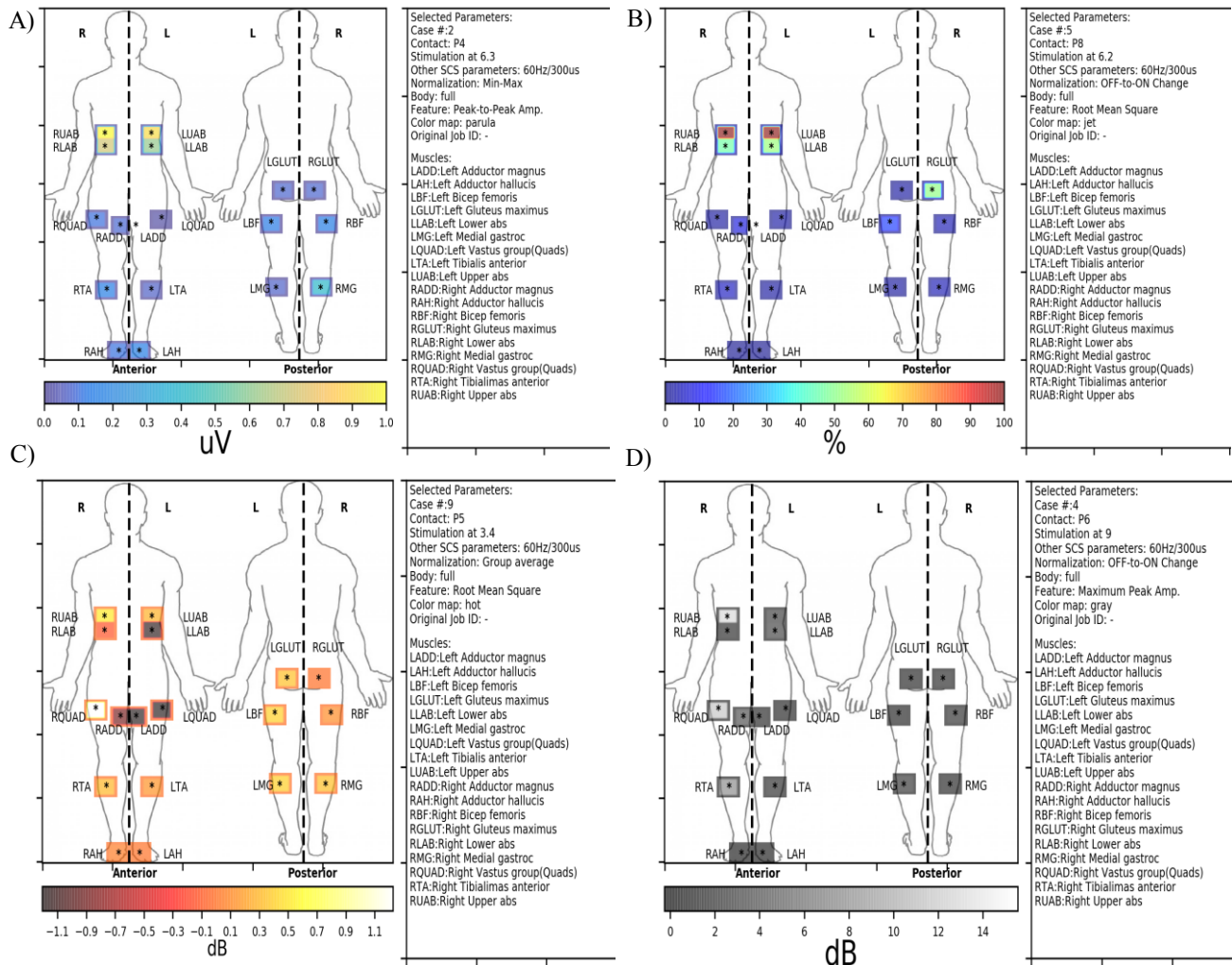


Fig.5. Generated heatmaps in each patient demonstrating distribution of different features of the triggered EMGs and recruitment threshold of the muscle groups. Details of the input parameters and the muscle names can be seen on the right side of each map.

performed on hundreds of such studies years down the line. The system package of DCMAP with source code, a fully documented guideline of the system with prerequisites and installation details and all ongoing updates will be provided on our lab website (<https://amc.edu/Profiles/PiliusJ.cfm>).

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REFERENCES

- [1] K. Kumar, R.S. Taylor, L. Jacques, *et al.*, "The effects of spinal cord stimulation in neuropathic pain are sustained: a 24-month follow-up of the prospective randomized controlled multicenter trial of the effectiveness of spinal cord stimulation," *Neurosurgery*, 63(4), pp.762-770, 2008.
- [2] J. L. Shils and J. E. Arle, "Neuromonitoring for spinal cord stimulation lead placement under general anesthesia," *J. Clin. Neurol.*, vol.14, pp. 444-453, Oct. 2018.
- [3] J. Holsheimer and G. Barolat, "Spinal geometry and paresthesia coverage in spinal cord stimulation," *Neuromodulation*, vol. 1, pp. 129-136, July 1998.

- [4] C. Collison, J. Prusik, S. Paniccioli, *et al.*, "Prospective study of use of intraoperative neuromonitoring in determining post-operative energy requirements and physiologic midline in spinal cord stimulation," *Neuromodulation*, vol. 20, pp. 575-581, Aug. 2017.
- [5] S. G. Roth, S. Lange, J. Haller, *et al.*, "A prospective study of the intra- and postoperative efficacy of intraoperative neuromonitoring in spinal cord stimulation," *Stereotact. Funct. Neurosurg.*, vol. 93, pp. 384-354, Oct. 2015.
- [6] E.L. Air, G.R. Toczyl, G.T. Mandybur, "Electrophysiologic monitoring for placement of laminectomy leads for spinal cord stimulation under general anesthesia," *Neuromodulation*, 15:573-579, 2012.
- [7] S.M. Falowski, A. Celii, A.K. Sestokas, *et al.*, "Awake vs. asleep placement of spinal cord stimulators: a cohort analysis of complications associated with placement," *Neuromodulation*, 14:130-134, 2011.
- [8] R. Hwang., N. Field., V. Kumar, *et al.*, "Intraoperative Neuromonitoring in Percutaneous Spinal Cord Stimulator Placement," *Neuromodulation* 22: 341-346, 2019.
- [9] C. De Luca, "The use of surface electromyography in biomechanics," *Journal of Applied Biomechanics*. 13:135-63, 1997.
- [10] M. Halaki and K. Ginn, "Normalization of EMG signals: to normalize or not to normalize and what to normalize to," *Computational intelligence in electromyography analysis-A perspective on current applications and future challenges*, 17:175-94, 2012.
- [11] M.P. Snyder, T.R. Gingeras, J.E. Moore, *et al.*, "Perspectives on ENCODE," *Nature*, 583(7818), pp.693-698, 2020.
- [12] J. Lee, E. Ribey, J.R. Wallace, "A web-based data visualization tool for the MIMIC-II database," *BMC medical informatics and decision making*, 16(1):1-8, 2015.