# Electrodiagnosis support system for localizing neural injury in an upper limb

Hanjun Shin,[1] Ki Hoon Kim,[2] Chihwan Song,[1] Injoon Lee,[1] Kyubum Lee,[1,3] Jaewoo Kang,[1,4] Yoon Kyoo Kang[2]

▸ Supplementary appendix is published online only. To view these files please visit the journal online http://jamia.bmj.com/content/vol17/issue3

▸ Availability. The software package and supplementary documentation are available at http://infos.korea.ac.kr/ess.php

[1]Department of Computer Science and Engineering, College of Information and Communication, Korea University, Seoul, Korea
[2]Department of Rehabilitation Medicine, College of Medicine, Korea University, Seoul, Korea
[3]College of Life Sciences and Biotechnology, Korea University, Seoul, Korea
[4]Department of Biostatistics, College of Medicine, Korea University, Seoul, Korea

**Correspondence to**
Jaewoo Kang, Anam-dong Seongbuk-ku, College of Information and Communication, Korea University, Seoul, Korea 136—705; kangj@korea.ac.kr
Yoon Kyo Kang, Anam-dong Seongbuk-ku, Department of Rehabilitation Medicine, College of Medicine, Korea University, Seoul, Korea 136—705; yoonkang@korea.ac.kr

Received 20 October 2009
Accepted 11 February 2010

## ABSTRACT
Needle electromyography (EMG) is used for the diagnosis of a neural injury in patients with a cervical/lumbar radiculopathy, plexopathy, peripheral neuropathy, or myopathy. Needle EMG is a particularly invasive test and thus it is important to minimize the pain during inspections. In this paper, we introduce the Electrodiagnosis Support System (ESS), which is a clinical decision support system specialized for neural injury diagnosis in the upper limb. ESS can guide users through the diagnosis process and assist them in making the optimal decision for minimizing unnecessary inspections and as an educational tool for medical trainees. ESS provides a graphical user interface that visualizes the neural structure of the upper limb, through which users input the results of needle EMG tests and retrieve diagnosis results. We validated the accuracy of the system using the diagnosis records of 133 real patients.

## INTRODUCTION
Electrodiagnostic testing consists of two major parts, electromyography (EMG) and nerve conduction study (NCS). NCS is an effective method to detect and localize a nerve injury, which is performed by measuring the amplitudes and latencies of evoked nerve action potentials after stimulating motor and sensory nerves. In the case of EMG, a sharp needle is used to test the patient's muscles, and the results help find a nerve injury. These tests are valuable methods for finding the location and severity of a nerve or muscle injury and predicting recovery from a nerve lesion.

Although these two tests seem simple, patients suffer a great deal of pain, especially when they undergo the needle EMG test, because for this test a sharp needle must penetrate the patients' skin and pierce the muscles' fascia directly. Moreover, this needle insertion must be performed several times before the correct diagnosis can be made; thus, minimizing the number of needle insertions is an important goal for the medical practitioners.

The systems used for analyzing neural structures, and supporting needle EMG tests for localizing neural injury, have been developed over the past several decades. These systems can be categorized into the three groups based on the method employed including the rule-based method,[5 6 8 10 12 15 18 19] probabilistic method,[1 15 18] and knowledge-based method.[2 4 13 16] The rule-based systems evaluate a set of rules predefined by domain experts in order to make clinical decisions. The systems employing probabilistic methods predict the location of nerve injuries using probability models such as Bayesian networks and joint probability distributions. The anatomical knowledge embedded in the probability model provides the methodology for reasoning about the location of injuries. The knowledge-based systems interpret complex neural structures and model a given interpretation using data structures such as tables and networks, which can be used to systematically predict lesions.

Although each method has unique strengths and values in its target domain, there is room for improvement. First, the input and diagnosis steps could be more interactive. Some systems require that the patient's EMG test results are entered in batch before the diagnosis step. For both educational tools and clinical decision support systems, immediate feedback after each input of a test result is important, because it helps users to make the optimal decision during each step. Second, some systems require that damage to the nervous system be numerically graded according to the clinicians' subjective estimation, and this can be biased. Third, in the case of an educational tool, it is important to make the system extensible. There are different interpretations of the human nervous system structure, and even across patients there could be some differences in wiring. For improved educational experiences, it is important to provide an intuitive interface allowing users to change the existing neural structures or load their own interpretation of neural structures to incorporate into the system. Finally, an interactive visual interface for the system is desirable. The user experience could be substantially improved if the system could provide an abstract view of complex nerve structures through which users could interact with inputs and results. The purpose of this paper is to describe how these problems are addressed by ESS. We describe the design, implementation, and pilot evaluation of the ESS system. We also outline technical considerations and challenges in developing this system.

## SYSTEM OVERVIEW AND CASE DESCRIPTION
ESS is a systemized tool developed in C++ for localization of a neural injury in an upper limb. Users can model their own brachial plexus using an input data file reflecting the user's (eg, doctor's) interpretation of the neural structure. Alternatively, users can choose to use a default file provided with the system, which is based on the interpretation of.[12] Other interpretations can be also used, such as Dumitru, Haymarker, or Kendall's.[3 7 9] ESS parses the input data file and constructs an internal data structure that is then used to build a model of the brachial plexus reflecting the specification in the

input file. ESS supports a rich graphical interface that can represent the brachial plexus in a window, as shown in figure 1 in the appendix, available as an online data supplement at http://jamia.bmj.com. The graphical interface is also clickable, enabling users to easily input the results of patients' EMG tests.

The 'Load' button to the bottom left of the interface in figure 1 is used for loading the input data file, which forms the basis for the internal data structure. An example of an input file, based on the book by Rubin and Safdieh,[11] is shown in figure 2 available in the appendix. The internal data structure is a sparse matrix consisting of 0s and 1s, as shown in figure 3 in the appendix. It is used not only for injury diagnosis but also for simplifying the complex neural structure. Users can choose a normal or abnormal muscle by double clicking its abbreviation on the simplified upper limb graph. The full name of the muscle is identified in the list-box to the bottom left. At any point of time during the test, whenever the user clicks on the 'Diagnosis' button, ESS begins the diagnosis in order to localize the nerve injury. The result is presented in the list-box 'Impression' or 'Other possibilities' to the bottom right. The 'Impression' box indicates the site most likely to be damaged given the test results so far, and the 'Other possibilities' box means that there is a chance of an injury at a site, but it is low.

For example, suppose the biceps brachii (BB) and first dorsal interosseus (FDI) are normal, and the pronator teres (PT) and extensor digitorum communis (EDC) are abnormal. For this case, the ESS diagnoses that this patient has a high chance of damage to the 'middle trunk' and a 'C7 radiculopathy', as shown in figure 1. Also, it says that the patient might have a lesion in the 'posterior cord'. In fact, this patient has been diagnosed with a C7 radiculopathy by Korea University Anam Hospital (KUAH).

The ESS diagnosis algorithms were validated using 149 test cases from 133 real patients who visited the Department of Rehabilitation at KUAH. The full results of evaluation are given in the appendix.

## METHODS OF IMPLEMENTATION

### Diagnosis of nerve injury

Established neural structures and myotomes of upper limbs were used for the logical mapping of the upper limb muscles and neural pathways, which are separated into peripheral nerve, cord, trunk, and root. With this mapping, we can identify the injury sites as follows.

First, let the set of muscles with normal findings be $X$, and that with abnormal findings be $Y$, such that $X=\{x_1, x_2, \ldots, x_i\}$ and $Y=\{y_1, y_2, \ldots, y_j\}$, where $x_i$ and $y_j$ are the $i$-th and $j$-th muscles that tested normal and abnormal, respectively. Each muscle, $x_i$ and $y_j$, is represented as a vector corresponding to the row of the matrix in figure 3. Each vector dimension represents a position of the bundle in the neural pathway, and has the following values; 1 means normal, −1 means abnormal, and 0 means unknown status. For example, suppose we have a patient with normal findings on the biceps brachii (*BB*) and first dorsal interosseus (*FDI*), and abnormal findings on the pronator teres (*PT*) and extensor digitorum communis (*EDC*). For this patient, $X=(BB, FDI)$ and $Y=(PT, EDC)$. *BB* and *FDI* are vectors that are the same as the corresponding rows of the matrix in figure 3, given by

$$BB = [\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 1\ 0\ 0\ 1\ 1\ 0\ 0\ 0\ ]$$

$$FDI = [\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 1\ 0\ 0\ 1\ 0\ 0\ 0\ 1\ 1\ ]$$

Similarly, PT and EDC are given by

$$PT = [\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ -1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ -1\ 0\ -1\ -1\ 0\ 0\ -1\ -1\ 0\ 0\ ]$$

$$EDC = [\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ -1\ 0\ 0\ 0\ 0\ -1\ 0\ 0\ 0\ -1\ -1\ 0\ 0\ -1\ -1\ 0\ ]$$

Note that the two vectors of abnormal findings are shown as a negative number in order to indicate that the muscle paths are potential injury candidates.

Second, once the vectors are created, we can construct summary vectors of both normal and abnormal findings. The summary vector of normal findings, $N$, is constructed by adding up all the vectors in $X$. The summary vector of abnormal findings, $A$, can be constructed similarly by adding up the vectors in $Y$. The resulting $N$ and $A$ vectors are given by

$$N = [\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 1\ 1\ 1\ 0\ 1\ 1\ 1\ 0\ 1\ 1\ ]$$

$$A = [\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ -1\ 0\ -1\ 0\ 0\ 0\ 0\ 0\ -1\ -1\ 0\ -1\ -2\ -1\ 0\ -1\ -2\ -1\ 0\ ]$$

Finally, we construct a diagnosis vector, $D$, from $N$ and $A$, given by

$$D = [\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ -1\ 1\ -1\ 0\ 0\ 0\ 1\ 0\ -1\ 1\ 1\ 1\ -1\ 1\ 1\ 1\ -1\ 1\ 1\ ]$$

The 9th dimension corresponding to the median nerve (refer to figure 3) is set to −1, indicating an injury, because of the four muscles tested, only one muscle, *PT*, passes through the median nerve and it tested abnormal. The 10th dimension corresponding to the musculocutaneous is set to 1, indicating normal, because only *BB* passes through the musculocutaneous and is tested normal. On the other hand, the 18th dimension corresponding to the medial cord is set to normal despite that the summary vector of abnormal findings indicate that it is an injury candidate, for the following reason. For the case of non-peripheral nerves such as the medial cord, the route by which a nerve passes through an abnormal muscle is a candidate injury site; however, if it intersects a route that controls a normal muscle, it is excluded from the candidate group, because the route ought to be normal if the muscle it controls is found normal. In this particular example, two muscles, *BB* and *PT*, pass through the medial cord and *BB* is found normal, while *PT* is found abnormal. Since *BB* is found normal, the medial cord is removed from the candidate group.

For the peripheral nerves, however, the diagnosis cannot be completed at this stage if there are contradictory findings, because we need to also consider the order of the muscles in the same nerve pathway, and the number of tests performed on them. In this case, the nerve is not removed from the candidate group and we wait until the localization step to make the final call. This process is explained in the next section.

As such, we can retrieve all candidate injury sites from $D$ by selecting the positions with −1. In this example, the candidate injury sites include the median nerve, radial nerve, posterior cord, and middle trunk and C7 segment. The aforementioned process is formally described in algorithm 1 in the appendix, available as an online data supplement at http://www.jamia.org.

### Localization of nerve injury

Of the candidate injury sites identified in the previous step, the peripheral nerves can be localized further in order to identify the potential injury region more precisely. In this section, we explain how to perform this localization and how to divide candidate injury sites into two groups—namely, 'impression' and 'other possibilities', using clinical heuristics.

Continuing with the previous example, the candidate injury sites were the median nerve, radial nerve, posterior cord, middle trunk, and C7 segment. Of these five sites, the median and radial nerves are peripheral nerves. For peripheral nerves, we attempt to localize the injury site only if nerve inspection has been made more than once. Peripheral nerves tested just once are classified as 'other possibilities,' because if the physician suspected the nerve to be a likely injury site, he or she might have tested it more than once. In our example, the two nerves were tested only once, and according to such clinical heuristics, the median and radial nerve injuries are classified as 'other possibilities.'

On the other hand, for a brachial plexus, we use the following heuristics to determine the 'impressions' list. The site with the most intersections of injury routes has a high chance of injury, and when there are an equal number of intersections, the more proximal region has a higher chance of injury. In our example, there are three brachial plexus candidate injury sites including the posterior cord, middle trunk and C7 root segment. Of these three candidates, we removed the posterior cord injury from the 'impressions' candidates, as the number of abnormal findings is smaller than the others. The posterior cord was found abnormal once, while the other two candidates were found abnormal twice. Of these two candidates, the C7 segment injury was selected for the 'impressions' list, because it is closer to the root than the middle trunk. This process is formally described in algorithm 2, available in the appendix.

For localization of peripheral nerve injuries, we use the following principle. If more than two muscles have an abnormal finding in the same peripheral nerve, there is a chance of a peripheral neuropathy, and when the proximal muscle is normal and the distal muscle is not, this indicates a nerve injury between the muscles. The detailed localization process is formally introduced in algorithm 3, available in the appendix.

## DISCUSSION

In summary, ESS is a CDSS for neural injury diagnosis. Although ESS is proposed primarily for educational purposes, we envision that its core diagnosis could be also embedded in medical devices after further improvements. ESS is interactive, as it narrows down the candidate injury sites by interacting with users. Users can trigger a diagnosis at any point in time. ESS then computes the candidate injury sites given the input provided by the user up to that point. ESS is highly extensible, as it allows users to modify the input file in order to reflect their own interpretation of the neural structure. Its core software logic is also designed to be easily extended to other neural systems such as lower limb. The ESS diagnosis algorithms employ both structural analysis of the neural system and fine-tuned clinical heuristics. The diagnosis algorithms were validated using 149 test cases from 133 real patients and the results are reported in the appendix.

Given the positive validation results, we believe that the current version of ESS can be effective as an educational tool for medical trainees. However, the number of test cases that we used for validation could be too small to establish reliability for clinical applications. More research would be needed to establish reliability for clinical use. In the future, we plan to incorporate NCS test results in the diagnosis process, which could improve the accuracy of results further, especially for the diagnosis of a brachial plexopathy. We also plan to extend the system to deal with other neural structures such as the lumbosacral plexus.

**Funding** This work was partially supported by the Second Brain Korea 21 Project Grant, Microsoft Research Asia Grant, the Korea Research Foundation Grant funded by the Korean Government (MOEHRD, Basic Research Promotion Fund) (KRF-2008-331-D00481), the National Research Foundation of Korea (NRF) grant funded by the Korean government (MEST) (2009-0077688, 2009-0086140), and the Korea Science and Engineering Foundation (KOSEF) grant funded by the Korean government (MEST) (R01-2008-000-20564-0).

**Competing interests** None.

**Provenance and peer review** Not commissioned; externally peer reviewed.

## REFERENCES

1. **Andreassen S,** Falck B, Olesen KG. Diagnostic function of the microhuman prototype of the expert system MUNIN. *Electroencephalogr Clin Neurophysiol* 1992;**85**:143–57.
2. **Cruz J,** Barahona P, Figueiredo AP, *et al*. A knowledge-based system for the diagnosis of neuromuscular disorders. In: Filipe J, Antunes L, eds. *Proceedings of EPIA95 Workshop on Applications of Expert Systems*. Funchal Portugal: Springer-Verlag 1995:27–e38.
3. **Dumitru D,** Amato AA, Zwarts M. *Electrodiagnostic medicine*. 2nd edn. Philadelphia: Hanley & Belfus, 2002.
4. **First MB,** Weimer BJ, McLinden S, *et al*. LOCALIZE: computer-assisted localization of peripheral nervous system lesions. *Comput Biomed Res* 1982;**15**:525–43.
5. **Fuglsang-Frederiksen A,** Ronagar J, Vingtoft S. PC-KANDID: an expert system for electromyography. *Artif Intell Med* 1989;**1**:117–24.
6. **Gallardo A,** Padron O. Artificial intelligence in the electromyographic diagnosis of cervical roots and brachial plexus lesions. *Electroencephalogr Clin Neurophysiol* 1987;**66**:37.
7. **Haymaker W,** Woodhall B. *Peripheral nerve injuries: principles of diagnosis*. Philadelphia: W.B. Saunders, 1953:209–72.
8. **Jamieson PW.** Computerized interpretation of electromyographic data. *Electroencephalogr Clin Neurophysiol* 1990;**75**:390–400.
9. **Kendall FP,** McCreary EK, Provance PG, *et al*. *Muscles: testing and function with posture and pain*. Baltimore: Williams & Wilkins, 2005:27–30.
10. **Rialle V,** Vila A, Besnard Y. Heterogeneus knowledge representation using a finite automaton and first order logic: a case study in electromyography. *Artif Intell Med* 1991;**3**:65–74.
11. **Rubin M,** Safdieh JE. *Netter's concise neuroanatomy*. Philadelphia: Saunders, 2007:310–11.
12. **Schofield IS.** HINT—high level inferencing tool: an expert system for the interpretation of neurophysiological studies. *Proceedings of the Twelfth International Congress of the European Federation for Medical Informatics MIE-94* 1994:144–9.
13. **Starita A,** Majidi D, Giordano A, *et al*. NEUREX: a tutorial expert system for the diagnosis of neurogenic diseases of the lower limbs. *Artif Intell Med* 1995;**7**:25–36.
14. **Todd BS.** A probabilistic simulation model to assist the localization of nerve lesions. *Med Inform* 1994;**19**:209–27.
15. **Vila J,** Reymond F. Experimental EMG expert systems as an aid in diagnosis. *Electroencephalogr Clin Neurophysiol* 1985;**61**:S240.
16. **Woldbye M,** Sørensen AR, Rosenfalck A, *et al*. An interactive neuroanatomy knowledge base for EMG. *Computer aided electromyography and expert systems*. Amsterdam: Elsevier Science, 1989.
17. **Xiang Y,** Pant B, Eisen A, *et al*. PAINULIM: a neuromuscular diagnostic aid using multiply sectioned Bayesian networks. *Proc ISMM Internat Conf on mini and microcomputers in medicine and healthcare*. Long Beach, CA, USA: ACTA press 1991:64–e9.
18. **Yaar I.** Automated localization of nerve damage: hypothesis, technique and performance appraisal. *J Electromyogr Kinesiol* 2002;**12**:147–58.
19. **Yaar I.** The logical choice of muscles for the needle-EMG evaluation of lumbosacral radiculopathy. *J Electromyogr Kinesiol* 2006;**16**:205–13.