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Bayesian characterization of external anal sphincter muscles using quantitative electromyography

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ABSTRACT

Objectives: Based on the analysis of electromyographic (EMG) data muscles are often characterized as normal or affected by a neuromuscular disease process. The objective of this work was to compare the accuracy of Bayesian muscle characterization to conventional means and outlier analysis of motor unit potential (MUP) feature values.
Methods: Quantitative MUP data from the external anal sphincter muscles of control subjects and patients were used to compare the sensitivity, specificity, and accuracy of the methods under examination.
Results: The results demonstrated that Bayesian muscle characterization achieved similar accuracy to combined means and outlier analysis. Thickness and number of turns were the most discriminative MUP features for characterizing the external anal sphincter (EAS) muscles studied in this work.
Conclusions: Although, Bayesian muscle characterization achieved similar accuracy to combined means and outlier analysis, Bayesian muscle characterization can facilitate the determination of "possible", "probable", or "definite" levels of pathology, whereas the conventional means and outlier methods can only provide a dichotomous "normal" or "abnormal" decision. Therefore, Bayesian muscle characterization can be directly used to support clinical decisions related to initial diagnosis as well as treatment and management over time. Decisions are based on facts and not impressions giving electromyography a more reliable role in the diagnosis, management, and treatment of neuromuscular disorders.
Significance: Bayesian muscle characterization can help make electrophysiological examinations more accurate and objective.

1. Introduction

Based on the analysis of electromyographic (EMG) data muscles are often characterized as normal or affected by a neuromuscular disease process. The degree to which a muscle is involved and/or the pattern and degree to which groups of muscles are involved provide important information used to support clinical decisions. Previous work by one of the authors and his collaborators using conventional means and outlier quantitative analysis of concentric needle detected motor unit potential (MUP) data established normative values for the external anal sphincter (EAS) muscle and evaluated the diagnostic sensitivity and specificity of various individual MUP features (Podnar and Mrkaic, 2002; Podnar and Vodusek, 2001; Podnar et al., 2000; Podnar, 2004). That work did not comprehensively examine whether different combinations of feature values used simultaneously (i.e. multivariate classification methods) could improve the characterization of EAS muscles, and establish discriminative feature sets. A method for characterizing a muscle can have more discriminatory power if several MUP feature values are considered simultaneously. The distributions of individual MUP feature values of normal and abnormal have a great deal of overlap (Chan, 2002). A broad search of numerous combinations of MUP features can be useful for determining feature sets that can be used to accurately characterize a muscle in a clinical setting.

Another unresolved problem of using the conventional means and outlier methods is that increasing the number of features required to declare abnormality or increasing the thresholds to establish the limits of normative data resulted in increased specificity at the expense of reduced sensitivity (Podnar, 2004). It was concluded that it would be difficult to set the number of features or thresholds to find a good balance between sensitivity and specificity. In addition to accuracy, the aim of this work was to compare the use of pattern recognition to conventional techniques for their ability to balance between sensitivity and specificity without needing to choose parameter values such as the number of features or their thresholds.

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Pfeiffer (1999) showed that Bayes theorem can be used to combine the MUP feature values of a set of MUPs detected from a muscle to produce an accurate electrophysiological characterization of the muscle. Across a set of detected MUPs, he used recursive Bayesian updating to combine estimates of the conditional probabilities of each MUP being detected from a myopathic, normal or neuropathic muscle given the feature values of each MUP. The work reported here evaluated recursive Bayesian updating and compared it with conventional means and outlier quantitative analysis across different sets of MUP features. Numerous combinations of feature sets taken two, three and four at a time were examined for sensitivity, specificity and accuracy using the same MUP data as used previously (Podnar, 2004) to determine which combination of features used simultaneously is the best choice for a sensitive and specific muscle characterization.

This paper includes Section 2 that briefly reviews the data used, describes the Bayesian method (including two methods used for estimating MUP conditional probabilities), and describes the conventional methods compared. Section 3 reports the best five feature sets per method and compares the sensitivity, specificity, and accuracy of the methods across different combinations of feature sets, and Sections 4 (Discussion) and 5 (Conclusions).

2. Methods

Quantitative MUP data from a group of 86 (58 men) patients (Podnar et al., 2002) (called patient-sensitivity) was used to study sensitivity. Data from a group of 77 (49 female) control subjects (Podnar, 2004) (called control-specificity) was used to study specificity, and data from a separate group of control subjects sampled from 64 control subjects (Podnar et al., 2002) (called control-reference) were used to establish normative thresholds. The patients had cauda equina or conus medullaris lesion. The control-specificity group consisted of subjects referred for minor pelvic floor dysfunction but whose examination showed no neuromuscular or other related disorders. The normative thresholds of the control-reference data were set at ±2 SD for the means and at the 5th–95th percentiles for outliers and were previously published (Podnar et al., 2002). The diagnosis of the subjects and patients was made as per standard clinical practice reported previously (Podnar and Mrkaic, 2002; Podnar and Vodusek, 2001; Podnar et al., 2000; Podnar, 2004).

Intramuscular EMG signals were detected using a concentric needle electrode and a commercial EMG system (Keypoint; Alpine Biomed Neurodiagnostics, Skovlunde, Denmark) with a bandpass of 5 Hz to 10 kHz as previously described (Podnar and Vodusek, 1999). Using the multi-MUP technique described previously (Podnar et al., 2002; Stålberg et al., 1995) individual MUP waveforms were estimated and their feature values were calculated.

2.1. Bayesian muscle characterization

Bayesian muscle characterization is intended to characterize a single muscle at a time. The method can be used to characterize the clinical state of a muscle. Although not a focus of this study, the characterizations across a set of muscles can be combined to provide a characterization for a patient.

Consider that the clinical state of a muscle can be assigned to one of K specific categories with labels $\{y_1,\ldots,y_k,\ldots,y_K\}$ (i.e. myopathic, normal, or neuropathic). The characterization of a MUP is defined by a set of K MUP conditional probabilities, one for each category. Each MUP conditional probability $P(y_k|\mathrm{MUP})$ measures the probability of category y_k given the detected MUP. Given a set of N MUPs $\{\mathrm{MUP}_1,\mathrm{MUP}_2,\ldots,\mathrm{MUP}_N\}$ detected from a muscle under examination, the information provided by each MUP can be effectively combined using Bayes rule for probability to create suggestions related to the clinical condition of the muscle (Pfeiffer, 1999). A muscle characterization is defined as a set of K muscle conditional probabilities, one for each category. Each muscle conditional probability, $P(\mathrm{muscle}=y_k|\{\mathrm{MUP}_1,\mathrm{MUP}_2,\ldots,\mathrm{MUP}_N\})$ measures the probability of the muscle being of category y_k given $\{\mathrm{MUP}_1,\mathrm{MUP}_2,\ldots,\mathrm{MUP}_N\}$ and can be calculated using the following equation:

$$P(\mathrm{muscle}=y_k|\{\mathrm{MUP}_1,\mathrm{MUP}_2,\ldots,\mathrm{MUP}_N\}) = \frac{\prod_i^N P(y_k|\mathrm{MUP}_i)}{\sum_{j=1}^K\left(\prod_i^N P(y_j|\mathrm{MUP}_i)\right)} \quad (1)$$

where muscle $=y_k$ denotes muscle is of category y_k. $\{\mathrm{MUP}_1,\mathrm{MUP}_2,\ldots,\mathrm{MUP}_N\}$ is the set of N MUPs sampled from the muscle. MUP_i is the ith MUP of the set $\{\mathrm{MUP}_1,\mathrm{MUP}_2,\ldots,\mathrm{MUP}_N\}$.

In this study, two categories were considered (normal and neuropathic), and the prior probabilities used were the same for each category (i.e. $P_0(\mathrm{normal})=P_0(\mathrm{neuropathic})=0.5$), to obtain an unbiased muscle characterization that is based solely on the electrophysiological evidence provided by the detected MUPs. Eq. (1) assumes that all prior probabilities are equal, i.e. $P_0(y_1)=P_0(y_2)=\cdots=P_0(y_K)$ where $P_0(y_k)$ is the prior probability of category y_k. The numerator of Eq. (1) is the product of all the individual MUP conditional probabilities related to category y_k. The denominator is the sum of products – one product for each category. Eq. (1) is mathematically identical to recursive Bayesian updating used by Pfeiffer (1999) but is presented in this form to emphasize that the order in which the MUPs are detected or considered is not important. Eq. (1) assumes that evidence provided by each MUP is conditionally independent of the evidence provided by other MUPs. Further information about how Bayes rule can be used to combine multiple pieces of evidence can be found elsewhere (Duda and Hart, 2001). A muscle was characterized as normal or neuropathic based on the higher of the two probabilities provided by Eq. (1). A diagram showing how Eq. (1) works for three muscle categories is shown in Fig. 1.

MUP data representative of each muscle category is required to estimate the MUP conditional probabilities (i.e. the MUP characterizations).

2.1.1. Methods for estimating MUP conditional probability

Any method capable of estimating conditional probabilities can be used with Eq. (1). Two different methods were compared in this work. Pattern discovery (PD) was chosen because of its ability to provide transparent (able to explain its conclusions) characterizations and has been previously described (Pino et al., 2008). Linear discriminant analysis (LDA) was chosen because it was previously used by Pfeiffer for Bayesian aggregation of MUP data (Pfeiffer, 1999). Each method estimates the conditional probability of category y_k (i.e. myopathic, normal or neuropathic) given a detected MUP (i.e. MUP_i) and is expressed as $P(y_k|\mathrm{MUP}_i)$. The characterization of a MUP consists of the set of conditional probabilities for each of the muscle categories being considered. Since, in this work, only two broad categories ($K=2$) were considered: normal and neuropathic, a MUP characterization has two conditional probabilities – one being the conditional probability of normal given the detected MUP and the other the conditional probability of neuropathic given the detected MUP. The PD and LDA methods for estimating MUP conditional probabilities are described in Appendix A.

B-PD and B-LDA refer to Eq. (1) using PD and LDA, respectively, to estimate MUP characterizations. For convenience, B-PD and B-LDA are referred to as the Bayesian methods.

2.2. Means and outlier muscle characterization

The means and outlier methods used in this study are consistent with the previous work using EAS muscle data (Podnar and