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Adaptive fuzzy k-NN classifier for EMG signal decomposition

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Abstract

An adaptive fuzzy k-nearest neighbour classifier (AFNNC) for EMG signal decomposition is presented and evaluated. The developed classifier uses an adaptive assertion-based classification approach for setting a minimum classification threshold. The similarity criterion used for grouping motor unit potentials (MUPs) is based on a combination of MUP shapes and two modes of use of motor unit firing pattern information: passive and active. The performance of the developed classifier was evaluated using synthetic signals with specific properties and experimental signals and compared with the performance of an adaptive template matching classifier, the adaptive certainty classifier (ACC). Across the sets of simulated and experimental EMG signals used for comparison, the AFNNC had better average classification performance overall, but due to the assignment of higher numbers of MUPs it made relatively more errors. Nonetheless, these increased error rates would still be acceptable for most clinical uses of decomposed EMG data. An independent and a related set of simulated signals were used for testing. For the independent simulated signals of varying intensity, the AFNNC had on average an improved correct classification rate (CC_r) (8.1%) but an increased error rate (E_r) (1.5%) compared to ACC. For the related simulated signals with varying amounts of shape and/or firing pattern variability, the AFNNC on average had an improved CC_r (5%) but a slightly increased E_r (0.3%) compared to ACC. For experimental signals, the AFNNC on average had improved CC_r (6%) but an increased E_r (2.1%) compared to ACC. The greatest gains in AFNNC performance relative to that of the ACC occurred when the variability of MUP shapes within motor unit potential trains was high suggesting that compared to a template matching assignment strategy the NN assignment paradigm is better able to ameliorate the classification problems caused by MUP instability.

Keywords: EMG signal decomposition; Motor unit firing patterns; Nearest neighbour classification; Fuzzy k-NN

1. Introduction

An electromyographic (EMG) signal is obtained by measurement of the electrical activity of a muscle during contraction, and reflects the electrical depolarization of excitable muscle fibre membranes that create electrical signals called muscle fibre potentials (MFPs). Clinically, EMG signals are used to diagnose neuromuscular disorders, to analyze the neuromuscular system, and in biofeedback training.

The forward problem in electromyography is the composition of the electrical signal detected during a muscle contraction. In normal mammalian skeletal muscle, the fibres never contract as individuals. Instead, small groups of them contract in concert. All the fibres of each group of muscle fibres are controlled by the terminal branches of one nerve fibre or axon whose cell body is in the interior horn of the spinal grey matter. The nerve cell body, the long axon running down the motor nerve with its terminal branches, and all the muscle fibres controlled by these branches constitute a motor unit (MU) [1]. The summation of all of a MU's spatially and temporally dispersed MFPs results in a signal called the motor unit potential (MUP). In order to sustain a muscle contraction, motor units must be repeatedly activated and each motor unit generates multiple MUPs. The collection of MUPs generated by one motor unit, positioned at their times of occurrence or separated by their inter-discharge intervals (IDIs) is called a motor unit potential train (MUPT) [20]. The

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superposition of the MUPTs of all recruited motor units and background noise comprises an electromyographic signal.

The inverse problem in electromyography consists of using the detected EMG signal to infer the MUPTs, of the recruited MUs, comprising the EMG signal and perform EMG quantification. The process of resolving a composite EMG signal into its constituent motor unit potential trains is called EMG signal decomposition and can be considered as a classification problem.

Many automatic EMG signal decomposition techniques have been developed with different methodologies in the time, frequency or wavelet domain being followed for quantitative analysis ([3,5,6,9,12,13,19,21,22,26]). A review of the basic aspects regarding the composition of EMG signals and methods for EMG signal decomposition can be found in [20].

The objective of EMG signal decomposition is often the extraction of relevant clinical information from quantitative EMG (QEMG) analysis of individual MUPs and MU firing patterns. The first task in EMG signal decomposition is the segmentation of the EMG signal and detection of possible MUP waveforms, which is then followed by the main task of MUP classification. The classification task involves dividing detected MUPs into groups such that each set of grouped MUPs represents the activation of a single MU, or a MUPT, and through which the activation of each active MU can be discriminated. QEMG analysis then often involves the calculation, for each MUPT, a representative MUP waveform, which reflects information regarding individual motor unit morphology, and statistics related to the firing pattern of the MU.

The classification task in most EMG signal decomposition techniques is based on template matching. LeFever and De Luca [9]; Stashuk and his research group ([19,20,22–24]) developed decomposition techniques that identify and classify MUPs based on both waveform template matching in the time domain and firing time statistics. McGill et al. [12,13] used template matching in their ADEMG system based on coefficients of the Fourier transform, while Stashuk and de Bruin [21] proposed a method to decompose single fibre EMG signals using power spectrum template matching. Fang et al. [3] developed a technique to classify single motor unit potentials to decompose multiunit EMG signals based on spectrum matching in the wavelet domain. Zennaro et al. [26] developed a method to decompose multichannel long-term intra-muscular electromyogram signals in which the classification task is based on template matching using wavelet coefficients.

This paper addresses using the nearest neighbour (NN) classification rule instead of template matching for supervised MUP classification during EMG signal decomposition. The primary use of nearest neighbour techniques involves situations where the a priori probabilities and class conditional densities are unknown [14]. Of the many nearest neighbour techniques, we chose the fuzzy k-NN classification rule, proposed by Keller et al. [7] as it deals with vagueness and uncertainty; and it provides a confidence measure regarding the classification results.

Based on the fuzzy k-NN classification rule, an adaptive supervised technique for MUP classification is described and evaluated using synthetic EMG signals with specific properties and experimental EMG signals and its performance is compared with the performance of the adaptive certainty classifier (ACC). The similarity criterion for grouping MUPs is based on a combination of MUP shape and an active use of MU firing pattern information. In this work, active use of MU firing pattern information refers to the use of time specific firing pattern information to determine to which MUPT a MUP should most likely be assigned. The adaptive aspect of the developed classifier is the setting of a minimal assertion threshold for each MUPT, which might be changed based on firing pattern statistics of the train. Following each classification pass through the MUP data, if, based on firing pattern statistics, it is expected that a train has too many erroneous assignments, its minimal assertion threshold is increased or otherwise it is decreased. This firing pattern analysis allows the algorithm to modify the required assertion of a MUP classification for each train individually based on an expectation of the number of erroneous assignments. Trains to which MUPs can be confidently assigned will have a lower minimal assertion threshold and have a higher MUP identification (ID) rate. Alternatively, trains to which MUPs cannot be confidently assigned will have a higher minimal assertion threshold and have a lower MUP identification rate. In both cases, the number of errors expected will be approximately constant. Therefore, over all the trains a maximum number of MUPs should be assigned while maintaining an acceptable MUP assignment error rate. The adjustment of the minimal assertion threshold of each MUPT based on the pattern of MUP occurrences in the train represents a passive use of firing pattern information. Specific assignments are not actively determined by the firing pattern information. Rather the firing pattern information is used to allow or deny MUP assignments in general. The ACC classifier employs the same adaptive classification strategy. Where it uses the same similarity criterion for grouping MUPs and an adaptive certainty-based supervised classification approach.

The remainder of the paper includes a description of fuzzy k-NN classification followed by descriptions of supervised MUP classification using certainty and fuzzy k-NN classifiers. The passive use of motor unit firing pattern information for MUP classification is discussed and descriptions of adaptive versions of fuzzy k-NN and certainty classifiers are presented. Methods used to evaluate the classifiers are then described along with a presentation of the evaluation results, a discussion and conclusions.

2. Fuzzy k-NN classification

The crisp nearest neighbour classification rule assigns a pattern, which is of unknown classification, to the class with