CLEANEMG: ASSESSING THE QUALITY OF EMG SIGNALS

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INTRODUCTION

CleanEMG is an ongoing research project that aims to provide open source, user friendly methods to assess the quality of surface electromyography (sEMG) signals. It is part of a larger effort looking to provide clinically applicable electromyography-based assistive, assessment, and rehabilitation tools.

sEMG has potential to be used clinically to diagnose neuromuscular and musculoskeletal disorders and to control prostheses, in ergonomic and sport science studies to infer muscle condition during activity, in rehabilitation, in applied psychotherapy via biofeedback, and in research to study biological phenomena. However, sEMG applications are not widely accepted, in part, because it is difficult to obtain reliable sEMG recordings and even more difficult to discern their quality.

Characteristic EMG parameters have been studied extensively as indicators of fatigue and various neuromuscular conditions. For instance, muscle conduction velocity (CV), muscle conduction velocity distribution (CVd), and frequency parameters such as Mean Frequency (MF), Median Frequency (MdF) and more recently, Normalized Spectral Moments (FI_{nsmK}) are all EMG parameters which have assessment/diagnostic significance. Changes in CV and CVd have been associated with myopathies such as Amyotrophic Lateral Sclerosis (ALS) [1], Muscular Dystrophy [2], and Chronic Myositis [3]. Also, changes in CV leading to changes in MF, MdF, FI_{nsmK} have been demonstrated extensively during sustained contractions in which fatigue is evident [4], [5], [6].

Much of the correlation between EMG parameters and muscle pathology/fatigue has been confirmed using invasive measurement strategies employing penetrating wire or needle electrodes. Widespread acceptance of non-invasive clinical assessment and diagnosis with surface measurements has been hindered by difficulties in estimating and interpreting parameters measured at the skin surface. There is no generally accepted method for estimating CVd with sEMG [7], though Ledoux et al. [8] recently showed promising preliminary results. Measurements of CV are plagued with high variability caused by electrode placement and fibre termination effects [9], [10], though as Ledoux et al. [8] point out, CV *can* be measured via sEMG if performed properly. Also, almost all parameters useful in assessing muscle fatigue (MF, MdF, FI_{nsmK} for instance) are generally accepted only under static conditions, when joint angle and muscle force are held constant [11], though recent progress has been made to include cyclic and random conditions through advances in signal processing techniques such as time-frequency and wavelet analysis [12], advanced spectral analysis [13] and multivariable analysis [14].

To some extent, sEMG applications have better penetrated ergonomics, sport science, and rehabilitation, but mostly as a means for qualitative assessment, based on coarse observations such as 'active' vs 'nonactive' or other gross intensity comparisons. For instance, level of muscular activity as indicated by course amplitude estimates of the sEMG are often used in assessment of exercise regimes [15], and it is not uncommon to include a rough sEMG analysis during gait examination [16].

Despite drawbacks inherent in sEMG, its utility continues to be demonstrated in applications such as prosthetics control [17], and with recent increases in attention to work place musculoskeletal injuries, sEMG is being promoted as an important assessment tool [18]. Still, more work needs to be conducted

before we can expect widespread acceptance of clinical applications such as on-site monitoring to help mitigate against workplace musculoskeletal injuries. With the onset of small, wireless and even wearable sEMG technologies, such applications are becoming more attractive to clinicians, but until sufficient advances in sEMG are made to ensure easy and reliable measurement and interpretation, sEMG will remain relatively untapped in clinical assessment and diagnosis.

QUALITY ASSESSMENT SOLUTION: CLEANEMG

Clinicians need their tools to be portable, and easy to use - to be potentially used unmonitored by an expert. While we can build a portable sEMG measurement system, without expertise in signal processing and instrumentation, it is difficult to know how to set it up properly, since optimal settings are context (subject, condition, and environment) sensitive and the sEMG signal is difficult to interpret visually. Deficient measurement setups and/or limited or deficient instrumentation can degrade quality in sEMG. Even when the measuring system is set optimally, contamination in recordings can still be forthcoming from sources of interference. To be reliable, sEMG-based applications must include quality assessment of the sEMG. In research this is usually done through inspection by the research expert. Clinically, this is often not possible and an automated solution is required. The purpose of the CleanEMG project is to produce such a solution.

A software framework is being developed in Matlab (Mathworks Inc., Natick, MA) to support access to a set of units also developed in Matlab, each being designed to identify a particular source of quality degradation and specify quantifying parameters about it. Implementing the solution in Matlab enables seamless third party contributions. The open software artifacts being developed in this project have the potential to be packaged into standalone sEMG quality assessment tools, deployed as part of an e-service offering sEMG quality assessment, or integrated as a signal integrity component embedded within a medical/clinical device.

The focus for CleanEMG is on identifying and quantifying sEMG quality degradation caused by deficient measurement set-ups, limited or deficient instrumentation, and interference. These categories collectively cover motion artifact, baseline wander, amplifier saturation, analog-to-digital converter (ADC) over-ranging and quantization error, powerline and physiological interference (ECG for instance), and poor electrode contact.

In the context of this work, physiologic interference does not include signals produced by neighbouring muscles, known as crosstalk. This is not meant to imply that crosstalk has no influence on sEMG quality; instead it is recognition of the current challenges associated with identifying and quantifying quality degradation due to this kind of interference. Further developments will be necessary before crosstalk can be brought into the mandate for CleanEMG. The same can be said for degradation due to poor electrode positioning (the influence of proximity to innervation zone and tendon regions, for instance).

Figure 1 depicts a typical set-up for capturing sEMG data.

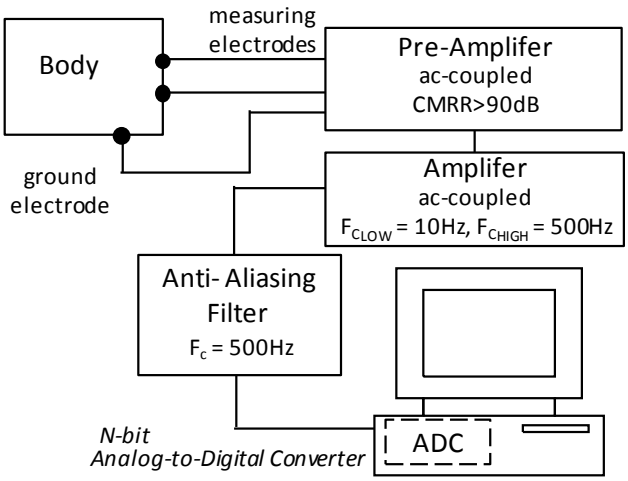

Figure 1: Typical components used to capture sEMG

Each of the components must be tuned optimally to mitigate against degradation. For instance, the amplifier is often equipped with low and high pass filters, which when set properly, can reduce degradation due to both measurement issues and interference. Even with well set up instrumentation, in some

cases, contamination can still be forthcoming. Checking a signal before using it in research or in a clinical setting is warranted. If a single record is available, validating its quality is practical so that measurement system parameters can be adjusted to improve quality or, when this is not possible, limiting conditions for use can be specified. If more than one record is available, comparing the quality of each may be practical in selecting records for use. With the onset of technologies which can efficiently store large data sets this is becoming increasingly important because collection of redundant data is commonplace.

The following briefly summarizes approaches currently being explored as part of CleanEMG to identify and/or quantify target quality degradation types.

Baseline Wander and Motion Artifact

Baseline wander and motion artifact both manifest as low frequency components in sEMG and thus can be quantified in the same ways. Sinderby [19] proposed a signal to motion artifact ratio (SMR) which can be generalized to both target sources. It is defined as the ratio between the sum of power densities across all frequencies and the sum of power densities that exceed a straight line between the axis origin and the highest mean power density above a threshold frequency (e.g. 35 Hz).

Amplifier Saturation, ADC Over-ranging and Quantization Noise

Amplifier saturation and ADC over-ranging are similar phenomena in that they both result from inputs which exceed the dynamic range of the instrumentation. When input to the ADC is much larger than its dynamic range, overranging can be identified by observing regions of contiguous samples with values equal to the max/min output values possible by the ADC. Quality degradation can then be quantified by establishing a ratio between the number of samples collectively in these flat regions and the total number of samples.

When amplifier saturation occurs but input to the ADC remains within its dynamic range, small fluctuations may still be apparent in otherwise 'flat' regions (as long as the ADC step size is sufficiently small to resolve the small analog variance in the saturated signal). It may therefore be necessary to use sEMG modeling to identify saturation. For instance, sEMG signals are characterized by a Gaussian distribution of amplitude values. Asymmetry in the distribution of these values, could be used as an identifier for saturation.

Another source of quality degradation associated with the ADC is quantization noise, caused by rounding analog inputs to their closest digital values. For a uniform quantizer, the worst-case quantization error is half the step size from one digital value to the next. Generally quantization noise is small in comparison to the signal, for instance SQNR = $20\log_{10}(2^N) \approx 6.02 \cdot N$ dB for a signal distributed uniformly across all quantization levels. However, if the full scale range of the ADC is not being utilized, quantization noise can become substantial in comparison to the signal and an alternative model can be used to quantify its effect on signal quality.

Power line Interference

Power line interference is 60 Hz interference caused by electromagnetic coupling and should be readily identified in a power spectral density. Two approaches are currently being investigated to quantify it, both attempting to estimate the power in the signal, in order to calculate SNR_{60Hz}: 1) Iteration of the spectrum about the 60 Hz component and 2) adaptive filtering with a 60 Hz sinusoid reference signal. Both of these methods could also be used to clean the sEMG data, as long as the method does not introduce other degradation, reducing the quality further.

Physiologic Interference

The electrocardiogram (ECG) is the primary source of physiologic interference in sEMG since other signals, such as nerve trains, should be negligible in surface recordings. If an ECG reference signal is available, adaptive filtering can be used similarly to power line interference quantifying methods, to quantify the physiologic interference. Otherwise, Sinderby's [19] Omega ratio can be used. This is an index of spectral deformation which is sensitive to symmetry. Since lower frequencies are more

dominant in ECG compared to EMG, ECG content should increase the Omega ratio.

Poor Electrode Contact

Assuming a bipolar electrode configuration, if one electrode has poor contact, this will likely result in a large DC bias in the signal causing asymmetric saturation of the amplifier. Common mode signals may also appear as differential signals, increasing power line interference. Both of these sources of quality degradation have already been discussed and poor electrode contact could be identified if saturation and power line interference are indicated simultaneously. More subtle effects of poor electrode contact may require sEMG modeling similar to saturation for identification.

CONCLUSIONS

This work summarizes the current state of the CleanEMG project. The need for automated quality assessment in sEMG has been identified and rationalized, and a set of Matlab-based, open source software artifacts has been proposed for the solution.

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REFERENCES

[1] J Partanen, U Nousiainen, "Motor unit potentials in a mildly affected muscle in amyotrophic lateral sclerosis," Journal of Neurological Science 95, pp 193-199, 1990.

[2] JH van der Hoeven, TP Links, MJ Zwarts, TW van Weerden, "Muscle fiber conduction velocity in the diagnosis of familial hypokalemic periodic paralysis - Invasive versus surface determination," Muscle and Nerve, 17 pp 898-905, 1994.

[3] A Cruz Martinez, JM Lopez Terrades, "Conduction velocity along muscle fibres in situ in Duchene muscular dystrophy," Archives of Physical Medicine and Rehabilitation, 71, pp 558-561, 1990.

[4] CJ De Luca, "Myoelectrical manifestations of localized muscular fatigue in humans", CRC Critical Reviews in Biomedical Engineering, 11(4), pp 251 - 279, 1984.

[5] NA Dimitrova, TI Arabadzhiev, J-Y Hogrel, GV Dimitrov, "Fatigue analysis of interference EMG signals obtained from biceps brachii during isometric voluntary contraction at various force levels," Journal of Electromyography and Kinesiology, 19(2), pp. 252-258, 2009.

[6] D MacIsaac, PA Parker, KB Englehart, D Rogers, "Fatigue estimation with a multivariable myoelectric mapping function," IEEE Transactions on Biomedical Engineering, 53(4), pp. 694-700, 2006.

[7] JA Gonzalez-Cueto, PA Parker, "Deconvolution Estimation of Motor Unit Conduction Velocity Distribution," IEEE Transactions on Biomedical Engineering, 49(9), pp 955-962, 2002.

[8] I Ledoux, M-T Garcia-Conzalez, J Duchene, J-Y Hogrel, "Motor unit conduction velocity distribution estimation from evoked motor responses," IEEE Transactions on Biomedical Engineering, 53(4), 2006.

[9] D Farina, R Merletti, M Nazzaro, I Caruso, "Effect of joint angle on EMG variables in leg and thigh muscles," Engineering in Medicine and Biology Magazine, IEEE , 20(6), pp 62-71, 2001.

[10] S Martin, D MacIsaac, "The Effects of Innervation Zone Migration in the Brachial Biceps" Journal of Electromyography and Kinesiology, 16(2), pp. 144-148, 2005.

[11] P Bonato, SH Roy, M Knaflitz, CJ De Luca, "Time-frequency parameters of the surface myoelectric signal for assessing muscle fatigue during cyclic dynamic contractions," IEEE Transactions on Biomedical Engineering, 48(7), pp 745-753, 2001.

[12] S Karlsson, J Yu, M Akay, "Time-frequency analysis of myoelectric signals during dynamic contractions: A comparative study," IEEE Transactions on Biomedical Engineering, 47(2), pp 228-238, 2000.

[13] Dimitrov GV, Arabadzhiev TI, Mileva KN, Bowtell JL, Crichton N, Dimitrova NA, "Muscle fatigue during dynamic contractions assessed by new spectral indices," Medicine and Science in Sports Exercise, 38(11) pp 1971–1979, 2006.

[14] D Rogers, D MacIsaac, "Training a multivariable Mapping function to Estimate Fatigue", Journal of Electromyography and Kinesiology, 20(5), pp 953-960, 2010.

[15] K Hildebrand, L Noble, "Abdominal muscle activity while performing trunk-flexion exercises using the ab riller, ABslide, FitBall, and conventually performed trunk curls," Journal of Athletic Training, 39(1), pp. 37-43, 2004.

[16] DH Sutherland, "The evolution of clinical gait analysis part I: kinesiological EMG," Gait and Posture, 14(1), pp. 61-70, 2001.

[17] Hargrove, L, Hudgins B, Englehart K, "A Training Strategy to Reduce Classification Degradation due to Electrode Displacements in Pattern Recognition Based Myoelectric Control", Biological Signal Processing and Control, 3, pp 175-178, 2007.

[18] R Merletti, F Benvenuti, C Doncarli, C Disselhorst-Klug, R Reffabone, HJ Hermens, R Kadefors, T Laubli, C Orizio, G Sjogaaard, D Zazula, "The European project 'Neuromuscular assessment in the elderly worker' (NEW): achievements in electromyogram signal acquisition, modelling, and processing," Medical & Biological Engineering and Computing, 42, pp 429-431, 2004.

[19] Sinderby C, Lindstrom L, Grassino AE, "Automatic Assessment of Electromyography", Journal of Applied Physiology, vol. 79, no. 5, pp. 1803-1815, 1995.