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sEMG-based detection of poor posture: a feasibility study

Haritz Zabaleta[1], Cristina Rodriguez-de-Pablo[1], Nadica Miljkovic[2], Thierry Keller[1] and Gonzalo A. Garcia[1]

[1]TECNALIA, Health Unit
P Mikeletegi, 1
20011 Donostia, Spain

[2]Biomedical Engineering
School of Electrical Engineering
University of Belgrade, Serbia

haritz.zabaleta@tecnalia.com

***Abstract*— The cost of the medical treatment of low back pain (LBP) was estimated to be $24 billion in the early 90s. Also, 80% of the LBP is estimated to be due to poor or inappropriate posture. The ultimate goal of the project is to develop a surface electromyography (sEMG)-based device that could be used to prevent and treat LBP by postural re-education or simply for on-the-spot sEMG feedback. In this paper we present the results and conclusions of a feasibility study for sEMG-based poor posture classifier.**

The results show that a s-EMG based poor posture classifier could be possible. The sensitivity for the best linear classifier model was 72% and the specificity was 78%. The same signal feature returned very different results from one participant to another. This inter-subject variability could be due to different muscular activation patterns during posture correction.

I. INTRODUCTION

The incidence of low back pain (LBP) in the U.S. has been reported to be second after the incidence of the common cold [1]. Taking into account the whole population, there is an 80% chance that a person will seek medical care for a LBP disorder prior to age 55 [2]. The annual prevalence rate of LBP is between 15 and 20% and it is the most common reason for disability in individuals less than 45 years of age. As stated by Andersson in [3], the mean number of days of restricted activity is 23.5 days and the mean number of days lost from work is 8 days due to LBP. In terms of economic costs, the annual medical treatment of LBP in the U.S. is estimated to be $24 billion [4]. Additionally, it is estimated that 80% of back pain is due to poor or inappropriate posture [5]. This study showed that asymmetry can be one of the main factors to develop LBP: 97.5% of 200 patients with back pain showed 20% or higher level of asymmetry; on 40 subjects without pain, the imbalance was between 5 and 10% . In the United States, LBP is common. Moreover, LBP is the most common reason for office visits to orthopaedic surgeons, neurosurgeons, and occupational medicine physicians. Additionally, it is the second second most frequent reason for a primary care physician office visit [6].

Surface electromyography (sEMG) has been widely used for biofeedback [7] [8] and it seems to be a good candidate for future use in postural reeducation in LBP prevention and treatment.

The final goal of the project is to study the feasibility of a sEMG-based device that could be used to prevent and treat LBP by postural re-education via on-the-spot feedback for people that have suffered from LBP, are in treatment due to LBP or have high risk of suffering LBP. The goal of the present study is to a) feature selection derived from sEMG signals and b) evaluation of the classifiers based on the selected features, in order to select the most relevant feature to be used in a poor posture detection.

II. METHOD

A. Subjects

Three female (mean age 27.00 $\pm$ 3.60 years, mean BMI 20.30 $\pm$ 1.62 kg/m^2) and 7 male (mean age 32.86 $\pm$ 4.88 years, mean BMI 22.95 $\pm$ 3.00 kg/m^2) subjects participated in this study. Their mean age was 31.10 $\pm$ 5.17 years and mean BMI 22.16 $\pm$ 2.87 kg/m^2). All procedures were in accordance with the Declaration of Helsinki. All subjects gave written informed consent for participation.

B. Instrumentation

Eight pairs of disposable surface F-TC1 Skintact electrodes (1cm^2, Ag/AgCl) where attached to the target muscles. The sEMG signals were amplified and digitalized using a 16-channel 24 bit biosignal g.USBAmp data acquisition device (g.tec Guger Technologies, Graz, Austria). The raw sEMG signals were band-pass filtered between 5 and 2000Hz and with a notch filter at 50Hz. The sampling rate was 4800Hz.

Synchronous video data was also recorded (lateral and posterior) at a 10 Hz frame-rate using two WebCams (HD Webcam C310 of Logitech). The physiotherapist could see all sEMG signals and the lateral and posterior videos.

C. Assessments

After literature review on the influence of muscular groups involved in back posture [9] [10] [11] [12] [13] [14] [15], the following muscle groups were selected to be monitorized: *Erector Spinae* (ES), *Latissimus Dorsi* (LD), *Quadratus Lumborum* (QL) and *Abdominal External Oblique* (EO).

Two of the participants participated in a back school program during 8 weeks and were monitored weekly. The back school program consisted in daily exercises during 45 minutes. The set of exercises were designed by a physiotherapist experienced in LBP. Before starting the back school program the two participants were monitored for three weeks, as well as after the end of the back school program. Eight control participants conducted only one day test.

Each monitoring session consisted on 2 blocks of 6 posture corrections (three in a sitting down position and three in standing up position). If the participant was not tired, he/she was encouraged to perform another posture correction trial at the end of each block in their preferred position (standing up or sitting down). Between each block the participant had a 5 minute break relax (walk, stretching, drink, ...).

Each posture correction was divided in three phases.

- **Natural Posture:** The participant was asked to maintain during 25 seconds as steady as possible the posture that he considered as *normal*. Figures 1a and 1c.
- **Correction Phase:** The participant followed the instructions of the physiotherapist until the correct posture was reached
- **Corrected Posture:** The participant was asked to maintain during 25 seconds the same posture as steady as possible with no further correction indications. Figures 1b and 1d.

(a) Natural posterior view

(b) Corrected posterior view

(c) Natural lateral view

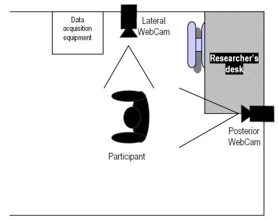
(d) Corrected lateral view

Fig. 1: Natural and corrected postures pictures

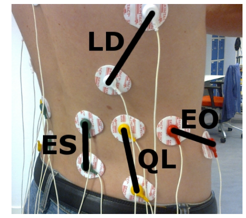
D. Electrode placement

Eight pairs of electrodes (4 in each side) recorded the trunk muscle activity of the target muscles on both left and right sides: *Erector Spinae* (ES), *Latissimus Dorsi* (LD), *Quadratus Lumborum* (QL) and *Abdominal External Oblique* (EO). The electrodes were placed following the indications of [16], shown in Figure 2b.

- ***Erector Spinae*** **(ES):** The electrodes were placed parallel to the backbone. With the hands on the iliac crest, the thumbs will rest at either L4 or the L4-L5 space. By palpation, the L2 can be easily located. The electrodes were placed in both sides of the L2 and L4 as in [10] and [11].
- ***Latissimus Dorsi*** **(LD):** The first electrode is placed at the last rib height. The second electrode is placed at around 45 degrees upwards from this one to about 3cm.



(a) Location of participant, video and sEMG data acquisition equipment



(b) Detail of the placement of the electrodes in low back

Fig. 2: Experiments setup

- ***Quadratus Lumborum*** **(QL):** The first electrode is placed at about 3cm to the external side from the L3 electrode of the ES. The second electrode is placed parallel to the spinal cord, at the same level of the L5.
- ***Abdominal External Oblique*** **(EO):** The first electrode is placed parallel to the L5 at the lateral, and the second one at about 45 degrees downwards following the muscular fibers' direction.

Both reference and ground electrodes were placed on the thoracic 7 vertebral segment.

1) Signal conditioning and processing: The sEMG signal treatment was done according to the European Recommendations for Surface Electromyography [17]. The sEMG signal was first high-pass filtered at 20Hz to suppress movement artifacts.

2) Feature extraction: We obtained eight signals $s_{1\ to\ 8}$ corresponding to the differential signal for each pair of electrodes placed as shown in Figure 2b. $s_{1\ \mathrm{to}\ 4}$ targeted the left side ES, LD, QL and EO muscles, whereas the $s_{5\ \mathrm{to}\ 8}$ targed the right side ES, LD, QL and EO muscles. Each signal was divided in two chunks. Each signal chunk of N = 120000 samples (25 seconds) corresponding to the natural posture and corrected posture. Figure 3 shows the signal after the chunk corresponding to the correction phase has been removed. For each chunk (natural and corrected posture), a set of 32 features were extracted to characterize the sEMG signals.

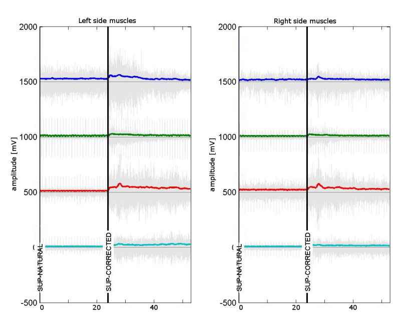


Fig. 3: Chunked signal (in gray): left and right muscular activity during natural posture and corrected posture. The envelope of the signal is highlighted. The signals were displaced by 500mV for visualization purposes. Top to bottom: ES, LD, QL, EO.

The feature vector Γ_i is composed by:

Average muscular activity (10 features)

- Mean Absolute Value (MAV) $|\overline{s_{1\ to\ 8}}|$ for each muscle, P_Amp_k(equation 1). Features 1 to 8.
- Average of the left and right side muscles independently, P_Amp_L and P_Amp_R (equations 2 and 3). Features 9 and 10;

Muscular symmetry related (6 features)

- Difference of activity among left and right homologous muscle, $P\_\mathrm{Dif}(k)$ (equation 4). Features 11 to 14.
- Difference of activity among sides, P_Dif_{LR} (equation 5). Feature 15.
- Uniformity of activity of all muscles, P_unif (equation 6). Feature 16.

Correlation between muscles (16 features)

- Correlation between homologous muscles, $P\_Corr\_Homo(k)$ (equation 7). Feature 17 to 20.
- Correlation between left muscles, $P\_Corr\_LSide(k)$ (equation 9). Features 21 to 26.
- Correlation between right muscles, $P\_Corr\_RSide(k)$ (equation 10). Features 27 to 32.

Formulae:

$$P\_Amp(k) = \frac{\sum_{k=1}^{N} |s_k(t)|}{N} \quad \text{for} \quad k = 1\ to\ 8 \quad (1)$$

$$P\_Amp_L = \frac{\sum_{k=1}^{4} P\_Amp(k)}{4} \quad (2)$$

$$P\_Amp_R = \frac{\sum_{k=5}^{8} P\_Amp(k)}{4} \quad (3)$$

$$P\_\mathrm{Dif}(k) = P\_Amp(k) - P\_Amp_{(}k+4) \quad \text{for} \quad k = 1\ to\ 4 \quad (4)$$

$$P\_Dif_{LR} = P_{amp_L} - P_{amp_R} \quad (5)$$

$$P\_\mathrm{unif} = \sqrt{\frac{\sum_{i=1}^{n} (P_i - \bar{P}_{1\ to\ 8})^2}{n-1}} \quad \text{being } n = 8 \quad (6)$$

$$P\_Corr\_Homo(k) = s_k(t) \star s_{k+4}(t) \quad \text{for} \quad k = 1\ to\ 8 \quad (7)$$

$$P\_Corr\_LSide(k) = s_i(t) \star s_j(t) \quad \text{for} \quad k = 1\ to\ 7 \quad (8)$$

$$\text{and} \quad (i,j)_k \in \{(1,2),(1,3),(1,4),(2,3),(2,4),(3,4)\}$$

$$P\_Corr\_RSide(k) = s_i(t) \star s_j(t) \quad \text{for} \quad k = 1\ to\ 7 \quad (9)$$

$$\text{and} \quad (i,j)_k \in \{(5,6),(5,6),(5,8),(6,7),(6,8),(7,8)\}$$

E. Statistical analysis

A database was built from the trials of all the subjects using the described features for natural and corrected postures. Thirty-two classifier models were created, one for each feature independently, and trained and tested with leave-one-out crossvalidation. The leave-one-out crossvalidation is trained multiple times removing a different sample from the training set and using it as test target each time. This technique permits computing complete tests using a relatively small dataset. As a first step, the best classifier model was chosen taking into account the performance of the classifier with leave-one-out crossvalidation. The false positives in uncorrected and corrected postures were not taken into account in this case, but analyzed aftwer when the best classifier was selected.

In order to evaluate intersubject variations, the process was repeated also for each subject independently when sufficient data was collected.

III. RESULTS

In all, 297 trials were recorded which gave 297 samples for normal posture and 297 samples for corrected posture. Therefore, the database consisted in 594 samples with a feature vector of 32 parameters. Some of these samples, had to be removed due to movement artifacts, cough during the trial, etc. The final database consisted on 474 trials. These features were analyzed using linear discriminant functions and classified into natural ond corrected groups.

The Table I shows the 5 features with which the best classifier models were created according to their performance.

In order to graphically view the sensitivity and the specificity of the two best binary classifier models, receiver operating characteristic (ROC) curves were drawn for the top 5 classifiers. The ROC curves of the top 5 classifiers are shown in Figure 4.

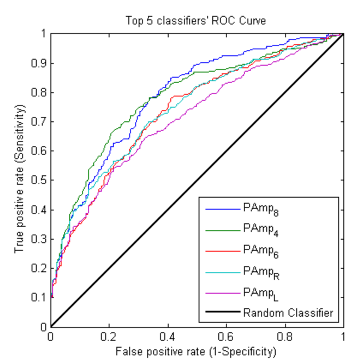


Fig. 4: ROC curve of the best 5 linear binary classifier models

In Table I the data of the best 5 classifier models' ROC curve are presented. We also created independent databases, one for each subject with sufficient data, in order to see the intersubject variability. These were subjects #1, #2, #3 and #8 with 220, 188 (skipped two days due to health problems -not related to LBP-), 34 and 32 samples respectively. The last two were monitored only one day. The result of the two best classifiers according to their performance are shown in Table II.

IV. DISCUSSION

As we can see in Table I the classifier based on the left and right EO are the ones that have the best performance. Also, when the classifiers are designed for each subject separately, the EO activity based classifiers show, in all of the cases

TABLE I: ROC curve data of top 5 classifiers

Parameter	AUC[1]	S.E.[2]	95% C.I.[3]		S.AUC[4]
P_Amp_8	0.79606	0.01832	0.76016	0.83197	16.1617
P_Amp_4	0.78681	0.01867	0.75022	0.82341	15.3600
P_Amp_6	0.71418	0.02098	0.67307	0.75529	10.2110
P_Amp_R	0.68792	0.02162	0.64555	0.73030	8.6924
P_Amp_L	0.64996	0.02239	0.60607	0.69384	6.6977

TABLE II: Best classifiers by subject

	Best feature			Second Best Feature		
S#[5]	P	AUC[1]	SE[2]	P	AUC[1]	SE[2]
1	$PAmp_8$	0.78	0.03	$PCorr\_Homo(4)$	0.70	0.04
2	$PAmp_4$	0.87	0.03	$PAmp_8$	0.82	0.03
3	$PAmp_4$	0.74	0.09	$PCorr\_LSide(5)$	0.68	0.09
8	$PAmp_4$	0.79	0.08	$PAmp_8$	0.77	0.08

[1]Area under the curve
[2]Standard error of the area
[3]Confidence interval vector of the AUC
[4]Standarized AUC.
[5]Subject number

the best scores (see Table II). The 5 classifiers with best performance across all subjects and all trials were P_Amp_8, P_Amp_4, P_Amp_6, P_Amp_R and P_Amp_L. We counted the number of times that these features appeared in the best 10 classifiers using individual datasets for each subject. P_Amp_4 is one of the best 10 classifiers in all of the 4 subjects, P_Amp_8 is one of the best 10 classifiers in 3 of subjects, P_Amp_6 and P_Amp_R in two subjects and P_Amp_L only for the subject #8.

We expected that the symetry feature of muscular activity P_Dif_{LR} would be one with the most robust classification performance, but only in the subject #4 appears this feature as one of the best classifiers in 9th place (AUC=0.6680, SE=0.0965).

The subject that did not follow back school repeatedly reported tiredness during the test. This lead us to think that the correct posture was uncomfortable to them, and the muscular activity was altered due to stress and tiredness during the tests. The two subjects that followed back school, also reported tiredness during the first trials, but not during the last ones. The results show much better performance in the subjects #1 and #2. These subjects have followed back school program and have gone through many monitoring tests (11 and 9 respectively). We used sensitivity (True positive) and specificity (True negative) to measure the performance of the single parametric linear classifiers. The sensitivity for the overall linear classifier for the P_Amp_8 feature was 72.0% and the specificity was 78.1%.

Although the performance of the classifiers are still too low, the achieved sensitivity was taking into account only one parameter with a single parameter and linear classifier. Therefore, we conclude that a sEMG-based poor posture detection could feasable with more sophisticated classifiers. The method should be studied further extracting different features, using multi-parametric analysis or applying of neural networks.

This same database will be used to apply other techniques such as PCA to extract the optimum features to use. Mutiple feature and clustering techniques will be also analyzed.

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REFERENCES

[1] R. Deyo, Y. Tsui-Wu *et al.*, "Descriptive epidemiology of low-back pain and its related medical care in the united states." *Spine*, vol. 12, no. 3, p. 264, 1987.
[2] H. Taylor and C. De Luca, "Development of new protocols and analysis procedures for the assessment of LBP by surface EMG techniques," *Development*, vol. 34, no. 4, pp. 415–426, 1997.
[3] G. Andersson, "The epidemiology of spinal disorders," *The adult spine: Principles and practice*, 1997.
[4] R. Deyo, D. Cherkin, D. Conrad, and E. Volinn, "Cost, controversy, crisis: low back pain and the health of the public," *Annual review of public health*, vol. 12, no. 1, pp. 141–156, 1991.
[5] J. Cram, *Clinical EMG for surface recordings*. Clinical Resources, 1991.
[6] P. Brisson, M. Skovron, and S. Lewis, "Low back pain assessment training of industry-based physicians," *Development*, vol. 34, no. 4, pp. 371–382, 1997.
[7] K. Calderon and W. Thompson, "Biofeedback relaxation training: a rediscovered mind-body tool in public health," *American Journal of Health Studies*, vol. 19, no. 4, p. 185, 2004.
[8] R. Gatchel, R. Robinson, C. Pulliam, and A. Maddrey, "Biofeedback with pain patients: Evidence for its effectiveness," in *Seminars in Pain Medicine*, vol. 1, no. 2. Elsevier, 2003, pp. 55–66.
[9] E. Swinnen, J. Baeyens, R. Meeusen, and E. Kerckhofs, "Methodology of electromyographic analysis of the trunk muscles during walking in healthy subjects: A literature review." *Journal of electromyography and kinesiology: official journal of the International Society of Electrophysiological Kinesiology*, 2011.
[10] S. Roy, C. De Luca, M. Emley, L. Oddsson, R. Buijs, J. Levins, D. Newcombe, and J. Jabre, "Classification of back muscle impairment based on the surface electromyographic signal," *Journal of rehabilitation research and development*, vol. 34, no. 4, pp. 405–414, 1997.
[11] L. Oddsson, J. Giphart, R. Buijs, S. Roy, H. Taylor, L. DE *et al.*, "Development of new protocols and analysis procedures for the assessment of LBP by surface EMG techniques," *Journal of rehabilitation research and development*, vol. 34, no. 4, pp. 415–426, 1997.
[12] Y. Hu, J. Mak, and K. Luk, "Application of surface EMG topography in low back pain rehabilitation assessment," in *Neural Engineering, 2007. CNE'07. 3rd International IEEE/EMBS Conference on*. IEEE, 2007, pp. 557–560.
[13] Y. Hu, S. Siu, J. Mak, and K. Luk, "Lumbar muscle electromyographic dynamic topography during flexion-extension," *Journal of Electromyography and Kinesiology*, vol. 20, no. 2, pp. 246–255, 2010.
[14] J. van Dieën, L. Selen, and J. Cholewicki, "Trunk muscle activation in low-back pain patients, an analysis of the literature," *Journal of Electromyography and Kinesiology*, vol. 13, no. 4, pp. 333–351, 2003.
[15] M. Cairns, K. Harrison, and C. Wright, "Pressure biofeedback: A useful tool in the quantification of abdominal muscular dysfunction?" *Physiotherapy*, vol. 86, no. 3, pp. 127–138, 2000.
[16] W. Marras and G. Mirka, "Electromyographic studies of the lumbar trunk musculature during the generation of low-level trunk acceleration," *Journal of Orthopaedic Research*, vol. 11, no. 6, pp. 811–817, 1993.
[17] D. Stegeman and H. Hermens, "Standards for surface electromyography: the european project surface emg for non-invasive assessment of muscles (SENIAM)," *http://www.med.uni-jena.de/motorik/pdf/stegeman.pdf*, 2007.