Using Surface Electromyography (SEMG) to Classify Low Back Pain Based on Lifting Capacity Evaluation with Principal Component Analysis Neural Network Method

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Abstract— **Low back pain (LBP) is a leading cause of disability. The population with low back pain is continuously growing in the recent years. This study tries to distinguish LBP patients with healthy subjects by using the objective surface electromyography (SEMG) as a quantitative score for clinical evaluations.**

There are 26 healthy and 26 low back pain subjects who involved in this research. They lifted different weights by static and dynamic lifting process. Multiple features are extracted from the raw SEMG data, including energy and frequency indexes. Moreover, false discovery rate (FDR) omitted the false positive features. Then, a principal component analysis neural network (PCANN) was used for classifications.

The results showed the features with different loadings (including 30%, and 50% loading) on lifting which can be used for distinguishing healthy and back pain subjects. By using PCANN method, more than 80% accuracies are achieved when different lifting weights were applied. Moreover, it is correlated between some EMG features and clinical scales, on exertion, fatigue, and pain. This technology can be potentially used for the future researches as a computer-aid diagnosis tool of LBP evaluation.

I. Introduction

Low back pain (LBP) is a leading cause of disability and is the most common reason for medical consultations. It occurs in similar proportions in all cultures, interferes with quality of life and work performance [2]. The population with low back pain is continuously growing in the recent years. According to current researches, there are about 80% people who experience LBP at sometimes in their lives [1]. Even though some people are correctly diagnosed by the physicians, there are still 85% people are diagnosed as unspecific low back pain. However, the current clinical evaluation methods, by applying with the Pain score, may be biased by subjects' prejudiced opinions [2].

Research supported by Taiwan Ministry of Science and Technology.

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Lower back pain refers back to the 12th thoracic vertebra the following line to hip, excluding reproductive, urinary diseases and acute lumbar spine trauma. LBP classification terms of time can be divided into: 1. acute low back pain which symptoms persist for less than six weeks; 2. sub-acute low back pain which symptoms persist for six weeks to three months; 3. chronic low back pain: symptoms lasting more than three months. Acute lower back pain which can be achieved remission in four weeks, although the recurrence rate is very high (up to 70%). Some patients (10-40%) turn into chronic lower back pain. Therefore, to quantify the LBP helps physicians to diagnose lower back pain properly, assists therapists assessment of occupational injuries, and achieves the best recovery results [1,2].

Chronic back pain has been found in medical controversies [2], so many doctors also order elaborate studies to verify non-specific back pain, such as X-rays and magnetic resonance imaging (MRI) [1]. Current studies also used electromyography for assessment of LBP [3,4]. It was found that electromyographic (EMG) were obtained during a muscle fatigue test. Subjects with pain produced significantly lower force values than those without pain by using linear regression analysis on fatigue indexes [3,6,11]. However, it is still not clear how other indexes to affect LBP population.

Functional Capacity Evaluation (FCE) is widely used as a criterion for laborer injury compensation and other insurance issues for decision making on whether laborers are recovered for work [5]. Lifting capacity evolution (LCE) is one of the most important indicators in FCE to evaluate if the injured laborers may return to work. Astonishingly, some researchers showed that the lifting capacity evolution only has low correlation with the period of back-to-work scheduled progress [5]. Hence, the lately studies indicates that the pain factor also needs to be considered. Also, based on previous studies, there is a high correlation between median frequency slope of surface electromyography (SEMG) and fatigue/pain. The body pain is the very important factor to influence large laborer population, so we need to find the relationship of exertion, fatigue and pain in back pain patients by using SEMG.

The aim of this research is to set a pain quantization standard based on EMG. The values of quantization LBP are to help physician's diagnosis, to evaluate the laborer injury, and to monitoring rehabilitation, so the patients can recover sooner than the regular treatments.

978-1-4244-7929-0/14/$26.00

II. Methodology

This study has been approved by institutional review board (IRB) of Buddhist Tzu Chi General Hospital with number IRB098-112. There are 26 healthy and 26 chronic low back pain subjects who involved in this research. The primary diagnosis ICD-9-CM codes are 720, 721, 722, 724, and 847.9. After the squat lifting demonstration, the same technique of lifting was taken by all participants lifted different weights (fig.1). The average ages of LBP and healthy groups are 33.27 and 32.65 years with BMI values 22.06 and 21.87, respectively. There is no significant difference between the two groups on age and BMI. For LBP group, the average scores of Oswestry Low Back Pain Disability Questionnaire and Quebec Back Pain Disability Scale are 16.31 and 11.58. Roland-Morris Disability Questionnaire has the average score under 5.8. The duration of low back pain was on average 40.73 months. Here were 16 cases with the pain on both sides; Here were each five cases with the pain in either left or right side.

Figure 1. Lifting capacity evolution (LCE) process

The data has been collected at Department of Orthopedics and Rehabilitation, Buddhist Tzu Chi General Hospital at Hualien. The collection time was in the morning from 8:00 to 9:00 pm. The subjects excluded people from unconsciousness, pregnant women, those who have a history of heart disease, acute lower back pain, back rack users, spine surgery and upper limb injuries, which may affect the performance of lifting operation. In LCE, 30% and 50% lifting loading were examed. The entire LCE procedure was recorded by video camera to confirm the correction of lifting operation.

In the experiment, Biocapture 150 (Clevemed, Inc. USA) is used for EMG data acquisition at sampling rate 960Hz. Fig.1 shows the bio-signals from device, including four low back EMG channels, two arm EMG channels, two accelerator channels and one reference channel on wrist.

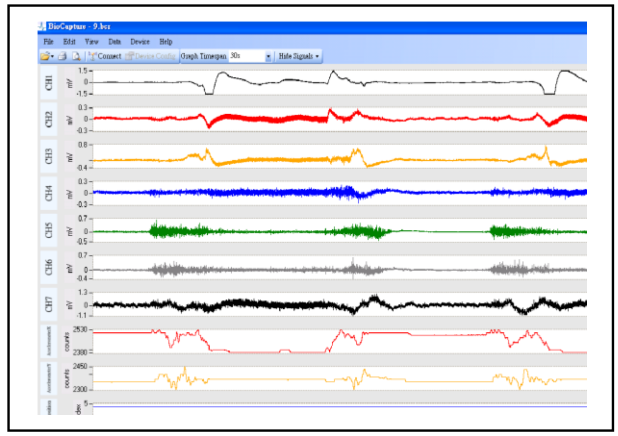

Figure 2. Raw EMG data recorded from Biocapture 150 (Clevemed, Inc. USA)

The paired electrodes with 2cm center distance were placed on the surface of different muscles, including multifidus (CH1~2), longissimus (CH3~4), and biceps (CH5~6) in fig. 2. Odd numbers represent right side channels and even numbers represent left side channels [9].

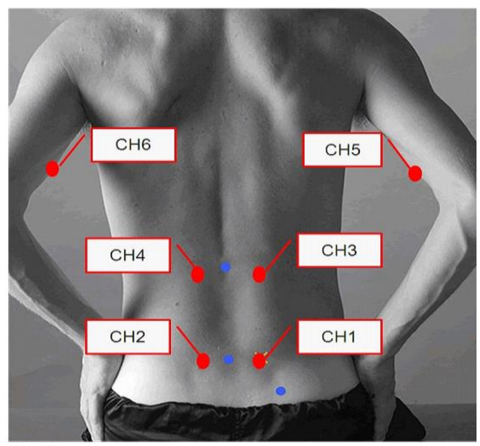

Figure 3. EMG electrodes locations

After data collection, multiple features are extracted from the raw EMG data, including energy and frequency indexes from EMG. Then independent T test was applied to find significant features and false discovery rate (FDR) omitted the false positive features. Finally, principal component analysis neuron network (PCANNs) were used for further classifications. The details describes as following:

A. Surface Electromyography (SEMG) features

Technically, SEMG records the activation surface signal of muscles for this clinical applications [8]. There are two major group parameters that are computed for EMG evaluation, including time and frequency domain parameters. In time domain, EA (Electromyographic Activity) is the factor which integrals SEMG over certain time period and divides by time *T*.

$$EA = \frac{\int_{t}^{t+T} SEMG\ (\tau)dt}{T} \quad (1)$$

RMS (Root Mean Square) is defined as the square root of the average SEMG in a certain time period T, which can be used to evaluate the muscle force.

$$RMS = \sqrt{\frac{\int_{t}^{t+T} SEMG^{2}(\tau)dt}{T}} \quad (2)$$

In frequency domain, the conduction velocity, MDF (Median Frequency) and MPF (Mean Power Frequency) are essential parameters. The MDF is defined as the particular frequency that would divide the power spectrum into two parts of equal areas. According to Erfanian's study [6], the conduction velocity v is linearly proportional to the median frequency (MDF).

$$v = \left(\frac{f_{MDF}}{f_{m0}}\right)v_0 \quad (3)$$

where f_{m0} is the initial median frequency when the conduction velocity is at its initial value v_0. The coefficient v is related to muscle fatigue. Hence, MDF is used for fatigue compensation. The MDF formula is described as equation (4).

$$\int_{0}^{MDF} PSD(f)df = \int_{MDF}^{\infty} PSD(f)df = \frac{1}{2}\int_{0}^{\infty} PSD(f)df \quad (4)$$

where PSD means power spectrum density. Also the mean power frequency (MPF) is defined as the frequency location of average power at spectrum.

$$MPF = \frac{\int_0^\infty f \cdot PSD(f)df}{\int_0^\infty PSD(f)df} \quad (5)$$

Other features were also involved, including median frequency slope (MF slope), initial Median frequency (INMF), final median frequency (finalMF), and intercept of median frequency (MFintercept). It should be noted that right/left hands and genders are considerable factors in EMG calibration.

B. False discovery rate (FDR)

False discovery rate (FDR) is a statistical method used in multiple hypothesis testing to correct for multiple comparisons. FDR procedures are designed to control incorrectly rejected null hypotheses. FDR controlling procedures exert a less stringent control over false discovery compared to familywise error rate (FWER) procedures to reduce the probability of even one false discovery [7].

C. Principal component analysis Neural Network (PCANN)

Principal component analysis (PCA) is a statistical procedure that uses Karhunen – Loeve transformation to convert a set of observations of possibly correlated variables into a set of values called principal components. The number of principal components is less than or equal to the number of original variables. PCANN [10] applies artificial neural network learning process to adapt minimum $\| x - Tx \|^2$ among all $n \times n$ matrices T whose rank p is less than n, where x is the feature vector and T is transformation matrix. The PCANN learning formula is listed as follows,

- Iterative formula to compute

$$w' = Cw(n) \quad (6)$$

$$w(n+1) = \frac{w'}{\| w' \|} \quad (7)$$

where w is the weight vector of PCANN and C is covariance matrix as

$$C = \frac{1}{K}\sum_{k=1}^{K}[x(k) - m][x(k) - m]^T$$

where $m = \frac{1}{K}\sum_{K=1}^{K} x(k)$ is the mean vector.

- Online update formula :

$$C(n) = C(n-1) + \alpha\, x(n) x^T(n), \quad (8)$$
$$C(0) = 1, \quad 0 < \alpha < 1$$

where $C(0)$ is initial covariance matrix and C updates in each iteration.

$$\begin{aligned} w' &= C(n)\, w(n) \\ &= \left[C(n-1) + \alpha\, x(n) x^T(n) \right] w(n) \\ &\approx \mu \left[w(n) + \frac{\alpha}{\mu} x(n) y(n) \right] \end{aligned} \quad (9)$$

where μ is a constant. Then the weight vector is normalized in each iteration.

$$w(n+1) = \frac{w'}{| w' |} \quad (10)$$

where the approximation $C(n-1)\, w(n) \approx \mu\, w(n)$ is applied.

III. RESULTS

The results showed the features with different loadings (including 30% and 50% loading) on lifting which can be used for distinguishing healthy and back pain subjects. Features especially contained normalMF, normalMPF and normalRMS fit both tasks as general biomarkers. Fig. 4 shows that MF and MF slope are distinguishable features between LBP and healthy groups. Overall, LBP group has larger MF reduction and less MF slope values at all channels from 1 to 4. More significant SEMG features on 30% loading test. In addition, the results also found that LBP group has significant larger RMS values than normal controls at all channels (fig.5). The correlations between subjective pain and normalMF (or normalMPF) are moderate(-0.41~ -0.49).

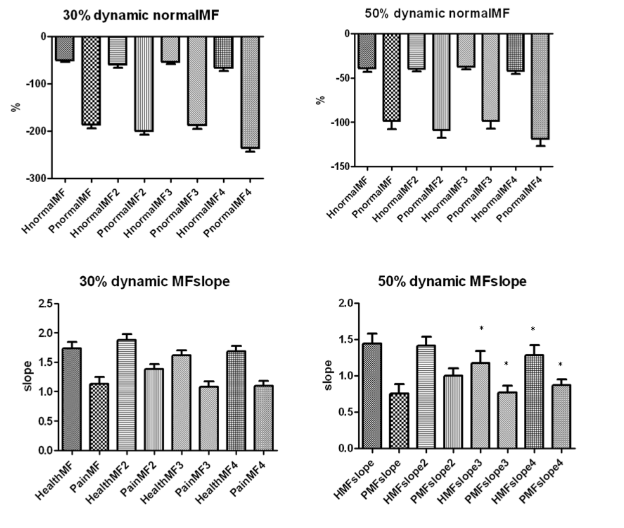

Figure 4. Compare EMG features (MF and MF slope) between two groups with different loading. Please note that * represents nonsignifiant features.

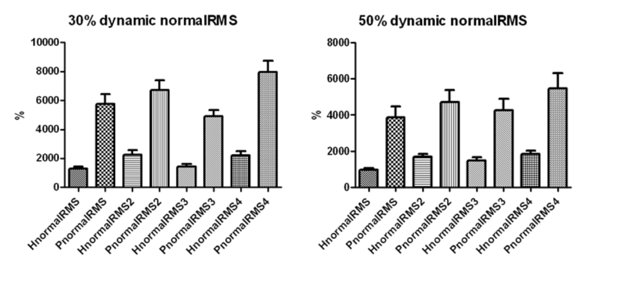

Figure 5. Compare RMS between two groups with different loading.

ROC curves verified our system performance. The results demonstrated that PCANN method has AUC=0.93 with 30% loading and AUC= 0.85 with 50% loading. The 30% loading test provided the better outcome on distinguish between LBP and healthy groups.

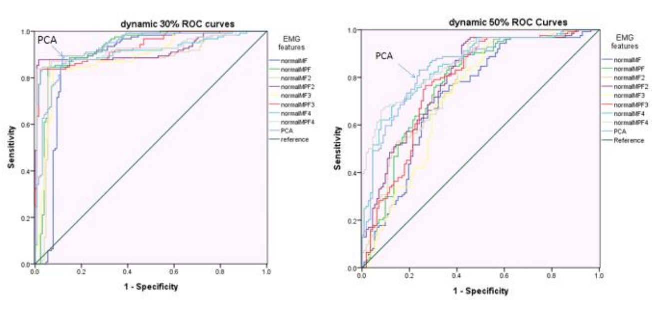

Figure 6. ROC curves with different lifing loadings (PCANN: 30% loading AUC=0.93; 50% loading AUC= 0.85)

After applying PCANN method with FDR feature selection, 90% sensitivity, 88% specificity and 89% accuracy were achieved when dynamic 30% weight lifting was applied. In contrast, 83% sensitivity, 76% specificity and 79% accuracy were achieved when dynamic 50% weight lifting was applied. If the weight vector is observed, we found that RMS related features have lower weight values and higher weight values appear on normalMF and normalMPF features.

IV. Conclusion

Our research successfully proposed a method to classify LBP and control groups based on SEMG when lifting capacity evaluation applied. Specifically, the SEMG features obtain from 30% lifting loading test provided most significant information for identification LBP. Hence, the technology can be potentially used for the future research after reproducibility of the measurements as a computer-aid diagnosis tool for quantization and evaluation of low back pain in clinics.

Acknowledgment

Thanks department of physical medicine and Rehabilitation at Tzu Chi Hospital, Hualien for the great support for the project. This work was supported by the Taiwan Ministry of Science and Technology under grant.

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