A Novel Automated Algorithm for Computing Lumbar Flexion Test Ratios Enhancing Athletes Objective Assessment of Low Back Pain

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Abstract: **INTRODUCTION:** Low Back Pain is a common muscular disorder that most adults would experience over their lives. In healthy patients at the end of a lumbar flexion occur a phenomenon called the Flexion Relaxation Phenomenon. Ratios between different phases of lumbar flexion can help diagnosing LBP patients. The aim of this work is to create an automated algorithm to compute this ratios helping to discriminate between healthy and LBP athletes. **MATERIALS AND METHODS:** 21 participants were recruited: 10 LBP and 11 healthy. Participants were tested with Lumbar Flexion Test for evaluating LBP. sEMG were recorded in low back muscles. **RESULTS:** Athletes diagnosed with LBP showed ratios lower than 1.5. For healthy participants we observed results greater than 1.5. **DISCUSSION AND CONCLUSION:** Our results are contained between rates found in literature. Our algorithm can help the diagnose of athletes with a non-intrusive method and with little knowledge of sEMG analysis.

1 INTRODUCTION

Low Back Pain (LBP) is a common disorder involving the muscles, the bones and the nerves of the low back. About eighty percent of adults experience low back pain at some point in their lifetimes. It is the most common cause of job-related disability and a leading contributor to missed work days (NIH, 2017). A commonly used test for diagnosing LBP is the Lumbar Flexion Test (LFT). LFT helps diagnosing LBP patients because of the phenomenon that occurs toward the end of the lumbar spine flexion, named Flexion-Relaxation Phenomenon (FRP) using surface electromyography (sEMG) (Colloca and Hinrichs, 2005)(Tabard et al., 2018)(Desai and Bisen, 2017). Toward the end of the lumbar spine flexion the sEMG activity should be near to zero, producing what is called myoelectric silence in healthy patients. However this not occur in LBP patients where the sEMG activity maintains similar values as when performing the flexion.

LBP is of prevalence in athletes whom perform high intense sport activity, as well as other types back abnormalities. (Kujala et al., 1992)(Schmidt et al., 2014). An objective evaluation of LBP and an objective tool for recovery measurement is of crucial importance to improve athletes muscle's health.

The aim of the study was to develop an automatic detection algorithm for computing Lumbar Flexion Test ratios from sEMG and accelerometer signals to discriminate between those who suffer from LBP and healthy athletes.

2 MATERIALS AND METHODS

2.1 Materials

We used a sEMG and inertial sensor (Shimmer Sensing, Dublin, Ireland). Data were obtained and processed using mDurance (Banos et al., 2015), a software for sEMG analysis (MDURANCE SOLUTIONS SL, Granada, Spain).

Recording of raw EMG signals took place at a frequency of 1024Hz, via two channels. IMU signals were recorded at the same frequency. The raw EMG signal was band-pass filtered (cutoff frequencies, 20 Hz, high pass; 400 Hz, low pass).

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2.2 Protocol

21 participants were recruited: 10 LBP and 11 healthy. Participants were tested with LFT for evaluating LBP. Characteristics of participants can be observed in 1

Table 1: Mean and SD of athletes' characteristics.

	Height	**Weight**
LBP Athletes	1.67 ± 0.054	64.75 ± 7.17
Healthy Athletes	1.736 ± 0.11	70.30 ± 7.16

	Age	**IMC**
LBP Athletes	37.33 ± 9.05	22.04 ± 1.92
Healthy Athletes	26.70 ± 6.59	23.436 ± 2.60

Electrodes were placed at the Erector Spinae (longissimus) both left and right, following the guidelines for electrode placement of the Surface ElectroMyoGraphy for the Non-Invasive Assessment of Muscle project (SENIAM), as presented in Figure 1.

sEMG sensor was placed on the back, as presented in Figure 2.

Participants were asked to perform the FLT. The FLT consists of the following phases. The participant starts from a vertical position. This is named as Vertical phase. He is asked to perform a lumbar spine flexion, trying to touch his toes. This is named as Flexion phase. He is asked to maintain this lumbar spine flexion position between three and five seconds. This is named as Maximum Voluntary Flexion (MVF) phase. He is asked to return to a vertical position. This is names as Extension phase. A visual representation of FLT can be observed in Figures 3 and 4 .

Figure 1: Electrodes placement in the Erector Spinae (longissimus).

2.3 Automatic Measurement of Posture

The measurement of the posture is crucial in order to run the algorithm. The IMU sensor combines triaxial accelerometer, gyroscopes and magnetometers, enabling the measurement of the absolute attitudes or

Figure 2: sEMG sensor positioning in the back of the athlete.

Figure 3: Vertical phase of LFT.

Figure 4: MVF phase of LFT.

inclinations of the body part to which the sensor is fastened. IMU technology has been exploited during recent years for body movement analysis. (Banos et al., 2012)(Banos et al., 2013) (Banos et al., 2014) (Mannini et al., 2013) (Lin et al., 2015)

IMUs provide raw acceleration, magnetic field data and angular rate that need to be fused together to obtain a sole, optimal estimate of orientation. Different algorithms have been proposed in the literature to that end, including Kalman filters (Roetenberg et al., 2005), least squares filters (Luinge et al., 2007) or Gaussian particle filters (Zhang et al., 2010).

In our work, we have used Madgwicks algorithm (Madgwick et al., 2011), which outperforms most existing approaches in terms of implementation complexity, sampling rate requirements and computational needs. This technique does not suffer from the well-known limitations of other solutions, like the singularity problem associated with the Euler angle representation (gimbal lock). Besides, this method also omits the use of computationally expensive trigonometric functions, making it more efficient and easier to implement for real-time purposes. Madgwicks algorithm employs acceleration, angular rate and magnetic field measurements to analytically derive, through an optimized gradient-descent method, a quaternion representation of motion (Harrison, 1999). Thus, the output of the algorithm is a quaternion, a compact vector in the form (q1,q2,q3,q4), which dynamically represents the orientation of the sensor.

Quaternions are frequently used in orientation estimation algorithms because of their numerical stability and computational efficiency. However, this representation is difficult to interpret and visualize, since it defines a $\mathbb{R}^4$ space that cannot be represented in a human-understandable three-dimensional view. Accordingly, a translation into Euler angles is performed here, after all of the calculations to estimate the quaternion are carried out. Euler angles represent the possible rotations around the three cardinal axes, namely yaw (φ), for the X axis, pitch (θ), for the Y axis, and roll (ϕ), for the Z axis. Given the estimated quaternion, the Euler angles can be simply obtained as follows:

$$\varphi = \arctan\left(\frac{2(q_1q_4 - q_2q_3)}{1-2(q_1^2+q_3^2)}\right) \tag{1}$$

$$\theta = \arcsin(2(q_1q_3 - q_4q_1)) \tag{2}$$

$$\phi = \arctan\left(\frac{2(q_1q_2 - q_3q_4)}{1-2(q_2^2+q_3^2)}\right) \tag{3}$$

2.4 Automatic Detection of Lumbar Flexion Test Phases and Angle Variation

2.4.1 Automatic Detection of Local Maximums and Minimums

After we have obtained the measurement of posture from the IMUs signal, a Savitzky-Golay filter (Savitzky and Golay, 1964) is applied to the values computed, in order to obtain a smoothed signal. In smoothing, the data points of a signal are modified so that individual points that are higher than the immediately adjacent points (presumably because of noise) are reduced, and points that are lower than the adjacent points are increased. This naturally leads to a smoother signal (and a slower step response to signal changes). As long as the true underlying signal is actually smooth, then the true signal will not be much distorted by smoothing, but the high frequency noise will be reduced. Compared to other smooths of the same width, the Savitzky-Golay smooth is less effective at reducing noise, but more effective at retaining the shape of the original signal.

Local maximums and minimums of signal data are obtained using the first and second derivative. The value of the slope at a local maximum or minimum would be equal to 0. The value of the slope is computed using the first derivate. The second derivative is used in order to label the point as a maximum or a minimum depending on the sign of the second derivative at the point where the slope is 0. If the value is less than 0 it is a local maximum. If it is greater than 0 it is a local minimum.

2.4.2 Automatic Creation of Lumbar Flexion Test Phases based on Local Maximums and Minimums

The algorithm automatically create phases based on the list of local maximums and minimums. It tests if appear first a maximum or minimum in IMUs signal. Depending on the result, it would start concatenating maximums and minimums points, until there are *n* number of maximum and minimum pairs, representing *n* different phases.

Only phases where the angle variation is significant are preferred. For making the algorithm robust when facing little angle variations, a threshold is applied in order to discard phases where this variation is not significant. This threshold is computed using the three greater angle variations, represented as a_i where $a_i > a_{i+1} > a_{i+2}$, in the phases found as follows:

$$threshold = \frac{a_1 + a_2 + a_3}{3} \tag{4}$$

This posture's angle variation is also used to label the phases found by the algorithm. In a Flexion phase, the posture's angle variation is negative while in an Extension phase it is positive. Maximum Voluntary Flexion (MVF) and Vertical phases are between Flexion and Extension phases. If the phase is between a Flexion and Extension phases then it is labeled as MVF. On the other hand, if it is between an Extension and Flexion phases, it is labeled as a Vertical phase.

The pseudocode for algorithm's steps described in subsections 2.4.1 and 2.4.2 is as follows:

```
obtain_smoothed_posture_signal(posture_signal)
get_indexes_local_maximums(smoothed signal)
get_indexes_local_minimums(smoothed signal)

if local_maximums[0] < local_minimums[0]:
        for max_i,min_i in maximums,minimums:
       create_new_phase(max_i,min_i)
       compute_local_variation(new_phase)
       if angle variation < 0:
              label_phase_as_flexion(new_phase)
```

```
        else:
                label_phase_as_extension(new_phase)

        previous_phase_vector.add(new_phase)
else:
    for max_i,min_i in maximums,minimums:
        create_new_phase(min_i,max_i)
        compute_local_variation(new_phase)
        if angle variation < 0:
                label_phase_as_flexion(new_phase)
        else:
                label_phase_as_extension(new_phase)

        previous_phase_vector.add(new_phase)

compute_threshold(previous_phases_vector)

for phase in previous_phases_vector:
        if phase[angle variation] > threshold:
           final_phases_vector.add(phase)

add_MVF_and_vertical_phases(final_phases_vector)
```

2.5 Computation of Ratios between Phases

During the execution of the LFT test, the muscles are normally subject to an important level of activity and stress. To monitor the electrical activity produced by the skeletal muscles a wearable electromyography or EMG sensor is used. This sensor consists of a set of surface electrodes, which are attached to the skin of the body part to be monitored. The electrodes measure the potential difference between them, which is translated by the sensor into EMG signals. There exist some well-known metrics that help categorize the level of the muscle fatigue. The root mean square (RMS) and the maximum voluntary muscle contraction (MVC) are generally used as indices of muscle fatigue. (Al Zaman et al., 2007) (Kim et al., 2007). RMS and MVC can be computed as follows:

$$RMS = \sqrt{\frac{\sum_{k=1}^{N} EMG^2(k)}{N}} \tag{5}$$

$$MVC = \max(EMG) \tag{6}$$

RMS is computed for each phase found by the algorithm and it is normalize by the maximum historical MVC of the patient. RMS is normalize by the MVC as follows:

$$RMSnormalized = \left(\frac{RMS}{MVC}\right) * 100 \tag{7}$$

RMS ratios between Flexion and Extension phases and MVF and Vertical phases have been proved as good discriminators between healthy and LBP patients (Watson et al., 1997)(Sánchez-Zuriaga et al., 2015)(Neblett et al., 2013). Ratios are computed between phases. The mean and standard deviation from all repetitions ratios is obtained.

The pseudocode for the computation of ratios between phases by the algorithm is as follows:

```
for phase in final_phases_vector:
   get_RMS_normalized_by_MVC(phase)

compute_flexion_mvf_ratios(phases)
compute_extension_mvf_ratios(phases)

get_mean_flexion_mvf_ratios(flexion_mvf_ratios)

get_mean_extension_mvf_ratios(extension_mvf_ratios)
```

3 RESULTS

Flexion/MVF and Extesion/MVF are the main ratios of interests for discriminate between healthy and LBP athletes. In MVF phase is where the FRP occurs. Therefore much greater ratios' values must be obtained in healthy athletes than in LBP athletes.

Athletes diagnosed with LBP showed ratios lower than 1.5. For healthy participants we observed results greater than 1.5. Results are showed in Table 2.

Table 2: Mean and standard deviation of ratios between phases in healthy and LBP athletes.

	Flexion/MVF	Extension/MVF
LBP Athletes	1.22 ± 0.33	1.58 ± 0.28
Healthy Athletes	3.07 ± 0.67	6.10 ± 0.96

4 DISCUSSION

Following the aim of developing a quantitative method for monitoring LBP athletes, we saw an evident threshold to discriminate between athletes with LBP and healthy.

Our results are enclosed in the same rates as those found in literature, both for healthy and LBP participants. (Watson et al., 1997) , (Alschuler et al., 2009) and (Neblett et al., 2013) showed similar results. A comparison of our results with the one presented in (Watson et al., 1997), (Alschuler et al., 2009) and (Neblett et al., 2013) can be observed in Tables 3 and 4. Our results prove the validity of the algorithm comparing our results with those found in literature.

Table 3: Comparison of our results with those found in literature for Flexion/MVF ratios in healthy patients.

	Flexion/MVF
Our results	3.07 ± 0.67
(Watson et al., 1997)	13.98 ± 11
(Neblett et al., 2013)	15.1 ± 7.7

Table 4: Comparison of our results with those found in literature for Flexion/MVF ratios in LBP patients.

	Flexion/MVF
Our results	1.22 ± 0.33
(Watson et al., 1997)	2.72 ± 2.7
(Alschuler et al., 2009)	0.19 ± 0.47

5 CONCLUSION

Our algorithm helps automate the evaluation of the athletes without any knowledge of sEMG nor of LFT and our results agree with other studies. Our results prove the validity of the algorithm for computing ratios based on those presented in literature. This tool would help sport specialists to evaluate their sportsmen and observe an objective progress over their rehabilitation with little preprocessing that can be performed with sEMG analysis software (Banos et al., 2015).

Our algorithm could increase the objective assessment during the sportsmen injury time as well as a tool during injury free periods to evaluate if LBP could be a plausible consequence of an overload training. Automatically computed ratios can served as a guide to perform changes in the recovery plan, decreasing injury's time.

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