Knee Functional State Classification Using Surface Electromyographic and Goniometric Signals by Means of Artificial Neural Networks[1]

Clasificación del estado funcional de la rodilla usando señales de electromiografía de superficie y goniometría empleando redes neuronales[2]

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Abstract

In this article a methodology for a medical diagnostic decision support system to assess knee injuries is proposed. Such methodology takes into account that these types of injuries are common and arise due to different causes. Therefore, the physician's diagnostic and treatment may lead to expensive and invasive tests depending on his medical criteria.

This system uses a surface Electromyographic (sEMG) and goniometric signals that are processed with signal analysis methods in time-frequency space through a spectrogram and a wavelet transform. Artificial neural networks are used as a learning technique by having a multilayer perceptron.

EMG signals were measured in four external and internal muscles associated to the joint through flexion and extension assessments. These tests also registered the goniometric measures of the sagittal plane. This system shows above 80% of effectiveness as a performance measure that makes it an objective measure leading to help the physician in his diagnosis.

Keywords:

Knee injury; sEMG; *ANN;* goniometry; Wavelet Transform

Resumen

En este artículo se propone una metodología para el diagnóstico de lesión de rodilla, patología común y de múltiples causas. El diagnóstico y el tratamiento de las lesiones de rodilla se realizan por medio de valoraciones por parte de un profesional en el área, quien según su criterio puede solicitar exámenes invasivos y/o de alto costo. El sistema propuesto emplea señales electromiográficas de superficie (EMGS) y señales de goniometría, evaluadas con métodos de análisis de señales en el dominio del tiempo-frecuencia como el espectrograma y la transformada *wavelet*. Como técnica de aprendizaje de máquina se emplean redes neuronales artificiales, por medio de un perceptrón multicapa. Las señales EMGS fueron tomadas en cuatro músculos internos-externos asociados a la articulación, por medio de exámenes físicos de flexión y extensión, en los cuales se registró, además, la goniometría en el plano sagital. Con este sistema se obtuvieron rendimientos superiores al 80 % en la efectividad como medida de desempeño, por lo cual esta propuesta se constituye en una solución objetiva que puede darle más elementos de juicio al profesional para el diagnóstico.

Palabras clave:

Lesión de rodilla; EMGS; RNA; goniometría; transformada *wavelet*

1. Introduction

The knee injuries are due to different causes such as accidents that can have an occupational origin i.e military or sports [1]. There are also injuries due to degenerative diseases including knee osteoarthritis (OA). Regardless of the type of knee injury, a distortion leading to movement limitation may be present [2], therefore, physiotherapy and rehabilitation treatments are needed. These treatments may require the use of different elements such as prostheses, wheelchairs, crutches, orthoses, exoskeletons in order to overcome the limitation to a certain extent. These include pain reduction, normalize mobility, build muscle, etc, and therefore, improve the quality of life. A study that reports 17,397 patients suffering 19,530 sports injuries in a 10 year span has been published. It showed that 6,434 (37%) had 7,769 injuries (39.8%) related to the knee joint [1].

Techniques for diagnosing and assessing the knee condition include interpretation of joint symptoms (presence of pain, functional loss or swelling), scanning and physical inspection of the knee by using varus stress test, the Lachman test at 30°, posterior drawer test at 90°, slump test, or the McMurray test. However, these treatments depend on the criteria of the rehabilitation professional. Radiographic examination is another technique for assessing knee condition, although, it is not decisive in the diagnosis. Both arthroscopy and biopsy are invasive techniques, the former allows joint assessment through photography, and the later allows biochemical analysis and Magnetic resonance that although effective is quite expensive [3]. Finally, electromyography (EMG) measures and records the signals of muscle activation [4], and plays a fundamental role in the diseases assessment, along with other clinical processes since they show typical signs of the existence of some form of myopathy [5]. Some studies [6] and [7] may show EMG signals associated to speed, acceleration or dynamic analysis of the joints.

There are several muscles involved in the biomechanics of the knee and they serve to perform different movements. Such movements may become altered due to any pathology. The flexion-extension movement measure has shown some pairs of muscles directly involved in such movement, for example the rectus femoris muscle (RF) that is the knee extensor and flexor hip, the vastus medialis muscle (VM), that serves extension, biceps femoris muscle (BF) as well as Semitendinosus muscles (ST) that are involved in knee flexion, the medial or lateral rotation and hip extension [8].

EMG has been used to diagnose neuromuscular [9] disorders and kinematics has been used to explore the joint anatomically [10]. Both EMG and kinematics through EMG signals and goniometry respectively lead to analyze muscle activation of movements including [11] squat [12], standing and sitting [13]. The question arises linking EMG analysis and kinematics. Could this proposal be used to diagnose the functional status of the knee and support medical diagnosis regarding treatment and outcome in case of injury, if considering characterization methods and Machine Learning techniques that biomedical equipment can fit?

2. Materials and methods

This study develops a methodology by using signal processing and Machine Learning techniques to have an automatic classification between an injured knee and a healthy knee. A standardized measurement protocol serves to obtain specific features of the EMG and goniometry signals. These signals are analyzed with these techniques.

2.1. Electromyography (EMG)

An action potential is generated if a nerve muscle is activated through an appropriate stimulus (threshold). The action potential is a brief flow of ions across the cell membrane. An axon can transmit action potentials generated by an excited cell from one cell to neighboring cells. An electric field is produced and spread through the biological tissue due to a large number of cells activation. This phenomenon is explained with an Electromyography [14].

The neuromuscular junction (NMJ) is the system responsible for the transmission of electric activity in motor nerve terminal (neuron) to muscle membrane. This is possible with a synaptic cleft to produce muscle contraction. The motor neuron and the muscle fibers that innervate constitute a functional unit; this in turn results from recurrent discharges of groups of muscle fibers called motor units (MU) [15]. EMG signals are those electrical signals detected due to the electrical potential difference, when a muscle is activated by using a needle electrode or a surface electrode. The latter is called surface electromyography (sEMG). An EMG signal is composed of a mixture of action potentials motor unit (MUAPs). Signals can show different degrees of muscle activity. When the force of contraction increases, the MU are triggered and the EMG signal becomes complex. This makes individual MUAPs unlikely to be easily identified; unless a large amount of needle sensors are simultaneously used on different muscles. Although this may make the patient feel uncomfortable, this signal is recognized as the interference pattern (IP). IP analysis serves to describe muscular activity, muscular fatigue, chronic muscle pain, and to diagnose patients with neuromuscular disorders [9], [15]. sEMG is a noninvasive technique for assessing and recording the activation signal of muscles by the use of electrodes. sEMG is recommended for biomechanical analysis, gait analysis, muscle fatigue studies, etc. since it allows to study muscle activity in dynamic actions and to analyze different muscles in movement. The analysis of sEMG signals provides amplitude and frequency parameters for descriptive and comparative studies [16].

2.2. Participants

11 male participants older than 18 years were tested. All of them had been diagnosed of a knee disease in one of their knees by a professional and had not started a rehabilitation process. Six participants had injury to the anterior cruciate ligament (ACL), four participants had meniscus injury and one participant sciatic nerve injury. Tests were performed at BATALLON DE SANIDAD DEL EJERCITO NACIONAL OF COLOMBIA and Tecnoparque SENA, Manizales venue. A control group of eleven participants with no knee injuries or pain also participated in this study.

2.3. Instruments

The Datalog MWX8 electromyography was used in this study. This electromyography has a Bluetooth link to collect signals and data from a wide range of sensors including goniometers, torsiometers, accelerometers, etc. and an acquisition software to record and store data in real time.

The SG150B goniometer measures angles in flexion-extension, it includes 2 channels, accuracy of $\pm 2°$ measured of an interval $\pm 90°$ that works between 10 ° C and 50 ° C, and has a weight of 28 grams. This goniometer is standardized and compatible with the signals recorded by the datalog MWX8. Surface electrodes, 20mm spacing between electrodes, high input impedance, more than 10 MΩ (allowing sampling without requiring a conductive gel), sample rate 1000Hz, 14-bit resolution and it works on a bandwdith between 20 and 460 Hz[7].

[7] http://www.biometricsltd.com/datalog.htm

2.4 Physical test: Kinematic data acquisition and sEMG

A goniometer was used to have the kinematic data acquisition. This allows measuring the angle of flexion-extension exercises. An electromyography measures sEMG, both measures are simultaneously while the exercises described below are performed: surface electrodes are fixed by a professional therapist in the 4 affected muscles. These electrodes are fixed in muscle fiber orientation in their most prominent area and the goniometer is placed on the external side of the knee joint. The 3 physical tests are chosen because they are common exercises in diagnosis, they do not use extra weight with weights, dumbbells, fitness equipment, etc. which would affect the speed and acceleration [17]. Comfortable clothing is worn in order not to interfere with measurement equipment. 3 minute pauses are between each exercise.

Signals sEMG in leg movement for open simple movement in chain kinematics (sitting). Physical test is performed at different times, bench sitting, back straight and maximum thigh support on the bench, feet in the air (no shoes). Physical test is repeated 4 times per participant. *Moment 0* - 90° at rest (no contraction) for a period of 2s. *Moment 1* - Movement extension: lower limb raises in a smooth, continuous motion, no additional load to achieve the greatest possible extension (0°) (t = 2s). *Moment 2* - Keep the extension for two seconds. *Moment 3* - Movement flexion to return to the initial position (t = 2s) in one smooth motion time. *Moment 4* no contraction (t = 3s), total time of sitting exercise (t = 36s).

The Figure 1 depicts an example of two physical tests regarding the sitting and standing position.

Figure 1. Open and simple kinematic chain (siting and standing)

Source: authors' own presentation

2.4.1. sEMG in leg movement in simple kinematic chain (Standing)

Physical test is repeated 4 times per participant. *Moment 0* – at rest at 0° (no contraction) for a span of 2s, standing (upright) both feet on the ground as support (no shoes) upright, no bending the spine, holding onto a chair for balance. *Moment 1* – flexion motion: lower limb rises slowly (no extra load) to achieve maximum flexion (90° - 120° approx) (t = 2s), no movement of the top of the leg; only the knee. *Moment 2* – keep position (t = 2 s). *Moment 3* – flexion movement is slowly performed to return to the initial position (t = 2 s). *Moment 4* - No contraction (t = 3s), total time of foot exercise (t = 36s).

2.4.2. sEMG in leg for simple gait

Moment 0 – at rest at 0° (no contraction) for a 2s period, standing (upright position) both feet on the ground as support (no shoes), straight position no bending the spine, then four steps starting with the right foot. Both feet together as at rest position at 4th step, turn 180 °, wait 2s, and perform moment 1. *Moment 1* - at rest (no contraction) for a 2s period, standing (upright position) both feet on the ground as support (no shoes) straight position no bending the spine, then four steps starting with the left foot on a regular and flat surface, (t=14 s) as total time of gait exercise.

The physical tests exhibit five signals for each participant in each muscle test: 4 EMG measured for each muscle and the last signal measured by the goniometer. This depicts the angle of motion of the knee sagittal plane. That is, for every test participant 15 signals were recorded. It means 15 signals recorded by participant. Although, these signals were conferred by an International repository, now they are part of the Automatic research group of the Autonoma University[8].

2.5. Signal processing

After having sEMG, the signal was filtered taking the flexion and extension moments that the goniometry shows. They may have a variable size due to the speed displacement of each participant. Equipment entries are set to ± 3 mV, where sEMG signals in any sample exceeds 2mV. This ensures no saturation of the ADC. A second order Chebyshev filter is applied to remove signals that are outside the extent of the electromyographic signals between 20Hz and 460Hz. Attenuation ripple (*Rp*) is 3 dB and attenuation of unwanted signals (*Rs*) is

[8] http://archive.ics.uci.edu/ml/datasets/EMG+dataset+in+Lower+Limb

40dB. The filtered signals and the original ones exhibit no major change due to the default filter that the measuring equipment has, however, this procedure was performed to avoid unwanted signals that may affect their characterization. Goniometer signal received a general smoothing generally known as 1-D denoising, which is given by

$$s(n) = f(n) + w(n)$$

Where $n = 0,1,2,\ldots m-1$, $w(n)$ is the White noise Gaussian generated and $f(n)$ is the expected signal of goniometry.

2.6. Characterization of the EMG

The literature [9] and [18] states that EMG processing in frequency domain as well as in time-frequency techniques lead to apply such techniques to obtain relevant signals. This is to classify functional conditions of the knee.

Normalization of a Standard Normal Distribution in sEMG records was implemented (where the mean ($\mu = 0$) and standard deviation ($\sigma = 1$)). The following features for normalized EMG records are calculated by using the following expression:

$$P(x) = \left|S_{STFT}(x)\right|^2$$

Where $P(x)$ is the Power Spectral Density, and $S_{STFT}(x)$ is the estimated spectrogram obtained from a Hamming window of length of 8 samples and overlapping 7 samples. Components of relevant frequency can be captured through the length of the window [19].

It is well known that frequency components of the signal on a frequency range between 20 and 250 Hz are relevant [19]. These are extracted from $P(x)$ for each time span and normalized in order to obtain 2 features that correspond to the total concentration of power in the movement performed (v1), and are estimated 400 ms as distance between two maximum peaks of the EMG signal. These correspond to the minimum time it takes muscle stimulation (v2). With the EMG (x (t)) signal range (v3) is gotten, and the maximum of $|x|$ (v4).

Average frequency *MNF* (v5) is estimated and can be expressed as

$$MNF = \sum_{j=1}^{M} f_j P_j \Big/ \sum_{j=1}^{M} P_j$$

Where P_j is the power spectrum of sEMG signals at frequency j (fj) [20]. Median Frequency (*MDF*) (v6) is estimated and can be expressed as [20]:

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M} P_j$$

It has been shown that v5 and v6 features are quite useful for recording cyclic dynamic contractions especially as an indicator of fatigue [20].

2.6.1. Wavelet analysis

The mother wavelet function ψ (t) defines the *wavelet* $\psi a,b(t)$ through joint operations of scale and translation change as defined [21]:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right)$$

Where *a* represents the scale change and *b* the translating change.

If mother wavelet function ψ (t) is real, then the family of functions defined by translation and scaling up make a comprehensive database of space. Therefore, any function can be represented by a linear combination of the functions $\psi_{a,b}(t)$, calculating the coefficients of the decomposition in the form of the scalar product [21].

There are various types of mother *wavelet* that fulfill the above conditions, the most notable ones are the types of Haar, Morlet, Daubechies wavelets [22].

Daubechies mother wavelet type 4 (DB4) is applied to each EMG signal in the muscle. This has a good performance for sEMG analysis. This function serves to extract the peaks of the wavelet transform that are generated by a set of MUAP of the EMG signal. The decomposition is generally used between 3 and 5 levels [23].

With these attributes, 11 peaks obtained from the following transforms are: 1 maximum of approximation coefficients 4, 1 maximum of detail coefficients 4, 2 maximum of detail coefficients 3, 3 maximum of detail coefficients 2 and 4 maximum of detail coefficients 1 (v7:17). Means and variances of the detail coefficients of the 4 levels and the coefficient of approximation (v18:27) were also obtained. 27 features are taken for each of the four muscles of each participant with a total of 3 muscle tests. This means, a matrix of 11 x 27 for the control group and the same size for participants with any of the knee pathologies above mentioned. The following is the standard set which represents the characteristics of sEMG:

$$V_i^j \in \mathbb{R}^{27}$$

Where $i = \{1,2, \ldots, 22\}$ corresponds to the number of test participants and $j = \{1, \ldots, 4\}$ are the four muscles registered.

2.7. Characterization of movement signals

Angular speed and acceleration serves to extract the displacement signal through a goniometer. Taylor[9] theorem was used to obtain the 2 signals. The first derivative provides speed and its derivative results in acceleration.

With the 3 movement signals, displacement, speed and acceleration, 12 goniometry features are identified (*GF*): μ, σ^2, maximum and minimum of the 3 movement signals. The standard set representing the characteristics of goniometry is defined by

$$GF_i \in \mathbb{R}^{12}$$

Features *V* and *GF* are normalized by using a Standard Normal Model.

2.8. Classification

An *ANN* served to classify the experimental and the control group. The inputs are a number of combinations of the features sEMG *V* of ST, RF, VM and BF muscles and *GF* also lead to observe the relationships between the proposed combinations and the influence of goniometry on sEMG.

Four combinations of muscles are proposed: external, internal and crossed muscles, each combination with GF. External ($\boldsymbol{V_{RF}}$, $\boldsymbol{V_{BF}}$, $\boldsymbol{GF}$), internal $\boldsymbol{V_{VM}}$, $\boldsymbol{V_{ST}}$, $\boldsymbol{GF}$), and external-internal crossed ($\boldsymbol{V_{RF}}$, $\boldsymbol{V_{ST}}$, $\boldsymbol{GF}$) and internal-external crossed ($\boldsymbol{V_{VM}}$, $\boldsymbol{V_{BF}}$, $\boldsymbol{GF}$).

2.8.1. Artificial Neural Network (*ANN*)

ANNs are simplified models of biological neural networks. They function as a parallel distributed and connected processor that stores some experimental

[9] Theorem that gives an extraction of polynomial approximations of a function at a given point of a differentiable function. [24].

knowledge. The *ANN*s use a nonlinear transfer function and a linear combination of inputs and weights that correspond to adaptive coefficients of such linear combination. Each neuron can be described as a series of functional transformations that include synaptic connection, a polarization and an activation connection [25]. The set of synaptic connections is given by *M* linear combinations of the input variables $x_1, \ldots, X_D$ of the form [25],

$$a_j = \sum_{i=1}^{D} w_{ji}^{(1)} + \omega_{j0}^{(1)}$$

Where $j = 1, \ldots, M$, and the superscript (1) indicates the appropriate parameters that correspond to the first layer of the network. The $\omega_{ji}^{(1)}$ are weights and the parameters $\omega_{j0}^{(1)}$ are constants of polarization. The parameter a_j is known as activation, and a differentiable nonlinear activation function transforms each activation, $z_j = h(a_j)$

The z_j outputs are the response of the called hidden units. The nonlinear functions $h(\cdot)$ are usually chosen as sigmoidal functions. Values are again linearly combined to obtain the activations of the output units [25],

$$a_k = \sum_{j=1}^{M} \omega_{kj}^{(2)} + \omega_{k0}^{(2)}$$

Where $k = 1, \ldots, K$ and K is the number of outputs. This is for the second layer network.

The *ANN* used in this study is a perceptron with one hidden layer, that is trained with the backpropagation algorithm. The training data is 70%, 15% for the validation and 15% for the test [26]. 10 neurons are set in the hidden layer and a 6 training epoch is performed.

Values of Sensitivity (*Se*), Specificity (*Sp*) and Accuracy (*Acc*) are applied in order to measure the classification performance. These values determine the system's capacity to quantify the ratio successfully classified in normal and pathological samples. Defining t_{pos}, t_{neg}, f_{pos} y f_{neg} as true positive, true negative, false positive and false negative, respectively [27], *Se, Sp and Acc* is estimated as shown below

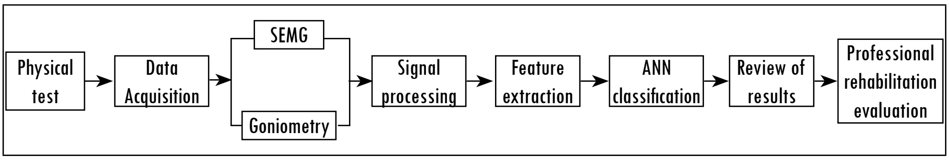
$$Se = \frac{t_{pos}}{t_{pos} + f_{neg}}, Sp = \frac{t_{neg}}{t_{neg} + f_{pos}}, Acc = \frac{t_{pos} + t_{neg}}{t_{pos} + f_{neg} + t_{neg} + f_{neg}}$$

These measures are estimated by using the average of multiple iterations of the neural network with different sets of testing and validation.

2.9. Proposed Methodology

The Figure 2 shows the proposed methodology which is developed when all tests and classification results with *ANN* are performed. This methodology provides a diagnosis support to a professional rehabilitation by using sEMG records and goniometry.

Figure 2. Proposed methodology



Source: author's own presentation

3. Results

Combination features for EMG and *GF* are shown. In the results tables, the first column corresponds to the combination of muscles and goniometry. The following columns are the performance measures for each physical test.

The combinations of external-internal and crossed muscles show the best *Acc* without *GF*, that is an average of 91%, that is higher than other muscle combinations. This high performance can be related to their antagonism[10] in the knee extension. It is observed that in the three exercises, *Acc*, *Se* and *Sp* remain the same when added *GF*, however, improvements ranging up to 14% in *Acc* and 21% in the internal muscle combination in the sitting test are evident. The physical tests exhibit a greater *Sp* to 77%. This means that the system classifies all normal subjects with good performance. *GFs* exhibit the lowest value of *Acc* of 79%. The best classification responses were obtained by using *GF*. These results were evident in the sitting physical tests, where the *Acc* showed an average of 94%. It is important to note that the *Acc* with the proposed classification model and the used features exhibited above 82%. The sitting physical test is the largest contributor to the ratio of sEMG signals and goniometry to the classification process, when comparing the three physical tests and their performance with *GFs* and without them.

[10] Antagonist muscles work in opposition and generate control and adequate balance to execute opposite movements. [28].

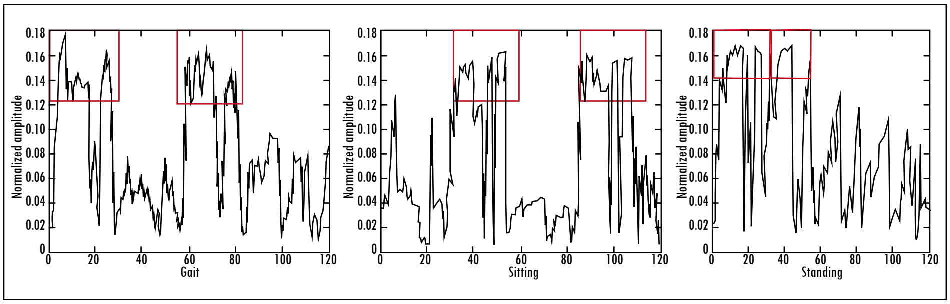
Similar studies with *ANN* with only EMG features as [9], where 27 test participants showed values of *Acc* higher than 90% and [4] to classify six hand movements had *Acc* greater than 76% correspond to the classification results of this research.

In [29] is performed a combination of EMG features and kinematics with a principal component analysis (PCA) as a classifier among people with tremor and people with Parkinson's disease with an *Acc* of 91%. In relation to this study a different classifier was applied, an *ANN* and improvements in the *Acc* were observed between 4% and 15% when adding the *GFs*.

3.1. Relevance of sEMG features and goniometry

The contribution of the characteristics in the classification process is assessed by using the algorithm *Q*-α relevance analysis [30]. This takes into account the contribution of each feature in the natural separability of data through a quadratic affinity matrix. This leads to establish connections between features and physiological assessment to reduce the computational cost.

Figure 3. Relevance of features



Source: author's own presentation

Figure 3 shows the normalized amplitudes of the 120 features (27 for each of the 4 muscles and 12 of goniometry). These values lead to determine that the most important features for the gait are provided by the RF muscle and VM muscle corresponding with the maximum values of relevance. Features provided by BF and ST muscle are the most related for the sitting position, whereas for the standing position are the ones provided by RF and BF muscle. All antagonists' cases in knee extension lead to assume the strong relationship of EMG signals into antagonistic muscles and descriptive role in the classification.

4. Conclusions

A physical test to measure EMG and goniometry values was determined. This test consists of three muscle test: gait, standing and sitting. The EMG signals and corresponding motion measurements (position, speed and acceleration) were characterized resulting in 39 features (27 sEMG and 12 movement measures). After all processing, characterization and classification of signals, it can be determined that sEMG is a suitable method to provide information about the muscle performance, particularly for this research that requires movement measurement. Results obtained in the classification processes with *ANN* are better when taking into account the features provided by the goniometry than when excluded as shown in Table 1.

A methodology for the automatic classification of knee injuries with *ANN* in EMG signals and goniometry is proposed. This methodology is quantitative and could serve as a diagnostic support and monitoring, and can be implemented with the current electronic technology.

A more comprehensive study with a larger number of participants and uniformity of injury to deepen in the methods proposed is recommended.

Table 1. Gait performance classification

	Gait			Standing			Sitting		
Muscle combinations	Acc	Se	Sp	Acc	Se	Sp	Acc	Se	Sp
External muscles	0.82	0.89	0.77	0.91	0.85	1.00	0.95	0.92	1.00
External muscles, GF	0.86	1.00	0.79	0.95	0.92	1.00	1.00	1.00	1.00
Internal muscles	0.91	0.85	1.00	0.91	0.85	1.00	0.86	0.79	1.00
Internal muscles, GF	0.91	0.85	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Crossed- external and internal muscles	0.95	0.92	1.00	0.82	0.73	1.00	0.95	0.92	1.00
Crossed external–internal, GF	0.95	0.92	1.00	0.95	0.92	1.00	1.00	1.00	1.00
Crossed internal–external muscles	0.82	0.77	0.89	0.91	0.85	1.00	0.86	0.90	0.83
Crossed internal-external muscles, GF	0.82	0.77	0.89	0.91	0.85	1.00	0.86	0.90	0.83
Average	0.88	0.87	0.92	0.92	0.87	1.00	0.94	0.93	0.96

Source: authors' own presentation

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