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OPTIMIZATION OF THE KINETIC TREATMENT OF OSTEITIS
PUBIS IN SOCCER PLAYERS

Andrei-Cătălin Ionițe (a)*, Gloria Rață (b), Dragoș Arotăriței (c), Mariana Rotariu (d)

*Corresponding author

(a) National University of Physical Education and Sports, 140 Constantin Noica St., Bucharest, Romania

(b) National University of Physical Education and Sports, 140 Constantin Noica St., Bucharest, Romania

(c) “Grigore T. Popa” University of Medicine and Pharmacy, 16 Universității St., Iași, Romania

(d) “Grigore T. Popa” University of Medicine and Pharmacy, 16 Universității St., Iași, Romania,

Abstract

Osteitis pubis is a constantly increasing syndrome among soccer players and not only, affecting their sports performances. Simulation and comparison of functional parameters of osteitis of the pubis use new computational techniques, neural networks, in the establishment and optimization of kinetic treatment in pubalgia. In this direction, the present study is conducted on a total of 35 patients (healthy and affected by osteitis of the pubis). Both healthy and affected patients benefited from the initial testing, which contained different parameters that were recorded at the level of the plantar region, and those affected by osteitis of the pubis benefited from kinetic treatment. The kinetic treatment was performed over a four-week period and consisted of various kinetic techniques, such as physical exercises, proprioceptive techniques etc. At the end of the treatment period, we performed the final test, and the obtained data were compared with the original ones using modern techniques of interpretation of the experimental results, which supported the idea of creating techniques for optimization of the kinetic treatment and implicitly the reduction of the convalescence period. This paper aims to introduce a modern computational concept, neural networks, in sports medicine, but also to find and implement an optimal treatment plan to recover from osteitis pubis and to reintegrate as quickly as possible into sports activity.

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Keywords: Osteitis pubis, neural network, kinetic treatment, sports medicine..



1. Introduction

In recent years, soccer has had tremendous growth, in qualitative terms, by increasing the intensity and frequency of the game, as well as by the increased number of competitions a soccer player has to play in a competitive year/season. All this development has increased the intensity of both matches and training, increasing the number of training sessions, training camps, matches played in domestic and international championships etc. All these factors have led to the overuse of the mio-arthro-kinetic chain, thus favoring the emergence of new pathologies such as osteitis pubis.

Osteitis pubis is a noninfectious inflammation of the pubic bone that causes pain in the muscles with insertion at this level (Fricker, Taunton, & Ammann, 1991; Major & Helms, 1997; Albers, Spritzer, Garrett, & Meyers, 2001; Zaoui et al., 2012; Elattar, Choi, Dills, & Busconi, 2016; Turnea, Rotariu, Ionițe, Arotaritei, & Ilea, 2017). In 2011, this pathology was present in the soccer game in a percentage of 10-13% of the total accidents within a year (Litwin, Sneider, McEnaney, & Busconi, 2011). The main causes of this pathology are stress overload or training errors and biomechanical features (McIntyre, Johson, & Schroeder, 2006; Ilea, Turnea, Arotaritei, Rotariu, & Popescu, 2015).

2. Problem Statement

The literature does not have many studies to address osteitis pubis in terms of kinetic treatment. The vast majority of studies address pharmacology, surgical interventions and diagnostic methods, thus identifying a lack of information on the approach of osteitis pubis in terms of kinetic treatment, as confirmed by Choi, McCartney and Best in 2011. Two studies, one in 2001 and the other in 2012, addressed the problem from a rehabilitation point of view, by using manual therapy and proprioceptive neuromuscular facilitation (PNF) techniques (Rodriguez, Miguel, Loma, & Heinrichs, 2001; Vijayakumar, Nagarajan, & Ramli, 2012). But the two studies were not enough to convince Cheatham, Kolber and Shimamura in 2016. They have stated that there is little evidence suggesting the effectiveness of rehabilitation programs in recovering athletes and bringing them to the pre-set level.

3. Research Questions

1. By applying a kinetotherapeutic treatment, can we alleviate the symptoms of osteitis pubis?
2. Can multi-layer neural networks help improve the quality of the recovery program?

4. Purpose of the Study

The aim of the study is to optimize the kinetotherapeutic treatment and to highlight its effects in the recovery of osteitis pubis. Using mathematical simulations in vivo, we can achieve a multitude of scenarios, thus leading to a personalised treatment for each patient.

5. Research Methods

The study was conducted on 5 soccer players affected by osteitis pubis. All 5 subjects are 20 to 30 years of age, male, body weight between 60-90 kilograms, size between 170-190 cm, size of the sole

between 22.5 and 28.5 cm and a minimum of 8 years in sports activity in this branch. They benefited from initial and final evaluations.

Subject evaluation was performed with a postural test, “Pedana OEM/DF, CLASS I MED. DEVICE”, along with the “Dr Foot Analysis 4.0” (Figure 01) (Ionite, Rotariu, & Gheorghita, 2017). Through them, we collected data on plantar footprint and plantar pressure for both the right foot and the left foot and the surface of the gravity centre (Rotariu et al., 2017).

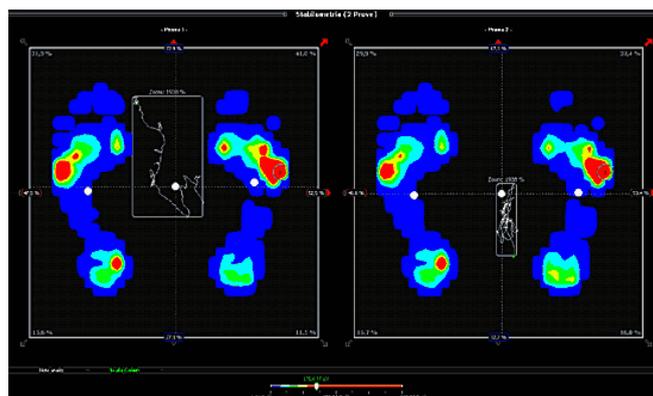


Figure 01. Dr Foot Analysis 4.0 – Plantar surface, plantar footprint, pressure points, together with the position of the centre of gravity

Between the two initial and final evaluations, the subjects underwent kinetotherapeutic treatment. The treatment protocol was performed over a period of four weeks (twenty sessions), with each treatment session lasting between 50 and 70 minutes. The treatment protocol was the same for each subject and was structured as follows: massage techniques (10 minutes), stretching (5-10 minutes), massage techniques (5-10 minutes), PNF techniques (5-10 minutes), massage techniques (5-10 minutes), a combination of stretching with PNF techniques (5-10 minutes), massage (5 minutes) and therapeutic physical exercises (5-10 minutes).

After the initial and final evaluations, the data obtained were quantified. Through the multi-layer neural networks, the data collected were compared with data from the study of Ionite, Rotariu and Gheorghita (2017).

Multi-layer neural networks are known as universal approximators (Hornik, Stinchcombe, & White, 1989). After local processing of the input signal, depending on the information stored in the synaptic weights (multiplying it with the stored information values), a global summary of the obtained results is produced – a process similar to that taking place in the cellular body of a real biological neuron. If the global response obtained exceeds a certain threshold of significance imposed by the user, the information is forwarded (Haykin, 1998; Lippmann, 1987; Arotaritei & Negoita, 2003).

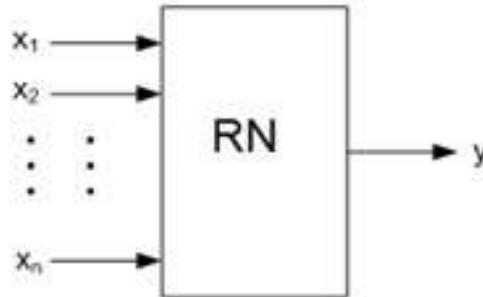


Figure 02. A single out neural network

Artificial neural networks (ANNs) are structures that attempt to mimic the way the human brain functions and are constructed from multiple processing elements (EPs) or artificial neurons grouped into layers, each layer having a variable number of elements (Figure 02 and Figure 03).

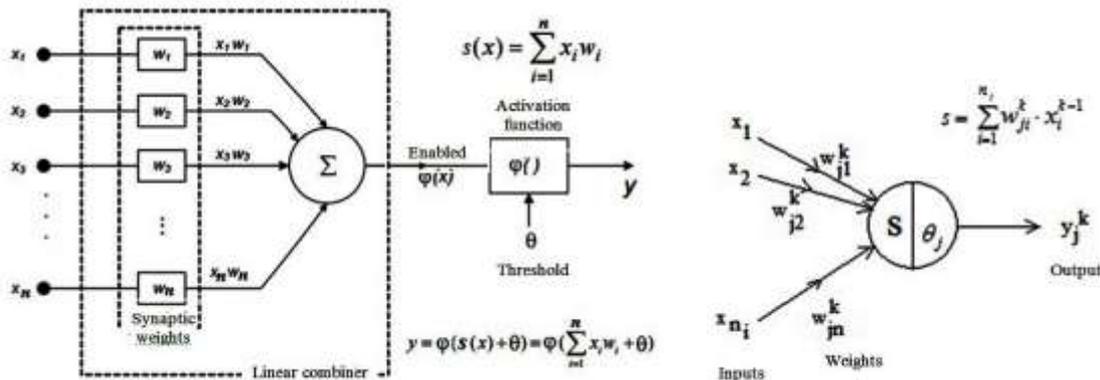


Figure 03. The mathematical model of artificial neuron, full presentation on the left side and simplified on the right side

Signal propagation is made from input to output according to the equations in Figure 03 or in compact form according to equations (3.1) - (3.2) (Haykin, 1998).

$$y_j^k = \varphi\left(\sum_{i=1}^{n_j} w_{ji}^k \cdot x_i^{k-1} + \theta_j\right) \quad (3.1)$$

$$y = \varphi(w^T \cdot x + \theta) \quad (3.2)$$

After assimilation/storage, the network fulfils its role as a classifier or predictor. Applying a vector to the input, we get, at the output, the desired class or the prescribed value (or even a prediction sequence) (Arotaritei, 2011; Arotaritei & Negoita, 2002).

6. Findings

Following the initial (I) and final (F) evaluations, the data on right plantar footprint (rPF), left plantar footprint (lPF), right plantar pressure (rPP), left plantar pressure (lPP) and the surface of the gravity centre (sGC) were collected and analysed. Synthetically, we present them in Table 01.

Table 01. Results of the initial and final evaluations

S	rPF (%)			IPF (%)			rPP (kgf)			IPP (kgf)			sGC (cm ³)		
	I	F	Df.	I	F	Df.	I	F	Df.	I	F	Df.	I	F	Df.
1	34.2	39.2	5	63.8	60.8	3	13.8	20.8	7	56.3	50.3	6	0.145	0.17	0.025
2	31.6	38.6	7	68.4	61.4	7	14.5	15.5	1	60.1	55.1	5	0.121	0.161	0.04
3	37.9	38.9	1	62.1	58.1	4	25.6	26.6	1	70.6	66.6	4	0.171	0.211	0.04
4	32.2	32.2	0	67.8	66.8	1	24.9	24.9	0	51.3	50.3	1	0.125	0.139	0.014
5	22.3	24.3	2	67.7	62.7	5	31.4	32.4	1	65.6	61.6	4	0.116	0.126	0.01

We can see, in Table 01, the changes in parameters from the initial to the final assessment, changes produced by the kinetherapeutic treatment. If, in Table 01, we see how the parameters have changed, in Figure 04, we can see, through multiple neural networks, the data taken at the initial and final evaluations, as well as the reference data used to determine the acceptance threshold (Ionițe, Rotariu, & Gheorghita, 2017).

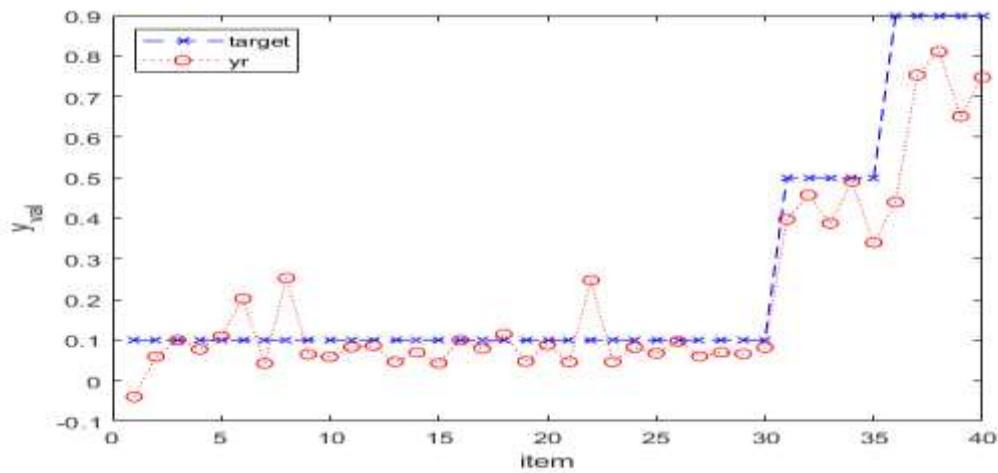


Figure 04. Multi-layered neural networks – Initial, final and reference evaluations

The value 0.1 is marked with class A (reference value), value 0.5 with class B (final assessment), and value 0.9 with class C (initial assessment).

There is a change in parameters ranging from class C to class B. This passage shows a tendency to normalise the parameters to class A, which is also visible in Figure 05.

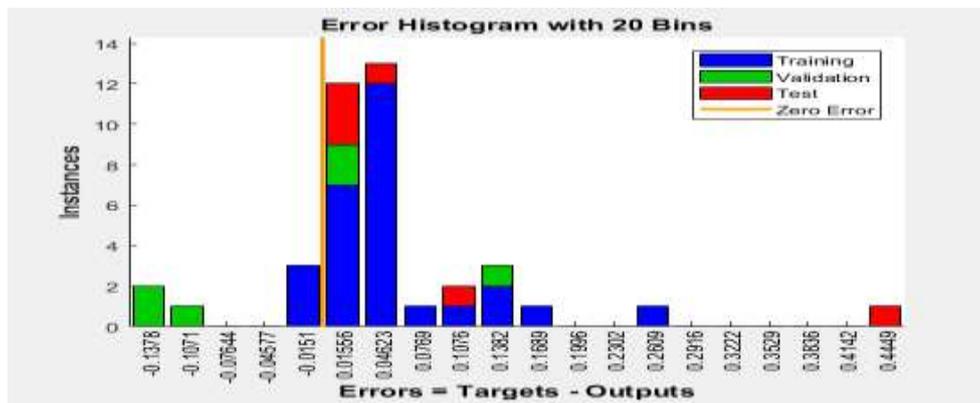


Figure 05. Histogram error in order to validate the acceptance value on each layer

The built-in histogram gives us the training errors after building the classifier. A good classifier should give small errors for both sets of data, as described in Figure 06. According to Bonferoni's principle, there is a probability that a correct prediction will have enough chances to be found in the "bunch". In order to adjust the data and the acceptance threshold, the spindle has to be validated in compliance with the mean squared error.

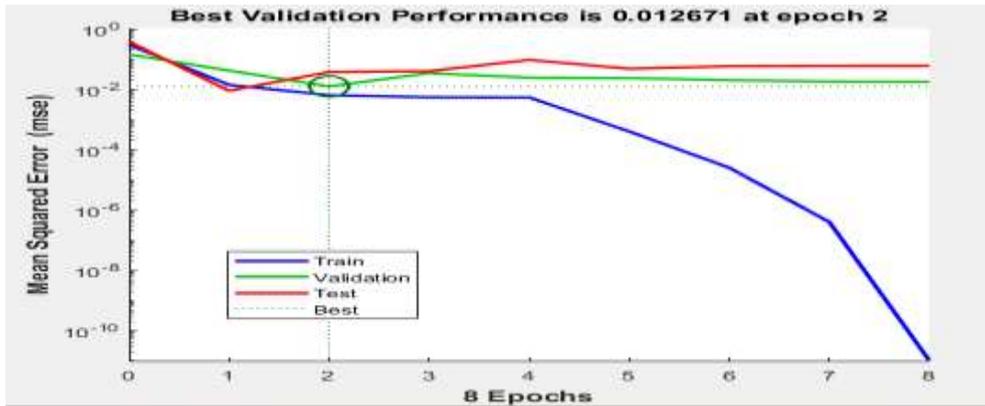


Figure 06. Portrait of the status of the mean squared error evolution

According to Figure 06, we see that the required acceptance level, 0.012671, obtained by testing the binary assumptions considered in this study, is reached at level 2. In this regard, for the validation of the model, the matrix of confusion is built, a statistical tool in the validation of neural networks.

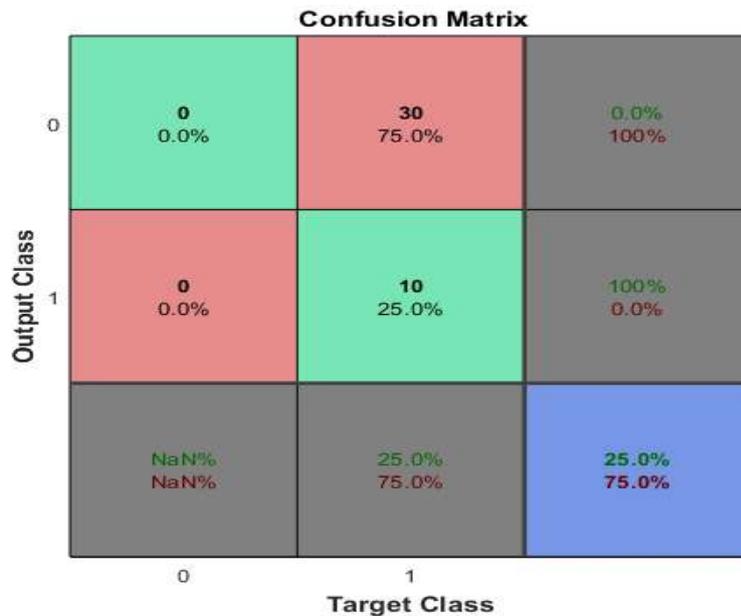


Figure 07. Matrix of confusion to determine optimal treatment

The results obtained in testing a two-tier form recognition system are synthesised in the confusion matrix in Figure 07, for statistical data validation. So:

- we determine how many shapes we have in each of the two classes according to the reference distribution (the test data set);
- we determine how many forms have been recognized by the recognition system in each of the two classes;
- we interpret the values in all cells on row 2 of the matrix of confusion.

We can see that 25% of in vivo tests meet the required acceptance threshold. Thus, the parameter values to be considered are on these layers (level 2) in the description of the optimal kinetic treatment. This “learning” process leads to the personalisation of treatment and the creation of optimal treatment.

7. Conclusion

Once osteitis pubis is established, it produces changes in the lower limbs, changes that can be recorded at the plantar level.

The kinetotherapeutic treatment plan used in this study has had positive effects, improving the symptom of osteitis pubis, which leads to a positive answer to the first question.

Multi-layer neural networks have helped to better understand the results obtained in this study and compare them with the results of other studies in the specialised literature, which means a positive answer to the second question. Through neural networks, we have demonstrated how, after applying the recovery treatment, class C changed and became class B, with a tendency towards normalisation, class A.

In addition to the above mentioned, the multi-layer neural networks helped us to classify small errors for datasets, adjust data and regulate the required acceptance level, 0.012671, obtained by testing the binary assumptions reaching level 2, and, through the matrix of confusion, we succeeded in statistical data validation. All this information provided by the multi-layer neural network helped us optimize the kinetotherapeutic treatment and automatically increase the quality of the therapeutic program

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