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Research Article - Basic and Applied Anatomy

An application of the graph theory to the study of the human locomotor system

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Abstract

The study of the relationships between the different structures of the human locomotor system still raises great interest. In fact, the human body networks and in particular the "myofascial system network" underlie posture and movement and new knowledge could be useful and applied to many fields such as medicine and prosthetics. The hypothesis of this study was to verify the possibility of creating a structural network representing the human locomotor system as well as to study and describe the relationship between the different structures considered. The graph theory was applied to a network of 2339 body parts (nodes) and 7310 links, representing the locomotor system. The open source platform software Cytoscape was used for data entry (nodes and links) as well as for debugging. In addition, the "NetworkAnalyzer" plugin was used for the descriptive statistics of the network obtained. In order to achieve a better rendering, the results of the network parameters gained were then imported into Gephi graph platform. At the end of this procedure, we obtained an image of a human being in an orthostatic position with a precise distribution of the nodes and links. More specifically, "the shortest pathways analysis of the network" demonstrated that any two randomly selected nodes on the network were connected by pathways of 4 or at most 6-8 nodes. Moreover, the Edge Radiality Distribution analysis was carried out in order to define how a single node is functionally relevant for other nodes: the probability distribution ranged from 0.4 to 0.77. This indicates that the majority of nodes tend to be functionally relevant for the others, but none of these is predominant. As a whole, the Cluster Coefficient (0.260) demonstrates that the network is neither random nor "strongly organized".

Keywords

Anatomy, graph theory, tensegrity, social network, kinesiology, posture.

Introduction

Although in some branches of medicine such as anatomy and kinesiology as well as osteopathy the relationship between different parts of the body and in particular of the musculoskeletal system is taken into consideration, no precise indications are yet given in this regard (Esteve-Altava et al., 2011; Swanson, 2013; Diogo et al., 2015).

The human locomotor system is a complex system that affects thousands of anatomical structures; each part with its own morpho-functional peculiarities, showing specific functions both individually and together (i.e. to support the person and allow movements, connect, protect other organs), thus creating a complicated system of relationships that characterizes the musculoskeletal system itself.

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Consequently, studies aimed at an increasing in-depth knowledge of the human body and the relationships between the different systems in static and dynamic conditions is still raising great interest (Diogo et al., 2015; Esteve-Altava et al., 2011).

Some authors have tried to answer this question by applying the principles of tensegrity to the study of the musculoskeletal system, human movement and posture and relationships between the different body segments (Levin, 2002; Swanson, 2013; Dischiavi et al., 2018).

Tensegrity refers to structures that maintain their integrity by balancing continuously braided tensile forces along the structure (Chen and Ingber, 1999; Ingber, 2008). In this sense, it is known that the forces acting in human connective tissue can be represented as a continuous network affecting all structures of the musculoskeletal system. This would allow us to overcome the limits of a segmental study and to explain more complex properties of locomotor system through a holistic approach (Chen and Ingber, 1999, Dischiavi et al., 2018).

Moreover, in recent years the human body and the relations between its different parts has been studied using the theory of networks (Bolwijn et al., 1996; Fling et al., 2014; Esteve-Altava et al., 2015). This approach has allowed the study of the human body from a different perspective.

The results achieved by the generation of a structured network representing the musculoskeletal system can be further studied and graphically represented with the use of the graph theory (Mason and Verwoerd, 2008; Murphy et al., 2018).

In this sense, graph theory in scientific literature is applied to several fields, including the medical (Bullmore and Sporns, 2009, van Wijk et al., 2010) and social one (Makagon et al., 2012; De Vico Fallani et al., 2014; Zang et al., 2018). Recently, some authors have studied the human posture by applying the graph theory to achieve a simple model, but at the same time an accurate and faithful picture of the original system (Thome et al., 2006; Tahir et al., 2007; Liu and Zhan, 2013; Boonstra et al., 2015). In particular, the graph theory can allow the objective representation of the data set of the network obtained from the anatomical examination of the human musculoskeletal system, as has been done in the present study.

An approach considering these theories, as a mathematical measure of the relationships inside the musculoskeletal system, could help to better understand the relationships between the different structures of this system and become a new way to investigate anatomical complexity, that could be widely applied.

The aim of the present study was to verify the possibility to create a network representing the human musculoskeletal system and then define a structural network applied to anatomy to study and describe the relationship between the different structures considered.

Materials and Methods

In this study, as a whole, numerous interconnected parts (nodes) of the musculoskeletal system were identified, in order to create a structural network that allows an in-depth topological analysis of the musculoskeletal system itself. In this sense, we considered a total of 2339 anatomical structures (Table 1). Specifically, all the osteo-musculo-ligamentous structures of the arthrodial system, the diaphragm, the pelvic

Table 1. Body parts considered in this research: typology and number.

Anatomical structures	N°
Ligaments	1062
Bones	216
Muscles	590
Fasciae	103
Cartilages	124
Innards (eye)	2
Other	5
Tendons	237
Total	**2339**

floor muscles, the supra and subhyoid muscles and the pharyngeal muscles were considered. Bone, capsuloligamentous and joint structures of the inner ear were not considered.

Among these structures (nodes), the undirected links (the connection is not associated with a direction) have been defined according to the existing anatomical relationship. The study of the network following the analysis of such a large number of nodes, that is, the "graphic" representation, even if not univocal, of every single part of the musculoskeletal system was aimed at obtaining a graphic representation of such network (graph) and therefore of the relationships between the structures.

In this sense, the open source software platform Cytoscape (www.cytoscape.org) was used for data entry (nodes and links) as well as for their debugging. In addition, the plugin "NetworkAnalyzer" was used for the descriptive statistics of the network obtained.

The resulting network parameters were then imported into the open-source and multiplatform software Gephi (www.Gephi.org) for a better rendering, using the plugin "ForceAtlas 2" with the option "Dissuade hubs".

The structured network obtained and expressed through a graph was characterized by its own density. The formula applied to calculate the network density, that is, how many links are there in the network compared to the maximum number of links that a network with the same number of nodes N can have was the following:

$$D = \frac{2(E - N + 1)}{N(N - 3) + 2}$$

where D is the graph density, N is the number of nodes inside the network and E is the number of possible links that a network with N nodes can contain.

The diameter of a graph G it is the greatest distance between any pair of vertices and it was considered as the number of edges in the shortest path between the most distant vertices.

The clustering coefficient is the measure of the degree to which nodes in a graph tend to cluster together and results from the number $\boldsymbol{n}$ of links existing between the $\boldsymbol{k_i}$ nodes next to $\boldsymbol{i}$ and the maximum number of possible arches between them. This value was calculated as follows:

$$C_i = \frac{2e_i}{k_i(k_i - 1)}$$

where k_i is the number of neighbours of the i'th node and e_i is the number of connections between these neighbours. Closeness centrality measures the importance of a node in a network according to the notion that "An important node is typically *close to*, and can communicate quickly with, the other nodes in the network"; it was cal-

Table 2. Anatomical network parameters.

Clustering coefficient:	0.260	Number of nodes:	2339
Connected components:	1	Network density:	0.003
Network diameter:	14	Network heterogeneity:	1.397
Network centralization:	0.033	Isolated nodes:	0
Shortest paths:	5468582 (100%)	Number of self-loops:	6
Characteristic path length:	6.682	Multi-edge node pairs:	7310
Avg. Number of neighbors:	6.253	Analysis time (sec):	9.389

culated as the sum of the length of the shortest pathways between the node and all other nodes in the graph (Friedkin et al., 1981; Mason and Verwoerd, 2008; Opsahl et al., 2010).

Results

This study allowed us to create a network and thus obtain a connected graph in which self-organization shows a clear reconstruction of the human musculoskeletal system. In particular, the topological analysis defined a network of 2339 anatomical parts (nodes) and 7310 links (Tables 1, 2).

The definition of the network is the result of two consecutive steps. After the full definition of a first network (preliminary network), debugging was carried out to find imperfections and oversights. At the end of the debugging process, data entry errors (about 100) were found and were corrected, obtaining the "final" network considered in this study. From the comparison of the two networks (preliminary vs. final) it was possible to verify how the difference in the numerical results achieved was less than the fourth decimal place ($<10^{-4}$ error).

The descriptive parameters of the final network achieved by Cytoscape processing are listed in Table 2. In particular, the network density was 0.003, while the graph diameter graph resulted 14, and the clustering coefficient was 0.260.

The shortest pathway analysis of the network demonstrated that any two randomly selected nodes on the network were connected by pathways of 4 or at most 6-8 jumps and each network node was connected on average with 6.25 other nodes (Figure 1).

The results of the Edge Radiality Distribution analysis showed that the "probability" of a node to be functionally relevant for several other nearby nodes ranged from 0.4 to 0.77.

Discussion

In this study, we created an anatomical network model of the locomotor system by evaluating all its anatomical structures and, within this set, the relationships that each single structure (node) has with the others through the definition of edges.

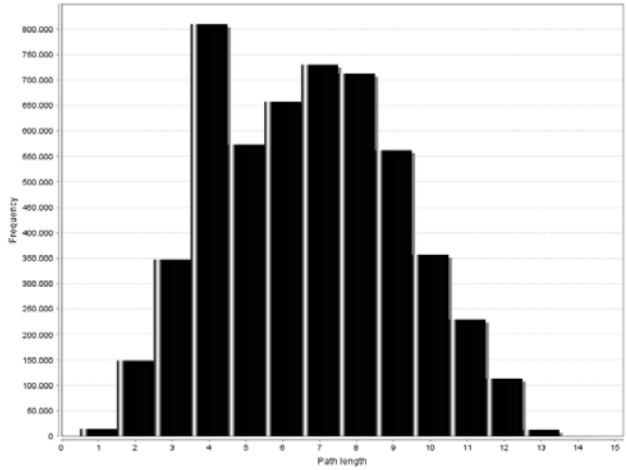

Figure 1. Shortest Path Histogram.

We carried out this study with the same approach as previous ones on the human head (Esteve-Altava et al., 2015), body (Thome et al., 2006) posture (Tahir et al., 2007) and hand grasp posture (Liu and Zhan, 2013) and analysis using the theory of data graphs has allowed a new and more detailed description of the locomotor system. This result could be an important step forward in the study of the relationship between the different structures of locomotor system and of this with other body systems and the environment in static and dynamic conditions. Contrary to other studies (Murphy et al., 2018) we defined nodes as all the structures considered, while links indicate an anatomic relationship between the nodes.

In particular, processing the network step by step (see Figures 2-5) created an image of a man in orthostatic position, that is a precise distribution of the nodes and the links resulted from the graphic representation of the outcomes.

It is worthy noting that the data histograms, screened by the plugging network analysis of Cytoskape (Network Analizer), fitted precisely with the theoretical curves without points that distinctly deviate from those curves (Figures 2).

At the same time, the density value of the generated network demonstrated that the network and its structure is very flexible and elastic, the Cluster Coefficient obtained from the analysis of the network resulting from this study is 0.260, which can be considered a intermediate value indicating that the network is neither random nor "strongly organized". In this sense it is known that the Cluster Coefficient (or transitivity) value of a randomly generated network tends to be very low while in networks resulted from "engineered" structures it is usually a higher value. The heterogeneity of a network should measure the diversity in the node degrees compared to a full homogeneous network with the same number of nodes. In this study it was 1.397 indicating that there are no structural holes in the network and its nodes, that affect the whole network (Burt, 2004; Mason and Verwoerd, 2008; Jacob et al., 2017).

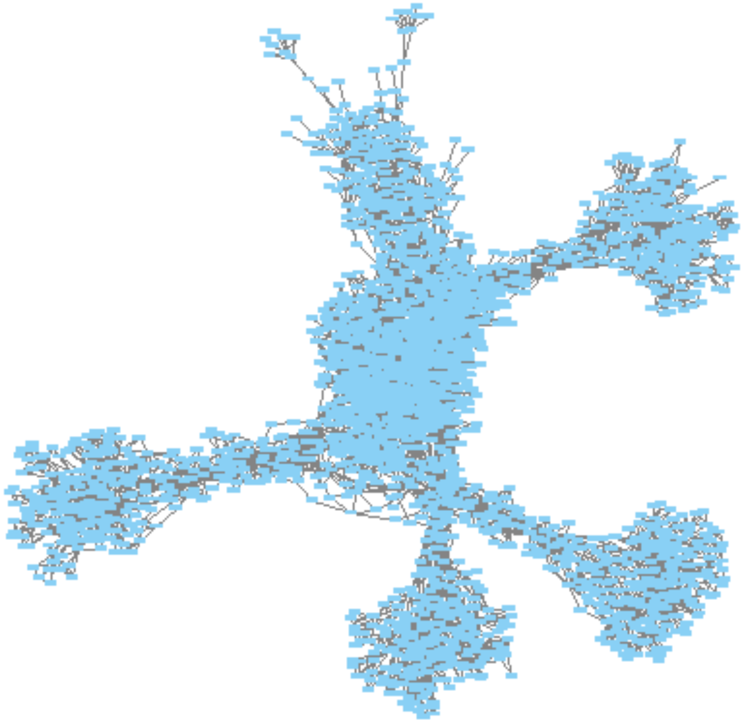

Figure 2. Anatomical Network data rendering with Cytoscape.

All this suggests that the "locomotor" network of a human being is at the same time robust, elastic, redundant. In the analysis of these results, we did not the need to consider this structure to adapt to the environment in which it lives and, therefore, the reciprocal relationship between man and the environment; this network could paradoxically appear not "perfected".

The approach to the analysis of the musculoskeletal system of this pilot study could open new perspectives and find areas of application in many disciplines interested in the study and treatment of the locomotor system. In fact, this method could lead to an integrated study of human movement and posture considering the relationships between each structure by also applying the principles of tensegrity. As previously reported, among the several fields of this approach application there are the medical and movement ones. Within these branches, there are real global health emergencies such as patients with diabetes and in particular with history of neuropathy, or greater or lesser amputation who could be studied by the approach proposed in this study for the serious and typical alterations of movement caused by this condition (Anichini et al., 2017; Francia et al., 2017, 2018). This should theoretically be useful for the definition of tailored patients treatments for impairments affecting the musculoskeletal system.

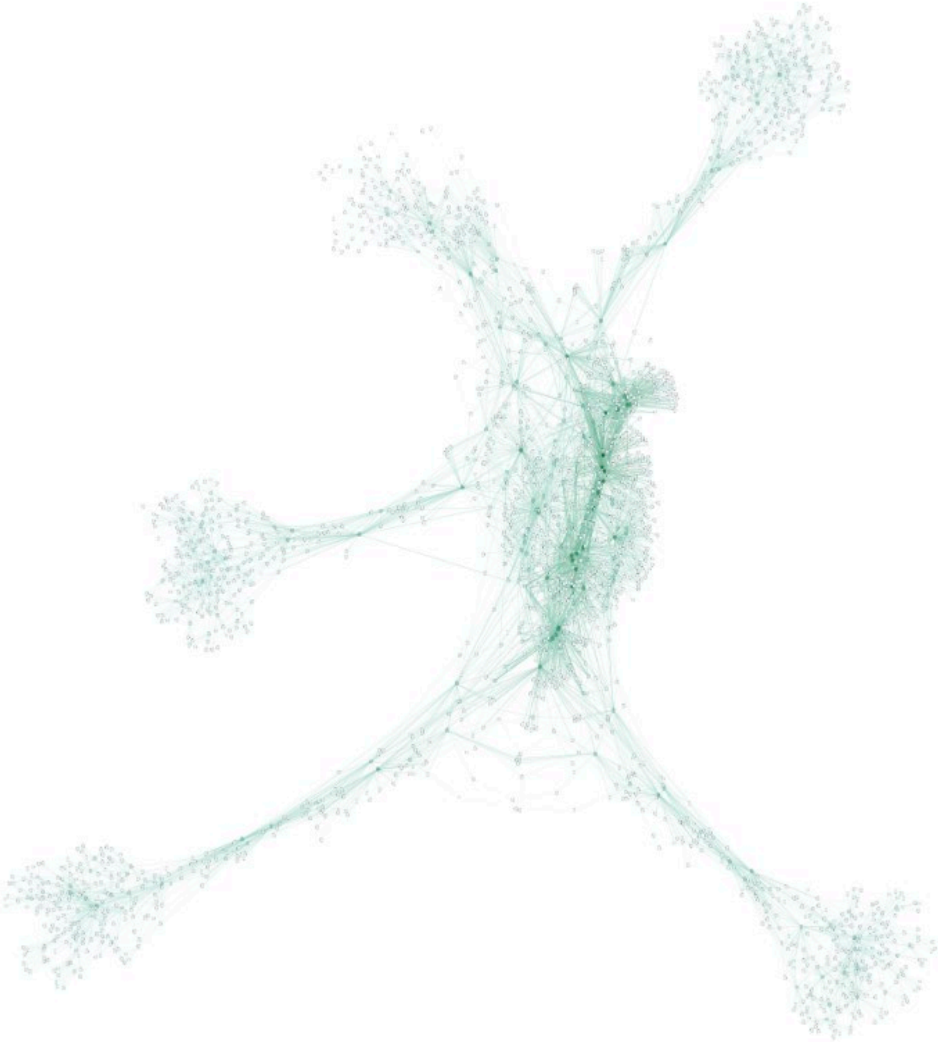

Figure 3. Cytoscape Rendering imported in Gephi.

Conclusions

By applying certain concepts of tensegrity to the human body, in this study it has been possible to develop a complete anatomical network of the locomotor system and its graphical representation. The resulting network is well representative of the different anatomical parts of the locomotor system and describes important structural characteristics of the system and of their interdependent relationships. This result can be a useful means for further understanding the musculoskeletal system and designing better targeted treatment and therapy of disease.

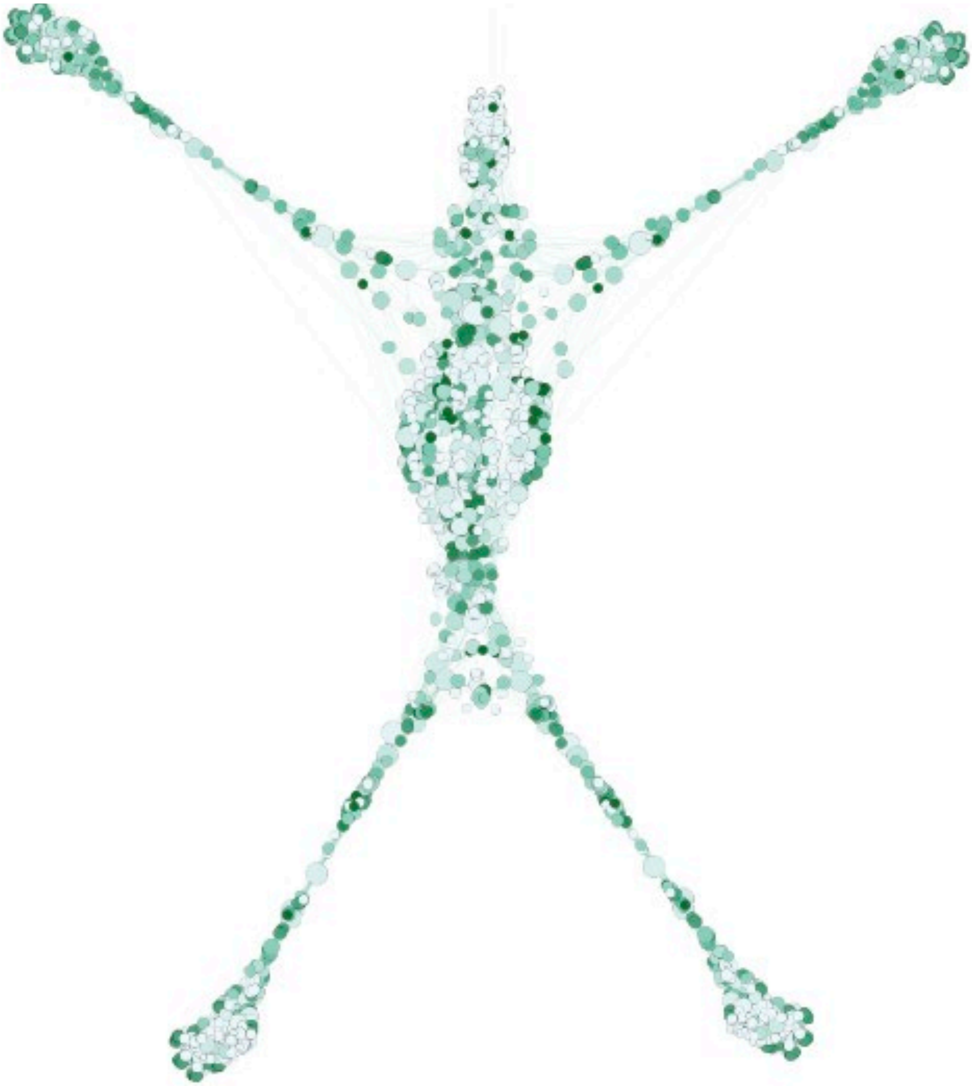

Figure 4. Anatomical network rendering with ForAtlas 2.

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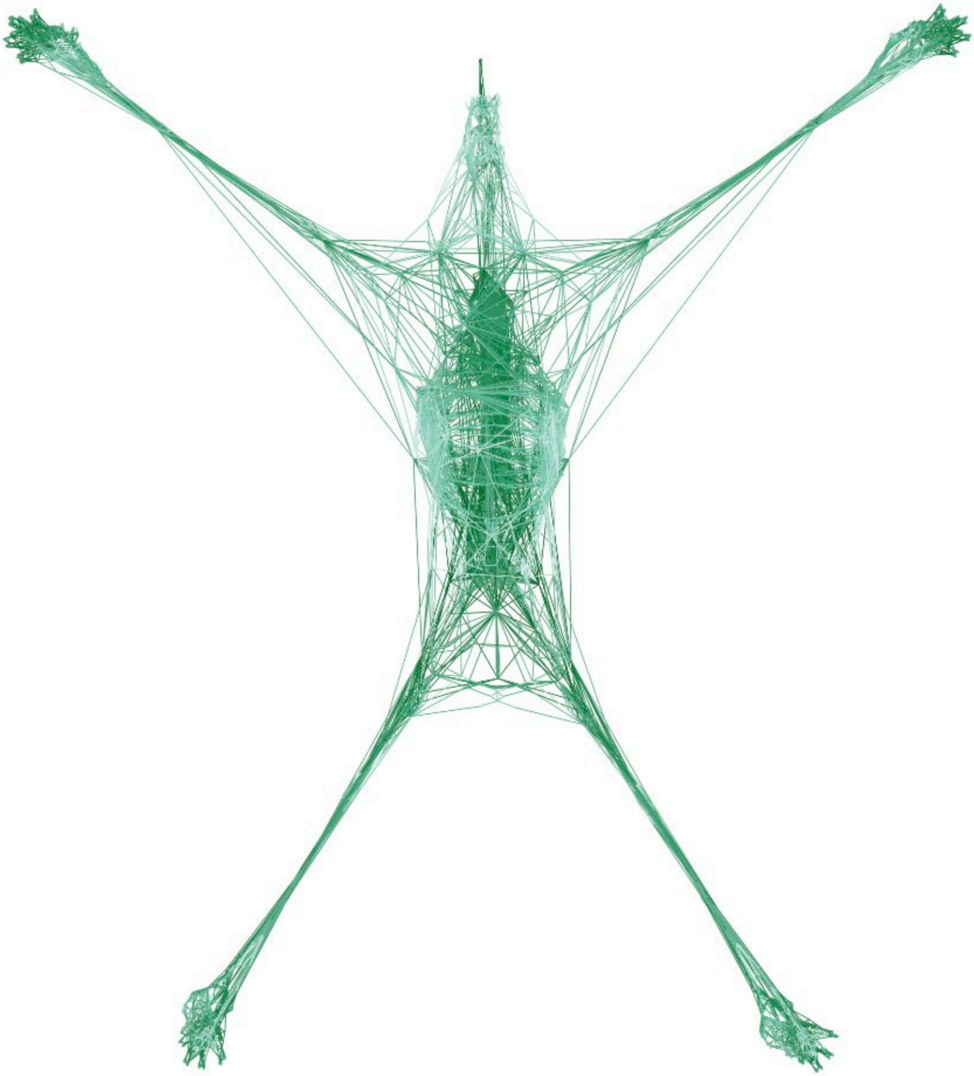

Figure 5. Final rendering of the anatomical network of human locomotor system.

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