The Methodology for Assessing the Individual Norm in the Diagnosis of the Musculoskeletal System

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Abstract.

The article proposes a methodology for assessing the individual norm of functioning of the musculoskeletal system based on goniometric control data, which will improve the accuracy and efficiency of the diagnosis of the musculoskeletal system. During the diagnosis of the musculoskeletal system the evaluation of an individual norm involves a temporary analysis of the dynamics of the range of motion of a particular patient and the identification of pathological changes against the background of an individual norm. According to the methodology, it is proposed to evaluate the individual rate of movement when registering the movement parameters with personalized wearable systems based on displacement sensors (accelerometers, gyroscopes). Sensors record the dynamics of the parameters of the movement of the elements of the musculoskeletal system in the process of everyday physical activity. The resulting time series are scaled by time, filtering and subsequent classification of movements according to their angular parameters. An individual patient model is formed on the basis of a basic model, which contains general norms of permissible deviations of controlled parameters. The applied processing algorithms are based on neural networks. For practical verification of the developed methodology, from September 2019 to March 2020, measurements were made of the mobility of the knee joint in 10 students. As can be seen from the results obtained, each observed student can be distinguished by their parameters of flexion of the knee joint, as well as the individual style of flexion during the day. Despite the described shortcomings of the introduction and testing of the proposed methodology, the results obtained during the study indicate the possibility of applying the developed methodology and the need for its further development.

Keywords: musculoskeletal system, individual norm, diagnostics

1. Introduction

The timely detection of the development of pathological diseases at an early stage is the main task of medical diagnosis. Currently, in medical diagnostics of functional abnormalities of the musculoskeletal system, there is a problem of low efficiency in diagnosing diseases, which is caused not only by errors in diagnostic hardware, but also by deficiencies in diagnostic methods (Sullivan & Beales, 2007).

One of the drawbacks of diagnostic methods is the lack of consideration of the individual norm of movement indicators, as a result of which the diagnosis of the disease is carried out according to the parameters of the statistical norm. In turn, the parameters of the statistical norm were obtained at the turn of the 20th-21st centuries and were recorded on the basis of less accurate measurement systems compared to modern ones (Phillis & Nagel, 2009).

Currently, taking into account the rapid development of personalized technical monitoring tools (Dao et al., 2015; Dorofeev et al., 2019), the main problems that determine the lack of methods for assessing an individual norm during the diagnosis of the musculoskeletal system are the need to develop principles and algorithms for intelligent processing and analysis of recorded data on motor dynamics. Algorithms of this class should be aimed at solving the problems of detecting and classifying a useful goniometric signal, be trained on the basis of the parameters of the individual norm of a particular patient, be stable with respect to the interference parameters, and also meet the requirement of stabilizing the probability of false detection and skipping of a violation (errors of the first and second kind).

The aim of the work is to increase the accuracy and efficiency of the diagnostics of the musculoskeletal system by developing a methodology for assessing the individual norm, intended for use in inertial automated systems for diagnosing motion parameters that operate on a quasi-real time scale.

2. The concept of individual norms of human movement

Currently, the diagnosis of diseases of the musculoskeletal system is mainly carried out by assessing the output of the range of movement parameters beyond the average norm (Newton & Rogers, 2014). However, in medical practice there are a large number of cases where the patient’s movement indicators are outside the statistical norm (for example, in people with increased flexibility, the joints can extend up to 15º more than the average statistical norm), but the patient is healthy (Ibraimova and Polishchuk, 2007) And vice versa, making movements in accordance with the norm of indicators, the patient develops a disease of the musculoskeletal system. In addition, human movements are a set of parameters, the norm of which is individual and changes not only during the physiological development and aging of the body, but also in individual periods of activity, taking into account indirect factors (level of biorhythms, complex state of health, season, etc.) (Udochkina et al., 2016).

The concept of assessing an individual norm during the diagnosis of the musculoskeletal system involves a temporary analysis of the dynamics of the range of motion of a particular patient and the identification of pathological changes against the background of an individual norm. In order to increase the effectiveness of personalized diagnosis of diseases, parameters of a person’s movements during everyday physical activity are recorded, which are subsequently processed and analyzed using the method of assessing an individual norm of indicators.

3. The methodology for assessing the individual norm in the diagnosis of the musculoskeletal system

According to the methodology, it is proposed to evaluate the individual rate of movement when registering the movement parameters with personalized wearable systems based on displacement sensors (accelerometers, gyroscopes). Sensors record the dynamics of the parameters of the movement of the elements of the musculoskeletal system in the process of everyday physical activity. The resulting time series are scaled by time, filtering and subsequent classification of movements according to their angular parameters.

When processing data, the human movement is represented by the set of angular vectors of each of the n-links $\mathbf{M}=[zv_1,\ldots, zv_i,\ldots, zv_n]$ in the 3-dimensional space of attributes Q. Moreover, each vector of goniometric parameters of the i-link under study belongs to a certain class of movements Ω_j, from the set of which the transposed vector $\boldsymbol{\Omega_n}^T=[\Omega_1\ \ \Omega_2\ \ldots\ \Omega_M]$ is formed. Each of the classes of movements (states) corresponds to some disjoint subset q_j, which is located in the attribute space Q: $\cup\ q_j = Q$.

Each of the classes of movements is formed by individual norms on the values of angles (features). The inclusion of the angular values of the vector $\vec{zv_i} = \{\alpha_i, \beta_i, \gamma_i\}$, where $(i = 1 \ldots n)$ of each link of a complex object in the subset q_j will mean that the movement made by the object belongs to the class Ω_j:

$$\mathbf{M} \in q_j. \tag{1}$$

From the provisions of the verification of statistical hypotheses it follows that the set of goniometric data under study belongs to the class Ω_j of human movements. In the case of solving the goniometric control problem, one should consider the probability of the components of the vector of goniometric parameters falling into the zones of an individual norm ($P_{(1,1)}$) or deviation ($P_{(0,0)}$), as well as the probability of errors of the first ($P_{(1,0)}$) and the second kind ($P_{(0,1)}$), which are estimated based on the expressions (Derrick et al., 2016):

$$P_{(1,1)} = \frac{\pi - \varphi - \Delta\varphi}{\pi}; \quad P_{(0,0)} = \frac{\varphi - \Delta\varphi}{\pi}; \quad P_{(1,0)} = P_{(0,1)} = \frac{\Delta\varphi}{\pi}. \tag{2}$$

Then the classification of the recorded parameters according to the criteria of norm and deviation is accompanied by classification errors with the probability:

$$P_{(1,0)}{}^{\Omega_k/\Omega_j}(zv_i) = P_{(0,1)}{}^{\Omega_k/\Omega_j}(zv_i(t)), j \neq k \tag{3}$$

where zv_i is the angle of inclination in space (feature 1); $zv_i(t)$ is the rate of change of the angle (feature 2); Ω_k, Ω_j are motion classes.

Moreover, the total number of probabilities of occurrence of an error of the first kind for a certain class $P_{(1,0)}{}^{\Omega_k/\Omega_j}$ is $P = (P\text{-}1)$. The probability of an error of the first kind is the probability of assigning a vector of goniometric parameters belonging to the class of motions Ω_j to another class of motions Ω_j':

$$P_{(1,0)}{}^{\Omega_j} = \sum_{\substack{k=1 \\ k\neq 1}}^{M} P_{(1,0)}{}^{\Omega_k/\Omega_j}; \; P_{(1,0)}{}^{\Omega_j} = \begin{cases} 1 - P_{(0,1)}{}^{\Omega_j}, at \quad R \in q_j \\ 0, at \quad R \notin q_j \end{cases} \tag{4}$$

The probability of an error of the second kind is the probability of an erroneous assignment of the vector of goniometric parameters to the class of motions Ω_j':

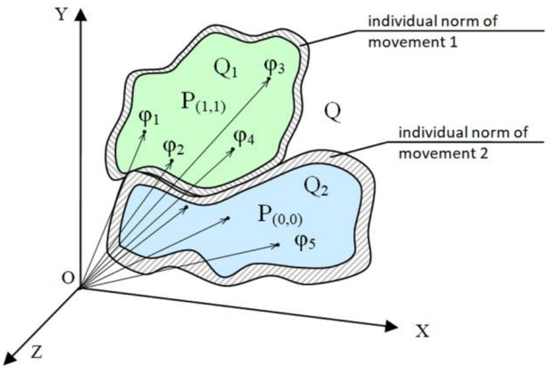
$$P_{(0,1)}{}^{\Omega_j} = \sum_{\substack{k=1 \\ k\neq 1}}^{M} P_{(0,1)}{}^{\Omega_k/\Omega_j} \quad P_{(0,1)}{}^{\Omega_j} = \begin{cases} 0, at \quad R \notin q_j \\ 1 - P_{(1,0)}{}^{\Omega_j}, at \quad R \in q_j \end{cases}$$

Moreover, according to the concept of assessing an individual norm, the boundary between the intersections of the classes of movements for each patient is determined individually:

$$\Omega_k / \Omega_j \neq \text{const} \tag{5}$$

In the parameters of goniometric signals, two signs are subject to the control of the i-link: the angle of inclination in the space zv_i (sign 1) and the rate of its change $zv_i(t)$ (sign 2). Estimating the belonging of the controlled quantities to the parameters of the individual norm for a certain class of movements of the control object, the space Q is divided into areas Q_1, Q_2 ... Q_N., The number of which is equal to the number of possible classes of movements of the control object (Figure 1).

Figure 1: The formation of many features for individual classes of movements



For a probabilistic description of the reliability of the assessment of individual norms of angular parameters in the goniometric control system, it is necessary to compile a vector of operational characteristics $\mathbf{L}_{\Omega}(\mathbf{M})$, which includes a set of operational characteristics $\mathbf{L}_{\Omega j}(\mathbf{M})$ of motion classes Ω_j:

$$\mathbf{L}_{\Omega}(\mathbf{M}) = \begin{bmatrix} \mathbf{L}_{\Omega_1}(\mathbf{M}) \\ \dots \\ \mathbf{L}_{\Omega_j}(\mathbf{M}) \\ \dots \\ \mathbf{L}_{\Omega_M}(\mathbf{M}) \end{bmatrix} \tag{6}$$

where $\mathbf{L}_{\Omega j}(\mathbf{M})$ is the dependence of the probability of assigning a set of goniometric parameters to the class of motion Ω_j, due to the results of measurements of $\mathbf{X}$ angles $\mathbf{M}$ in the region qj from the true values of the angles $\mathbf{M}$:

$$\mathbf{L}_{\Omega j}(\mathbf{M})=W(X \in q_j)=\int_{q_j} f_X(\xi, \mathbf{M})\, d\xi, \tag{7}$$

where $f_X(\xi, \mathbf{M})$ is the distribution density of the measurement results of the angular parameters $\mathbf{M}$. It should be noted that the operational characteristic depends on the law of distribution of measurement errors $\mathbf{\Delta}^{\mathbf{T}}=[\Delta_1\ \ \Delta_2 \ldots \Delta_N]$ of goniometric parameters $\mathbf{M}$:

$$\mathbf{L}_{\Omega j}(\mathbf{M})=W(\mathbf{X} \in q_j)=\int_{q_j} f_{\Delta}(\boldsymbol{\delta}-\mathbf{M})\, d\boldsymbol{\delta}, \tag{8}$$

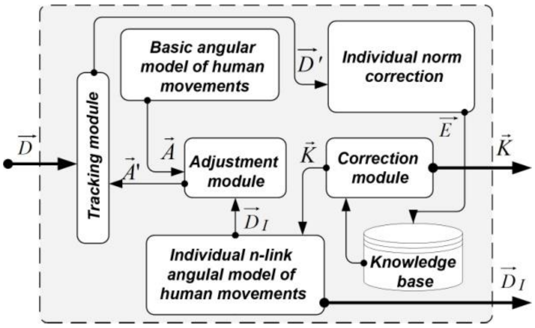
where $f_{\Delta}(\boldsymbol{\delta})$ is the density distribution of the measurement error $\mathbf{\Delta}$.

For signs 1 and 2, the estimate of the measurement errors Δ_1 and Δ_2, which are independent random variables characterized by a normal distribution, zero mathematical expectation and standard deviation $\sigma[\Delta_1]$ and $\sigma[\Delta_2]$:

$$f_{\Delta 1}(\delta_1) = \frac{1}{\sqrt{2\pi}\sigma[\Delta_1]} \cdot \exp\left\{-\frac{\delta_1^{\ 2}}{2\sigma^2[\Delta_1]}\right\};\ f_{\Delta 2}(\delta_2) = \frac{1}{\sqrt{2\pi}\sigma[\Delta_2]} \cdot \exp\left\{-\frac{\delta_2^{\ 2}}{2\sigma^2[\Delta_2]}\right\} \tag{9}$$

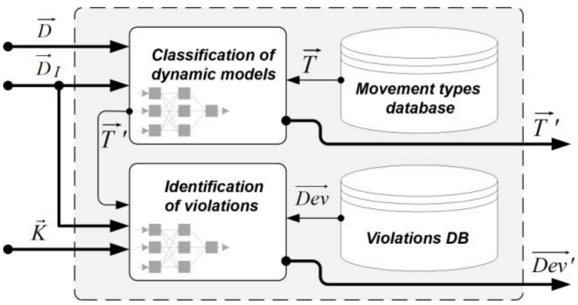
According to the methodology, an individual patient model is formed on the basis of a basic model that contains general norms of permissible deviations of controlled parameters. If it is not possible to measure some parameters of a particular patient, data from the base model is loaded into the individual model. Subsequently, during a longer operation of the system and accumulation of data, the basic parameters in an individual model are replaced by the individual parameters of a particular patient. Thus, in case parameters go beyond permissible limits, an expert assessment is carried out on the basis of neural networks (in some cases, with the involvement of experts), as a result of which a preliminary reason for the deviations of the parameters from the norm is revealed: individual characteristics or pathology. All decisions are stored in a database for its expansion and an individual patient card (Figure 2).

Figure 2: Data processing model for adaptive adjustment of an individual patient norm



The vector of detected deviations from the norm $\vec{K}$, the individual patient model and the recorded data are fed into the pathology assessment subsystem, a generalized model of which is presented in Fig. 3.

Figure 3: Generalized pathology assessment model



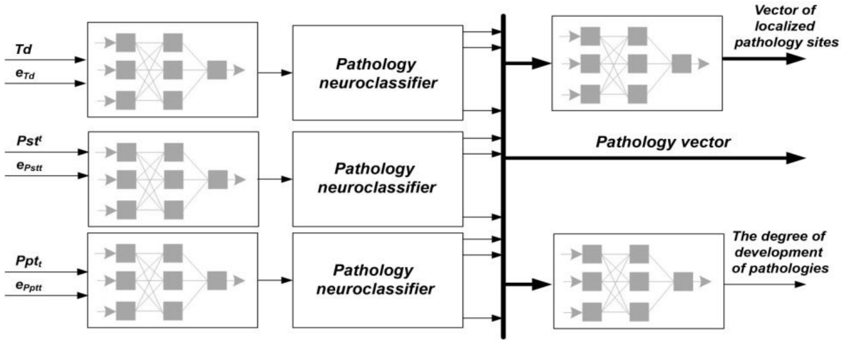
In assessing pathologies, two neural networks are involved. The first is intended to assess (determine) the type of current movement $\vec{T}'$ according to goniometric and electrophysiological data. The classification of movements occurs on the basis of pre-formed patterns of motor actions. The motion pattern can be described by a vector:

$$\vec{T}(t) = \left\{\vec{T}_D(t), \vec{P}st, \vec{P}pt\right\}, \tag{10}$$

where $\vec{T}_D(t)$ is the vector of spatial changes in the position of kinematic pairs; $\vec{P}st$ is a vector that describes the spectral-temporal characteristics (frequency, power spectra, etc.) of goniometric signal patterns; $\vec{P}pt$ is a vector describing the spatio-temporal characteristics of motion (tempo, amplitude, speed, acceleration, etc.). Motion patterns are stored in a database, supplemented for individual features and various pathologies. Database updates are necessary for automatic training and retraining of a neural network.

The second neural network makes an assessment (determination) of the pathology and its localization (assessment of the place of development in the body) $\vec{D}ev'$ according to the type and parameters of the movement, the vector of deviation from acceptable values. The vector $\vec{D}ev' = \{Dev_i, \vec{L}oc\}$ is described by the *i*-th element (pathology) from the pathology database $\vec{D}ev = \{Dev_1, ..., Dev_i, ..., Dev_N\}$, if the diagnosis is confirmed at local points described by the vector $\vec{L}oc$, where the *i*-th number of the confirmed pathology $Dev_i = \{\vec{T}_D(t), \vec{P}st, \vec{P}pt, \vec{R}d\}$ are the displacement parameters, etc., characteristic of the *i*-th pathology, $\vec{R}d$ is the description and possible recommendations for the treatment of confirmed pathology.

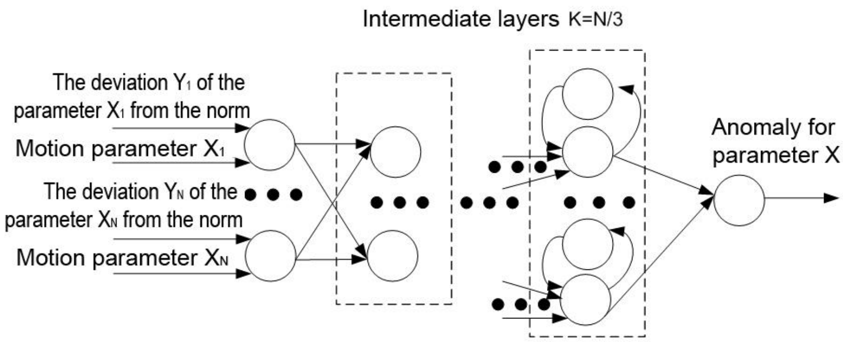
Figure 4: Generalized structure of a neural network for processing recorded data



The general structure of the neural network for decision-making during diagnosis is given in (Grecheneva et al., 2016). In addition to it, a neural network for processing recorded data was developed, the generalized structure of which is shown in Fig. 4.

In the given structure of the neural network, each block is formed on the basis of the core network (Fig. 5), the setting of the weights of each block is individual and depends on the type of pathology, individual characteristics (parameters of an individual model), type and parameters of movement.

Figure 5: The generalized structure of the basic neural network



The core network is recurrent, with storage and processing times equal to the size of the time window of useful signals. The number of intermediate layers is three times less than the number of processed parameters.

4. Results

For practical verification of the developed methodology, from September 2019 to March 2020, measurements were made of the mobility of the knee joint in 10 students. All students had the following parameters: height 165±3 cm, weight 58±2 kg, leg length from groin to heel 78±2 cm, leg length from knee to heel 50±1 cm. The individual parameters of knee flexion during the day are given in Tab. 1.

Table 1: Results of measurements

Observed	Maximum bending angle, degrees	The maximum extension angle, deg	The most frequent bending angle, degrees	The most common extension angle, degrees
1	138	1	52	4
2	141	10	58	12
3	135	5	60	5
4	137	-3	55	6
5	130	-2	54	4
6	132	7	53	2
7	138	5	62	7
8	136	5	63	4
9	142	6	64	8
10	137	8	58	11

5. Conclusion

As can be seen from the results obtained, each observed student can be distinguished by their parameters of flexion of the knee joint, as well as the individual style of flexion during the day. Note that to increase the accuracy of constructing an individual norm, it is necessary to break down individual norms of movement depending on the time of day, day of the week, and month. Time parameters show a change in lifestyle in different periods. It is also necessary to take into account the volume of muscle mass on the analyzed limbs and other parameters of flexion of the analyzed joint and other joints in the complex during the movement. These parameters were not taken into account in the framework of this study. However, despite the claimed shortcomings, the results obtained during the study indicate the possibility of applying the developed methodology and the need for its further development.

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