IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received August 18, 2019, accepted August 26, 2019, date of publication September 2, 2019, date of current version September 18, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2939006

Lower Limb Exercise Rehabilitation Assessment Based on Artificial Intelligence and Medical Big Data

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This work was supported by the Key Project funded by the Scientific Research of Institutions of Higher Learning in Henan Province under Grant 20A890009.

ABSTRACT This paper firstly compares the common virtual reality technology production methods, determines the reasonable lower limb rehabilitation exercise modeling method, establishes a more accurate human lower limb musculoskeletal rehabilitation posture mechanism model, analyzes the passive movement work mode of lower limb rehabilitation exercise, and simulates the changes of human musculoskeletal changes during passive movement of lower limb rehabilitation which exercise robots were analyzed. Secondly, the research is on robust controller for omni-directional mobile lower limb rehabilitation based on artificial intelligence and medical big data. The error dynamic model of omni-directional moving lower limb rehabilitation exercise system is established, and the technical problems of standard design, dissipative and gain are analyzed. By constructing the storage function and using the inverse push method, the nonlinear robust controller for omnidirectional moving lower limb rehabilitation motion is designed. The stability of this control law is proved based on Lyapunov's theorem. Finally, an experimental study on the omni-directional moving lower limb rehabilitation exercise system and rehabilitation evaluation system. Seven human gait and online detection methods for rehabilitation exercise were proposed. The simulation study on the omni-directional moving lower limb rehabilitation robot using nonlinear robust controller is carried out to verify the effectiveness and correctness of the lower limb exercise rehabilitation method.

INDEX TERMS Artificial intelligence, medical big data, lower limb exercise rehabilitation, robust control.

I. INTRODUCTION

The combination of emerging artificial intelligence and medical big data technology and traditional medical and health fields will bring new opportunities to traditional medical models, help patients to develop medical solutions and medical institutions to integrate medical resources in the process of medical treatment. This limits the improvement in medical outcomes and does not make full use of medical resources. And there is great potential for development in improving the quality of treatment in hospitals, reducing the risk of patient deterioration and saving medical costs. The artificial intelligence and medical health big data industry has now become an important industry in many countries and has formulated relevant policies, even rising to a national-level approach. Due to the freedom of lower extremity joints, the balance and coordination mechanism of human walking is still unclear. Lower limb exercise rehabilitation training is more difficult than upper limb rehabilitation in terms of mechanism, exercise planning and control strategy, and research progress has been slow. At present, the research on lower limb running rehabilitation training is still in its infancy. Disadvantages include: fewer types of training actions, the scope of motion is mainly limited to training the front of the body; the range of motion is small, generally limited to plane motion; the control strategy is single, mainly based on the speed or position servo control mode to provide passive training for patients, patients could not exercise independently; Rehabilitation evaluation indicators still use traditional clinical evaluation methods, so the relationship between the data extracted during the training process and the training effect is still unclear.

The associate editor coordinating the review of this manuscript and approving it for publication was Ying Song.

One of the most important applications of artificial intelligence and medical health big data is the prevention and control of diseases, which has attracted the attention of many countries, research institutions and major Internet companies around the world. Through the mining and analysis of historical data, they establish mathematical models to identify the pathogenic factors, predict the development trend of the disease, assess the risk level of the disease, and finally develop corresponding treatment plans for the patients. At present, medical big data analysis technology has made great breakthroughs both in theory and in practical applications. One of the most successful cases in the field of medical health is the special study on heart disease research [1]–[3]. Project researchers have long tracked the heart data of a fixed group and then analyzed the data using big data technology. The way to dig out the cause of heart disease, and finally develop relevant countermeasures based on specific reasons. Using big data technology modeling analysis [4]–[6], it is to explore the key risk characteristics of the disease, including body index and personal habits: blood lipids, blood pressure, diabetes, weight, smoking, eating habits and exercise. The Heart Research Program helps the public understand clearly the pathogenesis of heart disease and provides scientific and personalized guidelines for preventing heart disease. In the big data technology based on artificial intelligence and machine learning, massive data sources are necessary to utilize big data analysis [7]–[10]. Only with sufficient data to support the data analysis method can we provide users with a very good personalized solution. Whether the lower limb rehabilitation training can achieve the purpose of treatment and rehabilitation depends on whether the completion of exercise rehabilitation training, in a sense to replace or assist the therapist, can be achieved through effective robot control strategies, including training mode control, Remote control, virtual reality, biofeedback, security policy and many other aspects [11]–[14]. The ideal functional recovery depends on proper rehabilitation, and the correct rehabilitation must rely on the correct rehabilitation assessment. The function of the lower limbs is mainly walking, and the rehabilitation evaluation of the lower limbs mainly focuses on the evaluation of walking ability. Hoffer walking ability grading is a kind of macro-level grading. It is a kind of grading method for patients who can't walk, and can walk at home or in the community [15]–[18]. Holden's functional walking classification (Functional ambulation clarification (FAC) is a relatively detailed qualitative assessment method [19]–[22]. Functional ambulation profile (FAP) assessment is suitable for patients with moderate to moderate walking dysfunction, belonging to a semi-quantitative nature [23]–[25]. However, so far, although medical institutions and research institutes have accumulated a large amount of clinical data, before artificial intelligence developed to a certain stage, we did not have enough software technology to deal with such massive data to explore the laws behind big data. The diagnosis process of disease and exercise rehabilitation is a comprehensive judgment that needs to consider a lot of complicated factors.

Therefore, based on artificial intelligence and medical big data, the study of lower limb exercise rehabilitation and rehabilitation evaluation methods is proposed, which lays a theoretical and technical foundation for the application of lower limb exercise rehabilitation training. This paper firstly compares the common virtual reality technology production methods, determines the reasonable lower limb rehabilitation exercise modeling method, establishes a more accuratei human lower limb musculoskeletal rehabilitation posture mechanism model, analyzes the passive movement work mode of lower limb rehabilitation exercise, and simulates The changes of human musculoskeletal changes during passive movement of lower limb rehabilitation exercise robots were analyzed. Secondly, the research is on robust controller for omni-directional mobile lower limb rehabilitation which based on artificial intelligence and medical big data. The error dynamic model of omni-directional moving lower limb rehabilitation exercise system is established, and the technical problems of standard design, dissipative and gain are analyzed. By constructing the storage function and using the inverse push method, the nonlinear robust controller for omnidirectional moving lower limb rehabilitation motion is designed. The stability of this control law is proved based on Lyapunov's theorem. Finally, an experimental study on the omni-directional moving lower limb rehabilitation exercise system and rehabilitation evaluation system. Seven human gait and online detection methods for rehabilitation exercise were proposed. The simulation study on the omni-directional moving lower limb rehabilitation robot using nonlinear robust controller is carried out to verify the effectiveness and correctness of the lower limb exercise rehabilitation method.

II. ANALYSIS OF LOWER LIMB EXERCISE REHABILITATION BASED ON MEDICAL BIG DATA

A. LOWER EXTREMITY MOTION ANALYSIS

The main function of the lower limbs is to support weight and movement and to maintain the body's upright posture. When the human body is upright, the center of gravity is generally located behind the pith joint, slightly above the frontal axis of the ankle joint. Its left and right position is slightly to the right near the median plane of the human body; its anteroposterior position is between the bone and the pubis [26]–[28]. The lower limb bone consists of the medullary bone and the free lower extremity bone. Free lower extremity bones include the femur, tibia, tibia and foot bones, of which the foot bones include 26 bones. The hip joint consists of the hip and femoral heads and has considerable stability to accommodate weight and walking functions for triaxial movement. The knee joint consists of the femoral end, the lower end of the hip bone. It is the largest and most complex joint in the human body and has many ligaments to increase the stability of the joint [29]–[31].

The complex shape of the joint, the number and position of the axis of motion determine the form of motion of the joint. The form of movement of the joint is essentially a

TABLE 1. Range of hip joint angles of young men.

	Casual exercise				Forced movement			
Stretch forward	Maximum	Minimum value	Average value	Standard deviation	Maximum	Minimum value	Average value	Standard deviation
Stretch backwards	63	119	98	17.0	99	124	112	9.2
Lateral stretching	26	70	48	12.9	41	75	56	10.4
Inward twist	39	98	70	17.0	65	101	79	10.4
Twist outward	39	80	61	15.2	45	90	73	16.6
Stretch forward	24	48	37	6.6	39	60	46	6.7

TABLE 2. The angle of the knees of young men's calves during exercise.

Casual exercise				Forced movement			
Maximum	Minimum value	Average value	Standard deviation	Maximum	Minimum value	Average value	Standard deviation
118	136	127	6.7	128	150	140	6.8

TABLE 3. Range of angles of ankle joint activity of young men (right half).

	Casual exercise				Forced movement			
	Maximum	Minimum value	Average value	Standard deviation	Maximum	Minimum value	Average value	Standard deviation
Bend down	18	43	28	7.6	22	55	36	9.9
Upward bending	25	46	37	6.6	35	52	44	4.7

movement along three mutually perpendicular axes, including flexion, extension, extension, rotation and rotation. The range of motion angles of the joints of young men's lower extremities is shown in Table 1-3.

B. PASSIVE MOTION ANALYSIS OF LOWER LIMB EXERCISE REHABILITATION BASED ON MEDICAL BIG DATA

Lower limb exercise rehabilitation In passive exercise, the simulated joint movement of the foot during the flexion and extension of the leg, the hip joint and the knee joint can also be exercised during the flexion and extension of the large and small legs. The human lower limb is a complex body composed of many bones and muscles. The theoretical modeling of the lower limbs is the focus and difficulty of research. At present, there is still no successful mechanical model applied to common motion and dynamics analysis. Taking into account the complexity of the later calculations and the focus of the research, the characteristics of the lower limbs, the following human lower limb model assumes that the role of the lower limb muscle system is not considered; the role of articular cartilage and ligaments is not considered; ithe basic measurement parameter modeling function is not specific human body influence.

One of the most important steps in the analysis of processed data using medical big data algorithms is data preprocessing. In practical applications, when the medical big idata algorithm is used to learn the data features, the feature data can be improved by pre-processing the original feature data to improve the learned feature quality. The object of machine learning analysis and processing is to collect all kinds of data from the real world, and due to the uncertainty, diversity, complexity and other reasons of the real world [32], the raw data collected is not regular, and the performance is more scattered. These data generally do not meet the specifications and standards required by the Medical Big Data for the Institute of Feature Learning. The data preprocessing structure based on medical big data as shown in Fig. 1:

The first step in data preprocessing is to normalize the feature data. There are many ways to normalize data, and the specific normalization method usually chooses different normalization methods according to the specific application background of the data. In general, the usual methods for normalizing feature data are: minimum-maximum normalization: if min and max represent the minimum and maximum values of the dataset features, respectively, the minimum-maximum normalization is a simple linear

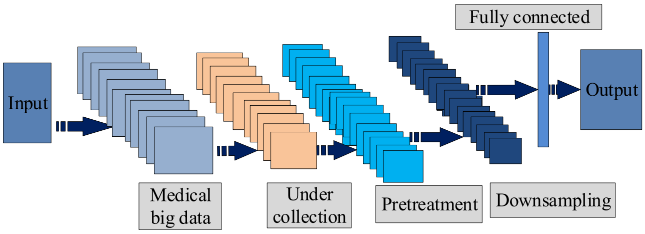

FIGURE 1. Data preprocessing structure based on medical big data.

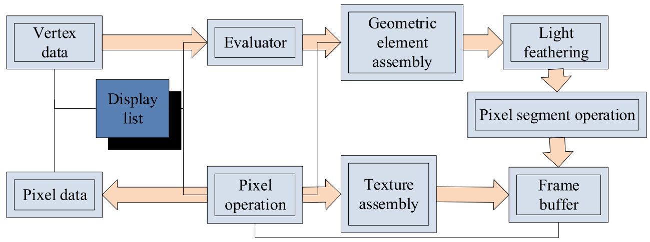

FIGURE 2. Passive analysis of lower extremity motion based on medical big data.

scaling. The minimum-maximum normalization is calculated by [33]–[35]:

$$v' = \frac{v - \min}{max - \min} \tag{1}$$

where max is the maximum value of the original set data, and min is the minimum value of the original set data. However, this standardized algorithm also has some disadvantages. When there is new data, it is possible that the changes of the maximum value max and the minimum value min need to be re-discovered the maximum and minimum values and then recalculated. The essence of minimum-maximum normalization is a simple linear transformation of the feature set, thus maintaining the correlation between the transformed data and the original data.

Feature normalization: Feature normalization is designed to have features with zero mean and unit variance in each dimension. This normalization method is widely used in data and preprocessing. In the actual standardized calculation, the specific process of feature standardization is: first, calculate the mean of the data set in each dimension, and subtract the average from the data of each dimension; then, divide by the standard of the size difference data. The specific calculation method is:

$$v' = \frac{v - \mu}{\sigma_A} \tag{2}$$

where μ, σ_A is the mean and standard deviation of the attribute respectively, and the z-score normalization algorithm is applicable to the case where the maximum and minimum values of the attribute A in the data set cannot be accurately obtained, or the data noise is too large, exceeding the normal value.

After doing a simple normalization, in order to make the algorithm work better, and then perform motion passive analysis on the normalized data, in fact, many deep learning algorithms rely on whitening to make the algorithm make its network parameters. Achieve optimal conditions and improve the accuracy and timeliness of the algorithm. Before the final data is written to the frame buffer, the geometry data and the data are rasterized and the primitive operations are performed. All data is stored in the display list or processed directly.

As shown in Fig. 2, each skeletal muscle is divided into two parts: the muscle abdomen and the tendon. The muscle abdomen is composed of muscle fibers, which are cord-like or membranous dense connective tissues at the ends of the muscles, promoting muscle adhesion and fixation. The muscle bond of a muscle is attached to two or more different bones, and the muscle leg pulls the muscle contraction to drive the movement of different bones.

Let the two ends of the muscle be A, B, the length is l, the vector is r_1, r_2, and the muscle forces acting on the two bones are F_1, F_2. During the contraction of muscles, the work done by muscle strength is:

$$\delta W = F_1 d_{r_1} + F d_{r_2} = F_1 \times d(r_1 - r_2) = F_1 \times dl \tag{3}$$

In the process of isotonic contraction, the work done by muscle strength is:

$$W = \int_{L_0}^{L} -F_1 \times dl = F_{dl}(L_0 - L) \tag{4}$$

Let $L_0 - L = d$ be the length of muscle contraction, then $W = F_{dl} \times d$, that is, during isotonic contraction, the work of muscle strength is equal to the product of muscle strength and muscle contraction length [36]–[38].

C. PASSIVE MOTION ANALYSIS

In the feature extraction phase, this paper applies a feature of learning original signals composed of artificial intelligence and medical big data and two layers of down sampling layers. When training the parameters of the network, through continuous iteration and experimentation, the optimal parameter combination of the network is obtained; in the health state evaluation stage, the learned features are applied to the multivariate Gaussian distribution. Firstly, the multivariate Gaussian model is used to obtain the probability distribution of features. Then, it is divided into different probability intervals. Some feature points of the small probability interval are considered to be characteristic representations of the rehabilitation state of the lower extremity medical big data. The feature points of the probability interval are classified according to the size of the interval feature point probability mean to rank the medical big data lower limb exercise rehabilitation state.

As shown in Figure 3, with the increase of the number of iterations, the medical big data lower limb exercise rehabilitation state tends to be stable after zero, the reconstructed signal is almost identical to the original signal, when the medical big data lower limb exercise rehabilitation state is

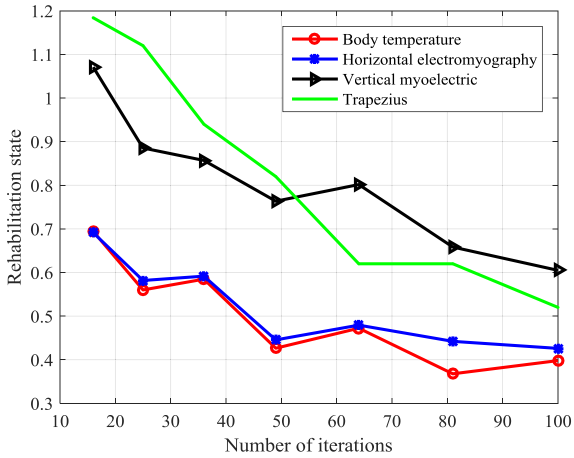

FIGURE 3. Curve relationship between iteration number and medical big data rehabilitation state of lower extremity exercise.

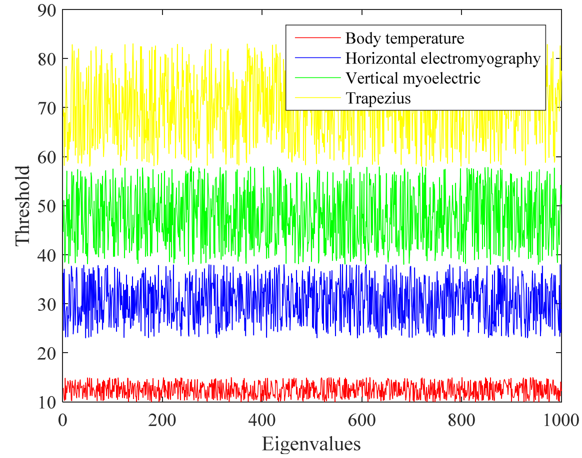

FIGURE 5. Feature points with different thresholds.

small to a certain trend Nearly and with a decimal, the learned feature is another effective expression of the original signal.

When learning the characteristics from the original signal, and providing it to the multivariate Gaussian model for the medical big data evaluation of the lower limb motion rehabilitation state, it is also necessary to consider whether the learned features conform to the Gaussian distribution.

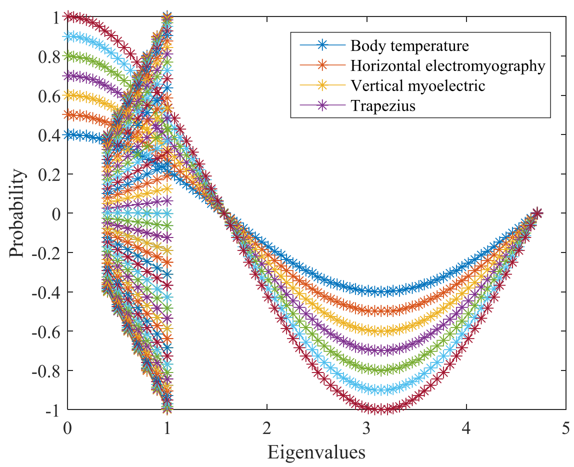

FIGURE 4. Gaussian distribution of features.

As shown in Figure. 4, Figure. 5, as the probability value changes continuously, its health state also changes to varying degrees. Although the Gaussian distribution has many features in advance, its health status is also the best. As the threshold changes continuously, the interval probability feature distribution map is obtained respectively. Tests on the dataset show that the proposed method can extract key feature representations of multidimensional physiological data. Then, the feature points of the same probability interval are calculated, and the health state level of the user is obtained according to the probability of these feature points. In this way, big data-based analysis can help users understand their health status. If analyzed by a doctor or a professional, such data information can be helpful for doctors to diagnose early signs of some diseases. Therefore, the model is also a useful tool to help professionals diagnose potential diseases.

III. COMPREHENSIVE LOWER LIMB Motion REHABILITATION ANALYSIS AND ROBUST DESIGN BASED ON ARTIFICIAL Intelligence AND MEDICAL BIG DATA

A. NON-HOLONOMIC CONSTRAINED KINEMATICS MODEL FOR OMNI-DIRECTIONAL MOVEMENT OF LOWER EXTREMITY SPORTS REHABILITATION

The lower limb motion rehabilitation is divided into 4 omnidirectional wheels and 1 platform with a total of 5 rigid bodies, numbered 1 to 5, and the platform number is 5:

$$\begin{aligned} d_1\omega + f_1^T\hat{e} &= -a\hat{\theta}_1 \\ d_2\omega + f_2^T\hat{e} &= -a\hat{\theta}_2 \\ d_3\omega + f_3^T\hat{e} &= -a\hat{\theta}_3 \\ d_4\omega + f_4^T\hat{e} &= -a\hat{\theta}_4 \end{aligned} \tag{5}$$

Superimposed:

$$\omega\sum_{i=1}^{4} d_i + e^T\sum_{i=1}^{4} f_i = -a\sum_{i=1}^{4}\hat{\theta}_i \tag{6}$$

The multivariate normal distribution is also called the multivariate Gaussian distribution, and the multivariate Gaussian model is an extension of the Gaussian probability density function of medical big data. In the multivariate Gaussian distribution model, in order to obtain the $p(x)$ of the feature, it is necessary to construct the covariance matrix E of the feature. The specific calculation method is as follows. Before this, the average value μ of all features is calculated first, and then the feature association is calculated. Variance matrix E:

$$\mu = \frac{1}{m}\sum_{i=1}^{m} x^i$$
$$\sum = \frac{1}{m}\sum_{i=1}^{m}(x_i-\mu)(x_i-u)^T = \frac{1}{m}(X-\mu)(X-u)^T \quad (7)$$

Finally, the probability value P(x) of the multivariate Gaussian distribution is calculated:

$$P(x) = \frac{1}{(2\pi)^{\frac{n}{2}}|\sum|^{\frac{1}{2}}}\exp(-\frac{1}{2}(x-\mu)^T(x-\mu) \quad (8)$$

In this paper, the Gaussian distribution theory is used to calculate the probability distribution of medical big data features based on the multivariate Gaussian distribution model. Then, according to the size of the feature point probability, the non-holonomic constrained kinematics evaluation model of sports rehabilitation training is constructed by dividing the feature probability interval. The following is a description of the specific theory and how to design a non-holonomic constrained kinematics assessment model for exercise rehabilitation.

The algorithm flow can be generally divided into the following three steps:

(1)Model is established, according to the actual application, select the appropriate Gaussian model, and then establish a Gaussian probability distribution function.

(2) Model training, input the characteristic data learned by the network into the network, calculate the parameters related to the Gaussian probability distribution function, obtain the probability model, and establish the lower limb exercise rehabilitation training according to the probability distribution of the original input data. Formal constraint kinematics assessment model for partitioning intervals;

(3) Model prediction, giving prediction results. For the new data, the probability distribution is calculated according to the trained network model. Then, by dividing the probability interval, the state level of the non-holonomic constraint kinematics assessment of the lower limb exercise rehabilitation training belongs to the feature point.

As shown in Figure 6, since most people have physiological parameters in general, the physiological data will become abnormal in only a few cases. Based on this idea, the number of features is the total number of features, the smaller the probability of features, the higher the degree of health hazard to which feature points belong, and the more incompletely constrained evaluation states. Differences in lower limb exercise rehabilitation.

B. ROBUST DESIGN OF OMNI-DIRECTIONAL MOBILE LOWER LIMB EXERCISE REHABILITATION TRAINING

According to the structural characteristics of omni-directional moving lower limb running rehabilitation training, a mathematical model of the system was established through kinematics analysis. For the multi-input and multi-output of omni-directional mobile lower limb rehabilitation training, there are uncertain interferences and their own characteristics. A nonlinear trajectory tracking robust controller design method is proposed.

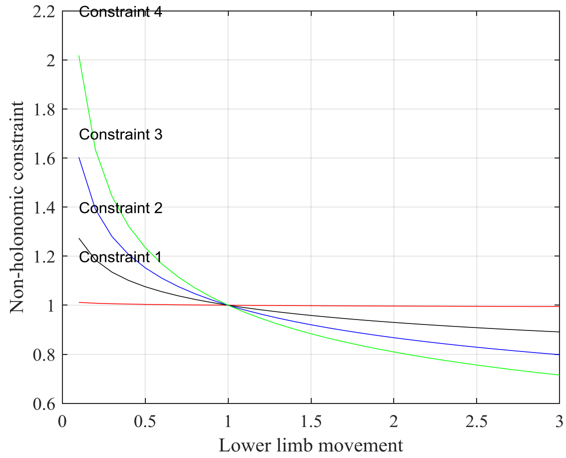

FIGURE 6. Non-complete constraint analysis of lower limb exercise rehabilitation.

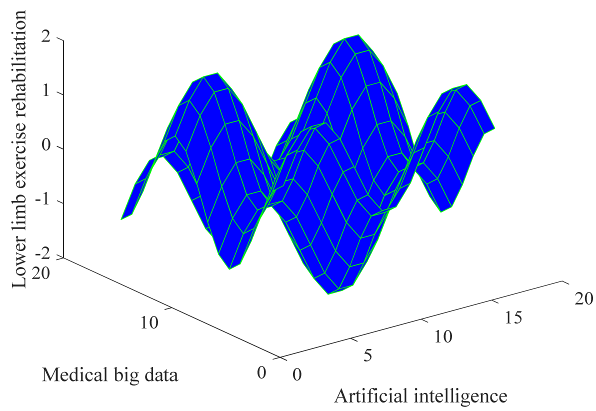

FIGURE 7. Mathematical model analysis chart.

Omni-directional mobile lower limb rehabilitation training achieves trajectory tracking by controlling four wheel speeds. To create a robust controller design, the simplified model is shown in Figure 7. Select the global coordinate system (x, y) and the local coordinate system (x_i, y_i) to describe the robot's working state space. The robot coordinate position on the 2D work plane can be expressed as $\varsigma = [x, y]^T$. When the robot moves, the angle between the two axes of the global coordinate system and the velocity vector is ϑ.

Considering the uncertainty of the system, its mathematical model can be described by:

$$\hat{x} = g_1(x)\omega + g_2(x)\mu + f(x) \quad (9)$$

$g_1(x)$ is a matrix function of ω, ω is undetectable interference, f(x) is a nonlinear vector function, $g_2(x)$ is a matrix function of u, and u is a control input. When designing the controller u(x) = k(x), we must consider not only the asymptotic stability of the closed-loop system when ω =0, but also the state of the closed-loop control system can still approach zero when the interference is not zero, or the deviation from the equilibrium point is as small as possible. To this end, this paper improves the system's suppression of interference by reducing the L_2 gain of the closed-loop system. For the signal ω (t), its L_2 norm is defined as:

$$||\omega(t)||_2 = \{\int_0^\infty \omega^T(t)\omega(t)d_t\}^{\frac{1}{2}} \tag{10}$$

If the signal ω (t) is considered to be a scalar, the above definition becomes:

$$||\omega(t)||_2 = \{\int_0^\infty \omega^2(t)d_t\}^{\frac{1}{2}} \tag{11}$$

In fact, in many cases the two norm of ω (t) defined by the above equation can be interpreted as the energy possessed by the signal. If the state feedback controller $\mu = k(x)$ is used, the closed loop system can be expressed as:

$$\hat{x} = g_1(x)\omega + f_2(x) \tag{12}$$

Let the initial state of the system be x(0) = 0. For a given interference signal ω (t), the dynamic response of the system is obtained by solving the upper differential equation. In order to describe the system's ability to suppress interference, define the evaluation signal:

$$z = h(x) + d_2(x)\mu \tag{13}$$

where h is the function vector after weighting and $d_2(x)$ is the function matrix of u. The smaller the L_2 norm for a given interfering signal, the smaller the system's influence on the interfering signal, the system has a stronger ability to suppress external interference signals. This indicates that the system's ability to suppress interference can be described by the ratio of the norm of the evaluation signal to the norm of the interfering signal.

C. ROBUST SIMULATION STUDY

The omni-directional mobile lower limb rehabilitation training robust control tool software is MATLAB, and the mathematical model module and controller module are written in M language. The trajectory is simulated and analyzed within 60s. When there is disturbance, the motor rotation speed changes rapidly to balance the disturbance. Under L_2 robust control, the system converges to 0 in about 20s, the system is globally asymptotically stable, and the speed is 0.5m/s to meet the rehabilitation training requirements.

As shown in Figure 8, Figure 9 and Table 4, in order to verify that this can be tracked to any curve and its tracking performance under interference, four different curves for circle, sine curve, Lissajous and sine are respectively Tracking simulation under interference. The above curve tracking simulation results show that the omnidirectional mobile controller with L_2 algorithm has good trajectory tracking performance. This nonlinear model can suppress the interference while tracking the arbitrary curve.

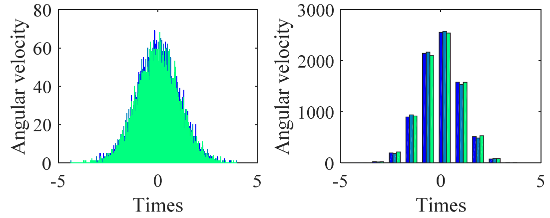

FIGURE 8. Four-wheel angular velocity.

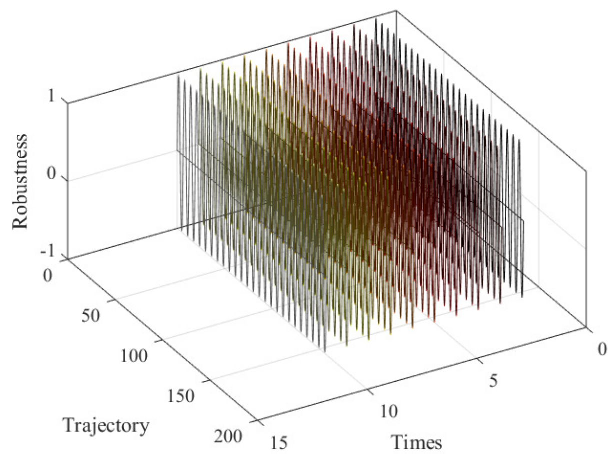

FIGURE 9. Trajectory tracking.

TABLE 4. Step frequency test.

Normal gait	Landing on the inside of the foot	Landing on the outside of the foot	Inside and heel of the sole
0.75	1.35	null	1.0
0.8	null	1.42	null
0.8	null	null	1.0

IV. EXPERIMENT AND ANALYSIS

Three aspects of experimental research on rehabilitation evaluation and rehabilitation training were carried out: (1) In order to verify the effectiveness of the rehabilitation evaluation method established in this paper, an experimental study on gait and dynamic balance rehabilitation evaluation methods was carried out. Seven gait pattern detection algorithms are proposed, and the established online gait detection device is used to detect and judge the unsynchronized state of the human body during rehabilitation training. (2)The dynamic balance ability of normal people and patients was compared and analyzed by using the dynamic balance detection device and the human body dynamic balance parameter analysis algorithm built on the arm support platform. (3)In order to verify the effectiveness of the designed L_2 robust control strategy, an experimental platform based on machine vision was established to perform trajectory tracking experiments on circular trajectories and linear trajectories.

TABLE 5. Gait state definition.

Serial number	Foot touch part	Grounding sensor	Gait
1	heel	A. B	3
2	Inside and outside of the sole	A. B. C	2.5
3	All of the feet	A, C	5
4	Inside of the sole	B. C	1
5	Outside of the sole	C	2
6	Inside and heel of the sole	B	4
7	Outer heel and heel	A	4.5

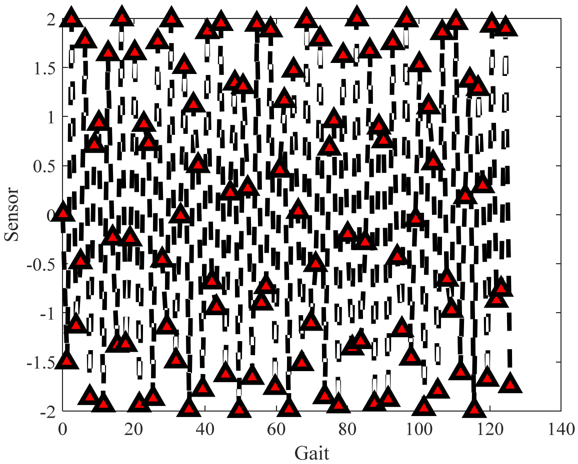

FIGURE 10. Sensor signal and gait state waveform for normal walking.

A. GAIT ANALYSIS EXPERIMENT

To achieve gait detection, the asynchronous state is first defined, as shown in Table 5. The sensors are placed in three different positions on the inside of the sole of the foot, on the outside of the sole of the foot, and on the heel. The sensor that defines the inside of the foot is A, the sensor outside the foot is B, and the heel sensor is C. During a single walking cycle, the left lower limb and the right lower limb experience a standing phase that is in contact with the ground and carries weight. The normal gait consists of the heel strikes the ground, the feet flat, the heel off the ground, and the swing. Due to organic lesions, the patient may have a center of gravity movement, pelvic movement, and inconsistent movements of the lower extremity joints and muscles during walking, resulting in an inward (outer) swing, tilting, and touching abnormalities inside and outside the heel. The gait defined in Table 4 contains the normal and abnormal gaits described above, allowing for a better analysis of the gait.

Complete the automatic judgment of the gait state. After the system collects three sensor input values, it compares with the previously set thresholds to determine whether the human body generates pressure on the sensor, thereby distinguishing the state of the three force sensors from grounding, and obtaining the final human gait by numerical calculation in the Fig.10 to Fig.12. The following are the original waveforms of

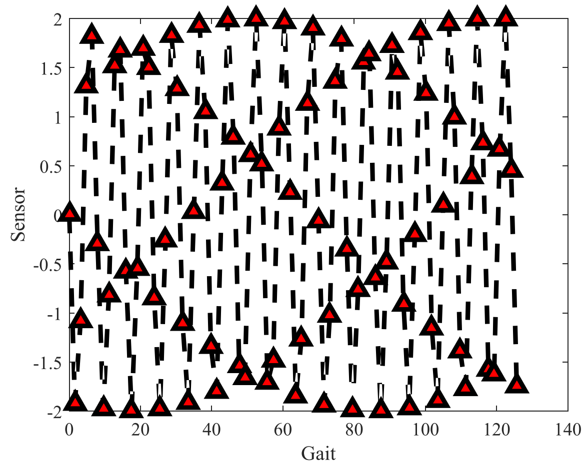

FIGURE 11. Sensor signal and gait state waveform on the inside of the foot.

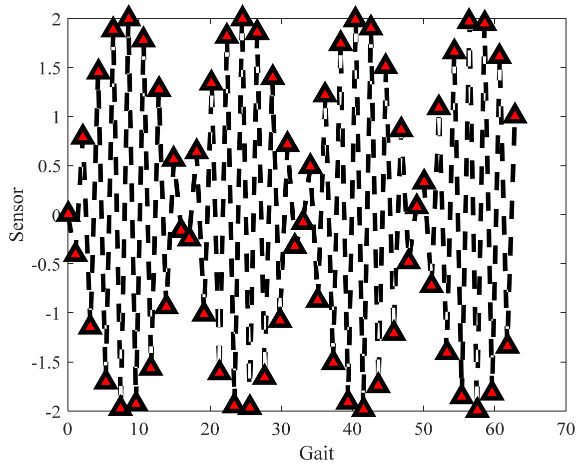

FIGURE 12. Sensor signal and gait state waveforms on the inside of the sole and the heel.

the normal and abnormal gait sensors collected. The threshold of this experiment is 50mV.

(1) Normal gait transition: swing - heel ground - standing - heel off the ground - swing.

(2) The inside of the sole of the foot is on the ground.

(3) The inside of the sole and the heel strike: the order of the sensor landing is A, C-NULL.

B. DYNAMIC EQUILIBRIUM ANALYSIS

Figure 13 is the waveform of the arm pressure when a normal person walks forward during rehabilitation training, where C, D, and E are the values of the three pressure sensors M1, M2, and M3, respectively.

When the human body walks, the center of gravity moves up and down twice in a walking cycle, and its amplitude is 4.5cm; the lateral movement occurs once every right and left in a walking cycle, and its amplitude is 3 cm.

Figure 13, Figure 14 and Table 6 show the lateral movement distance of the patient during training, which is the

TABLE 6. Range of human lower limb joint motion (degrees).

	Flexion	Stretch	Adduction	Outreach	Pronation	External rotation	Overstretch	Back	Tuo Qu	Side curve
Hip	130-145	10-15	20-35	30-45	40-50	30-40				
knee	120-155				10	20	0-10			
ankle					30	30-55		20-35	40-55	
Lumbar spine	85	30			30	30				40

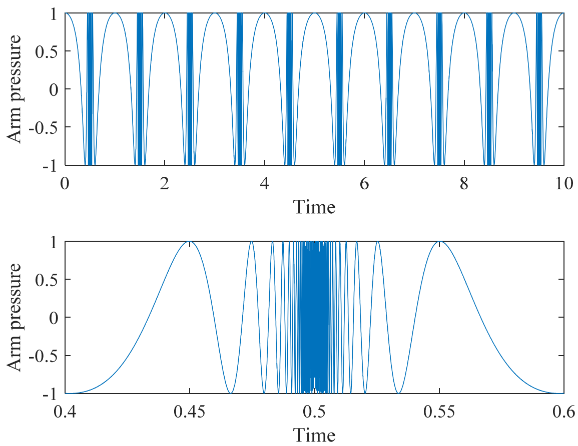

FIGURE 13. Pressure curve of the forward walking arm of patients with leg sprains.

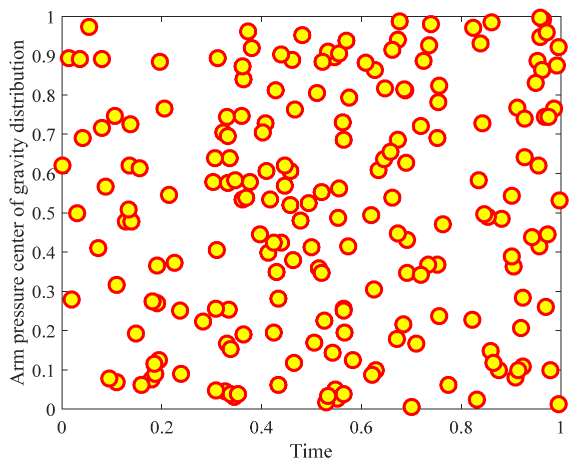

FIGURE 14. Distribution of the center of gravity of the patient's forward walking arm.

patient's arm pressure curve and center distribution map. It can be seen that the walking information of normal people and patients is different. The average force of the normal person's arm pressure is in the first quadrant, and the average force of the patient's arm pressure is in the third quadrant. It shows that the patient is mainly assisted by the strength of the rehabilitation robot and is in a towed state, while the normal person mainly walks on his own ability. The patient's single arm relies on the strength of the rehabilitation robot to account for 19% of its weight, compared to 11% for normal people. Two important factors in human walking are the mastery of leg strength and balance, which can indirectly reflect the supporting force of the human leg. In the process of using the rehabilitation robot, the support of the human body is mainly supported by the support force and the leg strength provided by the support surface, and indirectly reflects the lack of strength of the human leg. Normal people's arm activity center of gravity radius is larger than the patient's range, and the dispersion is higher.

C. TRAJECTORY TRACKING AND ROBUSTNESS VERIFICATION OF MOBILE LOWER LIMB EXERCISE REHABILITATION TRAINING

In order to verify the running trajectory of the robot under the L_2 robust controller, the experimental platform was developed to record the running trajectory data through the camera placed on the indoor roof. After the computer processing, the coordinate posture of the robot was obtained and imported into the upper computer.

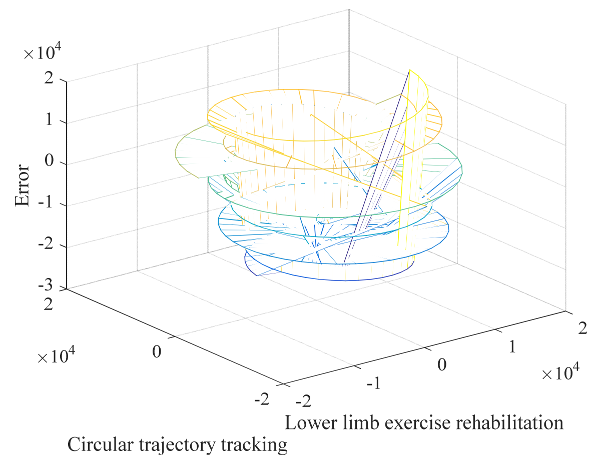

FIGURE 15. Circular trajectory tracking error.

As shown in Figure 15, Figure 16 and Figure 17, in the circular trajectory tracking test, the curves of the horizontal and vertical coordinates with time are disturbed by the patient during operation, and there is a tendency to deviate from the original trajectory. The L2 robust controller can be quickly

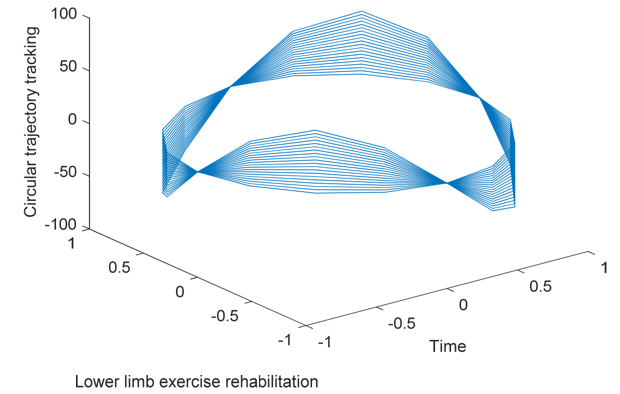

FIGURE 16. Trajectory tracking experiment results.

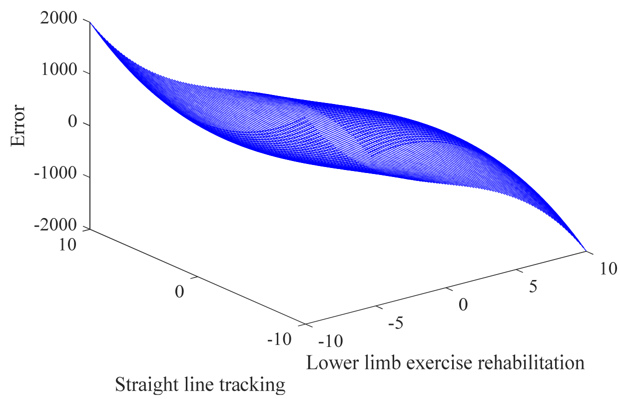

FIGURE 17. Straight line tracking error.

adjusted. This gesture enables operation on a predetermined trajectory. In the trajectory tracking test, the horizontal and vertical coordinates versus time curve can track a predetermined trajectory of about 20 s to meet the patient's reflection speed.

V. CONCLUSION

Based on the analysis of medical health big data, this paper focuses on applying artificial intelligence and medical big data methods is to the evaluation of lower limb exercise rehabilitation, combining traditional medical and emerging big data technologies to construct a physiological big data. We identified a reasonable modeling approach that included most of the lower extremity bones and the dynamic muscles that pull the lower jaw, knees and joints. By analyzing the main and passive movement modes of lower limb rehabilitation training, the movement pattern of the musculoskeletal model apex of the lower limbs is calculated when the lower limb pedal drives the ankle joint to reciprocate and when the patient exercises autonomously, thereby simulating the lower limb rehabilitation training during passive movement. The angle at which the joint turns is less than 30. The effect is good, greater than 30. When the muscles are severely deformed, there is an overlap between the bones, and the effect is deteriorated.

In view of the fact that the current rehabilitation evaluation equipment could not measure the dynamic balance parameters, the measurement method of human dynamic balance parameters based on omni-directional mobile lower limb exercise rehabilitation training was proposed for the first time. By developing a dynamic balancing force platform based on artificial intelligence and medical big data arm support structures, the human body dynamic balance data was successfully detected, which filled the blank of the human rehabilitation parameter measurement method. For the nonlinear and uncertain rehabilitation training system, a L2 robust controller design method is proposed for the first time. The omnidirectional moving lower limb rehabilitation trajectory tracking and system uncertain disturbance problem of multi-input and multi-output nonlinearity are summarized as L2 robust controller design problems. The kinematics and dynamic error models are established, the storage function is constructed and the control rate is designed by the inverse push method. The robust control theory is applied to prove that the L2 control algorithm satisfies the conditions of dissipative inequality and system asymptotic stability. The tracking trajectory is round, sinusoidal, Lissajous curve and star curve analysis under the set disturbance. The tracking and anti-interference performance of the omni-directional moving lower limb exercise rehabilitation training using nonlinear L2 robust controller are verified. Experimental study on the evaluation system of omni-directional moving lower extremity exercise rehabilitation. In order to evaluate the functional parameters of lower limbs during rehabilitation training, seven gait mode detection methods were proposed. Through the developed gait detection program, the gait pattern and the step frequency parameter online detection and recording during human rehabilitation training can be realized. The experimental results prove that the proposed method is feasible.

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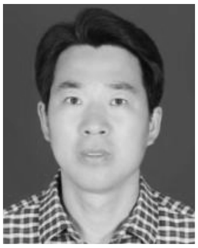

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