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RESEARCH ARTICLE

Rehabilitation and Motion Symmetry Analysis With a TACX Smart Cycling Trainer Using Computational Intelligence

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethics Committee of the Neurological Center at Rychnov n. Kn., Czech Republic.

ABSTRACT Motion analysis provides important information in rehabilitation, performance evaluation, and movement symmetry assessment, with applications including neurology, biomedicine, surgery, and sports monitoring. The integration of virtual reality, wearable sensors, and signal processing forms a robust interdisciplinary platform for such analysis. Specific methods are based on monitoring physiological and motion responses during controlled exercises that simulate real-world motion scenarios. This study focuses on processing of signals from wearable sensors collected from smart indoor trainers, enabling motion monitoring under predefined load conditions. The acquired datasets include heart rate (HR), motion accelerometric and gyrometric signals, and fitness parameters (cycling speed). The research objectives include analysis of motion patterns, evaluation of motion symmetry under varying loads, and examination of heart rate responses to load variations. Signal processing is conducted using advanced methods that include computational intelligence, digital signal processing, and artificial intelligence tools for data classification. Results point to the mean delay of the HR drop to 97% of the HR range in 15s after the change from the cycling on the slope of 8% to the rest period and the following drop to 5% in next 54s. The classification of spectral features evaluated separately for the left and right legs pointed the classification accuracy of 94.5% for accelerometric data and 99.1% for gyrometric data estimated by the use of the two layer neural network and the symmetry coefficient of 1.05 for the slope of 8%. In general, the paper presents selected processing methods and experimental results pointing to the effectiveness of computational intelligence in motion analysis.

INDEX TERMS Computational intelligence, wireless sensors, accelerometers, rehabilitation, physical activity monitoring.

I. INTRODUCTION

Motion monitoring and data analysis form fundamental tools in rehabilitation [1], evaluation of movement performance, and analysis of its symmetry [2] with important applications in neurology, biomedicine, surgery, or in assessment of

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sports activities [3], [4] and fitness level. Implementation of wearable sensors and analysis of separate signals form an important research platform for different interdisciplinary applications [5]. Some studies are devoted to the relation of the heart rate changes and the fitness level [6], [7], [8]. Detailed motion analysis often results in the implementation of robotic systems in physical rehabilitation [9], [10], including the use of rehabilitation bicycles for training of the patients with lower limb disfunctions [11], [12], and robot assisted neural rehabilitation [13].

There exist many different sensors and technologies to follow motion features. The use of accelerometric and gyrometric sensors [14], [15], [16] combined with the use of video, depth, and thermal cameras [17] form a very common approach for data acquisition in the clinical environment. More sophisticated methods follow physiological function during the different cycling activities [18] and load using home exercise bikes [19], smart trainers like TACX systems, data acquisition in real conditions [20], and telemonitoring [21]. Some studies are oriented to instrumentation of a city bicycle with different sensors to measure the interaction of cyclists with road infrastructure [22], [23]. Most sophisticated systems are based on virtual reality [24] implemented in the virtual environment (VE) to train habits important for real situations [25], [26], to improve muscle activity and balance in patients with neurological injuries [27], and to improve motion safety in the road traffic.

Correct and precise data acquisition is fundamental for their following processing using sophisticated mathematical methods of computational intelligence (CI), interdisciplinary methods of digital multichannel and multidimensional signal processing (DSP), and general methods of artificial intelligence (AI). These methods [28], [29] can be applied for automated signal analysis, pattern recognition, and performance classification. Signal processing may include reduction of noise due to terrain vibration with adaptive thresholds and deep learning [30], feature estimation to characterize and classify differences in cycling behavior on flat, uphill, and downhill slopes, and to identify specific leg movements [31].

Specific data processing methods include the application of the dynamic systems theory, application of body kinematics [32] using a controlled bicycle configuration, and studies of movement variability [33], [34]. Local dynamic stability analysis [35] allows a better understanding of the effect of diseases and aging that influence the walking gait mechanics and cycling habits. Deep learning techniques often integrate the pose estimation and signal processing techniques [36].

This paper is based on data acquired on home smart trainers that allow data acquisition for defined load conditions and selected virtual routes with associated data recording. Signals include both physiological data (heart rate), motion data (acquired by accelerometric and gyrometric sensors), fitness data (cycling speed], and positioning data of the global navigation satellite system (GNSS). The goal of this study is in (i) analysis of motion sensors, (ii) specification of motion symmetry for different load conditions, (iii) study of heart rate changes related to changes of the load, and (iv) implementation of artificial intelligence for data processing and classification.

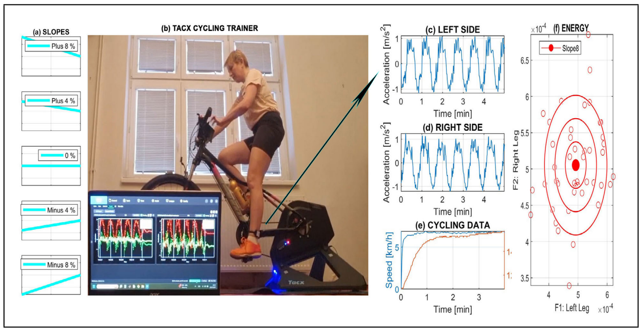

FIGURE 1. Principle of cycling data acquisition presenting (a) slope selection, (b) TACX cycling trainer used for data recording for chosen cycling conditions, (c,d) selected segments of left and right sides of accelerometric signals, (e) cycling data recorded by the TACX system, and (f) distribution of energy between left and right sides for a selected slope.

The following parts of the paper include Section II with description of data acquisition system and general methods of data processing, Section III that includes results of specific experiments, Section IV discussing results, and Section V with conclusions.

II. METHODS

The sports equipment includes a bicycle mounted on a TACX Neo 2T trainer, which tracks virtual cycling position, speed, and virtual distance during exercises. A Garmin cadence sensor monitors the pedal rotation speed, while a Garmin heart rate belt measures the subject's heart rate. Acceleration and angular velocity are recorded using WitMotion WT901SDCL-BT50 sensors, which are positioned above the subject's ankles. These sensors allow specification of the sampling frequency and recording of the chip time.

The proposed research flowchart for analysis heart rate and for classifying cycling symmetry, based on wearable accelerometric and gyrometric sensors, as presented in Fig. 1, involves the following steps:

(a) Initialization of the sensors and specification of the cycling slope.
(b) Recording of specified variables with the given sampling frequency.
(c) Export of positioning, accelerometric and heart rate data.
(d) Analysis of heart rate data and their relation to the cycling slope.
(e) Evaluation of the symmetry coefficient using data recorded on the remote drive.
(f) Detailed processing of accelerometric signals and their classification.

This methodology employs wearable sensors and implements data processing through selected computational intelligence tools.

A. DATA ACQUISITION

The dataset consists of data captured by the TACX device, a heart rate sensor, and Witmotion sensors. Motion sensors, and heart rate monitor are connected via Bluetooth to the computer. Recorded Garmin signals are automatically saved to Garmin Connect cloud storage. This data, stored as TCX files, is then exported and converted into XLSX files for further processing and analysis. The motion sensors are connected to the WitMotion desktop application via Bluetooth. Recorded acceleration and angular velocity data are saved locally as CSV files, which are later converted into XLSX tables for further processing.

Experiments included 7 virtual cycling sessions on 5 selected slopes (-8,-4,0,4,8 %) performed by one individual. Each of these 35 exercises 240s long was divided into 60 subwindows 4 seconds long for analysis of accelerometric data recorded by sensors located above ankles on the right and left legs. The sampling frequency was 100 Hz. The total number of 2100 data segments was used for the classification of motion features.

All procedures involving human participants were in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki Declaration and its later amendments. Detailed descriptions of the observations can be found on IEEE DataPort (doi: 10.21227/vjfa-1b64, Virtual Cycling Load) for further investigation. This repository contains (i) all signals used in the present study, (ii) a fundamental interface for data analysis, and (iii) a graphical video abstract of the paper.

B. SIGNAL PROCESSING

Data processing procedures are intrinsically linked to the characteristics of the sensors used for data acquisition. The database of records was composed of both accelerometric and physiological signals acquired with different sampling frequencies and associated with time stamps enabling their time synchronization and processing.

Individual accelerometric signals acquired for each experiment were captured by tri-axial sensors positioned on the left and right legs above ankles. These data generated three sequences $\{s_x(l,n), s_y(l,n), s_z(l,n)\}_{n=0}^{N(l)-1}$ for each location l. The modulus of these sequences was calculated by the following relation:

$$s(l,n) = \sqrt{s_x(l,n)^2 + s_y(l,n)^2 + s_z(l,n)^2} \tag{1}$$

with their mean value $\bar{s}(l) = \sum_{n=0}^{N-1} s(l,n)/N$.

In the signal preprocessing stage, digital filtering of the given data was applied. This involved the median filtering of selected order and FIR filtering to remove undesirable noise components. Spectral components were then estimated by the discrete Fourier transform:

$$S(l,k) = \sum_{n=0}^{N-1} (s(l,n) - \bar{s}(l))\, e^{-j\,k\,n\,2\,\pi/N} \tag{2}$$

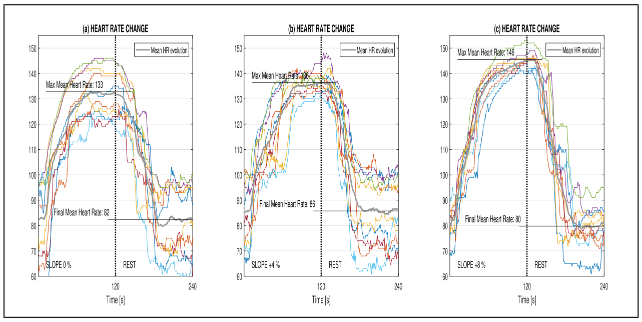

FIGURE 2. The evolution of the heart rate during ten cycling experiments for (a) cycling on the flat surface, (b) for slope 4 %, and (c) for slope 8 % during 2 minutes of the load and 2 minutes of the rest.

for $k = 0, 1, \cdots, N-1$ and application of the Hanning window for data segments extraction. The relative power $E_p(l,d)$ for each data segment d in the frequency band $\langle fc_1, fc_2 \rangle$ was then evaluated for each position p of the sensor and experiment l by relation:

$$E_p(l,d) = \frac{\sum_{k\in\Phi_w} |S(l,k)|^2}{\sum_{k=0}^{N/2} |S(l,k)|^2} \tag{3}$$

where Φ_w denotes the set of indices for the spectral components within the selected frequency range $\langle fc_1, fc_2 \rangle$.

The symmetry index was then estimated as the ratio of energy for the left and right side of the body by relation:

$$C(d) = \frac{E_{Left}(l,d)}{E_{Right}(l,d)} \tag{4}$$

for each data segment d.

Values of relative energy both for the left and right side of the body was then used for construction of the pattern matrix

$$\mathbf{P} = \begin{bmatrix} E_{Left}(l,d) \\ E_{Right}(l,d) \end{bmatrix} \tag{5}$$

and target vector T that associated each feature column vector of matrix P with class s_k that specified the slope for the following classification. Machine learning and computational intelligence methods were further applied. During the learning process, a function that transforms the space of features $\mathbf{P}_{R,Q}$ into the vector $\mathbf{T}_{1,Q}$ specifying the classes is estimated.

Bayesian probabilistic classification is based on the estimation of class s_k generated by vector p with its probability

$$B(s_k|\mathbf{p}) = \frac{B(\mathbf{p}|s_k)\; B(s_k)}{B(\mathbf{p})} \tag{6}$$

where $B(\mathbf{p}|s_k)$ stands for the probability of generating instance $\mathbf{p}$ given class s_k, $B(s_k)$ represents the probability of the occurrence of class s_k, and $B(\mathbf{p})$ stands for the probability of the occurrence of $\mathbf{p}$.

Assuming the independence of feature sets and the Gaussian distribution of their values, it is possible to find for each class s_k the mean μ_{s_k,p_j} and variance $\sigma^2_{s_k,p_j}$ of

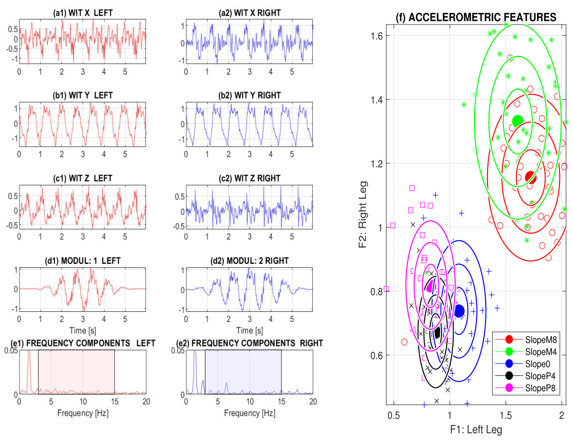

FIGURE 3. **Data acquired during a selected experiment presenting (a1-d1) results of signals recorded by sensors on the left leg, (a2-d2) results for a sensor on the right legs located above ankles and the experimental slope of 8%, (e1-e2) spectral frequency components associated with both legs, and (f) distribution of features of the same experiment for different slopes with centers of their clusters and c multiples of standard deviations for $c = 0.5, 1, \ldots, 1.5$.**

each attribute p_j. The corresponding Gaussian distribution associated with each class s_k is then defined as

$$B(p_j|s_k) = \frac{1}{\sqrt{2\,\pi\,\sigma^2_{s_k,p_j}}}\,\exp\left(-\frac{(p_j-\mu_{s_k,p_j})^2}{2\,\sigma^2_{s_k,p_j}}\right) \quad (7)$$

Results of Bayesian classification were compared with those obtained by the support vector machine and neural networks methods. Verification was done by the evaluation of the k-fold cross validation method.

III. RESULTS

Data acquisition was conducted using accelerometric, gyrometric, motion, and heart rate sensors. The implemented algorithm is accessible through the IEEE DataPort [37] mentioned above. All evaluations were done in the environment of Matlab 2025a (MathWorks, Natick, MA).

Figure 2 presents the evolution of the heart rate during ten cycling experiments for cycling on the flat surface, for slope of 4%, and for slope of 8% during 2 minutes of the load and 2 minutes of the rest. The final heart rate is in average 83 bpm for all experiment achieved after 60 seconds following the beginning of the rest period. The maximum heart rate decreased by 30% of the HR range during 15s for the cycling on the slope of 8%. Table 1 presents detailed numerical results of mean heart rate changes for the cycling period of 120s on the specified slope and the following rest period. The differences of the final rest period HR can be explained by the actual physical condition of the tested individual.

Accelerometric signals acquired during a chosen experiment for sensors attached above ankles on the right and left legs are presented in Fig. 3(a-c) for experimental cycling on the slope of 8%. Absolute values of these signals presented in Fig. 3(d) are modified by the Hanning window for the following application of the discrete Fourier transform. Figure 3(e) presents associated spectral components with regions used for specification of features associated with

TABLE 1. **Comparison of mean heart rate (HR) changes for the cycling period of 120s on the specified slope and the following rest period.**

Slope [%]	Max HR [bpm]	Min HR [bpm]	Time delay [s] for the given drop 3%	30%	90%
8	146	80	15	32	69
4	136	86	15	30	57
0	133	82	7	30	62

TABLE 2. **Comparison of energy ratio for seven experiments with features evaluated in the frequency range of ⟨3, 20) Hz for different cycling slopes and data recorded by accelerometric and gyrometric sensors with the sampling frequency of 100 Hz located above ankles on the right and left legs with their mean and standard deviation (STD) values.**

Exp.	Slope:	Accelerometeric Sensors above Ankles -8%	-4%	0%	4%	8%
1		0.74	0.84	0.74	0.85	0.91
2		0.88	1.13	0.84	0.91	0.85
3		0.81	0.93	0.73	0.74	0.86
4		0.73	0.78	0.68	0.95	1.03
5		0.72	0.85	0.94	0.78	1.12
6		0.85	0.96	1.02	1.19	1.24
7		0.77	0.84	1.06	1.27	1.36
Mean		0.78	0.90	0.86	0.96	1.05
STD		0.06	0.11	0.15	0.20	0.20
Exp.	**Slope:**	**Gyrometric Sensors above Ankles -8%**	**-4%**	**0%**	**4%**	**8%**
1		0.53	0.51	0.74	1.09	1.06
2		0.49	0.39	0.73	0.79	1.09
3		1.26	0.95	1.29	1.16	1.06
4		0.47	0.55	0.71	0.91	0.96
5		0.61	0.52	0.76	0.69	0.89
6		0.51	0.44	0.53	0.64	0.70
7		0.55	0.51	0.63	0.57	0.89
Mean		0.63	0.55	0.77	0.84	0.95
STD		0.28	0.18	0.24	0.23	0.14

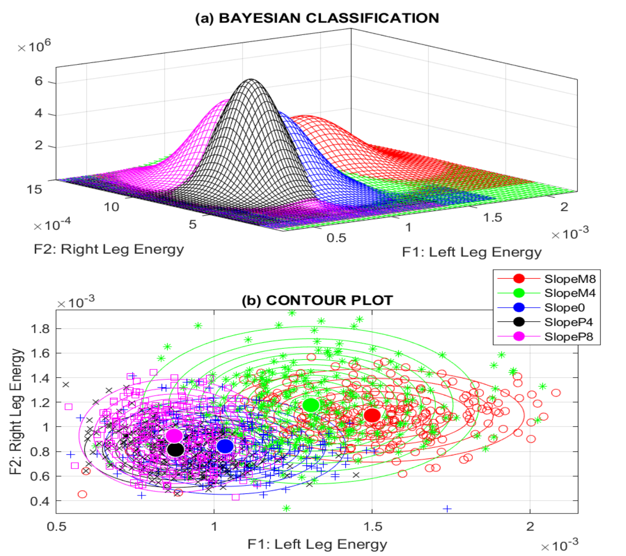

FIGURE 4. **Distribution of spectral energy evaluated for accelerometric data recorded on different slopes, no overlapping segments 6 seconds long, and relative energy in frequency bands ⟨3, 20) Hz forming features for the left and right legs with centers of clusters presenting (a) Bayesian classification and (b) contour plots separating data acquired on selected slopes.**

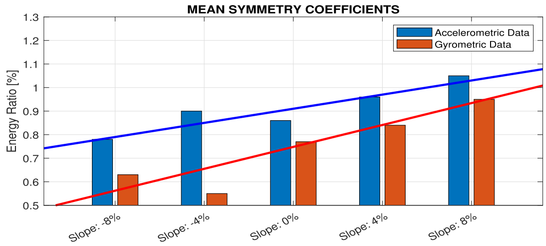

FIGURE 5. Mean values of symmetry coefficients for different slopes and relative frequency values evaluated for the left and right legs in frequency bands ⟨3, 20⟩ Hz based on accelerometric and gyrometric data with the linear approximation of these values.

separate legs. Similar results were obtained for gyrometric signals.

To obtain more reliable results, observed signals were segmented into 4 seconds long periods, and the distribution of separate features is presented in Fig. 3(f) for five different constant slopes specified by the TACX smart trainer. Results show different positions of associated clusters that were further used for specification of motion symmetry with centers of their clusters and c multiples of standard deviations for $c = 0.5, 1, \cdots, 1.5$.

Table 2 presents the comparison of energy ratio for seven experiments and signals evaluated for accelerometric and gyrometric observations. Results include features evaluated in the frequency range of $\langle 3, 20\rangle$ Hz for different cycling slopes and data recorded with the sampling frequency of 100 Hz located above ankles on the right and left legs with their mean values.

Figure 4 presents the distribution of spectral energy evaluated for accelerometric data recorded on different slopes, with no overlapping segments 4 seconds long. Features are estimated as relative energy in frequency bands $\langle 3, 20\rangle$ Hz forming features for the left and right legs with centers of clusters. Figure 4(a) presents 3D results of the Bayesian classification into five classes associated with different slopes, and Fig. 4(b) presents associated contour plots of individual clusters.

Figure 5 presents mean values of symmetry coefficients for different slopes and relative frequency values evaluated for the left and right legs in frequency bands $\langle 3, 20\rangle$ Hz. With the increasing slope from -8% the efficiency of the movement is increasing and the coefficient of symmetry is approaching value of one. For more heavy load associated with cycling on the slope of plus 8% the dominant role of the more strong right leg prevails according to accelerometric data and coefficient of symmetry differs from its optimal value of one again.

Figure 6 presents results of analysis of relative energy acquired from the left and right legs and feature classification into class A (downhill cycling) and B (uphill cycling) by the Bayes method and neural network with two layers and sigmoidal/softmax transfer functions using accelerometric and gyrometric data. Classification accuracy and cross validation errors estimated by the 10-fold cross/validation method are presented in Table 3.

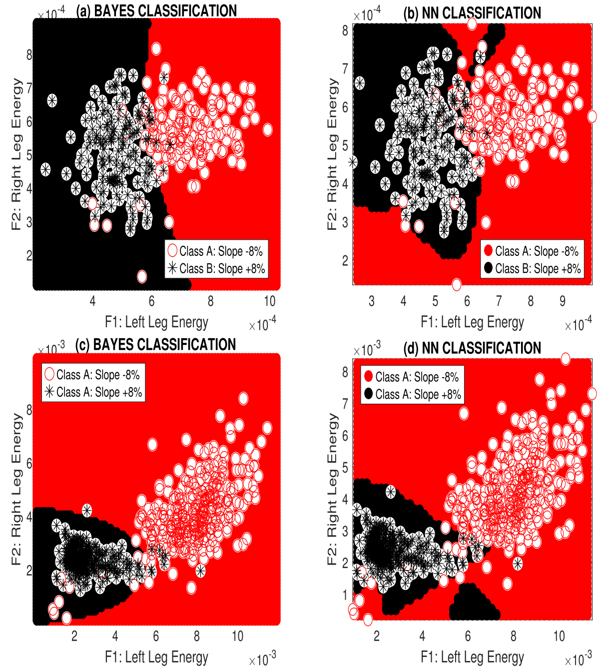

FIGURE 6. Classification of relative energy associated with (a,b) accelerometric and (c,d) gyrometric data acquired from the left and right legs into class A (downhill cycling) and B (uphill cycling) by the Bayes and neural network methods.

TABLE 3. Comparison of the classification accuracy (ACC) and cross validation errors (CV) for data acquired by the accelerometric and gyrometric sensors using Bayes and neural network methods.

Method	Accelerometric Data		Gyrometric Data	
	ACC [%]	CV	ACC [%]	CV
Bayes	93.5	0.55	97.3	0.033
Neural network	94.5	0.45	99.1	0.019

IV. DISCUSSION

Present paper is devoted to the analysis of cycling patterns for virtual cycling on different slopes. Results point to the mean heart rate change from its peak values to its new equilibrium state, associated with the change from the load to the rest period, within about 60s for the selected individual. This characteristics, often referred to as heard rate recovery (HRR) or heart rate variability (HRV) can be a significant indicator of cardiovascular health [38], [39]. Its abnormalities can point to a variety of diseases or risks. The drop higher than 51 bpm within the first minute of the post-exercise period for all slopes in the given case is considered as a normal response from the medical point of view. The proposed type of experiments can thus be considered as a tool for detection of a fitness level and a risk of cardiovascular disease.

Motor control mechanism [40] and differences in spectral components between the left and right legs during cycling can be meaningful and may point to motion disorders or neuromuscular asymmetries. This type of analysis included in biomechanical signal processing is often used in clinical motion analysis, sports performance, and rehabilitation. The classification of spectral features evaluated separately for the left and right legs for a given individual pointed to the classification error of 94.5% estimated by the neural network method and the symmetry coefficient of 1.05 for the slope of 8% and accelerometric signals. Harmonic content of pedaling motion is normal in the given case, and this process can be useful as a general methodology for motion analysis.

The paper forms a pilot study for evaluation of rehabilitation exercises in the clinical neurological practice, for assessment of the fitness level, and for the possible analysis of virtual cycling on real routes segmented according to their slopes.

Artificial intelligence can help to identify incorrect habits during cycling and it can be used both for professional training and rehabilitation setting. By combining sensor data, deep learning [41], and real-time feedback, computational intelligence systems can detect patterns that indicate inefficiencies or bad posture during specific exercises.

The paper presents selected data acquisition methods and data processing using vector modulus that reduces dimensionality and eliminates problems with axis orientation. Modulus or z-axis data provide enough information for terrain/slope classification. For more detailed study of joint kinematics, information provided in all three directions are necessary, and computational intelligence applied to motion analysis is preferred.

V. CONCLUSION

The widespread availability of wearable sensors is driving a rapid accumulation of human data, prompting the application of innovative computational and machine learning methods in clinical predictions. The proposed methodology based on the use of smart trainers can both improve the fitness level, point to cardiovascular diseases, and evaluate neurological disorders. The use of these devices for virtual cycling can moreover motivate physical training and the use of mathematical methods for data analysis.

Using motion and physiological sensors in rehabilitation forms a useful data-driven system with applications for improving patient recovery after surgeries, in detection of motion problems, and in increasing the fitness level. Specific applications include estimation of quantitative motion changes in medicine for gait abnormalities evaluation and Parkinson's or multiple sclerosis therapy.

Artificial intelligence can help in multimodal fusion of motion kinematics, voice recordings, and handwriting integrated with magnetic resonance imaging to detect different neurological problems. It can be used in combining sensor fusion with neural networks for robust classification under noisy or variable conditions. Further applications include construction of digital twins that provide sophisticated tools for motion analysis in the virtual cycling environment.

Future research will be devoted to more sophisticated data acquisition systems, to application of more advanced computational intelligence tools for early diagnostics of health problems, and to the detail monitoring of rehabilitation exercises.

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