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Enhanced algorithm for energy optimization and improvised synchronization in knee exoskeleton system

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ABSTRACT

Purpose: The purpose of the study is to develop an augmented algorithm with optimised energy and improvised synchronisation to assist the knee exoskeleton design. This enhanced algorithm is used to estimate the accurate left and right movement signals from the brain and accordingly moves the lower-limb exoskeleton with the help of motors.

Design/methodology/approach: An optimised deep learning algorithm is developed to differentiate the right and left leg movements from the acquired brain signals. The obtained test signals are then compared with the signals obtained from the conventional algorithm to find the accuracy of the algorithm.

Findings: The obtained average accuracy rate of about 63% illustrates the improvised differentiation in identifying the right and left leg movement.

Research limitations/implications: The future work involves the comparative study of the proposed algorithm with other classification technologies to extract more reliable results. A comparative analysis of the replaceable and rechargeable battery will be done in the future study to exhibit the effectiveness of the proposed model.

Originality/value: This study involves the extended study of five frequency regions namely alpha, beta, gamma, delta and theta, to handle the real-time EEG signal processing exoskeleton, model.

Keywords: Knee exoskeleton, Feature extraction, Data classification, ANN algorithm

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BIOMEDICAL AND DENTAL MATERIALS AND ENGINEERING

1. Introduction

The advancement in science and technology has led to a revolution in many sectors, especially in the medical field. The development of modernised types of equipment and methodologies has changed the lifestyle of many people who are suffering due to various problems. One such is the exoskeleton, a type of robot that helps nerve-damaged people move their limbs like normal people. This additional assistance gives power to the limb muscles for the rehab and movement of nerve-damaged patients. The earlier assistive methods, like wheelchairs, only enable movement on a flat surface, have limitations like space constraints, and do not support easy transportation. The exoskeletons are an excellent assistive system that helps the patients move on their own to any place without any constraints.

It is also an economic fact that spinal cord-injured persons have a huge impact on the healthcare economy [1]. It was also estimated that about more than 50 persons per million rehabilitees are there every year around the world [2]. Among them, 60% were partially paralysed, which includes young and middle-aged men who have to work to support their families. But when paralysed, they must depend on the health care system and others to perform their own activities [3]. Due to economic constraints, most affected people do not even opt for rehabilitation. Orthotic types of equipment developed to serve the purpose have many practical constraints and limited functionalities [4,5]. They are only used as supportive rather than assistive devices hence being passive devices [6]. Hence to assist the disabled person, researchers concentrated on the development of active assistive devices, which led to the invention of exoskeletons around the 1960s [7]. With the recent development in technology and science, wearable exoskeletons have been designed in recent years [8-15]. Artificial Intelligence algorithms and neural network algorithms were used in coordination to synchronise the muscle activity with the brain [16].

Generally, the development of the mind synchronised assistive devices for the lower limb was much less than that of the upper limb research [17]. EEG signals are utilised for the identification and extraction of the dataset that synchronises the active devices with the brain [18]. This study also includes a detailed investigation of the EEG signal classification for the right and the left limb using ANN algorithms to augment synchronisation accuracy.

In spinal injured patients, there is no synchronisation between the conceptualised and the executed movements. This is fixed in the active assistive devices by mirroring the signals using motors. Generally, mirroring of the signals is not only executed when the patient conceptualises the movements but also when another person executes the movement [19]. This helps in the locomotive of brain-impaired patients as well.

To study the EEG signals from the patient, electrodes were fixed at the head of the patient. Two electrodes are fixed at each side to catch the right and left brain activity. Also, two additional electrodes were fixed at the lower head to record the spinal activities. In the existing studies, only alpha and beta frequencies were used, but in this proposed model, alpha, beta, gamma, delta and theta frequencies were picked up to analyse the accurate synchronisation and the associated limb movements [20].

The aim of this study is to develop an effective active assistive device, aka knee exoskeleton model, which is pulled by the external motor simulated through the brain signals. The following section involves the literature survey analysis, design considerations and hardware requirements of the proposed design, respectively.

2. Literature review

The study of the previous research and the discoveries throws some light on the knowledge about the challenges faced and the development made from scratch in research. Marchel et al. (2009) suggested that the control system can be categorised as assistive control, solution control, reality control and trained control [21].

Assistive control in robotic devices is obtained through the body weight balance and based on the functionality of the limbs [22]. Customisation of the limb movement is based on the specific functions assigned to each controller [23].

There were different studies and research on assistive devices for nerve-damaged patients. Earlier designed assistive devices were too rigid and didn't support the movement of the foot separately [24]. The exoskeletons that assist the knee movement can be categorised as passive, active and semi-active according to their design and functionality [25-28].

Passive, assistive devices are rigid design that helps move the lower limbs without any control. They just support the body weight balance and do not help in the conceptualised movement [25]. Semi-active assistive devices help move the knee and limbs in different directions but with a controller that has pre-programmed control [26].

Active assistive devices are the ray of hope for nerve-impaired patients where the limb movements are synchronised with the brain activity, and the assistive devices execute the conceptualised movements [28].

In 1981 first assistive device using a D.C. motor was discovered by Jaukovic. The DC motor in this device was located externally at the ankle extension. Then came the design of the walking exoskeletons, designed by Argo medical technologies and Ekso Bionics [29-30]. These devices are controlled through the motors fixed at the hip region of the wearer, along with the sensors.

In our current study, the area of interest is the knee joint. In this, the research pioneer was Berlin University which developed a spring-controlled knee structure [31]. This design was commercially marketed by AlterG and was used in real time [32]. But these devices had limitations like a heavy-weight and minimised performance efficiency [33]. These knee systems were designed with a single-axis joint which enables only one-directional movement. Whereas the normal knee joint is Omni directional due to its ball socket joint. This swing phase of the movement was later considered and included in the computer-controlled devices [34].

Then sensors like foot sensors, motion sensors and torque sensors were used to monitor and observe the movement of the functioning limbs to customise the assistive devices. Then a complete set, including the controller and the motor setup, was designed [35].

To design a real-time assistive device brain wave interface was incorporated into the exoskeleton design [36]. This helps disabled patients with normal brain activity with damaged limb nerves [37]. The major difficulty in extracting this brain feature is eliminating the noise signal to attain accurate EEG signals [38]. Hence classification feature is used for the data extraction from the brain signals. These devices are powered by an internal battery connected to the exoskeleton. Complex neural algorithms do not achieve power optimisation in the existing systems. Hence, this study focuses on developing an energy-optimised algorithm to extract the data signals by eliminating noise and processing through the proposed hybrid algorithm.

3. Research methods

3.1. Methods

The methods of the proposed research start from the relative identification of the right and left brain signals and their synchronisation using the electrode signals in Alpha (α), Beta (β), Gamma (γ), Delta (δ) and Theta (θ) frequencies.

The dataset of 16 healthy subjects with no history of knee or nerve damage was obtained from Adrienne et al. (2021). In this work, the data was obtained from two different sessions to get the average data with improvised reliability [38]. In this study, the participants were given a head cap connected with 64 electrode channels. These electrodes were preset with the optimal impedance level of 5000 ohms so that no channel gets dropped during the brain signal acquisition. During each session, the data corresponding to the conceptualisation and execution was acquired at the frequency rate of 1000 Hz. First, the conceptual movement data was captured. Then the participants were belted in a lying position which restricted their knee movement to analyse the executed movement, as shown in Figure 1.

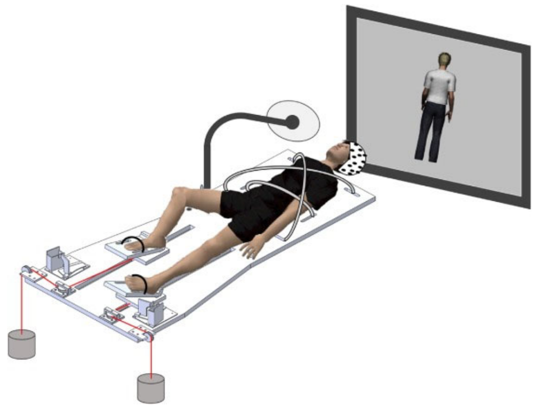

Fig.1. Experimental setup to collect the executed movement dataset [38]

The limbs are attached to a foot pad with a spring-loaded mechanism in this experimental setup. Whenever the subject rises and lowers his knee, the spring sets the position of the leg back to its original position. Thus the controlled movement of the lower limbs was recorded. First, the left leg was lifted and stretched to obtain the correct data set, followed by the right leg. This was done six times to obtain 12 dataset cycles. A visual stimulus is given in the monitor to track the phase and to replicate the conceptual stimulus.

3.2. Data acquisition

About 18 electrodes were placed, as illustrated in Figure 2. Among them, four electrodes were fixed on the head at the lower and upper quadrants, namely E1, E2, E3 and E4. These electrodes were analysed using the MATLAB simulation software developed by Mathworks. Corresponding dc offset data of the electrodes were corrected in this simulation tool. Eye blinking may cause induced noise in the EEG signals, which is cancelled using the Electro oculography channel. These channel thresholds and marks the wave on the graph during every blink, omitted during data processing and considered an error. Pre-processing these signals involves the elimination of the noise by passing through the bandpass filter. The second-order bandpass filter with a frequency range of [5,60] Hz was used to obtain noise-free signals.

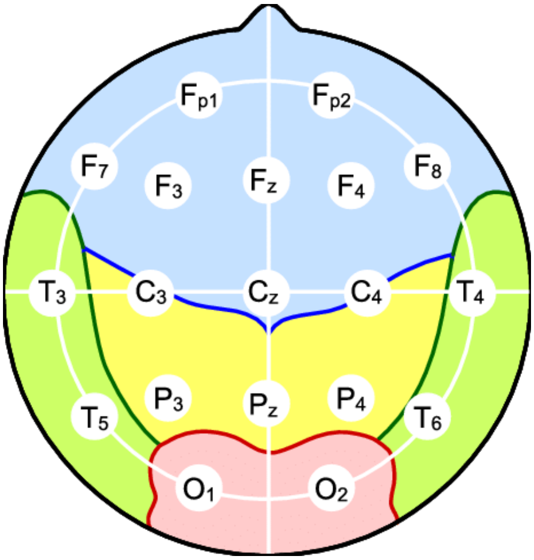

Fig. 2. Placement of electrodes in the scalp

Data classification was done to identify the feature of the signals at their respective frequency bands like Alpha (α), Beta (β), Gamma (γ), Delta (δ) and Theta (θ). To classify the feature of the signal, Discrete Fourier transformation is applied with different frequency ranges of Alpha (8-12 Hz), Beta (13-15 Hz), Gamma (16-30 Hz), Delta (31-45 Hz) and Theta (46-60 Hz). The resolution of the frequency at each band was 0.9645. This resolution was obtained by sampling the frequency at the rate of 2^8 samples per period. The normalisation of the obtained samples follows this step with respect to the spectral frequency. The entire process flowchart is illustrated in Figure 3.

3.3. Data analysis

The reliability of the obtained dataset was verified by averaging the data across the sessions. Separate simulations were done for each side (Left and Right) with the attributes N.P.=16 (Number of subjects), N_{EC}=60 (Electrode channels), and N_S=2 (number of sessions). Before executing the simulation, the dataset was marked as random with a reliable G-coefficient index range [0,1]. The reliability of the data is higher with higher values. The following conditions were considered during the simulations:

The obtained dataset is binary, corresponding to L=0 and R=1.

The predictor signals should be continuous, corresponding to the EEG waveform.

Multi-dimensional processing for channels is iterated 16 times, corresponding to the number of subject considerations.

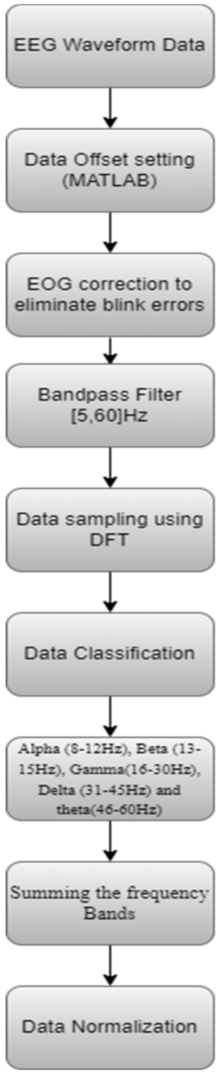

Fig. 3. Data processing flowchart

Classification techniques involve the supervised neural learning algorithm. The CNN algorithm complicates the data processing and uses extended memory, which requires more power. The ultimate aim of this study is to optimise the power utilisation during data processing, and hence Supervised ANN algorithm is used. This reduces the computational complexity, which further reduces energy utilisation, thus achieving energy optimisation. Also, this algorithm can easily customise the performance attributes depending on the training group size. More stable results were obtained at the ratio of 3:1 of the training group to the testers.

The designed code was then simulated in the MatLab simulator, and the corresponding dataset was given as the input to the knee exoskeleton. The knee exoskeleton is powered by a replaceable battery and is moved through the dc motor.

4. Results

The generalised coefficient of the EEG signals obtained from the conceptualised movement at different frequency combinations was 0.65, considered a moderate value. The overall variation of the dataset was 0.5% which is considered to be more reliable and robust. The variance ratio of a number of subjects is 12.5%, to the number of electrode channels is 1.8%, to the product of participant and sessions is 10.5%, to the product of participant and trail is 3%, and to that of the error is 70%, respectively.

Table 1.
Overall correct percentage of synchronisation between the conceptual and executed movements in Left and Right

Subjects	L (correct) in %	R (correct) in %	Average in %
1	70.8	62.2	66.5
2	64.2	65.4	64.8
3	50.4	63.1	56.8
4	63.6	55.8	59.7
5	55.2	68.3	61.8
6	56.8	59.8	58.3
7	51.8	71.5	61.7
8	72.6	55.9	64.3
9	61.5	66.5	64.0
10	72.8	55.1	64.0
11	72.9	68.3	70.6
12	79.1	49.5	64.3
13	62.8	78.2	70.5
14	63.8	53.9	58.9
15	66.3	66.3	66.3
16	47.6	76.1	61.9

Table 1 presents the synchronisation percentage of the conceptual and executed movement. For each subject, an average of 63.4% synchronisation was achieved between the left and right. The results of this experiment illustrate that the electrodes in the upper quadrants identify the important region to fix the sensor to obtain accurate EEG signals to obtain enhanced synchronisation between the conceptual and executed limb movements. The electrodes fixed at the lower quadrants identify the region of sensors that differentiates the right and left brain activity. The corresponding results achieved at the different frequency bands are closely associated with the executed movements. The correspondence between the frequency bands was consistent with the existing studies and had significant considerations.

The overall correctness of 63% features the challenge of identifying the right and left leg signals from the brain. The rate of accuracy is much more effective than the other existing techniques.

5. Discussion

The rationale of the current study is to identify the right and left limb movement signals from the brain's cortex region, which are collected through the electrodes. From the analysis, it is clear that Electrodes C1 and C2 hold a trivial role in estimating the right and left limb movements, interpreting the importance of the sensi cortex region in the brain for the differentiation of the signals. Particularly to differentiate the limb movements, the signals obtained from the electrodes PO3 and PO4 are useful as they are associated with the mirror neuron stimulus. Alpha, beta and gamma waves are very closely related to lower limb movements, and the corresponding results of this current study are obtained from the delta and theta waves.

The average classification ratio of 63% features difficulties differentiating the right and left limb signals. Thus this study is considerately demonstrated to prove the difficulty in classifying the right and left limb movements from the brain signals. The future work involves the augmentation of the accuracy through deep learning methods, and the obtained results will be compared against the other conventional algorithms.

6. Future work and conclusion

The proposed study is to design a knee exoskeleton synchronised with the brain signals to obtain proper limb movement from the brain signals. This study has proved the success rate in identifying the left and right leg signals from the brain with a considerable result. The study with five frequency bands gave a novel methodology to improvise the synchronisation between the conceptual and the executed leg movements. Thus compromised mobility with nominal success rate is achieved in the simulation.

The future work involves the comparative study of the proposed algorithm with other classification technologies to extract more reliable results. To produce an extended analysis of the better algorithm for feature extraction detailed comparative study will be done with the other neural network algorithms. The dc motor in the active assistance device is powered by a replaceable battery which is expensive. To overcome this issue, solar rechargeable battery is designed using the MPPT algorithm to enhance battery durability. A comparative analysis of the replaceable and rechargeable battery will be done in the future to exhibit the proposed model's effectiveness.

Additional information

The work presented in this paper was presented in "Two Days Virtual National Meet on Nano Interface Science (NIS-2021)", Chettinad Academy of Research & Education, Chennai, India, 2021.

References

[1] G. Pfurtscheller, C. Brunner, A. Schlogl, F.H. Lopes da Silva, Mu rhythm (de) synchronisation and EEG single-trial classification of different motor imagery tasks, NeuroImage 31/1 (2006) 153-159. DOI: https://doi.org/10.1016/j.neuroimage.2005.12.003

[2] C. Neuper, G. Pfurtscheller, Post-movement synchronisation of beta rhythms in the EEG over the cortical foot area in man, Neuroscience Letters 216/1 (1996) 17-20. DOI: https://doi.org/10.1016/0304-3940(96)12991-8

[3] Y. Hashimoto, J. Ushiba, EEG-based classification of imaginary left and right foot movements using beta rebound, Clinical Neurophysiology 124/11 (2013) 2153-2160.
DOI: https://doi.org/10.1016/j.clinph.2013.05.006

[4] D. Hamacher, F. Herold, P. Wiegel, D. Hamacher, L. Schega, Brain activity during walking: a systematic review, Neuroscience and Biobehavioral Reviews 57 (2015) 310-327.
DOI: https://doi.org/10.1016/j.neubiorev.2015.08.002

[5] M. Wieser, J. Haefeli, L. Bütler, L. Jancke, R. Riener, S. Koeneke, Temporal and spatial patterns of cortical activation during assisted lower limb movement, Experimental Brain Research 203 (2010) 181-191. DOI: https://doi.org/10.1007/s00221-010-2223-5

[6] D.T. Jeffery, J.A. Norton, F.D. Roy, M.A. Gorassini, Effects of transcranial direct current stimulation on the excitability of the leg motor cortex, Experimental Brain Research 182 (2007) 281-287.
DOI: https://doi.org/10.1007/s00221-007-1093-y

[7] J. Decety, Do imagined and executed actions share the same neural substrate?, Cognitive Brain Research 3/2 (1996) 87-93. DOI: https://doi.org/10.1016/0926-6410(95)00033-X

[8] M. Lotze, U. Halsband, Motor imagery, Journal of Physiology-Paris 99/4-6 (2006) 386-395. DOI: https://doi.org/10.1016/j.jphysparis.2006.03.012

[9] G. Rizzolatti, L. Craighero, The mirror-neuron system, Annual Review of Neuroscience 27 (2004) 169-192. DOI:
https://doi.org/10.1146/annurev.neuro.27.070203.144230

[10] J. Decety, J. Grezes, The power of simulation: imagining one's own and other's behavior, Brain Research 1079/1 (2006) 4-14.
DOI: https://doi.org/10.1016/j.brainres.2005.12.115

[11] J.B. Nielsen, A. Butorina, A. Prokofyev, M. Nazarova, V. Litvak, T. Stroganova, The mirror illusion induces high gamma oscillations in the absence of movement, NeuroImage 103 (2014) 181-191.
DOI: https://doi.org/10.1016/j.neuroimage.2014.09.024

[12] G. Pfurtscheller, C. Neuper, Motor imagery activates primary sensorimotor area in humans, Neuroscience Letters 239/2-3 (1997) 65-68.
DOI: https://doi.org/10.1016/S0304-3940(97)00889-6

[13] J.T. Gwin, K. Gramann, S. Makeig, D.P. Ferris, Electrocortical activity is coupled to gait cycle phase during treadmill walking, NeuroImage 54/2 (2011) 1289-1296.
DOI: https://doi.org/10.1016/j.neuroimage.2010.08.066

[14] S. Jain, K. Gourab, S. Schindler-Ivens, B.D. Schmit, EEG during pedaling: evidence for cortical control of locomotor tasks, Clinical Neurophysiology 124/2 (2013) 379-390.
DOI: https://doi.org/10.1016/j.clinph.2012.08.021

[15] S.S. Gupta, S. Agarwal, Classification and analysis of EEG signals for imagined motor movements, Proceedings of the 2015 IEEE Workshop on Computational Intelligence: Theories, Applications and Future Directions "WCI", Kanpur, India, 2015, 1-7. DOI: https://doi.org/10.1109/WCI.2015.7495499

[16] A. Guillot, C. Collet, V.A. Nguyen, F. Malouin, C. Richards, J. Doyon, Brain activity during visual versus kinesthetic imagery: an fMRI study, Human Brain Mapping 30/7 (2009) 2157-2172.
DOI: https://doi.org/10.1002/hbm.20658

[17] C.-J. Olsson, B. Jonsson, A. Larsson, L. Nyberg, Motor representations and practice affect brain systems underlying imagery: an fMRI study of internal imagery in novices and active high jumpers, Open Neuroimaging Journal 2 (2008) 5-13.

[18] I. Constant, N. Sabourdin, The EEG signal: a window on the cortical brain activity, Paediatric Anaesthesia 22/6 (2012) 539-552.
DOI: https://doi.org/10.1111/j.1460-9592.2012.03883.x

[19] H. Yuan, B. He, Brain-computer interfaces using sensorimotor rhythms: current state and future perspectives, IEEE Transactions on Biomedical Engineering 61/5 (2014) 1425-1435.
DOI: https://doi.org/10.1109/TBME.2014.2312397

[20] J. Wagner, T. Solis-Escalante, P. Grieshofer, C. Neuper, G. Müller-Putz, R. Scherer, Level of participation in robotic-assisted treadmill walking modulates midline

sensorimotor EEG rhythms in able-bodied subjects, NeuroImage 63/3 (2012) 1203-1211. DOI: https://doi.org/10.1016/j.neuroimage.2012.08.019
[21] M. Seeber, R. Scherer, J. Wagner, T. Solis-Escalante, G.R. Muller-Putz, High and low gamma EEG oscillations in central sensorimotor areas are conversely modulated during the human gait cycle, NeuroImage 112 (2015) 318-326. DOI: https://doi.org/10.1016/j.neuroimage.2015.03.045
[22] ReWalk – More than Walking. Accessed on 23.12.2014, Available from: http://www.rewalk.com
[23] K.A. Strausser, T.A. Swift, A.B. Zoss, H. Kazerooni, B.C. Bennett, Mobile Exoskeleton for Spinal Cord Injury: Development and Testing, Proceedings of the ASME 2011 Dynamic Systems and Control Conference and Bath/ASME Symposium on Fluid Power and Motion Control. ASME 2011 Dynamic Systems and Control Conference and Bath/ASME Symposium on Fluid Power and Motion Control, Vol. 2. Arlington, Virginia, USA, 2011, 419-425. DOI: https://doi.org/10.1115/DSCC2011-6042
[24] K.A. Strausser, H. Kazerooni, The Development and Testing of a Human Machine Interface for a Mobile Medical Exoskeleton, Proceedings of the 2011 IEEE/RSJ International Conference on Intelligent Robots and Systems “IROS”, San Francisco, CA, USA, 2011, 4911-4916. DOI: https://doi.org/10.1109/IROS.2011.6095025
[25] H. Kawainot, S. Lee, S. Kanbe, Y. Sankai, Power Assist Method for HAL-3 using EMG-based Feedback Controller, Proceedings of the IEEE International Conference on Systems, Man and Cybernetics “SMC’03”, Washington, DC, USA, 2003, 1648-1653. DOI: https://doi.org/10.1109/ICSMC.2003.1244649
[26] C.-R. Phang, L.-W. Ko, Global cortical network distinguished motor imagination of the left and right foot, IEEE Access 8 (2020) 103734-103745. DOI: https://doi.org/10.1109/ACCESS.2020.2999133
[27] C.J. Walsh, K. Pasch, H. Herr, An Autonomous, Underactuated Exoskeleton for Load-Carrying Augmentation, Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems “IROS”, Beijing, China, 2006, 1410-1415. DOI: https://doi.org/10.1109/IROS.2006.281932
[28] C.J. Walsh, K. Endo, H. Herr, Quasi-passive Leg Exo-skeleton for Load-carrying Augmentation, International Journal of Humanoid Robotics 4/3 (2007) 487-506. DOI: https://doi.org/10.1142/S0219843607001126
[29] Y.-H. Liu, L.-F. Lin, C.-W. Chou, Y. Chang, Y.-T. Hsiao, W.-C. Hsu, Analysis of electroencephalography event-related desynchronisation and synchronisation induced by lower-limb stepping motor imagery, Journal of Medical and Biological Engineering 39 (2019) 54-69. DOI: https://doi.org/10.1007/s40846-018-0379-9
[30] M. Tariq, P.M. Trivailo, M. Simic, Classification of left and right foot kinaesthetic motor imagery using common spatial pattern, Biomedical Physics and Engineering Express 6/1 (2020) 015008. DOI: https://doi.org/10.1088/2057-1976/ab54ad
[31] P.N. Smith, K.M. Refshauge, J.M. Scarvell, Development of the Concepts of Knee Kinematics, Archives of Physical Medicine and Rehabilitation 84/12 (2003) 1895-1902. DOI: https://doi.org/10.1016/S0003-9993(03)00281-8
[32] T. Fitzsimons, Knee Disarticulation a Whirlwind Tour. Accessed on 24.11.2014, Available from: https://slideplayer.com/slide/1416810/
[33] M.P. Greene, Four Bar Linkage Knee Analysis, Orthotics and Prosthetics 37/1 (1983) 15-24.
[34] S.A. Gard, D.S. Childress, J.E. Uellendahl, The Influence of Four Bar Linkage Knees on Prosthetic Swing Phase Floor Clearance, Journal of Prosthetics and Orthotics 8/2 (1996) 34-40.
[35] M.R. Tucker, A. Moser, O. Lambercy, J. Sulzer, R. Gassert, Design of a Wearable Perturbator for Human Knee Impedance Estimation during Gait, Proceedings of the 2013 IEEE 13th International Conference on Rehabilitation Robotics “ICORR”, Bellevue, Washington, USA, 2013, 1-6. DOI: https://doi.org/10.1109/ICORR.2013.6650372
[36] C.M. Gaspar, G.A. Rousselet, C.R. Pemet, Reliability of ERP and single-trial analyses, NeuroImage 58/2 (2011) 620-629. DOI: https://doi.org/10.1016/j.neuroimage.2011.06.052
[37] S. Gudmundsson, T.P. Runarsson, S. Sigurdsson, G. Eiriksdottir, K. Johnsen, Reliability of quantitative EEG features, Clinical Neurophysiology 118/10 (2007) 2162-2171. DOI: https://doi.org/10.1016/j.clinph.2007.06.018
[38] A. Kline, C.G. Ghiroaga, D. Pittman, B. Goodyear, J. Ronsky, EEG differentiates left and right imagined Lower Limb movement, Gait and Posture 84 (2021) 148-154. DOI: https://doi.org/10.1016/j.gaitpost.2020.11.014