Journal of
Biomedical Systems & Emerging Technologies

Research Article Open Access

Method on Pattern Recognition of Various Limb Postures

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Abstract

The purpose of rehabilitation is to recover the degradation of human body strengths and flexibility caused from damaging by disease or injury. Improper posture practices in a long-term rehabilitation, however, might cause secondary injuries. To avoid these predicaments, the paper presents a machine learning algorithm for motional pattern recognition of various upper limb motions and wrist rotations. The proposed hardware scheme included single triple-axis accelerometer and a personal smart device. The accelerometer was setup on subject's wrists to detect and then record the time-dependent sequential signals, and the acquired datasets were downlinked to the personal smart devices. The information of time sequence of limb motions was then analyzed using our proposed algorithm. The main data cluster numbers were estimated using data density functional method, and locations of data centroids were then measured using the Gaussian mixture model. Thus, swing angles of the limb motions can be further analyzed using the combinational machine learning algorithm. Under the proposed experimental framework, swing angles of the limb motion and wrist rotation can be clearly measured even though the motions of subjects were unstable. Then the feedback results fed to the time sequences can assist the posture corrections. Therefore, the technique can be used for analyses of accident circumstances and then dangerous alarms. In a nutshell, the proposed framework not only provides highly plausibility and objectivity but also reinforces the commercialization.

Keywords: Pattern recognition; Limb postures; Accelerometer; Data density functional; Machine learning; Swing angle

Introduction

The origin of musculoskeletal impairment might mainly result from injury and/or disease. Chronic back pain and arthritis (includes osteoarthritis and rheumatoid arthritis) are two common musculoskeletal conditions [1-3], associated with functional degenerations caused by daily activity and sports-related injury. Joint surgery would also cause temporary musculoskeletal conditions and often lead to needs of rehabilitation and physical therapy [1]. Additionally, several known diseases, such as heart failure [4], stroke [2,5-7], Parkinson's disease [8], osteoporosis [9], and so forth, also might lead to the musculoskeletal impairment and the impacts on inconvenience of daily life and on lost personal social activities are significant [2]. In order to improve the quality of life of the subjects, the methodologies of rehabilitation and relevant skills of physical therapy are inevitably pursuing. In order to conquer these predicaments, several methodologies of rehabilitation and physical therapy have revealed fruitful performances for the purpose of recovery of muscle strength. Amount these investigations, subject's activities and locations can be detected and recorded by means of wireless sensors network [10], personal wearable devices [5,11], radar based technique [12], or robotic assistances [12-14], and so forth. To reinforce the recognition of morphological variations of human body, those acquired results would be fed into relevant dynamic-image-based techniques [6-8,12,14-16] for further human posture or gesture recognitions.

The methods of sensor-based assistance reveal merits of portable convenience, contactless frame, and low cost [5,10-11]. The human activities are detected and recorded by employing accelerometers and then acquired analog signals are analyzed using statistical estimations [5] or machine learning methods [11]. Thus the mobility and the activities of the subjects can be further studied without interventions in the duration of data collections. Additionally, the wireless sensors network can even record the detailed locations of the subjects. The minute variations of gesture or posture, however, are difficult to be detected using the proposed sensor-based assistance, thus the robotic assistances and the image-based techniques should be employed. The advantages of robotic assistance are that the gesture changes can be recorded in detail and the employed robotic aids can correctly guide the gesture motions [12-14]. Technology of virtual reality provides an alternative [6-8] for guiding correct motions of rehabilitation and can simultaneously motivate psychological emotions of subjects. However, high-budget apparatus, requirement of database, and multi-functional hardware operations might possibility reduce the acceptance from users. Therefore, the paper proposes a new avenue of approach by merging the merits from the sensor-based and the image-based techniques.

By employing single accelerometer and methods of machine learning, the article proposes a new method for motional pattern recognition of various limb postures. Single triple-axis accelerometer was set on the wrist of a subject, and time-dependent sequential signals were detected and recorded then downlinked to personal smart-phone. Data density functional (DDF) method was utilized for estimation of data cluster numbers [17], then data centroids and the corresponding boundaries were measured using Gaussian mixture model (GMM). Thus the swing angles of subject's limb motions can be further analyzed using the combinational machine learning algorithm. Eventually, the analyzed results providing from the proposed algorithm will indicate corrections of the rehabilitated motions.

Method

By considering the merits of the sensor-based technique, only one triple-axis accelerometer was employed in the study for the subject's

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Received April 05, 2018; **Accepted** May 14, 2018; **Published** March 21, 2018

Citation: Wu CJ, Haung SJ, Chen CC (2018) Method on Pattern Recognition of Various Limb Postures. J Biomed Syst Emerg Technol 5: 118.

comfortability. However, in order to improve the sensitivity and the flexibility of the proposed framework, on the contrary to the contactless approaches, the accelerometer was set on the wrist of the subjects, as shown in Figure 1A. The employed accelerometer was product by Laboratory of Translational Research, Institute of Brain Science, and National Yang-Ming University, Taiwan. As shown in Figure 1B, the critical length of entire accelerometer is only 4 centimeters and its load has 7 grams. Acquired analog time-dependent signals will be uploaded to either cloud storage or personal smart device by means of XenonBlue (Bluetooth 4.0) protocol [18], as illustrated in Figure 1C. The sampling rate is up to 50 Hz per axis. Thus, the proposed scheme of hardware may match the requirements of convenience and comfortability for the purpose of rehabilitation. Eventually, the acquired analog signals were analyzed using the proposed DDF method associated with the common machine learning method GMM.

To sense and detect the motional patterns of subject's upper limb, the accelerometer was tied on subject's left wrist in the study. As shown in Figure 2, a series of upper limb motions was investigated by detecting and recording the changes of swing angles, wherein a reference point was set to near subject's articular cavity. The series of (A), (B), (D) and (E) in Figure 2 were used to recognize the changes of swing angles from normal upper limb motions, whereas the detected analog signals from C and F were also used to compare the different motional patterns between the normal motions, error motions introduced in the normal motions, and the additional motions from wrist rotations. It is noted that the axes of accelerometer, as illustrated using cyan coordinates in Figure 1B, ideally would not be changed in the duration of limb swing for the convenience of data analysis. However, the motional patterns from error motions and wrist rotations of the subject exhibit the real circumstances in rehabilitation processes. For the purpose of rehabilitation in reality, therefore, these motions should be naturally added into the investigation of motional pattern recognitions.

Several popular statistical learning methods can be employed for the purpose of motional pattern recognitions in the duration of rehabilitation. For instance, the method of convolutional neural network (CNN) is often assigned for multi-layer data analysis, especially for the applications of two-dimensional biomedical imageries. Since the convolution estimation in learning processes is assigned as an encoder or a decoder between local information and weighting matrix, the CNN method can be used to extract the local connectivity and invariance to local transition within signals [19]. Thus CNN method can be applied to the fields of image segmentation of biomedical datasets [20], pattern recognitions of imageries [21], and so forth. In the other hand, the method of recurrent neural network (RNN) provides a route for dealing with the sequential information having some specific structural cycle connections [19]. Thus, the output sequential signals extracted using the RNN method can carry the past information embedded in the input sequential datasets [22-24]. Therefore, inspiring by the merits of these mentioned deep learning methods, the proposed algorithm was built on the foundation of local connectivity and structural cycle connections [25].

As shown in Figure 2, the common exercises in the duration of rehabilitation are mainly cycling motions. Thus, there should be some specific structural cycle connections embedded within the acquired sequential signals. Meanwhile, the features hidden in the motional patterns could be also extracted by considering the fine structure of the local information. However, the computational complexity by simultaneously employing these deep learning methods may obstruct the possibility of real-time demonstrations. Therefore, under the concepts of CNN and RNN methods, we propose a new algorithm by combining the DDF method and GMM algorithm. The algorithmic flow is illustrated in Figure 3. The DDF method provides a convenience to simultaneously measure the data locality and data connectivity by respectively considering the localized density functionals [17]:

$$t[\rho] = \frac{2\pi^2 D}{D+2} \cdot D^{2/D} \cdot \rho^{2/D} \tag{1}$$

And

$$u[\rho] = \sum_{n=1}^{N} \frac{\rho(r'_n)}{\left| r'' - r'_n \right|_{r'' \neq r'_n}} \tag{2}$$

The parameter D and N represent the dimension and length of studied system, respectively. Data probability density function (PDF), ρ, can be estimated by means of the employed GMM method or other popular PDF estimator. $\boldsymbol{r}''$s listed in Eq. (2) are feature coordinates of observation and $\mathbf{r}_n'$s are data points that sampled by GMM algorithm. Thus, the most probable data boundaries and cluster number can be respectively measured by:

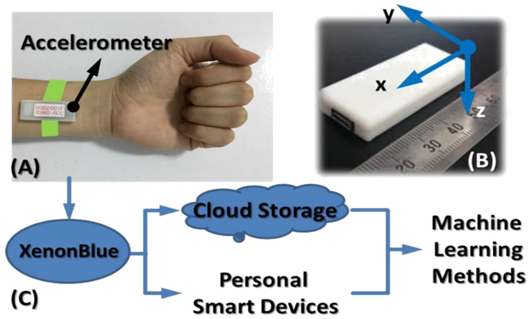

Figure 1: The appearance of employed accelerometer and the experimental scheme. The accelerometer was tied on subject's wrist as shown in (A). Length and weight of the accelerometer were 4 centimeters and 7 grams, respectively. The detecting analog signals were uplinked to cloud storage or personal device using XenonBlue protocol [18] as shown in (C).

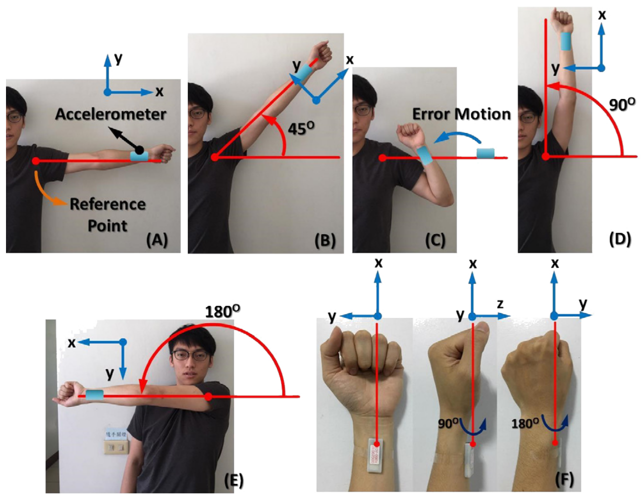

Figure 2: Proposed upper limb motions and wrist rotational motions in the experimental scheme. Several combinational scenarios can be used for the investigations of motional pattern recognitions: procedures of 45°-, 90°-, and 180°-swing-angle motions of upper limb swing motions and/or wrist rotational motions. Error motions shown in (c) can also be introduced into those motioned procedures.

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$$L[\rho] = \gamma^2 t[\rho] - \gamma u[\rho] \tag{3}$$

and

$$HF = \frac{\gamma^2 \langle t[\rho] \rangle + \gamma \langle u[\rho] \rangle}{N} \tag{4}$$

where γ represents an adaptive factor that can be uniquely and automatically determined by the properties of studied system:

$$\gamma = \frac{1 \langle u[\rho] \rangle}{2 \langle t[\rho] \rangle} \tag{5}$$

Consequently, the adaptive scaling factor is simply the ratio of global expectations between the localized functionals $u[\rho]$ and $t[\rho]$.

Analyses and Results

In order to investigate hidden pattern features embedded in various swing motions, several different scenarios were adopted to analyze the cluster boundaries from their owning analog sequential signals. Figure 4 illustrates the acquired three-dimensional analog sequential spectra detected and recorded by the proposed framework. The procedures of steps (A)-(B) and (A)-(B)-(D) illustrated in Figure 2 were used to imitate the normal swing motions with swing angles of 45° and 90°, and the corresponding analog sequential signals have been respectively shown in Figure 4A and B. Because of the rotation axes in these adopted procedures were both in z-directions, the acquired analog sequential signals in z-direction would not be used for cluster segmentations. It should be emphasized that there are three color belts marked in those analog sequential signal spectra. These three different colour regions were segmented using the proposed machine learning methods. The green region indicates the final state of swing motions, in which the upper limb of the subject has been swung with a specific swing angle. The white region bounded by green and blue belts shows a transient region that the upper limb of the subject moved from the initial to the final states. The blue region indicates the initial state in which the upper limb of the subject was just at the circumstance as shown in Figure 2A. Each swing angle was measured from initial to final states with respect to the reference point.

The corresponding cluster segmentations of the studied cases in Figure 4A and B are shown as in Figure 5A and B, respectively. Since the swing axis was set in z-direction in the normal motion studies (Figures 1B and 2), the analog sequential signals both in x- and y-directions were mapped into a physical space, as shown in Figure 5A and B, for further analyses using the proposed machine learning methods. Additionally, due to the location of the reference point only can be estimated in

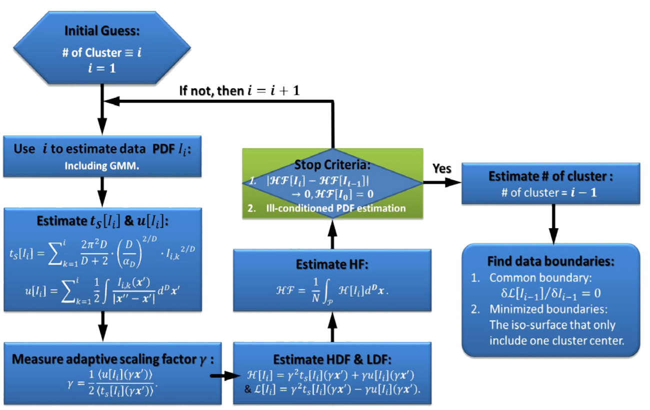

Figure 3: Detailed execution of the proposed combinational machine learning algorithm.

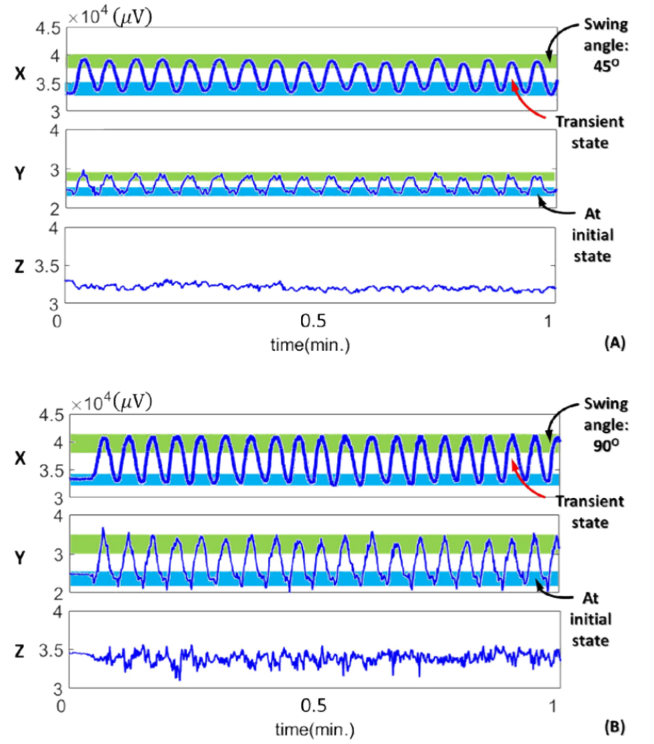

Figure 4: The analog sequential signals of (A) 45°- and (B) 90°-swing-angle procedures of upper limb swing motions. The different color regions respectively represent the final state (green belt), transient state (white belt), and initial state (blue belt).

the case of 90°-swing-angle, the transform map shown in Figure 5B was first used for cluster segmentation. In the analyses of the cluster segmentation, the data PDFs in the physical space were estimated using GMM algorithm and the results were then fed into DDF method to measure the most probable cluster number. Detailed execution of the proposed algorithm is illustrated in Figure 3. Once the cluster number has been estimated, each centroid of the clusters can be then estimated as well as the corresponding data variations. Thus, the corresponding swing motional states, as shown in Figure 4, can be well arranged using the locations of the centroids and their variation respectively in x- and y-directions. In the case of 90° swing angle, the centroids of initial and final states were respectively at (33mV, 24mV) and (41mV, 33 mV), thus the most probable location of the reference point in the physical space was about (33mV, 33mV), as shown in the insertion of Figure 5B.

The location of the reference point was then used in the case of 45° swing angle, as illustrate in Figure 5A, to estimate the most probable swing angle. In that case, the centroids of initial and final states were respectively at (34mV, 24mV) and (39mV, 27mV). The swing angle in the case, however, exhibited a offset with a value of 21°, as shown in the insertion of Figure 5A. The reason of the exist of undesired offset can be deduced to that the mismatch of reference point and the inaccuracy of swing angle estimations. The latter should be significantly crucial in the studied case. The subject has adequate reference postures in the cases of 90°- and even 180° swing angle, as shown in Figure 2D and E, but they can only find the final state in the case of 45°-swing-angle by means of their experience. Thus, there would be a significant value of offset in this studied case.

For further mining the pattern features, the procedure of steps (A)-(B)-(D)-(E) and (F) were then respectively used to imitate the normal upper limb and wrist swing motions with angles of 180°. The corresponding analyzed results are respectively shown in Figure 5C-E. The reference point estimated in the case of 90°-swing-angle was also used to be that in the case of 180° in upper limb motions, and the estimated centroids in the case were respectively (34mV, 24mV) and (33mV, 42mV). It is obvious that the transform map as shown in Figure 5C reveals a semi-circle as expected. Similar procedure was used to estimate the most probable location of the reference point in the cases of wrist swing motions. As shown in Figure 5D, the centroids of initial and final states were respectively at (32mV, 25mV) and (24mV, 34mV), thus the most probable location of reference point should be at (32mV, 34mV). The result was then fed into the case of 180° swing angle of wrist motions to estimate the swing angle, and the corresponding transform map shown in Figure 5E illustrated as a semi-circle as expected.

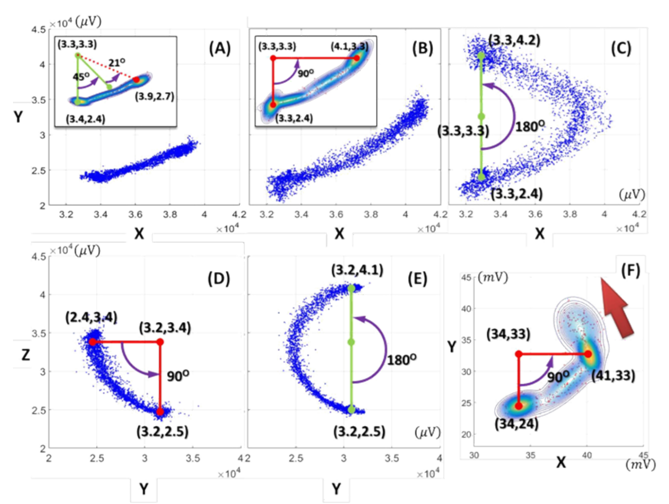

Figure 5: The transform maps of (A) 45°-, (B) 90°-, and (C) 180°- swing-angle procedures of upper limb swing motions. (D) and (E) are respectively the transform maps of 90°- and 180°- swing-angle procedures of wrist rotations. (F) exhibits the transform map of error motions. There is an obvious date scattered distribution in the y-direction, as indicated by the arrow.

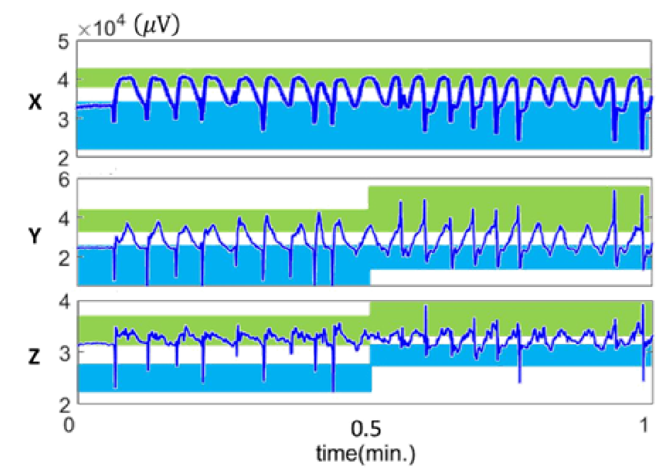

Figure 6: The analog sequential signals of arbitrary swing motions with 90°-swing-angle procedure of limb motions, 180°-swing-angle procedure of wrist rotations, and arbitrary error motions. In the first 30 seconds, the subject sedulously swung upward faster than the that in the normal motions, whereas he sedulously swung downward faster in the later 30 seconds. The different color regions exhibit the segmentation results.

To investigate the pattern features hidden in the error motions, the procedure of step (A)-(B)-(C)-(D) was artificially added into the study of motional pattern recognitions. Figure 5F shows the transform map with a corresponding cluster segmentation of the employed procedure. By comparing the result to the original normal procedure shown in Figure 5B, an obvious scattered expansion of data points occurred in the region of final states in y-direction, as shown by the arrow in Figure 5F. As indicated in Figure 2C, the most moving direction of the employed error motion was roughly in the y-axis of the accelerometer. Thus, the adopted error motion can easily cause peaks in the analog sequential signals of y-direction. Fortunately, the estimated locations of centroids in the transform map associated with the error motions were similar with that in the normal motions. Therefore, the segmentation procedure built in the normal motions is still feasible to the motional pattern recognitions with error motions. Figure 6 shows a series of arbitrary upper limb swing motions with 90° swing angle procedure, including wrist rotations with 180° swing angle. In the first 30 seconds, the subject sedulously swung upward faster than that of the normal motions, whereas he sedulously swung downward faster in the later 30 seconds. The segmentation results are as illustrated with the different color belts and show the feasibility of the proposed method.

Conclusion

A method for dealing with the problem of motional pattern recognition of various limb postures is presented. For the comfortability and the feasibility in the duration of rehabilitation, only single accelerometer was employed in the motional sensing and detections, in which the data streams were downlinked using XenonBlue protocol. In order to reduce the computational complexity from the combinational deep learning methods, the data density functional method and Gaussian mixture model were employed for the cluster segmentation. Several combinational motions have been detected and analyzed using the proposed hardware and machine learning algorithms. Normal upper limb swing motions and pure wrist rotating motions reveal the same motional features as shown in their corresponding transform maps. The map of error motions exhibits an obvious scattering data distribution in some specific direction, and still reveals similar motional features as that in the normal studied cases. The most probable swing angles in each employed procedure can be estimated by simultaneously defining the reference point and measuring the cluster centroids in the transform maps. Furthermore, these data features can be fed back to original analog sequential signals for the time-dependent segmentations. Therefore, the outcomes that have been analyzed using the proposed method can directly indicate the user performances and accuracy in the duration of rehabilitation using the time sequential spectra. Alarms of accident or dangerous circumstances providing by the proposed method make it possible for other further applications.

Acknowledgement

We would like to acknowledge the support from Veterans General Hospitals and University System of Taiwan Joint Research Program (VGHUST107-G4-2-2). We also thank Prof. Terry BJ. Kuo in Laboratory of Translational Research, Institute of Brain Science, National Yang-Ming University, Taiwan., for providing the high performance accelerometers and the Xenon Blue protocol.

References

1. Kristensen J, Franklyn-Miller A (2012) Resistance training in musculoskeletal rehabilitation: a systematic review. Br J Sports Med 46: 719-726.
2. Ma VY, Chan L, Carruthers KJ (2014) Incidence, Prevalence, Costs, and Impact on Disability of Common Conditions Requiring Rehabilitation in the United States: Stroke, Spinal Cord Injury, Traumatic Brain Injury, Multiple Sclerosis, Osteoarthritis, Rheumatoid Arthritis, Limb Loss, and Back Pain. Archives of Physical Medicine and Rehabilitation 95: 986-995.

3. Reginster JY (2002) The prevalence and burden of arthritis. Rheumatology 41: 3-6.

4. Sagar VA, Davies EJ, Briscoe S, Coats AJS, Dalal HM, et al. (2015) Exercise-based rehabilitation for heart failure: systematic review and meta-analysis. Open Heart 2: e000163.

5. Capela1 NA, Lemaire1 ED, Baddour N, Rudolf M, Goljar N, et al. (2016) Evaluation of a smartphone human activity recognition application with able-bodied and stroke participants. J Neuroeng Rehabil 13: 10.

6. Shapi'i A, Bahari NN, Arshad H, Zin NAM, Mahayuddin ZR (2015) Rehabilitation Exercise Game Model for Post-stroke using Microsoft Kinect Camera. 2nd International Conference on Biomedical Engineering (ICoBE).

7. Sin H, Lee G (2013) Additional virtual reality training using Xbox Kinect in stroke survivors with hemiplegia. Am J Phys Med Rehabil 92: 871-880.

8. Rose T, Nam CS, Chen KB (2018) Immersion of virtual reality for rehabilitation – Review. Appl Ergon 69: 153-161.

9. Pfeifer M, Sinaki M, Geusens P, Boonen S, Preisinger E (2004) Musculoskeletal Rehabilitation in Osteoporosis: A Review. J Bone Miner Res 19: 1208-1214.

10. Chu HC, Lee TH, Chang LH, Li CJ (2013) Modeling of Location Estimation for Object Tracking in WSN. J Appl Math 2013: 10.

11. Olguin DO, Pentland AS (2006) Human Activity Recognition: Accuracy across Common Locations for Wearable Sensors. IEEE 10th International Symposium on Wearable Computers.

12. Asokan A, Pothen AJ, Vijayaraj RK (2016) ARMatron - A wearable gesture recognition glove, For control of robotic devices in disaster management and human Rehabilitation. International Conference on Robotics and Automation for Humanitarian Applications (RAHA).

13. Polygerinos P, Wang Z, Galloway KC, Wooda RJ, Walsh CJ (2014) Soft robotic glove for combined assistance and at-home rehabilitation. Rob Auton Syst 73: 135-143.

14. Zhang F, Wang X, Yang Y, Fu Y, Wang S (2015) A Human-machine Interface Software Based on Android System for Hand Rehabilitation Robot. IEEE International Conference on Information and Automation.

15. Ke SR, Thuc HLU, Lee YJ, Hwang JN, Yoo JH, et al. (2013) A Review on Video-Based Human Activity Recognition Comp 2: 88-131.

16. Chiu CY, Wu CC, Wu YC, Wu MY, Chao SP, et al. (2006) Retrieval and constraint-based human posture reconstruction from a single image. J Vis Commun Image R 17: 892-915.

17. Chen CC, Juan HH, Tsai MY, Lu HHS (2018) Unsupervised Learning and Pattern Recognition of Biological Data Structures with Density Functional Theory and Machine Learning. Scientific Reports 8: 10 pages.

18. Hsieh IT, Chen CY, Lin YC, Li JY, Lai CT, et al. (2012) Application of cloud computing in physical activity research. IEEE sensors.

19. LeCun Y, Bengio Y, Hinton G (2015) Deep learning. Nature 521: 436-444.

20. Ning F, Delhomme D, LeCun Y, Piano F, Bottou L, et al. (2005) Toward automatic phenotyping of developing embryos from videos. IEEE Trans Image Process 14: 1360-1371.

21. Milletari F, Navab N, Ahmadi SA (2016) V-Net: Fully Convolutional Neural Networks for Volumetric Medical Image Segmentation. Fourth International Conference on 3D Vision (3DV).

22. Petrosian A, Prokhorov D, Homan R, Dasheiff R, Wunsch D (2000) Recurrent neural network based prediction of epileptic seizures in intra-and extracranial EEG 30: 201-218.

23. Kiros R, Zhu Y, Salakhutdinov R, Zemel RS, Torralba A, et al. (2015) Skip-thought vectors. Adv Neural Inf Process Syst 3276-3284.

24. Luong MT, Pham H, Manning CD (2015) Effective approaches to attention-based neural machine translation. arXiv: 1508.04025.

25. Ngiam J, Khosla A, Kim M, Nam J, Lee H, et al. (2011) Multimodal deep learning. 28th International Conference on International Conference on Machine Learning 689-696.