Affordable eRehabilitation Monitoring Platform

Majid Janidarmian, Atena Roshan Fekr, Katarzyna Radecka, Zeljko Zilic
Department of Electrical and Computer Engineering, McGill University, Montreal, Canada
{majid.janidarmian, atena.roshanfekr}@mail.mcgill.ca, {katarzyna.radecka, zeljko.zilic}@mcgill.ca

***Abstract*— People who have suffered a motor function disability need to practice appropriate rehabilitation treatments. Motion sensors such as accelerometer and gyroscope in fact are increasingly being embedded in wearable computing devices and can provide a quantitative measure of the human movement for assessment. In this paper, we present a low-cost eRehabilitation platform employing efficient algorithms to provide high accuracy feedback. The provided online rehabilitation service is removing the traditional face-to-face services by using cutting-edge mobile and sensors technologies. It allows doctors to give the patients qualitative feedback and track their progress over time. This system considers the variability in movement speed and accurate angle measurements. To this end, the golden standard pattern collected under physiotherapist supervision is compared with the patient's exercises based on Dynamic Time Warping (DTW) algorithm. The experiments were conducted in a laboratory with different subjects, and results confirm that low-cost MEMS technology achieves an acceptable accuracy level in real-time rehabilitation monitoring. We also address different encountered issues and discuss how to efficiently tackle with them.**

Keywords—rehabilitation, motion sensors, calibration, sensor fusion, Bluetooh Low Energy, orientation, qualitative feedback

I. Introduction

Many new intelligent, context-aware pervasive sensing platforms are emerged due to recent advances in wearable computing and wireless sensor technology [1]. The on-body detachable sensor devices enable the remote monitoring of vital signals, the early detection of critical conditions and the remote control of certain medical treatments [2]. They generally are widely employed for assessing and recognizing activities especially for standing, walking, running, jumping or cycling activities [3]. Most human-activity recognitions achieve high accuracies employing hidden Markov model (HMM), principle component analysis (PCA), support vector machines (SVM), linear discriminant analysis (LDA), artificial neural networks (ANN) and dynamic time warping (DTW) [4].

In rehabilitation point of view, physiotherapists prescribe movement exercises to help the patients improve or recover muscle strength, endurance and range of motion. They typically observe the patient while they perform the exercises to ensure that such exercises are well performed. Therefore, there is a need for advice regarding effectiveness and safety of exercise programs, but it is very expensive to provide over extended periods of time. Even if financial factors are not a barrier, insufficient time to visit a hospital, residing far from the hospital or personal privacy preferences are other traditional rehabilitation issues [5]. Therefore, more and more interest has been drawn toward the development of home based rehabilitation schemes [6]. There are some approaches in literature which discuss different aspects of this filed. Zhou et al introduced a novel tracking strategy for human upper limb motion in which there were six joint variables to be considered [7]. They exploited an extended Kalman filter that fused the data from the on-board accelerometers and gyroscopes due to depressing noise. The technique proposed in [8] can automatically capture the number of repetitions and provide feedback on the performance of individual resistance repetitions using smartphones. They show that how smartphones without additional equipment can be leveraged to capture resistance training data and provide a reliable feedback.

In [9], a kinematics-based approach is developed to estimate human leg posture and velocity from wearable sensors during the performance of typical physiotherapy and training exercises. Inertial measurement units are attached to patients undergoing physiotherapy. The authors in [10] proposed a method to recognize upper body postures. They evaluate the system for a set of gym exercises and show that the system is able to support resistance training exercises. Melzi *et al* used accelerometer sensor to capture the movement stream for supervision of resistance training while a PC is used to analyze the data and to provide feedback on the quality of exercising [11].

In this paper, we present how to design a mobile platform which offers low-cost, real-time and accurate therapies for people living with the effects of disabilities. We also benefit from Bluetooth smart technology and backend cloud storage to achieve a power-aware and responsive remote rehabilitation service. The general view of this system is shown in Fig. 1.

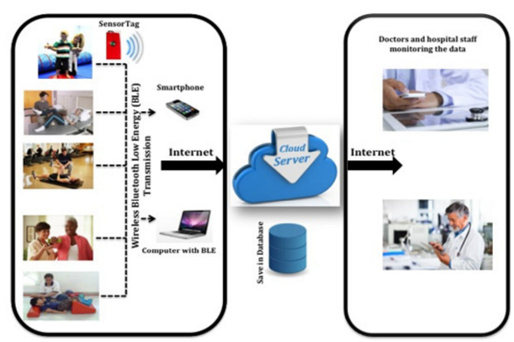


Fig. 1 General view of the rehabilitation monitoring system

II. System Overview

A. *Sensory Node and Data Filtering*

In our system we used SensorTag from Texas Instruments as our sensor node and it costs 25$. SensorTag is the first Bluetooth low energy development kit on the market focusing on wireless sensor applications and design has passed FCC(US), ETSI(Europe), IC(Canada) and ARIB (Japan) RF certifications [12]. It includes 6 low-power MEMS sensors (TMP006 infrared temperature, SHT21 digital humidity, T5400

2014 IEEE Canada International Humanitarian Technology Conference - (IHTC)
978-1-4799-3996-1/14/$31.00 ©2014 IEEE

barometric pressure, KXTJ9 tri-axis accelerometer, IMU-3000 tri-axis gyroscope and MAG3110 3D magnetic sensors). It is equipped with the Bluetooth Smart radio powered by a single CR2032 coin cell battery and Texas Instrument also released its SDK for developers. The sensor and the battery supply are presented in the figure below.

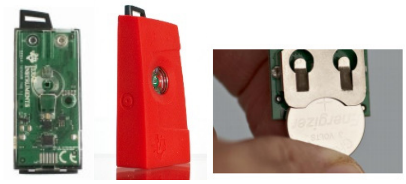


Fig. 2. SensorTag [12]

The samples received from motion sensors carry noise and applying denoising algorithms is essential to facilitate accurate assessment of human movement in body sensor networks (BSN). In our design, the signals are smoothed with a seven point frame third order Savitzky-Golay (SG) smoothing filter since it does not delay the signal and is able to preserve features such as local minima and maxima.

B. Mobile Application and Cloud Database

In the presented platform, the sensors' data are transferred wirelessly to the smartphone/PC based on Bluetooth Low Energy (BLE) technology. The received sensors data are then stored in backend cloud storage in order to real-time and post-exercise analysis. There are some well-known scalable, highly secured and available backend servers which can be employed in such a monitoring system. Therefore, it enables the remote monitoring of motions, and control of certain medical treatments. We utilized different algorithms to analyze the signals and provide rich feedback on performance accuracy. A baseline prototype has been developed running on an iPhone and obtained very promising results on a dataset delivered by different participants. It actually advances knowledge concerning the best rehabilitation services delivery at a distance, and reduces the cost of trained professionals' time.

III. Signal Similarities

Rehabilitation exercises should be prescribed and supervised to get favorable effects on muscular or joint problems. These exercises generally are recommended at a frequency of a couple of time per week or day. It is very important for patients to follow exact instructions since otherwise it may cause problems such as over-extension.

In this system, the clients are asked to perform rehabilitation exercises under supervision of professional therapists to record a golden standard profile. The training patterns are then compared with the reference ones while the patients are performing the prescribed exercises wherever they are, regardless of their proximity to the doctors. Through quality feedback on performance accuracy, patients are informed how well they are executing the exercises. In the following sections we will discuss different design considerations and show how pattern matching algorithms, signal processing and data analysis retain qualitative information and help professionals to remotely assist the patients.

A. Signals Synchronization

Signal synchronization aids to align two signals in time and make the patterns overlap in their equivalent places. Sometimes in multi-sensor system, the signals received from different nodes actually have different lengths and sampling rates. In order to calculating the differences between two signals, they should have identical sampling rates. To this end, we first use rational fraction estimation and then resample data by an anti-aliasing low pass FIR filter during the resampling process. In order to find the best starting match point, the maximum value of their cross-correlation implies the time leads or lags between two signals. By following this method, we can align two signals and delete unnecessary exercise sensory data from the beginning and end of each action.

B. Dynamic Time Warping

Dynamic Time Warping (DTW) has been originally used to compare different speech patterns and also extensively studied in the clustering algorithms [13]. It is very applicable for measuring similarity between two patterns and for automatically coping with time deformations and different speeds associated with time-dependent data [14].

We employ DTW to identify all subsequences within a continuous sensor data stream that are similar to a given reference pattern.

Here is the formal definition of classical DTW which is mostly derived from [14].

Assume that we have two time sequences, X and Y, of length N and M, respectively, where

$$X := (x_1, x_2, \dots, x_N), \qquad N \in \mathbb{N}$$
$$Y := (y_1, y_2, \dots, y_M), \qquad M \in \mathbb{N}$$

An *(N,M)*-warping path is a sequence $P = (p_1, p_2, \dots, p_l)$ with $p_l = (n_l, m_l) \in [1{:}N] \times [1{:}M]$ for $l \in [1{:}L]$ which assigns x_{n_l} the element of X to $y_{n_l}$the element of Y and should satisfy the following conditions:

(i) Boundary condition:

$$p_1 = (1,1) \text{ and } p_l = (N, M)$$

(ii) Monotonicity condition:

$$n_1 \leq n_2 \leq \cdots n_L \text{and } m_1 \leq m_2 \leq \cdots m_L$$

(iii) Step size condition:

$$p_{l+1} - p_l \in \{(1,0), (0,1), (1,1)\} \text{ for } l \in [1{:}L-1].$$

The cost of a warping path *p* between X and Y is defined as:

$$c_p(X, Y) := \sum_{l=1}^{L} c\left(x_{n_l}, y_{m_l}\right)$$

which $c(x_n, y_m)$ is the Manhattan distance (absolute value of the difference) between $x_n \, and \, y_m$. A warping path actually defines an alignment between two sequences X and Y. The alignment is optimal in the sense that a cumulative distance measure between the aligned samples is minimized [15]. It means we are required to find the optimal warping path (p^*) between X and Y which has the minimum total cost among all possible warping paths. Therefore, the matching cost

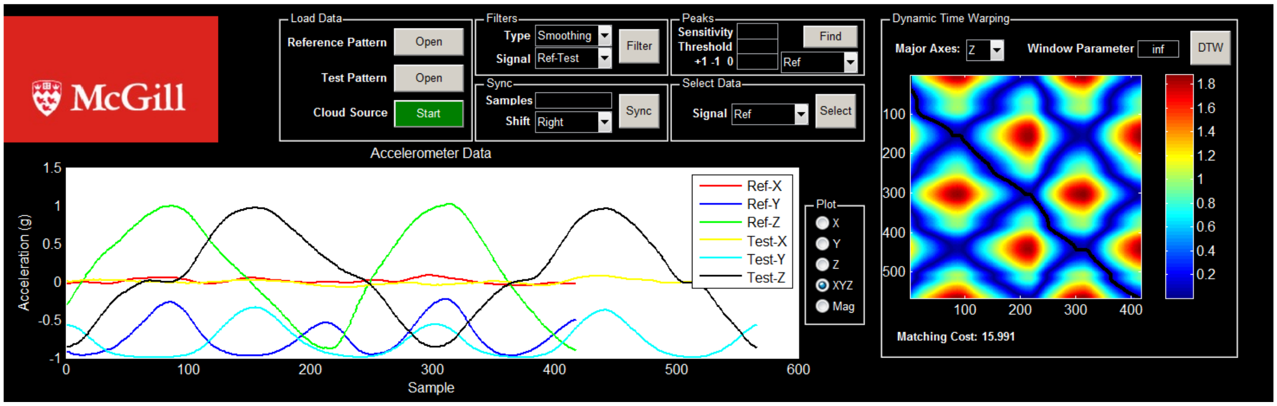


Fig. 3. A part of the developed MATLAB GUI

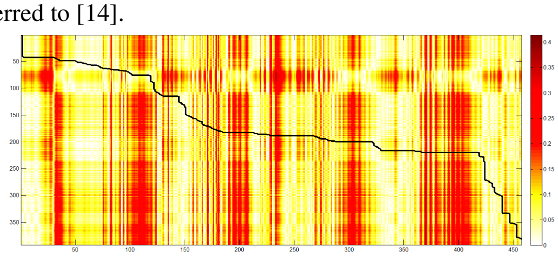
considered as an indicator of the similarity of two patterns is then defined as:

$$Matching\ Cost = DTW(X,Y) = c_{p^*}(X,Y)$$
$$= min\{c_p(X,Y) \mid p\ is\ an\ (N,M) - warping\ path\}$$

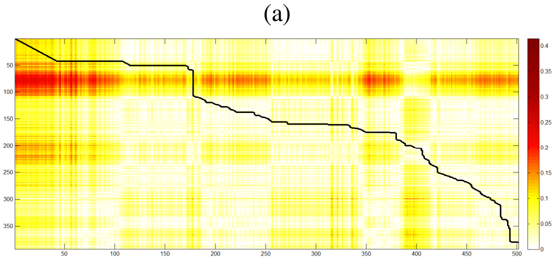
To determine an optimal path p^*, the exhaustive search leads to an exponential computational complexity; however, an $O(NM)$ algorithm based on dynamic programming is utilized using accumulated cost matrix. This matrix is computed as:

$$D(n,m) := \begin{cases} 0 & if\ n = m = 0 \\ \sum_{k=1}^{n} c(x_k, y_1) & if\ m = 1 \\ \sum_{k=1}^{m} c(x_1, y_k) & if\ n = 1 \\ \min\{D(n-1,m-1), D(n-1,m), D(n,m-1)\} & \\ +c(x_n, y_m) & ,otherwise \end{cases}$$

and $D(N,M) = Matching\ Cost = DTW(X,Y)$. For further details and thorough explanation of DTW, the reader is referred to [14].



(a)



(b)

Fig. 4 Warping path to compare the reference signal R with test signals T1 (a) and T2(b) – The colorbar represents the absolute difference between them

Through an example, you can see how DTW works. We recorded a reference pattern (R) derived from accelerometer values of forearm motion. Then, we performed an exercise trying to simulate the reference activity ($\boldsymbol{T_1}$). In the next round, we did not execute it very well ($\boldsymbol{T_2}$) to see the differences. The results are shown in the Fig. 4, and as can be found out, the matching costs of signal R with signal $\boldsymbol{T_1}$ and $\boldsymbol{T_2}$ are 13.89 and 28.41, respectively. Hence, DTW is a very effective method that calculates an optimal match between two given sequences. A part of developed GUI in MATLAB for the algorithms mentioned up to now is shown in the Fig. 3.

IV. Issues in Accuracy performance

A. *Sensors Calibration*

Due to inherent deficiency or aging problems in cyber-biological systems, sensors calibration is suggested. Calibration, which is defined as the process of mapping raw sensor readings into corrected values, can be used to compensate the systematic offset and gain [16]. Since accelerometer is the main sensor for e-rehabilitation system, we need to improve its readouts accuracy. Generally, calibration of sensors requires experience and special accurate tools; however, a straightforward method to calibrate an accelerometer is performed at 6 stationary positions [17]. We need to collect a few seconds of accelerometer raw data at each position. Then the least square method is applied to obtain the 12 accelerometer calibration parameters (Fig. 5). The calibration procedure is simple, and needs to be executed once. The calibration procedure can be briefly explained as:

$$[A_x, A_y, A_z] = [A_x\ A_y A_z\ 1].\begin{bmatrix} ACC_{11}\ ACC_{21} ACC_{31} \\ ACC_{12}\ ACC_{22} ACC_{32} \\ ACC_{13}\ ACC_{23} ACC_{33} \\ ACC_{10}\ ACC_{20} ACC_{30} \end{bmatrix}$$

$$Y = w.X$$

Where:

- Matrix X is the 12 calibration parameters that is determined as below:

$$X = [w^T.w]^{-1}.w^T.Y$$

- Matrix w is accelerator sensor raw data collected at 6 stationary positions
- Matrix Y is the known normalized Earth gravity vector.

The details of this method are explained in [17]. After sensor calibration, the presented platform provides very high accuracy e.g. in yielding the tilt angles for steady positions; the errors are within 0.5 degree.

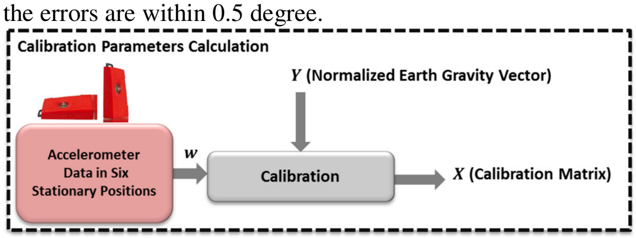


Fig. 5 Finding matrix "x" for accelerometer calibration (It is an offline procedure and executed once)

B. *Sensor Fusion*

Over the past few years, we have witnessed vast application for sensing and monitoring devices in cyber-physical systems motivated by their dropping cost, size and power consumption [18]. Consequently, it is demanded to deliver accurate sensor readouts especially for real-time health monitoring systems and be tolerant to multiple faults. Multi-sensor data fusion is an efficient approach which combines data from multiple sensors to achieve more accurate readouts compared to the case where a single sensor is used [19]. In our platform, we apply an optimal homogenous linear data fusion technique introduced in [20] when we have multiple accelerometer or gyroscope sensors in the same position. It uses convex optimization scheme to maximize accuracy in the average case, while keeping the precision high in the worst-case of sensor measurements. It significantly improves mean-square-error (MSE) and precision compared to the other methods regardless of the number of faulty sensors.

C. *Orientation Algorithm*

In e-rehabilitation platform, the accurate measurement of orientation is an important factor to provide the patient with corrective feedback. For a non-moving object, the pitch and roll angles can be obtained with 3-axis accelerometer. This method is also very useful in calibrating accelerometer sensor to improve the readouts accuracy as we discussed earlier. But, the orientation is not valid if the sensory node moves due to consequence of a force and so the calculated orientation is not accurate anymore. Gyroscope that gives angular rate around the 3 axes cannot be used alone as it suffers from drifting values. Hyde *et al* [21] have implemented frequency domain filters to favour accelerometer and the integrated gyroscope measurements of orientations at low and high angular velocities, respectively. Many modern techniques [22][23] and commercial inertial orientation sensors focus on algorithms which ameliorate the computational load and parameter tuning burdens associated with conventional Kalman-based approaches. However, in [24], a novel orientation algorithm for IMU (Inertial Measurement Unit) and AHRS (Attitude and Heading Reference Systems) was presented offering significant reduction in the computation load relative to a Gauss-Newton method. It also permits gains to be defined based on observable system characteristics and eliminates the predefined direction of magnetic field. We use this approach in our platform because it not only achieves similar levels of performance at different frequencies but also the provided accuracy (e.g. static error $< 2°$, dynamic error $< 7°$ with sampling rate 10Hz) is sufficient for human motion applications. It actually covers the diversity in signal characteristics, both rotational and linear movements.

V. Experimental Results

In this section, we describe our experiments for four rehabilitation exercises referenced from [25]. Considering all issues and algorithms discussed earlier, this approach is validated through a user study consisting of eight subjects performing arm, knee and hip rehabilitation.

To summarize it up, we want to remotely analyze rehabilitation exercises. For each exercise, there is a reference pattern recorded under supervision of experts. Sensors values are wirelessly sent to a smartphone (in our case, iPhone) with Bluetooth Low Energy (BLE) protocol, and then stored in the cloud storage. Any desktop or phone application which is connected to the cloud database can sync with data in a near real-time. The application performs denoising, calibration and sensor fusion algorithms on the training signal; and then provides the angle pattern deriving from orientation algorithm.

In order to easily distinguish the count for each action, which is conducted by the subjects, they are asked to remain stationary for a few seconds after each complete action. For each determined exercise, the angle patterns of reference and training signals are synchronized to each other, and DTW algorithm starts finding their matching cost. If the matching cost is reasonable, angles and duration analysis are run to provide qualitative visual feedback on exercising performance.

Two angle patterns of reference and training signals can be investigated in terms of time and angle analysis using the horizontal and vertical peak to peak intervals. As shown in Fig. 6, the training pattern has a smaller duration compared to reference one which means the patient should be advised to perform his movement slower. And this figure also demonstrates how the patients are able to refine their motions referring to vertical peak to peak intervals. The workflow of the system is shown in Fig. 7.

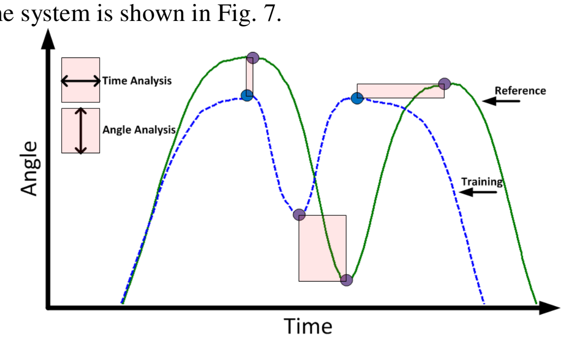


Fig. 6. Comparision of referecne and training angle patterns

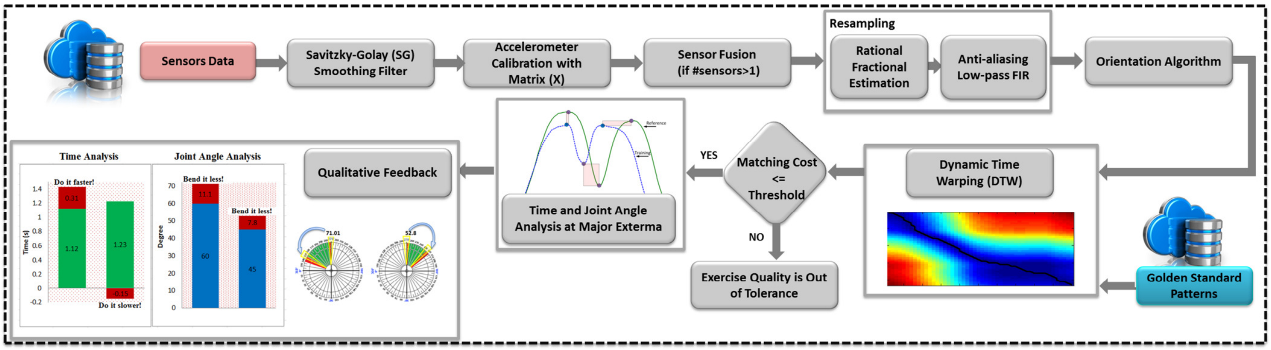


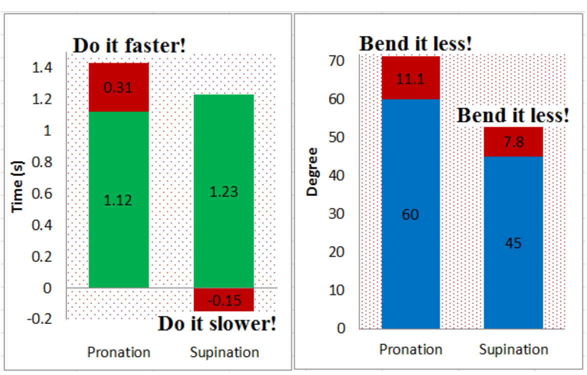
Fig. 7. Workflow of the system

Here are the results for a subject in four different exercises while considering the range of movements.

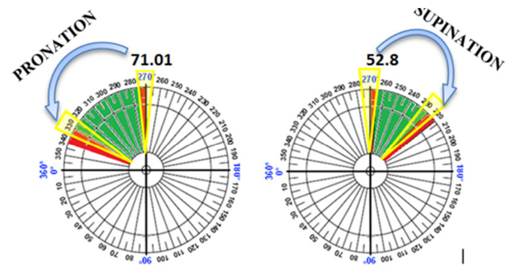
A. *Motion of the Forearm*

To measure the movement of the forearm the SensorTag is attached on the palm. The wrist first rotates 45° and then rotates in opposite for 60°. The subject's movements are shown in Fig. 8 (a). The forearms should be at the side of the body and the elbow flexes 90°. This motion can be simply expressed as: Pronation (turning the forearm left) = 60° and Supination (turning the forearm right) = 45°. Fig. 8 (b) demonstrates how the subject can refine their movements in terms of speed and final joint angles. The circles shown in Fig. 8 (c) depict the average range of angles in the motion for five consecutive exercises. The transparent yellow area in this figure shows the allowed range of error for the exercise, which is set to ±5° in our experiments. Note that it was selected arbitrarily to show that some activities might be beyond the allowed range of angles. In real practice, this value can be selected by a therapist based on the requirements of a given treatment. The red sections represent the error between reference and measured angles. The bold number above the circle shows the average measured angle for the pronation and supination.

(a)



(b)



(c)

Fig. 8. (a) Forearm motion, (b) feedback in terms of speed and movement quality, (c) average range of angles in the forearm motion (pronation: 0°→60° and supination 0°→45°),

B. *Motion of the Arm at the Shoulder*

Forward flexion is the forward upward motion of the arm in the anterior sagittal plane of the body from zero to 180° (we set it here to 120°). The opposite motion to the zero position maybe termed "depression" of the arm, Fig. 10 [25]. To gather the motion data, in this exercise the SensorTag is mounted on the arm. As described before, the prescribed angle for this activity is 120°; however, the imprecisions of the subject's movements are in average 2.76° which means that she could properly manage to follow the desired angle. In the circle, the measured angles of motion are presented in green, while the red are refers to the exercise execution error w.r.t. required value.

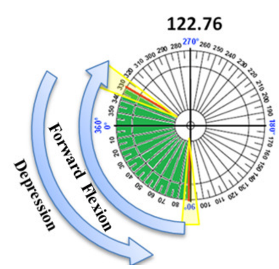


Fig. 10. Average range of angles in the arm motion

C. *Motion of the Elbow*

In this scenario, the elbow flexes from 0°→30°, 0°→45°, 0°→60° and 0°→90°. The subject followed the elbow movements as shown in Fig. 9.

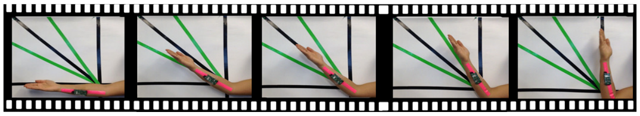


Fig. 9. Elbow motions

The sensor node has been mounted on the forearm to record sensors readouts. The differences between the prescribed angles (30°, 45°, 60° and 90°) and the joint angles measured from subject's elbow motions in average are: 3.17°, 3.53°, 3.54° and 5.48°, respectively.

D. Motion of the Hip

In this case, the SensorTag is attached on the thigh. In the first part of this movement the leg should be at 0° and then moved to 120° bended from the knee. The motion in flexion is recorded from 0°→120°. The imprecision of the subject's flexion is in average 10.52° (Fig. 11). Therefore, the subject needs to correct her movement and follow the prescribed hip flexion.

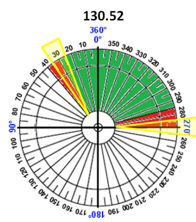


Fig. 11. Average range of angles in the hip motion

VI. Conclusion

In this paper, we discussed about different challenges in designing of a rehabilitation monitoring platform. Its main objective is to achieve a prescribed level of physical and psychological functioning while keeping affordability and accessibility up. The analysis of the data during the experiments illustrate that our system is capable of precise tracking different rehabilitation exercises, and can surpass the human estimation of the activity quality. The presented cost-effective system for measuring and improving patient outcomes in the home could be further evidence of the consequent demand for technology to seamlessly work. The prominent benefits of such systems are those of cost, convenience, patient comfort and quality of service. The presented system potentially lifts the patient's motivation up towards treatment while accurately tracks the patient's real condition and improvement at low cost.

References

[1] S. Thiemjarus, "A Device-Orientation Independent Method for Activity Recognition," Body Sensor Networks (BSN), 2010 International Conference on , pp.19-23, 2010.

[2] ETSI, "Machine to Machine Communications (M2M): Use Cases of M2M Applications for eHealth," Draft TR 102732 v0.4.1, Mar. 2011.

[3] I. Kale, J. Lee, R. Lotfian, and R. Jafari, "Impact of sensor misplacement on dynamic time warping based human activity recognition using wearable computers" Proceedings of the conference on Wireless Health (WH '12), pp.1-8, 2012.

[4] P. Turaga , R. Chellappa , V. S. Subrahmanian and O. Udrea, Machine Recognition of Human Activities: A Survey, IEEE Transactions on Circuits and Systems for Video Technology, v.18 n.11, p.1473-1488, November 2008.

[5] M. Kranz, A. Möller, N. Hammerla, S. Diewald, T. Plötz, P. Olivier, and L. Roalter, "The mobile fitness coach: Towards individualized skill assessment using personalized mobile devices" Pervasive and Mobile Computing, pp. 203—215, 2013.

[6] H. Zhou and H. Hu, "Human motion tracking for rehabilitation-a survey," Biomedical Signal Processing and Control, vol. 3, no. 1, pp. 1 - 18, 2008.

[7] H. Zhou, and H. Hu, "Inertial motion tracking of human arm movements in stroke rehabilitation", Proceedings of IEEE International Conference on Mechatronics and Automation, Canada, pp. pp.1306,1311 2005.

[8] I. Pernek, K. Hummel and P. Kokol, "Exercise repetition detection for resistance training based on smartphones" Personal Ubiquitous Comput., 17(4), 771–782, 2013.

[9] J. Lin and D. Kulic, "Human pose recovery using wireless inertial measurement units", PHYSIOLOGICAL MEASUREMENT, Institute of Physics and Engineering in Medicine, pp. 2099-2115, 2012.

[10] C. Mattmann, O. Amft, H. Harms, G. Troster and F. Clemens, "Recognizing upper body postures using textile strain sensors" 11th IEEE international symposium on wearable computers, ISWC 2007, pp 1–8, 2007

[11] S. Melzi, L. Borsani and M. Cesana, "The virtual trainer: supervising movements through a wearable wireless sensor network" 6th IEEE communications society conference on sensor and AdHoc communications and networks, SECON workshops, pp 1–3, 2009.

[12] www.ti.com/sensortag

[13] I. Mahmood, "Speech Recognition using Dynamic Time Warping,", IEEE International Conference on on Advances in Space Technologies, pp.74-79, 2008.

[14] M. Muller, "Information Retrieval for Music and Motio", book series Database Management & Information Retrieval, Springer publisher, XVI, 318 p, 2007.

[15] K.-H. Chang, M. Y. Chen, and J. Canny, "Tracking free-weight exercises" Proceedings of the 9th international conference on Ubiquitous computing, UbiComp '07, pp. 19–37, 2007.

[16] O. Sarbishei, B. Nahill, A. Roshan Fekr, M. Janidarmian, K. Radecka, Z. Zilic and B. Karajica, "An efficient fault-tolerant sensor fusion algorithm for accelerometers," IEEE International Conference on Body Sensor Networks (BSN), pp.1-6, 2013.

[17] Tilt measurement using a low-g 3-axis accelerometer, Application note AN3182, STMicroelectronics, 2010.

[18] G. Z. Yang, Body Sensor Networks. London, U.K.: Springer-Verlag, 2006.

[19] Z. Zilic and K. Radecka, "Fault tolerant glucose sensor readout and recalibration," Proceedings of Wireless Health, WH 2011, 2011.

[20] O. Sarbishei, M. Janidarmian, A. R. Fekr, B. Nahill, Z. Zilic and K. Radecka,"Multi-sensory Integration Dependability" , Chapter 18 in BookTechnologies for Smart Sensors and Sensor Fusion, edited by K. Yallup and K. Iniewski, pp. 319-335, 2013.

[21] R. A. Hyde, L. P. Ketteringham, S. A. Neild, and R. J. S. Jones, "Estimation of upper-limb orientation based on accelerometer and gyroscope measurements," vol. 55, pp. 746–754, 2008.

[22] R. Mahony, T. Hamel, and J.-M. Pflimlin, "Nonlinear complementary filters on the special orthogonal group," IEEE Transactions on Automatic Control, vol. 53, pp. 1203-1218, 2008.

[23] P. Martin and E. Salan, "Design and implementation of a low-cost observer-based attitude and heading reference system," Control Engineering Practice, Special Issue on Aerial Robotics, vol. 18, no. 7, pp. 712 - 722, 2010.

[24] S.O.H. Madgwick, A. Harrison and R. Vaidyanathan, "Estimation of IMU and MARG orientation using a gradient descent algorithm," IEEE International Conference on Rehabilitation Robotics (ICORR), pp.1,7, 2011.

[25] American Academy of Orthopaedic Surgeons, "METHOD OF MEASURING AND RECORDING", Chicago, Illinois, US