Design of Augmented Reality 3D Rehabilitation Application using an Inertial Measurement Unit

A Pilot Study

G. Kontadakis, D. Chasiouras, D. Proimaki[1]

***Abstract*—This work introduces an innovative gamified 3D rehabilitation application intended for patients that underwent Total Knee Replacement surgery, in collaboration with the Chania General Hospital in Crete, Greece. The application uses a custom-made, portable sensor node consisting of an Inertial Measurement Unit (IMU) attached on a lower limb in order to capture its orientation in space. The aim is to increase patient engagement during physiotherapy by motivating them to participate in a 3D game using as input the proposed sensor node attached on the lower limb and provide feedback via a gamified experience offering rewards. The game projects a graphical image of the patient's limb motion as part of a 3D computer graphics scene. It then classifies the exercise performed during physiotherapy as accurately performed or not and increases patient compliance via a reward system. Our goal is to reduce the need for the physical presence of a physiotherapist by aiding the efficient performance of exercise sessions at home. In order to instruct the classifier and maximize success rate, machine learning methods are applied. The custom-made, low-cost sensor node put together consists of a Raspberry Pi model A+ and the MPU-9150 nine axis module. The latter is similar to the ones used in many commercial wearable devices. The application can run on both PC and a smartphone in order to increase functionality. The system side presented here is currently being implemented using entirely the Java programming language with the help of the JMonkeyEngine game engine and the Weka data mining tool.**

***Index Terms*—Binary classifier, IMU, Machine Learning, Virtual Rehabilitation, Serious Game, TKR**

I. INTRODUCTION

THE aim of this project is to design and implement a custom-made portable, mobile and low cost 3D rehabilitation application intended for patients that underwent Total Knee Replacement (TKR) [5]. The first weeks following knee surgery are crucial so that the range of movement (ROM) of the operated knee is deemed fully operational. If the patient does not perform adequately the exercises appointed by the physiotherapist during this recovery period, an otherwise technically accurate operation might result in poor functional outcome leading to reduced quality of life. The aim of our gamified application is to motivate the patient to exercise efficiently by providing feedback while the physiotherapy exercises are performed. Initially, a randomly selected control group performs the exercises under physiotherapist supervision who marks them as accurately performed or not. In order for the application to obtain such input and provide adequate feedback, an Inertial Measurement Unit (IMU) node is utilized worn by the patient recognizing limb rotation and acceleration. The challenging research issue addressed in this work is whether the proposed application classifies the exercises reliably utilizing just a single sensor node. Previous work has put forward a proposed classifier using Machine Learning techniques, achieving 83% accuracy [1]. The goal of this work is to train a classifier achieving higher accuracy than in previous work. Providing gamified feedback to the patient at home using widely available smart phones or tablets minimizes the need for expensive physiotherapy under supervision, resulting in more engaging and accessible rehabilitation. This paper focuses on the implementation of the software framework which will support the sensor attached to patients' limb while undergoing physiotherapy treatment.

II. EXISTING TECHNOLOGIES

Several approaches listed below have been employed to track limb motion of different precision, cost and complexity [2],[7]:

Optical systems. They use visual data captured by one or more cameras to triangulate the 3D position of a set of points detected. Some of them can reach a high precision, i.e, of a few millimeters, but also have very high cost. A cheaper solution of lower precision, i.e, of a few centimeters is represented by Microsoft Kinect, which uses only one RGB camera and an infrared depth sensor. However, it suffers from lack of portability due to its cumbersome setup.

Exo-skeletons are rigid structures of jointed, straight metal or plastic rods linked together with potentiometers or encoders that articulate at the joints of the body. These systems offer real-time, high precision acquisition and have the advantage of not being influenced by external factors, such as visual occlusion, quality and the number of cameras. Their main

[1]submitted for review: 09/02/2015

G. Kontadakis, Graduate Student in the Department of Electronic and Computer Engineering of the Technical University of Crete (e-mail: gkontadakis@isc.tuc.gr).

D. Chasiouras, Trauma & Orthopaedics Resident at Chania General Hospital, Greece (e-mail: dr.chasiouras@yahoo.com).

D. Proimaki, Physiotherapist at Chania General Hospital, Greece (e-mail: despiproimou@gmail.com).

disadvantage is the movement limitation imposed by the mechanical constraints of the exoskeleton structures.

*Electrogoniometer systems. Electrogoniometers are w*idely used to measure human joint movements. Their advantage over conventional potentiometric goniometers is that they adapt better to body parts and are not sensitive to misalignments. Their major weakness is their high cost.

Magnetic systems. They calculate the position and orientation of a magnetic sensor probe. Their main disadvantage is that they are susceptible to electromagnetic interference from metal objects in the environment or electromagnetic sources.

Inertial systems. IMUs are based on miniature inertial sensors (accelerometer and gyroscopes), biomechanical models and sensor fusion algorithms. They can also include a magnetic sensor, although these are susceptible to electromagnetic noise. Benefits of using inertial systems include low cost, small dimensions, portability and large capture areas. Disadvantages include lower positional accuracy and positional drift.

III. IMU FUNCTIONALITY

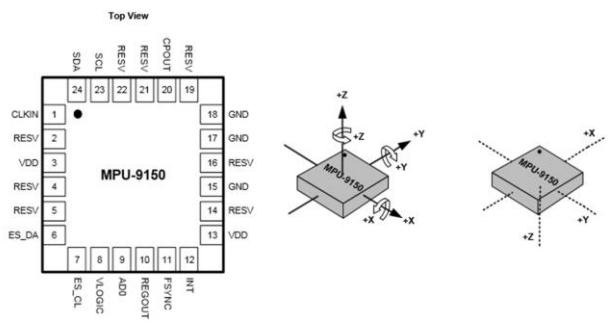

Figure 1. MPU-9150 schematic from manual. Left, IMU pins. Middle, accelerometer and gyroscope orientation axes. Right, magnetometer axes.

IMUs provide the leading technology used in smartphones and wearable devices in order to measure rotational and translational movements. For this purpose, it combines a number of sensors:

3-axis Accelerometer. The accelerometer measures inertial force caused by gravity and acceleration. It can accurately measure rotation, however, it is susceptible to noise caused by rapid changes of acceleration. Moreover, an accelerometer measures orientation on 2 axes. The gravitational force measured will not be affected by z-axis rotation, only by x,y axes rotation. In order to be able to capture orientation along the z-axis, a magnetometer (compass) is used complementary to the accelerometer.

3-axis Gyroscope. The gyroscope does not measure any angle directly. It measures the rate of change of any angle at a specified frequency, e.g. 100 Hz. This makes it suitable for short- term observations and fast rotational signal changes. In relation to long-term observations, it is susceptible to drift errors. Drifting occurs when the gyroscope output is integrated. Measurement errors are then also integrated resulting to large amount of cumulative errors. When measurements are not sampled in exact intervals according to a specified frequency this phenomenon is more apparent.

3-axis Magnetometer. The magnetometer measures the earth's magnetic field. It is used in conjunction to the gyroscope sensor in order to capture rotation around z-axis. Because it measures electromagnetic forces, it is susceptible to electrostatic interference present in a home environment which may affect the readings received.

Temperature sensor. Temperature sensors measure environmental temperature changes. The temperature also affects the measurements collected by the accelerometer, the gyroscope and the magnetometer.

In order to get improved rotational estimation measurements, it is a common practice [2] to apply a filtering method combining an accelerometer and a gyroscope and if necessary magnetometer readings. In this project, the IMU MPU-9150 is used (Figure 1). The utilized sensor node contains the sensors mentioned above.

A. *Filtering Method*

In order to obtain accurate orientation measurements and minimize cumulative errors we need to combine the accelerometer long term measurements (low pass filtering) with the gyroscope accurate short term measurements in order to capture fast changes in rotation (high pass filter). As a result, the accelerometer measurements of orientation are used at low angular velocities and the integrated gyroscope measurements at high angular velocities. Such a simple approach may only be effective under limited operating conditions. Certain algorithms in research literature employ a complementary filter process, using adaptive parameters [3],[4]. This algorithm structure has been shown to provide a good trade-off between effective performance and computational expense, when compared to Kalman filtering techniques that achieve optimal results in the expense of high computational load.

IV. APPLICATION FUNCTIONALITY

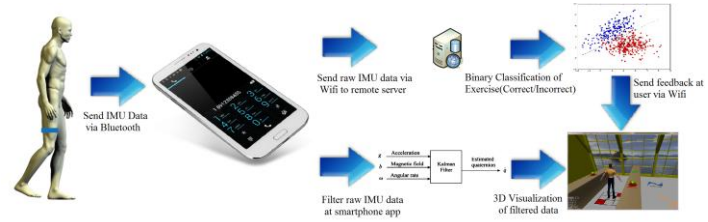

Figure 2. Application Procedure.

A. *Application Procedure Example*

The end functionality of the proposed application is shown in Figure 2 and described in detail below.

Initially, a training session including patients has taken place which drove the classifier design. The IMU is fitted on the patient at a specified limb location depending on the exercise performed. The session starts with the patient in a neutral pose ready to perform one of the predetermined exercises. The raw data collected from the IMU is sent via Bluetooth to a mobile device or personal computer. The application computes an orientation with the use of a filtering method. Real-time visualization on a mobile platform or personal computer offers feedback in the form of a 3D game presented to the patient. At the same time, the raw and/or filtered data are transmitted via Wi-Fi at a remote server. The server applies the designed classifier to the current data and decides whether the exercise was accurately performed. This delayed classifier feedback is then sent to the end user displayed on a mobile device or PC in a readable form translated to a 3D visualization, after the end of the motion. The procedure is then concluded and the subject can perform another or the same exercise again. At this point the overall performance of the system can be evaluated by the end users.

B. *Gamification Feedback*

The main goal of the application is to improve compliance to the physiotherapy protocol, increase patient engagement, monitor physiological conditions and provide feedback using a reward process via a gamified experience. This is achieved using the following methods:

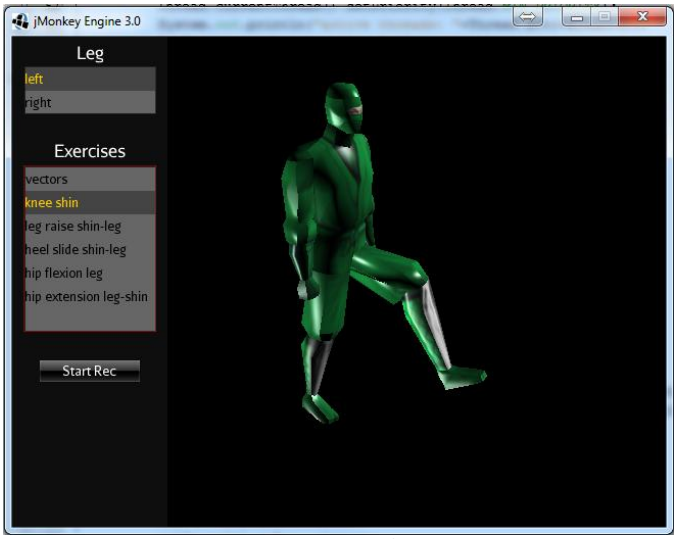

Figure 3. Training Application Real-time feedback example on the knee flexion exercise.

Real-time IMU feedback. Raw data from the IMU are filtered and limb orientation is determined. By collecting this data, the proposed framework visualizes in real-time and in 3D an approximation of the user's motion. For example, during a knee extension exercise, the patient can actually see a virtual character extending and flexing his knee (Figure 3). In this context, a user engages in a serious game of a specific objective, for instance, the patient is instructed to try and kick a ball or lead a ball out of a small maze with his knee (Figure 4). The serious game will be designed so as to motivate the user. For example, the visual character could be visualized as a bird and based on the orientation motion of the limb, the bird may try to fly. Ideally, at least one mini-game is to be designed for each exercise specified by the physiotherapist. The scope of this project involves the examination of the different kind of mini-games that can be implemented for rehabilitation exercises commonly performed after TKR surgery. These exercises are briefly described in Table 1.

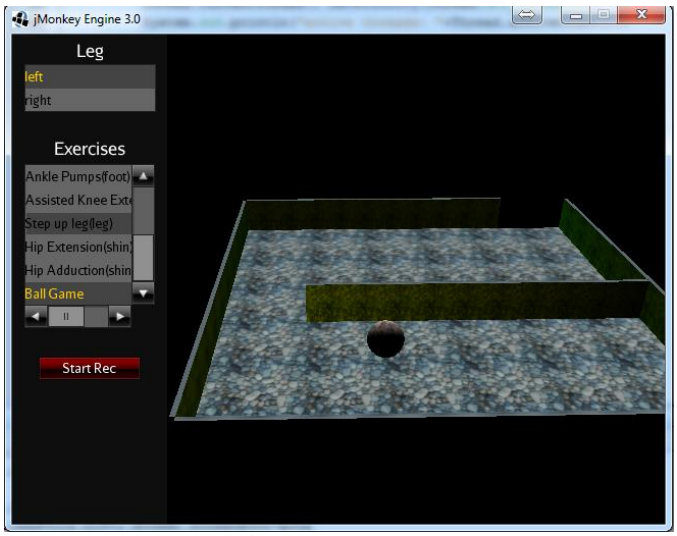

Figure 4. Ball Maze Game for Knee Extension. The patient can control the ball by moving his shin in order to get it out of the maze.

Delayed Classifier feedback. The raw data of the IMU are inserted in the classifier. The classifier decides whether the exercise has been performed accurately. The appropriate feedback provided by the classifier is sent to the user. If the exercise was classified as accurately performed, the player is awarded, e.g. by increasing a score attribute or by playing an appropriate animation. If the exercise was classified as inaccurately performed, then the application informs the user of the correct movement, e.g. by providing a limb movement animation and encourages the patient to try again. The classifier can run either locally on the PC or smartphone, or on a remote server. In either case, the feedback will appear after a certain delay of a few seconds depending on classifier complexity, processing speed and bandwidth in the case of a remote server classifier. The local classifier benefits of a smaller delay depending on processing speed of the CPU/GPU. The remote classifier can have the benefit of additional online feedback by the physiotherapist as an extension of the current application.

Exercise	Sensor Placement	Description
Knee Extension	Shin	From sitting position leg is extended, then lowered back to starting position.
Straight Leg Raise	Shin	From lying on back position leg is lifted and then slowly lowered back to starting position.
Heel Slide	Shin	From lying on back position the heel is slowly moved up and then slowly moved down to starting position.
Lying Kicks	Shin	From lying on back position an object is inserted under the knee thus raising it. Then the leg is raised and lowered back again.
Ankle Pumps	Foot	From lying on back position an object is inserted under the shank raising the whole leg. Then the foot only is flexed and set loose to its anatomical position.

Table 1. Common rehabilitation exercises for TKR studied in this project.

V. CLASSIFIER DESIGN

There exists an increasing number of works that employ IMU nodes for evaluation of limb rehabilitation exercises [1],[8],[9]. Previous work achieved promising results indicating that the number of IMUs employed does not differentiate classification results (3, 2 and 1 IMUs were tested [1]). Moreover, it has been shown that the classification of variant exercises reached success rates of 83%. These results drive the further investigation of the classification problem using a single IMU ensuring maximum portability in conjunction with potential higher success rates. It is a challenging research problem to manage to train a classifier that achieves higher percentage of success under certain conditions. These conditions include constant room temperature and correct positioning of the sensor. In order to address this research challenge, machine learning methods are employed such as Relevance Vector Machines (RVMs) which are probabilistic basis models. The trained RVM utilizes fewer basis functions than the corresponding Support Vector Machine (SVM) model and typically has superior test performance [6].

A. *Training the Classifier*

Having briefly discussed the layout of the application, it is worth summarizing the training procedure. The exercises in question are selected by the physiotherapists based on the American Academy of Orthopaedic Surgeons TKR exercise guide [5]. The physiotherapists also supervise each exercise in order to determine whether it was performed in a compliant manner during the training session. The sensor is worn by the subject on the appropriate limb location. The first exercise is performed a number of times. The physiotherapist evaluates the exercise result. A binary evaluation would indicate if an exercise is successful or unsuccessful under the specified criteria. The raw data of the IMU for each exercise are saved on a database. The data collected will eventually end up at the remote server or local machine (PC or smartphone) that will be used to train the classifier. The subject proceeds to the next exercise in the same manner. When sufficient data are collected, the same procedure is repeated for the next subject. When all users have completed the procedure, the data gathered can be used to train and test the classifier e.g. via cross-validation. In order to instruct the classifier, we use a random group of healthy adults of diverse ages and sexes. The training procedure takes place at the Chania General Hospital under the supervision of a physiotherapist.

B. *Testing the Classifier*

The initial formal testing of the application and therefore the classifier, on patients after TKR surgery will be conducted in a similar manner at the Chania General Hospital under the supervision of a physiotherapist. Note that factors such as room temperature should remain constant in order to obtain optimal results since temperature variations affects IMU measurements. The data gathered from the testing procedure can be later used as training data to further improve our classifier results by adding diversity to the population sample. It is important to design a generalized classifier that can avoid overfitting.

VI. IMPLEMENTATION

Figure 5. Prototype node.

A. *Node Hardware Setup*

An initial prototype node can be seen in Figure 5. The research contribution of this work is not the actual design of the node's hardware configuration but the complete software framework and application that employs the node communicating feedback to the patient. Therefore, an important factor for the node setup described below is its simplicity. The readings received by the IMU are independent of the hardware setup. This applies to the accelerometer and gyroscope readings. The magnetometer readings cannot be used in this hardware configuration due to the electrostatic interference caused by Raspberry Pi A+ switching regulators and the 4 AAA batteries. This configuration however provides 2 axes of rotation which is adequate in the majority of simple rehabilitation exercises and applications. The current project setup can be used by any wearable device that employs an accelerometer and gyroscope. Having observed that, the components of the node and their functionality are briefly discussed.

A *Raspberry Pi model A+* is a credit card sized computer that runs Raspbian (Linux Based kernel). It includes a pin header of 26 pins used for connections with all sorts of hardware peripherals, in our case an IMU. The IMU model used in the current work is *MPU-9150*. It contains an accelerometer, a gyroscope, a magnetometer and a temperature sensor. It is connected to Raspberry Pi and sends the raw data captured signifying rotational motion. The connection to Raspberry Pi is achieved via the I2C protocol. This protocol employs the use of 4 pin connections: VCC, GND, SDA and SCL. The IMU pins are simply connected to the appropriate Raspberry Pi pins that implement the I2C protocol. A *Bluetooth Dongle* is used to send the raw data received from the node to our application that runs on a PC or smartphone. The dongle is connected to the single usb port of the Raspberry Pi model A+. A *4 AAA Battery Pack* is also employed. The node will be attached on the patient's limb during the training/testing phases. Therefore, a considerable amount of battery autonomy for our node is necessary. By employing 4 AAA fully recharged 1100 mAh batteries, the node can send data for 7 hours and 40 minutes on full capacity.

B. Node software setup

The Raspberry Pi node utilizes a variety of programming languages. Java is selected for the proposed application mostly due to its platform independent characteristics and the compatibility with the JMonkeyEngine 3 (JME3) game engine. The external libraries used were the *Pi4j* library, which provides a friendly object-oriented I/O API and implementation libraries for Java Programmers to access the full I/O capabilities via the Java programming language. This way the raw data from the IMU are transferred to Raspberry Pi. Moreover, the *Bluecove* library has been employed which is a Java library for Bluetooth A compiled version of bluecove for ARM architecture is employed. ARM is the architecture used for Raspberry Pi and the leading architecture for smartphones.

This program simply receives the raw data from the IMU and sends them via Bluetooth to a PC, laptop, or smartphone. Specifically, the node acts as a server to incoming Bluetooth connections. When a connection is received, it sets up the IMU, e.g. the gyroscope is sampled at 100 Hz. A received connection means the application is running on the end user. Then the accelerometer, gyroscope and temperature data are collected and sent via the bluetooth connection to the application at a rate of 100 Hz. This procedure continues until the user exits the application, or the battery depletes.

C. Application Software setup

In order to visualize the IMU readings received we used the JME3 game engine. JME3 is an open source cross-platform Java OpenGL Game Engine. It has very low minimum requirements that allow it to run fast on outdated PCs or smartphones. Even though it runs based on minimum OpenGL 2.0, it can operate on reduced functionality based on OpenGL 1.1. The IMU readings are received on the client side and the user chooses a mini-game to perform that corresponds to the appropriate exercise. Then the feedback is received as described above and the exercise is labeled as correct or incorrect. The framework used for the Machine Learning analysis is Weka, an open source data mining software written in Java containing tools for data pre-processing and classification, enabling benchmarking of different techniques.

VII. CONCLUSIONS

Wearable technologies over the past years have been emerging for wide use in everyday activities. The need is arising, mostly for applications that exploit wearable sensors in order to improve quality of life. The current framework explores this need by introducing a virtual rehabilitation application on patients that have undergone TKR surgery. This application engages the patient to perform the recovery exercises accurately through a gamified 3D experience minimizing physiotherapist supervision. A 3D mini-game for each exercise appointed by the physiotherapist is being implemented. This framework can run on android smartphones with the use of a single sensor node maximizing portability and ease of use. Machine Learning methods are being tested in order to perform binary classification of exercises and improve feedback results. Through this feedback accurate patient exercise and compliance can be achieved by succeeding each mini-game objective. Further investigation can extend binary into multiclass classification enabling the identification of the exact error in patient limb motion. Also, further testing is needed in order for the application to support online physiotherapist feedback and online training of the classifier.

ACKNOWLEDGMENT

G. Kontadakis Author thanks Chania General Hospital for approving this project and Associate Professor in the Department of Electronic and Computer Engineering of the Technical University of Crete K. Mania for her valuable feedback.

REFERENCES

[1] GIGGINS, Oonagh M.; SWEENEY, Kevin T.; CAULFIELD, Brian. Rehabilitation exercise assessment using inertial sensors: a cross-sectional analytical study. *Journal of neuroengineering and rehabilitation*, 2014, 11.1: 158.

[2] BUONOCUNTO, Pasquale; MARINONI, Mauro; SANT'ANNA, Scuola Superiore. Tracking limbs motion using a wireless network of inertial measurement units. 2014.

[3] BACHMANN, Eric R., et al. Inertial and magnetic posture tracking for inserting humans into networked virtual environments. In: *Proceedings of the ACM symposium on Virtual reality software and technology*. ACM, 2001. p. 9-16.

[4] MAHONY, Robert; HAMEL, Tarek; PFLIMLIN, Jean-Michel. Nonlinear complementary filters on the special orthogonal group. *Automatic Control, IEEE Transactions on*, 2008, 53.5: 1203-1218.

[5] CONVERY, F. Richard; BEBER, Carol A. Total knee arthroplasty: indications, evaluation and postoperative management. *Clinical orthopaedics and related research*, 1973, 94: 42-49.

[6] TIPPING, Michael. *Relevance vector machine*. U.S. Patent No 6,633,857, 2003.

[7] WANG, Po T., et al. A durable, low-cost electrogoniometer for dynamic measurement of joint trajectories. Medical engineering & physics, 2011, 33.5: 546-552.

[8] LEE, K., et al. A pilot study of activity recognition on rehabilitation exercise of frozen shoulder using wireless inertial sensor node. In: *Medical Information and Communication Technology (ISMICT), 2013 7th International Symposium on*. IEEE, 2013. p. 117-120.

[9] GIGGINS, Oonagh; KELLY, Daniel; CAULFIELD, Brian. Evaluating rehabilitation exercise performance using a single inertial measurement unit. In: *Proceedings of the 7th International Conference on Pervasive Computing Technologies for Healthcare*. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2013. p. 49-56.