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Gamified platform for rehabilitation after total knee replacement surgery employing low cost and portable inertial measurement sensor node

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Abstract

This paper introduces an innovative gamified rehabilitation platform comprising of a mobile game and a custom sensor placed on the knee, intended for patients that have undergone Total Knee Replacement surgery, in collaboration with the General Hospital in Chania. Initial testing of the system is conducted in the Hospital Orthopaedic Clinic, in collaboration with Orthopeadic Surgeons and Physiotherapists. The application uses a single custom-made, light, portable and low-cost sensor node consisting of an Inertial Measurement Unit (IMU) attached on a lower limb in order to capture its orientation in space in real-time, while the patient is completing a physiotherapy protocol. The aim is to increase patient engagement during physiotherapy by motivating the user to participate in a game. The proposed sensor node attached on the lower limb provides input to the gamified experience displayed on an Android mobile device, offering feedback to the patient in relation to whether the performed exercises were accurately conducted. A classification algorithm is proposed that automatically classifies an exercise in real-time as correct or incorrect, according to physiotherapists' set criteria. 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 any location, e.g. at home, indoors and outdoors by just utilizing a light sensor and an Android device. Initial testing of the application in the Chania's General Hospital Orthopaedic Clinic, Greece, indicates that patient engagement is enhanced in most cases, even when elderly patients are concerned.

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1 Introduction

The term 'Serious' applied to games denotes the application of gaming technologies and playful design strategies to domains of society and culture that are traditionally not associated with entertainment such as the medical domain. What sets Serious Games (SGs) apart from entertainment games is their focus on intentional learning outcomes which are measurable promoting sustained changes in the attitude and performance of individuals. SG academic research, in combination with several successful practical applications, promoted the 'serious' use of games to the forefront of the agendas of diverse fields. SGs have been successfully employed to promote transformation of processes and protocols to education, as well as practical training and medical activities [23, 33]. Among diverse areas, research has shown that SGs are effectively enhancing motivation as well as efficiency of rehabilitation training [24, 35]. Research challenges that are still prominent in this area include accuracy of training performance, accuracy of motion capture when sensors attached to patients' body are involved, efficient feedback to the doctor in clinical settings as well as to the patient at home or in any location, portability of the training environment and implementation of medical and physiotherapy protocols in SG training environments which are proven to be equally, if not more efficient than traditional rehabilitation methods [19]. Portability is most often restricted to either the home or clinical environment because of motion capture and other associated equipment.

The work presented in this paper puts forward the design and implementation of a custom-made ultra-portable and low cost rehabilitation application intended for patients that have undergone Total Knee Replacement (TKR) [7], using only an Android mobile device and a small sensor placed on the patient's limb to track movement (Fig. 1).

2 Motivation

The knee is the largest joint in the body. Healthy knees are essential in order to perform most everyday activities. Knee components should work in harmony. Disease or injury can disrupt this harmony, resulting in pain, muscle weakness and reduced function. When the compartments of the knee are damaged, a total knee prosthesis may be necessary. The main cause of need for a total knee prosthesis is Osteoarthritis [28]. There are external risk factors that can cause knee osteoarthritis. For example, being overweight, having previous knee injuries, the (partial) removal of a meniscus [3]. Other causes are rheumatoid arthritis, fractures and congenital factors.

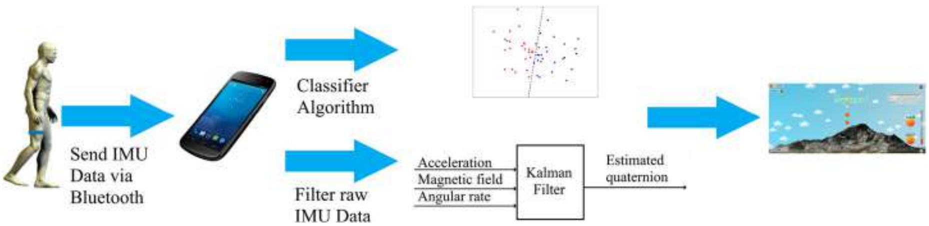

Fig. 1 Application Procedure. Motion data are sent to the mobile application and are visualized in a virtual environment

These conditions can effectively limit the joint's Range of Motion (ROM). Range of Motion is the measurement of movement around a specific joint or body part (Fig. 2). It is measured in degrees from the center of the knee. ROM is measured using an instrument called a "goniometer". For instance, a completely straight knee joint measures 0° while a fully bent knee clocks in at about 135° degrees of flexion.

TKR is the most effective way to relieve pain and restore function. The most common reason for knee replacement is that other treatments such as weight loss, exercise/physical therapy, medicines, and injections, have failed to relieve arthritis-associated knee pain. The goal of knee replacement is to relieve pain, improve quality of life, and maintain or improve knee function. The procedure is performed on people of all ages, with the exception of children, whose bones are still growing. The most important reasons for total knee replacement are significant pain and/or disability. Joint prosthesis is susceptible to wear and tear over time and has a finite lifespan. Therefore, delaying knee replacement until it is absolutely necessary is generally recommended by healthcare providers.

Total Knee Arthroplasty (TKA), also known as Total Knee Replacement (TKR), is one of the most commonly performed orthopaedic procedures. As of 2010, over 600,000 total knee replacements were being performed annually in the United States and were increasingly common [21]. Among older patients in the United States, the per capita number of primary total knee replacements doubled from 1991 to 2010 from 31 to 62 per 10,000 Medicare enrollees annually. The number of total knee replacements performed annually in the United States is expected to grow by 673% to 3.48 million procedures by 2030. After total knee replacement, interventions including physiotherapy and exercise show at least short-term improvements in physical function [1]. If the patient fails to perform the exercises appointed by the physiotherapist during this recovery period, an, otherwise, technically accurate operation might result in poor functional outcome leading to reduced ROM and quality of life.

The aim of the gamified rehabilitation system proposed is to motivate the patient to exercise efficiently by providing feedback to the patient in relation to performance, while the physiotherapy exercises are performed in any setting, e.g. clinical, at home, indoors, outdoors or even in public areas. There is consistent evidence that supervised programs are not superior to home-based programs in uncomplicated patients after TKA [14]. Important success factors for home-based programs is to include patients with a favourable prognosis and increasing adherence to the program, for instance by tele-rehabilitation [32].

There can be variant categories of post-operative physiotherapy intervention. Hydrotherapy, e.g. exercise in a warm water environment when recovering from knee surgery, was associated with comparable outcomes with land-based rehabilitation up to 26 weeks post-surgery [15].

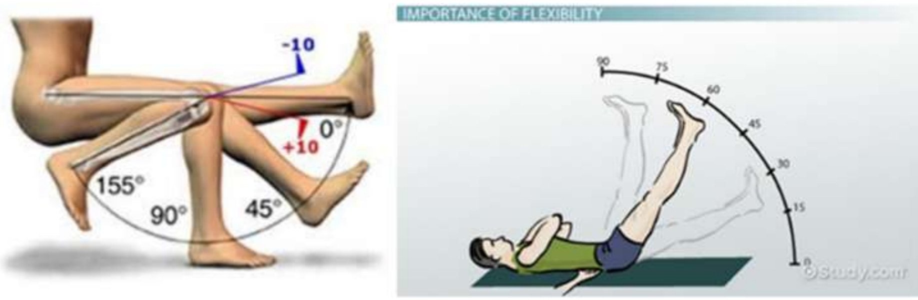

Fig. 2 Rom Examples. Left, Knee Extension Exercise Setup. Right, Straight Leg Raise Exercise Setup

Hydrotherapy, though, requires specific environmental set-up restricting rehabilitation portability. Electrotherapy through muscle neuromuscular electrical stimulation (NMES), initiated 48 h after TKR, effectively improved functional performance following TKR [30]. The method proposed in this work motivates the patient to actively put effort in order to perform the exercises, in contrast with electrotherapy for which the motion is performed passively based on electrical stimulation of the muscle cells.

The scope of this work is to examine whether a visually interactive stimulation through gaming can help the patient to focus on the game instead of the pain or discomfort of the exercise. The application proposed in this paper, uses a single custom-made, light, portable and low-cost sensor node consisting of an Inertial Measurement Unit (IMU) attached on a lower limb in order to capture its orientation in space in real-time, while the patient is completing a physiotherapy protocol. The aim is to increase patient engagement during physiotherapy by motivating the user to participate in a game. For this to occur, a novel classification algorithm is proposed that automatically classifies an exercise in real-time as correct or incorrect, according to physiotherapists' set criteria and provides immediate feedback to the patient.

During the system's initial evaluation phase in Chania's General Hospital Orthopaedic Clinic, a randomly selected control group of users performed the exercises under physiotherapist supervision who marked them as accurately performed or not. An Inertial Measurement Unit (IMU) node was utilized worn by the patient recognizing limb rotation and acceleration. It is challenging to identify whether the proposed application classifies the exercises reliably utilizing just a single sensor node. Providing gamified feedback to the patient at home or in other locations in relation to performance using widely available mobile devices, is also challenging, minimizing the need for expensive physiotherapy under supervision, resulting in more engaging and accessible rehabilitation.

This paper focuses on the description of the rehabilitation system involving the hardware sensor placed on the limb as well as the gamified environment and the testing of the software framework in the hospital, while patients are undergoing physiotherapy treatment commonly performed after TKR surgery. The main goal is to improve compliance to the physiotherapy protocol, increase patient engagement, monitor physiological conditions and provide feedback based on rewards via a gamified experience.

3 Background

3.1 Existing technologies for limb motion tracking

Several approaches listed below have been employed to track limb motion of diverse precision, cost and complexity [5]:

a) *Optical systems*. They use visual data captured by one or more cameras to triangulate the 3D position of a set of points detected. High precision can be reached, e.g. of a few millimeters, but at a high cost. A cheaper affordable solution of lower precision, e.g. of a few centimeters, is achieved by Microsoft Kinect [4], which uses only one RGB camera and an infrared depth sensor. However, it suffers from lack of portability when compared to wearable and mobile devices.
b) *Exo-skeletons*. These are rigid structures of jointed metal or plastic rods linked together with potentiometers or encoders that articulate at the joints of the body [29]. These

systems offer real-time, high precision acquisition and are not being influenced by external factors [22], such as visual occlusion, quality and the number of cameras. Their main disadvantage is the movement limitation imposed by the mechanical constraints of the exoskeleton structures [13]. Furthermore, commercial medical devices of this type have a prohibitive cost for the majority of the patients, not yet allowing their widespread use for home rehabilitation. Still these devices can be a useful acquisition in clinics and rehabilitation institutes.

c) *Electrogoniometers*. They are widely 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 weakness is their high cost [34].
d) *Magnetic systems*. They calculate the position and orientation of a magnetic sensor probe. They are used for motion tracking on high end applications with a reasonable cost for this usage, but still high cost considering home based rehabilitation solutions [36]. Their main disadvantage is that they are susceptible to electromagnetic interference from metal objects in the environment or electromagnetic sources.
e) *Inertial Systems*. Inertial Motion Capture technology is based on miniature inertial sensors (IMUs), biomechanical models, and sensor fusion algorithms [26]. The motion data of the inertial sensors (inertial guidance system) is often transmitted via wireless network to a computer, where the motion is recorded or viewed. Most inertial systems use gyroscopes and accelerometers to measure rotational speed. These rotations are translated to a skeleton by the software. Inertial motion systems capture the full six degrees of freedom body motion of a human in real-time and can also include a magnetic sensor to achieve nine degrees of freedom, although these have a much lower resolution and are susceptible to electromagnetic noise. The benefits of using inertial systems are low cost, small dimensions, portability, and large capture areas. The disadvantages include lower positional accuracy and positional drift.

The building block of this work is to use a single IMU sensor placed on the patient's limb so that its motion is tracked, as this is the option that optimally satisfies the main design constraints of the application: portability and low-cost.

3.2 Related work in rehabilitation

Various rehabilitation systems have been proposed that employ limb motion tracking. An Augmented reality (AR) system is proposed for the rehabilitation of hand movements which have been impaired due to illness or accident [27]. Through the proposed system, the patient can practice daily at home utilizing a standard computer, a webcam and two wireless 5DT data gloves (Fig. 3). Using AR technology, a highly controllable environment including tasks of varied difficulty levels is provided to the patients for them to perform the exercise gradually and systematically. The use of the data gloves, however, raises the cost and the technical complexity of this system which may require specialized technical support and maintenance.

Three methods were proposed for representing changes in human motion symmetry during injury rehabilitation [9]. In this context, a high-cost motion capture suit requiring technical set-up was employed, including seventeen inertial sensors, each worth about 2000 $, to measure body postures (Fig. 4). The methods are tested on an injured athlete over four months of recovery from an ankle operation and validated by comparing the observed improvement to the variation among a group of uninjured subjects. The results indicate that gradual changes are detected in the motion symmetry, thus, providing quantitative measures to aid clinical decisions.

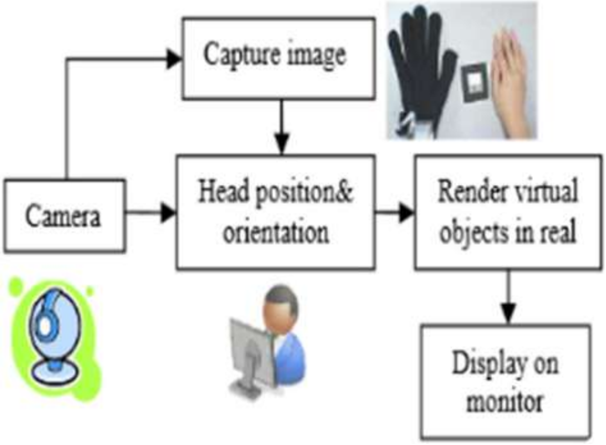

Fig. 3 Hand movement rehabilitation using motion capture and data 5DT gloves [27]

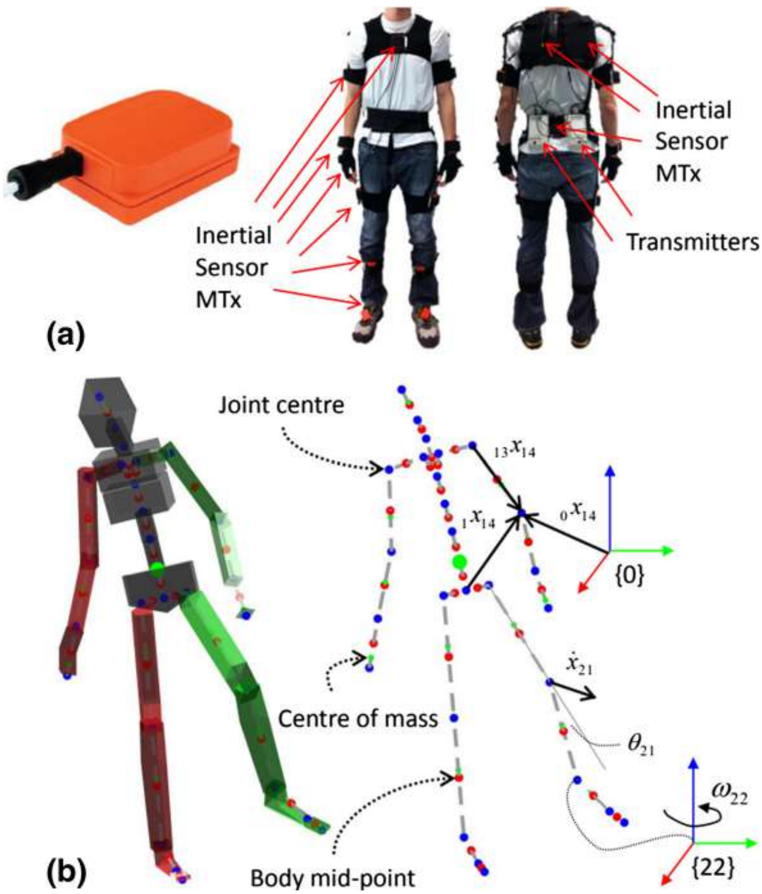

Fig. 4 Inertial sensor network consisting of 17 IMUs [9]

Fig. 5 Use of Kinect in conjunction with p5 glove [8]

Several rehabilitation studies using motion tracking employ the Kinect optical system, which, however, requires specialized set-up and technical support. Previous research has identified patients' general expectations for rehabilitation games and evaluated two newly developed low-cost puzzle and archery rehabilitation games through surveys [8]. Patients expressed preference to low-cost systems (< \$100), demonstrating ease of use, interesting game contents, proven clinical efficiency and access to rehabilitation games without prescription although welcoming therapists to follow their progress (Fig. 5). This study identified the need to improve reliability and precision of the low-cost hardware as well as to demonstrate clinical benefits. Another study assessed the possibility of rehabilitating two young adults with motor impairments using a Kinect-based system in a public school setting [6]. This study was carried out according to an ABAB sequence in which A represented the baseline and B represented the intervention phases. Data showed that the two participants significantly increased their motivation for physical rehabilitation, thus improving exercise performance during the intervention phases.

Fig. 6 A screenshot of the Dexteria app developed to train fine motor skills [25]

There also exist mobile, tablet-based applications [25] that exploit sensory input such as light, touch and accelerometer in order to improve hand function post-stroke (Fig. 6). Preliminary findings point to the potential of using apps in the process of post-stroke hand rehabilitation. However, the input for this method is limited at finger tapping, not suitable for more complex exercises and not based on motion tracking data providing feedback to the patient.

New interactive technologies have been recently applied to rehabilitation sessions with the aim to increase strength and balance while improving patient stimulation, compliance and satisfaction with treatment. The effectiveness of an activity coaching system including an accelerometer-based activity sensor, alongside a home-based exercise program has been examined [14]. A hand-held electronic device was connected to a mobile application on a smartphone providing information and advice on exercise behavior during the day. There are no conclusive results yet, but the expectation is that using the system will result in an increase of physical functioning in the group receiving the activity coaching system. The use of integrating the Wii-Fit game into a rehabilitation paradigm after TKA has been investigated [10]. In addition to standard therapy, users received 15 min of Wii-Fit gaming activity, while the control group received 15 min of additional lower extremity exercise. There were no differences between groups for ROM. These findings suggest that the addition of Wii-Fit as an alternative to lower extremity strengthening may be an appropriate rehabilitation tool.

The use of new digital technologies encourages the further investigation of automatic exercise rehabilitation classification. There exists an increasing number of past research that employs IMU nodes for evaluation of limb rehabilitation exercises [11, 16, 18]. Previous work indicates that when multiple IMUs are employed, satisfactory exercise classification accuracy results are achieved based on three, two and one IMUs [11]. Such results drive the further investigation of the challenging classification problem using just a single IMU in this paper, enhancing maximum portability compared to multiple IMU systems, in conjunction with sufficiently high success rates of movement detection. Employing more than two sensor nodes can achieve higher accuracy in ROM measurement under certain conditions, e.g. when accurate node placement is ensured [16], however, such systems are difficult to operate and of limited portability.

The system proposed in this paper, based on a single IMU sensor, aims to maximize portability while maintaining acceptable motion detection success rates along with patient engagement and training. Accurate measurements based on a single sensor node depend on conditions such as the correct positioning of the sensor.

4 IMU functionality

Inertial Measurement Units (IMUs) provide the leading technology used in smartphones and wearable devices in order to measure rotational and translational movements. In this project, the IMU MPU-9150 is used (Fig. 7), which is small in size, cheap and portable. The utilized IMU contains the following sensors:

a) *3-axis Accelerometer*. The accelerometer measures inertial force caused by gravity and acceleration. It can accurately measure rotation around the x and y axes (pitch and roll angles), however, it is susceptible to noise caused by rapid changes of acceleration. For capturing orientation along the z-axis, a magnetometer (compass) is used complementary to the accelerometer.
b) *3-axis Gyroscope*. The gyroscope 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

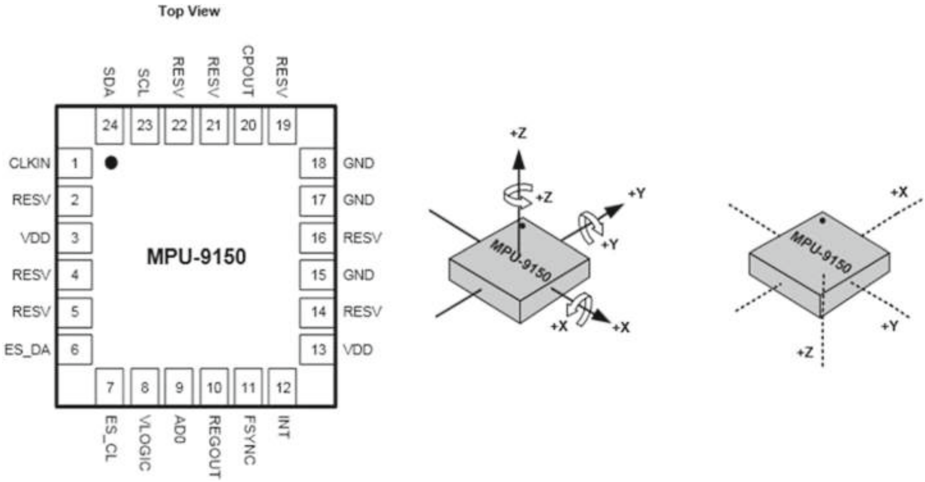

Fig. 7 MPU-9150 Pins, axes of sensitivity for accelerometer, gyroscope and magnetometer as indicated in MPU-9150 specification

signal changes. In relation to long-term observations, it is susceptible to drift errors. Measurements should be sampled in exact intervals according to a specified frequency.

c) *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 (yaw angle).
d) *Temperature sensor*. It measures environmental temperature.

IMUs have the disadvantage of lower positional accuracy and positional drift. In order to obtain accurate orientation measurements and minimize cumulative errors we need to combine the accelerometer's long term measurements (low pass filtering) with the gyroscope's accurate short term measurements in order to capture fast changes in rotation (high pass filter) [5]. Research literature puts forward a number of filtering methods for this purpose:

a) *Complementary Filter*. These filters follow a frequency-based approach, and this is one of the first methodologies used to address IMU drift and positional accuracy issues. The key idea is to treat one signal through a low-pass filter, the other one through a high-pass filter, and combine them to obtain the final rate. In case of IMUs, it can be more effective to combine slow moving signals from the accelerometer and/or magnetometer and fast moving signals from the gyroscope. The result is to favor accelerometer measurements of orientation at low angular velocities and the integrated gyroscope measurements at high angular velocities. Such an approach is simple but may only be effective under limited operating conditions. There are algorithms [2, 20] that employ a complementary filter process, using adaptive parameters. This algorithm structure has been shown to provide a good trade-off between effective performance and computational expense.
b) *Kalman Filter*. The Kalman filter [12, 17] has become the basis for the majority of orientation algorithms and commercial inertial orientation sensors, like Xsens, Intersense, and many others. The widespread use of Kalman-based solutions is a guarantee of their optimal accuracy and effectiveness. Nevertheless, the Kalman filter implementation imposes a high computational load due to the high volume of recursive formulas that need to be calculated in order to minimize the least mean squared error.

The selection of a filtering method depends on the positional accuracy and computational complexity of the application. The filtering procedure in the present system is not handled in the sensor node containing the IMU. Instead, it is handled by the application software. The application software runs on Android devices. These devices usually follow ARM architecture using new generation multicore CPUs that can handle higher filtering computational load. In this work, Kalman filtering is preferred for its optimality over complementary filtering. Complementary filtering was also tested and provided very similar angle measurements to these of Kalman filtering.

5 Application functionality

5.1 Application summary

The IMU is fitted on a specified limb location depending on the exercise performed. The patient user starts the game by having the leg in a neutral pose ready to perform one of the predetermined exercises. The raw data collected by the IMU is sent via Bluetooth to a mobile device. The application computes an orientation measurement based on Kalman filtering. Real-time visualization on a mobile device offers feedback in the form of a game presented to the patient. The filtered data received are then provided as input to an automatic exercise classification algorithm. The algorithm decides if the exercise was accurately performed. This classification feedback is displayed on the mobile device in a readable form translated to a 3D visualization, after the end of the motion (Fig. 1). The procedure is then concluded and the patient can perform another repetition of the same exercise or can select a different exercise.

5.2 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, using the following methods:

a) *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 an approximation of the user's motion in a 3D scene. In this context, a user engages in a serious game of a specific objective, for instance, the patient is instructed to try and fly an airplane while moving the knee (Fig. 8) in the vertical axis in order to collect coins. The game is designed so as to motivate the user. A number of mini-games are designed for the four TKR exercises specified by the physiotherapists (Table 1). The exercises in question are selected by the physiotherapists based on the American Academy of Orthopaedic Surgeons TKR exercise guide [7] (Table 2). For testing purposes, the user can select any combination of gamified TKR exercises listed in Table 2 for every game implemented. The application's main menu provides a simple way of selecting exercises, games, as well as adding users (Fig. 9).
b) *Classification feedback.* The raw data of the IMU are inserted in the classification algorithm. The algorithm decides whether the exercise has been accurately performed. If by the end of a single repetition, the exercise was classified as accurately performed, the player is rewarded, e.g. by increasing a coin score attribute and by providing animated information related to the success of movement. If the exercise was classified as inaccurately performed, in which case the movement violates angle or acceleration constraints, the

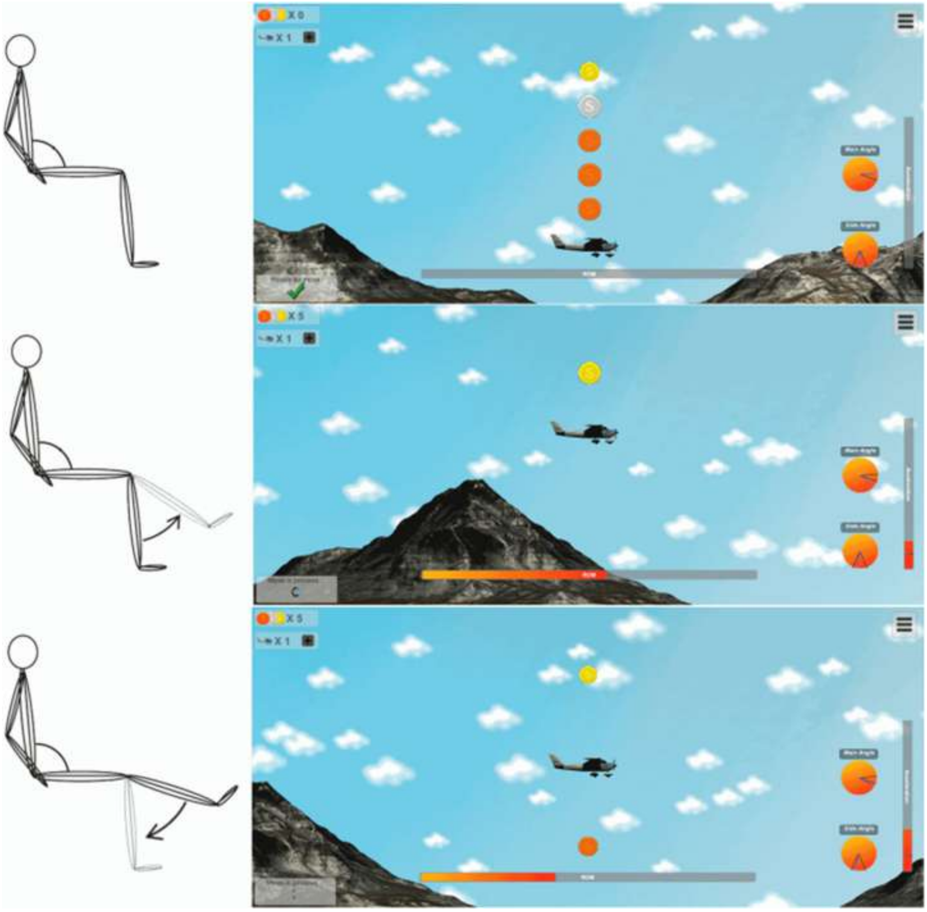

Fig. 8 Knee extension neutral position, upwards movement and downwards movement for airplane game

application informs the user of the correct movement, e.g. by providing a limb movement animation and encourages the patient to try again. Along with the classification result, the algorithm also outputs the maximum ROM percentage of the achieved movement for this repetition. A 100% percentage means that the patient achieved maximum rotation of the knee. The maximum rotation of the knee differs in each designated exercise. For instance, in relation to the Knee Extension, it is 90° degrees. When a patient achieves a maximum ROM percentage of 50% in a single repetition then this corresponds to 45° degrees orientation. The generated repetition data are serialized in a local mobile database and are used through the Automatic Graph Generation procedure of this application.

c) *Automatic Graph Generation feedback*. An important feature of this framework is its graph generation capability. It is used during the testing of the application on inpatients in order to track their progress during physiotherapy sessions and analyze collected data. This data serves as an initial assessment of the physiotherapy framework capabilities and improvements. It also helps the users monitor their daily exercise progress through easily readable graphs. Moreover, it can be a useful tool for physiotherapists and orthopaedic

Table 1 Implemented games for exercises in Table 2

Game	Screen Shot	Description
Airplane Game		When the user moves the operated knee, the airplane also moves vertically following the movement of the knee in order to gather coins.
Fish Game		When the user moves the operated knee, the fish also moves horizontally following the movement of the knee in order to gather coins.

surgeons in relation to tracking ROM improvements of patients over time. The generated graphs track the progress of users for each repetition in respect to the maximum achieved ROM and records which physiotherapy exercises were accurately conducted and which were not. Two graph types are extensively utilized as indicated in the Results section, in this paper. The percentage in relation to ROM per correct repetition plot graphs and the Correct/Wrong pie graphs.

6 Implementation

6.1 Node hardware setup

The accelerometer and gyroscope readings received by the IMU are independent of the hardware setup. The application is responsible for filtering the received data and not the sensor node. This configuration provides two axes of rotation which is adequate for 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 and complies with the raw data communication format. The sensor node consists of a Raspberry Pi model Zero W, the IMU MPU-9150 and a 1200 mAh Li-Ion battery (Fig. 10).

Raspberry Pi model Zero W is a credit card sized computer that runs Raspbian with Pixel (Linux Based kernel). It includes a pin header of 40 pins used for connections with all sorts of hardware peripherals, in our case an IMU. In this work, the IMU model used is the 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

Table 2 Common rehabilitation exercises for TKR

Exercise	Placement	Description
Knee Extension	Shin	From sitting position, the leg is extended, then lowered back to starting position.
Straight Leg Raise	Shin	From lying on back position, the leg is lifted and then lowered back to starting position.
Heel Slide	Shin	From lying on back position, the heel is moved up, then 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.

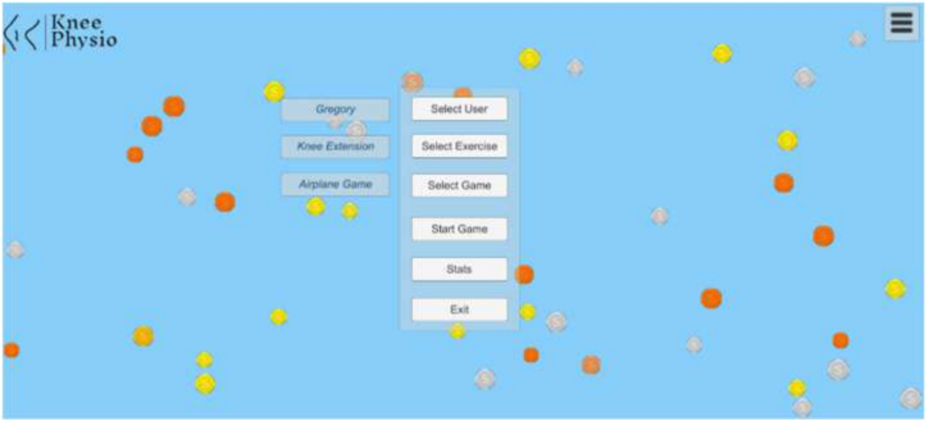

Fig. 9 Main Menu of the application

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 (Fig. 11). Raspberry Pi Zero W integrates Bluetooth Low Energy (BLE) 4.1 which makes it possible to send the raw data received from the node to our designed application that runs on an Android mobile device. By employing a rechargeable 1200 mAh Li-ion battery, the node can send data for seven hours on full capacity. This is more than enough in order to perform the initial testing of the designed framework for TKR patients.

6.2 Node software setup

The data are collected by Raspberry PI using a custom script implemented in the Python programming language. Then the sensor node acts as a Bluetooth server waiting for incoming connections from Android devices. When a connection is established, the sensor begins sending the raw IMU data to the client (Android device). When a connection is received by the client, 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. The accelerometer, gyroscope and temperature data are collected and sent via Bluetooth to the application at a rate of 100 Hz. This continues until the user exits the application, or the battery depletes. The script waits for incoming connections from nearby devices. If one is found it configures the sensor using the appropriate I²C registers and continuously sends data till the connection is interrupted. This happens if the Android device gets out of range and the connection is reset, or if the battery on the sensor depletes and the script stops executing. If the connection is reset the process is repeated, the sensor device is reset and data are sent continuously at a frequency of

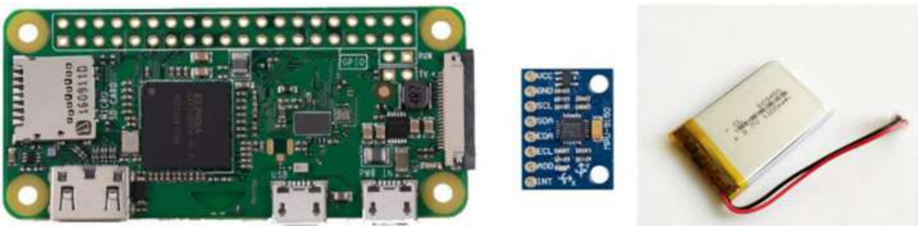

Fig. 10 Node components. Left, Raspberry Pi. Center, IMU. Right, battery

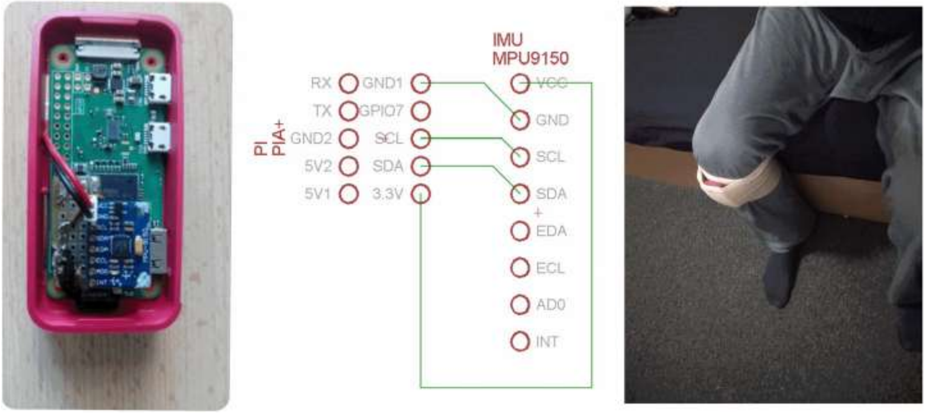

Fig. 11 Left, I2C connection implementation between Raspberry Pi Zero W and MPU-9150. Center, resulting sensor node. Right, node placement on the shin of the leg

100 Hz per second. The register configuration reading and writing of the sensor is achieved using the Register Map documentation for MPU-9150.

6.3 Application software setup

The client receives the data using an Android activity implemented in Java. The Unity Game Engine is utilized for visualization. The Java Native Interface (JNI) is used in order to transfer data from Java to C#, since C# is the programming language used by Unity. Unity provides leading architecture for game development along with a number of assets available for free. The application guides the user in order to become familiar with the application gameplay and furthermore, to try and improve his ROM through implemented physiotherapy exercises. The user selects the exercise to be performed, for instance, the Knee Extension exercise. The system then guides the user in order to perform a few initial training exercises. The system classifies the exercise performed as correct or incorrect and provides visual feedback to the user. When the users feel comfortable

Fig. 12 Main gameplay user interface (GUI) with text animation after repetition classified as correct

performing the selected exercise, they can select to engage in a series of mini-games. By performing the limb motion, e.g. moving their knee, the users interact with objects in 3D space.

Indicative games are the Airplane game and Fish game (Table 1). When selecting the Airplane game, the users try to move an airplane in the vertical axis and gather as many coins as possible while performing the physiotherapy exercises. When a repetition is correct, the user is informed with the help of the displayed visual hints (Fig. 12) and his ROM is recorded in order to generate ROM graphs. A high value for ROM percentage means that the user gathered more coins and achieved a greater coin score, therefore, a greater reward. Lower ROM represents lower reward. Both cases are rewarded depending on their ROM percentage.

When a movement is incorrect, the system will not reward the users. It will offer hints and visual guidance in order for physiotherapy to continue by correcting limb motion (Fig. 13). The reward is greater for larger ROMs so that the patient is motivated to improve movement. Similarly, when engaging with the Fish game, the user moves a fish horizontally this time based on the movement of the knee and tries to collect as many coins as possible depending on the ROM achieved. Along the whole process, the system prompts the user by offering additional visual hints according to detection of motion as captured by the sensor in order for the patient to accurately perform the designated physiotherapy exercises.

The Main Gameplay Interface actively contributes to the user experience of the application as it provides the following helpful information regarding the status of a repetition and the status of the sensor itself:

a) *ROM bar*: It provides real-time feedback in relation to the ROM percentage. The ROM percentage indicates the main angle of the knee rotation the patient achieved for a specific exercise. For instance, in relation to Knee Extension a 100% percentage corresponds to 90° degrees.
b) *Acceleration bar*: It displays information about the acceleration of the movement. It also indicates the maximum acceleration threshold of motion during the calibration phase.

Fig. 13 Main gameplay user interface with text animation after repetition classified as incorrect indicating to the user to try the movement again

c) *Main Angle*: This is the main angle value computed by the filtering process. It is used to determine the ROM. It also indicates the range of the main angle to be adopted (*minimumMainAngle, maximumMainAngle*) during the calibration phase.
d) *Side Angle*: This is the side angle value computed by the filtering process. It indicates the range of the side angle (*minimumSideAngle*, *maximumSideAngle*) to be adopted during the calibration phase.
e) *Status of the detection algorithm*. It informs the user of the current repetition status. The status can be Calibrating, Ready for Move, Move in Progress, Completed Please Rate and Place Sensor Correctly.
f) *Pain feedback*. The user is asked to rate the amount of pain experienced during the previously completed repetition. 1 out of 5 stars means no pain and 5 out of 5 stars represent maximum pain imaginable.
g) *Latest Rom*: It indicates the latest maximum ROM percentage achieved in degree values, in relation to the last repetition performed.
h) *Coin Panel*: The reward of the user is measured in coins gathered during a repetition.

6.4 Automatic exercise classification algorithm

A first iteration of the automatic exercise classification algorithm uses angular and acceleration predefined thresholds to fine-tune the system (Fig. 14). In relation to future iterations, these thresholds will be inferred from variant Machine Learning techniques, e.g. RVMs [31], using the filtered sensor data collected. Such methods will maximize the success rate of the current algorithm, using just a single node. A significant requirement is the correct and stable sensor placement on the *Shin* of the patient's limb. Correct placement can be illustrated by a doctor or physiotherapist. If the wearable device isn't placed with the correct orientation when patients perform an exercise, they will be prompted that the sensor is not positioned correctly. The input data of the algorithm is the filtered smoothed data of the sensor listed below and are acquired using Kalman [12, 17]:

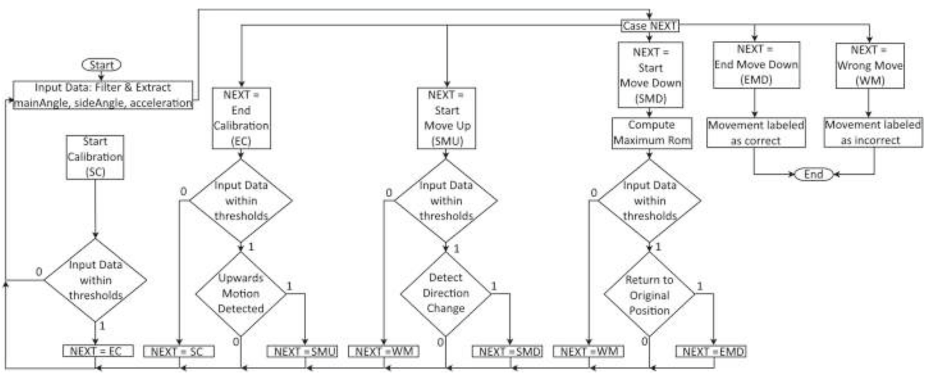

Fig. 14 Automated classification algorithm flow chart

i) *mainAngle.* This is the angle at the direction of the exercise movement. It determines the maximum achieved ROM of the patient.
j) *sideAngle.* This is the angle that detects sideways limb motion. It is used along with *mainAngle* to determine when user movement deviates from what is perceived to be an accurately performed exercise.
k) *acceleration*. The limb acceleration is used to detect motion activity and probable wrong movement, e.g. if the limb movement is too fast.

The output of the algorithm is a computational decision whether the physiotherapy exercise is performed correctly or incorrectly by the patient. The training parameters are the following angle and acceleration thresholds:

a) *minimumMainAngle, maximumMainAngle.* These are the main angle's minimum and maximum thresholds in the direction of motion (pitch angle). If *mainAngle* exceeds these thresholds, the exercise is deemed incorrectly performed.
b) *minimumSideAngle, maximumSideAngle.* These are the side angle's minimum and maximum thresholds that detect sideways limb motion (roll angle). If *sideAngle* exceeds these thresholds, the exercise is deemed incorrectly performed.
c) *maxAcceleration.* This is the maximum allowed acceleration. If acceleration exceeds this threshold, the exercise is deemed incorrectly performed.

The simplified algorithm chart of automatic exercise classification indicates the possible states of the repetition (Fig. 14). The system constantly checks the incoming filtered acceleration and gyroscope data. If this data obey the acceleration and angle constraints then the algorithm continues from calibration phase to movement phase until motion is successfully completed. If, at any time, constraints are violated, movement is either restarted (calibration phase) or labeled incorrect (movement phase). The user can be informed of the current state of the repetition by simply checking the status of the detection algorithm located at the lower left corner of the gameplay GUI.

The implemented algorithm is designed to work for each one of the specified exercises and can be generalized to additional exercises of similar format (Table 2). Each exercise will just require different training parameters. Currently, these parameters are manually defined for the exercises implemented, taking into account the training samples collected. When the first iteration of the designed application is completed and more samples are collected from patients with TKR, these parameters can be automatically adjusted using machine learning techniques in order to reliably measure success rate. This is not a trivial task as the data collected from training must be of a significant amount and variance in order to provide reliable and generalized results.

7 Experiments

Two evaluation sessions of this framework were performed comprising of a training session and a testing session. The initial training round was performed on six users. They were three healthy users of ages 30–50 and three walking TKR patients of ages 64–80. Ten patients (eight female, two male, range 64–80) underwent TKR surgery at General Hospital of Chania and agreed to participate to the second testing round of this framework. The patients had no background with Android devices or gaming.

The selected exercise for testing was Knee Extension. The patients positioned themselves in a neutral sitting pose presented with the Airplane Game. The goal was to raise their knee as high as possible and at the same time accurately perform the exercise while observing the visual stimulus. This stimulus was the movement of the airplane along with the movement of the knee. Patients were instructed to perform a minimum of four repetitions of this exercise. There was the possibility to perform additional repetitions and stop when they felt tired or in pain. This procedure was common in both training and testing phases.

7.1 Training – healthy subjects & recovering TKR patients

Initially, the application was utilized by healthy subjects. This contributed to a first iteration of fine-tuning neutral position angles for each exercise. A main concern when trying the application in healthy subjects is that these angle constraints are not representative for the case of TKR patients. Healthy subjects demonstrate full ROM while TKR patients, even at the stage of recovery, have limited ROM of their knees. Therefore, a second iteration was deemed necessary in order to fine-tune angle constraints with respect to patient limited ROM.

A recovering TKR patient, is an outpatient in physiotherapy follow up, 12–14 days post-operation after suture removal. This patient still has a limited ROM but can operate the knee normally and walk. We applied the same procedure to the recovering patient. An operated knee of limited ROM when bent has a neutral position angle smaller than a healthy user. This fact allowed us to record new neutral pose angle constraints and automatic classification algorithm thresholds and make the appropriate changes in the respective implementations. These changes involve fine-tuning the algorithm global thresholds for the Knee Extension exercise after all recovering TKR patients feedback is received to represent the specific population sample from Chania General Hospital. In both cases, a single session was performed with each patient. Each patient used the application for one day compared to hospital inpatients for whom multiple data readings could be collected in a span of several days. The duration of this training phase was 15 days.

At this point, a simplified evaluation of the proposed system could be performed by the participants. This evaluation aimed at improving the current framework in terms of performance and usability. The users were asked whether it was easy to play the games while they had the sensor on their limb and whether there were confusing aspects of their experience. They were encouraged to offer suggestions for system improvement.

Furthermore, the physiotherapists' feedback during this training phase was invaluable as it helped finalize the experimental procedure and the reward system that the game provided. Physiotherapists insisted that the coin reward system used should be as clear and simple as possible in order to be understandable by as many patients as possible independently of age criteria or other comorbidities. Also, they noted that the movement of the knee for a specific exercise should correspond to the visual stimulus in the physical world. For example, the upwards movement of the airplane should correspond to the upwards movement of the Knee Extension exercise.

7.2 Testing – TKR inpatients

The final testing phase of the application on patients after TKR surgery has been conducted in a similar manner at the Chania General Hospital Orthopaedic Clinic under the supervision of a physiotherapist using the same postoperative procedure. Patients were operated by the same surgical team using the medial parà patellar approach and started their physiotherapy protocol

Fig. 15 TKR inpatients in Chania's General Hospital Orthopaedic clinic that consented in participating in the experiment

48 h post op after the removal of the drain. Exclusion criteria were neurological deficit, previous operation on the ipsilateral or contralateral hip or knee, or functional deficit.

Ten TKR patients consented to try the application in order to gather motion data (Fig. 15). TKR surgery is a common operation. The frequency of this operation in the public General Hospital of Chania is approximately 5 patients per month. The data were collected in approximately 2 months of testing. A patient that has undergone TKR surgery usually stays in the hospital for a period of four days up to twelve days depending on individual recovery progress. A patient's recovery progress depends on age, physical condition and variant comorbidities. Younger patients tend to recover faster compared to people with obesity, respiratory problems or other comorbidities.

We performed one to three training sessions with each patient. A session is the testing of the application for a single day on a patient. During each session, the patient is advised to perform a number of repetitions of the Knee Extension exercise. The first session for each patient was performed two to five days after surgery depending on recovery progress. The second session for the same patient, was performed four to five days after the first session. Lastly, the third session if any, was performed eight to nine days after the first. This could happen if a patient's recovery progress was slow, resulting in staying longer in the hospital. The number of the repetitions in a session can be four to thirteen depending on the patient's physical condition. Based on these repetitions, motion data was collected by the application. Graphs are produced in real-time that showcase statistics about the ROM percentage for all correct repetitions of the patient performing the Knee Extension Exercise.

8 Results

8.1 Rom graphs

ROM graphs that are generated during the experimental procedure associated to the two-month testing sessions along with patient feedback provided input in relation to the strengths and weaknesses of the proposed rehabilitation system. The majority of the patients understood well the goal of the game and were engaged with the simple airplane scene. These patients exhibited higher ROM percentage over-time and on each session.

A single ROM measurement in the graph represents a correctly classified repetition of the Knee Extension exercise performed by the patient and detected by the exercise classification algorithm. The vertical axis shows the ROM percentage achieved according to accelerometer measurement. 100% is the maximum achievable percentage for Knee Extension that corresponds to 90° degrees. The horizontal axis indicates the session dates of the repetitions. Summarizing, these graphs represent the ROM percentages achieved by a patient based on the testing sessions in relation to the correct Knee Extension repetitions detected by the algorithm.

In 80% of the collected samples, the maximum ROM percentage measurements are increasing and follow a similar pattern as shown in Fig. 16. This indicates that patients were constantly trying to improve their previous repetition performance by raising the airplane even higher and gathering more coins. At the end of certain sessions, the ROM measurements declined, in some cases, indicating that the patient was tired by the performed repetitions. This was mostly the case for patients demonstrating slower recovery due to other comorbidities. The slower recovery of these patients didn't necessarily result in lower engagement during the airplane game. Patients were still trying to improve their previous repetition 80% of the examined cases.

A minority of patients didn't improve their ROM (Fig. 17). On these cases the patients didn't understand well the goal of the game and were not engaged with it. Therefore, patients only performed the repetitions because they were instructed to do so.

There was also a single case of a patient who performed a higher ROM repetition as recorded while the knee had actually a lower functional ROM. The patient achieved that by slowly positioning the entire body backwards in the direction of movement while sitting on a bed. The acceleration or angle constraints were not violated, so the ROM percentage was measured and was close to 100% (Fig. 18).

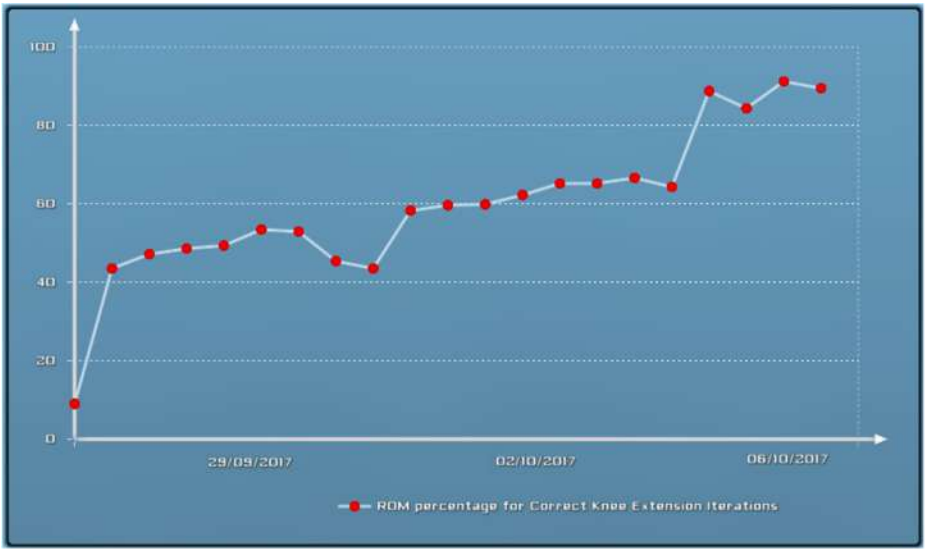

Fig. 16 Rom graph generated by the application for the knee extension exercise tested. This graph corresponds to engaged and improving patient

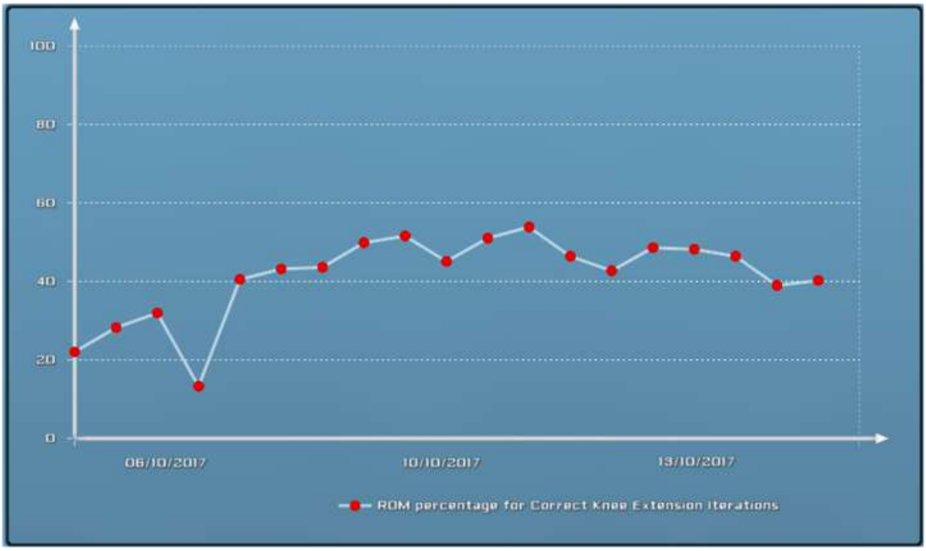

Fig. 17 Rom graph generated by the application for the knee extension exercise tested. This graph corresponds to non-engaged and declining progress patient

8.2 Classification charts

While this testing was focused mainly on measuring the ROM of the patient, gathering feedback and recording their reactions, an initial evaluation is also provided regarding the implementation of the exercise classification algorithm in this first iteration. Automatically generated graphs show the detected classification percentage of the algorithm. The

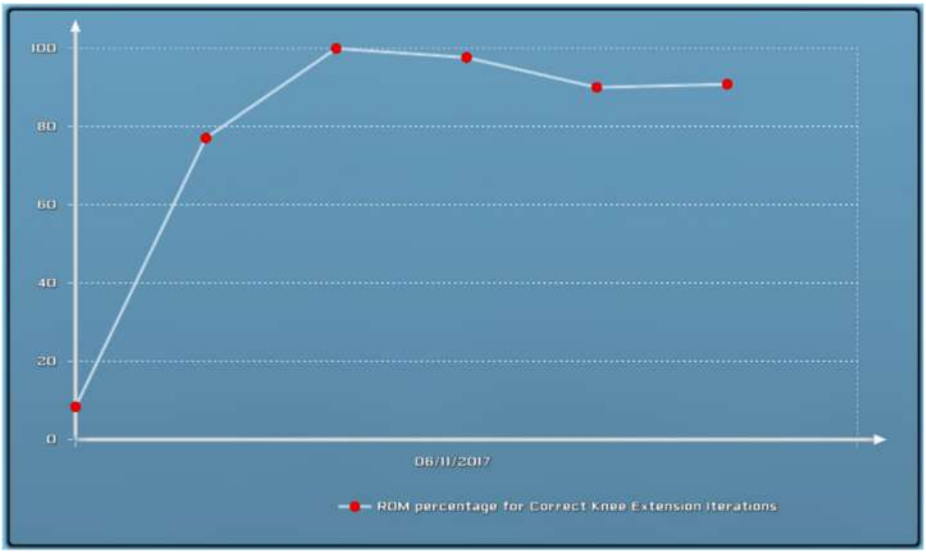

Fig. 18 Rom Graph generated in relation to the Knee Extension Exercise tested corresponding to the patient wrongly positioning the body

classification percentage indicates how many of the total repetitions performed for an exercise are classified as correct and therefore also indicates the repetitions classified as incorrect. This percentage is compared with the actual classification percentage that is provided by the supervising physiotherapist. Then the error percentage of the algorithm can be measured by comparing the actual physiotherapist percentage with the application's generated percentage using the relative difference of the values. One way to define the relative difference of two numbers is to take absolute difference divided by the maximum absolute value of the two numbers. So the error percentage is described by the following formulae (Fig. 19).

For instance, a patient achieving a correct classification percentage of 73.1% according to the automated algorithm (Fig. 20 left), that has an actual correct percentage of 69.2% according to the physiotherapist, provides an algorithm error percentage of 5.6% in this case. For a different patient who employed a strategy of demonstrating higher ROM than possible based on body positioning as explained above, the respective percentages were an algorithm correct percentage of 85.7% (Fig. 20 right), a physiotherapist's actual percentage of 14.3%, resulting in an algorithmic error percentage of 83.3%. The observed data indicates that there can exist large variation in resulting accuracy of the algorithm. It is challenging to implement a generalized algorithm that avoids overfitting based on having only a few samples during these two months of testing. Future iterations should optimally rely on a larger amount of data.

Detecting 'cheating' patient strategies when employing a single IMU sensor is significant. For such cases, there should be a minimum of two sensors, one placed on the shin and one on the thigh of the patient. However, this increases the cost of the application and reduces portability which were the main design constraints of the proposed system. There are two supplementary ways to resolve this issue. Firstly, the physiotherapist should train the patient to accurately perform the exercise such as the knee extension exercise so that, later, the patient can repeat the exercises alone with minimum supervision. Secondly, the user interface of the application should instruct the patient to maintain a neutral pose. This should be preferably implemented to include animations of humanoid postures rather than only text and image hints. Therefore, it is essential to provide a solid setup for the application. For example, while a knee extension exercise can be performed in bed, using a chair to sit on instead can avoid this form of 'cheating' by helping the patient to support the back and accurately exercise.

Throughout the experimental procedure it became apparent that the classification error is greatly influenced by the starting position of the sensor. It is essential that the sensor is accurately oriented so that side angle is close to 0° degrees in order to avoid inaccurate exercise repetitions. The IMU is very sensitive to misalignments. If the sensor is not placed correctly, the data collected from the sensor can lead to inaccurate results.

$$\%Error = \frac{|\,AlgorithmCorrect - PhysiotherapistCorrect\,|}{max(|\,AlgorithmCorrect\,|,|\,PhysiotherapistCorrect\,|)} \times 100$$

Fig. 19 Formulae for error percentage calculation of designed algorithm

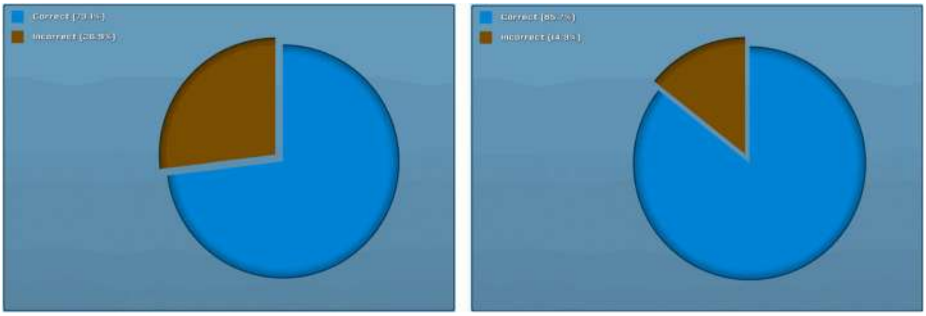

Fig. 20 Automatic generated pie charts of the application indicating correct and wrong repetitions of an exercise performed by different patients (left and right), according to the first iteration of the implemented algorithm

8.3 Remarks

We analyzed the data collected and interpreted the results. The goal is to understand in a qualitative manner the feedback collected from the patients. In this iteration, quantitative measures that include ROM and classification feedback were provided. The collected data provide qualitative feedback towards understanding the user's and physiotherapist expectations in relation to the proposed rehabilitation system.

Insight gained throughout the experimental procedure while working with TKR patients, is note-worthy. When the patients were asked to perform an exercise based on the proposed rehabilitation system, they were reluctant or hesitant at best. One of them even refused to perform the experiment. Once the orthopaedic surgeon or physiotherapist explained the procedure, they cooperated well and contributed to this research project although still hesitant in some cases. It was common for a patient to focus on the experienced pain before embarking on the experimental procedure. This fact negatively influenced the psychological state of the patient. After performing a single repetition, though, the patient was usually more tolerant of pain of the knee, ignoring it to a certain degree. There were many cases when after only a few repetitions, patients were heavily engaged in the game as indicated by their behavior and facial expressions. Examples of such expressions were smiling facial expressions, laughing or eagerness to start the next repetition. On the other hand, this eagerness could result in hasty movement and, thus, incorrect repetitions. In such cases, the patient was advised to perform slower and steadier movements of the knee. After a certain amount of repetitions, the pain was again more dominant than user engagement and the ROM percentage started to decline. By the end of the session, 80% of the participants were eager to perform another session.

When patients were asked if they had found the games helpful, only one patient doubted their effectiveness for training, although physiotherapists recorded noticeable improvement of the patient's limb motion. Other patients realized they were applying enhanced personalized effort into their physiotherapy protocol when utilizing the gamified application.

9 Conclusions

The current framework introduces an ultraportable rehabilitation application comprising of just a single IMU sensor linked to a serious game environment, to be adopted by patients that have undergone TKR surgery for their highly repetitive, but very significant post-operative physiotherapy, ultimately minimizing physiotherapist supervision, at most locations. This framework can run on Android mobile devices with the use of a single sensor node maximizing portability and ease of use. Through application feedback, accurate patient exercise and compliance can be achieved by succeeding at each mini-game objective. Future development should overcome limitations of few testing samples and derive a reliable accuracy result from the classification process. We continue to compare patient engagement between a control group that uses traditional physiotherapy treatment and a group that uses the proposed gamified approach in the hospital setting and validate even further which are the technological means through which patients are motivated and satisfied by gamified rehabilitation strategies.

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