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Human-Robot Sensor Interface for Cardiac Rehabilitation

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***Abstract*— Cardiovascular disease is the leading cause of death in the world. A program of cardiac rehabilitation (CR) is related to physical activities or exercises to regain the optimal quality of life. CR relies on the necessity to evaluate, control and supervise a patient's status and progress. This work has two objectives: on the one hand, provide a tool for clinicians to assess the patient's status during CR. On the other hand, there is evidence that robots can motivate patients during therapeutic procedures. Our sensor interface explores the possibility to integrate a robotic agent into cardiac therapy. This work presents an exploratory experiment for on-line assessment of typical CR routines.**

I. INTRODUCTION

Cardiovascular disease (CVD) refers to the conditions that involve narrowed or blocked blood vessels that might lead to a heart attack [1]. According to the World Health Organization, around 17.5 million people die each year from CVDs. This number represents approximately 31% of all deaths worldwide. In the same manner, in 2015 two CVDs were leading the death cause list in the world: ischaemic heart disease (8.76 million deaths) and stroke (6.24 million deaths) [2]. Also, more than 75% of CVDs deaths occur in low-income and middle-income countries and around 80% of all deaths from CVDs are a consequence of heart attacks and strokes [2].

Cardiac rehabilitation (CR) is commonly used to prevent CVDs or to treat a patient post a CVD event. CR covers different areas, from nutrition and weight management to assessment and management of depression, physical exercise and comorbidities, to health education and medical therapy, among others [3].

CR is necessary when a patient has suffered at least one of the following health incidents within the last 12 months: acute myocardial infarction, coronary angioplasty, heart or lung transplant, heart valve repair, percutaneous coronary intervention, coronary bypass surgery, heart failure, tachycardia or fibrillation. The CR treatment can be considered as a tool to enhance the quality of life of patients who have suffered a CVD and as a prevention tool. CR is related to physical activities or exercises for improving physical and mental levels aiming to recover an optimal daily living [4]. The main objective of the physical activities is to decrease coagulability, increase fibrinolysis, improve endothelial function and endothelium-depend vasodilation; leading to an overall improvement of myocardial flow. Physical activity also improves peak cardiac output, heart rate, stroke volume and reduces exercise intolerance.

CR is indispensable for patients who have suffered a CVD. Consequently, there is a high demand for CR services, and there is currently a higher demand than what is typically on offer in health institutions [5]. Additionally, not all the patients who had a CVD are enrolled onto CR. For example, a study in England [6] showed that only between 14% and 23% of infarct patients actively continue with the program, suggesting that CR is not a process with patients fully engage. This might be due to a common therapeutic program consisting of a large number of monotonous exercise routines.

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II. CARDIAC REHABILITATION

CR differs depending on the country of application, however, it is usually divided into three or four phases [7]. In Colombia, the Instituto de Cardiología at Fundación Cardioinfantil implements a protocol that consists of three phases: **Phase I** or inpatient phase takes place within 48 hours after a cardiovascular event. The beginning of this phase occurs when the patient is hemodynamically stable. In this phase, the patient performs passive movements in order to maintain muscular tone and to reduce risks or any complication. **Phase II** is an outpatient phase, which begins immediately after the patient leaves the hospital, lasts around 3 months and consists of weekly sessions (three times per week approximately). This phase includes an education program covering risk factors, healthy habits, adhesion to the treatment, motivation and exercise control. **Phase III** has an average time duration of nine months with one or two sessions per week. The objective is to reinforce the information and habits gained during the previous phase. The main challenge is assuring the patient's adherence to the program.

CR facilities are a blend between clinical and exercise training settings [8]. Usually, studies related to CR use exercises with treadmills, stairs or cycloergometers, as this equipment allows the administration of stress tests of varying levels (usually, called graded exercise tests). Stress tests are often performed within the first few weeks after a cardiac incident, and commonly use treadmills, where speed and inclination increase progressively through different stages of the test [8]. CR relies on the necessity to evaluate and control the current state of the patient. These variables depend on three main metrics:

- **Cardiopulmonary parameters:** these measure significant parameters such as peak oxygen uptake, peak work rate, peak ventilation rate, peak heart rate, heart rate variability and evolution of heart rate for tracking the complications within the cardiopulmonary system [9].
- **Gait spatiotemporal parameters:** these study the biomechanical performance during the exercise. However, the assessment varies depending on the routine or platform used for the therapy. For instance, when the exercise is performed using a treadmill, gait assessment is desirable, hence, parameters such as cadence, step length and speed are used to analyze the gait.
- **Physical activity difficulty parameters:** these evaluate the exercise difficulty in terms of physical parameters, this is assessed through questionnaires or qualitative interpretations such as the Borg Scale. The Borg Rating of Perceived Exertion (RPE) [10] is a way of measuring physical activity intensity level.

Although several commercial sensor systems allow the continuous measurement of cardiopulmonary parameters and the assessment of the patient's status, they are not aimed to clinical applications. For instance, Polar Incorporated [11] develops several products which are aimed to on-line assess and report vital signs for physical training. These sensors also allow to regulate the phases (warm up, training and cool down) in a physical training session and notify the user if any parameter is out of range. However, these sensors do not allow to continuously acquire the physical activity difficulty parameters and do not provide real-time monitoring of the gait spatiotemporal parameters.

In the context of CR at the Instituto de Cardiología at Fundación Cardioinfantil, these parameters are usually measured by means of several sensors. Additionally, the data management is manually registered by the therapist. Under these circumstances, this paper presents a sensor interface for online measurement of a set of variables commonly evaluated in CR using a treadmill for Phase II. These variables correspond to the cardiac patient's status, the physical activity levels (i.e. gait spatiotemporal parameters) and the difficulty perception using the Borg scale [10]. This interface opens the possibility of providing biofeedback during a CR session, where the optimal training effects generally depend on an appropriate feedback about the performance [12]. Additionally, there is evidence that biofeedback systems in parallel with functional task training intend to increase patient motivation. Besides that, the patient could progress toward a specific goal by means of the incorporation of patient's senses and challenges [13].

This work has two objectives, on the one hand, to provide a tool for clinicians to assess the patient's status during CR. On the other hand, as there is evidence (presented in Section III) that robots could motivate patients for therapeutic procedures, this sensor interface opens the possibility to integrate robotic agents into the cardiac therapy. Hence, an exploratory experiment to establish Human-Robot Interaction is presented in this paper. The task of the robot is to track the sensor readings and give feedback to the patient depending on the current and previous session's data, in order to create a personalized therapy assistant.

III. RELATED WORK

This section describes some of the robotic applications that have been developed in the context of CR. It is divided into two approaches: Assistive Robotics and Socially Assistive Robotics.

Assistive Robotics (AR) is the field of robotics for assistive and supportive robotics applications in physical and non-physical interactions. In the context of CR, robotic physical assisted therapy is a promising method for its implementation in the rehabilitation of patients who have suffered CVDs. AR supports the patients in performing exercises and provides real-time feedback for guiding the exercises. Different studies of AR as an application to CR have been developed in terms of the commonly used robotic platforms.

For example, robotic tilt tables were tested for its implementation as a cardiopulmonary robotic-assisted treatment in stroke patients [14]. This study concluded that this device is feasible for incremental cardiopulmonary exercise training, acceptable by patients and gives a positive cardiopulmonary response.

Treadmill-based devices are the most prevalent robotic rehabilitation methods, and Lokomat (Hocoma, Switzerland) [15] the most clinically tested system. This device allows controlling the hip and knee joints for the pelvic vertical movements through the orthoses linked to the treadmill frame. Lokomat is commonly used in the treatment of motor disabilities. The effects of Lokomat in assisting physical activities have been evaluated in CR [16].

Socially Assistive Robotics (SAR) shares with AR the goal to provide assistance to patients, but it specifies assistance through social interaction. Social robots perform tasks with a high degree of autonomy for a natural interaction with the patient [17].

However, SAR has not been fully explored in CR. According to the literature, initially, SAR was aimed at aiding the nurses for therapy and to overcome the nurse shortages in CR. In this study, a "hands-off" physical therapy assistant, CLARA, was developed [18], which aims to help patients in repetitive and painful spirometry exercises. Cardiac patients have to perform spirometry exercises to allow full expansion and contraction of lungs. CLARA has a color tracking server and a speaker to communicate with the patient, as well as a bed detector. The robot navigates, interacts with the patient and tracks the exercises. CLARA counts and records the repetitions of the patients through a spirometer with color marks, which in turn are registered by the server. In the end, CLARA reports the collected results and willingness of the patient to the hospital staff. This study concluded that the control strategy for all of CLARA's functionalities was performed successfully, and questionnaires showed that people were more motivated during the session with the robot resulting in an average satisfaction of 84.6%. Nevertheless, this study was performed with healthy people and the authors of the paper state that no clinical studies were conducted yet for this area.

As aforementioned, this work presents a sensor interface to on-line measure relevant variables during the therapeutic sessions in CR (Phase II). As a matter of fact, these patients usually perform exercises using a treadmill without aid or support to develop movements. This work explores the use of SAR in CR by means of the proposed sensor interface. This interface integrates a Heart Rate monitor, a Laser Range Finder (LRF) sensor to estimate the gait parameters and an Inertial Measurement Unit (IMU) sensor to measure the treadmill inclination. Additionally, a social robot is used to periodically ask the Borg Scale level to the patient (voice interface). After that, the user delivers the Borg Scale level into the user interface (Tablet).

IV. METHODOLOGY

This work presents the development of a sensor interface for CR on a treadmill. This system helps the therapist to assess a group of patients on-line in order to reduce the risks inherent to the therapy and measure their performance and progress. Fig. 1 shows an example of CR using a treadmill in Phase II, where the therapist personally and periodically measures the state of the patient.

Fig. 1. Current scenario of a CR based on treadmill at Instituto de Cardiología at Fundación Cardioinfantil (Colombia).

As mentioned above, this interface measures three types of variables selected by the medical staff measuring the patient's status during the therapy: **cardiopulmonary parameters**: peak heart rate, heart rate variability and evolution of heart rate, **gait spatiotemportal parameters**: cadence, step length and speed and **physical activity difficulty parameters**: Borg Scale and treadmill's inclination.

A. Sensor Integration

As shown in Fig. 2, this system integrates measurements from a heart rate monitor, an IMU (reporting the treadmill

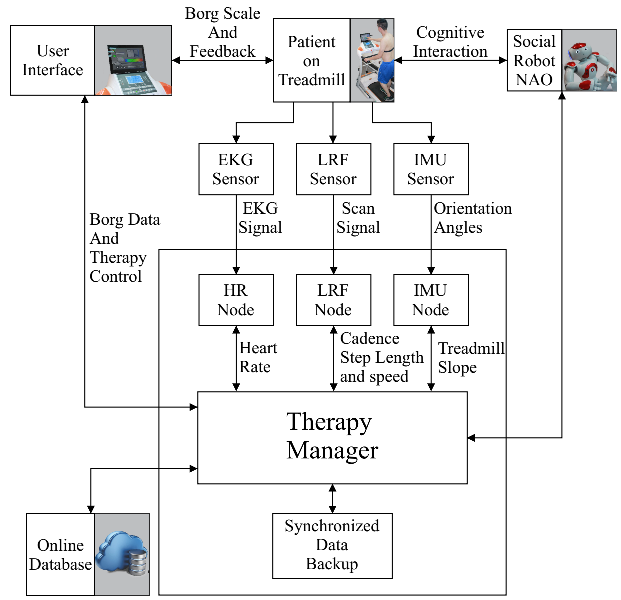

Fig. 2. Human-robot interface diagram used for cardiac rehabilitation.

inclination), a LRF (to estimate gait parameters) and periodic results from the Borg scale, as well as a user interface and an autonomous humanoid social robot platform, NAO (SoftBank Robotics Europe, France). The system is designed to present the three main metrics considered in CR measured as follows:

- **Gait spatiotemporal parameters**: as shown in Fig. 2, an LRF node reports measurements from an LRF which are used to estimate the cadence, step length, and speed of the patient. The estimation of these parameters was proposed and validated in a previous work [19]. This node estimates the parameters of the kinematics of lower limbs and performs filtering of the oscillatory components contained in the user movement intention [19]. The speed is obtained through the product of gait cadence (GC) and the gait step length from the leg detection process.
- **Cardiopulmonary parameters:** a heart rate monitor (Zehpyr HxM BT) is located on the chest of the user and reports a wireless and continuous measurement of the heart rate using Bluetooth communication.
- **Physical activity difficulty parameters:** two different metrics are used to measure the physical activity difficulty: the inclination of the treadmill and the reported difficulty of the exercise. As the inclination can not be accessed directly from the treadmill, a MPU9150 IMU is placed on the treadmill such that one of its rotation angles corresponds to the main rotation axis of the treadmill, thus, changes in the measured IMU angle are equal to changes in the treadmill slope. A tactile computer monitor (i.e. a tablet) uses a graphical user interface to measure the patient's fatigue using the Borg scale as shown in Fig. 3. In the context of a CR

supported by a social robot, a NAO robot periodically asks the patient to report a value on the Borg scale which is entered on the tablet.

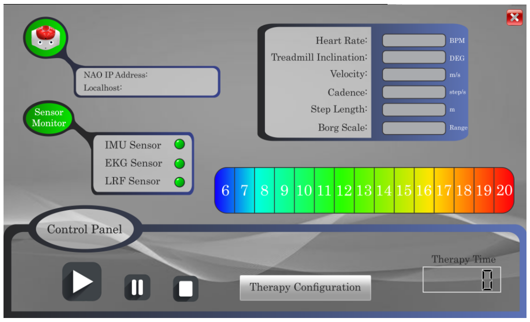

Fig. 3. User interface used to assess the patients fatigue, view the therapy parameters as a form of feedback, configure the robot, monitor sensors and control the therapy performance.

All of these sensors have different transmission rates and sampling frequencies which represent an issue in terms of on-line synchronization. To tackle this issue, a node is associated to each sensor which allows the main computer to have access in real time to the measurements. These nodes are designed as drivers of the incoming raw sensory data when the module is ready to acquire information. Therefore, a downsampling is performed by each node with a configurable sampling frequency (for this study, the configured sampling frequency for each node is set to 10Hz). Each module stores all the information in an internal backup, which allows recovering the data in case of any unexpected disconnection. These logs can also be used after the interaction by the medical team to evaluate the efficiency of the therapy.

The whole system is controlled by a therapy manager, which performs another downsampling in order to acquire simultaneous data from the sensor nodes (with a sampling frequency of 1Hz). In the same manner, the therapy manager is also able to control each processing module. The system includes a NAO robot which can be used to engage the user during the therapy. Currently, the robot is only used to ask the Borg Scale level and to provide feedback of the acquired parameters but in the future, the robot will be used in a more complex and personalized interaction aiming to increase the motivation and reduce the desertion of the patient.

As shown in Fig. 2 and Fig. 3, the patient has access to two main feedbacks from the system: the graphical user interface reports the synchronized and processed data from the sensors and the social robot periodically verbally informs the patient the status of the session, through the physiological variables, the expected values, the therapy time, or asks for the Borg Scale levels.

B. Data management

The data management system is designed to capture information from the therapy divided in two groups: (1) Basic information of the patient such as: name, age, gender and height. (2) Sensors' readings, such as: relevant events that occurred during the session, average data, and score of the therapy.

The storage procedure is carried out by a database handler which generates backup files at run-time, where all the measurements are stored. In case that any event is generated during the session, the database handler capture the event type, the reason that causes the event as well as some parameters related to it. Once the session has finished, there are two more processes that the database handler has to run: (1) Data wrapping, which structures all the information in the correct way to be stored on the database. (2) Data transferring from the backup files to the database.

The whole data is stored at the end of the session on a local MongoDB database. MongoDB is a well known non-relational database system that handles all the information as documents and data collections, this system was chosen because in future works the data analysis is meant to be performed using a frequency map enhancement technique [20], which was designed to obtain and process information collected from a MongoDB-based database.

C. Pilot study protocol

In order to validate the interface, a pilot study was conducted. As shown in Fig. 4, one healthy male (1.71 m, 63 Kg, 24 years old), without apparent physical contraindications to treadmill training, participated voluntarily in this study. The protocol was designed in order to simulate the treadmill part in an average CR protocol and to test the response of the parameters to a change in speed and inclination. Initially, the subject walks at 3 m/s on the treadmill for 10 minutes, then, the speed is increased to 5 m/s and the inclination is increased until its maximum (3.7^o). The subject walks in those conditions for 10 minutes. Finally, the subject stands still during 8 minutes to simulate the cool down phase and in order to observe the decrement in the heart rate after the exercise. The setup for this experiment can be seen in Fig. 4.

Fig. 4. Patient exercising on treadmill according to the pilot study protocol.

V. RESULTS AND DISCUSSION

According to the protocol described in the methodology section, the interface was on-line for 28 minutes. Fig. 5-7 present the continuous record of each parameter as collected by the therapy manager. The two vertical lines correspond to the two events: in green the increase of speed and inclination and in red the end of the physical activity and the start of the cool-down phase. Results are divided according to the three main metrics that were expected to be measured.

A. Gait spatiotemporal parameters

The patient's gait spatiotemporal parameters can be seen in Fig. 5. All of these parameters change instantaneously after an event, which indicates that the processing and feature extraction module is not interfering with the acquisition. All of the values are in a normal range and correspond to the values that can be seen on the display of the treadmill.

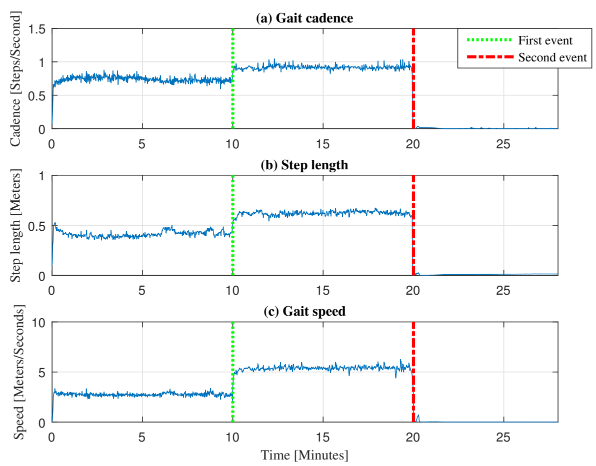

Fig. 5. Gait spatiotemporal parameters: patient's cadence (a), step length (b) and speed (c).

B. Physical activity difficulty parameters

The treadmill's inclination and the reported Borg scale data are shown in Fig. 6. The inclination curve shows clearly a sharp increase or decrease of the value following each event. As no change of the inclination was executed between events, the value stays constant except for small oscillations due to the impact of the steps of the patient on the treadmill. The Borg scale shows a continuous increase for the first 20 minutes of the session as the perception of fatigue increases during that period. The value decreases during the 8 last minutes and stabilizes. It is important to highlight that the Borg scale is a subjective measure.

C. Cardiopulmonary parameters

Fig. 7 shows the patient's heart rate during the session. As shown by the rapid increase and decrease of heart rate, the zephyr sensor has a response fast enough to be used in real time to report the heart rate and react to the events during the therapy. The absence of a clear convergence is due to

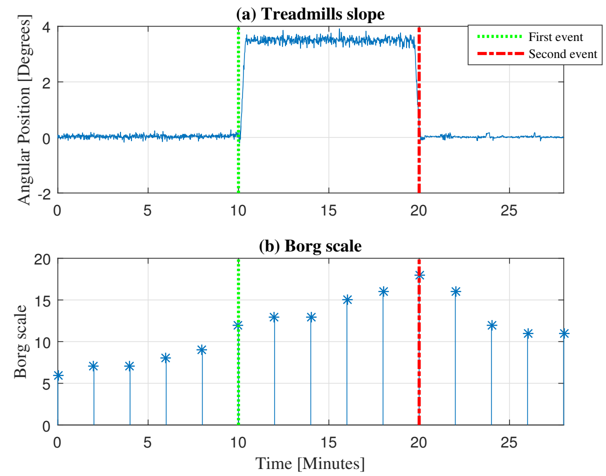

Fig. 6. The physical activity difficulty parameters: (a) Treadmill inclination angle recorded using the MPU9150 IMU sensor and (b) Patient's fatigue obtained from the user interface.

the physiological response of the cardiac system. The values in the signal change according to the normal range of heart rate in healthy patients with similar conditions in comparison with the voluntary patient. For example, when the patient was walking at the beginning, the heart rate was around 105 BPM, and when the velocity increased to 5 meters per second, the heart rate was around 145 BPM which represents a moderate effort.

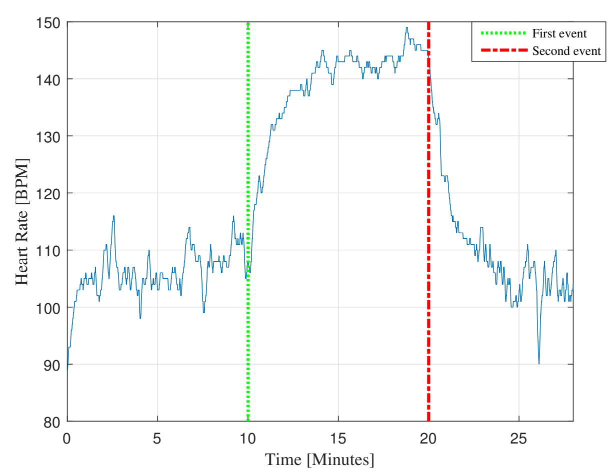

Fig. 7. Heart rate measurement using the HXM zephyr sensor.

VI. CONCLUSION

The results presented in this paper show the potential of this sensory system combining a laser range finder, a heart rate monitor, an IMU, and a graphical user interface for CR using a treadmill. Spatiotemporal gait parameter can be estimated from the LRF results, which can be used as an indication of the performance of the patient in the rehabilitation therapy, and the correctness of the gait. The system presented combines information from different sensors to present these values in real-time to the patient and store them in a log for post-hoc analysis by medical staff. The Borg scale collected by the user interface can be combined with the slope of the treadmill and the heart rate to evaluate the difficulty of each session.

These variables can be presented in real-time to the patient, and the logs can be used by the medical team supervising the rehabilitation to plan the following therapy session. Based on the fact that the measurements are on-line, allows recording the physiological indicators, such as the heart rate, in a more precise time, during or after the exercise, compared to the current situation where the measurements are taken by the medical staff.

In future work, these sensory inputs will be used by a personalized social robot to track the progress of the patient over multiple sessions, keep the patient engaged in the therapy with the aim of reducing their exertion level due to the exercise. These real time sensor values can also be used to detect events indicating a risk for the patient such that the robot can notify the nurse or the therapist, for example, if the heart rate is too high and presents a risk for the patient.

The results highlight the possibility of implementing the proposed interface to record data during a CR. The interface allows processing the data, its correspondent on-line visualization, and a recording for post-treatment. The parameters of inclination and speed as indicators of the difficulty of the exercise can be used either as an on-line feedback for the patient or as a follow up of the performance of the patient. It could be a tool for the multidisciplinary group that supervise the rehabilitation process to plan the following therapy sessions. Similarly, gait spatiotemporal parameters could be an indication of performance and a useful information for the medical staff and the patient. Further, the on-line measure of heart rate could allow the development of algorithms to detect events that may indicate a risk for the patient and a reaction to those events. For instance, the robot could call the medical staff in those cases. This on-line measure also allows to take some indicators such as the decrement of the heart rate at one minute of two minutes after the end of the treadmill exercises more precisely than if they are taken for the medical staff. These indicators are used as important parameters for health care, progress on the therapy and mortality risk assessment in CR. Finally, to have the recordings of all those parameters could be useful for future research and assessment of progress.

The development of this interface is a first step on the proposal to integrate social robotics into CR. Based on previous studies on social robotics it is hypothesized that SAR could be helpful to the medical staff, reduce risk of the therapy by identifying risk factors, increase performance of the patient and increase its motivation and engagement.

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