Automated Rehabilitation Exercises Assessment in Wearable Sensor Data Streams

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***Abstract*— This work stems from the Italian project H-CIM (Health-Care Intelligent Monitoring), aimed at developing a wearable sensor data streams based home-monitoring system to support self-rehabilitation of elderly outpatients. Different from the pervasive data stream applications, which are always accompanied by the evolution of unstable class concepts, this project requires stable standard and personalized rehabilitation exercises patterns be provided to assess outpatient's self-therapy progress at home. In this designed pipeline, the representation sequences of the personal standard rehabilitation exercises in wearable sensor streams is therefore first benchmarked, then an assessment system which integrates multistage data processing and analyzing is proposed to enable elders to manage their own rehabilitation progress properly. The system proved to be an effective tool for supporting compliance monitoring and personalized self-rehabilitation; it is currently under further development within the Italian project Home-IoT, with the aim to become a more general data stream analytics service, not only devoted to rehabilitation exercises assessment.**

***Keywords*—rehabilitation assessment system, wearable sensor, data streams.**

I. Introduction

The rapid aging population is one of the most pressing challenges all over the world. According to the population report, the number of older people (persons 65 years or older) is expected to have a staggering 170% increase by year 2060 [6], which brings unprecedented challenge to health care. With respect to rehabilitation, this challenge, especially in Italy, is further magnified by the number of caregiver available [4]. It is infeasible to handle this staggering number with the traditional rehabilitation, which being conducted in hospital settings and requires direct supervision of a skilled caregiver. Wearable sensor based home rehabilitation has therefore emerged as a viable and economical alternative of the traditional rehabilitation and further allows the rehabilitation to be tailored to individual needs at the same time.

Several research projects have been conducted to reform wearable sensor data stream based health care with applications ranging from posture recognition [7] and health monitoring [2] to identify and control chikungunya virus [5]. These wearable sensor based projects, just like other pervasive data stream applications, involve changing the concept of a given target and are further complicated by the skewed distribution [8]. Therefore, concept drift and class imbalance have to be addressed concurrently in such applications. In this project, however, outpatient's self-therapy exercises at home are to be referenced to the standard and personalized rehabilitation exercises patterns, which being recorded under the supervision of a qualified trainer in the medical department. The stabilized "golden standard" therefore has to be provided in order to assess outpatients' rehabilitation progress at home. In the proposed system, the representation sequences of the personal standard rehabilitation exercises in wearable sensor streams will first be benchmarked. When continuing rehabilitation exercise at home, outpatient mounts identical sensors on the same body locations. The sensor signals which record a patients movements will then being transmitted to the proposed assessment system for preprocessing. The preprocessed signals representing a patient's rehabilitation exercise patterns are compared, considering temporal scaling when performing pattern-based search, with his/her personal "golden standard" benchmarked in clinical settings to evaluate this patients therapy at home. Moreover, the physicians can also assess the patients progress and provide feedback accordingly through the recording of the system.

II. System Design

The overview of the overall system is reported in Figure 1. It consists of different computational modules and has been developed to be deployed at home with the aim to decentralize the computational effort and communicate, towards the remote control center, only information instead of raw data.

Starting from the bottom, different streams of data, from both envronmental and wearable sensors, are collected and transformed into a *unified data model* through the *Data Fusion* layer [1]. An internal clock system is used to synchronize data among the different sources. The other layers are related to data preprocessing, more precisely outlier detection and removal, missing value replacement, feature extraction and selection. The *Switch* component is a key module in the system's architecture: it allows to switch between *daily activity recognition* and *automated rehabilitation exercises assessment*, where these two tasks are mutually exclusive. Indeed, the data representation to use is different according

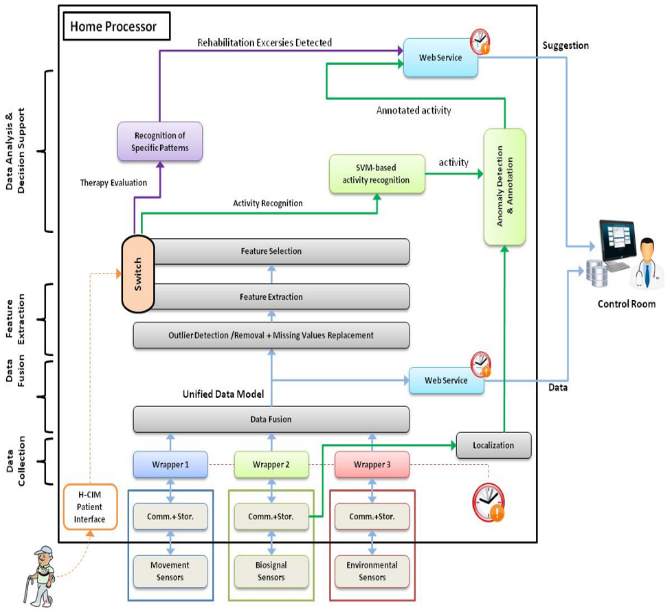

Fig. 1: The general structure of system design in assessing rehabilitation exercises.

to the currently active functionality. More precisely, the *daily activity recognition* requires the extraction of relevant features from the sensor signals and machine learning classifier - a Support Vector Machine, in this specific implementation - to identify the dailiy activity performed. On the other side, the *automated rehabilitation exercises assessment* functionality uses the raw stream of data collected during the rehabilitation exercises session performed by the patient at home. This paper focuses on the more innovative functionality for *automated rehabilitation exercises assessment*, only. The signals representing the set of patient's rehabilitation exercise patterns, previously acquired in a clinical setting with the supervision of a clinician ("golden standard"), are searched for into the overall stream of data, through a pattern-search algorithm [3]. The module devoted to this analysis is named *recognitioin of specific patterns* and is based on Dynamic Time Warping (DTW), a distance measure between time series which allows to deal with temporal scaling (movement performed more slowly or more quickly). All the computations are performed locally, then the number of repetions resulting coherent with respect to the "golden standard", for each exercises, are sent to the monitoring centre, allowing clinicians to monitor the compliance to the rehabilitation therapy for every patient. Moreover, the quality of self-rehabilitation performed by the patient is also assessed, based on the comparison between the expected and coherent number of repetitions for each exercise. Possible worsenings of the motor capabilities can be therefore detected on time and correlated to other clinical information stored at the centre (e.g. laboratory tests, medical vistis, etc.).

III. Benchmarking Patterns

To benchmark the personalized standard rehabilitation exercises patterns with real-time sensor data, each patient mounts three wearable Inertial Measurement Unit (IMU) on the anterior surface of his/her chest, dominant wrist and dominant ankle, with the y-axis of the sensors well-aligned to the long axis of the body segment. Each wearable sensor collects measures over the three axes, i.e., orientation, acceleration and velocity, and has a sampling rate of 10 Hertz. In particular to this project, the acceleration records the most relevant measures among the three axes and relating also to the strength performed by the patient to replicate the 5 rehabilitation movements as prescribed by physicians. These 5 hospital designed rehabilitation exercises include:

- Flexo-extension of the knee when sitting.
- Raising and lowering arm when sitting.
- Trunk rotation when sitting.
- Standed backward extension of the leg.
- Light "squat".

Figure 2 illustrates the setup of the rehabilitation exercise system when one patient is doing backward extension of the leg with the guidance.

Fig. 2: The patient performing one of the prescribed rehabilitation therapies, the standed lower back limbs extension.

After the rehabilitation is initially performed in the clinical settings under the supervision of a qualified trainer, the data (3D accelerations on the three axes X, Y and Z over time for each sensor and each exercise) associated with each patient's personal "golden standard" will be further verified by a medical expert. The final benchmarked patterns will be used to help patients perform home based rehabilitation movements, and assist physicians in assessing the effectiveness of patients' self-managed rehabilitation progress. Figure 3 exemplifies one patient's verified "golden standard" related to one axis of one wearable sensor.

IV. Experiment Results

In the following Figure 4 two examples for two different exercises are reported, more precisely *flexo-extension of the knee* and *backward extension of the leg*. As far as the first exercise is concerned, all of the 5 repetitions performed by the subject are considered coherent according to the associated golden standard pattern. On the contrary, only 9 repetitions of

Fig. 3: The verified “golden standard” of one patient’s trunk rotation when sitting from the acceleration on y-axis of sensor mounted on chest.

the second exercise - out of the 10 expected - are classified as coherent. In this case, the coherence between the golden standard and the last repetition performed by the patient does not result sufficient. This is a quite usual situation: the last repetition in a long sequence of movements might be not executed with the same goodwill as the first ones, in particular in the case of elderly patients. The core paramter of the system is a threshold on the level of coherence, basically a minimum value for the DTW computed between the golden standard and any subsequence in the data stream. The lower is the threshold the higher the coherence required; while this allows to correctly filter out aspecific movements (i.e. movements which are not rehabilitation exercises), on the other side it reduces flexibilities in recognizing the golden standard when performed slowly or quickly. Thus, setting a suitable value for the threshold might be, in some cases, a time consuming task. For the experiments presented in this paper it was carefully identified with the supervision of the clinical staff.

Tests on the small set of patients proved that the DTW-based pattern search algorithm can identify, correctly, the movements which are more coherent with the golden standard of each exercise and for each patient. This proves that the system offers a personalised health digital service which can potentially improve effectiveness of self-rehabilitation at home.

V. Conclusion

Motivated by the pressing challenge of the traditional rehabilitation of elder care, this work developed a wearable sensor data stream based home-monitoring system to support the self-rehabilitation of elderly patients, which allows outpatients to take the full benefit of rehabilitation exercise and manges progress effectively along with physicians just like inpatients. This system uses three wearable Inertial Measurement Units as the signal source and extracts the signal’s time domain information to assess outpatients’ self-rehabilitation exercises. The practical experiments demonstrated the usability of the proposed mechanism, which fulfills the requirements of elders’ rehabilitation at home. The system provides a viable and economical alternative of the traditional rehabilitation, and it is expected to alleviate the pressing challenge of the traditional rehabilitation of elder care. We are now working on the Home-IoT project, as an extension of the H-CIM, in order to strengthen the system to support a wider range of health care services.

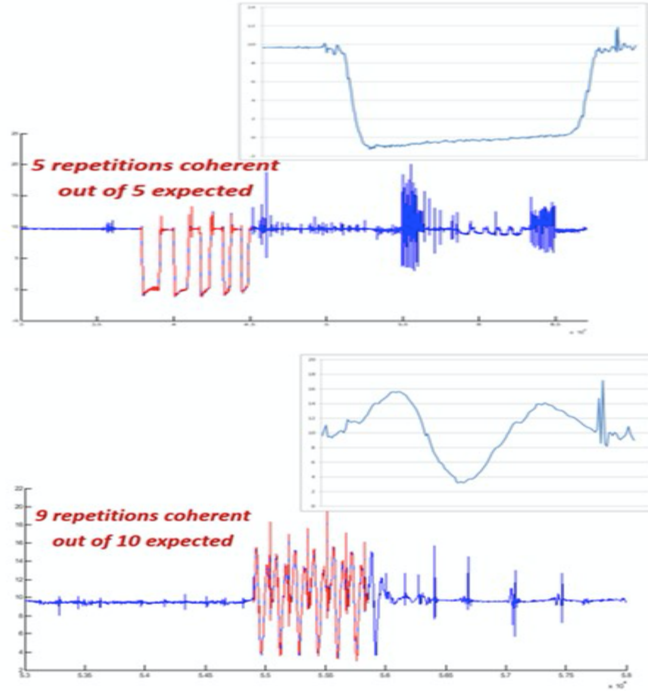

Fig. 4: The assessment of one patient performing flexo-extension of knee and backward extension of leg exercises.

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