Demonstration Paper: Monitoring Mobility Disorders at Home using 3D Visual Sensors and Mobile Sensors

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ABSTRACT

In this paper, we present *PoCM*^{2} (*Point-of-Care Mobility Monitoring*), a generic and extensible at-home mobility evaluation and monitoring system. PoCM^2 uses both 3D visual sensors (such as Microsoft Kinect) and mobile sensors (i.e., internal and external sensors embedded with/connected to a mobile device such as a smartphone) for complementary data acquisition, as well as a series of analytics that allow evaluation of both archived and real-time mobility data. We demonstrate the performance of PoCM^2 with a specific application developed for freeze detection and quantification from Parkinson's Disease mobility data, as an approach to estimate the medication level of the PD patients and potentially recommend adjustments.

Categories and Subject Descriptors

H.2.8 [**Database Management**]: Data Mining

General Terms

Design, Algorithms

1. INTRODUCTION

A variety of disabilities, e.g., cerebral vascular accident/stroke, spinal cord injury, aging-related balance and gait disorders, Parkinson's disease (PD), and traumatic brain injuries, affect mobility of the patients. Toward coping with this trend, the process of mobility disorder evaluation plays a key role in devising rehabilitation plans and medication prescriptions for such patients. This process is usually carried out by asking the subject to perform several standard tasks while clinicians observe mobility characteristics of the patients. For example, repeated walk-back-and-forth and repeated sit-and-stand are two components of the United Parkinson's Disease Rating Scale (UPDRS) [2].

With the traditional approach for mobility evaluation, the patient is required to frequently visit a medical center. This approach suffers from a number of shortcomings as follows: (1) with the traditional approach the entire process can be time consuming considering that the patient needs to travel to the medical center, while possibly having to take medication in advance; (2) patients usually prefer to stay at home instead of traveling to the clinic to avoid higher risk of injury; (3) patients may behave differently when examined in the outpatient clinics; (4) currently there are not sufficient medical resources to satisfy all patients' day-to-day needs, while some patients can benefit from more frequent evaluations; and finally (5) the clinicians' evaluation is mostly subjective instead of quantitative (although there are clinical scales such as UPDRS, these tools suffer from low resolution and they require significant training before one can obtain valid and reliable measurements).

We argue that a reliable and accurate mobility evaluation and monitoring system at home is an attractive alternative that can address the aforementioned shortcomings. Such a system acquires the patient's data at home. Thereafter, the collected data is processed and analyzed on-the-fly to objectively characterize mobility of the patient, and accordingly generate recommendations for the patient. The processed data can also be sent to the clinician via network for further clinical recommendations. The home monitoring system then provides feedback to the user by combining the clinician's and the system's recommendations. With this approach, since the mobility evaluation is carried out in an environment familiar to the patient, the data are more ecologically valid, while the inconvenience and potential risks associated with a clinic visit are avoided. More importantly, the recommendations are now based on, not only clinician's experience, but also quantitative, accurate, and objective analysis. In addition to addressing the shortcomings of the traditional approach, our proposed approach can enable frequent medication-level adjustment and long-term evaluation and prediction of the patient status.

In the rest of this paper, we review the related work, describe a proof-of-concept system we have developed to investigate and demonstrate the effectiveness of at-home mobility monitoring (here customized for PD mobility monitoring), and finally describe the setup of our demonstration.

2. RELATED WORK

Several attempts have been made at automating mobility disorder evaluation and monitoring. The most prevailing methodology suggests using one or a combination of motion sensors, such as ac-

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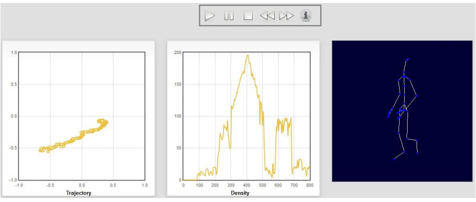

Figure 1: Graphical user interface of PoCM^2 showing results of the analytics

celerometer, gyroscope, magnetometer, pedometer, etc. The clinically meaningful indicators are further extracted by recognizing the patterns from the time series data generated by these sensors (e.g., see [4]). On the other hand, a few solutions have been proposed that use visual sensors for mobility monitoring (e.g., see [1]). While the former allows for making accurate measurements at certain parts of the body equipped with sensors, the latter is superior in the coverage of the entire body, but at lower resolutions.

To the best of our knowledge, our proposed system is the first that leverages both 3D visual sensors and mobile sensors (consisting of a variety of internal and external sensors, including motion sensors) for mobility evaluation and monitoring. This hybrid solution allows for compensation of inherent deficiencies with each sensing modality as discussed above. Moreover, while in addition to motion data mobile sensors can provide context data (e.g., vitals and environment data) and are also applicable in the entire home and outdoor, visual sensors mainly collect visual data and are often designed to concentrate on a specific area at home (e.g., living room) and only for indoor usage; hence, complementary.

3. POCM^2 AND PD MOBILITY MONITORING

As a proof-of concept, we have developed a system, dubbed *PoCM^2* (*Point-of-Care Mobility Monitoring*) for at-home mobility monitoring. For data acquisition, PoCM^2 allows for collecting data from 3D visual sensors as well as internal and external sensors (including motion sensors) of a mobile device. There are two types of 3D visual sensors in the market. The Time-Of-Flight (TOF) 3D sensors (e.g., SoftKinetic) calculate the depth per pixel by measuring the time it takes for the light to traverse in space, whereas the Structured-Light 3D sensors (e.g., Kinect) measure depth using the principle of stereo vision. With PoCM^2, we use stereo-based 3D sensors because they are less expensive while supporting relatively high resolution. In particular, we have experimented with both Microsoft Kinect and Asus Xtion cameras which perform equally well (they both incorporate the same sensor from PrimeSense); for demonstration purposes we will use Microsoft Kinect. In addition to a 3D visual sensor, PoCM^2 uses a mobile device (i.e., a smartphone) to collect both context data (from the internal GPS, temperature and light sensors of the smartphone) as well as motion data. The motion data are captured by four external Shimmer 9DoF motion sensors that communicate with the smartphone via Bluetooth, and provide nine degrees of freedom motion capture via their on-board tri-axial accelerometer, tri-axial gyro, and tri-axial magnetometer.

On the other hand, for data processing and analysis, PoCM^2 allows the user (patient, care-giver, or clinician) to locally or remotely apply an extensive and extendible series of data visualization and/or analysis tools to the acquired data via a web-based graphical user interface (see Fig. 1). These analytics are applicable both to the archived data collected in a session in the past, and to real-time data on-the-fly. In particular, in order to demonstrate the use of PoCM^2 in a specific scenario, we have developed a series of analytics for freeze detection and quantification from PD mobility data as an approach to estimate the medication level of the PD patients. These analytics include PCA-based data reduction for effective visualization of mobility data, density-based freeze detection from digested mobility data, and quantification tools to measure step size, step time, postural swing level, and hand swing level. Moreover, in order to prepare data for the aforementioned analysis, PoCM^2 implements a data preparation pipeline with which the skeletal stream is pre-processed to decouple the complex spatiotemporal information and generate a representative skeletal sequence which exhibits the patient's most consistent motion pattern. Fig. 2 illustrates the PoCM^2 data preparation pipeline (for more details see [3].

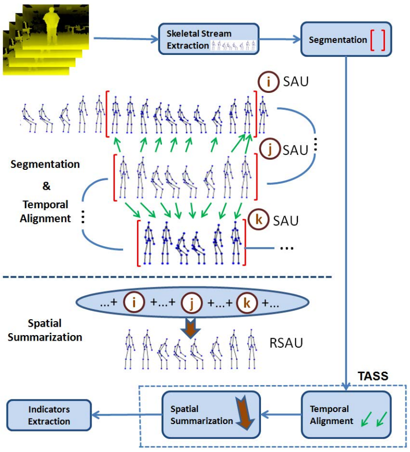

Figure 2: PoCM^2 data preparation pipeline

4. DEMONSTRATION SETUP

With our demonstration, we showcase the use PoCM^2 for both on-line (live) and off-line PD mobility monitoring and analysis. For the on-line part of the demonstration, we will set up the PoCM^2 system at the conference venue and show how one can use this system to acquire and analyze mobility data collected from live subjects. For the off-line part of the demonstration (i.e., to demonstrate how one can use PoCM^2 to analyze *archived* PD mobility data), we will use real mobility data collected from 15 PD patients in both on-medication and off-medication states. To collect the aforementioned mobility data, we arranged five focus groups with the patients and accordingly designed a set of 5 tasks (namely, *walking, walking-while-counting-down, walking-while-counting-down-by-3, walking-while-carrying-glass-of-water, walking-while- maneuvering around-obstacles*). Each task was performed (in both on- and off-medication states) by each patient repeatedly for 5 rounds while we used PoCM^2 to collect the mobility data from patients. We will show how PoCM^2 can be used to visualize and analyze this dataset.

5. REFERENCES

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