A Multimedia Big Data E-Therapy Framework

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***Abstract*—Due to the low cost and high availability of wearable health sensors and motion tracking devices, home based therapy monitoring has come to a reality. In this paper, we propose a gesture controlled e-therapy online framework that can monitor physical and occupational therapy exercises using multimedia data produced by different sensors such as Kinect2, Leap, and Myo. The multimedia therapeutic data is then stored in a big data repository with proper annotation. We have developed analytics to mine therapeutic information from the big data platform, such as finding the most appropriate therapy regime for a patient, based on her age, ethnicity, gender, disability level and geo-spatial location. We will show key queries that can be answered by our developed analytics.**

Keywords- physical therapy; occupational therapy; motion sensors; video annotation

I. INTRODUCTION

The proliferation of personal health sensors has brought a revolution in the area of low cost healthcare in the past few years. The ability of these devices to provide clinical data combined with their popularity due to low cost has resulted in the availability of a very large amount of multimedia data. To make the best use of this data, it has to be stored first, after which intelligent algorithms need to parse it efficiently to produce analytics that are of use to the health community. Multimedia big data has recently attracted the attention of researchers too, due to the abundance of text, images and videos on the internet. For example, in [1] the authors have discussed a scheme for tagging image data. However, annotating video data remains a big challenge.

In this paper, we present a big data framework for storing sensor generated multimedia health data. Our framework consists of data coming from different sources, such as health sensors, emails, text messages, audio and video sessions, etc. A Microsoft Kinect2 sensor is used to receive data for 25 joints at the rate of 60 frames per second (fps), producing about 32KB of data per second. The data is received in the form of a JSON text file by the system. Kinect2 is also used to record video of the exercise session for storage. A Leap motion controller tracks finger joints and other gestures of the two hands at about 30fps, producing 36 KB of frame data per second [3]. We also use the Electromyogram (EMG) signal based Myo controller, which produces about 1.6KB of frame data per second. The system allows disabled users to connect to a Philips Hue Bridge to control lights and electrical appliances to perform occupational therapy exercises. In addition to such exercises, the system allows the user to perform movement improving physiotherapy exercises using virtual reality games [2],[4]. The multimedia data stored in our big data storage framework is retrieved later to perform queries to discover recovery patterns in patients from different backgrounds. Examples of such queries include finding the best time of day and the best number of repetitions for exercise based on the ethnicity, age, gender level, and disability level of the user.

The remainder of the paper is divided into two sections. Section 2 gives a brief overview of the framework. Section 3 explains the implementation details of the framework with different demonstration scenarios.

II. SYSTEM ARCHITECTURE

Fig. 1 shows the underlying details of the proposed system architecture. A variety of multimedia sensors and devices are used to gather different kinds of therapeutic data. This includes text, images, audio, video, gestures and sensory data. The **Data Manager** parses data coming from every sensor individually.

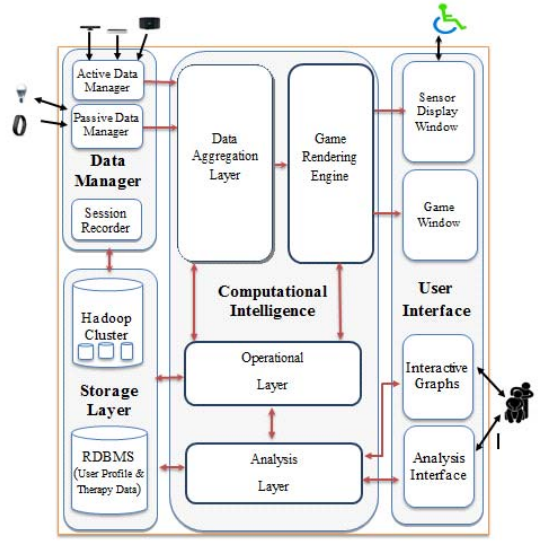

Figure 1. High-level architecture of the e-Therapy platform

Results from each of these parsed data streams are afterwards combined at the **Data Aggregation** layer into a single file for every exercise session. This information is transferred to the **Operations Layer**, which maintains operational control of the entire system, linking user authentication and session data to the **Storage Layer**. It also

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generates games specific to therapies assigned to the user. The record of user profile and information (therapist, patient, caregiver) and all predefined therapies and exercises is maintained in a **Relational Database Management System** (RDBMS), while all session data is redirected by the Operations Layer for storage in a **Hadoop** based **Big Data** cluster. The **Analysis Layer** then uses specific MapReduce jobs to provide big data analytics on the session information volume gathered over a significant period of time, to provide useful analytical information in the **Analytical Interface**.

III. IMPLEMENTATION

Capturing, Parsing and Encoding: In each session on the patient's side, the client machine gets raw feed from a variety of sensors. In our implementation, therapy session data is collected from Kinect v2, Leap and Myo. These sensors give an array of frames for the different types of captured media. This includes EMG and IR depth sensor based skeletal joint tracking as well as full HD RGB video and audio. A sample set up of the framework is shown in Fig. 2.

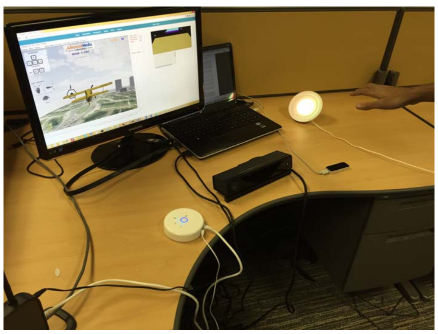

Figure 2. Snapshot of an operational environment

The skeletal tracking data is used to annotate timestamps in the audio and video feed to mark the start, progress and end of each gesture that makes up the exercise being performed. At the end of each session, the JSON encoded skeletal data, combined with the annotated audio and video streams is sent to the server.

Storage: Data collected from the patient by the system can be categorized as either active or passive. Active session data comes from therapy which consists of data integrated from multiple sources including wearable devices. This data contains skeletal tracking, audio, video and other biometric data such as blood pressure and heart rate. In addition to session based data, the system also passively collects ambient activity data such as sleep duration and steps taken over the course of the day. The predefined exercises as well as the profiles of patients, therapists and their caregivers are maintained by a traditional RDBMS.

The active session and passive patient data collected over the course of the patients' rehabilitation is of high volume. This large amount of data requires a base platform that can provide scalable, fault-tolerant, and distributed storage. It should also provide the facility to perform big picture health analytics on the data. Hadoop, a popular java based big data storage and processing platform, is utilized by our system for this purpose. The active session and passive patient data JSON files are stored in a Hadoop cluster under HDFS.

Analysis: In order to answer queries related to rehabilitation that require analysis of each patient's partial or entire dataset stored in our system, we utilize a parallel and distributed processing platform. The MapReduce paradigm allows us to write analytical tasks to be executed on the Hadoop cluster. The analysis layer maintains MapReduce tasks ready to be executed. These tasks are sent to the master MapReduce node called the JobTracker, which then distributes the tasks to be performed on the Hadoop cluster. The results are stored in the file system and are read by the analysis layer which visualizes these results to the therapist on demand.

Although the MapReduce paradigm allows us to distribute, parallelize and in turn accelerate our analytical computation, to the best of our knowledge, there are no existing indexing systems for the combination of data being analyzed by our system. We are working on special purpose indexing schemes compatible with HDFS to further optimize processing.

During the demonstration, we will show different scenarios where patients or therapists can record multimedia sessions for different exercises by interacting with the motion sensors, store the session to the big data repository, replay the corresponding session in 3D VR environment, and see live plots consisting of quality of improvement metrics by analyzing current or past therapy session data. Moreover, we will show gesture based controlling of home appliances where each gesture is mapped to a certain therapy and disability of a patient.

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