

MotionSynthesis Toolset (MoST): A Toolset for Human Motion Data Synthesis and Validation

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ABSTRACT

Wearable computing devices and body sensor networks (BSNs) are becoming more prevalent. Collecting the data necessary to develop new concepts for these systems can be difficult. We present the MotionSynthesis Toolset (MoST) to alleviate some of the difficulties in data collection and algorithm development. This toolset allows researchers to generate a sequence of movements (i.e. a diary), synthesize a data stream using real sensor data, visualize, and validate the sequence of movements and data with video and waveforms.

ACM Classification Key Words

J.2 Physical Sciences and Engineering: Engineering

General Terms

Design, Experimentation, Human Factors, Verification.

Keywords

Wearable computers, databases, data synthesis, body sensor networks.

1. INTRODUCTION

Wearable computing devices and body sensor networks (BSNs) are becoming more prevalent. They are being used for health monitoring [1], activity tracking [2, 3], and fitness applications [4]. Developing new algorithms and techniques to recognize daily activities more efficiently and with higher precision is an important area of research. One key component of this research is the collection and validation of data for testing new approaches.

Collecting the data necessary to develop new concepts can be difficult for multiple reasons. First, there may be technical limitations. Depending on the data collection method, certain scenarios are very difficult to capture. For example, if a sensor

must be tethered to a PC, the range of movements that can be monitored are limited. Time is also an issue for data collection. Collecting 10 minutes of data typically takes much longer than 10 minutes. Time is spent setting up the necessary equipment (i.e. PC, validation systems, etc.), ensuring proper set up of the sensors on the subject, and finally collecting the data.

Additionally, during long term data collection, coordinating with multiple subjects may cause a problem. If a large dataset is needed, multiple data collection sessions over many days or weeks may be needed. This requires time from the subjects and the data collector to ensure everything functions correctly.

Beyond collecting data, the data must be validated. Using the incorrect configuration or placing a sensor in the wrong orientation can cause problems with data that has been collected. With all of the time spent on data collection, validation is critical to ensure the data is usable. Depending on the data collection methodology, there may not be a straight forward way to carry out the data validation.

Some researchers are interested in developing BSN algorithms, but they are unable to generate their desired data due to lack of hardware. Without sensors to collect their own data, they are left to use existing databases and repositories, but have no control over the data they receive. They are limited by sensor positions and sequences of activities that the group that recorded the database determined. Also, multiple sensors can be useful for determining relationships between certain body parts during activities. Having a set of sensors to cover multiple body parts can be cost prohibitive in some cases.

To alleviate some of the difficulty in data collection and algorithm development, we present the MotionSynthesis Toolset (MoST). This toolset allows researchers to generate a sequence of movements, synthesize a data stream using real data, visualize, and validate the sequence of movements and data with video and waveforms.

MoST will save time and provide an opportunity for those with and without the requisite hardware to synthesize their own experiments and trials. Using this toolset allows for a variety of scenarios to be developed with authentic sensor data and straightforward validation with a variety of movements and subjects which will hasten algorithm development.

The rest of this paper is arranged in the following manner. The next section of the paper reviews related works. That is followed by section 3 which explains our data collection process. Section 4 introduces the diary generation tool. Sections 5 and 6 cover the data synthesis tool, and the data visualization tool respectively.

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MobileHealth'14, August 11–14, 2014, Philadelphia, PA, USA
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<http://dx.doi.org/10.1145/2633651.2637472>

Finally, we present enhancement ideas in section 7 and our conclusions sections 8.

2. RELATED WORKS

Wearable computers and body sensor networks (BSN) for activity monitoring resemble cyber-physical systems. Wearable computers with inertial sensors, (i.e. the cyber world), are tightly coupled with the underlying physical system; the human body. Many optimization techniques aiming at reducing the power consumption, form factor, or enhancing the performance must be closely coupled with the movements performed by users. Therefore, data plays a critical role in the design, optimization and validation of wearable computers.

Various datasets for motion sensing wearable platforms have been made available. WARD, a dataset released by UC-Berkeley, consists of data collected from 20 human subjects using tri-axial accelerometers and bi-axial gyroscopes covering common actions such as standing, sitting and walking [5]. A similar dataset was released by the University of Rio de Janeiro that includes data from 4 human subjects [6]. A dataset was offered by ETH Zurich that includes 17 activities for 2 users [7]. USC-Human Activity Dataset (USC-HAD) provides a dataset collected using a single wired motion sensor over 14 subjects while ensuring diversity with respect to the gender, age, height and weight of human subjects [8].

Despite the fact that all these datasets offer comprehensive data for human activity recognition platforms, none offers the ability to synthesize a sequence of movement that is of interest to the designers. The feature of data synthesis offered by our platform enables creating data streams for various scenarios without the need to involve human subjects performing the activities, reducing the burden on the study, investigations, human subjects and designers. This feature will reduce the costs of the prototyping while accelerating design and validation tasks. Most importantly, the ability to synthesize data for various scenarios will enable more extensive validation and verification of wearable platforms.

PlaceLab dataset, released by MIT, includes data acquired from a fully instrumented house with various types of environmental sensors including cameras and temperature sensors [9]. A similar dataset acquired from an instrumented Kitchen was released by Carnegie Mellon University. The dataset includes various sensing modalities (motion capture, audio, video and inertial measurements) while subjects are performing tasks involving cooking and food preparation [10]. These datasets are also fixed, static and do not offer the ability to synthesize data streams for scenarios of interest to the designers, a feature that is particularly important for rapid prototyping and validation.

Validation and verification for cyber physical systems has been investigated in several other domains leveraging theoretical and software-based techniques. Examples are validation techniques for networked control systems [10] and cruise control systems in automobiles [11].

Data management for wearable sensors has been also investigated. However, data management techniques often involve efficient management of data repositories and enhancing the speed of recognition and query processing [11, 12, 13, 14, 15, 16]. They do not emphasize offering data for design and validation of wearable computers.

The proposed platform offers all of the capabilities of the existing datasets, yet it enables designers to synthesize data streams for users, activities and scenarios of their choice. This feature accelerates the design, prototyping and validation efforts, reduces the costs associated with system development and potentially provides more extensive data for validation and system refinement.

3. DATA COLLECTION

The first step in the process of creating a database and related tools for data synthesis is to collect the initial data. For our purposes, data collection refers to the gathering of a large amount of reliable data, for different human movements, using inertial measurement units (IMUs). To do this, a consistent collection process must be determined along with the hardware and software tools needed to ensure all data collected is reliable and able to be validated.

3.1 Process

The movements in the database should be useful for many research activities. With this in mind, a set of common human movements based on the activities of daily living (ADL) [17] were determined. We then added variations to some of these movements. For example, we added sitting with legs crossed and sitting with the legs extended as well as basic sitting. We also added movements with various degrees of dynamism like jumping or grabbing items from shelves. Each movement is associated with a beginning posture. The subject must be in the appropriate posture to do the associated movements. The full set of movements and the associated posture can be seen in Figure 1.

For consistency and to properly capture the set of movements described above, six sensors were used on the subjects for each recording. Specifically, the body parts on which the sensors were deployed, are the right ankle, left thigh, right thigh, waist, right wrist, and right arm as shown in Figure 2. This configuration was used during the entire data collection phase for all of the movements and will be used for future data collection.

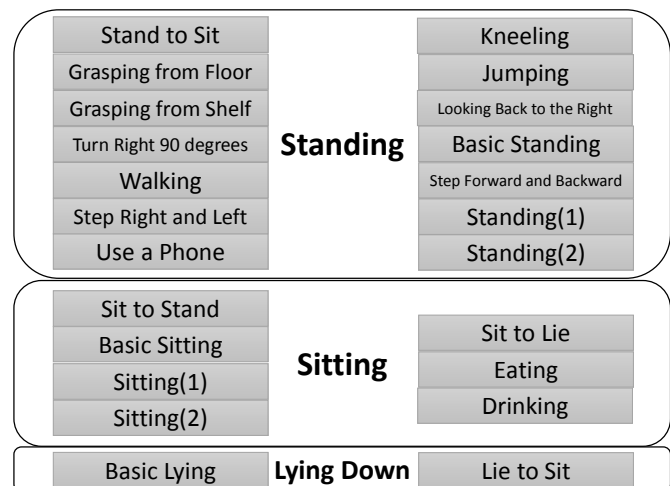


Figure 1: Captured movements for each posture.

The first consideration for this set up was maintaining consistent placement of sensors to allow easier merging and manipulation of data. The second consideration was to ensure every major limb could be captured. Due to the limitation of Bluetooth supporting

a maximum of seven connections at a time, we decided to work, primarily, with a single side of the body. We believe these are sensor locations that are likely for wearable devices and this configuration makes it possible to effectively monitor the movements of interest. Some sensors may be of little significance for some movements, but this data should still be kept to cover the entire set of movements consistently. The additional sensor data may also allow users to determine redundancies and correlations between sensors that would not have been possible with a smaller set of sensors. The number and the location of sensors may be altered in the future provided that the users recognize that not all data collection sessions provide data acquired from all human body joints and limbs.

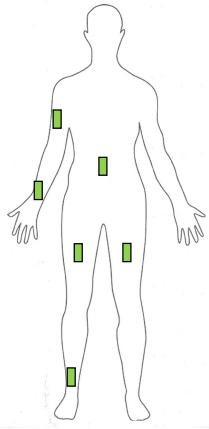


Figure 2: Sensor location for data collection

Our initial data capture included 2 female subjects and 2 male subjects. Each subject performed each movement 15 times consecutively with a short pause between repetitions. This was done to increase the variety and randomness of the data set. Every repetition of the movement was slightly different even if it was performed by the same person.

3.2 Hardware

The primary hardware that we use for data collection is a set of custom built sensor boards as shown in Figure 3. The primary components on each board are an MSP430 microcontroller, a Bluetooth module, and an MPU9150 which has a 3-axis accelerometer and a 3-axis gyroscope. The sensors were configured to sample at a rate of 200Hz which is fast enough to collect normal human movement. The accelerometers were configured with a range of $\pm 2g$, and the gyroscopes were set with a range of $\pm 250^\circ/\text{second}$. The data is captured with 16 bit analog to digital converters (ADCs) and passed through I²C to the MSP430. The processor time stamps the data and transmits the packets through Bluetooth to a base station PC where the data is written into a text file.

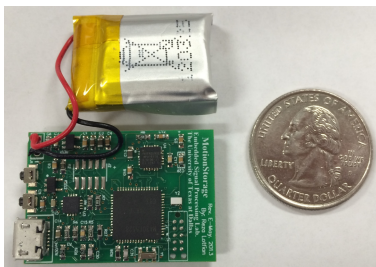


Figure 3: Custom sensor board

As the data is collected from the sensors, we record video with a camera connected to the same PC at 15 frames per second (FPS) with 720p resolution to allow visual validation and annotation of the movements. The hardware tools are extremely functional toward the goal of collecting quality data that is consistent and that can be validated.

3.3 Software

The software tools on the PC are the last component in the data collection and validation. As the sensor data and video are received, each sensor has its data stored based on the subject, the movement, and the sensor. The video is stored based on the subject and the movement. Each sensor has a tab delimited data file with the following format: *AccelX, AccelY, AccelZ, GyroX, GyroY, GyroZ, MagX, MagZ, SensorPkt#, SensorTime, PCPkt#, PCTime*. The first three columns are accelerometer data and the second three are gyroscope data. Columns seven through nine are magnetometer data which are not calibrated and unreliable. The next two columns contain the packet number and a time stamp from the sensor. The final two columns are the PC packet number and time stamp.

As was stated, the subjects performed each movement 15 times. This data needed to be parsed by individual movements for the database. Using the Data Visualization tool discussed in section 6, we were able to see the sensor data and the associated video. Using this tool, the start and end of the movements were annotated through video and sensor data inspection. After this, the sensor data and the corresponding video were parsed. These new data files and video clips represent the building blocks for the database that is used in the MotionSynthesis Toolset.

4. DIARY GENERATION TOOLS

The Diary Generator is the primary input tool in this toolset. It is a Java based tool with a graphical user interface (GUI) that allows users to select the relevant aspects of the motion diary.

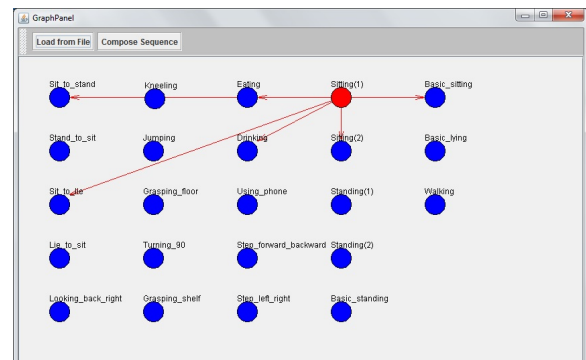


Figure 4: Graph Panel Display

4.1 Graph Panel

The first part of the Diary Generation Tool is the Graph Panel. The Graph Panel is used to load the file which lists the movements and the relationships between movements. As shown in Figure 4, the Graph Panel shows a graphical representation of the movements and the relationships between them. Each movement is a node in the graph. When a movement (i.e. node) is selected, each directed edge shows a movement that can be performed after the selected movement. Possible movement progressions, which are shown by the edges, are based on the ending posture of the selected movement. New movements can be added to the graph by right clicking on the graph. When

creating a new movement, the movement name, starting and ending posture must be selected. Existing movements can also be removed from the graph. If the graph is modified in any way, the updated file can be saved. The final graph will directly drive the movements available in the Diary Generator.

4.2 Diary Generator

When starting a new diary, the user can select between one and six sensor locations. The sensor modalities (*i.e.*, the gyroscope and accelerometer axes) can be chosen for use in the visualization tool. Finally, the user can select the subject for the diary generated. In the initial data set, there are two males and two females. Additional data will be collected and added to the tool over time.

The Diary Generator GUI is split into two panels as shown in Figure 5. The panel on the left is split into two sections. The top section is static and includes the file control for the diary and the tool. The controls are used to manage the diary generation.

The bottom section of the left panel is reserved for loop controls and movements. The loop control allows the user to set up repetitions for a single movement or for a set of movements. For each loop iteration, the movement can be randomly selected from various available instances in the dataset. The movements in the left panel include all actions that can currently be performed. Based on the current posture of the subject in the diary (e.g. standing, sitting, or lying), the list will update dynamically to include the allowable movements as described in section 3 and as shown in the Graph Panel.

Depending on the movement selected, one or two options are available. All movements have the “Mode” option which allows users to select the “Best”, which is the default, or a “Random” movement from the database of movements for the chosen protagonist. In the current implementation, selecting “Best” mode will select the first captured trial of the movement in the database for the chosen protagonist. Selecting “Random” mode will randomly select one trial from all available trials of the movement for the chosen protagonist.



Figure 5: Diary Generator

Some of the static movements (e.g. sitting, standing, etc.) have an additional duration option. This allows the user to determine how long that an action is performed in the diary. For example, a user could select the “Basic_sitting” movement with a duration of 60 seconds. This allows greater variety in the data sets that can be generated.

The panel on the right displays the current diary selections as they are made. This panel allows the user to keep track of the movements that have been selected as well as the options selected for each movement. This serves as a preview of the diary file that

will be generated. The diary output file is saved as a text file with all of the necessary information for synthesis.

The diary file is saved to the UserSpace folder on the PC. The file has the movement listing as well as information about the subject selected, sensors selected, and sensor modalities chosen. Once the file is saved, it can be modified by hand to allow quick tests and updates such as increasing loop iterations or changing the mode or duration of a movement in the diary.

5. DATA SYNTHESIS TOOL

Once the diary is completed, the Data Synthesis tool can be started from MATLAB®. When launched, the Data Synthesis tool will request an input diary file. Once selected, the Data Synthesis tool parses the diary file to resolve all loops and determine which movement data is necessary for synthesis. The movements are retrieved based on the diary data and stitched in order to generate the output data streams.

The Data Synthesis tool provides the primary outputs of MoST. These outputs are the sensor data files which represent the full stream of movements described in the diary file. One data file is generated for each sensor requested in the diary file. These files represent synthesized data sequences based on the real data collection and the diary generated. Each tab delimited file will have sensor data in the 13 column format described in section 3.3, the Software subsection of the Data Collection section.

```
START , M1 , Fri Feb 21 22:46:21 CST 2014

Sit_to_stand /B,
Walking /B,
Stand_to_sit /REX,
STOP! * 0:0(Right Ankle, Right Thigh, } <Acc X, >
```

Figure 6: Sample Diary File

Figure 6 shows a sample diary generated by the Diary Generator tool. Based on this diary, the Data Synthesis tool will find the related movement data files and synthesize two files with the *AccelX* data, for the right ankle sensor and right thigh sensor. Figure 7 shows the plot for the generated data for the right thigh sensor from the sample diary.

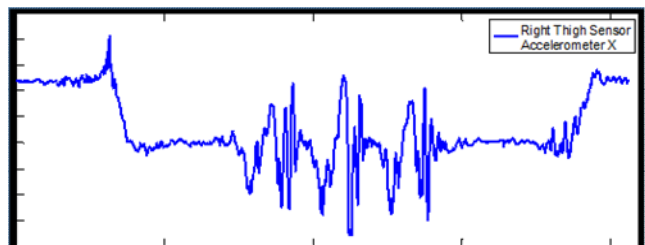


Figure 7: Synthesized Right Thigh Data

As was discussed, the final four columns in the file are packet counts and time stamps for the sensor and PC. Because the data output files are built from a collection of movement specific files, the columns which represent packet numbers and timestamps are generated in the tool as the data stream is synthesized. This ensures that the packet numbers and timing information are monotonically increasing which makes the data similar to data that was captured in a single session. This step is necessary for the data to work properly in the Data Visualization tool and it also adds another level of realism to the synthesized data.

In addition to the sensor data files, the Data Synthesis tool outputs two files used by the Data Visualization tool, an annotation file and a sequence file for the diary. The annotation file lists the sample numbers for the end of each movement in the synthesized data. The sequence file lists the order of movements to allow for video creation.

6. DATA VISUALIZATION TOOL

The Data Visualization tool is the final tool in MoST. It is required that the Data Synthesis tool has been run on a diary before the Data Visualization tool can be run. When launched, the user will select which diary output to view.

As shown in Figure 8, the Data Visualization displays two main areas, the data plot area and the video area. The data plot area loads the synthesized data files from the appropriate folder. Based on the sensor locations and sensor modalities selected in the Diary Generator, the relevant data will be displayed. There will be a single plot for each sensor modality. Each sensor will have its data plotted in a different color across the axes.

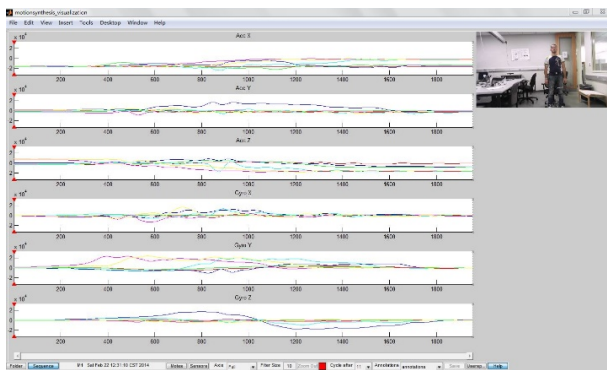


Figure 8: Data Visualization Tool

The annotation file generated by the Data Synthesis Tool is read by this tool and used to display the divisions between the movements in the sequence. In large data sequences with a lot of movements, this is useful for finding and investigating specific parts of the sequence. The annotation file can also be used outside of the tool for similar purposes.

The video panel in the upper right corner, which is synchronized to the data plots, will show the video that was captured with the data. Based on the sequence file generated by the Data Synthesis tool, the videos related to the data will be retrieved and linked together. This video offers two types of validation for the user. First, the user can confirm that the activities selected in the diary were properly synthesized. Secondly, the user can look at the specific movements to gain a better understanding of the related data.

7. ENHANCEMENTS

Currently, MoST allows the creation of varying sequences of data which can be used for development of wearable computing algorithms. As the toolset matures, additional data and capabilities will be added to increase the utility.

First, more user data will be added to the back end database. Capturing an increased number of subjects will immediately add to the variability of the data set. Some new data captures can also occur in different context. Walking on different surfaces or sitting on different types of furniture will provide new sources of data variability.

We also plan to add variations in the synthesized data by modeling common sensor problems and modifying the captured data. For example, there has been work in activity detection with unknown sensor orientation [18]. We can model changes in orientation and sensor positions and apply these models to create new synthesized data. This would allow users of the toolset to explore concepts and to improve the robustness of their signal processing algorithms in the presence of variations.

We would also like to develop a mechanism for others to contribute to the toolset. Additional contributors from the community may add compatible data or even new models which could be used to add further variation to the outputs of MoST. We will leverage techniques used in the existing public webpages designed for data dissemination (e.g., Physionet [19]), and will incorporate novel mechanisms that will facilitate the community contribution to the data sets. In particular, we will incorporate reconfigurable interface engines that will translate data added by the scientific community to the format suitable for the MoST toolset. The users will only need to incorporate XML files describing their data format, and the remaining tasks will be handled by the interface engines.

8. CONCLUSIONS

We have developed the MotionSynthesis Toolset which will allow researchers to generate varying data sets. Generating relevant data more quickly will allow for quicker initial analysis and faster improvement of new algorithms. Being able to select specific sensors positions and modalities will allow system designers to make trade-offs without building multiple systems. This will speed up the validation and refinement process.

The toolset is available at <http://motionsynthesis.org>. Our plans are to support the tool through increased number of subjects, additional movements, and community input. Usage and feedback will be tracked to add features and improve the overall usability and efficiency of the tool.

9. ACKNOWLEDGMENTS

This work was supported in part by the National Science Foundation, under grants CNS-1150079 and CNS-1012975, and the TerraSwarm, one of six centers of STARnet, a Semiconductor Research Corporation program sponsored by MARCO and DARPA. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the funding organizations.

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