IoT Framework for 3D Body Posture Visualization

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***Abstract*—Visual feedback is a powerful tool that can assist in both the training and recovery processes. During training, athletes may correct poor posture or identify potentially hazardous movements. Likewise, physicians may be able to identify postures that would lead to further injury. Additionally, such a system could also be beneficial during fall detection to provide greater insight into the patient's position and status. Current models for providing feedback to the user rely on full-body sensor sets or video representations, which may cause discomfort or may not fully capture the user's motion. We propose a new system architecture that we will define as a 3D-BPV (Body Posture Visualization) system. This paper seeks to design a less intrusive sensor system, based on Internet of Things (IoT) technology, which visualizes patient movement in a 3D model. A Kalman Filter will also be used to eliminate sensor drift during operation. The system should minimize the size and number of sensors attached to a patient while providing sufficient data for generating such a model. To demonstrate such a design, a system using accelerometers has been constructed with the 3D model generation accomplished using a Biovision Hierarchy Animation (BHV) file.**

I. INTRODUCTION

Visual feedback provides an effective means of self-improvement. This can be applied directly to areas of injury as well as for sports injuries. For the case of athletes, there is an increasing interest in identifying the impact of form on the effectiveness of an athlete's performance [1]. In the event of an injury that affects an individual's movement capabilities, such as a lower extremity injury or stroke, therapy is often an effective means of regaining lost mobility. These sessions are often instruction periods during which a physician guides a patient through physical activity meant to improve motor functions. An efficient recovery method is known as mirror therapy. When undergoing such treatment, patients perform physical activity in front of a mirror or camera and TV screen/computer monitor. By observing their own movement, patients can benefit from visual feedback, speeding along their recovery. Research has indicated that patients benefit from increased balance and leg motion when recovering from a lower extremity injury [2, 3, 4]. Mirror therapy has also seen large success in treating patients that have suffered a stroke [5, 6]. Due to the effectiveness of mirror therapy, we propose the use of an IoT body sensor network and 3D modeling software in the place of a mirror or camera setup. By integrating IoT devices, physicians will be able to receive additional positional and angle data of the patient. This data can be further analyzed to provide insights into possibly hazardous posture.

An alternative use of this system would be for integration into a fall detection system. When caring for a patient that is prone to falling, monitoring is critical for increasing response times should a hazardous event occur. By providing for visual representation of the patient, this system can aid physicians in identifying whether a detected fall was a false alarm or a life-threatening event. Additionally, by providing information prior to the fall, physicians may also receive valuable insights into what may cause patients to lose their balance and fall. Our system would be easily integrated into existing fall detection systems due to its reliance on gyroscope and accelerometer readings that are common in such systems [7, 8, 9, 10].

This paper outlines our proposed system for capturing a user's movement and position for personal improvement. The system design flow will be presented along with an example implementation. An analysis of our microcontroller, communication node, and used filter design will also be introduced.

II. 3D-BPV FRAMEWORK

Our proposed system is composed of two primary components, the body sensor network and the computing resource. During operation, the body sensor network will be responsible for collecting user accelerometer and gyroscope data. This network will be composed of several discrete nodes that will be worn at various places on the user's body. For flexibility, the body sensor network is scalable based on the application. As an example, a patient that has suffered a broken leg may only require two or three sensors to analyze their recovery. Alternatively, an athlete may desire more sensors in order to monitor more complex movements, such as a pitcher's form when throwing a baseball. The data collected by the sensor network will then be transmitted via a wireless communication protocol to a central node for collection and data processing. For the purposes of our experiment, we elected to use the ZigBee protocol but Wi-Fi and Bluetooth would also be acceptable means of communication. Each sensor node will be designed with a microcontroller, a wireless communication module, and 10-DOF sensor [11].

Upon reaching the central computing resource, a Kalman filter will be applied in order to eliminate sensor drift and bias that accumulates during operation. Finally, the data will be visualized using the Biovision Hierarchy Animation File (typically referred to as the *bvh* file). This format was initially developed in order to provide motion capture data and can be viewed using a BVH viewer. Fig. 1 displays an overview of our proposed framework design.

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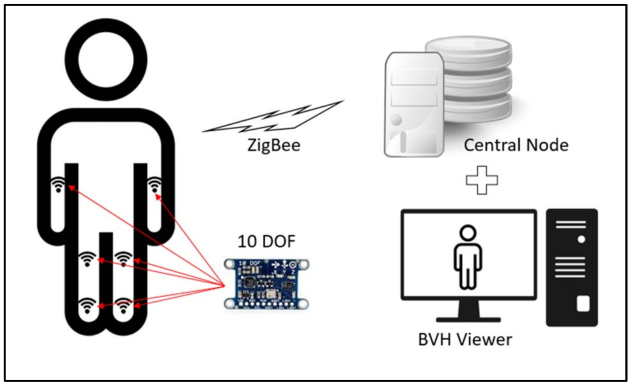

Fig. 1. Overview of 3D-BPV (Body Posture Visualization) Framework

Prior body sensor networks prioritize the use of sensors in order to detect human position [12, 13, 14, 15, 16, 17] without providing a visual representation of the user. Due to the lack of visual feedback, greater effort needs to be taken on behalf of the physician for achieving the same potential mobility benefits.

III. SYSTEM CONFIGURATION

In order to demonstrate our framework, we created a small proof of concept system to test our design. This system was constructed using three nodes as our body sensor network and a single desktop computer to serve as our computation node. During testing, we focused on recording leg movements along with the scalability of the system by adding and subtracting nodes. These nodes were constructed using an Arduino Pro Mini for controlling the device activity, an Adafruit 10-DOF IMU Breakout for collecting gyroscope and accelerometer data, and a Digi XBee S2C module for communication. The data was gathered using a desktop computer equipped with a Digi XBee S2C module and would run C++ code for processing and creating the visualization for the user. The final node sensor node configuration can be seen in Fig. 2. We also customized a 3D enclosure for the device which provided a flat surface to contact the user and also allowed us to attach the device to the user via a Velcro strap. The enclosure can also be seen in Fig. 2.

For this project, we decided to make use of the Arduino Pro Mini as the computation source for each of our sensor nodes. These devices are built to operate at 5 V at 16 MHz and was selected due to its small size profile. Since the device is equipped with pinouts to support the UART, I^2C, and SPI protocols, we were able to connect to both the XBee and 10-DOF. For collecting data from the 10-DOF we relied on the I^2C protocol, while communication with the XBee was accomplished via a UART serial connection. The device was simple to set up and was programmed through the Arduino IDE, which provides a C++ programming style. For the purposes of this project, we sent data over wireless every 50 milliseconds.

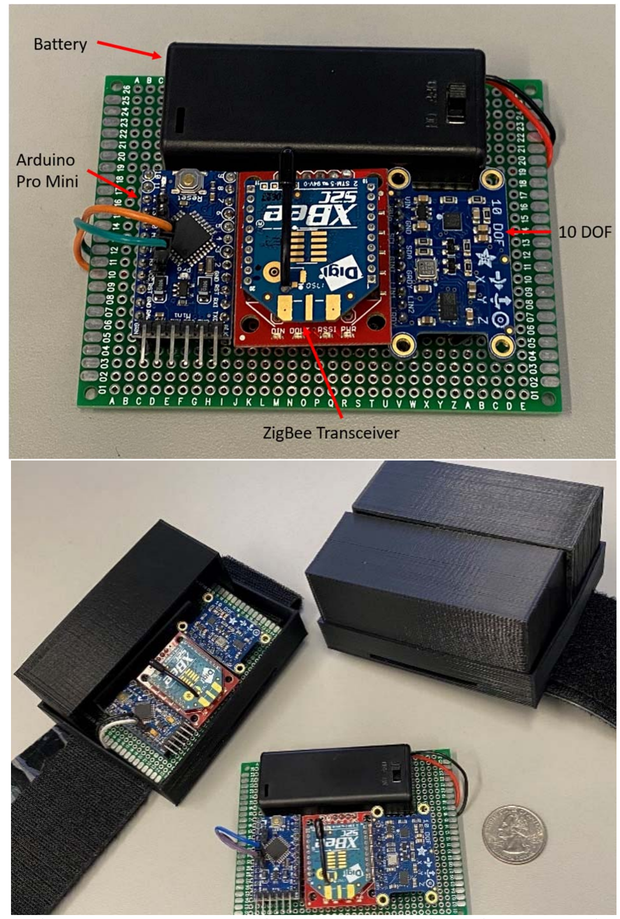

Fig. 2. 3D-BPV Sensor Node Component Configuration (Top) and Enclosure (Bottom)

In order to collect our gyroscope data, we relied on the Adafruit 10-DOF IMU Breakout. This device is equipped with the L3DG20H gyroscope, LSM303DLHC accelerometer, and BMP180 barometric/temperature sensor [11]. However, only the gyroscope and accelerometer were used for this project. In order to allow our system to remain accurate over long periods of time, we introduced a Kalman Filter to our system in order to combat sensor drift that is common in IMU applications.

The last component of our sensor node was the Digi XBee S2C module, operating in the 2.4 GHz frequency range. The device was chosen as it offers a low-powered alternative to a Wi-Fi enabled system while also providing for larger network configurations. Each sensor node and our central computing node were equipped with an XBee transceiver. The overall network was generated using the API mode that was created by Digi International. This protocol is advantageous due to its use of packets, which allows us to create a more complex network structure. In addition, since the destination can determine the source with the packets, we did not need to have separate code for each of the sensor nodes, providing us with greater flexibility. Data was read into our main node via a serial USB connection and was read using an array in C++. Further data processing was also accomplished in C++ on the desktop computer.

After collecting sensor data from our devices, we then proceeded to implement our Kalman Filter Design. For our purposes, we based our design on an Arduino implementation from Kritian Lauszus [18]. The design was primarily broken down into two phases. The first of these phases would involve predicting the value at given time k based on the previous real values. After this is accomplished, the real and predicted values are compared and the prediction matrices are updated to account for the deviations in the recorded and predicted data.

IV. Results

After constructing the sensor nodes and configuring our local network, we then proceeded to test our system's ability to provide a visual representation of the user. This was completed using a C++ program which proceeded to append the filtered user data into a Biovision Hierarchy Animation File. This file could then be played on the desktop computer for the user to receive visual feedback of their activity. A few example comparisons between the user and the visualization can be seen in Fig. 3 and 4 below. As shown, Fig. 3 displays the user's raised knee and the associated visualization. This is also shown with a second backwards movement in Fig. 4.

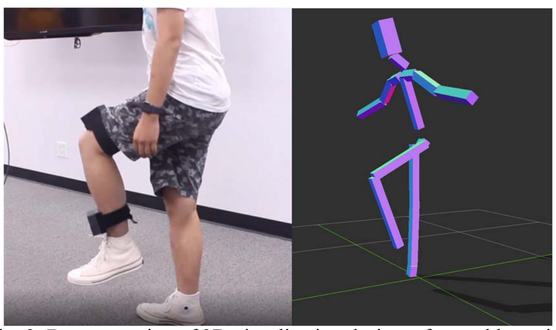

Fig. 3. Demonstration of 3D visualization during a forward leg-raise motion. Human activity is shown (left) with representation in the BVH Viewer (right)

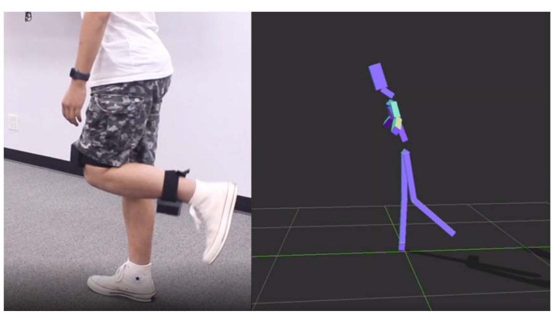

Fig. 4. Demonstration of 3D visualization during a backwards leg-sweep motion. Human activity is shown (left) with representation in the BVH Viewer (right)

V. Conclusion

Overall, our system was successful at achieving visualization of the user during physical activity. The implementation was able to collect data from a variable number of end nodes and also filter the collected data using the Kalman Filter. Future work could include exploring the downsizing of the sensor nodes as they were larger compared to other wearable sensor implementations. In addition, we could also explore additional forms of filter implementations. Specifically, we did not have time to compare the timing considerations of the Kalman Filter compared to other filters.

During future work we intend on converting from the Biovision Hierarchy Animation files to visualization using the rviz libraries from the Robot Operating System (ROS). This real-time compatible system makes use of a set of trap frames to determine sensor position and movement. By using a data type rather than the file format itself we would gain greater flexibility in data processing and applications. For instance, position identification machine learning can be more easily accomplished by calling the data type as opposed to using the data file or creating a separate buffer system.

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