DEVELOPMENT OF AN INTELLIGENT KNEE BRACE TO TRACK KNEE GAIT PATTERNS

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ABSTRACT

Assistive technologies are important for post-operative rehabilitation of lower limbs, training the limbs for specific activity and re-training the limbs to maintain proper gait as the body ages.

In the Smart Knee Brace project, an RNN classifier (for real-time human motion recognition through IMU sensor inputs) is implemented. Besides building the classifier and verifying its performance, the output of the classifier is shown in real-time visualization. Lastly, despite its simple design, the project has performed beyond expectations.

1. INTRODUCTION

Assistive Technologies, particularly Motion Recognition (MR), is becoming a significant field of research because of its contributions to human-centered studies which aim to improve a person’s mobility and dexterity or prevent their degradation.

According to the US CDC, one in three seniors citizens will experience a fall-incident each year. However, the fear of falling which will cause serious bone, head and spine injuries makes seniors limit their activities which in turn weakens the muscles and more prone to falling. An Automatic fall detection system that are body-worn IMU sensors is one of the ways in which MR is used to address such concerns. It is done by gathering signals from wearable sensors and classifying the motion patterns through machine learning algorithms [1].

The Smart Knee Brace (SKB), as shown in figure 1, is designed to provide physical therapists an intelligent tool with visualization to enhance the training with patients [2] and to encourage patients to train typical gait movements regularly. It can also be designed for use in the training of specific movement, for example, parachutists must be trained to keep their knees together and land with a roll [3].

In this project, the motion data is collected by the sensors in the SKB which is then used to train the machine-learning algorithms. The trained model will know and be able to tell the different activities, such as walking or sitting. A long-short-term-memory neutral network model is used to classify pattern inputs in real-time. A simple visualization GUI is also created to demonstrate this classifier. Finally, an evaluation is made on the prediction and accuracy of the classifier in real-time both quantitatively and qualitatively.

Figure 1: Smart Knee Brace

2. RELATED WORKS

The concept of a Smart Knee Brace has been articulated previously by the University of Delaware as a computer-control knee brace [4] designed to allow unrestricted knee motion during swing while dynamically controlling the knee during stance. Sensors on the thigh position of the knee brace will include gyro and triaxial-accelerometers to measure acceleration and rotations, respectively. A potentiometer will measure the knee angle and the closing foot switches detect the posture and gait movement. A gait event detection algorithm (GED) is used to detect the phases of the gait-cycle using only kinematic data.

Unfortunately, with the advancement of electronics, the smaller low-cost Inertial Measurement Unit (IMU) is able to provide better performance with higher accuracy and faster response than the combination of individual potentiometer, gyroscope and biaxial accelerometer. The IMU will dynamically detect the measurement for acceleration and angular velocity during the entire gait cycle, exercising or another process. These signals reflect the motion information of test subjects directly.

In addition, the application of deep learning for human motion recognition has led to great strides in the enhancements of the motion/activity recognition accuracy. The strength of the DL approach is in the ability to automatically and dynamically extract the important features in a task dependent manner. It also avoids the dependency on heuristic hand-crafted features by experts and scales better for the complex human motion-recognition tasks. The efficient learning of discriminative features from raw data has led to high-level abstractions from low-level features.

Hence, the availability and unbridled use of these sensing techniques is generating an enormous amount of meta data, this coupled with the increment of computational power has led to more feasible and flexible applications of the deep learning methods.

These methods have been utilized in our project to extract valuable contextual information from physical activities in an unconstrained environment.

3. PROPOSED APPROACH

3.1. Methods

The activity data from Nodemcu ESP8266 and MPU9250 (Figure 2 and Figure 3) are streamed into a local PC. The raw data are recorded as training data and used directly in real-time testing.

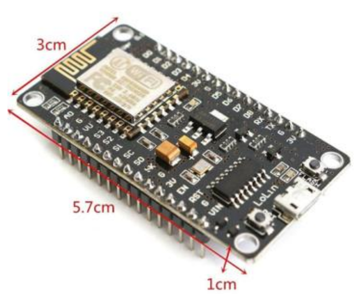


Figure 2: Nodemcu ESP8266

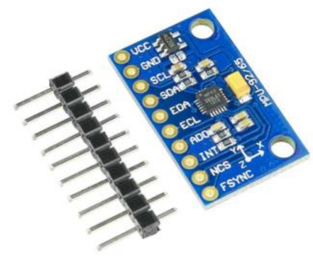


Figure 3: IMU – MPU9250

Sensor fusion techniques has solved the major motion sensing performance issues of the 6-axial modules, which consists of the 3-axis accelerometer sensors and a 3-axis gyroscope sensor or a 3-axis accelerometer sensor and a 3-axis magnetic sensor. See figure 4.

- A 6-axial inertial module with an accelerometer sensor and the gyroscope sensor will lose its absolute orientation due to the gyro drifts over time, so this requires calibration to restore accurate heading reference.

- A 6-axis module with accelerometer sensor and magnetometer sensor is prone to data corruption in the presence of any ferrous/magnetic materials in the immediate surrounding.

- A 9-axis module with an accelerometer sensor, and the gyroscope and also a magnetometer sensor will eliminate the drift factor that occurs with stand-alone sensor modules. However, this can be subjected to the magnetic interference in the immediate surrounding. So, sensor fusion algorithms which will compute the actual sensor data from raw data are required to compensate for any magnetic interference in the surrounding.

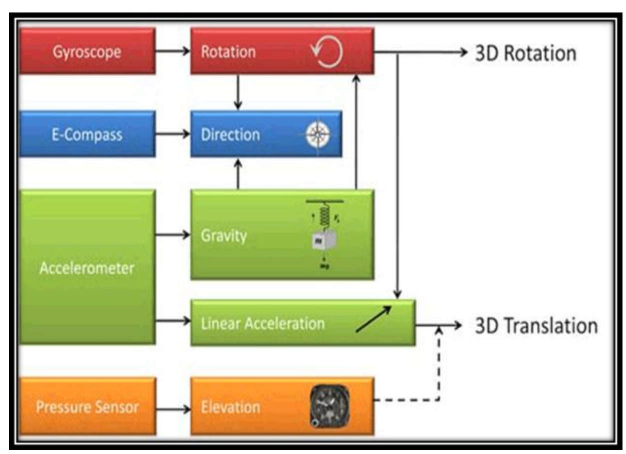


Figure 4: Sensor Fusion

The purpose of applying the sensor fusion technique is to take into consideration each of the sensor module data as input and then apply a stacked digital filtering algorithm to compensate for each other drift and to output the accurate and attitude measurements as results. This is given by the Yaw,Pitch and Roll. See figure 5.

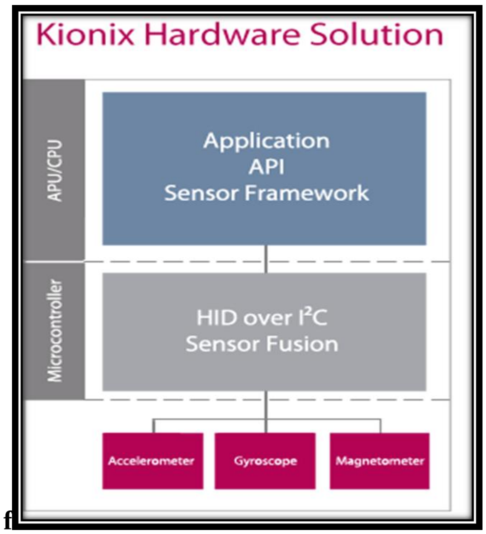


Figure 5: Filtering of Input Data

Besides generating, fusing and collecting the data, the other processes include extracting the features from the data, building the neural network model, training/testing it with the input data, creating the visualization GUI.

3.2 Collection of Data

Some 90,000 data points are collected and annotated pertaining to 5 different activity from 5 different subjects.

The data stream from IMU is recorded into a text file after a keyboard input "start" and a keyboard input "end". Each data set is a sequence of raw data which has a predefined start and ending time. A label (e.g. walking or sitting) is tagged to describe the gesture pattern for each data sample.

3.3 Feature Extraction

Both the pose and the position of the IMU chips should be taken into account in order to classify a specific activity pattern accurately. The quaternions are calculated in order to track the rotation of the IMU. The inputs from the gyroscope and accelerometer are also normalized.

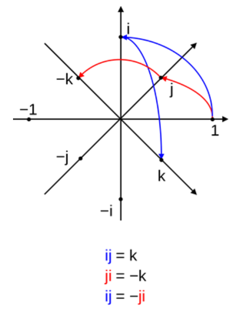


Figure 5 : Quaternions

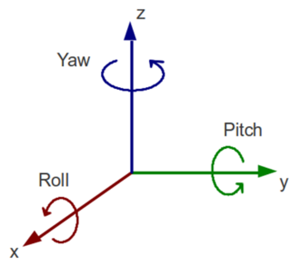


Figure 6 : Yaw/Roll/Pitch Inputs

The combination of data from quaternion, gyroscope and accelerometer exhibit the best performing features. This combination provides 14 dimensions to be used at each time step in the Neural Networks model. See figure 7 below.

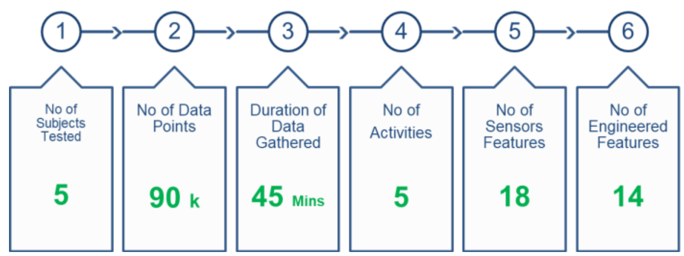


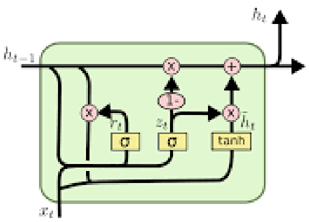
Figure 7 : Feature Combination

3.4. Long Short-Term Memory (LSTM)

The Long Short-Term Memory (LSTM), is a special type of recurrent neural network. It has been designed to identify the long-range dependency in the input frame to its output label. This has led to the competitive performance on action/motion recognition task [5]. Thus, it enables us to track the gait motion which is highly dependent on the temporal representation of our motion.

In particular, LSTMs are built up with a sequence of short term memory cells, each of which contains an internal memory state to store the input sequence to a given time 'T'. Also, to store the memory with reference to a context in a given long period, three types of gate-logic units are present in the architecture this is to control which data would be given as input and which data segment to leave the memory cell over time. These gate-logic units are activated by a non-linear function of output and input sequences as well as the internal states of the LSTM, this makes them a powerful model for learning a dynamically changing context given that the human motion evolve at various time frames.

To preserve the sequential pattern from the data, the standard LSTM node is used in our model architecture. As shown in Figure 6 below, each LSTM node unit will take the input x_t of every feature at a specific time step frame, then the input x_t will flow to the internal gates of the LSTM node with corresponding weights which are learned during the back propogation.



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$
$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$
$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Figure 6: LSTM node

Next, as shown in figure 7, the LSTM layer is stacked sequence of two LSTM nodes with node taking its own input. Each of the input data is a sequence of 14 dimensional feature arrays which represents the status of the IMU sensor at a specific time step.

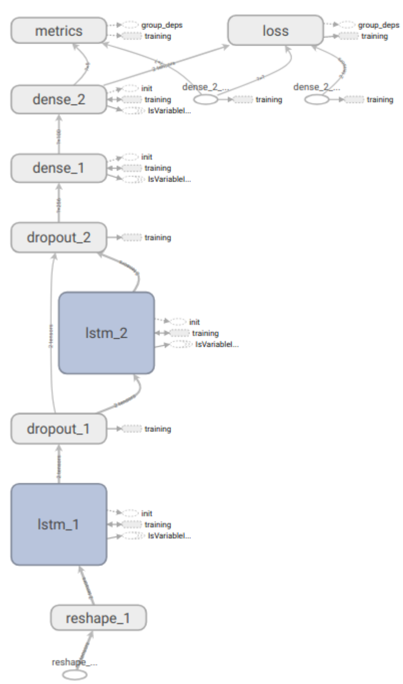


Figure 7: LSTM model

In our neural networks model architecture, there are two identical stacked LSTM layers. Then we use a dense layer with ReLU activation function to approximate the output lable.

f = ReLU(Wx + b) ……………….(1)

The final layer is another Dense layer with softmax as a softmax classifier.

f = softmax(Wx + b)………………… (2)

Then when the construction of the complete model is completed, the cross-entropy loss is computed. The model is trained using Adam optimizer.

3.5.Visualization

A simple visualization has been created to visualize how the classifier perform in real-time on IMU sensor input stream. Testing data from IMU is streamed directly into visualization engine through a serial port.

The neural networks model is designed to show from the data generated by the sensors in the SKB, whether the wearer is doing any of the activities that the model has been trained to know.

4. EXPERIMENTAL RESULTS

4.1. Evaluation

The classifier is able to predict motion pattern with good accuracy. As shown below, after 30 epochs, the accuracy of the validation set over the training data is almost spot-on.

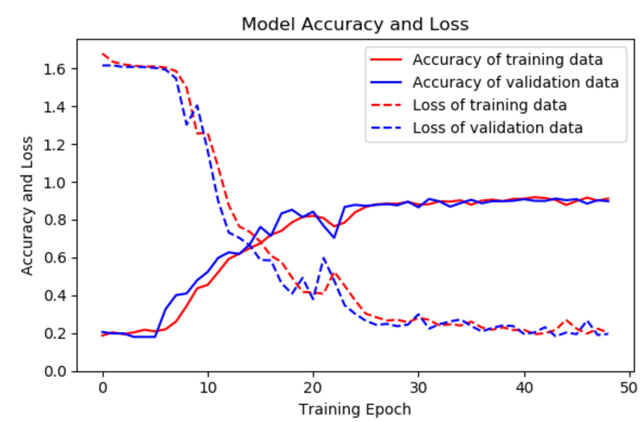


Figure 8: Loss and validation plot

4.2 Discussion

There is still scope for improving the model. In terms of implementation we have trained and tested this model on a very limited sample space. We know the gait movements vary greatly by demography and health condition. To generalize the model over varied gait cycles, we need to collect data from a much larger sample space consisting of all age group and body type.

Once this data is available then we can use features such as height, weight and age as proxy for body type and health condition.
In terms of knowledge representation, we can see that the model misclassifies between ‘walking’ and ‘sitting on a chair’. This can be rectified by including the data for standing still also. That way the model will learn a representation that differentiates better between ‘walking’ and ‘sitting on a chair’.

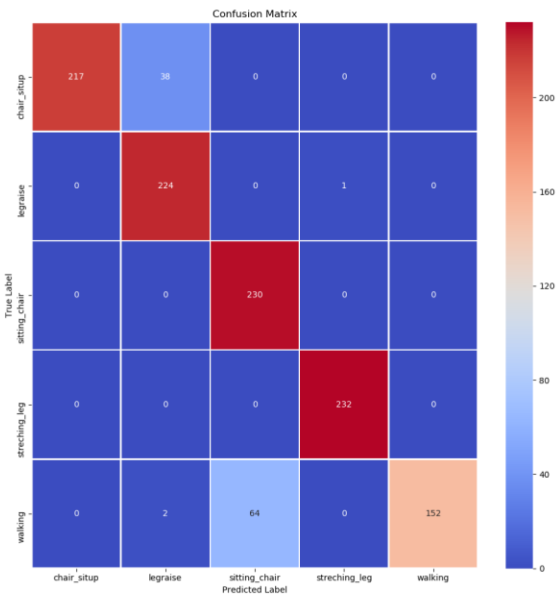
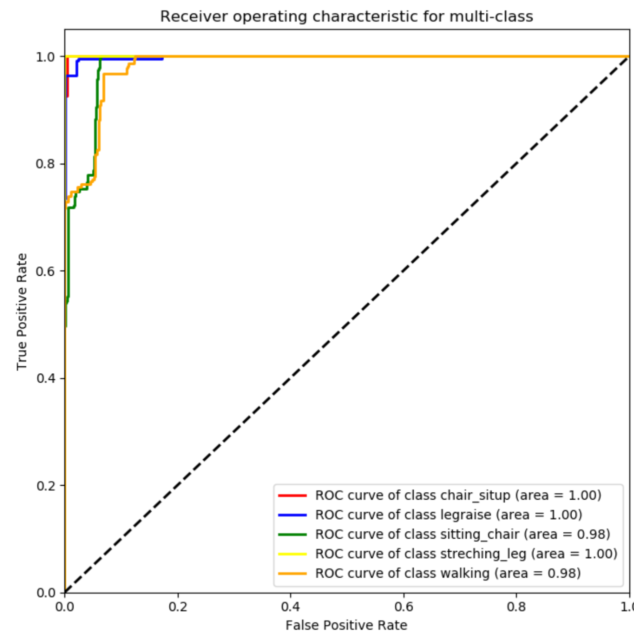


Figure 9: Confusion Matrix

5. CONCLUSIONS

Although errors are made by the classifier, they appear well within limits. As shown by the ROC curves for each of the classifications, the area depicting True positive rate against False positive rate is at least 0.98. The performance of the Smart Knee Brace is good and within an accuracy that could be applied in real time.



The performance of the Smart Knee Brace is good and within accuracy in-spite of its simple design. Its overall design should be further investigated as to whether it may be patentable against other knee brace designs [6].

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