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Joint-based model using centre of pressure and muscle movement for motion attempt detection of lower-limb exoskeleton

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In the last few decades, the exoskeletons have been developed to assist patients in their rehabilitation process or provide extra power for industry workers. Regardless of the applications, user motion attempt recognition is of its paramount importance to provide timely accurate assistance as well as more flexible and comfortable experience. Past studies had limited success in estimating the wearer motion intentions, but the setup is often complex and dependent on specific scenarios to predict effectively. Our study focuses on three main types of sensors and develops an algorithm to detect the user intention for a single knee joint exoskeleton. Three force-sensitive resistors are used to calculate the user's changes in centre of pressure (COP) and a novel buffer sensor joint is designed to detect any immediate motion. The data collected was processed under a Finite State Machine (FSM) model to classify the exoskeleton into states. Additionally, the user's thigh muscle activation is also monitor using Mechanomyography (MMG) signal. MMG is a new technique that utilises the mechanical manifestation of muscle movement to capture the vibration from the muscle fibre when placed at core muscle groups responsible for knee motion. The signal is collected by placing six accelerometers at the key positions. We then use a Support Vector Machine (SVM) model to train the MMG signal retrieve from different movement scenarios (including sit-to-stand, walking, stand-to-sit and stair-ascending, descending) in order to build a predictive model that works out the knee movement attempt. The key usage of the trained SVM model in conjunction to the buffer sensor joint is to determine whether the wearer require support in certain motions, such as during walking or transition from sitting to standing. The SVM model prediction is used as switching conditions in the FSM model into different states, such as following and supporting state. For each SVM prediction, a score is given to determine the level of confidence of the model on the prediction itself. The FSM model then take the prediction score into account along with user's changes in centre of pressure to decide whether joint support is needed. The proposed system and models can follow the user's movement while monitoring its motion states and provides assistance. The study aims to lay the groundwork for smoother exoskeleton motor control with lighter weight and comfortable design.

1. Introduction

In the last few decades, exoskeletons have been developed and improved to assist people with movement difficulties or provide extra muscular power for heavy works. An exoskeleton is a structural linkage system with joints that match the human body. For the patients involving in injuries that result in paralysis of the lower half of the body, the exoskeleton plays a major role in their gait rehabilitation training, in addition to prolonged and expensive medical treatment. Other applications for exoskeleton include extending the user strength above their natural ability to perform inconvenient tasks. Normally, an exoskeleton user depends on the exoskeleton sensors rather than direct controller to actuate their movements. In ideal cases, an exoskeleton should be able to follow the user's motion and provide movement to the user as natural as possible. (Islam, Xu, and Bai, 2018) Regardless of the exoskeleton application, it is vital to develop a constructive mean to capture the user's motion attempts when using the device for assistance control. (Choi et al., 2018) The parameters that can be used to estimate the human intention may include joint torque, joint angle, limb acceleration, and body tilt. Different exoskeletons have different methods to detect the user's attempt by choice of sensors and control of joint parameters, therefore, several existing systems were developed to achieve this goal. Nevertheless, existing methods and sensor systems are often intensive, complex, and dependent on strict requirements, thus, restricting the applications of the device for daily life usage. For this paper, a sensor system and algorithm for the lower limb exoskeleton is being developed and validated. This project aims to reduce the complexity of the existing sensor system and algorithm while providing a lighter, more comfortable, and less obstructive yet effective mean to detect the user motion attempt.

2. Sensor System

2.1 Buffer Sensor Joint

The buffer consists of a baffle and a circular box with four springs attached to it. This device is intended to place at the knee joint to detect movement of the user momentarily. The buffer includes a potentiometer to monitor the user momentary motion. The buffer sensor joint 3D model and 3D printed prototype are shown in Figure 1. The figure also shows how the servo motor is connected to the buffer.

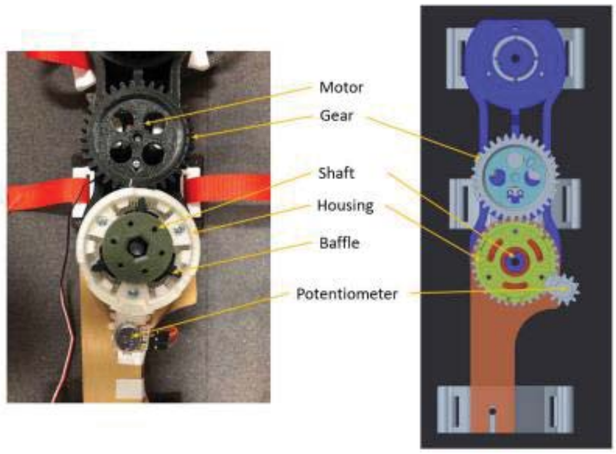

Figure 1: Buffer CAD design (right) and 3D-printed prototype (left)

The design of the buffer is crucial as it allows a range of joint motion for the user to move to when using the exoskeleton. The baffle is locked in place when the motor is on, and the user can only move within a 10-degree angle. When standing still, there is no change in potentiometer voltage as the buffer does not move. The change in this signal indicates how much the exoskeleton needs to move to "compensate" the user's movement. In other words, the exoskeleton shall "follow" the user's movement in this instance. The potentiometer's voltage changes can be interpreted as the buffer rotational angle that the exoskeleton needs to move to

2.2 Foot Pressure Sensors

Foot pressure sensors are commonly used in the lower-limb exoskeleton to detect moments when users are about to initiate their motions. Usually, when standing, the user will exert a certain amount of pressure on their foot. The foot pressure sensors chosen are the force-sensitive resistors Tekscan 401 Flexi force, which demonstrated the force-sensing capability for lower limb motion in (Kim et al., 2015)'s and (Choi et al., 2018)'s studies. Three FSRs are placed insole of the user left foot in three locations according to the pressure distribution when standing, as shown in Figure 3. The pressure distribution at the three locations allows us to calculate the centre of pressure (COP) in the y-axis (direction of motion) of the user's foot by the following equations (Kim et al., 2015):

$$\mathrm{SumPressure} = \sum_{i=0}^{3} P_i$$

$$\mathrm{CoPy} = \sum_{i=0}^{3} \frac{P_i * y_i}{\mathrm{SumPressure}} \qquad (2)$$

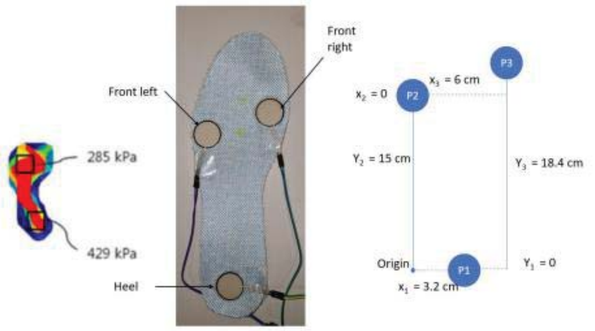

Figure 2: FSRs locations (middle) compared with pressure distribution of the left foot when standing (left) (Kim et al., 2015) and the distance between them (right)

On the right, the drawing indicates the distance between the FSRs; this information is used in equation (2) to calculate the COP. The user foot length determines the location for optimal pressure change during motion. The shift in COP during foot motion toward a direction provides information about when the user is about to perform lower limb motion. For instance, when standing, the COP calculated from the FSRs is expected to be in the centre of the foot. As the user is about to walk, the COP would shift toward the front as there is reduced pressure from the heel and increased pressure in the front. If no pressure is detected, the leg is in mid-air during motion. As we are only considering one joint motion of one leg, there is no need to know about the pressure distribution from the other foot; the data from one foot is sufficient to identify the motion attempt of that foot knee joint.

2.3 Mechanomyography (MMG)

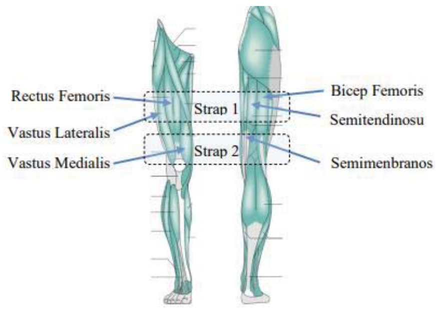

Figure 3: MMG Sensors Location

The MMG sensor system is used to read MMG signals from leg muscles. It is first used in collection of data, taking MMG signals in different movement scenarios. After a machine learning classification model is trained with the collected data, the MMG sensor system is used to provide MMG signal in real time to the loaded trained classification model which will detect the type of ongoing knee movement such as knee extension and knee flexion.

Knee flexion and knee extension is the primary motion of knee joint. Knee flexion is controlled by the hamstring muscle group and knee contraction is controlled by the quadriceps muscle group. To read the MMG signal relating to knee motion. We added three accelerometers on Bicep Femoris, Semitendinosus and Semimembranosus for monitoring knee flexion. We added another three accelerometers on Vastus Lateralis, Rectus Femoris and Vastus Medialis for monitoring knee extension. These MMG sensors are embedded in two leg straps. The locations of the sensors and straps are shown in Figure 3.

3. Support Vector Machine (SVM) Classification

In the experiment, we selected five sets of movement scenarios to collect the MMG signal for training the support vector machine. They are Standing, Sitting, Walking, Stair-ascending, and Stair-descending. In each movement scenario, we designed a set of knee movements sequence on a set interval. For example, in Standing scenarios, user will do standing (6s) – knee flexion (2s) – holding at flexion (2s) – knee extension (2s) – holding at knee extension (2s). After repeating knee flexion and extension for a few times, the user back to standing state and finish the test. Similar sequences are designed for every movement scenario.

During each experiment, MMG signal are getting from the three axes of each of the six accelerometers, providing 18 channels of input. There is an additional input of the user's knee angle from the potentiometer for determining the actual state of the knee movement and later data labelling. All data are collected with 500 Hz sampling rate since the muscle vibrational frequency ranges from 2Hz to 100 Hz (Ibitoye et al. 2014) and the majority of signal lines between 2Hz to 35Hz. The data is sampled at least twice the frequency of the signal to achieve reliable reproductivity. The higher sampling rate could provide a higher accuracy of the MMG signals.

After the data collection, the data is then processed and labelled to generate seeds for later training the machine learning classification model as shown in figure 4. The initial data read from the accelerometers are largely influenced by the motion artifacts which are usually below 2 Hz. Therefore, an order 20 digital Butterworth band pass filter between 2- 35 Hz was applied to the data.

The filtered MMG data is then being categorised into 4 motion subgroups, namely Relaxing, Knee Flexion, Knee Extension and Holding, by referencing to the elapsed time and knee angle. Several instances were picked from each motion subgroups for generation of seeds to train the machine learning model.

The mean of absolute value (MAV) of the 18 channel MMG signal in a 200 ms window at the picked instance is calculated which will become the features of the seed and marked with a motion subgroup label. If the MMG signal at the picked instances are used directly, the system will be vulnerable to error and noise given the stochastic nature of the MMG signal. The generated seeds will be a 19-column matrix consisting of 1 label and the 18 features which are the MAV of MMG signal from the 3 axes of the 6 accelerometers.

The seeds are used to train a Support Vector Machines (SVM), a machine learning algorithm. SVM is chosen because it has similar accuracy with artificial neural network but require less data input (Toledo-Pérez et al. 2019). SVM will identify a hyperplane to separate the input data with different feature points to different classes (Toledo-Pérez et al. 2019). In this case, the trained model accepts 18 MAV of MMG signals as input and predicts the ongoing movement type of the user. With the classification learner in MATLAB, we trained a Gaussian SVM with Kernel scale of 0.03205 and Box constraint level of 952.824 based on trial and error.

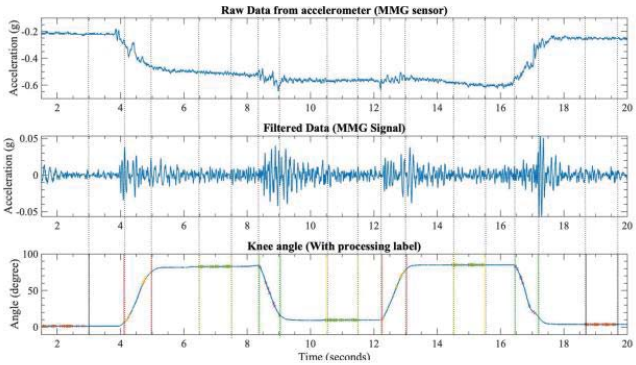

Figure 4: Data obtained from one of the 18 channels of MMG signal

To apply the trained model to predict the knee joint movement, we read the 18 channel MMG data in real time with a sampling rate of 500 Hz. The MMG data then undergoes the similar processing in data collection. The MMG data is filtered by a bandpass filter. Then a moving MAV is calculated on the data with the data within the previous 0.2 seconds before being input into the SVM trained Model to detect the knee movement attempt.

4. Finite State Machine (FSM)

A Finite State Machine (FSM) model is built in Simulink using the StateFlow add-on. The model places all inputs and output in perspective and allows the exoskeleton to operate in states. The model takes all sensors input and discretely monitors these inputs at a frequency of 100 Hz. FSM model features a succinct and transparent display of exoskeleton states and state switching conditions. Only one state can be active at any given time. The user may calibrate the buffer sensor joint for the upper and lower threshold voltage signal when the system is first turned on. The initial state of the exoskeleton is Standing. The algorithm constantly checks for a change in voltage in the potentiometer. Once it reaches the upper threshold, the exoskeleton shall perform flexion motion by moving the motor. Likewise, reaching the lower threshold would trigger extension motion. If the algorithm detects a backward shift of COP and a low encoder reading during flexion motion, the state shall be switched into Sitting. During the Sitting state, the user can perform extension or flexion. And a detection in the forward shift of COP and high knee angle results in a state switching from Sitting to Standing. The logic of this FSM model lay the groundwork for further modification of the model to provide more functionality. This proposed FSM model allows the exoskeleton to follow the user while knowing the state of motion the user is currently in.

3. Results

The potentiometer integrated buffer is a reliable and accurate system sensor that tells the user's joint movement direction. This information is used to drive the motor and allows the exoskeleton to follow the user's joint movement. This method provides more freedom to the user when using the exoskeleton rather than using predetermined sets of motion. The Finite State Machine algorithm implemented in Simulink provides a succinct framework that oversees all sensors' performance and determines the joint angle motion. The project uses a servo motor to test the response of the FSM model, and the system achieves a promising result that the prototyped knee exoskeleton can follow the user's movement and accurately determine the current state of motion the user is in. By closely examining the foot pressure data and the SVM prediction score, the FSM model is enhanced in capability and can support the user during the walking motion.

Figure 5 shows the real time prediction from the trained SVM model and the actual knee angle when the user slowly performs knee motions. Exact matching predictions are shown in green line, opposite predictions are shown in red line. The figures indicate that majority of the knee movement can be detected by the SVM model with some mislabelling. The delay between the actual movement and the prediction from the SVM model diff in different movement scenario is about 0.2 second. The minimum delay time allowed between the intended knee movement and actual knee movement should not be larger than 0.3s which could be perceivable by the subject (Englehart & Hudgins 2003). The current delay period is within the acceptable range.

The result also shows the importance of the integration of the Buffer and SVM model and the consideration of the classification score. Due to the transient nature of the MMG signal and the interference from the hip joint movement, it is challenging to detect the knee joint movement in different movement scenario where the knee joint movement is not isolated. This explains the accuracy and the delay time in the SVM model output. If the SVM model output is used to directly control an exoskeleton to provide support, it would cause unwanted movement.

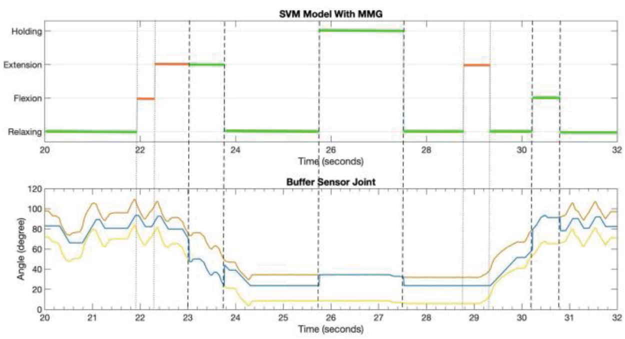

Figure 5: Motion prediction when the user attempt knee motion

The occurrences of unwanted support should be minimised because this may cause the exoskeleton to move to the opposite direction that the user attempt, disrupting the user experience. It is acceptable to not provide support to every single knee movement. The user does not require support in subtle knee joint movement. By considering the classification score, we can identify joint movements that are predicted with high confidence, minimising the occurrence of unwanted support and movement.

3. Conclusions

We developed a system to detect the knee movement and provide support by integrating both FSM model and MMG data based SVM trained model. The FSM model could provide accurate and reliable detection of knee movement attempt, but it cannot work solely to provide knee movement support without predetermined movement pattern. The MMG data based SVM trained model could detect the knee movement attempt without relying on the knee angle and current movement direction but has lower accuracy. We combine the benefits of both system and offset the limitation of each other. We relied on the FSM model to follow the knee movement and relied on the SVM model to provide insight about when and how to support the knee movement.

The current design presents a clean and minimal obstructive sensor system that detects the user joint motion attempt from the moment their foot is about to move and recognises the pattern. The sensor system and algorithm in this work do not target a specific type of user to lay the groundwork for broader applications of future exoskeleton development. This study and results contain valuable information to construct a natural and flexible joint movement while providing assistance to the users. With the performance results achieved with this lower limb exoskeleton design, the model can be implemented in two separate applications. The following function of the device can be further developed to provide a static frame for industrial workers performing repetitive tasks to lean on. The support function using the predictive model from the SVM demonstrates the capability of providing walking support effectively used in gait rehabilitating applications where it can provide aids to patients with lower limb difficulties.

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