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Pison Technical Interview Challenge

The task for this assignment is to utilize the provided dataset to detect and potentially classify specific wrist motions conducted by a user. At the beginning of any new project, it's important to identify any assumptions up front so that the fidelity of the processing is maintained throughout. Initial assumptions are as follows:

- Label standing #1 and standing #2 represent the same body movement (i.e. inert standing) as opposed to the user "standing" up from the seated or prone positions.
- The repetition number indicates a single prompt of specific wrist motions to the user that are then the same across all body movements.
- Within a repetition number, there may be multiple distinct wrist motions.

With some initial assumptions out of the way, we can now start into the data. Whenever one begins to investigate and explore a new data set, it is imperative to ensure that the data is free of contamination that may later cause issues when trying to model the data. This includes such low-hanging fruit as guaranteeing that there are no null values within the data set as well as removing any potential duplicated entries. In doing so, we can also confirm the fidelity of the sensor and, should any problems arise in future data collections, we can track when these bugs were introduced into the pipeline.

Now having confidence in the structure of the dataset, we can then move onto determining how the data actually behaves. What are the variables, span within the variables, resolution, etc? All of this can lead us to potential preprocessing steps that need to be completed before any further processing can take place. This was the case in this dataset as the accelerometer readings had not been preprocessed to remove the gravity component. Thus, the device, at rest, was still registering 9.807m/s^2. It is an easy-to-solve problem as we can utilize the quaternion to create a gravitational vector estimate. This estimate can then be subtracted from the respective accelerometer readings to negate the effects of gravity from the response data. Unfortunately, the quaternion information was recorded in a different reference frame and had to be rotated prior to any gravity estimation. This was done utilizing a simple rotational trick to quaternions as the rotation needed was only in the x and y directions.

With the data properly preprocessed, it's possible to look into what the data is actually telling us. The easiest way to get a feel for the behaviors we're tasked with determining is to employ the gravity vector we just computed. This will give us an estimate of the orientation of the sensor as it is moved throughout the recording. If we can follow how the device moves, then we should be able to identify the type of wrist motion being performed by the subject in this experiment. Additionally, we can identify whether there may be repeat motions or whether there are multiple distinct motions throughout each collection period.

To fully understand what the gravity vector is telling us, first we must assume the orientation of the sensor. I am operating under the premise that the x-axis points positively out of the right side of the device. Thus, if the user is wearing the device on their right wrist, this would mean that the x-axis points positively up the arm. The y-axis then points positively out the top of the device perpendicular to the axis of the arm. And lastly, the z-axis points positively up and out of the device, or away from the outside of the arm.

Using this convention, we can now begin to parse the orientation of the device through the recorded session. To make things easier, we will use the first body movement as a template. This is because the first body movement relates to the subject standing still. With an inert subject, any signal response is from only the arm/wrist motion and not contaminated by the body's movement while walking or running.

With the stage set, it's possible to trace the orientation of the device through the motion. As we see from the plot represented in [15] of the attached notebook, there look to be several repeated motions or, at least, similar motions associated with the cyclical nature shown in the graph. At the beginning of the collection, the orientation of the device starts with the gravity vector pointing negatively, almost entirely, in the y-direction. This implies that the user is potentially holding their hand out in front of them with their palm facing to their left. The orientation then begins to shift from the y-axis more to the x-axis. As these two are perpendicular, this suggests the user is lowering their arm. However, the z-axis also begins to rise indicating that the user is rotating their wrist counter-clockwise as well. Thus, the overall motion appears to be a counter-clockwise rotation of the wrist while the user lowers their arm roughly half-way to their side.

An interesting conclusion from this is that we can likely gain an enormous amount of information about the wrist motion from the gyroscope sensor on the device. All general motion of the device within the user's frame of reference can be characterized through the rotational response recorded during each session. This includes arm motions (gait analysis while walking, arm raises/lowers, wrist rotations, etc.) Unfortunately, it lacks the ability to characterize specific behaviors associated with the fingers as the subtle motion likely wouldn't change the orientation of the device. This also pertains to the motion of bending or flexing the wrist. Although there may be slight responses registered on the gyroscope, it should show up in the microvoltage channels much more clearly since the microvoltages responsible for wrist bends likely to have much greater SNR in comparison to the gyroscope data. In the interest of brevity, I will focus my initial detection scheme on utilizing the gyroscope to gain a somewhat general attempt at motion detection.

Given the time-series nature of our data and the unknown potential motions we are aiming to classify, I will be implementing a heuristic approach to motion detection. To handle this many unknowns, Dynamic Time Warping can be applied to the signal data. While a normal comparison between two signals would use a Euclidean distance measure to calculate a similarity/distance score, Dynamic Time Warping allows for the signal to attempt to stretch and compress the time axis to find the most likely matched data points between the signals. For example, if we compare two sine waves that are slightly out of phase from one another, the Euclidean distance metric would register a fairly large distance score. Meanwhile, the Dynamic Time Warping measure would be able to handle the slight time offset and deliver a much more accurate similarity score.

Unfortunately, there is very little data available in the supplied dataset. In an effort to increase our data supply, I will segment the data in overlapping windows and use these waveforms to perform the Dynamic Time Warping distance measure. Eyeballing the above plots for each repetition number show behavior that appears to have a period of roughly 0.5 seconds. Thus, that will be our window size and we will use a 50% overlap. Since we are not building a specific model for each waveform, we can utilize the entire dataset to locate matched signals and, thus, detect the specific motions registered during each repetition number and body movement.

Upon full processing, the algorithm detected at least three distinct motions from the first repetition, about two in the second repetition, and three more from the third and last repetition. Referring to the visualizations represented in the figures plotted in [17] of the attached notebook, we can see that there appear to be three distinct motions during the first repetition number. The first being the lowering of the arm to the subject's side from a position parallel to the floor. Then there is the reverse motion bringing the arm back up to the parallel. Lastly, we can characterize the remaining wrist motion as a rotation of approximately 45 degrees and back.

Within the second repetition number stage, there only appears to be rotational movement of the wrist. However, this time, the subject appears to complete nearly a full 90 degrees rotation from the palm facing left, to the palm facing down to the floor. Meanwhile, the arm's position mimics the initial setup from the first repetition; outstretched and parallel to the ground.

The third and last repetiton number looks to perform nearly the opposite behavior as the first repetition. One of the motions is raising the arm from the outstrected and parallel to the floor position. The second is the reverse action of bringing the arm back down to the parallel. And lastly, the third wrist motion is a rotation that mimics the rotational behavior from the first repetition.

It can be noted that reprocessing through the data utilizing the magnitude of the gravity compensated accelerometer response data yielded the same signal snippets as the gyroscope (with some exceptions) within the total recording. As the behavior I was looking to detect was more rotational/orientation based, it makes sense that the gyroscope would produce higher fidelity results.

Although we have identified the separate motions recorded by the gyroscope (and verified with the accelerometer), we still haven't touched the microvoltage channel data. When viewing the plot from [19] in the attached notebook, it's clear that there is some serious nerve activity during the last repetition number stage. So despite having roughly classified the wrist motion, it looks like there is still a lot we're missing. However, without any further explanation of how the voltage data may respond to wrist bends and/or finger curls/extensions, it's unclear as to how this information can be used to further characterize the subject's behavior.

In conjunction with the gravity vector data, we can utilize the Euler angles to confirm what we saw in each of the above wrist motions. By creating a heuristic detection and classification schema, we can employ all of the above to improve the accuracy and confidence of our classifications. Taking the first plot of [21] in the attached notebook, as described above, we can confirm that the oscillatory pitching is related to the rotational motion of the wrist. Meanwhile, the roll is related to the lowering and raising of the arm. And lastly, the yaw would indicate any side-to-side motion.

In conclusion, although this is a fairly basic exploration into the data, we have still come out with some interesting findings. With the task of the project being to attempt to detect and classify wrist motion, the decision was made to restrict the scope of our investigation due to both the time constraints as well as the immense number of assumptions that needed to be made. This includes the ambiguity of what is happening during each body movement, what the repetition number actually describes, whether there are multiple different wrist motions during a repetition number, how the channels are oriented on the device, what is the actual orientation of the IMU sensor on the device, as well as which wrist the user is wearing the device on. Additionally, there is no prior explanation as to what types of channel ADC count responses pertain to different kinds of motion (i.e. is there a significant response difference between wrist bends versus finger extensions, etc.).

Despite all of the uncertainty going into the problem, we were still able to produce reasonable results that have detected specific motions during the experiment. Compounded by the information gleaned from the gravity/orientation vector as well as the Euler angles, we were even able to classify what kind of behavior was detected!

Though there is still a significant amount of conjecture applied to this process, there is a mountain of future work that can be completed. The first would be a deep dive into the channel response data. It is clear that there is an incredible amount of information in the microvoltages sent along the radial and ulnar/median nerves. With a larger data set and known motion classes, we could begin to construct a supervised machine learning model that could parse out exactly how certain voltage profiles relate to their associated motions. However, without any further knowledge, we are unable to make any sensible predictions based on the two channels' signals.

Currently, the code operates fully heuristically and, thus, requires a non-insignificant human presence to sort through the output. Moving forward, I would like to build out a much more robust platform that can roll in all of the signal pairings we saw throughout the experiment into a controlled and trained bank of motions in their signal form. By training on a specific set of clean data, we can build a bank of classified waveform models to apply to the experimental data. This would automatically output the motion detection associated with the respective waveform and, thus, output a clean classification result.

Even further down the road, it would be absolutely imperative to perform these detections and classifications in real-time. Leveraging the waveform bank described above, we could cut the time of classifications immensely as there doesn't need to be any modeling performed in real-time. All training can be done offline and/or during a type of calibration phase whenever a new user puts on the device. In doing so, we create a baseline for the user which can then also be forecasted to produce anomaly alerts. This may include erratic readings from the microvoltage sensors, possibly indicating device failure or potential nerve damage in the user. With these user profiles, it'd also be possible to compare user baselines in order to determine more macro-level trends amongst certain populations and demographics.

Git Repository Link: https://github.com/Cetrantz/pison_interview.git