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Impact of mouse DPI on wrist fatigue

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Abstract. This Project mainly creates a model to test if the Arm and Wrist muscle is fatigue or not by analyzing the EMG signal, then find if the Muscle Fatigue has some connection to the Mouse DPI.

Keyword: IEEE, Muscle Fatigue, EMG Signal, Mouse DPI, Machine Learning.

1. Introduction

1.1. Background

With the development of all types of technologies, the number of people who have access to the internet has reached an unprecedented extent [1]. Meanwhile, as the use of electrical devices becomes gradually frequent, it raises our concern of muscle fatigue, especially the wrist part where we use it very often. Unfortunately, performing frequent and repetitive hand movements can cause inflammation in the synovial sheath, and would thus gradually increase the risk of tendon irritation also known as tenosynovitis [2]. Nowadays, a prolonged period of working in front of a computer that strains the fingers, wrist, and forearm is a great example that raises our concern.

As one of the most important parts of a computer, the mouse has many settings and standards. DPI, which stands for dots per inch, is one of them; it shows how many dots the cursor moves on the screen if the mouse moves by one inch. The mouse's DPI determines how the palm and wrist control the mouse. When the mouse has a low DPI, its distance of transverse movement for the wrist is relatively large, while more movements such as wrist lifting are needed. And this will result in a high workload on the wrist. On the contrary, when the mouse has a higher DPI, the wrist movement is reduced, but the cursor's speed on the screen gets faster, making it harder for users to adapt to the movement speed of the mouse [3,4].

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1.2. Motivation
Since the DPI affects the muscle movements and thus can make a difference in the duration of time to muscle fatigue, our team planned to use electromyography, or EMG, to research the impact of DPI on wrist fatigue and operational comfort in order to figure out the ideal DPI of the mouse that can minimize the possibility of illnesses like tenosynovitis.

2. Experimental setup
This section clarifies the experiment details including the experimental equipment, the location of electrodes and the process of the experiment.

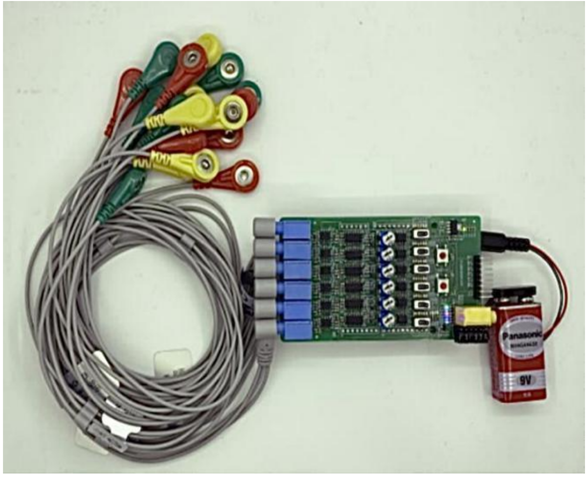

Figure 1. Material Object.

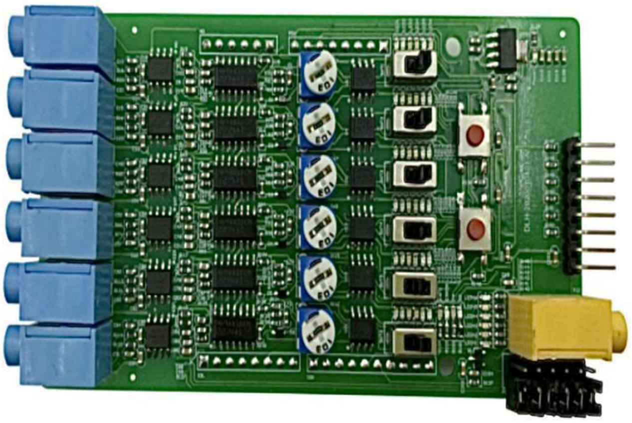

Figure 2. Sensor Module.

2.1. Experimental equipment
The six-lead muscle electrical module includes front-end analog circuit acquisition and back-end digital signal filtering processing [5]. The material object was demonstrated in Figure 1.

The front-end acquisition circuit collects muscle electrical signals from the human arm or legs through 1 to 6 channels, and the EMG signals are amplified and filtered through a series of amplifications. The sensor module was shown in Figure 2. The middle end can switch Envelope Mode and RAW Mode output signals through the SPDT switch. Envelope Mod uses envelope detection processing to obtain EMG dynamic detection signal; RAW Mode can output EMG original signal. And the channel gain of Envelope Mode and RAW Mode output signals can be adjusted through blue and white potentiometers. At the same time, an external single-channel Audio Output Interface outputs the

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original signal. The jumper cap jumper outputs the original waveform of a channel, which is convenient for users to use the external instrument through this interface to analyze the current EMG signal.

The back end uses the Arduino UNO compatible with the six-lead muscle electrical module to collect the output signal of the middle end. We can know the EMG signal intensity through the LED. The upper computer can record EMG envelope signals or original signals that view up to six different muscles. Users can write their own Arduino code for extended design.

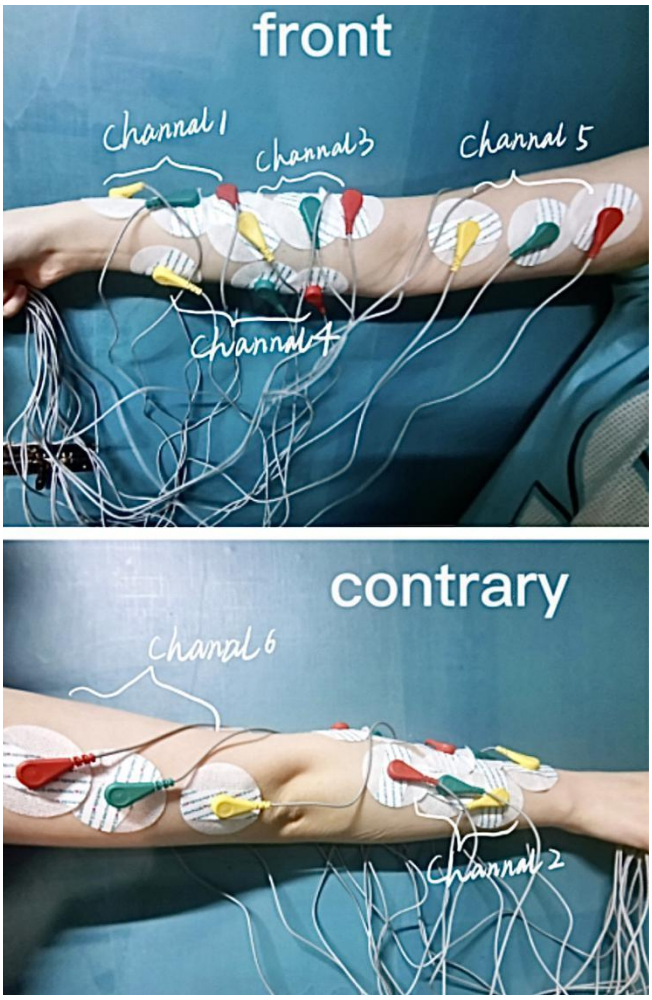

Figure 3. Electrode Location.

2.2. The locations of electrodes

According to our experience, using the mouse involves the finger, wrist, and whole arm movements. EMG signals can be recorded from intrinsic hand, forearm and upper arm muscles. However, the mouse is prone to touching EMG electrodes attached on wrist to arise electrode shift and the bluetooth achiever also sends signals, which will make noises during the collection of EMG signals, which may reduce the recognition accuracy [6]. Therefore, our team only consider the EMG activity over the forearm and upper arm muscles for feature extraction [7].

The muscles our team tested are shown in Table I [8] And the electrodes' location is shown in Figure 3.

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Table 1. Muscle for testing.

Muscle
Flexor Carpi Radialis
Extensor Digitorum
Extensor Carpi Ulnaris
Extensor Carpi Radialis Brevis
Triceps Brachii
Biceps Brachii

2.3. The process of the experiment

Each volunteer played the same computer game and used the same computer and mouse [9]. For every volunteer, we change the DPI of the mouse, we have chosen different DPI (250,500,1000,1500,2000,3000) and under every DPI we have collected about three minutes EMG signal which was taken in two circumstances which was that the volunteers were fatigue or not. And the data was output by Serialplot shown in Figure 4 [10].

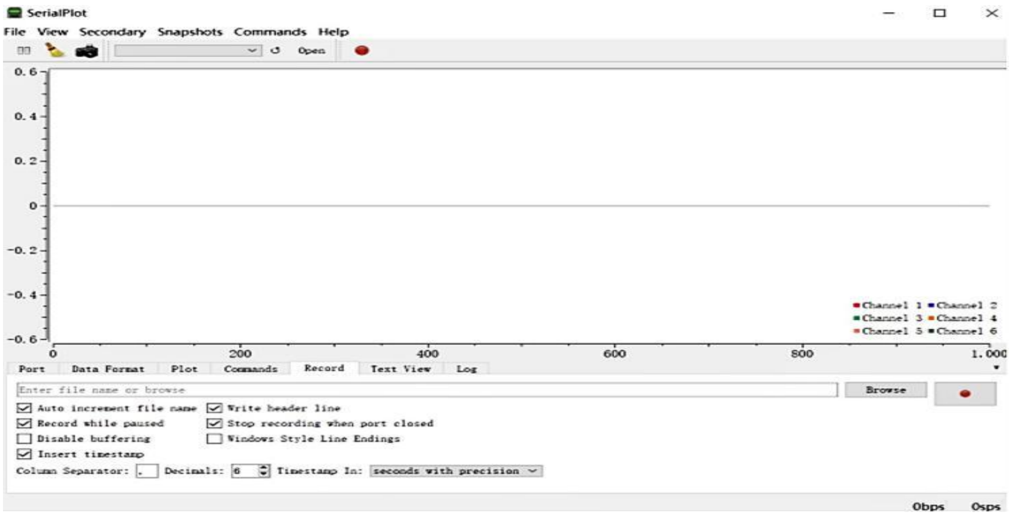

Figure 4. Serial Port.

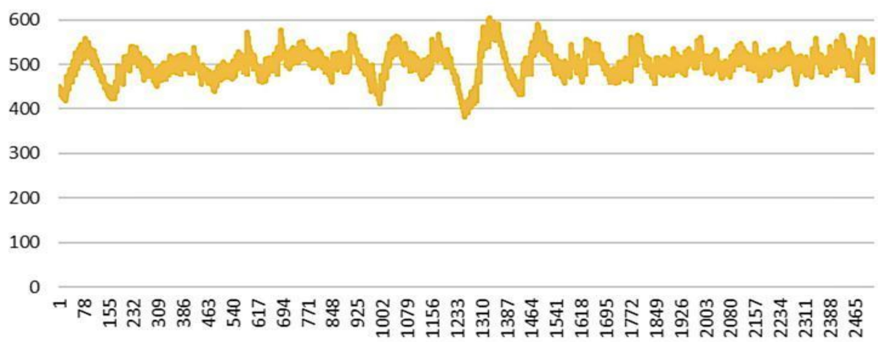

Figure 5. The Signal Plot of Channel 1.

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3. Data processing and training

3.1. Data format

The original Data we got from the muscle electrical module can be seen in Table II, while the signal plot of one of the channels can be seen in Figure 5. It is received in a Baud rate of 115200, and with a frequency of 300HZ. 6 Channels represents 6 ports from the module, in which the numbers represent the shape of the EMG signal from the muscles.

Table 2. The origin data.

Channel 1	Channel 2	Channel 3	Channel 4	Channel 5	Channel 6
547.0	318.0	97.0	193.0	45.0	63.0
542.0	327.0	96.0	193.0	46.0	63.0
537.0	337.0	97.0	192.0	44.0	62.0
532.0	350.0	95.0	190.0	44.0	62.0
527.0	335.0	94.0	190.0	44.0	63.0

3.2. Data processing

Considering that the 6 channels have different scales, our team implemented the Normalization method, which can rescale the data from different channels, so that the model can get a better predicted accuracy. To Normalize the data, the module uses the function

$$X_{Normalized} = \frac{X - X_{min}}{Xmin_{max}}$$

and the normalized data can be found in Table III

Table 3. The normalized data.

Channel1	Channel2	Channel3	Channel4	Channel5	Channel6
0.578224	0.333683	0.102429	0.203586	0.047269	0.061584
0.572939	0.343127	0.101373	0.203586	0.048319	0.061584
0.567653	0.353620	0.102429	0.202532	0.046218	0.060606
0.562368	0.367261	0.100317	0.200422	0.046218	0.060606
0.557082	0.351522	0.099261	0.200422	0.046218	0.061584

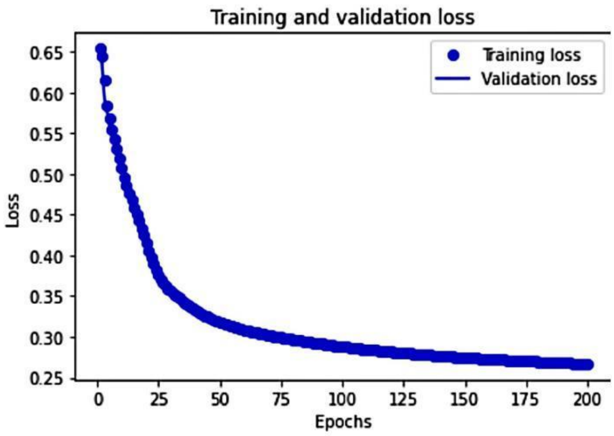

Figure 6. The Training and Validation Loss.

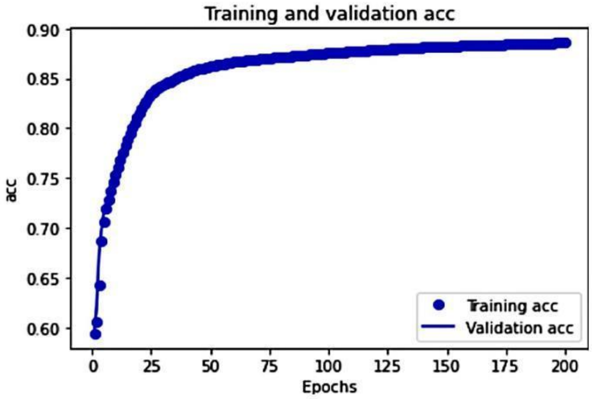

Figure 7. The Training and Validation Accuracy.

3.3. Training model and prediction

To give a good prediction to the model, our team splitted the dataset into a Training and Testing set, as a portion of 8:2. Then, a fully connected sequential model was implemented by the model, which can be seen in Table IV [11].

Table 4. The fully connection sequential model.

Layer	Output Shape	NumofParam
Dense	(N,24)	168
Sigmoid-1	(N,24)	0
dense- 1	(N,36)	900
Sigmoid-2	(N,36)	0
Dense-2	(N, 2)	74
Softmax	(N,2)	0

The Training was set to repeat 200 epochs, while the result produced by the model can be found in Table V, Figure 6 and Figure 7.

To use the module to predict if the muscle is fatigue or not, users can input the signal data into the module, then it will return the result with 1/0, which 1 means Fatigue and 0 means not Fatigue.

Table 5. Model training results.

	Train	Validation
Loss	0.2669	0.2678
Accuracy	0.8860	0.8852

4. Conclusion

Our team uses Machine Learning to make a prediction to Muscle Fatigue via EMG signal, and the module has a general accuracy of around 0.89. Then, the team concluded that 1000 DPI is the most suitable DPI for users to prevent their muscles from being fatigued.

5. Best mouse DPI

Considering that different DPIs used for testing and the result of the Data, our team concluded that when the Mouse

DPI is set to 1000, the muscle begins being fatigued later than when DPI was set into other values. As a result, in the DPIs we have measured, 1000 DPI is the most comfortable common Mouse DPI for users to prevent Muscle Fatigue.

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