

Using multi-label classification methods to classify finger movements for hand prosthesis control

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Losing a limb is a traumatic experience that greatly impacts a person's quality of life. To help the people who have suffered limb loss prosthetic devices were invented. The purpose of a prosthetic device is to mimic the function of the missing limb. As technology increased so did the functionality of these prosthetic devices yet even with today's technology there are still many limits.

In this work the problem of interest lies in controlling the movements of a myoelectric hand prosthesis. A myoelectric prosthesis refers to an electrically powered prosthesis that is controlled by measuring the electrical activity in the user's muscles. Once this activity has been measured pattern recognition methods are used to determine which movement the electrical activity relates to. Pattern recognition is a type of process in which an algorithm looks at a set of labelled data and then tries to create a model so that it can determine what labels future data has. An example of this would be to show a pattern recognition method pictures of forests while simultaneously telling the method that the pictures contain forests, this is referred to as training the method. Once training has been completed then if the method is shown a picture it should be able to say whether or not it contains a forest.

Modern hand prostheses have a small range of motion often as few as only eight grips or less. This limit comes from the fact that as the number of possible movements increases it becomes more difficult to determine which movement the user wants to make. This problem is inherent in the pattern recognition methods that are normally used for this type of task. The purpose of this work is to test a different type of pattern recognition methods called multi-label classification methods to see if this problem can be avoided or diminished. When using the normal classification methods each observation is restricted to one label these methods can therefore be referred to as single-label classification methods. If the task is then to describe a picture that might

contain mountains, forests and lakes then seven different classes would be needed, one for each possible combination. When using multi-label classification an observation is instead assigned a number of labels, so a picture of a mountain and a lake would have the mountain and lake label but not the forest label. The idea is then to shift the focus from learning all possible combinations to instead just learn the individual labels and let the method figure out the combinations on its own.

In this work the testing was done by classifying finger movements. The movements tested were most often the thumb, index, long, and ring finger movements. The results showed that multi-label classification methods did not possess any inherent advantage compared to single-label classification as long as both methods were trained on both individual finger movements and finger combination movements. The results also showed that at least one multi-label method possesses the ability to learn label combinations when it has only been trained on individual labels. These results were obtained by recording electromyographic data produced by the finger movements and then testing on four different single-label methods and four different multi-label methods.

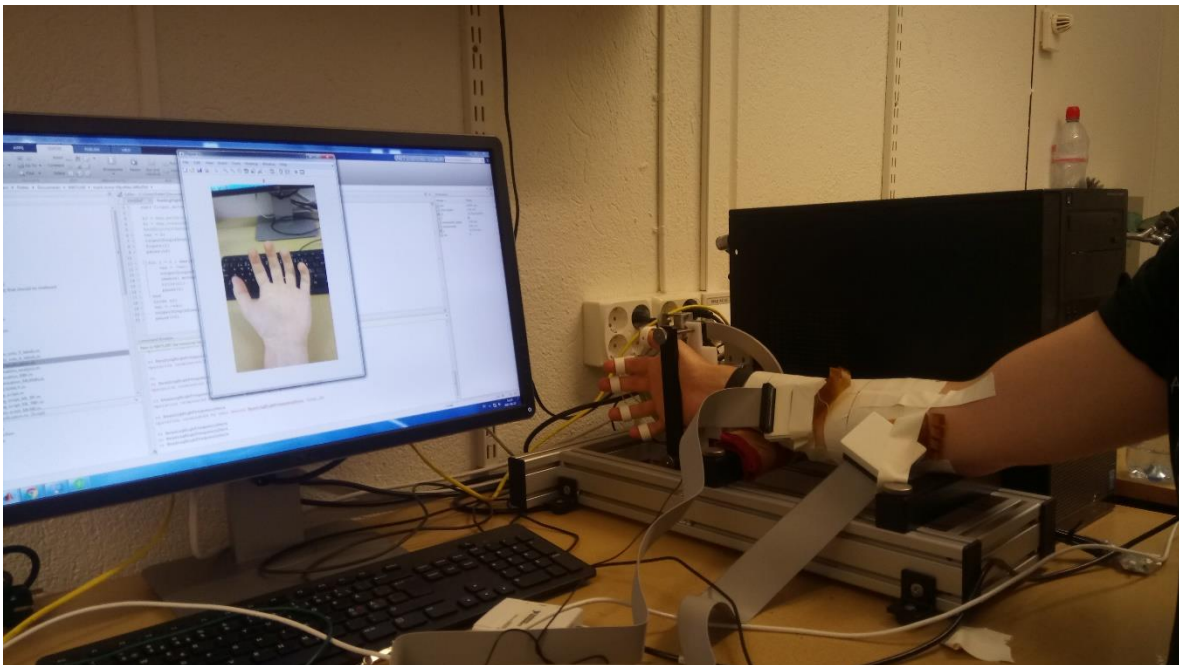


Figure 1. An example of an EMG recording session.

In the end the results show that further study into the use of multi-label classification methods for the purpose of classifying electromyographic signals is still needed.