Joint Torque Estimation Model of Surface Electromyography(sEMG) based on Swarm Intelligence Algorithm for Robotic Assistive Device

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Abstract

The conventional robotic assistive device was based on pre-programmed functions by the robot expert. This makes it difficult for stroke patients to use it effectively due to difficulty of torque setting that is suitable for the user movement. Electromyography (EMG) signal measures the electrical signal of muscle contraction. The EMG-based robotics assistive technology would enable the stroke patients to control the robot movement according to the user’s own strength of natural movement. This paper discusses the mapping of surface electromyography signals (sEMG) to torque for robotic rehabilitation. Particle swarm optimization (PSO) has been applied as a control algorithm for a number of selected mathematical models. sEMG signals were determined as input data to the mathematical model where parameters of the mathematical model were optimized using PSO. Hence, the good correlated estimated torque as output was obtained.

Keywords: Electromyography, Joint torque estimation model, biomechanics human motion, robot rehabilitation, feature extraction, particle swarm optimization.

1. Introduction

There are an increasing number of people who are affected by stroke worldwide for each year [1]. Muscular dystrophy, arthritis and regional pain syndrome are also major causes of disabilities of stroke patients [2]. Rehabilitation that involved the physical therapy helps the recovery of limb functions [3,4]. Conventional rehabilitation therapies required high labour intensive especially for lower limb rehabilitation [5]. In addition, conventional therapy leading to failure because of the repetitive training needs a long duration and excessive fatigue for the therapist [6].
One of the expanding technologies to enhance the recovery process for post stroke patients is robotic assistive device for rehabilitation. The advanced robotics technology is able to perform consistent training with less supervision from the therapist [7]. The robotic assistive device utilizes the surface electromyography signals (sEMG) as a control input to estimate the magnitude and direction of torque for the robotic joint exoskeleton. Advantages of EMG signals as a controlling signal of assistive device are EMG signals able to measure muscle activities and recognize the intended movement by the patients. The information from the EMG signals can be applied to estimate the human desired movement[8].

Researchers have done several works on mathematical models and black box model to estimate the joint torque based on force produce of the muscle contraction. Hill-based muscle model referred to three element model of muscle mechanical response that is used to convert sEMG signals to joint torque to maintain the posture of arm [9]. Hill-based muscle model also has been obtained to predict joint torque for leg [10], ankle [11,12] exoskeleton and also arm exoskeleton applications [13]. Research has been done using polynomial equations to convert sEMG signals for prediction joint torque isometrics and quasi-isometric contraction[14]. Research on sEMG has been carried out on detection, analysis, feature extraction, joint-torque estimation using genetic algorithm in [15,16, and 17]. Regression analysis has been performed to estimate the joint torque using mathematical models as proven of best fit mathematical model with optimization using Levenberg-Marquardt [18], simulated annealing and genetic algorithm [19] for the upper limb function.

The estimation of joint torque is important to control the motion of robots for rehabilitation. The Mathematical model is used to convert the sEMG signals for estimation of torque value. The estimated joint torque would be determined by optimizing the parameters of the mathematical model to the nearest value of actual torque. Artificial intelligence algorithms are used to optimize the internal parameters of the mathematical model to find the best fit mathematical model and minimize the error between estimated joint torque and actual joint torque. The aim of this paper is to establish mathematical models for sEMG signal conversion to estimated joint torque using particle swarm optimization (PSO) algorithm.

2. Theory and Technique

2.1. Mathematical model of sEMG to joint torque conversion

The mathematical models represent the non-linearity of the physical system that is being represented. The mathematical model for estimated joint torque is given in Equations (1) to (9) [18], [19]:

\[
MM_{(1)} = x_1u_i + x_2u_i^{\frac{1}{2}}
\]

\[
MM_{(2)} = x_1u_i^{x_2}
\]

\[
MM_{(3)} = x_1e^{\frac{u_i}{x_2}}
\]

\[
MM_{(4)} = x_1u_i^{x_2} + x_3u_i^{x_4}
\]

\[
MM_{(5)} = x_1u_i^4 + x_2u_i^3 + x_3u_i^2 + x_4u_i^{\frac{1}{2}} + x_5u_i^0
\]

\[
MM_{(6)} = x_1 + x_2\sqrt{u_i}
\]

\[
MM_{(7)} = u_i^{x_3}e^{(x_4-x_3_u_i)}
\]

\[
MM_{(8)} = x_1 + x_2\cos(u_i) + x_3\sin(u_i)
\]

\[
MM_{(9)} = x_1 + x_2\sin(u_i)
\]

where, 
\[
MM_{(1)} \text{ to } MM_{(9)} = \text{mathematical model for estimated joint torque}
\]
\[
u_i = \text{processed sEMG data sample}
\]
\[
x_i = \text{where, } i = (1,2,3...) \text{ as random value parameter associated}
\]
\[
\text{with selected mathematical model.}
\]
2.2. Fitness function

The fitness function in Equation (10) is used to evaluate the performance of each selected mathematical model from Equation (1) to Equation (9):

\[ SSE = \sum_{i=1}^{n} \left( T_{m(i)} - MM_{(i)} \right)^2 \]  \hspace{1cm} (10)

where,
- \( SSE \) = sum square error as fitness function
- \( T_{m(i)} \) = measured joint torque
- \( MM_{(i)} \) = mathematical model, \( i=1,2,3,\ldots \)

2.3. Regression analysis

The fitness function (sum of squared error (SSE)) in Equation (10) forms regression analysis that can be minimized using particle swarm optimization (PSO). PSO searches the optimum values of parameter \( x_j \) associated with the selected mathematical model. Fig.1 shows the flowchart of particle swarm optimization (PSO) and Table 1 parameter setting of PSO.

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Fig.1: Flowchart of Particle Swarm Optimization (PSO)
2.4 Correlation Analysis

The correlation between estimated joint torque and measured joint torque using Pearson correlation \((R)\) and Coefficient of determination \((R^2)\) is expressed in Equations (11) and (12).

\[
R = \frac{\sum_{i=1}^{n} (T_{m(i)} - \text{mean}_m) (MM_{i(i)} - \text{mean}_MM)}{\sqrt{\sum_{i=1}^{n} (T_{m(i)} - \text{mean}_m)^2 \sum_{i=1}^{n} (MM_{i(i)} - \text{mean}_MM)^2}}
\]

\[
R^2 = \frac{\sum_{i=1}^{n} (MM_{i(i)} - \text{mean}_MM)^2}{\sum_{i=1}^{n} (T_{m(i)} - \text{mean}_m)^2 + \sum_{i=1}^{n} (MM_{i(i)} - \text{mean}_MM)^2}
\]

where,

- \(i = \) data sample
- \(MM_{i(i)} = \) estimated joint torque using mathematical models, \(i = 1,2,3 \ldots\)
- \(T_{m(i)} = \) measured joint torque
- \(\text{mean}_m = \) mean of measured joint actual torque
- \(\text{mean}_MM_{i(i)} = \) mean of estimated joint torque

3. Method

Raw data from the database from [20] has been used using ‘vastus lateralis’ muscles for movement task of knee extension 80\(^\circ\)of one subject with five trials which provide the raw data of sEMG signal and measured value of actual torque from torque sensor. Signal processing analysis was carried out using the software, EMGWorks Analysis ver. 4.07. Signal processing of sEMG signals are as follows:

3.1 Filtering

Bandpass filter of the 4th order Butterworth filter is applied to remove the noise signal. The cutoff frequency has been set to be between 20Hz - 400Hz. The Butterworth filter was chosen since it produces flat frequency response in band pass filter and resulting in steep roll offs in higher order filters.

3.2 Feature extraction

Root mean square (RMS) has been selected from time domain feature extraction. as shown in Equation (13).

\[
\text{RMS} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} x_n^2}
\]

Where, \(x = \) sEMG data and \(N = \) number of samples(13)
3.3 Muscle activation

Detection of offline method is applied in DelsysEMGWorks Analysis ver.4.07. The lowest value from sEMG signals was considered as noise level. An active region of muscle was considered as the RMS sEMG signals value.

4. Results and Discussion

Figs 2 to 5 show the results by plotting the estimated joint torque from $MM_{(1)}$ to $MM_{(6)}$ with the measured joint torque for knee extension 80° using PSO for trial 1 (T1) of one subject. The rest of the results are not shown here due to page limitations.

![Fig.2 Estimated joint torque for $MM_{(1)}$](image1)

![Fig.3 Estimated joint torque for $MM_{(2)}$](image2)

![Fig.4 Estimated joint torque for $MM_{(3)}$](image3)

![Fig.5 Estimated joint torque for $MM_{(6)}$](image4)

Table 2 and Fig. show the result coefficient of determination ($R^2$) for each mathematical model of trial 1(T1), trial 2 (T2), trial 3 (T3), trial 4 (T4) and trial 5 (T5) optimization of PSO algorithm.

<table>
<thead>
<tr>
<th>MODEL</th>
<th>T1</th>
<th>T2</th>
<th>T3</th>
<th>T4</th>
<th>T5</th>
<th>Average</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$MM_{(1)}$</td>
<td>0.92</td>
<td>0.83</td>
<td>0.85</td>
<td>0.76</td>
<td>0.72</td>
<td>0.82</td>
<td>0.08</td>
</tr>
<tr>
<td>$MM_{(2)}$</td>
<td>0.92</td>
<td>0.84</td>
<td>0.86</td>
<td>0.77</td>
<td>0.74</td>
<td>0.83</td>
<td>0.07</td>
</tr>
<tr>
<td>$MM_{(3)}$</td>
<td>0.92</td>
<td>0.83</td>
<td>0.87</td>
<td>0.78</td>
<td>0.75</td>
<td>0.82</td>
<td>0.07</td>
</tr>
<tr>
<td>$MM_{(4)}$</td>
<td>0.92</td>
<td>0.84</td>
<td>0.86</td>
<td>0.77</td>
<td>0.73</td>
<td>0.82</td>
<td>0.07</td>
</tr>
<tr>
<td>$MM_{(5)}$</td>
<td>0.84</td>
<td>0.71</td>
<td>0.67</td>
<td>0.61</td>
<td>0.73</td>
<td>0.71</td>
<td>0.09</td>
</tr>
<tr>
<td>$MM_{(6)}$</td>
<td>0.89</td>
<td>0.83</td>
<td>0.86</td>
<td>0.77</td>
<td>0.74</td>
<td>0.82</td>
<td>0.06</td>
</tr>
<tr>
<td>$MM_{(7)}$</td>
<td>0.92</td>
<td>0.84</td>
<td>0.86</td>
<td>0.79</td>
<td>0.76</td>
<td>0.84</td>
<td>0.06</td>
</tr>
<tr>
<td>$MM_{(8)}$</td>
<td>0.92</td>
<td>0.82</td>
<td>0.83</td>
<td>0.75</td>
<td>0.72</td>
<td>0.81</td>
<td>0.08</td>
</tr>
</tbody>
</table>

![Error Bar $MM_{(1)} - MM_{(9)}$ of $R^2$ Knee Extension 80°](image5)
Table 3 and Fig.7 show the result Pearson correlation ($R$) for each mathematical model of trial 1(T1), trial 2 (T2), trial 3 (T3), trial 4 (T4) and trial 5 (T5) optimization of PSO algorithm.

<table>
<thead>
<tr>
<th>MODEL</th>
<th>T1</th>
<th>T2</th>
<th>T3</th>
<th>T4</th>
<th>T5</th>
<th>Average</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$MM_{(1)}$</td>
<td>0.96</td>
<td>0.91</td>
<td>0.92</td>
<td>0.87</td>
<td>0.85</td>
<td>0.90</td>
<td>0.04</td>
</tr>
<tr>
<td>$MM_{(2)}$</td>
<td>0.96</td>
<td>0.91</td>
<td>0.92</td>
<td>0.88</td>
<td>0.86</td>
<td>0.91</td>
<td>0.04</td>
</tr>
<tr>
<td>$MM_{(3)}$</td>
<td>0.96</td>
<td>0.91</td>
<td>0.93</td>
<td>0.88</td>
<td>0.87</td>
<td>0.91</td>
<td>0.04</td>
</tr>
<tr>
<td>$MM_{(4)}$</td>
<td>0.96</td>
<td>0.91</td>
<td>0.93</td>
<td>0.88</td>
<td>0.86</td>
<td>0.91</td>
<td>0.04</td>
</tr>
<tr>
<td>$MM_{(5)}$</td>
<td>0.92</td>
<td>0.84</td>
<td>0.82</td>
<td>0.78</td>
<td>0.77</td>
<td>0.83</td>
<td>0.06</td>
</tr>
<tr>
<td>$MM_{(6)}$</td>
<td>0.94</td>
<td>0.91</td>
<td>0.92</td>
<td>0.88</td>
<td>0.86</td>
<td>0.90</td>
<td>0.04</td>
</tr>
<tr>
<td>$MM_{(7)}$</td>
<td>0.96</td>
<td>0.92</td>
<td>0.93</td>
<td>0.89</td>
<td>0.87</td>
<td>0.91</td>
<td>0.04</td>
</tr>
<tr>
<td>$MM_{(8)}$</td>
<td>0.96</td>
<td>0.91</td>
<td>0.91</td>
<td>0.87</td>
<td>0.85</td>
<td>0.90</td>
<td>0.04</td>
</tr>
<tr>
<td>$MM_{(9)}$</td>
<td>0.96</td>
<td>0.91</td>
<td>0.91</td>
<td>0.87</td>
<td>0.85</td>
<td>0.90</td>
<td>0.04</td>
</tr>
</tbody>
</table>

From Table 2 and represented graphically in Fig.6 and Table 3 and represented graphically in Fig.7, it can be found that the best mathematical model is $MM_{(7)}$, based on to the average value for all subjects of $R^2$ and $R$ comparison between estimated joint torque and modelling joint torque for task movement of knee extension 80°. For $MM_{(7)}$, it can be seen that the average value of $R^2$ is 0.84±0.06 and the average value of $R$ is 0.91±0.04. The mathematical model of $MM_{(3)}$ is the second best mathematical model which the average value of $R^2$ is 0.83±0.07 and the average value of $R$ is 0.91±0.04. The results obtained from $MM_{(3)}$ is found the lowest average value of $R^2$ that is 0.71±0.09 and lowest average value of $R$ that is 0.83±0.06.

Fig.8 illustrates an example of graph of fitness value with respect to the number of iterations for knee extension 80° using PSO algorithm of $MM_{(1)}$.

The result of the sum of squared error (SSE), number of iteration and execution time is represented in Table 4 for each mathematical model for trial 1(T1), trial 2 (T2), trial 3 (T3), trial 4 (T4) and trial 5 (T5) for movement knee extension 80° optimization of PSO algorithm.
Table 4: Result of sum of squared error (SSE), number of iteration and execution time for knee extension 80°

<table>
<thead>
<tr>
<th>MODEL</th>
<th>SSE(Nm)</th>
<th>No. of iteration</th>
<th>Execution time(s)</th>
<th>SSE(Nm)</th>
<th>No. of iteration</th>
<th>Execution time(s)</th>
<th>SSE(Nm)</th>
<th>No. of iteration</th>
<th>Execution time(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MM(1)</td>
<td>8669.91</td>
<td>20</td>
<td>3.21</td>
<td>13544.4</td>
<td>16</td>
<td>3.865</td>
<td>15590.4</td>
<td>38</td>
<td>7.07</td>
</tr>
<tr>
<td>MM(2)</td>
<td>8998.3</td>
<td>2</td>
<td>2.49</td>
<td>14046.2</td>
<td>2</td>
<td>2.43</td>
<td>25330.1</td>
<td>4</td>
<td>50.57</td>
</tr>
<tr>
<td>MM(3)</td>
<td>6579.26</td>
<td>26</td>
<td>2.36</td>
<td>32517.1</td>
<td>104</td>
<td>28.75</td>
<td>70084.8</td>
<td>8</td>
<td>17.02</td>
</tr>
<tr>
<td>MM(4)</td>
<td>6805.7</td>
<td>2</td>
<td>10.043</td>
<td>52554.5</td>
<td>8</td>
<td>18.31</td>
<td>13178.9</td>
<td>2</td>
<td>3.298</td>
</tr>
<tr>
<td>MM(5)</td>
<td>25574.4</td>
<td>34</td>
<td>3.06</td>
<td>21747</td>
<td>48</td>
<td>2.547</td>
<td>36763.9</td>
<td>8</td>
<td>1.268</td>
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<tr>
<td>MM(6)</td>
<td>8888.41</td>
<td>2</td>
<td>3.458</td>
<td>15859</td>
<td>6</td>
<td>4.13</td>
<td>12036.5</td>
<td>6</td>
<td>9.191</td>
</tr>
<tr>
<td>MM(7)</td>
<td>6148.26</td>
<td>4</td>
<td>2.532</td>
<td>16427.7</td>
<td>4</td>
<td>6.31</td>
<td>11177.1</td>
<td>4</td>
<td>1.868</td>
</tr>
<tr>
<td>MM(8)</td>
<td>6833.67</td>
<td>40</td>
<td>4.06</td>
<td>61241.3</td>
<td>30</td>
<td>17.14</td>
<td>18356.6</td>
<td>30</td>
<td>14.894</td>
</tr>
<tr>
<td>MM(9)</td>
<td>6650.92</td>
<td>30</td>
<td>1.66</td>
<td>12562.7</td>
<td>4</td>
<td>1.66</td>
<td>16155.1</td>
<td>22</td>
<td>8.136</td>
</tr>
</tbody>
</table>

Table 4 – continued: Result of sum of squared error (SSE), number of iteration and execution time for knee extension 80°

<table>
<thead>
<tr>
<th>MODEL</th>
<th>SSE(Nm)</th>
<th>No. of iteration</th>
<th>Execution time(s)</th>
<th>SSE(Nm)</th>
<th>No. of iteration</th>
<th>Execution time(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MM(1)</td>
<td>26643.8</td>
<td>40</td>
<td>2.62</td>
<td>40433.4</td>
<td>30</td>
<td>3.33</td>
</tr>
<tr>
<td>MM(2)</td>
<td>26102.2</td>
<td>2</td>
<td>1.87</td>
<td>40231.4</td>
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<td>2.1</td>
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<td>MM(3)</td>
<td>49086.4</td>
<td>74</td>
<td>34.95</td>
<td>31098.1</td>
<td>20</td>
<td>17.71</td>
</tr>
<tr>
<td>MM(4)</td>
<td>19084.3</td>
<td>2</td>
<td>2.78</td>
<td>56656.7</td>
<td>6</td>
<td>9.508</td>
</tr>
<tr>
<td>MM(5)</td>
<td>34004.9</td>
<td>62</td>
<td>8.67</td>
<td>56656.7</td>
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<tr>
<td>MM(6)</td>
<td>30104.4</td>
<td>2</td>
<td>1.87</td>
<td>40240.1</td>
<td>2</td>
<td>1.87</td>
</tr>
<tr>
<td>MM(7)</td>
<td>30179.7</td>
<td>4</td>
<td>2.27</td>
<td>38104.4</td>
<td>4</td>
<td>2.55</td>
</tr>
<tr>
<td>MM(8)</td>
<td>23704.3</td>
<td>44</td>
<td>14.26</td>
<td>46412.6</td>
<td>34</td>
<td>4.58</td>
</tr>
<tr>
<td>MM(9)</td>
<td>27162.1</td>
<td>164</td>
<td>10.7</td>
<td>40970.6</td>
<td>24</td>
<td>3.24</td>
</tr>
</tbody>
</table>

From Table 4, it can be observed that the iteration number of particle swarm optimization (PSO) is less than 100 iterations for each mathematical model. The execution time for all mathematical models is less than 51 seconds. This shows that particle swarm optimization (PSO) algorithm is providing fast convergence time with reasonable iterations.

4. Conclusion

This paper has discussed the analysis of joint torque estimation of nonlinear mathematical model that map the sEMG signals to obtain estimated joint torque. The optimization of all parameters in each mathematical model was done through Particle swarm optimization (PSO). Correlation analysis was applied as the statistical results to verify if the estimated joint torque values closest to measured joint torque values. It can be deduced that the best mathematical model for estimated joint torque is the seventh mathematical model (MM(7)) for knee extension 80°. This mathematical model (MM(7)) has been chosen based on consistency of the average value of R² and R for five trials. Estimated joint torque could be used to control the exoskeleton in various applications such as ergonomics, gait analysis, rehabilitation and also sports exercise.

Acknowledgements

The authors would like to thank UniversitiTeknologi PETRONAS (UTP), Monash University Malaysia and University Selangor for their support and Ministry of High Education for sponsoring the project under the Prototype Research Grant Scheme: PRGS/1/13/TK02/UTP/02/01.

Reference