Scientific Journal of Impact Factor (SJIF): 5.71
e-ISSN (O): 2348-4470
p-ISSN (P): 2348-6406

International Journal of Advance Engineering and Research Development

Volume 5, Issue 03, March -2018

Fuzzy Logic Controller For Leg Movement Classification Using sEMG Signal

Iqbal Ahmed[1], Kuldeep Singh[2], Gurpreet Singh[3]

[1]*Student ,BUEST*
[2] *Assistant Professor ECE Department, BUEST*
[3] *Assistant Professor ME Department, BUEST*

Abstract —*The Surface electromyography is the most favourable method to witness muscle activity. It involves no risk to the subject as it is a non-invasive method. sEMG signals are processed and employed for rehabilitation engineering and varied prosthetic technologies. In these days, sEMG signals are used for development of numerous controlling prototypes based on gesture recognition modules. These modules distinguish different movements and utilise them to control a machine. This work proposed a classification of knee extension at three levels using fuzzy logic technique. Surface electromyography signals (sEMG) were acquired using hardware consisting of differential amplifier, non-inverting amplifier, band pass filter and interface module from Vastus lateralis muscle which is responsible for leg extension movements. MATLAB soft-scope was employed to import signals from hardware to system. For the task of classification, fuzzy logic controller was used. For signal analysis three parameters, Root Mean Square, Median and Standard Deviation were selected as inputs to fuzzy logic controller. Results showed that out of all three parameters, standard deviation was proved to be the best parameter for discriminating movements.*

Keywords-*Surface Electromyography; Vastus Lateralis; Leg extension; Fuzzy Logic Controller; FIS Editor.*

I. INTRODUCTION

Electromyography (EMG) is the electrical signal acquired from the muscles. For understanding of activation of muscles this signal is analyzed. Biomechatronics is the branch of Biomedical Engineering that utilizes electromyography signals for controlling prosthesis [1]. A small electric current and potential is produced by the exchange of ions at the muscle membrane. Specially designed electrodes were utilized for this potential acquisition. This electrical signal acquired during muscle activation is termed as myoelectric signal. Electromyography is employed to record and evaluate the electrical activities of human body muscles [2].The required force is generated by this signal to perform various tasks and interact with the environment. The number of muscles activated for the task depends on the gravity and utilization of body for the task. For heavy weight job, larger numbers of muscles were activated and vice versa [3,4]. The applicability of electromyography had a wide range of applications in various field. In curing neurological disorders such as back pain and disorders of motor control electromyography is used [5]. For the evaluation of tools in applied research, physiotherapy, robotic prosthesis and rehabilitation EMG is used. Sensing in an effortless and natural way EMG had become the first priority for sensing and classification of body movements. It is used in robotic mechanism having multi degree of freedom successfully for execution of human like motions. The microcontroller technology and electronics had advanced in a great amount. The application of these technologies with EMG had improved in a great way for the control options of robotic mechanisms. In the year 2008 a virtual leg was controlled by sEMG signal acquired from four thigh muscles viz. vastus lateralis, biceps femoris, rectus femoris and semitendinosus [6]. Kuldeep Singh et al (2011) employed a fuzzy logic controller to classify the hand movements to the sEMG signal acquired from the upper hand muscle. For calibration of force of gripping and sEMG signal a grip exerciser was used. The fuzzy controller comes out to be suitable for control of prosthetic grip[7,8]. The sEMG signals from sartorius, rectus femoris, vastus medialis, adductor magnus, biceps femoris short head, biceps femoris long head and semitendinosus muscles were used by Robert Hernandez et al (2013) for a neural machine interface that controls a artificial leg of a support vector machines [9]. In the next year Tatsushi Tokuyasu et al proposed a saddle height control system for cyclist. This paper puts light on the significance of saddle height for a cyclist. This paper utilizes the sEMG signal from rectus femoris, vastus lateralis, biceps femoris, gastrocnemius medialis, and gastrocnemius lateralis muscles. A fuzzy inference system is proposed to approximate the effective saddle height for a cyclist [10]. Ming-Kun Chang et al (2014) put up a fuzzy control method for the two joint leg rehabilitation devices driven by pneumatic artificial muscles [11]. sEMG signals are also used for pain treatment and analysis of muscle strength exercises. Sreekar Kumar Reddy et al (2014) studied the effect of different foot positions on vastus lateralis and vastus medialis oblique muscles. The study recommended that soft foot orthoses may be used for treatment of patellofemoral pain which is due to pronated foot [12]. In the same year Crook T et al studied sEMG signals of gastrocnemius lateralis and vastus lateralis muscles. It was concluded that draft loading may be implied for strength training [13]. Left vastus medialis, vastus lateralis, medial head gastrocnemius, lateral head of gastrocnemius, hip adductors, tibialis anterior and soleus were studied while exercising on a treadmill at various speeds. It was found that increase in velocity increases the load on muscles [14]. It was advised by the study of erector spine and vastus lateralis while performing bending forward and squatting down that to reduce low back pain in daily life activities trunk bending to be avoided and instead squatting down to be executed[15]. In the year 2016 an algorithm was proposed to predict knee angle from sEMG signals from vastus lateralis, semitendinosus, biceps femoris and rectus femoris muscles. It was concluded that the proposed algorithm may be employed for control of exoskeleton or other rehabitilisation devices [16]. Tsuyoshi Inoue et al (2017) proposed a technique to predict 'sit to stand' motion before a person's buttocks leaves the chair. For the prediction sEMG signals from five lower limb muscles and the angle of forward trunk inclination were employed in the study. The muscles used for the system were vastus lateralis, vastus medialis, rectus femoris, tibialis anticus and gastrocnemius [17].

It was noted that for classification of knee angle various muscles were used but only vastus lateralis muscle was not employed. In this article sEMG signal from Vastus lateralis was used for classification of leg extension by a fuzzy logic controller. This paper is organized into four sections. Section 2 gives details of methodology used. Section 3 provides the details of fuzzy logic controller. Section 4 deals with the results and discussion. The conclusion is drawn in sections 5.

II. METHODOLOGY

This set up consists of amplifiers, filters, interface module and finally fuzzy logic implementation. Two cup shaped Ag-Ag-Cl type electrodes along with conducting gel were used for the acquisition of sEMG signals from the vastus lateralis muscle. Three healthy males were selected as subjects to record sEMG signal with a sampling rate of 8000 Hz. For precise classification of leg movements, fuzzy logic technique is used. First of all, after acquiring the sEMG signal, this signal was filtered by using band pass filter. Then the values of selected three parameters like Root Mean Square (RMS), Median and Standard Deviation (Std. Dev.) were calculated for three different subjects. These parameters were then taken as input variables to the Fuzzy Logic Controller. After calculating the values of the selected parameters, the range of each parameter was calculated for fuzzification. From the range of each parameter, the rule set was formed to get desired precise output for no, half and full leg extension movements. Then by using trapezoidal membership function, the selected parameters were fuzzified to get fuzzy output level for precise movements. Each input variable had three membership functions. For root mean square input variable, RMS1, RMS 2 and RMS 3 were the membership functions. Similarly for median, Median1, Median2 and Median3 and finally for standard deviation, Std. Dev.1, Std. Dev.2 and Std. Dev.3 were the membership functions.

III. FUZZY LOGIC CONTROLLER

After calculating all three parameters for all subjects, these parameters were taken as input variables for Fuzzy Logic Controller. Figure 3.1 was showing simulink model with fuzzy logic technique. The SEMG based fuzzy logic controller was the main part of the thesis work. The first block will work as sEMG signal was taken from workspace. Then sEMG signal was filtered through band pass filter. After that statistical parameters were calculated. These inputs were multiplexed by using 3:1 MUX.

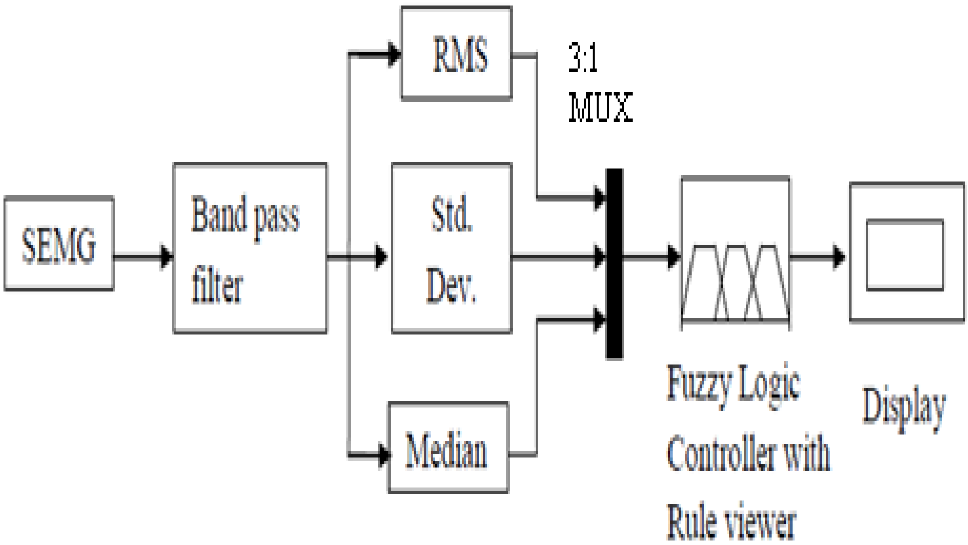
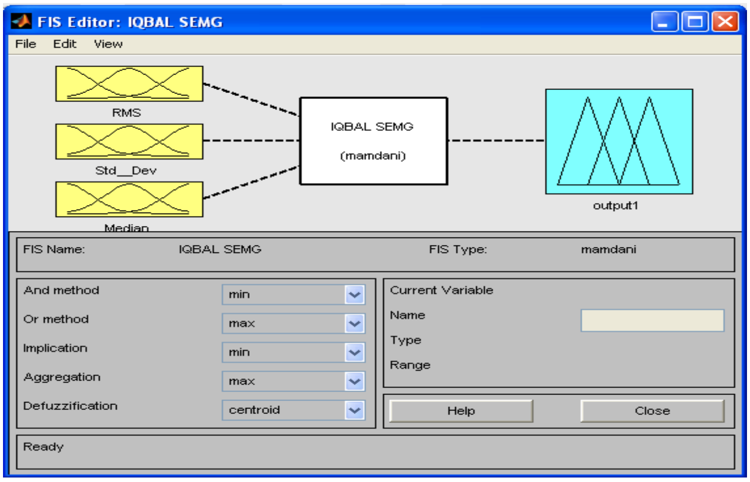


Figure 3.1 Simulink model with Fuzzy Logic Controller



The fuzzy logic controller was created in the FIS editor window with three inputs and one output. Figure 3.2 shows the view of FIS editor. The membership function for each parameter and output are set in the membership function editor.

3.1 Algorithm for fuzzification

1. Normalisation of original data values.
2. Computation of each parameter value for all three movements by simulink model.
3. Computation of range for each input parameter.
4. Present these values as input to Fuzzy Logic Controller.
5. Computation of range for Fuzzy Logic Controller output.
6. Make three membership functions for each input.
7. Make three membership functions for output obtained from Fuzzy Logic Controller.
8. Set the rules in fuzzy editor.
9. Note down the fuzzy output for all movements for each subject.

3.2 Rule set

The rule editor is used for framing various rule applied in this work. All three parameters for all movements were compared for obtaining fuzzy output using if-then statements. AND operator is selected for all the three parameters. Rules employed are as follows:
1. If input 1 is RMS1 and input 2 is Median1 and input 3 is Std. Dev.1, output is no leg extension movement.
2. If input 1 is RMS2 and input 2 is Median2 and input 3 is Std. Dev.2, output is half leg extension movement.
3. If input 1 is RMS3 and input 2 is Median3 and input 3 is Std. Dev.3, output is full leg extension movement.

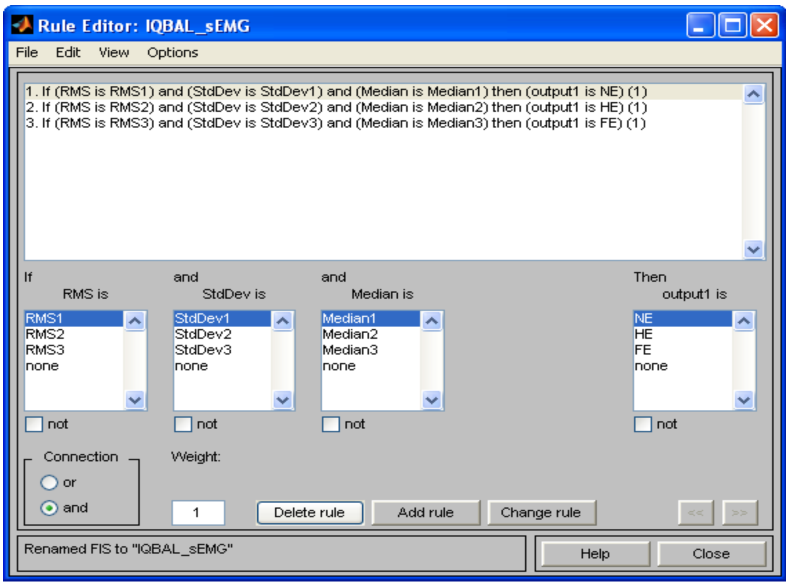


Figure 3.3 A view of rule editor with set of rules

IV. RESULTS AND DISCUSSION

Table 4.1, 4.2 and 4.3 compared all three parameters for all movements for subject P1, P2 and P3 respectively.

Table 4.1 Comparison of all parameters for all movements for subject P1

Movements	Parameters		
	RMS	Std Dev	Median
No Extension	0.612	0.123	0.552
Half Extension	0.685	0.480	0.800
Full Extension	0.730	0.382	0.820

Table 4.2 Comparison of all parameters for all movements for subject P2

Movements	Parameters		
	RMS	Std Dev	Median
No Extension	0.625	0.394	0.580
Half Extension	0.699	0.470	0.790
Full Extension	0.728	0.1128	0.81

Table 4.3 Comparison of all parameters for all movements for subject P3

Movements	Parameters		
	RMS	Std Dev	Median
No Extension	0.575	0.091	0.500
Half Extension	0.674	0.490	0.810
Full Extension	0.721	0.355	0.820

The data set for all subjects is shown graphically in fig 4.1,4.2 and 4.3 for subjects P1,P2 and P3 respectively. It can be easily seen that out of the three parameters Std Dev comes out be the best parameter to discriminate the three movements for all subject.

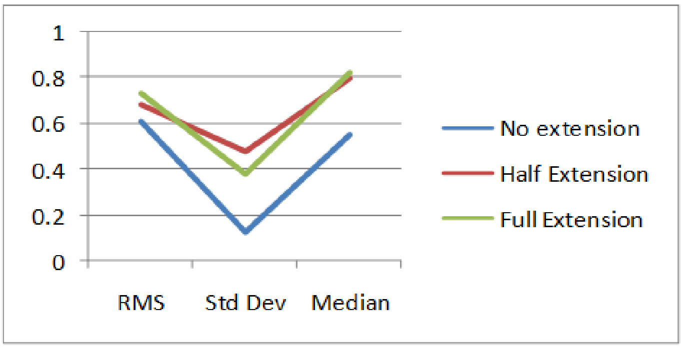


Figure 4.1 Graphical representations of parameters for all movements for subject P1

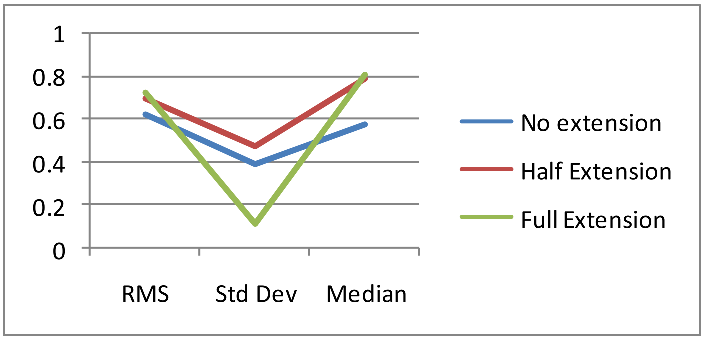


Figure 4.2 Graphical representations of parameters for all movements for subject P2

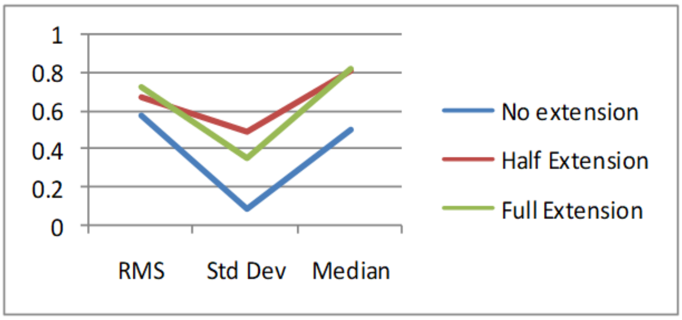


Figure 4.3 Graphical representations of parameters for all movements for subject P3

Table 4.4 was representing comparative results for the ranges of all three parameters collectively for all movements for all three subjects. Mean of the ranges for all the parameters was shown graphically in figure 4.4.

Table 4.4 Ranges of all parameters for all movements and for all subjects

Movements	Ranges		
	RMS	**Std Dev**	**Median**
No Extension	0.575-0.625	0.112-0.113	0.500-0.580
Half Extension	0.674-0.699	0.355-0.394	0.790-0.810
Full Extension	0.721-0.730	0.470-0.490	0.810-0.820

It was clear from graph that discrimination between the three movements is best shown by the ranges of standard deviation. RMS and median parameter also discriminate between all the three movements but the discrimination between half and full extension was very close. This proved standard deviation as the best parameter for classifying all the three movements of leg extension. Fuzzy logic controller output is obtained from the rule viewer as shown in fig 4.5.

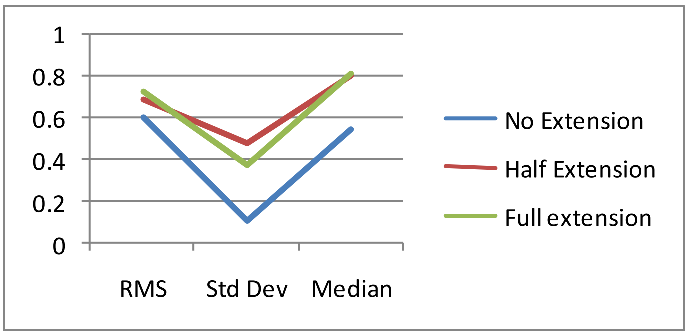


Figure 4.4 Graphical representations of parameters for all movements for all subjects

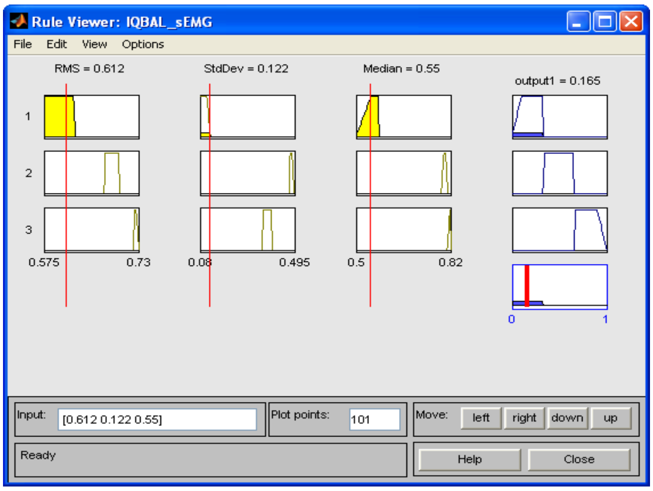


Figure 4.5 Fuzzy logic controller outputs with rule viewer

Table 4.5 was filled for various output obtained for all movements for all the subjects.

Table 4.5 Fuzzy controller outputs

Movements	**Subjects**		
	P1	**P2**	**P3**
No Leg Extension	0.165	0.21	0.160
Half Leg Extension	0.490	0.495	0.490
Full Leg Extension	0.795	0.795	0.790

To confirm that Std Dev is the best parameter to discriminate the three movements, percentage difference among movements at each parameter is calculated. Table 4.6 is filled after calculation. This was clear that percentage difference among all three movements at standard deviation parameter was the most as compare to others.

Table 4.6 Percentage difference among all movements at each parameter

Parameters	**Percentage Difference**		
	No extension and Half extension	**No extension and Full extension**	**Half extension and Full extension**
RMS	012.71%	018.35%	05.67%
Std Dev	126.53%	110.93%	24.04%
Median	038.09%	40.08%	01.98%

Now for more precise movement classification, these calculated statistical parameters were given to Fuzzy Logic Controller as inputs. Fuzzified outputs were obtained as shown in Table 4.5. It was clear from graph that fuzzified values from Fuzzy Logic Controller were precisely classifying movements for each subject. This can be shown by average percentage difference among output values of fuzzy controller for these movements in Table 4.7.

Table 4.7 Average percentage difference among all movements

Movement	**Average Difference**	**Average Percentage Difference**
No Extension and Half Extension	0.312	092.08 %
No Extension and Full Extension	0.610	124.93 %
Half Extension and Full Extension	0.297	046.18 %

V. CONCLUSIONS

Standard deviation was proved to be the best parameter for classification of leg movements among the three parameters used in the work viz. Root mean square (RMS), Standard deviation (Std. Dev.) and Median. Standard deviation discriminates no leg extension movement and half leg extension movement with 126.53 % average percentage difference between both the movements. No leg extension movement and full leg extension movements were discriminated with 110.93 % average percentage difference. Half leg extension and full leg extension movements were discriminated with only 24.04 % average percentage difference. Fuzzy Logic Controller discriminates all three movements with successful precision. Fuzzy Logic Controller discriminates no leg extension movement and half leg extension movement with 92.08 % average percentage difference.No leg extension movement and full leg extension movements were discriminated with 124.93 % average percentage difference. Half leg extension movement and full leg extension movement were discriminated with only 46.185 % average percentage difference.

REFERENCES

[1] G.A. Outten, S.J. Roberts and M.J. Stokes, "Analysis of Human Muscle Activity; Artificial Intelligence Methods for Biomedical Data Processing", *IEE Colloquium*, London 1996.

[2] M.L.A. Harba and G.E. Chee, "Muscle Mechanomyographic and Electromyographic Signals Compared with Reference to Action Potential Average Propagation Velocity", *Engineering in Medicine and Biology Society, IEEE 19th Annual International Conference*, Vol. 3, pp. 111-115, 2002.

[3] C.J. Luca, "*Use of Surface Electromyography in Biomechanics*", Journal of Applied Biomechanics, Springer, Vol. 3, pp. 145-148, 1997.

[4] C.J. Luca, "*Electromyography: Encyclopedia of Medical Devices and Instrumentation*", John Wiley Publisher, Elsevier, 2006.

[5] P.R.S. Sanches, A.F. Müller, L. Carro, A.A. Susin and P. Nohama, "*Analog Reconfigurable Technologies for EMG Signal Processing*" Journal of Biomedical Engineering, Research Gate, Vol. 23, pp. 153-157, 2007.
[6] M. Sartori and G. Chemello, "Control of a Virtual Leg via EMG Signals from Four Thigh Muscles," in *10 th international conference on intel. automation system*, 2008, pp. 1–8.
[7] K. Singh, "Precise and accurate multifunctional prosthesis control based on fuzzy logic techniques," in *International Conference on Communication Systems and Network Technologies*, 2011, pp. 188–193.
[8] K. Singh, R. Bhatia, and H. S. Ryait, "Fuzzy approach to classify hand movement using SEMG signal," in *Recent Advances in Electronics and Communication Technologies*, 2011, pp. 48–50.
[9] R. Hernandez, Q. Yang, H. Huang, S. Ieee, F. Zhang, and X. Zhang, "Design and Implementation of a Low Power Mobile CPU Based Embedded System for Artificial Leg Control," in Annual *International Conference of the IEEE EMBS*, 2013, pp. 5769–5772.
[10] T. Tokuyasu and S. Matsumoto, "*Development of Saddle Height Control System for Cycle Road Racer based on SEMG Signals of the Leg Muscles* ," J. Biomech. Sci. Eng., vol. 8, no. 1, pp. 94–103, 2013.
[11] M. Chang, "*Tracking Control of a Leg Rehabilitation Machine Driven by Pneumatic Artificial Muscles Using sComposite Fuzzy Theory*," Sci. World J., vol. 2014, no. March, pp. 1–12, 2014.
[12] S.K. Reddy, B.S. Kumar, N. Vamsidhar and G. Haribabu,"*electromyographic activity of the vastus medialis oblique and vastus lateralis during maximum voluntary isometrics in different weight bearing positions of the foot*," Int J Physiother, vol. 1, no. 3, pp. 120–126, 2014.
[13] T Crook, E.H. Tole and A Wilson, "Variations in muscle activity of vastus lateralis and gastrocnemius lateralis with increasing draft load," *Int. Conf. Equine Exerc. Physiol.*, vol. 46, no. June, pp. 38–39, 2014.
[14] K. Tsuji, H. Ishida, K. Oba, T. Ueki And Y. Fujihashi, "*Activity of lower limb muscles during treadmill running at different velocities*," J. Phys. Ther. Sci., vol. 27, pp. 353–356, 2015.
[15] J. Xiao, J. Gao, H. Wang, K. Liu, and X. Yang, "*The Surface EMG Characteristics between Erector Spinae and Vastus Lateralis during Bending Forward and Squatting Down Tasks*," Physiol. J., vol. 2015, pp. 1–6, 2015.
[16] I.S. Dhindsa, R. Agarwal, and H. S. Ryait, "*joint angle prediction from emg signals for lower*," Информационные технологии и нанотехнологии, pp. 56–61, 2016.
[17] T. Inoue, Y. Kato, and J. Ozawa, "Prediction Sit-to-Stand Movement Using Trunk Angle and Lower Limb EMG for Assist System," in *IEEE International Conference on Consumer Electronics (ICCE)*, 2017, pp. 9–10.

