Hand Movement Detection from Surface Electromyography Signals by Machine Learning Techniques

Chapter · January 2020

DOI: 10.1007/978-3-030-30648-9_29

Jose Alejandro Amezquita Garcia
Autonomous University of Baja California

Miguel Bravo-Zanoguera
Autonomous University of Baja California

Félix F. González-Navarro
Autonomous University of Baja California

Hand Movement Detection from Surface Electromyography Signals by Machine Learning Techniques

Jose Alejandro Amezquita-Garcia[1],
Miguel Enrique Bravo-Zanoguera[1](✉),
Felix Fernando González-Navarro[2], and Roberto Lopez-Avitia[1]

[1] Facultad de Ingeniería, Universidad Autónoma de Baja California, Mexicali, Mexico
{jose.amezquita,mbravo}@uabc.edu.mx
[2] Instituto de Ingeniería, Universidad Autónoma de Baja California, Mexicali, Mexico

Abstract. Surface electromyography (sEMG) signals offer information on the natural control of muscle contraction but struggle to identify temporal pattern parameters for several degrees of motion of voluntary hand movements. The complex nature of these signals renders the movement prediction task difficult; therefore, feature extraction and selection algorithms are a natural choice to transform time domain data into a new space domain to enhance recognition. The purpose of this work was to conduct an analysis of a former forearm sEMG database to improve a model to classify 15 defined hand movements. A simpler classification model was created from algorithms, such as naive Bayes (NB), linear discriminant analysis (LDA), and quadratic discriminant analysis (QDA). Also, novel preprocessing of the EMG signal data was employed and modeled the movement in virtual simulation software. In the preprocessing, outliers were eliminated, and a scatter matrix algorithm was used to transform the data into a new space to increase the differentiation between distinct classes. The processing window was 62.5 ms to generate a classification and integrate one video frame movement. Experiments yielded promising results, achieving a 93.76% recognition rate in an independent test set. The biomechanical wrist model available in OpenSim was completed by adding the missing degrees of freedom of the fingers to simulate the movement generated from the proposed classification model. The sequence of movement was converted to a biomechanical model and constructed into a video object with the potential for real time use.

Keywords: Electromyography · Stochastic signal · sEMG array · Scatter matrix · Probabilistic model

1 Introduction

The interpretation of surface electromyography (sEMG) is an active area of research to examine the direction of muscle movement. The electronic control of devices aims to create control commands that are more comfortable and easier to use. Devices and their software applications have more functionalities, and more complex systems are needed

C. A. González Díaz et al. (Eds.): CLAIB 2019, IFMBE Proceedings 75, pp. 218–227, 2020.
https://doi.org/10.1007/978-3-030-30648-9_29

to control or access these functions. Currently, devices are being developed that are controlled with body movements, some using cameras and images [1, 2] and others using EMG signals directly [3–20]. These signals are used to estimate strength and changes in muscle activation caused by neuromuscular abnormalities and the control of medical devices [10]. With machine learning techniques, it is possible to develop models that interpret complex systems, such as the progression of the movement of the hand through forearm sEMG array data, to determine gradual finger motion responses given the input sequencing [5, 7, 10]. Although there are a considerable number of investigations into the processing of EMG data [3, 21–26], there is not a model in which the signal between movements is sufficiently differentiable to generate a simple classification model that can be used in real time processing. The objective of this work was to generate a recognition model using typically selected features and transforming these measurements into a new space, such as a scatter matrix, to increase the separation of measurements between classes. Experiments yielded promising results achieving a 93.76% recognition rate in an independent test set. This study is complemented by the use of OpenSim motion simulation software to simulate hand movement that has been predicted with the classification model. Achievements of this kind offer possible applications in multifunctional prosthesis, exoskeletons, rehabilitation therapies, and new technologies, such as hand gesture control.

2 Methodology

2.1 EMG Database of Predefined Fingers Movements

A previously created database repository found in a website [27] was analyzed. The database consisted of 15 hand movements monitored with a ring of eight surface electrodes on the forearm (Fig. 1). Eight normal subjects were evaluated; the characteristics of the subjects and the form and type of acquisition can be found in [28], along with the related ethical approval for that study. Fifteen types of flexion movements were evaluated, i.e., thumb (T), index (I), middle (M), ring (R), little (L), the combined T-I, T-M, T-R, T-L, I-M, M-R, R-L, I-M-R, M-R-L, and finally the hand close (HC) motion. Each movement was performed for 5 s, which produced 20,000 sample readings, and repeated twelve times by each subject.

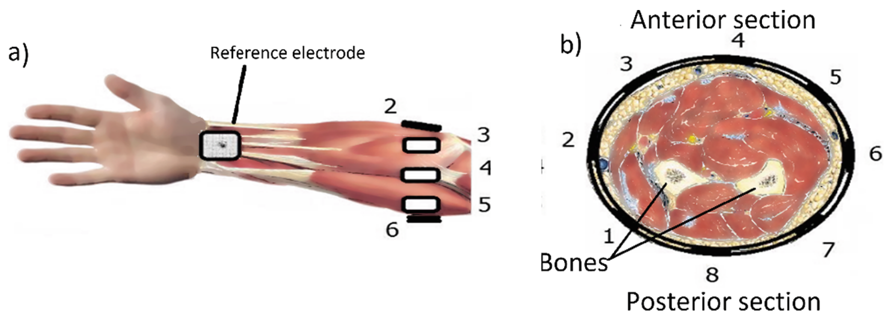


Fig. 1. Electrode position (a) Forearm (anterior section), (b) Forearm (cross-section).

2.2 Features Selected from Literature and Classification Issues

Time domain features have been widely used to extract useful information and improve the performance of classifiers. A major disadvantage of these features comes from the non-stationary property of the EMG signal, but typically, the data is assumed as a stationary signal [29]. It is desirable to have features that generate a differentiation between each of the evaluated classes and a decrease of the dispersion between the measurements of each class. Ten features in the time domain are proposed in this investigation as defined elsewhere [30]: mean absolute value, simple square integral, variance of EMG, temporal moments, waveform length, zero crossings, myopulse percentage rate, and slope sign change. Classification complications are commonly divided into two separate stages: the inference step, in which training data is used so that the model learns the probabilities of each of the classes, and the subsequent decision step, in which posterior probabilities are used for prediction based on variables independent of the class type.

Naive Bayes. This classifier is based on probabilistic theory in which the classification of n vectors is given, assuming that the data has a normal probability distribution. The prior probabilities are defined as $P(C_k)$, and the sum of the prior probabilities is $\sum_{k=1}^{N} P(C_k) = 1$. The prior probabilities indicate the likelihood that the vector belongs to a given class. Then, the probability of the class k given the vector x (posterior probability) is expressed as

$$p(c_k|x) = p(x|c_k)p(c_k)/p(x) \tag{1}$$

where $p(x) = \sum_k p(x|C_k)p(C_k)$. The vector belongs to the class C_k for which $C_k = argmaxp(C_k|x)$ [31]. As it is assumed that the data has a normal distribution, the density function can be written as

$$p(c_k|x) = \frac{1}{\sqrt{2\pi\sigma_k}} e^{\frac{-(x_k - \mu_k)^2}{2\sigma^2}} \tag{2}$$

Thus, a function is defined for each class, and each class is selected with the highest quality argument. In this way, the class to which a new vector belongs is selected.

Discriminant Functions. As a probabilistic classifier, it assumes that different classes generate data based on different Gaussian distributions [32]. The model for discriminant analysis follows that each class *(Y)* generates data *(X)* using a multivariate normal distribution. In other words, the model assumes X has a Gaussian mixture distribution [32]. For linear discriminant analysis (LDA), the model has the same covariance matrix for each class; only the means vary. For quadratic discriminant analysis (QDA), both the mean and covariance of each class vary [32].

2.3 Preprocessing and Signal Processing Techniques

The raw EMG data of the 12 repetitions of each subject were evaluated for each movement. A non-overlapping rectangular window was used to process the raw EMG signal data with a length of 250 samples per window (equivalent to 62.5 ms). The 10 selected features of each EMG channel were concatenated producing a vector of 80 data features in each window period per subject; one movement repetition equaled 80 windows. All the features for all the windows (a complete movement) were grouped and repeated 12 times producing a new feature database with 960 vectors. An algorithm for the elimination of outliers with chi-square distribution was used. Due to the dimensionality of the data, the features per window were evaluated with an algorithm for selecting the best features (method of sequential forward selections; SFS). Of the 80 given variables, those chosen increased the power of classification of the LDA classification algorithm, per the method presented in [33]. With the subset of the selected data, a transformation of our data was implemented to a new space with the display algorithm based on scatter matrices; a description of this method is detailed in [34] and a summary presented in Fig. 2.

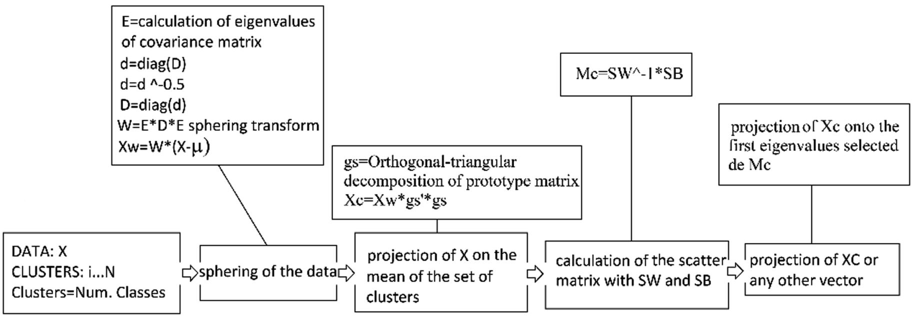


Fig. 2. Method of scatter matrices where X is the matrix of input data; g_s is the orthonormal set of basis vectors; E is the eigenvalue of the covariance matrix; and M^c is the scatter matrix, which is born from Sw and Sb, where Sw is the within-cluster matrix, and Sb is the between-scatter matrix.

2.4 OpenSim Model for Movement Simulation

OpenSim is a free biomechanical simulation program of the human body [35] that allows movement analysis and muscle evaluation with motion files. A limited wrist model is available in OpenSim SimTK [38] that has 10 degrees of freedom and a total of 23 actuator muscles with movement in the forearm, wrist, thumb (no flexion), and index fingers. This model of the wrist was modified, adding the missing degrees of freedom to the thumb, middle, ring, and little fingers to reproduce the complete movement of a real hand in simulation [37], accounting for 20 articulations. This more complete model was used for the simulation of the predicted movements of the hand motion classifier for a virtual visualization of each of the database movements. With each decision of the classifier, a certain degree of the articulation motion was advanced, creating a rotation vector. Video objects of the evaluated movements were created from the advancement of the rotation vectors.

3 Results

3.1 Preprocessing and Signal Processing Results

Method of Attribute Selection by SFS and Projection with a Scatter Matrix. After the removal of the outliers was applied, the SFS algorithm evaluated the performance of each attribute, and 52 of 80 attributes remained. With the subset of the selected data, the data was transformed into this new space (scatter matrix); these new features are grouped in regions defined between the classes (Fig. 3a).

Training, Validation, Testing and Opensim. The data, already selected and processed, was evaluated with three classification algorithms: NB, LDA, and QDA. Results were validated statistically through 10 × 10-fold cross-validation. The measurements were separated into 70% for training, 15% for validation, and 15% for testing. The first step was to assess the training measurements, which were randomized. Then, the training matrix was divided into 10 folds; the model was generated with nine folds and tested with the remaining fold. A recognition percentage in each tested classifier (NB, LDA, and QDA) was obtained 10 times, and an average was calculated. Then, the validation and training data were combined, and the same procedure was repeated. Average percentages of recognition were obtained. The model with the highest percentage was selected, and that model was tested with 15% of the testing data. This method of cross-validation was performed with a built-in function of MATLAB software (Fig. 4a). An error of 0.0624 was obtained for the most effective class differentiator, equivalent to 93.76% recognition in the test set for each subject individually (Table 1). Furthermore, a recognition percentage of 80.97% was obtained for the database created from the group of eight subjects (Table 2). Figure 4b presents the confusion matrix of the test set classification for the movements evaluated for a test subject. Every 62.5 ms (the duration time of the processing window), a new classifier output corresponded to an advance image frame of the movement. The advance vector corresponding to the degree of rotation for each of the joints of the biomechanical wrist model (Fig. 3b) created motion matrices. OpenSim used these motion matrices to visualize the virtual model. Movement files along with the videos can be found in [37].

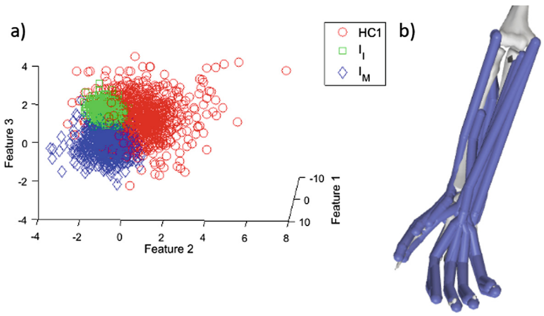
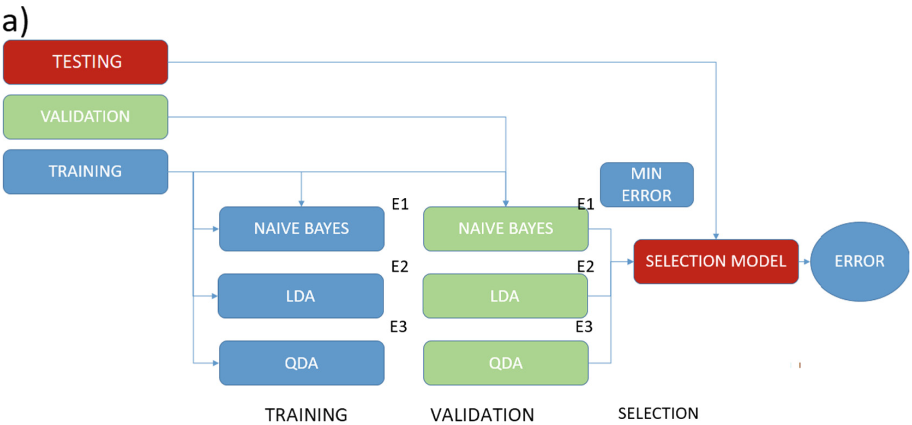


Fig. 3. (a) Visualization of three hand movements with scatter matrices, as a function of three new features, (b) Opensim wrist model.



b)

	T	I	M	R	L	T-I	T-M	T-R	T-L	I-M	M-R	R-L	I-M-R	M-R-L	HC
T	102	0	0	0	0	0	0	4	0	0	0	1	0	0	0
I	0	122	0	0	0	1	0	0	0	0	3	0	0	0	1
M	0	0	139	0	0	1	0	0	0	0	0	0	0	0	2
R	0	0	0	146	0	0	0	0	0	0	0	0	0	0	1
L	0	0	0	0	111	1	0	0	2	1	0	0	1	0	0
T-I	0	3	1	0	0	140	0	0	0	0	0	0	0	0	0
T-M	0	0	0	4	0	0	137	0	0	0	0	0	0	0	0
T-R	0	0	0	0	0	0	0	112	0	0	0	0	0	0	0
T-L	0	0	0	1	1	0	2	0	121	1	0	1	0	6	0
I-M	0	1	0	0	5	0	0	0	0	127	0	0	0	0	3
M-R	0	5	0	0	0	0	0	0	0	0	123	0	1	0	2
R-L	0	0	0	0	0	0	0	0	0	0	0	134	0	0	0
I-M-R	0	0	5	0	1	1	0	0	0	0	7	0	110	0	0
M-R-L	0	0	0	0	0	0	0	0	5	0	0	0	0	117	0
HC	0	5	0	0	0	6	0	0	0	0	1	0	0	0	124

Fig. 4. (a) Sequence to select the most effective classification model through cross-validation, (b) Confusion matrix of the 15 movements evaluated for a test subject.

Table 1. Average recognition percentages of the models evaluated for the eight subjects separately through cross-validation. Training = TRN, validation = VAL, testing = TST, standard deviation = SD.

Algorithm	TRN		VAL		TST	
	Mean	SD	Mean	SD	Mean	SD
Naive bayes	86.13	7.84	85.92	8.10	–	
LDA	93.96	3.88	93.88	4.11	93.76	4.07
QDA	90.36	6.47	90.22	6.67	–	

Table 2. Average and standard deviation of recognition percentages of the models evaluated for the group of eight subjects through 10 × 10-fold cross-validation. Training = TRN, validation = VAL, testing = TST, standard deviation = SD.

Algorithm	TRN		VAL		TST	
	Mean	SD	Mean	SD	Mean	SD
LDA	81.12	0.88	81.36	0.78	80.97	1.11

4 Discussion and Conclusion

The machine learning techniques applied to real world EMG array data produced a recognition rate of 93.76% of the hand motions, satisfactory for a linear model classifier. Notably, the use of LDA as the classification algorithm in the attribute selection method may have contributed to the superior performance of LDA during training, validation, and testing against the other recognition models. However, other features not used, such as those in the frequency domain, may improve performance. In any case, it would be necessary to analyze the required processing time of any new features as response time is an issue. The time domain features measured for each electrode channel were 10 of the most commonly cited in the literature. From the initial 80-feature vector, 29 were removed for irrelevant or negative impact. Most of these removals corresponded to electrodes 7 and 8, which only retained two and three features, respectively, after the selection. This result may be due to the fact that the most defined movements were flexor movements, and those electrodes were in a region of extensor muscles. Therefore, only six electrodes contributed significantly and may be sufficient for the recognition process. The processing time for each window was 62.5 ms, equivalent to 250 measurements over time, while other studies, such as [36], have larger window sizes for an equal or lower percentage of recognition. The procedure presented here is a valid method to define specific movements from EMG measurements since it has short processing times and includes transformations to new spaces, resulting in a classification model already trained for a group of eight subjects. The percentage of recognition is comparable with models generated by other published studies, though only time domain features were used here. The large number of different movements evaluated here is another factor that affected the resolution of our classification algorithms. Since a future objective is to increase the number of defined movements, it is essential to find features that best differentiate between the classes or evaluate new transformation spaces that maximize the differentiation between the classes. The present work enhanced the biomechanical model of the wrist in OpenSim, which is necessary to simulate the movements detected with the proposed classification model. Thus, this study contributes to the application of the output of movement classification methods in a virtual system for the analysis of multifunctional prosthesis response.

Declaration of Conflicting Interest. The authors declare that there is no conflict of interest.

References

1. Liu, Y., Ning, Y., He, J., Li, S., Zhou, P., Zhang, Y.: Internal muscle activity imaging from multi-channel surface EMG recordings: a validation study. In: 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC 2014, pp. 3559–3561 (2014)
2. Sun, Y., Li, C., Li, G., Jiang, G., Jiang, D., Liu, H., Zheng, Z., Shu, W.: Gesture recognition based on kinect and sEMG signal fusion. Mob. Netw. Appl. **23**(4), 797–805 (2018)
3. Wahid, M.F., Tafreshi, R., Al-Sowaidi, M., Langari, R.: Subject-independent hand gesture recognition using normalization and machine learning algorithms. J. Comput. Sci. **27**, 69–76 (2018)
4. He, J., Sheng, X., Zhu, X., Jiang, C., Jiang, N.: Spatial information enhances myoelectric control performance with only two channels. IEEE Trans. Industr. Inf. **PP**(c), 1 (2018)
5. Saikia, A., Kakoty, N.M., Phuka, N., Balakrisxnan, M., Sahai, N., Paul, S., Bhatia, D.: Combination of EMG features and stability index for finger movements recognition. Proc. Comput. Sci. **133**, 92–98 (2018)
6. Resnik, L., Huang, H.H., Winslow, A., Crouch, D.L., Zhang, F., Wolk, N.: Evaluation of EMG pattern recognition for upper limb prosthesis control: a case study in comparison with direct myoelectric control. J. NeuroEng. Rehabil. **15**(1), 113 (2018)
7. Feng, N., Shi, Q., Wang, H., Gong, J., Liu, C., Lu, Z.: A soft robotic hand: design, analysis, sEMG control, and experiment. Int. J. Adv. Manuf. Technol. **97**(1–4), 319–333 (2018)
8. Menegaldo, L.L.: Real-time muscle state estimation from EMG signals during isometric contractions using Kalman filters. Biol. Cybern. **111**(5–6), 335–346 (2017)
9. Kim, M., Chung, W.K.: Spatial sEMG pattern-based finger motion estimation in a small area using a microneedle-based high-density interface. IEEE Robot. Autom. Lett. **3**(1), 234–241 (2017)
10. Sheibani, A., Pourmina, M.A.: Study and analysis of EMG signal and its application in controlling the movement of a prosthetic limb. Health Technol. **6**(4), 277–284 (2016)
11. Paleari, M., Di Girolamo, M., Celadon, N., Favetto, A., Ariano, P.: On optimal electrode conguration to estimate hand movements from forearm surface electromyography. In: Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS 2015, pp. 6086–6089 (2015)
12. Castro, M.C., Arjunan, S.P., Kumar, D.K.: Selection of suitable hand gestures for reliable myoelectric human computer interface. BioMed. Eng. Online **14**(1), 111 (2015)
13. Kumar, D.K., Arjunan, S.P., Singh, V.P.: Towards identification of finger flexions using single channel surface electromyography – able bodied and amputee subjects. J. NeuroEng. Rehabil. **10**(1), 17 (2013)
14. Jeong, E.C., Kim, S.J., Song, Y.R., Lee, S.M.: Comparison of wrist motion classification methods using surface electromyogram. J. Cent. South Univ. **20**(4), 960–968 (2013)
15. Daley, H., Englehart, K., Hargrove, L., Kuruganti, U.: High density electromyography data of normally limbed and transradial amputee subjects for multifunction prosthetic control. J. Electromyogr. Kinesiol. **22**(3), 478–484 (2012)
16. Dennis, T., He, H., Todd, K.: Study of stability of time-domain features for electromyographic pattern recognition. J. NeuroEng. Rehabil. **7**, 21 (2010)
17. Arjunan, S.P., Kumar, D.K.: Decoding subtle forearm exions using fractal features of surface electromyogram from single and multiple sensors. J. NeuroEng. Rehabil. **7**(1), 110 (2010)

18. Walbran, S.H., Calius, E.P., Dunlop, G.R., Anderson, I.A.: A technique for optimizing electrode placement for electromyographic control of prostheses. In: Proceedings of the 31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society: Engineering the Future of Biomedicine, EMBC 2009, pp. 1331–1334 (2009)
19. Ryait, H.S., Arora, A.S., Agarwal, R.: Study of issues in the development of surface EMG controlled human hand. J. Mater. Sci. Mater. Med. **20**(Suppl. 1), 107 (2009)
20. Smith, R.J., Tenore, F., Huberdeau, D., Cummings, R.E., Thakor, N.V.: Continuous decoding of nger position from surface EMG signals for the control of powered prostheses. In: 2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 197–200 (2008)
21. Christov, I., Raikova, R., Angelova, S.: Separation of electrocardiographic from electromyographic signals using dynamic ltration. Med. Eng. Phys. **57**, 110 (2018)
22. Veer, K.: A flexible approach for segregating physiological signals. Meas. J. Int. Meas. Confed. **87**, 21–26 (2016)
23. Willigenburg, N.W., Daertshofer, A., Kingma, I., van Dieën, J.H.: Removing ECG contamination from EMG recordings: a comparison of ICA-based and other filtering procedures. J. Electromyogr. Kinesiol. **22**(3), 485–493 (2012)
24. Marque, C., Bisch, C., Dantas, R., Elayoubi, S., Brosse, V., Pérot, C.: Adaptive filtering for ECG rejection from surface EMG recordings. J. Electromyogr. Kinesiol. **15**(3), 310–315 (2005)
25. Kumar, D.K., Melaku, A.: Electrode distance and magnitude of SEMG. In: Proceedings of the Second Joint Engineering in Medicine and Biology, 24th Annual Conference and the Annual Fall Meeting of the Biomedical Engineering Society EMBS/BMES Conference, vol. 3, pp. 2477–2480 (2002)
26. Baratta, R.V., Solomonow, M., Zhou, B.H., Zhu, M.: Methods to reduce the variability of EMG power spectrum estimates. J. Electromyogr. Kinesiol. **8**(5), 279–285 (1998)
27. Repository of Dr. Rmi N. Khushaba online. http://www.rami-khushaba.com/electromyogram-emg-repository.html
28. Khushaba, R.N., Kodagoda, S.: Electromyogram (EMG) feature reduction using mutual components analysis for multifunction prosthetic fingers control, pp. 1534–1539. IEEE, December 2012 https://doi.org/10.1109/icarcv.2012.6485374
29. Lei, M., Wang, Z., Feng, Z.: Detecting nonlinearity of action surface EMG signal. Phys. Lett. Sect. A: Gener. Atom. Solid State Phys. **290**(5–6), 297–303 (2001). https://doi.org/10.1016/s0375-9601(01)00668-5
30. Phinyomark, A., Phukpattaranont, P., Limsakul, C.: Feature reduction and selection for EMG signal classification. Expert Syst. Appl. **6**(8), 7420–7431 (2012). https://doi.org/10.1016/j.eswa.2012.01.102
31. Havlik, J., Uhlir, J., Horcik, Z.: Comparison of k-means and bayes classifiers for human body motions classification. In: IFMBE Proceedings. FEE CTU (2009)
32. Fisher, R.A.: The use of multiple measurements in taxonomic problems. Ann. Eugen. **7**, 179–188 (1936)
33. Gutierrez-Osuna, R.: CSCE 666 Pattern Analysis—CSE@TAMU. http://courses.cs.tamu.edu/rgutier/csce666 f13/
34. Lisboa, P.J.G., Ellis, I.O.: Cluster-based visualisation with scatter matrices. Pattern Recogn. Lett. **29**, 1814–1823 (2008)
35. Seth, A., Habib, A.: SimTK Opensim, National Institutes of Health (NIH). https://simtk.org/projects/opensim
36. Oskoei, M.A., Hu, H.: Myoelectric control systems - to survey. Biomed. Signal Process. Control **2**(4), 275–294 (2007). https://doi.org/10.1016/j.bspc.2007.07.009

37. Amezquita-Garcia, J.A., Bravo-Zanoguera, M.E.: Bioingenieria, UABC. https://simtk.org/projects/moving-fingers
38. Gonzalez, R.V., Buchanan, T.S., Delp, S.L.: How muscle architecture and moment arms affect wrist flexion-extension moments. J. Biomech. **30**, 705–712 (1997)