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Design and manufacturing of 15 DOF myoelectric controlled prosthetic hand

15 serbeslik dereceli myoelektriksel kontrollü proztez elin tasarımı ve imalatı

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Abstract

This study's main purpose is to manufacture a low-cost, highly functional, myoelectric signal-controlled prosthetic hand for amputees in developing countries below a certain economic level. In this study, a prosthetic hand with five fingers was modeled on 15-degree freedom, and an independent joint movement was achieved through the use of a separate motor actuator for each joint in the fingers. The hand of the prosthetic can therefore keep the objects in the best possible way. The prosthetic was produced by hand using PLA material on a 3D printer to reduce cost. Bioelectric signals provide the human-prosthetic hand interaction, i.e. identification of the form of hand gesture. With 97 percent progress, the classification of a human hand with the SVM algorithm has been achieved. The prosthetic hand's total cost is US$ 450. The hand was compared in terms of qualitative and quantitative performance metrics with other high-priced rivals and the findings were interpreted.

Keywords: prosthetic hand, 3D Manufacturing, PLA, Myo-controlled-hand, EMG, Supported vector machine, Gesture recognition.

Öz

Bu çalışmanın temel amacı, belirli bir ekonomik düzeyin altındaki gelişmekte olan ülkelerdeki ampute'ler için düşük maliyetli, oldukça işlevsel, miyoelektrik sinyal kontrollü bir protez el üretmektir. Bu çalışmada, beş parmaklı protez el 15 serbestlik dereceli olarak modellenmiş ve parmaklardaki her bir eklem için ayrı bir motor aktüatörü kullanılarak bağımsız eklem hareketi sağlanmıştır. Protezin el bu nedenle nesneleri mümkün olan en iyi şekilde tutabilir. Protez, maliyeti azaltmak için bir 3D yazıcıda PLA malzemesi kullanılarak üretildi. Biyoelektrik sinyaller insan protezi el etkileşimini, yani el hareketi formunun tanımlanmasını sağlar. Yüzde 97 başarı ile bir insan elinin hareket türü tanımlaması SVM algoritması ile sağlandı. Protez elin toplam maliyeti 450 ABD dolarıdır. El, diğer yüksek fiyatlı rakiplerle kalitatif ve kantitatif performans metrikleri açısından karşılaştırılmış ve bulgular yorumlanmıştır.

Anahtar kelimeler: protez el, 3B imalat, PLA, Myo kontrollü el, EMG, Desteklenen vektör makinesi, Hareket tipi tanıma.

1 Introduction

Thirty million people around the world suffer without one or more limbs because of illnesses, injuries, and congenital defects. Approximately 80% of these people live in developed countries with low incomes and are deprived of robotic prosthetic [1],[2]. Many amputations occurred in the 0 to 5-year age group and 54% of 2,238 patients had hand-related amputations of trauma [3]. There are two groups of existing prosthetic hands on the market. The first group is non-functional prosthetics [4] that only solve the cosmetic requirements of the consumers, and the second group is functional prosthetics that can mimic the human hand movement. The second group of prosthetics can cost as much as $15,000-$50,000[5, 6] and the cost of repairing can make the price even higher for professional assistance. Most advanced technology companies in the United States and Europe will design and manufacture high-quality prosthetic hand with high functionality and realistic appearance and sell it at relatively affordable prices. Nevertheless, the prices are generally very high in the developing countries that need to import these goods, rendering them unavailable to most amputees. Functional, affordable, and easy-to-maintain prosthetics are therefore required for people living in economically disadvantaged communities with trans-radial amputations. In order to reduce prices, the design of the robotic prosthetic hands can be facilitated [7]. The most common way to simplify the hand design is by reducing the hand's degrees of freedom (DOF). Even though people have 27 DOFs in their hands [8], prosthetic modeling uses only the most useful DOFs. It reduces the ability to mimic forms with motion and grasp. Such devices have limited functionality, and many of them have either one open or closed hand function [9]. They lack the ability to maintain their daily lives. The second way to lower costs is to lower the material price used to make the prosthetic hand. 3D printer technology has been developed over the past decade and research has begun in the field of medicine and biomedical device design in the field of organ implants[10]. Three-dimensional printing technology makes it possible to produce an artificial hand using many different materials, e.g. Poly Lactic Acid (PLA), acrylonitrile butadiene styrene, styrene-maleic anhydride[11],[12]. Prosthetic and orthotic devices developed with three-dimensional design programs are translated to Stereolithography (STL) files and moved to a 3D printer system that transforms print codes into STL files [13], making it possible to produce low-cost [14]. The third way to

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reduce costs is to use less and inexpensive sensors that are as critical as the mechanical design of the prosthetic hand for the cognitive interaction user and prosthetic hand.

2 Material and method

We attempted to test five parameters when designing a prosthetic hand for amputees living in developing countries, i.e. low cost, high performance, reliability, profitability, and easy and fast manufacturing.

2.1 Structure of the human hand and designed prosthetic hand

The human hand has a high functionality and a very complex modeling mechanism. This is due to the high degree of freedom. In other words, a large number of joints act independently from one another have been placed in the human hand. The three tiny bones and joints compose of each finger as shown in Figure 1. These little bones are referred to as phalanx.

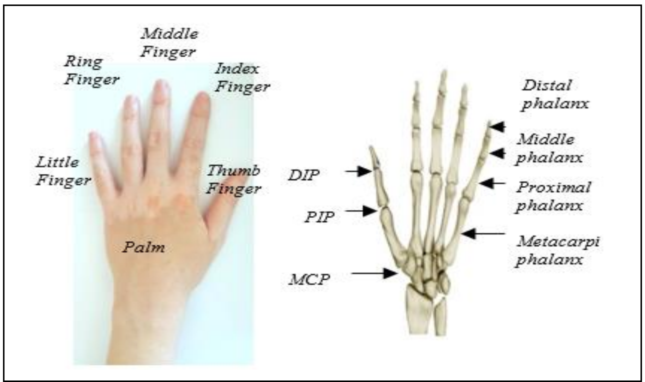

Figure 1. Structure of the human hand.

There are different studies on human hand anatomy, such as muscle and bone structure, the functional limit of joint, and age and sex determination according to bone structure [19]-[22]. Tables 1 and 2 describe the finger length and the angular articulation limits related to ideal functional orthosis for the finger [23],[24].

Table 1. Basic statistics of joint angles (degrees) [23].

Joints	Mean	SD	Min	Max	Range
Index MCP	32	16	−25	78	103
Index PIP	34	13	−1	84	84
Index DIP	15	10	−23	59	82
Middle MCP	34	17	−20	79	99
Middle PIP	38	14	2	87	85
Middle DIP	16	12	−8	70	77
Ring MCP	21	15	−18	66	84
Ring PIP	40	16	3	96	93
Ring DIP	12	10	−10	55	65
Little MCP	19	20	−25	80	105
Little PIP	38	16	−3	92	95
Little DIP	20	12	−6	68	74

Table 2. The lengths of phalanx [24].

Finger	pd-distal phalanx (mm)	pm-medial phalanx (mm)	pp-proximal phalanx (mm)
Index	15.82±2.26	22.38±2.51	39.78±4.94
Middle	17.40±1.85	26.33±3.00	44.63±3.81
Ring	17.30±2.22	25.65±3.29	41.37±3.87
Little	15.96±2.45	18.11±2.54	32.74±2.77

The 3D model of the mechanism was created after the determination of the size and motion limit of the finger orthosis and virtual motions were realized using SolidWorksTM. Figure 2 shows CAD views of the designed orthosis of the finger. With five fingers and 15 DoF, the prosthetic hand was made. Unlike the prosthetics used by the tendon powder and gear method, a single-motor is used for every joint in the present designed. The movement restrictions on these fingers are not mentioned in MCP DIP and PIP joint. The mounting difficulty has been reduced in comparison to the yield decreases induced by both the tendons and the pulley system. We tried to select engines with high torque as well as low cost. The ultra-Nano DC servo motors that drive each joint are developed as hollow finger joints to be placed inside the corresponding fingers, reducing the number of cables and conductors. This FiMec prosthetic allows the hand to be relatively light. The thumb is composed of three parts, the other fingers are of four parts and the palm is one piece. A FiMec hand has consist totally 20 parts. The assembly can be carried out sequentially. During the repair, only removal and repair of the damaged part is sufficient. Thanks to its high degree of freedom and functional design, the FiMec can hold objects of any size and feature manually. As biological hand anatomy, the dimensions of the prosthetic hand were determined (Table 1-2). A flat cylinder-shaped finger design, which is closer to reality and makes the object easier to understand, was preferred instead of the cylindrical fingers in all the other designs.

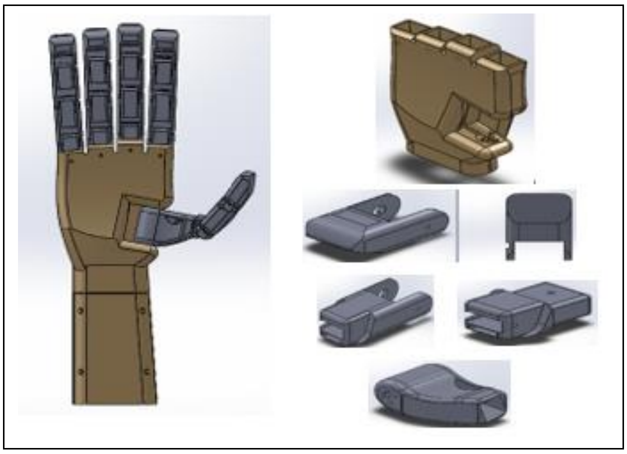

Figure 2. 3D design of FiMec Hand and parts.

The parts of FiMec hand were produced using the EDISON 3D printer with PLA filament. The solubility value of each manufactured part was selected as 0.01 cm, the amount of fullness was determined as 70%, and attempts were made to keep the resistance and strength as high as possible. Of course, the cost of producing the hand increases in direct proportion to the physical strength of the material used to produce the prosthetic hand. Produced using PLA material with 3D printing technology, the cost of prosthetics is very reasonable and its physical strength is also reasonable.

FiMec's physical performance characteristic are compared with the high-priced, high-tech i-LIMB, Bebionic products [25]-[27], the open-source Dextrus [28], and the Tact [29] prosthetic hands. The design and manufacturing of a prosthetic hand, shown in Figure 3, were conducted by examining the desired design and performance characteristics of anthropomorphic prosthetics and the problems encountered by prosthetic users.

Figure 3. Firat Mechatronics (FiMec) hand: the open-source, affordable, myoelectric prosthetic hand

2.2 EMG based control strategy of prosthetic hand

In literature, the features of the EMG signal are grouped under three different domain headings, i.e., time-domain features, frequency domain features, and time-frequency domain features. The time-domain features of the sEMG were described by Hudgins [30]. They refer to a bioelectric signal according to the mean absolute value, the mean absolute slope, changes in the sign of the slope, the wavelength, and the zero-crossing number of the signal [30]-[32], and the time-domain features are known as the 'Hudgins features.' When this feature set is used as an input to the classifier, the classification failure is much higher than the raw signal [33],[34]. To achieve the best accuracy performance of EMG signal gesture classification by Englehart et al., the proposed time-frequency domain features and the time-domain features proposed by Hudgins et al. [35] were compared [36]. Time-frequency domain properties are effective feature sets in the classification of bioelectrical signals, but, due to their high size and high resolution, the reduction of the dimension often is required [37]. The mean frequency, median frequency, mean peak frequency, spectral moments, frequency ratio, power spectrum ratio, and variance of central frequency give very successful results when used in the classification of EMG signals [38]. However, Artificial Neural Networks were used to compare the time domain, frequency domain, and wavelet coefficients with research in which the diagnostic performance was assessed, and the results were determined to be 78.3% for the time domain, 62.5% for the frequency domain, and 66.2% for the wavelet transform [39]. For that reason, time-domain feature-extraction methods were used in this study.

In this study, EMG signals from four muscle groups were used to develop an interaction network between human and prosthetic hand. The bioelectrical signals are recorded from *Flexor Policis Longus Muscles, Flexor Carpi Radialis Muscles, Brachioradialis Muscles, Extensor Carpi Radialis Muscles, Extensor Digiti Minimi Muscles, And Extensor Carpi Ulnaris Muscles* via Olimex four-channel EMG recorder. Channels 1, 2, 3, and 4 contained information about the motions of the little, ring, middle, and index fingers, respectively. The surface electrodes were placement according to the SENIAM protocol, are shown in Figure 4 [40].

EMG Signals were recorded respectively when a female subject made hand gestures in Figure 5, who is able-bodied with no neurological or muscular disorders. EMG signals are biometric features for the identification of human [41-42]. EMG signal; is directly related to the physiology of each individual. For these reasons contrary to other researches in the literature, the data belonging to a single person were taken and a unique control prosthetic hand was produced. This has both increased the classification success and removed the normalization process for using the signal from different people as the control signal.

Figure 4. Placements of the electrodes.

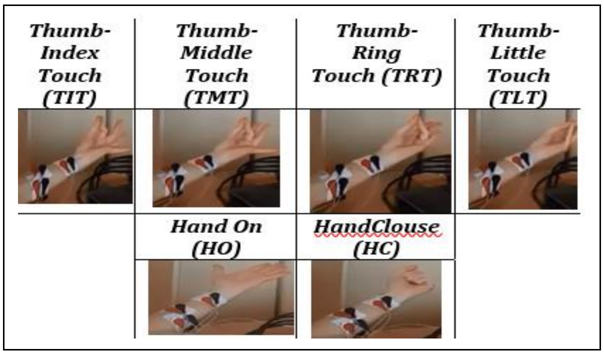

Figure 5. Photographs of recognized hand gestures.

The EMG signal was recorded at intervals of 0.001 seconds using the Olimex EMG recorder. The sampled signal was filtered through a band-pass filter (50-500 Hz). The EMG signals were separated from the frame using the Englehart optimal framing method. We used the framing and optimal framing values used in Englehart's study [43],[44], i.e., R = 256 and r=32 millisecond. The time-domain feature extraction method was used for the signals because bioelectrical signals contain characteristic information about the activities of muscles [45]. The values of five time-domain features were calculated, energy (E), maximum value (M), average value(AVR), effective value (RMS), and variance(VAR) as Eq.(1)-(4) (Figure 6) [45].

$$E = \int_{t_j}^{t_i} |m(t)| dt \tag{1}$$

$$AVR = \frac{1}{t_j - t_i} \int_{t_i}^{t_j} |m(t)| dt \tag{2}$$

$$RMS = \left(\frac{1}{T} \int_0^t \left(m(t)\right)^2 dt \right)^{1/2} \tag{3}$$

$$VAR = \frac{1}{T} \int_0^t (x - ORT)^2 m(t) dt \tag{4}$$

Motion recognition using EMG signals is used extensively in the control of multi-functional prosthetic devices. The types of classifiers that are used extensively to classify EMG signals are Artificial Neural Networks (ANNs), the Fuzzy Classifier, Linear Discriminant Analysis (LDA), Self-Organized Map (SOM), and Support Vector Machines (SVMs) [14].

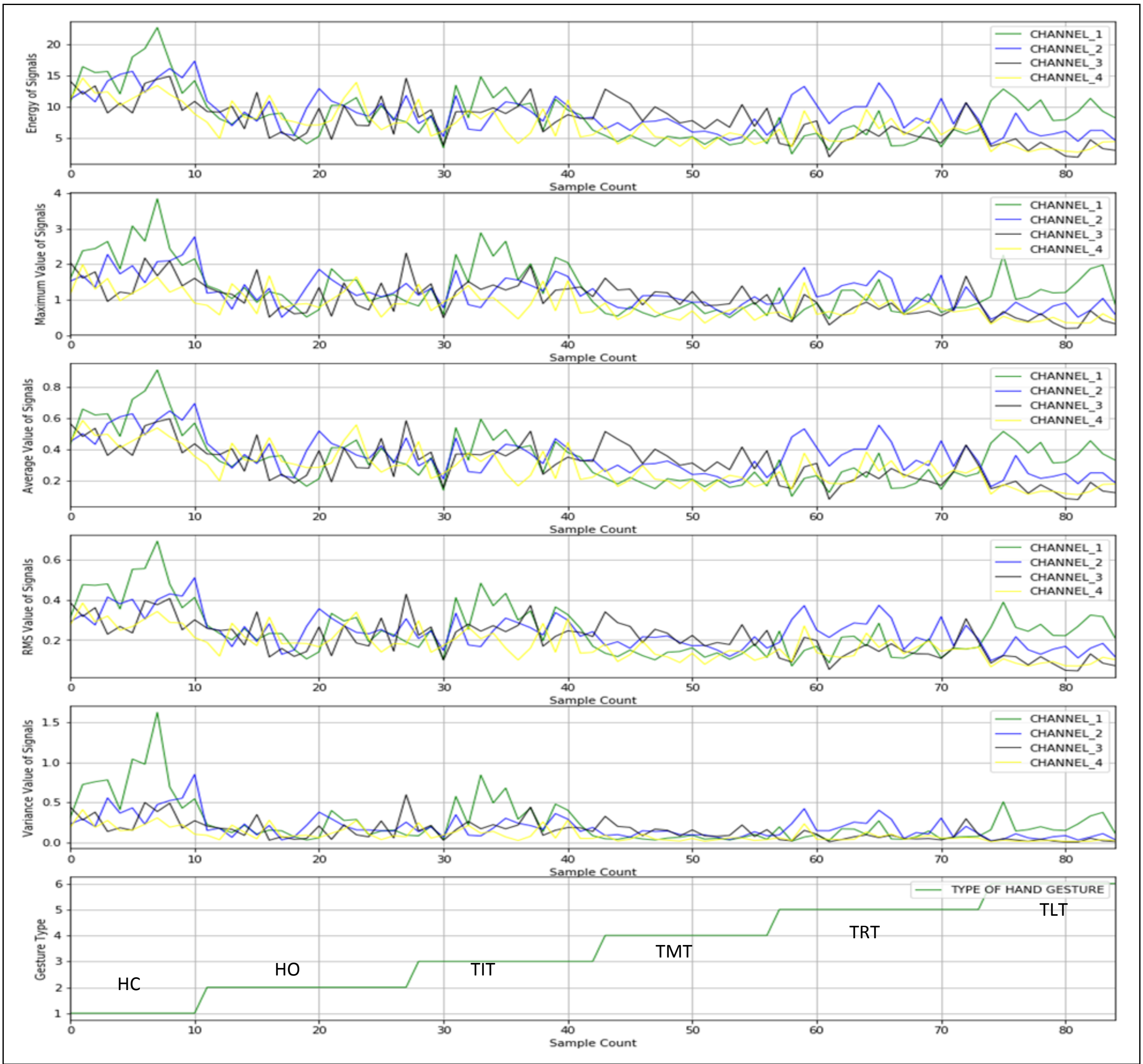

Figure 6. Features graphs of the EMG signal for selected six hand gestures.

Researchers prefer SVM and LDA classifiers for controlling prosthetic devices because of their simplicity and ease of training [47],[48]. Many researchers have used the artificial neural network classification algorithm to classify EMG signals for both linear and non-linear systems. For real-time classification applications of EMG, Del and Park stated that ANN is a suitable technique [49]. Some researchers have tried to teach the network of multi-layered Perceptron-type artificial neural networks, EMG data, with an uncontrolled learning technique, and then to recognize the test data automatically [50]. Tsuji et.al used a back-propagation artificial neural network model of six forearm gestures using the entropy of recorded bioelectrical signals [51]. They have developed a new EMG classification method based on the Hidden Markov model, and they named the new method the Recurrent Log-Linearized Gaussian Mixture Network [52]. To classify the wrist gestures Naik et. al. has tried four methods and compared their results. These four methods are Fast ICA, JADE-ICA, Infomax-ICA, and Temporal Decor-relation Source Separation (TDSEP) [53]. Khezri et al. used a neural-based fuzzy logic classification algorithm to classify hand gestures via EMG signals [54]. Subasi et al. suggested using two different classifiers together to determine EMG signals, i.e., the backpropagation artificial neural network and the wavelet neural network [55]. In order to detect neuromuscular disorders, Christodoulou and colleagues extracted the amplitude-frequency modulation characteristics of the EMG signals from 20 healthy and 11 myopathic patients [56] and compared the classification performances using the KNN, SOM, and SVM classification algorithms. The results indicated that the SVM algorithm was the most successful in classification [57]. For this reason, SVM classifier was used in this study.

The Support Vector Machines (SVM) classification was used to solve the gesture classification problem in this study. SVM an algorithm that is based on statistical learning theory. SVMs originally was designed for the problem of two-class classification and then generalized to multi-class classification [58-59]. Our classification problem consists of four different classes. Thus, we used the "one-against-one" approach [60] multi-class SVM classifier. According to this approach, k denotes the number of classes, and k(k−1)/2 classifiers are constructed, with each one training data from two classes. For training data from the ith and the jth classes, the two-class classification problem is solved in Eqs. (5-6) [60].

$$\min_{w^{ij},b^{ij},\xi^{ij}} \quad \frac{1}{2}(w^{ij})^T w^{ij} + C\sum_t (\xi^{ij})_t \tag{5}$$

$$\textit{subject to} \quad (w^{ij})^T \phi(x_t) + b^{ij} \geq 1 - \xi_t^{ij}, \textit{if } x_t \textit{ in ith class}, (w^{ij})^T \phi(x_t) + b^{ij} \leq 1 + \xi_t^{ij}, \textit{if } x_t \textit{ in jth class}, \xi_t^{ij} \geq 0 \tag{6}$$

3 Results

The experimental test set in Figure 7 consisted of a prosthetic with 15 degrees of freedom (DoF), an EMG signal recorder with four channels, and a MATLAB program to process and classify the EMG signals.

Figure 7. Photograph of the experimental setup.

The size of FiMec hand is 240 x 110 x 25 mm, the mass of the FiMec hand is about 328.45 grams. The characteristic value of FiMec is very similar to the biological hand. Finger has got flat cylindrical shape so it is very suitable to grip the object. The prosthetic hand was controlled via EMG signals for six hand gestures in Figure 8. Human motion desire can be classifying mean 97% success range with SVM algorithm. Its' total cost is 450 USD. This price is including fifteen motors, four-channel EMG recorder, Poly Lactic Acid (PLA) filament and other little connection equipment.

The multi-class SVM classifier was used to determine hand gestures [61]. Used function for multiclass Support Vector Machine was written by ANAND MISHRA (Machine Vision Lab. CEERI, Pilani, India) [62]. Calculated energy (E), maximum value (M), the average value(AVR), effective value (RMS), and variance(VAR) features for four channels were given to SVM for input values. SVM made real-time predict using input according to trained six hand motion type. The performances of multi-class SVM algorithms are estimated according to the Receiver Operator Characteristics Curve (ROC) analysis in Table 3.

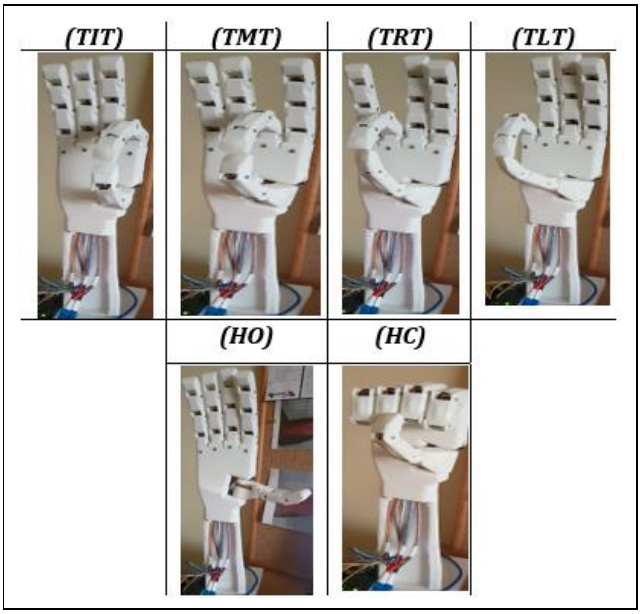

Figure 8. Firat Mechatronics (FiMec) hand: the open-source, affordable, myoelectric prosthetic hand with six gestures.

The performance values for each hand motion were calculated using Eqs. (7) - (10) [63]. (TP =True positive, TN=True Negative, FP= False Positive, FN= False Negative)

$$\text{Sensitivity(S)} = \text{(TP) / ((TP + FP))} \tag{7}$$

$$\textit{True positive rate (TPR)} = TP/(TP+FN) \tag{8}$$

$$\textit{True negative rate (TNR)} = TN/(FP+TN) \tag{9}$$

$$\textit{Accurcy rate (ACC)} = (TP+TN)/(TP+FP+TN+FN) \tag{10}$$

Table 3. Results of the ROC analysis for SVM.

HAND CLOSURE (HC)			HAND ON (HO)			THUMB- INDEX TOUCH (TIT)		
TP 15	FN 0	15	TP 15	FN 0	15	TP 14	FN 1	15
FP 0	TN 90	90	FP 0	TN 90	90	FP 2	TN 73	75
15	90	90	15	90	90	16	74	90
TPR= 1.00 S= 1.00 TNR=1.00 ACC=1.00			TPR= 1.00 S= 1.00 TNR=1.00 ACC=1.00			TPR= 0.93 S= 0.875 TNR=0.98 ACC=0.96		
THUMB- MIDDLE TOUCH (TMT)			**THUMB- RING TOUCH (TRT)**			**THUMB - LITTLE TOUCH (TLT)**		
TP 11	FN 4	15	TP 13	FN 2	15	TP 14	FN 1	15
FP 2	TN 73	75	FP 2	TN 73	75	FP 2	TN 73	75
13	77	90	15	75	90	16	74	90
TPR=0.73 S= 0.846 TNR=0.94 ACC=0.93			TPR=0.866 S= 0.866 TNR=0.97 ACC=0.95			TPR= 0.933 ; S= 0.875 TNR=0.98 ACC=0.96		

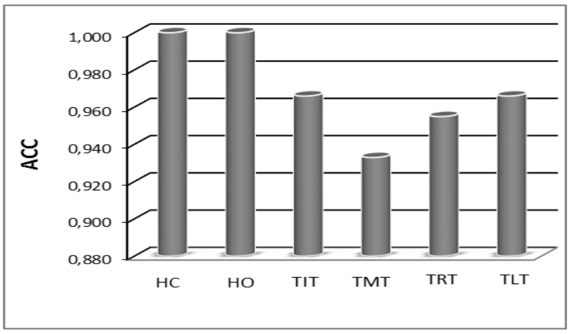

Figure 9. Accuracies of the classification algorithms.

The accuracy of the SVM classifier for six gestures of hand is shown in Figure 9. The little finger's muscle is located at the back of the forearm, some distance away from the muscles of the other fingers. The lowest classification success was achieved for the middle and ring fingers, and this was due to the fact that their muscles are very close to each other. When the signals for these two fingers were recorded by the sEMG electrode, they overlapped each other at times. Thus, the success in sorting the signals for these two fingers was somewhat limited. However, even for these fingers, the classification success exceeded 93%.

4 Discussion

The functional characteristics of I-Limb, BeBionic, and open-source Dextrus and Tact are presented in Table 4, which are comparable to the FiMec hand. The mass of the biological human hand is about 400 grams. However, those who use this weight of prosthetic hand have stated that these devices feel rather heavy [64]. For this reason, a light prosthetic hand will be more pleasing to the user. The mass of the FiMec hand ranges from 6 to 46% lighter than the others. The length and width of the FiMec are in the same range as other handsets. However, the thickness of the hand is only 25 mm, while the thickness of the hand is 41-50 mm for other devices. The most significant advantage of FiMec is that it has 15 DOFs, which means that all of the joints of the prosthetic hand can be moved independently of each other. The FiMec hand has got the highest thumb motion range. The width of the thumb fascia is crucial for easily grasping objects. Each joint is individually controlled by a DC motor. Although the DC motors placed on the finger links were chosen at ultra-Nano scale size, the prosthetic hand is the main reason for the width and length being 12-16% larger.

The PIP and MCP links are linked to each other by a tendon or pulley system. For this operation, the I-LIMB uses a DC motor with a worm gear and a bevel gear. The BeBionic hand uses a front-end DC motor to make a special linear actuator. The use of these special gears in commercial artificial hands increases their cost. Open-source, low-cost Dextrus does not have an addition for the movement of the DIP link, which was designed to keep the position, at 20 degrees. In the case of Tact, a spool system is used instead of special gear to reduce the cost. The FiMec hand with the highest thumb motion range is shown in Table 4. The width of the thumb fascia is crucial for easily grasping objects. In Tact and Dextrus, the thumb flexion, i.e., in the range of (0 - 105) and (0 - 120) degrees, is somewhat higher than it is in the commercial hand.

The choice of small-sized, high-powered engines is essential for an anthropomorphic myo-size constraint. The DC motor we chose for FiMec had the smallest size and weight. It is apparent that the FiMec hand is the lightest design with the highest torque. In terms of the costs of their engines, the Tact and Dextrus hands are passable, but I-Limb, a commercial rival, is 75% more suitable. In addition, the total cost of the FiMec hand is much more affordable since the inter-articular power transmission elements, i.e., the special gearing system and the reel system FiMec, which increase the cost of the I-Limb, Dextrus, and Tact hands, are not used in the FiMec hand. If the power that will be consumed is considered, it is obvious that the life of the battery, which is a major concern for users, will be much longer with the FiMec than others.

Four-channel EMG circuitry, electrodes, and microcontroller are required to control the FiMec hand. An EMG sensor circuit and a staggered microcontroller with electrodes can be purchased and installed at a price of $25. The microcontroller program that provides EMG signals and prosthetic hand control is presented as open-source information and code. Each is made from PLA material using 3D printing technology, a SolidWorks drawing, and STL files of the fingertip, all of which reduce the cost. Production and assembly are very easy and fast. Manufacturing details and assembly instructions for parts are open sources, allowing anyone to access these resources to produce FiMec hands at a low cost.

The entire production and installation of the FiMec hand, consisting of 21 pieces, takes between 10 and 16 hours. The production and assembly of a FiMec hand can be done easily by one person without the need for any assistance. The total cost is approximately 450 USD. This cost is very affordable given that other commercial products have prices that range between $15,000 and $50,000 and provide only 15 functionalities. Extensive studies of prosthetic and orthotic devices have indicated that the recognition of hand motions by sEMG is one of the most important steps in controlling these rehabilitation devices. To increase the percentages of successful recognitions of the hand motions, researchers are working to determine the optimum number of channels, the types of features that should be monitored, and the best classification algorithms. The results obtained in this study are compared to the results of other researchers in Table 5. The classification that was achieved in this research was reasonably good.

5 Conclusion

The low cost, prosthetic production research is an academic experiment not created for commercial purposes. It is planned to buy a high-prosthetic hand from those who are not strong financially. SolidWorks drawings and EMG-based control algorithm files of FiMec hand was shared with people free of charge over the internet in detail, so every amputee people, who want, can manufacture her/his own prosthetic hand according to instructions easily.

6 Acknowledgment

Ethical approval: All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Ethics Committee Permit Document for this study is the attachment.

Data Availability Statement: All data used to support the findings of this study are included in the article.

Table 4. Corporation the characteristics of hand.

		FiMec	Tact	Dextrus	İ-Limb	BeBionics
General Characteristic of the Hand	*Developer*	Firat University	University of Illinois	Open Hand Project	Touch Bionics	RSL Steeper
	Mass(g)	328.45	350	428	450-615	495-539
	Size (length x width x height)	240 x 110 x 25	200 x 98 x 27	205 x 88 x 45	182 x 80 x 41	198 x 90 x 50
	Link Shape	flat cylindrical	cylindrical	cylindrical	cylindrical	cylindrical
	DoF	15	11	15	11	11
	Number of Actuators	15	6	6	6	6
	Joint Coupling Method	Independent motion MCP, DIP, and PIP	Linkage Spanning MCP to PIP	Tendon and free-spinning pulleys	Tendon linking MCP to PIP	Linkage spanning MCP to PIP
Kinematic Characteristics of Hands	*MCP Joint Degree*	0-90	0-90	0-90	0-90	0-90
	PIP Joint Degree	0-90	23-90	0-90	0-90	0-90
	DIP Joint Degree	0-90	0-90	20	20	20
	PIP Joint Degree for Thumb	0-90	0-90	0-90	0-60	-
	PIP Joint Degree for Thumb	0-90	-	-	-	-
	Thumb Circumduction Degree	0-150	0-105	0-120	0-95	0-68
Characteristics of the motors used in the prosthetic hand	*Nominal Voltage (V)*	4.8	12	12	4.5	-
	Stall Current (A)	0.36	0.3	0.3	0.919	-
	Watt (J)	1.728	3.6	3.6	4.135	-
	Motor Stall Torque (Nm)	0.08	0.143	0.143	0.15	-
	Cost per Motor (USD)	21.02	13.95	13.95	208.88	-
	Size	18.6 x7.6 x15.5 mm	16 x52mm	16 x52mm	10 x 52.05mm	-
	Mass(g)	4.5	38	38	18	-
	Used Number of Actuator	15	6	6	6	-

Table 5. Comparison of the results of different EMG classification systems.

Recognition hand gesture	Classifier	Average Accuracy
Six hand motion gesture (Results of this study)	Supported Vector Machines	97%
Six hand motion gesture [68]	Adaptive Neuro-fuzzy interference system (ANFIS)	92%
Hand motion gesture[65]	BPANN with Levenberg-Marquardt training algorithm	89.2%
Eight hand motion gesture for control of a robotic arm. [69]	SVM	92-98%
Four hand motion gesturefor human-computer interaction [66]	BPANN (Gradient-descent algorithm)	97.5%
Six Motion discrimination [67]	Error back-propagation type neural networks	90%
Classify six different hand gestures [70]	BPANN (Gradient-descent algorithm)	99%
Chinese number gestures signifying the natural numbers zero through nine.[71]	k-NN, LDA and QDA algorithms	91-97%
Four hand gesture(flexion)[72]	ANN	83.5%

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Appendix

Open Source FiMEC hand design document: (https://grabcad.com/library/emg-controlled-prosthetic-hand-fimec-hand-1)