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Taguchi Design of Experiments Application in Robust sEMG Based Force Estimation

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***Abstract*—This paper investigates the impact of the parameters that affect the accuracy of the force estimation from sEMG signals, including signal acquisition factors, pre-processing and training ones. It offers a procedure for developing a reliable estimation approach to deal with uncertainties, such as the signal deviation while performing various daily tasks using the hand. For doing this, the Taguchi design of experiments (DOE) approach is used to determine appropriate levels of the factors to decrease the regression error. Factors such as the number of electrodes placed on the forearm and the arm, extracted features, the cropping window length and the training regularization term have been categorized as either controllable or uncontrollable in the DOE table. The experiments are conducted on four subjects who perform six different tasks. The L225 mixed-level orthogonal array is used to specify the levels of factors in each experiment. The orthogonal array drastically reduces the required number of executions compared to a full-factorial analysis. Using the Minitab software, the signal-to-noise ratios (SNR) are calculated to determine the optimum levels and significance of the factors. Results indicate that the number of forearm electrodes and their placements are the most influential factors. Moreover, the SNR delta for including the arm biceps muscle is about 0.66, which considering its placement difficulties, it does not justify its additional expense.**

***Keywords*—Grasp force, Robust estimation, sEMG, DOE, Taguchi.**

I. INTRODUCTION

Hands have an essential role in human daily life tasks and social communications. Hence, the lack of care for an amputee can cause severe psychological issues [1]. Although hand prostheses can improve life quality by recreating the human hand functionality, natural motion and facile control are required to increase the adoption of artificial hands [2]. To do so, controllable grasp force and adjustable mechanical impedance of prostheses can improve dexterity and enable more precise grasps [3]. Castellini's study showed that, despite the weakening of muscles in amputation, there is still adequate information on the remaining muscles [4]. In addition, clinical studies have indicated that regulating the co-activation of muscles adjusts the stiffness of joints to damp the hand vibration and deal with the external forces [5], [6]. Therefore, unlike most commercial prostheses that use unfamiliar muscles as the activation commands, decoding the sEMG signals of muscles that intrinsically are activated and co-activated during a grasp is a superior solution for determining the user's intention. Hence, many regression methods such as MLP, RBF, deep neural networks, and SVM have been introduced, each of which is practical in a compromise between the available processing power and the required accuracy. Some of these methods and their implementation working on classification problems are reviewed in the Parajuli et al. paper [7].

Grasp type detection or grasp force estimation are two main approaches in prosthetic hands sEMG based controlling. The first method classifies signals into several predefined classes. Hence, a limited number of grasp gestures will be available. To do so, Sánchez-Velasco et al. used extended associative memories (EMA) to classify the Myo armband data into eight different grasp types. Considering time-domain features, they also indicated that MAV and RMS present the best performance and obtained 95.83% accuracy [8]. In the same way, Jie Liu and Ping Zhou achieved an average accuracy of over 97% on nine subjects using LDA and KNN for seven classes [9]. Jiralerspong proposed an algorithm classifying 17 movements with an overall accuracy of up to 83% using six EMG sensors. Furthermore, using this method, considering nine classes improved accuracy up to 92% [10].

The other approach treats force estimation as a regression problem that requires a proper data acquisition system for synchronously recording sEMG signals and their corresponding grasp force. For this purpose, Yang et al. adopted a 6-dimensional force/torque sensor and six channels of EMG. Their results showed that the SVM method performs better than LWPR and ANN [11]. Tanausavaphol et al. proposed an algorithm to approximate the human hand applied force using the Myo armband employing a setup that simulates friction force against the movement during rectilinear motion. This research indicated that applying more resistance force reduces the estimation performance [12].

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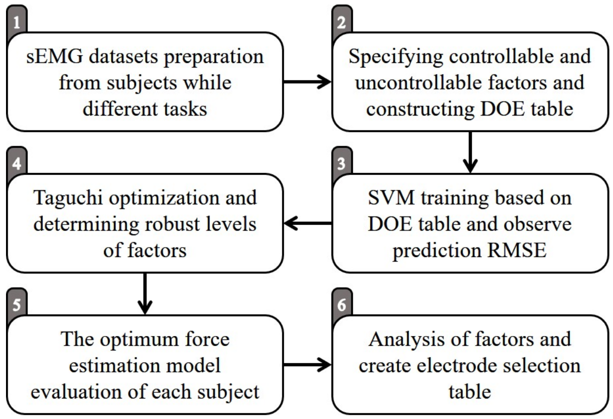

Fig. 1. Research procedure

In addition, some solutions instantly estimate the force or angle of individual fingers rather than a specific class or grasp force. By kinematics considerations, this solution provides shape-adaptive grasps. Ngeo et al. used a 3D motion camera system to extract the angle of phalanges during individual and simultaneous multiple finger flexion and extension [13].

The presented research implements the Taguchi design of experiments determining the optimum levels to achieve robust force estimation. Then, it evaluates the impact of parameters in force estimation from sEMG signals. Fig.1 depicts the procedure and stages of the study.

The remaining of this article is organized as follows. The dataset preparation and implementation are introduced in the next section. Moreover, the third section explains the considered factors and the design of the experiments table used for optimization and statistical analysis. The results are discussed in the fourth section, and a forearm electrodes selection table is suggested. Finally, conclusions and additional information are provided.

II. MATERIALS AND METHOD

The sEMG signals can vary throughout the day for reasons such as muscle fatigue or a nearby noise source. Even during a constant grasp force, hand pronation and arm extension can influence forearm signals. Therefore, accurately specifying data acquisition procedures such that to include daily tasks in the dataset is needed. So, different modalities that imitate daily living tasks, as well as grasp aperture size and object weight, have been defined to obtain a comprehensive dataset. The data acquisition system, the data modalities, and the used regression method are explained below.

A. Data Acquisition System

The utilized data acquisition system, providing synchronous sEMG and FSR recording, is depicted in Fig.2. The gathered dataset is suitable for force estimation by any regression method. Since the thumb is fundamental in the majority of grasp types [14], the FSR has been mounted on a plate such that the thumb can press it. Moreover, as depicted in Fig.2.c, this configuration can simulate the different object weights and sizes by changing the number of plates. Due to available electronics, there are a limited number of sEMG channels, as summarized in table I. Therefore, the muscles which have the most participation in the fingers movement have been selected [15]. In addition, to observe hand movement and orientation, the arm channels are included. The electrode placement and corresponding channels are depicted in Fig.2.b.

B. Data Recording Modalities

The dataset has been collected from two male and two female subjects performing six different tasks (data modalities). Each mode has been repeated for various numbers of plates, one to five, as well as five times replication. Hence, 25 data have been recorded for each data mode and 150 for each subject. Data recording starts from the initial position and ends at the same. The initial position is defined as the hand placed beside the body and the palm facing inside, while the elbow is bent about 90 degrees. Also, the FSR plate is located about 15cm from the edge of the desk. Data modalities are as follows:

1) *Continuous Force:* In this mode, the subjects had to gently increase the applied force to their threshold and release them after a while without moving the plates.
2) *Discrete Force:* This mode is similar to the continuous except that the force is exerted sequentially as weak, medium, and strong, according to the perception of each subject.
3) *Vertical Pick and Place:* In this mode, subjects were asked to elevate the plates to about 15cm height, put them on a ledge, and return them after a period.
4) *Horizontal Pick and Place:* The horizontal mode is similar to the vertical except that the subjects were conveying the plates sideways about 15cm distance over the desk and returning them.
5) *Infinity Signature Circulation:* In this mode, subjects were asked to travel the plates over an infinity sign path placed on the desk for one cycle that starts from the center of it.
6) *Hand Pronation:* This recording mode includes the effect of hand rotation in the dataset as subjects hover the plates over the desk, pronate their palms, and eventually reverse the process.

TABLE I
SELECTED MUSCLES AND THEIR FUNCTION

Num.	Muscle	Function
Ch.1	Flexor Digitorum Superficialis	Flexes fingers of 2-5 and contributes to fist
Ch.2	Flexor Carpi Ulnaris	Flexes the wrist
Ch.3	Flexor Carpi Radialis	Flexes the wrist
Ch.4	Extensor Digitorum	Extends the fingers
Ch.5	Biceps brachii	Flexes the elbow and is also a powerful supinator when the limb is pronated
Ch.6	Triceps brachii	Accomplishes extension of the elbow

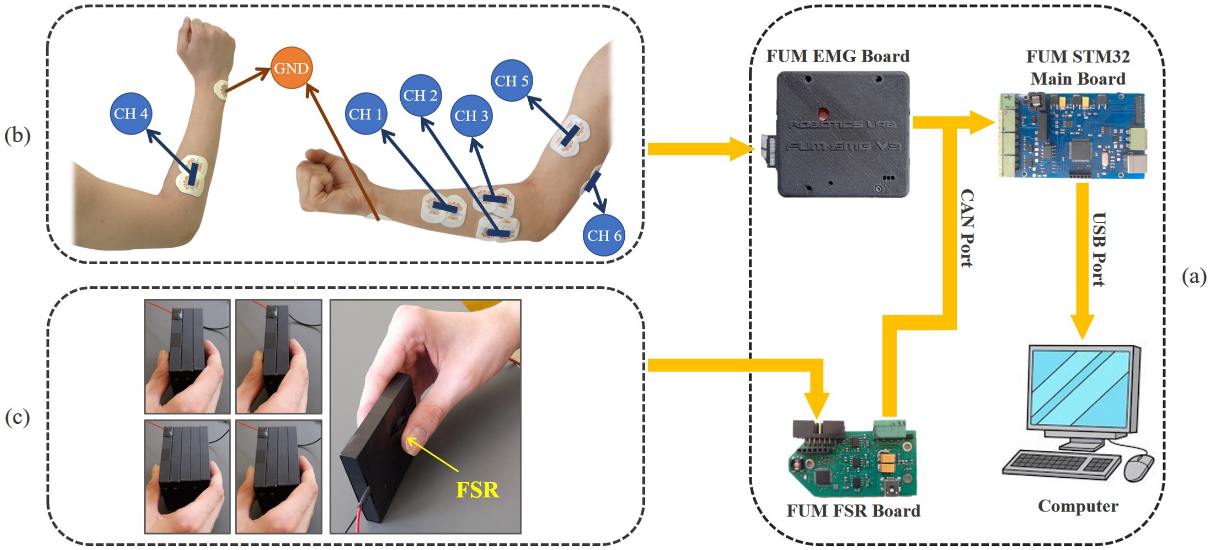

Fig. 2. (a) depicts utilized data acquisition electronics, (b) illustrates sEMG electrodes placement, (c) specifies grasp configuration and increasing plates in each recording stage

TABLE II
THE DOE TABLE FACTORS AND CORRESPONDING LEVELS

Inner factors (Controllable)					Outer factors (Uncontrollable)	
Forearm Ch.	Features	Arm Ch.	Window Len.	Reg. Term	Subject	Modalities
1	RMS	none	200	1	A	Continuous
2	MAV	5	300	10	B	Discrete
3	WL	6	400	100	C	Vertical
4	LOG	5,6	500	1000	D	Horizontal
1,2	RMS, MAV					Infinity
1,3	RMS, WL					Pronation
1,4	RMS, LOG					
2,3	MAV, WL					
2,4	MAV, LOG					
3,4	WL, LOG					
1,2,3	RMS, MAV, WL					
1,2,4	RMS, MAV, LOG					
1,3,4	RMS, WL, LOG					
2,3,4	MAV, WL, LOG					
1,2,3,4	RMS, MAV, WL, LOG					

C. Force Estimation Method

Although there are different regression methods, SVM has been used due to its simplicity and capability. Then the prediction error can provide a comparable reference point for further optimization. For this purpose, after applying the Notch and Butterworth filters, the dataset was randomly separated into training and testing portions. Dataset was initially normalized, then the features extracted from randomly cropped windows. Furthermore, training was performed five times by shuffling training data into five folds.

III. DESIGN OF EXPERIMENTS

Various parameters affect the quality of the sEMG signal and their accurate interpretation. Some of these parameters can be optionally selected to achieve desired purposes. But, parameters such as the subject's gender, skin type, and muscle fatigue can not be managed in practice. The Taguchi method is concerned with finding the best values of the controllable factors to make the problem less sensitive to the variations of uncontrollable ones. [16]. Therefore, properly constructing the Taguchi DOE table and determining influential factors are required. These factors must appropriately be assigned in the inner and outer arrays of the table for reliable analysis.

This study determined the main factors affecting force estimation. The factors such as forearm electrode placement arrangement, hand movement perception by considering arm electrodes, extracted features of signals, cropping window length, and the SVM regularization term all have been placed in the inner array to specify their suitable values for robust force estimation. Moreover, subjects and data modalities that indicate the uncertainties have been assigned to the outer array to protect force estimation from their changes. The levels of each experiment have been defined by a full-factorial for the outer array and the L225 mixed-level orthogonal array for the inner one. The orthogonal array obtained according to the Leung and Wang suggested algorithm [17] which significantly reduces the required run time. Values of levels have been defined in table II assuming all possible combinations of electrode selection. The Minitab software has been used to perform Taguchi analysis by manually importing the defined orthogonal array and the output of the experiments.

IV. RESULTS AND DISCUSSION

The Taguchi analysis has been performed to minimize the error of force prediction. The resulting SNR analysis diagram is depicted in Fig.3. In this figure, the larger SNR means a better level for error reduction. Accordingly, the presented levels in table III can be a suitable selection for each factor. As a result of the constructed statistical model, it is predicted that by performing estimation with optimum levels, the RMSE would be about 0.07. Hence, comparing the prediction of Taguchi with obtained optimum RMSE of each subject, reported in table III, verifies the statistical model. Despite these levels acquiring various errors on different subjects and sometimes not the minimum error, the statistical model is acceptable. The key point is that using these levels, the regression is more reliable due to statistically considering uncertainties such as different daily tasks, diverse skin types, and various muscles.

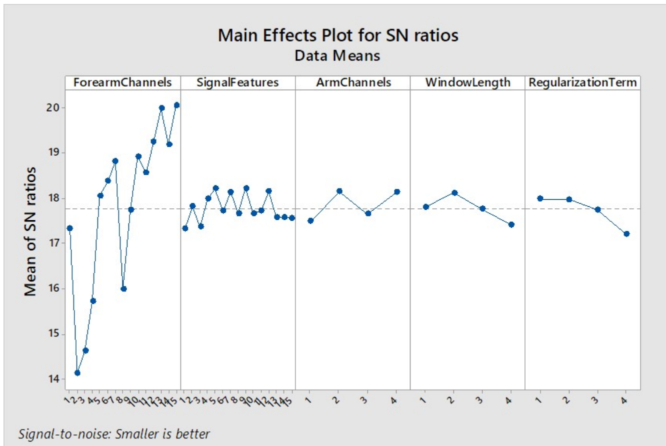

Fig. 3. Output SN plot for minimizing the SVM force estimation RMSE

According to Fig.3, the significance of each factor can be determined by defining the SNR delta, which is the difference between the maximum and minimum of each factor's SNR. Hence, factors are ranked by importance in table III, which shows that the placement of forearm electrodes considerably has the most impact on the estimation error. Furthermore, the arm channels can improve the estimation, but it is not as great as the forearm. Window cropping length has the same impact as arm channels. So that applying either a pair of features of [MAV, LOG] or [RMS, MAV] with the 300ms crop window length is acceptable. Eventually, the SVM training regularization term of 1 or 10 is a good choice for normalized data.

TABLE III
SIGNIFICANCE AND OPTIMUM LEVEL OF EACH FACTOR AND CORRESPONDING RMSE OF SUBJECTS

Factors					Output	
Factor	SNR Delta	Rank	Optimum Level	Value	Subject	RMSE
Forearm Ch.	5.91	1	15	1,2,3,4	A	0.066
Features	0.89	2	9	MAV, LOG	B	0.052
Reg. Term	0.77	3	1	1	C	0.048
Window Len.	0.70	4	2	300	D	0.075
Arm Ch.	0.66	5	2	5		

Despite using entire forearm electrodes being beneficial, several muscles are weakened or unavailable in amputees. Accordingly, a suggestion table based on the SNR of forearm electrodes is presented in table IV to help other researchers select suitable electrodes for practical applications. This table categorizes the selection based on the number of accessible muscles and is ordered by the best choice.

TABLE IV
FOREARM ELECTRODE SELECTION GUIDELINE

	Num. of Accessible Muscles			
Ranking	4 Ch.	3 Ch.	2 Ch.	1 Ch.
1	[1,2,3,4]	[1,3,4]	[3,4]	[1]
2		[1,2,4]	[1,4]	[4]
3		[2,3,4]	[1,3]	[3]
4		[1,2,3]	[1,2]	[2]
5			[2,4]	
6			[2,3]	

V. CONCLUSION

In this study, the Taguchi approach is utilized to investigate the impact of the factors on the force estimation with the SVM regression method. The DOE table was constructed by considering the mixed-level L225 orthogonal array and properly assigning the parameters to controllable and uncontrollable factors. Accordingly, the control factors consist of the arm and forearm electrode combination, the extracted features of signals, the cropping window length and the training regularization term. Also, the uncontrollable ones contain different subjects and data modalities to deal with the sEMG signal variation across individuals and inconsistency whilst performing daily tasks. As a result, the Taguchi method indicated that using the entire forearm and the biceps electrodes with extracting any pairs of [MAV, LOG] or [RMS, MAV] features can be a robust solution. Furthermore, results showed that the forearm electrodes have the most significance over the others, and the biceps channel is not essential. Finally, a forearm electrode selection is proposed to help users with the commercial prosthesis.

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