Handgrip estimation based on total variation denoising filtering for control applications

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***Abstract*— In many biomechanical studies and control applications, such as ergonomics studies, control of upper limb prosthesis, and sports performance is required handgrip force estimation for both monitoring and control purposes. As it was proven in previous works, features extraction from the extensor carpi radialis longus (ecrl) sEMG had a linear relationship with the gripforce of the hand. However, most of the developed estimations have shown high variation, which are not quite suitable for control applications. Therefore we propose a methodology to estimate the grip force, which models the extrated features as the handgrip force signal with the presence gaussian noise. In order to estimate the force, these features are filtered with a regularized optimization problem based on total variation denoising (TVD). Furthermore, since TVD is not a trivial minimization problem it was used ADMM algorithm as a meant to implement the proposed methodology. The developed methodology yielded promising results (**$\rho > 0.94$ $NRMSE < 0.07$**) between** $30\% - 50\%$ **MVC.**

I. INTRODUCTION

For a long time in fields such as biomechanics, clinical diagnosis, ergonomics, sports performance, and rehabilitation robotics [1], handgrip estimation had proven to be a valuable tool for clinical diagnosis and control applications. In clinical diagnosis the grip force is typically estimated in an off-line fashion after the experiments. However, in control applications such as prosthesis or exoskeleton control it is not an option, and there is a necessity for real-time force estimation.

Force estimation problem has been addressed by diverse approaches for force estimation, using different methodologies and models (i.e. [2][3][4]). Mostly based on feature extraction from the superface electromyography (sEMG) of a specific muscle or a group of muscles. Although some of these approaches had promising results, the estimation process gets more complex and its harder to implement. It can be seen mainly for those which use additional input variables [5], or its estimations systems are based on learning algorithms, that they need a great amount of data to generate a good predictor. On the other hand, some methods [6][7][8] estimates the force with extracted features from the sEMG of the forearm muscles, that have a linear relationship with the force. However, in most of the cases, to obtain these features its necessary a large window of data per feature, to make a good estimation. On the contrary the estimation presents a reduced correlation and the presence of abrupt changes.

We propose a novel methodology to estimate the handgrip-force based on the filtering of extracted features. This method extracts features from the sEMG signal, in a continous manner, obtained from the extensor carpi radialis longus (ecrl), that had a linear relationship with the measured force of the handgrip. In order to estimate the force, the extracted features are considered as the handgrip force signal corrupted by gaussian noise, and then their are filtered with a minimization problem based on total variation denoising (TVD). TVD is a noise reduction approach developed to preserve sharp edges on images. However, it is not restricted only to images, and it has proven to be a powerful tool for 1D signal denoising [9]. In addition, since TVD has no trivial minimization solution, the present work has considered the alternating direction method of multipliers (ADMM) as a minimization algorithm, in order to present a implementation proposal.

The paper is structured as follow: sec.II gives a brief review about TVD and ADMM, sec. III presents the proposed methodo, sec. IV presents the methodology to evaluate the data and the parameters used, and the paper is concluded with with the experimental results, the discution and the conclusion.

II. BACKGROUND

In this section, the theoretical background of total variation and ADMM will be presented due its main role in the proposed methodology.

A. Total Variation Denoising

Total variation denoising (TVD) is an approach for noise reduction developed to preserve sharp edges in the underlying signal [10]. In contrast of conventional low-pass filter, TV denoising is defined in terms of an optimization problem, based on a cost function. Any algorithm capable to solve the optimization problem can be used to implement TV denoising. However, it is not trivial because the TVD cost

This work was supported in part by DGI-70242.2137 and The Mechanical Engineering Section of the Pontificia Universidad Católica del Perú.

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978-1-4799-3163-7/13/$31.00 ©2013 IEEE

function is non-differentiable given the presence of the L1 norm. Numerous algorithms have been developed to solve the TVD problem [11]. TVD assumes that the noise or observed data b is of the form:

$$b = x + w \tag{1}$$

Where x is a (approximately) piecewise constant signal and w is white Gaussian noise. The TVD estimates the signal x by solving the optimization problem.

$$\underset{x}{\operatorname{argmin}} \frac{1}{2}\|x - b\|_2^2 + \lambda\|Dx\|_1 \tag{2}$$

Where $x \in R^n$ is the estimated signal and $b \in R^n$ is the noisy observed signal, D is the differential operator and λ is the regularization term. The regularization term ($\lambda > 0$) controls the degree of smoothing. An Increase in λ results in an increase of the restriction made by the second term, which measures the variation of the signal x.

B. Alternating Direction Method of Multipliers (ADMM)

In this section we give an overview of ADMM based on [12].

1) ADMM standard algorithm: The standard ADMM algorithm solves problems in the form:

$$\begin{array}{ll} \text{minimize} & f(x) + g(z) \\ \text{subject to} & Ax + Bz = c \end{array} \tag{3}$$

Where $x \in R^n$, $z \in R^m$, matrices $A \in R^{pxn}$, $B \in R^{pxm}$ and vector $c \in R^p$. Similar to the method of multiplier, the problem uses the augmented lagrandian to find a solution.

$$\begin{aligned} L_\rho(x, z, y) = f(x) + g(z) + y^T(Ax + Bz - c) \\ + \frac{\rho}{2}\|Ax + Bz - c\|_2^2 \end{aligned} \tag{4}$$

Where y is the lagrange multiplier corresponding to the equality constrain and ρ is the penalty parameter. The minimization process starts with an initial point (x^0, z^0, y^0) and $(0 \leq k)$. Then it is followed by these iterative steps:

$$x^{k+1} := \underset{x}{\operatorname{argmin}} L_\rho(x, z^k, y^k) \tag{5}$$

$$z^{k+1} := \underset{z}{\operatorname{argmin}} L_\rho(x^{k+1}, z, y^k) \tag{6}$$

$$y^{k+1} := y^k + \rho(Fx^{k+1} + Dz^{k+1} - c) \tag{7}$$

However this representation can be expressed in a more convenient way, by transforming the last two term of (4) into:

$$\begin{aligned} y^T(Ax + Bz - c) + \frac{\rho}{2}\|Ax + Bz - c\|_2^2 = \\ \frac{\rho}{2}\|Ax + Bz - c + \frac{y}{\rho}\|_2^2 - \frac{1}{2\rho}\|y\|_2^2 \end{aligned} \tag{8}$$

and using the relation $u = \frac{y}{\rho}$ (5), (6) and (7) are modified as:

$$x^{k+1} := \underset{x}{\operatorname{argmin}} \left(f(x) + \frac{\rho}{2}\|Ax + Bz - c + u\|_2^2\right) \tag{9}$$

$$z^{k+1} := \underset{z}{\operatorname{argmin}} \left(g(z) + \frac{\rho}{2}\|Ax + Bz - c + u\|_2^2\right) \tag{10}$$

$$u^{k+1} := u^k + Ax + Bz - c \tag{11}$$

2) Total Variation implementation in ADMM: As it is stated in [12] total variation denoising (2) can be expressed in ADMM form as follow:

$$\begin{array}{ll} \text{minimize} & \frac{1}{2}\|x - b\|_2^2 + \lambda\|z\|_1 \\ \text{subject to} & Dx - z = 0 \end{array} \tag{12}$$

This leads to the iteration steps:

$$x^{k+1} = (I + \rho D^T D)^{-1}(b + \rho D^T(z^k - u^k)) \tag{13}$$

$$z^{k+1} = S_{\frac{\lambda}{\rho}}(Dx^{k+1} - u^k) \tag{14}$$

$$u^{k+1} = u^k + Dx^{k+1} - z^{k+1} \tag{15}$$

Where S is a soft thresholding function whose, threshold parameter is equal to $\frac{\lambda}{\rho}$.

III. Force Estimation Method

Our method consist of two parts. First, sEMG and grip force recording, features extraction, filtering and linear model generation. Second, sEMG recording, features extraction filtering, data scaling and force estimation. The first stage of the method is necesary only once to generate a linear model for the data scaling. the second stage uses this model to scale the data and to estimate the force.

3) Features Extraction: The initial stage of the algorithm consists in acquiring the data and features extraction, (16).

$$X_i = \sum_{j=1}^{m} |x_j| \tag{16}$$

Where $x \in R^n$, m is the length of the subgroup of the data $(m < n)$ and X_i is L_1 norm of group of data. This features is used to extract informacion about the mean of small sections of data of an acquire window of time. Also reduces the amount of data to be used in the filtering process and to effect of large variations.

4) Filtering Process: Since this estimator has been considered for control processes, we require to obtain a smooth signal in a continuous fashion. This presents two challenges, the first one is to obtain a smooth signal with reduced variations or oscillations and the second, is to achieve this estimations in a small amount of time. To be able to deal with the first issue we take advantage of the regularization term of TVD, however this only assures the smoothing the values of window of data and not variations between the data of adjacent windows. This issue is handled by adding a regularization term which penalizes the variation between adjacent windows. In addition the boundary conditions will also present a problem between estimations in order to minimize this effects the methodology considers overlapping windows in each estimation. The second requirement can be easily achieved by using a small entry of data in each estimation, however this can present a negative effect in the estimation. This leads to the proposed optimization problem expressed in (17).

$$\text{minimize} \quad \frac{1}{2}\|x-b\|_2^2 + \frac{\beta}{2}\|D_{Ad}x\|_2^2 + \lambda\|Dx\|_1 \tag{17}$$

Where $x \in R^n$ is the filtered signal, $b \in R^n$ is the input signal, $D_{Ad} \in R^{nxn}$ is a differentation matrix between new and the previous estimation and β is a regularization term used to penalize this new restriction. D_{Ad} is a matrix used tu reduce the variation between the new estimated data and the previous estimations. This is done by subtracting its features term by term.

$$D_{Ad} = \begin{array}{cl} \begin{pmatrix} 0 & 0 & \cdots & \cdots & 0 & & \cdots & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & & \ddots & \ddots & \ddots & & & \vdots \\ \vdots & \ddots & 0 & \ddots & & \ddots & 0 & \ddots & \cdots & 0 \\ 0 & \cdots & 0 & -1 & 0 & \cdots & 0 & 1 & \ddots & \vdots \\ \vdots & & & \ddots & \ddots & \ddots & & \ddots & \ddots & 0 \\ 0 & \cdots & \cdots & \cdots & 0 & -1 & 0 & \cdots & 0 & 1 \end{pmatrix} & \begin{array}{l} \left.\begin{matrix} \\ \\ \\ \\ \end{matrix}\right\} pq \\ \left.\begin{matrix} \\ \\ \end{matrix}\right\} q \end{array} \\ \qquad\qquad\qquad\qquad \underbrace{\qquad\qquad\qquad\qquad\qquad}_{2q} & \end{array}$$

where q is the length of the features extracted from a window of data and p is the number of previous data estimations. In order to use the proposed methodology is necessary to record an initial data set. This can be done by recording p windows of data, extracting its features and filtering it with TVD. Once the required number of overlapping windows are recorded, (17) can be used. For this case, the input data is a vector formed by the features of previous estimations and the ones from a new data reading. The filtered data will be formed by a vector with smoothed features from the previous estimation and the new data. This last dataset is the *”not scaled estimations”* of the recorded window. This dataset will pass to the next stage of the estimation, and also be used as part of the previous data, for futures estimations.

Equation (17) in ADMM form is:

$$\begin{aligned} \text{minimize} \quad & \frac{1}{2}\|x-b\|_2^2 + \frac{\beta}{2}\|D_{Ad}x\|_2^2 + \lambda\|z\|_1 \\ \text{subject to} \quad & Dx - z = 0 \end{aligned} \tag{18}$$

and can be implemented using the following iteration steps:

$$x^{k+1} = (I + \rho D^T D + \beta D_{Ad}^T D_{Ad})^{-1}(b + \rho D^T(z^k - u^k)) \tag{19}$$

$$z^{k+1} = S_{\frac{\lambda}{\rho}}(Dx^{k+1} - u^k) \tag{20}$$

$$u^{k+1} = u^k + Dx^{k+1} - z^{k+1} \tag{21}$$

5) Data Scaling: The extracted features as presented in [6] can be scaled using a linear model, to this purpose we use linear regression based on least squares (22) to obtain the coefficientes of the model.

$$\frac{1}{2}\|Ax-b\|_2^2 \tag{22}$$

where $A \in R^{nx2}$ is a matrix formed with the filtered data and a vector of ones, $x \in R^2$ are the coefficients of the linear model and $b \in R^n$ is the measured force.

$$\mathbf{A} = \begin{bmatrix} x_0 & 1 \\ \vdots & \vdots \\ x_{n-2} & 1 \\ x_{n-1} & 1 \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} a \\ b \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} b_0 \\ \vdots \\ b_{n-2} \\ b_{n-1} \end{bmatrix}$$

To be able to generate the coefficientes it is necessary an initial data reading, once generated the coefficientes can be used to scale the data from the filtered features.

IV. Methodology

A. Participants

In order to realize the tests, four participant were recruited (three males and one female). All the subjects are self-report righ-handed with no history of musculoskeletal disorders. Their age ranged from 25 to 28 and had a MVC range from 120N to 260N. The force tasks where constant force contractracion of 2.5 and 5 seconds of durations. Between each trail the subjects had a rest of 1 minute. Taking into account the linear relationship between the features and the forces is higher between $30\% - 50\%$ MVC [8], it was analyzed only this range of force.

B. Acquisition Parameters

The experimental superficial EMG signal was recorded from the extensor carpi radialis longus, due its high correlation with the handgrip force [8]. BioPac system was use for data acquisition. EMG100c module enables us to register one cannel of sEMG signal at 1Khz simple rate and filtered band 10-500 Hz. The superficial electrodes used where standard Ag/Agcl of the 3M brand (2228). To register gripping force it was used the isometric dynamometer TSD121c and the general purpose transducer amplifier DA100c.

C. Experiment Set up

In order to applied the method we record raw sEMG data and grip force data with the Biopac system. All the obtained data was processed in a standard PC over the Matlab environment. The measured force has been normalized with the maximum voluntary contraction (MVC). In order to generate the linear model, it has been recorded a five seconds (5s) window of sEMG and grip force. Both signals where filtered, with the proposed methodology (only feature extraction, filtering) and low pass filtering respectively.

Finally, the scaled force is used to calculate the coefficients. As in the initial stage, all the filtering stages consider a $100ms$ time window and four windows of previous estimated data, and from each readed window of data there are extracted four features $(25ms)$. The regularization term λ was considered a linear function of the standard deviation from the data input. Finally for the parameters of the proposed method it was used aβ and ρ with constant value equal to 0.1 and 1e5 respectively.

V. Experiment Results

The extracted features of the 5 seconds window sEMG data, were filtered with the designed filter Fig. 1, and then it was scaled with the force pattern as show in Fig. 2. Ones obtained the linear model it is used for further estimations as seen in Fig. 3, where it can be used for differente patterns of force which are in the range of $30\% - 50\%$ MVC.

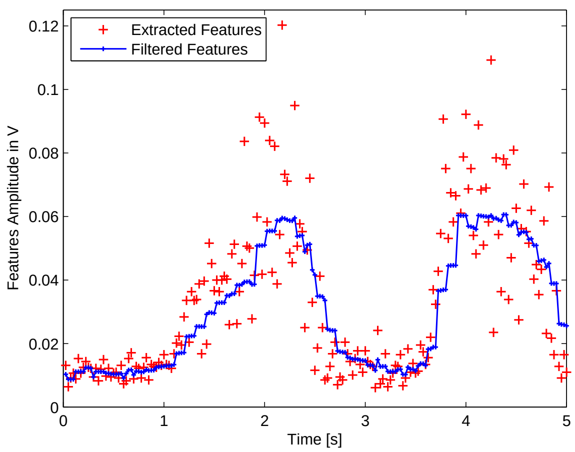


Fig. 1. Initialization stage of the estimation: extracted features (red crosses) from the recorded EMG window and the filtered features (blue crosses) using (17)

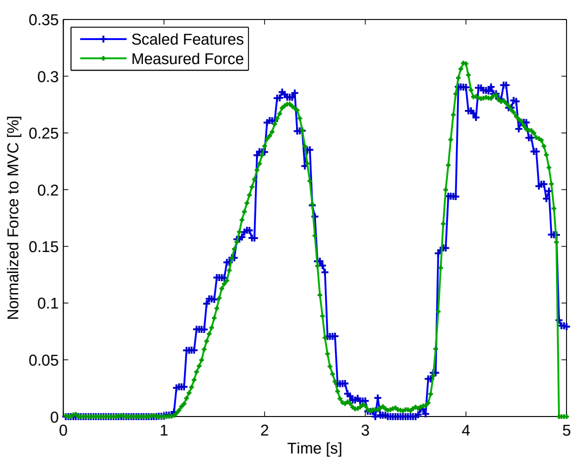


Fig. 2. Initialization stage of the estimation: scaled data (**??**) (blue line with blue cross) compared with the real measured force (green line green cross) $(\rho = 0.98 \& NRMSE = 0.02)$.

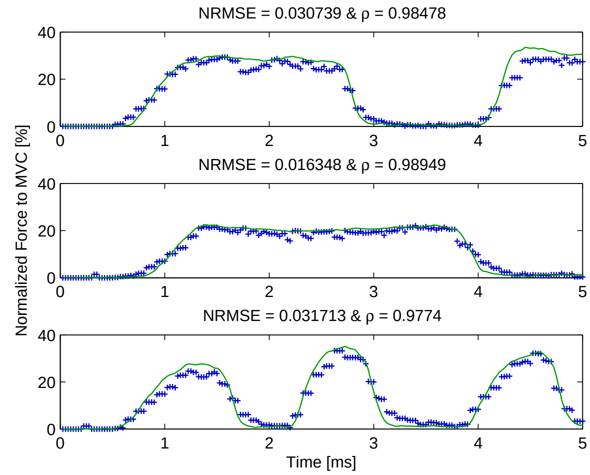


Fig. 3. Grip Force estimations generated with the modeleq. (**??**) from the initial data set. where the green line represents the real force and the blue crosses the estimated data

In order to show the benefits of filtering the extracted features with the proposed filter (17), it was compared with a low pass filter (Fir filter with cuf-off frequency 100Hz). Fig.4 shows the comparison of filtering the features with the proposed method and a low pass filter. It can be see that both methods show good results, however the proposed methodology show less abrupt changes and a more flat response than the estimation obtained with the low pass filter. On the other hand table I and table II, exhibit the statistical results for the NRMSE and the correlation of the estimations. The tables show that the numerical results of the proposed method are slightly better than the ones obtained with low pass filtering.

TABLE I
Statistical results for the NRMSE of the estimation for the proposed method and low pass filtering

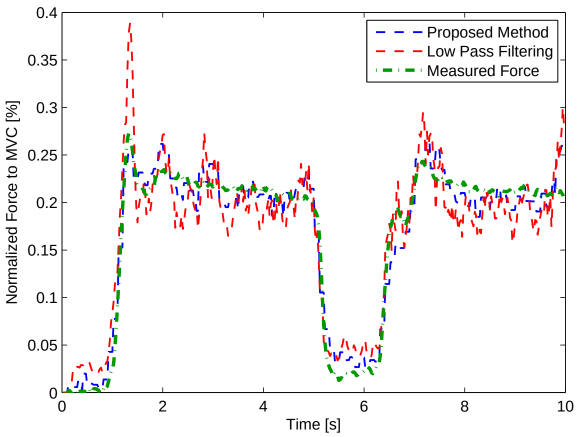
Method	Min	Max	Mean	Std. dev.
Proposed	0.02	0.07	0.048	0.021
Low Pass Filtering	0.03	0.09	0.048	0.023

TABLE II
Statistical results for the Correlation of the estimation for the proposed method and low pass filtering

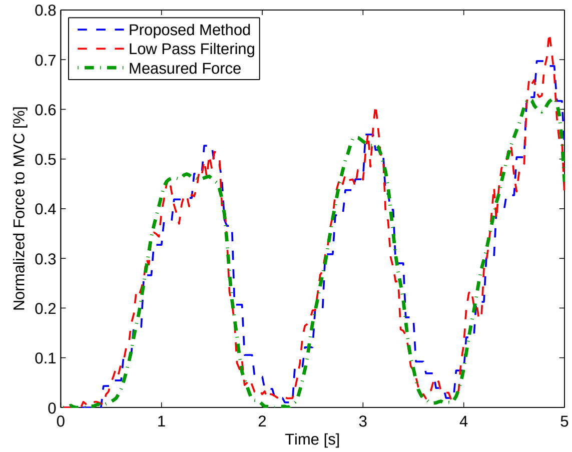
Method	Min	Max	Mean	Std. dev.
Proposed	0.94	0.98	0.96	0.01
Low Pass Filtering	0.89	0.99	0.95	0.03

VI. Discussion

The proposed method present promising results for hand-grip force estimation. However, more test must be done including other initial data set or considering different force



(a)



(b)

Fig. 4. Method comparison with different force traces. a) Blue dashed line represents the estimation of the force using the proposed methodology ($\rho = 0.98 \& NRMSE = 0.02$), red dashed line the data estimation with a low pass filter($\rho = 0.94 \& NRMSE = 0.03$) and the green line dashed line with dots the measured force. b) Blue dashed line represents the estimation of the force using the proposed methodology ($\rho = 0.97 \& NRMSE = 0.05$), red dashed line the data estimation with a low pass filter($\rho = 0.98 \& NRMSE = 0.04$) and the green line dashed line with dots the measured force.

ranges, in order to assure the sturdiness of the method. Another important point to be considered is the assumption of the presence of gaussian noise in the extracted features, TVD is designed to eliminate gaussian noise, in the presence of other noises there is no garanty that it will work. Its pendent a correct analisis or modeling of noise in the extracted features, in order to assure the use of TVD.

VII. Conclusion

In this paper, the authors have proposed a method for estimating handgrip force based on the sEMG of the $ecrl$. The simulations show the potential of the proposed methodology, with low normalized rms errors $nrmse < 0.07$ and aceptable correlations $\rho > 0.94$. In addition, the proposed methodology presented a flatter estimation in comparison of the obtained with only low pass filtering even thought it had a little less NRMSE. Furthermore, it was presented the algorithm for the method based on ADMM, which can be implemented easily on embedded systems. Finally, the present method does not rely on additional variables, or extra sensors.

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