Estimation of whole-body muscular activation from an optimal set of scarce electromyographic recordings

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Abstract. Monitoring workers' status is crucial to prevent work-related musculoskeletal disorders and to enable a safe human-robot interaction. This is typically achieved relying on muscle activation recordings, commonly performed via wearable electromyographic EMG sensors. However, to properly acquire whole-body muscular status, a large number of sensors is needed. This represents a limitation for a real deployment of wearable acquisition systems, due to cost and wearability constraints. To overcome this problem, we propose a solution to provide a reliable muscles estimation from a limited number of EMG recordings. Our method exploits the covariation patterns between muscles activation to complement the recordings coming from a reduced set of optimally placed sensors, minimizing the estimation uncertainty. Using a dataset of EMG data recorded from 10 subjects, we demonstrate that it is possible to reconstruct the temporal evolution of 10 whole-body muscles with a maximum normalized estimation error of 13%, using only 7 EMG sensors.

Keywords: Ergonomics, Human motion control, EMG, Optimal Sensing

1 Introduction

Despite the increasing importance that human robot collaboration has gained for increasing the quality of human work and decreasing the risk of injuries [1], more than half of workers in the European Union (EU) report disturbances in carrying out daily tasks, which often result in chronic Work-related MusculoSkeletal Disorders (WMSDs) [6]. The most commonly identified issues are muscles-related pain, especially at the back, upper limb and lower limb level [17]. WMSDs affect workers with different ages and types of occupations, with high costs for companies and the healthcare systems [7][13]. A possible way to reduce this problem is to monitor the biomechanical state of the worker during the day through wearable technologies [1].

To solve this problem, many works in literature provide solutions for the assessment of ergonomic indexes [15][11], fatigue quantification during working activities [4][16][8] and to enhance human-robot interaction [12]. Most of these approaches are based on recording of muscular activities to estimate fatigue and joints overload, relying on the usage surface ElectroMyoGraphic (sEMG) sensors. However, for a real deployment of this technology in large scale, it is important to recall that EMG sensors are usually expensive and, given the large number of muscles present in the human body, the amount of sensors needed to obtain a complete measure of the biomechanical state could be very large, with direct implications on costs and wearability of the sensing setup. Therefore, to increase the usability and acceptability of sEMG sensing systems, it is important to optimize the number and the placement of the sensor elements, without penalising the quality of the sensing.

A possible way to tackle the problem of dimensionality reduction is to exploit the concept of motor synergies. Introduced in [9], motor synergies are a set of strategies performed by the nervous system to handle the complexity of human body. This concept opens to the possibility to analyze the functional coordination of elemental motor variables targeting the execution of a given tasks. At the muscular level, a seminal work is [5], where authors found co-activation patterns during motion, usually named muscle synergies. From an observability point of view, the concept of synergies can be associated to the possibility to estimate the overall kinematic-muscular state in spite of a reduced amount of sensory information, exploiting the commonalities shared by the motor units. In [2], the authors presented a framework to estimate human arm biomechanical state (sEMG signals and joint trajectories) during daily-living activities from a reduced number of measurements. This approach relies on a Minimum Variance Estimation (MVE) algorithm combined with a representation based on functional Principal Component Analysis (fPCA) to exploit a dataset of recorded movements as *a priori* knowledge used to complement the whole-state estimation from a reduced set of optimal signals that minimize the estimation uncertainty in spite of scarce sensory information. However, the authors focused only on the application of this approach for the estimation of the human upper limb motion.

In this work, we validate the feasibility to generalize this approach to the estimation of the whole-body muscular state. To do this, we used a dataset containing movements performed during industrial tasks. Data were split in *a priori* and validation set. The first was used to identify the optimal sEMG placement to minimize estimation uncertainty, while the second was used to assess the performances of our method on data that were not used to build the a-priori knowledge. Interestingly, our results demonstrate that, starting from a set of 10 muscles, we can remove up to 3 sensors without substantially worsening the estimate obtained.

The paper is organized as follows: we first summarize the theoretical foundations of this method; then, we report the methods and the implementation of the optimization procedure on the whole-body dataset; finally, we discuss the results obtained in the reconstruction phase.

2 Theoretical Framework

As introduced in the previous section, the goal of this work is to provide an estimation of muscle activation signals using a limited number of sensor elements. To achieve this results we have choosen the Minimum Variance Estimation (MVE) approach to use the knowledge of *a priori* information provided by a set of data recorded in advance. However, to exploit the MVE approach, we need to represent movements in a static domain instead of the temporal domain. The strategy used in this work to solve the problem is the one presented in [2]. It relies on 3 different phases: i) an encoding phase to translate the signal from the time domain to a static representation obtained via functional Principal Component Analysis; ii) an estimation phase, in which MVE is used to estimate the missing information; and iii) a decoding phase to re-obtain the temporal evolution of state from the static representation.

2.1 Encoding Phase

The encoding phase is based on functional Principal Component Analysis (fPCA), an extension of Principal Component Analysis suitable to manage time-series. In a nutshell, given a dataset of time-varying data, fPCA extracts a basis of function ordered by importance (where the importance is represented by the explained variance of the dataset itself).

Considering a sEMG signal $m(t)$, its linear functional decomposition can be defined as:

$$m(t) \simeq \bar{m} + S_0(t) + \sum_{i=1}^{s_{max}} \alpha_i S_i(t), \tag{1}$$

where $\bar{m}$ is the average of the signal, $S_0(t)$ is the average temporal muscular activation profile through the whole dataset, $S_i(t)$ is the i^{th} functional Principal Component (fPC) and α_i is the weight associated to the element $S_i(t)$.

The first component of the basis of function $S_1(t)$ can be extracted from the dataset by solving the following problem:

$$\max_{S_1} \sum_{j=1}^{R} \left(\int S_1(t) m_j(t) dt \right)^2 \tag{2}$$

subject to

$$||S_1(t)||_2^2 = 1. \tag{3}$$

The other components $S_i(t)$ can be computed as:

$$\max_{S_i} \sum_{j=1}^{R} \left(\int S_i(t) m_j(t) dt \right)^2 \tag{4}$$

subject to

$$\begin{aligned} ||S_i(t)||_2^2 &= 1 \\ \int_0^{t_{end}} S_i(t) S_k(t) dt &= 0, \forall k \in \{1, ..., i-1\} \end{aligned} \tag{5}$$

For practical details on the implementation, the interested reader could refer to [14].

This decomposition can be applied to each recorded muscle to express the temporal activation profile into a set of weights. Given a set of M muscles, we can define an extended static state x_e representing a single trial as:

$$x_e = \left[\bar{m}_1 \ \alpha_{1,1} \ \dots \ \alpha_{1,k} \mid \bar{m}_2 \ \alpha_{2,1} \ \dots \ \alpha_{2,k} \mid \ \dots \ \mid \bar{m}_M \ \alpha_{M,1} \ \dots \ \alpha_{M,k} \right]^T. \tag{6}$$

2.2 Estimation Phase

The extended state defined in (6) permits to apply MVE for the estimation of temporal signals. In this section, we briefly summarize the principle behind the approach and we refer the interested reader to [3] for more details.

Considering a set of d sensors to measure the state of the system $x \in \mathbb{R}^l$, we can assume a linear relation between the state and the output and define the vector of measures $y \in \mathbb{R}^d$ as:

$$y = Hx + \nu \tag{7}$$

where $H \in \mathbb{R}^{d,l}$ is a full row rank measurement matrix and ν is the measurement noise. In the case where $d < l$ we have an infinite number of solutions defined as:

$$x = H^{\dagger} y + N_h \xi \tag{8}$$

where $H^{\dagger}$ is the pseudo-inverse of H, N_h represents the null space of H and $\xi \in \mathbb{R}^{l-d}$ is a free vector of parameters. Usually, the most common solution is to use the pseudo-inverse which returns the least-squared solution. However, this is not always the best solution in terms of error between the the real state and its estimation.

The solution proposed with the MVE is to exploit the covariation patterns between the elements of the state to reduce the estimation error. The information used is organized in a covariance matrix P_0 defined as:

$$P_0 = \frac{(X - \bar{x})(X - \bar{x})^T}{N - 1} \tag{9}$$

where $\bar{x}$ is a matrix whose columns contain the average μ_0 of X. Given P_0, the best estimate $\hat{x}$ of x is the vector which solves the following optimization problem:

$$\hat{x} = \operatorname{argmin} \frac{1}{2} (x - \mu_0)^T P_0^{-1} (x - \mu_0) \tag{10}$$

Assuming that ν is a zero mean Gaussian noise with covariance matrix R, the solution of (10) can be found in closed form as:

$$\hat{x} = (H^T R^{-1} H + P_0^{-1})^{-1} (H^T R^{-1} y + P_0^{-1} \mu_0) \tag{11}$$

We can also define the *a posteriori* covariance matrix as:

$$P_P = (H^T R^{-1} H + P_0^{-1})^{-1} \tag{12}$$

This matrix is important because it returns information regarding the uncertainty of the associated state estimation and can be used to select what element of the state has to be measured to maximize the information. To solve the problem we can set the following minimization:

$$H_{opt} = \operatorname*{argmin}_H \sigma_{max}(P_P(H)) \tag{13}$$

to find the optimal selection matrix H_{opt} and consequently the best set of muscle to be recorded.

2.3 Decoding Phase

After we computed the estimated extended state $\hat{x}_e$ we want to re-obtain the temporal evolution of the different signals represented by it. This step can be easily done using (1) to combine the original fPCs and obtain the reconstructed signal in the time domain.

3 Optimal Sensor Setup

3.1 Dataset

To validate our approach to whole-body muscles estimation we used the dataset available in [10], which consists of kinematic and muscular data of subjects performing different industrial-like tasks. The three tasks taken into account are: 1) lifting and lowering boxes with different weights from shelves at different heights; 2) drilling and 3) painting with a lightweight tool. Every subject involved in this dataset perfomed three repetition for each task condition. For the purpose of our study, we took into account only the post-processed muscular data of the right-handed subjects (10 out of 12). Muscular activation were recorded with a sEMG system (Delsys Trigno Wireless platform) and the signal processing consists in: normalization w.r.t. the maximum voluntary contraction, filtering with a 2^{nd} order Butterworth low-pass filter (cut-off frequency 2 Hz), and rectification. The list of the represented muscles can be found in Table 1. Given that each task is represented by a different number of movements, we randomly discarded part of the trials to create a task-balanced dataset.

Index	**Muscle**
1	Anterior Deltoid
2	Posterior Deltoid
3	Biceps Brachii
4	Triceps Brachii
5	Trapezius Descendens
6	Erector Spinae
7	Gluteus Maximus
8	Rectus Femoris
9	Biceps Femoris
10	Tibialis Anterior

Table 1: List of muscles recorded during task execution.

3.2 Sensor Optimization

Given the particular structure of the extended state, the matrix H is composed of block of k-dimensional diagonal matrices. To preserve this structure, we chose the genetic algorithm as method to solve the optimization problem, where each candidate solution is an N-element vector containing the N indexes of the muscles to be measured. In this way, given the single individual of the population, the matrix H can be easily computed and, combining it with the *a priori* knowledge, we can obtain the *a posteriori* covariance matrix P_P through (12). The optimal EMG sensor selection was identified minimizing the Shatten p-norm of P_P defined as:

$$\|P_P\|_p := \left(\sum s_n^p(P_P)\right)^{\frac{1}{p}} \tag{14}$$

The minimization of this cost function leads to the minimization of the maximum singular value of P_P, and consequently to the minimization of the uncertainty of estimation. The genetic algorithm was implemented using the software Matlab (Population size = 150, Max number of generations = 200, Elite Count = 10).

To verify the stability of our estimation procedure, the dataset was split in 10 groups, one for each subject, and a k-fold validation was implemented. For each iteration, one of the subjects was selected as a validation set, while the remaining ones was used to build the *a priori* knowledge. For each *a priori* dataset, we performed the fPCA to extract the principal components and the associated weights. Then, weights were used to compute the average μ_0 and the *a priori* covariance matrix P_0.

We performed the optimization for each fold with different number of sensors used (from 1 to 9). The results obtained, in terms of best values of the cost function reached, are reported in Fig. 1. We can observe that we can remove up to 3 sensors without

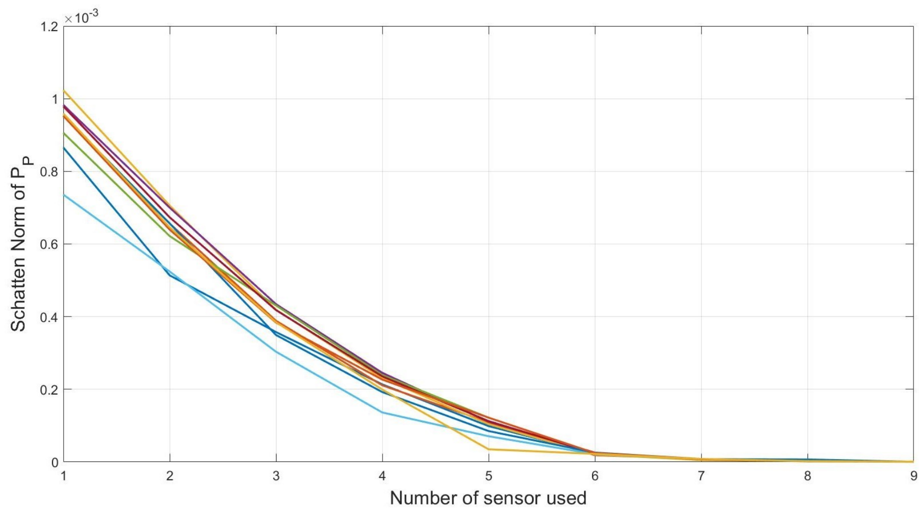

Fig. 1: Shatten Norm obtained for different subjects with different number of EMG sensors used

noteworthy deterioration of the estimation uncertainty. These 3 cases (usage of 7,8 and 9 sensors respectively) return also a stable muscle selection through different subjects used as validation set.

We have evaluated also the stability of the representation obtained with fPCA across different subjects. To do this, we performed the dot product to assess the similarity between fPCs of the same order and of the same degree of freedom. We obtained median values ranging from 0.998, for the first order component, to 0.952 for the fifth component. More details are reported in Table 2.

fPC Order	**0**	**1**	**2**	**3**	**4**	**5**
Median	0.9947	0.9980	0.9937	0.9858	0.9765	0.9524
75th Percentile	0.9978	0.9996	0.9989	0.9970	0.9947	0.9899
25th Percentile	0.9817	0.9908	0.9646	0.9148	0.8420	0.5962

Table 2: Median, 25^{th} and 75^{th} percentile of similarity index between functional components for each fPC order.

4 Results

To validate the reliability of our approach, we calculated the differences between the real recorded signal and the estimation for all the validation sets. We used as metric the Root Mean Square Error (RMSE). This procedure was repeated separately for the case with 7, 8 and 9 sensors used. In Fig. 2, the RMSE for all the muscles, in terms of percentage of

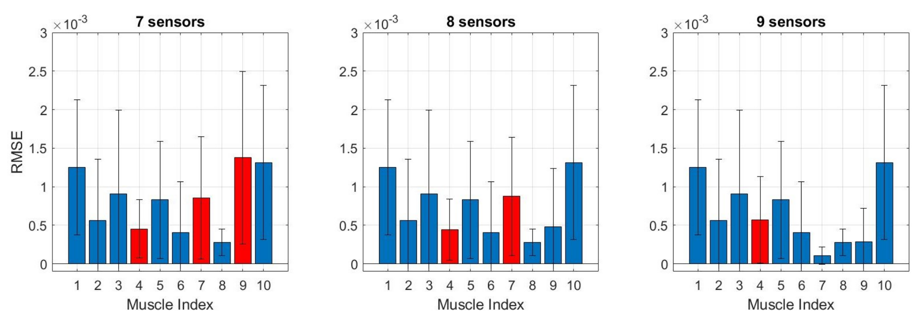

Fig. 2: RMSE (mean ± standard deviation) of optimal setup with different number of sensors. In blue the muscles directly measured while in red the muscles estimated with MVE

the maximum voluntary contraction, is reported as mean and standard deviation. Blue bars represent the muscles directly measured, while the red ones stand for the muscles estimated by the MVE. It is possible to observe that the estimation error made by the MVE is similar to the one introduced by the fPCA decomposition in measured muscles (which is the best achievable results given a fixed number of components used).

We also normalized the RMSE of each muscle with the maximum range reached on the dataset to compare the error with the muscle activation level of the tasks analyzed. The results in term of mean and standard deviation are represented in Fig. 3. In this case, there is a difference between recorded and estimated muscles. However, we can see that, even in the worst case, the average estimation error for the muscles is always below 13%.

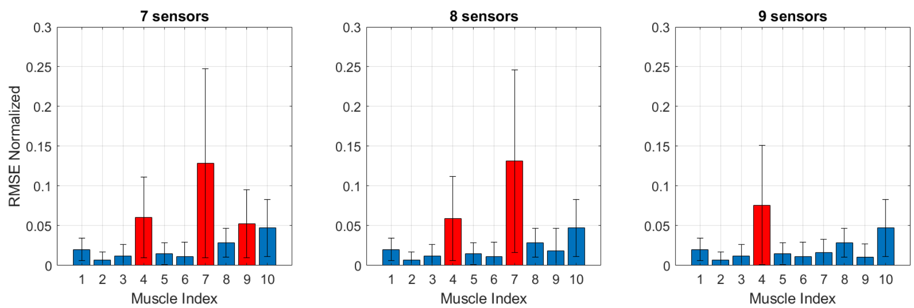

Fig. 3: RMSE normalized (mean $\pm$ standard deviation) with the maximum activation range for each muscles. In blue the muscles directly measured while in red the muscles estimated with MVE

However, these results can only inform on the average error of the reconstruction. To verify the reconstruction accuracy in time, we also compared the reconstructed temporal profile with the real data in time (see Figures 4 and 5). It is possible to notice that both the values and the shape obtained are very similar to the reference even with a modest sized sensory information available.

5 Discussions and Conclusions

Improve worker's body sensorization is a key factor to enhance human-robot interaction and assess its condition performing daily working activities. Obtaining a good estimation of the biomechanical state of the worker's body is essential to prevent injuries and ailments that - in the long term - can lead to chronic conditions that may affect the worker's daily life. One of the data necessary to carry out this assessment is that concerning the muscular activity which allows to monitor the state of fatigue of the worker. However recording all the muscles present in human body can be expensive and this type of measurement can be affected by different sources of noise. Furthermore, a system with a large number of sensors would create impairments to the worker in his activities, discouraging its use.

To reduce the number of sensor we took the Minimum Variance Estimation approach, which exploit the information contained in a *a priori* dataset to compensate for noisy or missing measurement, and we applied it to estimate whole body muscle activity. To do this, we used a dataset containing a set of working-like movement performed by different subjects.

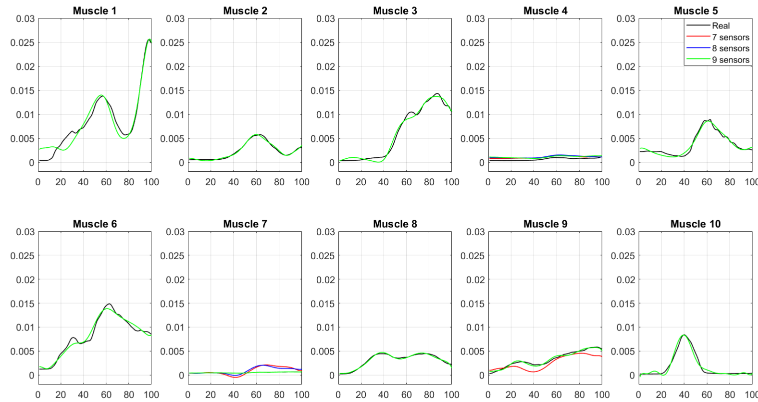

Fig. 4: Comparison between the real signal (black) and the MVE output using 7 (red), 8 (blue) and 9 (green) EMG sensors during a lifting action. The activation level is normalized with the Maximum Voluntary Contraction of each muscle. The estimated signals are Muscle 4 (for red, blue and green lines), Muscle 7 (for red and blue lines) and Muscle 9 (red line)

Given the small size of the dataset, we performed a k-fold validation using each subject as validation data. For each *a priori* set we performed an optimization to find the optimal sensor setup for each number of sensor elements possible. We found that, starting from a set of 10 sensors, we can remove up to 3 sensors without worsening the output. We also tested the consistency of the functional Principal Components representation through the different fold created. After that, we tested the goodness of the estimation obtained with this method evaluating the reconstruction error, both in absolute and in relative terms, for each validation set. The results obtained show that, in term of absolute error, the estimated muscles reach a level of precision similar to measured ones. In terms of relative error, the estimated muscles behave worst than the measured one. However only the Gluteus Maximum reaches an error higher than 10% (13.1%), while for the other 2 muscles the relative error is about 6%.

Despite the good result obtained, we believe that there is room of improvement for this work. The first step is to increase the number of muscles taken into account in order to obtain a more fine grained assessment of the entire body. However this approach requires a number of trials contained in the *a priori* dataset much larger of the dimension of the extended state and it is necessary to gather a new dataset containing an higher number of recorded movements. With a sufficient number of trials in the algorithm can be integrated also the kinematic data (as done in a previous work on human arm) to achieve a complete biomechanical estimation necessary for ergonomic assessment. Another point to be developed is the extension of this approach for real-time estimates. In fact, based on the fPCA decomposition to move from the time domain to the weight domain, it is necessary to have recorded the complete movement in time. An idea could

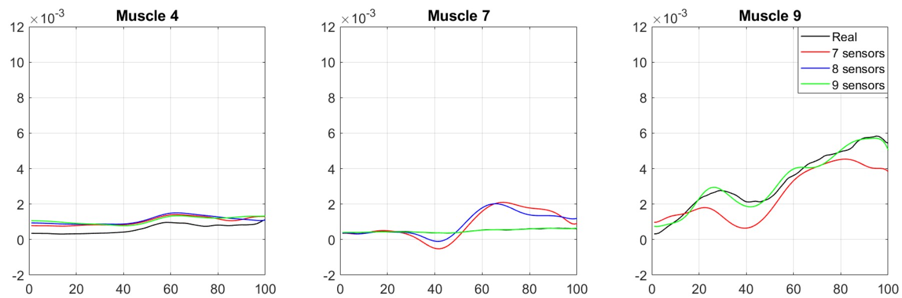

Fig. 5: Detail on the estimated muscles for action represented in Figure 4

be to iteratively perform this approach in real time using the movement recorded up to that moment. However, the feasibility of this solution is still under investigation.

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