2022 I-RIM Conference
October 7-9, Rome, Italy
ISBN: 9788894580532
DOI:10.5281/zenodo.7531398

Optimal electromyographic sensing for whole-body muscular activity estimation

Marco Baracca
Dept of Information Engineering
University of Pisa
Pisa, Italy
marco.baracca@phd.unipi.it

Giuseppe Averta
Dept of Control and Computer Engineering
Politecnico di Torino
Torino, Italy
giuseppe.averta@polito.it

Matteo Bianchi
Dept of Information Engineering
University of Pisa
Pisa, Italy
matteo.bianchi@unipi.it

***Abstract*—Recording the level of muscles activation while human perform daily-living activities is a key factor to obtain a comprehensive evaluation of the biomechanical state. This type of analysis is especially important in work environments to identify and then avoid possible risky behaviours which could lead to work-related musculoskeletal disorders. Usually, muscular activation is recorded via wearable electromyographic EMG sensors. However, to achieve a whole-body state estimation a large number of sensing elements is necessary. This leads to uncomfortable and very expensive setups that prevent their adoption for monitoring daily working activities. To overcome this problem, we propose a solution to provide a reliable estimation of muscular activation from a limited number of EMG recordings. Our method exploits the covariation patterns between muscular activation signals to complement the recordings coming from a reduced set of optimally placed sensors, minimizing the estimation uncertainty. We tested this approach with a dataset containing EMG data from 10 different subjects. We were able to reconstruct the temporal evolution of 10 whole-body muscular activations with only 7 sensor elements achieving a maximum normalized estimation error of 13%.**

***Index Terms*—Ergonomics, Human motion control, EMG, Optimal Sensing**

I. INTRODUCTION

Monitoring the biomechanical state of worker during daily activities is crucial to preserve quality of life and avoid injuries. Over 50% of European workers report disturbances while performing their daily working activities, which often results in chronic Work-related MusculoSkeletal Disorders (WMSDs) [1]. To reduce these risks different works in literature have addressed the assessment of ergonomics and fatigue level during working tasks [2] [3]. Most of them rely on the recording of muscular activation level which are usually captured using surface ElectroMyoGraphic (sEMG) sensors. However EMG sensors are expensive and, given the large number of muscles in human body, to achieve a full biomechanical assessment a large number of sensing elements is required with related problems of cost and wearability. Therefore, to increase the acceptability in the working environment, it is important to reduce the number of sensors and build a minimal sensing system capable to gather all the necessary information without impairing worker's motion.

This paper is part of a project that has received funding from European Union's Horizon 2020 Research and Innovation Program under Grant Agreement No. 101017274 (DARKO), and Grant Agreement No. 871237 (SOPHIA). The research leading to these results has received partial funding also from the Italian Ministry of Education and Research (MIUR) in the framework of the CrossLab project (Departments of Excellence), and in the framework of PRIN (Programmi di Ricerca Scientifica di Rilevante Interesse Nazionale) 2017 with the project TIGHT (Grant number 8182017SB48FP).

A possible way to tackle the problem of dimensionality reduction is to exploit the concept of muscle synergies. Introduced in [4], muscle synergies are co-activation patterns observed during human motion and, from an observability point of view, this concept opens to the possibility to estimate muscle temporal activity from a reduced set of sensors. In [5], the authors developed a new approach combining a Minimum Variance Estimation (MVE) algorithm with reduced representation based on functional Principal Component Analysis (fPCA) to estimate human arm biomechanical state from a reduced number of measurements. This framework is able to exploit a dataset of daily-living movements as *a priori* knowledge to complement the missing measurements. However, at the actual state, this methodology was applied only to upper limb estimation considering both joint trajectories and EMG signals.

In our work, we propose to extend this approach to whole-body muscular state estimation using as *a priori* information a dataset of industrial task recording. Interestingly, our results demonstrate that, starting from a set of 10 muscles, we can remove up to 3 sensors without substantially reduce the estimation accuracy.

II. THEORETICAL FRAMEWORK

In this work we propose to estimate whole-body muscle activation from a reduced number of sensor through Minimum Variance Estimation (MVE). For the sake of space, in this paper we give only a quick overview of MVE while for more detailed information we refer the interested reader to [6].

The MVE approach enables to exploit a dataset of recorded movement as *a priori* information to complete for missing measurements. Considering a system with a linear relation between the state x and the measurements y defined as:

$$y = Hx + \nu, \tag{1}$$

where H is a full row rank measurement matrix and ν is the measurement noise. If the dimension of the state vector

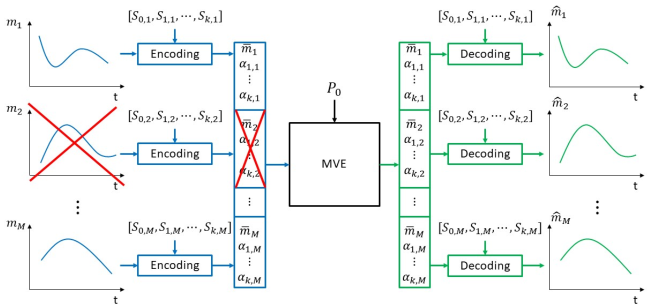

Fig. 1. Schematic overview of the estimation framework used in this work. Activation signals of a limited number of muscles are recorded and mapped in a static vector via a basis of functional Principal Components (fPCs) extracted in advance from an *a priori* dataset (Encoding phase). After that, the missing portionof the state is estimated using MVE exploiting the *a priori* covariance matrix P_0 (Estimation phase). Finally the whole temporal activations of muscles is reconstructed combining the fPCs with the estimated state (Decoding phase).

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 I
LIST OF MUSCLES RECORDED DURING TASK EXECUTION. THE OPTIMAL SETUP COMPOSED BY 7 SENSOR ELEMENTS IS ABLE TO ESTIMATE THE EMG SIGNALS OF *Triceps Brachii*, *Gluteus Maximus* AND *Biceps Femoris*.

is higher than the output vector there are infinite solution for a given measurement. Usually, the most used strategy in this case is to exploit the pseudo-inversion of matrix H to compute the least-squared solution. However, the results obtained with this approach are not always the closest to the real value of the state vector. MVE is able to exploit the covariation pattern between the elements of the state vector contained in a dataset recorded previously. This *a priori* information is organized in a covariance matrix P_0 defined as:

$$P_0 = \frac{(X - \bar{x})(X - \bar{x})^T}{N - 1}, \tag{2}$$

where $\bar{x}$ is a matrix whose columns contain the average μ_0 of X. Assuming that ν is a zero mean Gaussian noise with covariance matrix R, the best estimate $\hat{x}$ of x can be computed in closed form as:

$$\hat{x} = (H^T R^{-1} H + P_0^{-1})^{-1}(H^T R^{-1} y + P_0^{-1}\mu_0). \tag{3}$$

The uncertainty of this estimation can be evaluated through the *a posteriori* covariance matrix defined as:

$$P_P = (H^T R^{-1} H + P_0^{-1})^{-1}. \tag{4}$$

However, MVE is not able to handle temporal signals and it is necessary to encode the data in a static domain to enable a reliable estimation of P_0. To solve this problem we use an estimation framework divided in 3 different phases: i) the encoding phase, where the measured signals are translated from the time domain to a static domain; ii) the estimation phase where MVE is used to estimate the elements of the state vector related to the missing measurements; and iii) the decoding phase, where the estimated state vector is translated back in the time domain to re-obtain the temporal muscles activation. A graphical representation of this approach is depicted in Fig. 1.

To perform encoding and decoding phases we use functional Principal Component Analysis (fPCA), which is a functional extension of Principal Component Analysis. 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 signal $m(t)$, its linear functional decomposition can be defined as:

$$m(t) \simeq \bar{m} + S_0(t) + \sum_{i=1}^{s_{max}} \alpha_i S_i(t), \tag{5}$$

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 $S_i(t)$. More details on theoretical and practical aspects of fPCA can be found in [7]. With this approach we can translate easily a set of M time series in a static vector made by fPCs weights defined as:

$$x = \left[\bar{m}_1 \; \alpha_{1,1} \; \ldots \; \alpha_{1,k} \; | \ldots | \; \bar{m}_M \; \alpha_{M,1} \; \ldots \; \alpha_{M,k}\right]^T. \tag{6}$$

III. OPTIMAL SENSOR SETUP

A. Dataset and Validation

To validate our approach on whole-body muscles estimation we used the dataset available in [8], which contains data of subjects performing different industrial-like tasks (lifting and lowering boxes, drilling, and painting). During these tasks, the activity of ten different muscles (listed in Table I) were recorded in term of activation normalized w.r.t. maximum voluntary contraction. For more information on hardware and data processing we refer the interested reader to [8].

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 were used to build the *a priori* knowledge. The optimization was performed for each fold with different number of sensors used (from 1 to 9). Observing the values of the cost function obtained, we noted that we can remove up to 3 sensors noteworthy deterioration of the estimation uncertainty. We also observed that these 3 cases return a stable

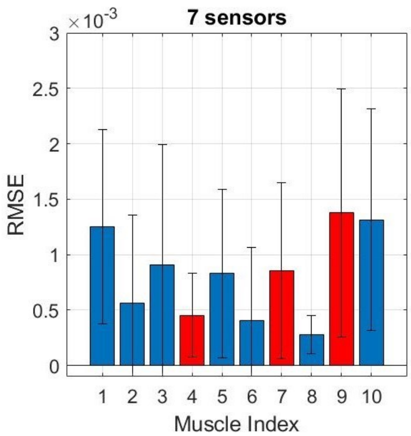

Fig. 2. Root Mean Square Error obtained by our approach using only 7 sensor out of 10. Blue bars represent the error performed by fPCA to reconstruct the measured muscles using the first 5 fPCs, while the red bars represent the estimation error performed by MVE using the same number of fPCs.

muscle selection through different subjects used as validation set.

B. Sensor Optimization

Given a fixed number of sensors, to select which muscles are the optimal in term of the estimation outcomes we have to choose an index which represent the goodness of the output as function of the sensor selection. For this purpose, the *a posteriori* covariance matrix P_P as defined in (4) can be the good choice to evaluate the estimation quality given a set of muscle measured. The optimal EMG sensor selection was identified minimizing the Shatten p-norm of P_P defined as:

$$\|P_P\|_p := \left(\sum s_n^p(P_P)\right)^{\frac{1}{p}} \tag{7}$$

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.

Given the particular structure of the state (defined in (6)), the matrix H is composed by blocks of k-dimensional diagonal matrices and we opted to perform optimization using a genetic algorithm to have guarantees on the structure of the matrix. For more information please refer to [5].

IV. Results

To validate the reliability of our approach, we have evaluated 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. For the sake of space, in this paper we show only the overall error regarding the setup with 7 sensors (Fig. 2). Values are reported as mean and standard deviation in terms of percentage of the maximum voluntary contraction. From the bar plot we can observe the estimation error made by the MVE is similar to the one introduced by the fPCA decomposition in measured muscles. In Fig. 3 we can also observe an example

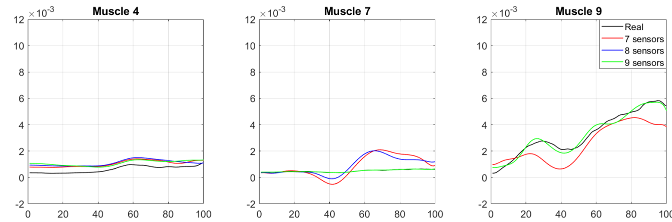

Fig. 3. Comparison between the real signal (black) and the estimation performed with our approach using 7 (red), 8 (blue) and 9 (green) sensors. Muscle activation profiles are represented as the electrical signal of the muscle normalized with the maximum voluntary contraction of the muscle itself.

of the reconstructed muscles with different number of sensor used (starting from 9 sensors setup, where only Muscle 4 is estimated, to 7 sensors setup where all muscles depicted are estimated). The plots show the capability of the approach to approximate well the shape of the real signal.

V. Conclusion

Muscular activity evaluation is fundamental to assess biomechanical state of human body. However the number of sensing elements can be a problem both in term of cost and wearability. For this reason reducing the number of sensors is crucial to produce more affordable whole-body sensorization. In our work we proved that we can exploit MVE combined with fPCA to find an optimal reduced sensor placement with an acceptable estimation error. The next steps of this work will be the increasing of the number of muscles involved in this analysis and the extension of this method to perform online estimation.

References

[1] J. De Kok, P. Vroonhof, J. Snijders, G. Roullis, M. Clarke, K. Peereboom, P. van Dorst, and I. Isusi, "Work-related musculoskeletal disorders: prevalence, costs and demographics in the eu," *European Agency for Safety and Health at Work*, vol. 1, 2019.

[2] H. Jebelli and S. Lee, "Feasibility of wearable electromyography (emg) to assess construction workers' muscle fatigue," in *Advances in informatics and computing in civil and construction engineering*. Springer, 2019, pp. 181–187.

[3] A. Ranavolo, A. Ajoudani, A. Cherubini, M. Bianchi, L. Fritzsche, S. Iavicoli, M. Sartori, A. Silvetti, B. Vanderborght, T. Varrecchia *et al.*, "The sensor-based biomechanical risk assessment at the base of the need for revising of standards for human ergonomics," *Sensors*, vol. 20, no. 20, p. 5750, 2020.

[4] A. d'Avella, P. Saltiel, and E. Bizzi, "Combinations of muscle synergies in the construction of a natural motor behavior," *Nature neuroscience*, vol. 6, no. 3, pp. 300–308, 2003.

[5] G. Averta, M. Iuculano, P. Salaris, and M. Bianchi, "Optimal reconstruction of human motion from scarce multimodal data," *IEEE Transactions on Human-Machine Systems*, 2022.

[6] M. Bianchi, P. Salaris, and A. Bicchi, "Synergy-based hand pose sensing: Reconstruction enhancement," *The International Journal of Robotics Research*, vol. 32, no. 4, pp. 396–406, 2013.

[7] J. O. Ramsay, *Functional data analysis*. Wiley Online Library, 2006.

[8] M. Lorenzini, W. Kim, and A. Ajoudani, "Human Kino-Dynamic Measurements Dataset for Factory-like Activities," 2021. [Online]. Available: https://doi.org/10.5281/zenodo.5575139