Project Network 2 “In Silico Models of Coupled Biological Systems”

PN2-4b: “Machine learning-based decomposition of the activity of individual motor units from synthetic and experimental data”

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1 Summary

Within this project, we aim to use synthetic data obtained from simulations to develop novel machine learning-based decomposition algorithms for identifying the activity of individual motor units in skeletal muscles. Compared to existing methods, we expect significant computational speed-ups and decomposition algorithms that identify with much better accuracy more motor units. The results of applying our newly developed algorithms to experimentally measured electromyographic (EMG) recordings will improve the overall understanding of the control of the neuromuscular system. These novel machine learning-based decomposition algorithms will be achieved by developing a 3D multi-domain model to simulate the activity of selected motor units during iso- and non-isometric contractions in muscles of arbitrary shape. The use of a conditional generative adversarial network (cGAN) will provide a flexible and powerful framework for EMG to motor unit activity translation, even in a nonlinear environment. As in silico experiments firing times of individual neurons are no longer unknown, computing the resulting EMG signal provides a basis for designing, training and validating novel machine learning-based decomposition methods. Since the exact motor unit distribution is not known, new measures for comparing synthetic and actual EMG data will need to be developed. A further aim of this proposal is to use these findings to extend the algorithms in such a way that it also can decompose motor units during non-isometric contractions – something that cannot properly be decomposed with existing methods yet. One path to achieve this is to utilise (continuum-mechanical) models to predict motion, and, hence, deformation and the shift of the motor units during contraction. As such, this project directly links to the vision of a Digital Human Model as outlined within the SimTech proposal.

2 State of the Art and Preliminary Work

2.1 State of the Art and Current Challenges

The decomposition of intramuscular or surface EMG signal is a blind source separation problem in practice. Given a single- or multi-channel or even high-density EMG measurement, one is interested to decompose the EMG measurement into trains of action potentials of individual motor units. The decomposition is called blind because the channel between the neurons of motor units as input to the EMG electrodes as output is unknown.

For this purpose, several decomposition algorithms have been proposed in the past decades, e.g., [L1, L2, L3, L4, L5, L6]. They rely on different principles. The quite simple precision decomposition (PD) algorithm in [L1] is a template matching technique. It detects sequentially activation potentials (pulses) in the EMG signal and assigns them to corresponding motor units based on a shape classification. This method assumes non-overlapping activation potentials in the time domain and fails in practice because, in the case of a large number of motor units, the activation potentials often overlap.

A more advanced method is known as convolution kernel compensation (CKC) [L2, L3, L4, L5]. It formulates the EMG measurement as a multi-input multi-output (MIMO) mixture of filtered trains of excitation pulses originating from the motor unit neurons. Under the assumptions of a) linear channel, b) overdetermined EMG measurement (i.e. more EMG channels than the number of active motor units) and c) uncorrelated pulse trains, a so called CKC operation eliminates the influence of the underlying channel between the neurons and electrodes and simplifies the decomposition problem to estimating the trains of possibly overlapping excitations. An iterative ad-hoc procedure is then applied to solve this problem. Recently, this technique is further combined with the fast independent component analysis (fastICA) algorithm [L6].

Despite of the continuous improvement in this area, there are still several challenges with respect to accuracy, reliability, and complexity. The assumptions of linear channel, overdetermined EMG measurement and independent/uncorrelated pulse trains are not always satisfied in practice. In addition, since the excitation pulse trains as input to the channel cannot be measured, all existing decomposition methods exploit the output EMG measurement only. Note that non-isometric contractions pose hereby a particular and largely unresolved challenge due to the movement of individual motor units during contraction.

This situation changes fundamentally because the applicant of the partner project PN2-4a has developed a 3D multi-domain model that is able to simulate the activity of selected motor units quite realistically during iso- and non-isometric contractions in muscles of arbitrary shape. The first time we have both access to the channel input (excitation pulse trains) and channel output (EMG measurement) of a possibly time-varying, linear or nonlinear, over- or underdetermined channel and can learn the channel for the inverse operation, namely decompose the EMG measurement into the excitation pulse trains.

2.2 Previous Work of the Applicants

The major research direction of the applicant is the algorithm development for model-based signal processing and data-driven machine learning, including deep learning, as well as the deployment of these algorithms in various applications. Some of these research works are closely related to the task in this project. In [P1], we studied the frequency-domain complex-valued instantaneous independent component analysis (ICA) for blind source separation and did a performance bound analysis for the demixing matrix. In [P2], the group of applicant studied, together with partners from the University Hospital Tübingen, spontaneous mechanical and electrical activities of human calf musculature by a joint magnetic resonance imaging (MRI) and sEMG measurement. In [P3], we used a deep fully convolutional neural network (CNN) to solve a special blind source separation problem, namely non-intrusive load monitoring (NILM). Given a single-channel total power consumption signal of a private household, a trained CNN is able to extract the binary activation profile (on/off at each time instance) of an individual electric device (e.g. fridge, microwave, wash machine). Different CNNs are required for the load monitoring of different electric devices. The task of blind source separation is thus solved by multiple single-load extractions. Recently, we deployed an even more modern deep learning framework, the conditional generative adversarial network (cGAN), to perform a signal-to-signal translation. This generative framework has been successively applied to different applications like motion correction, PET-to-CT translation in MR images [P4] as well as denoising of radar micro-Doppler spectrograms [P5].

2.3 Project-Related Publications of the Applicants

[L1] Lösch and B. Yang. Cramer-Rao bound for circular and noncircular complex independent component analysis. IEEE Trans. Signal Processing, 61:365–379, 2013.

[L2] M. Schwartz, G. Steidle, P. Martirosian, A. Ramos-Murguialday, H. Preissl, A. Stemmer, B. Yang, and F. Schick. Spontaneous mechanical activities in healthy human leg musculature visible in DWI and their relation to electrical activities in EMG. In Imaging in Neuromuscular Disease, 2017.

[L3] K. Barsim and B. Yang. On the feasibility of generic deep disaggregation for single-load extraction. In 4. NILM Workshop, 2018. (Best Paper Award)

[L4] K. Armanious, C. Jiang, M. Fischer, T. Küstner, K. Nikolaou, S. Gatidis, and B. Yang. MedGAN: Medical image translation using GANs. arXiv:1806.06397, 2018.

[L5] K. Armanious, S. Abdulatif, F. Aziz, B. Kleiner and B. Yang. Towards adversarial denoising of radar micro-Doppler signatures, arXiv:1811.04678, 2018.

3 Project Description

3.1 Project Goals

Within this project, we aim to use synthetic data obtained from simulations to develop novel machine learning-based decomposition algorithms for determining the activity of individual motor units in skeletal muscles. To do so we aim to

- develop strategies for motor unit recruitment (particularly including feedback),
- create a rich, artificial dataset comprising hundreds of neurons firing in different conditions and different geometries,
- develop novel machine-learning based decomposition methods,
- test the validity of decomposition in ideal conditions (prescribed vs detected spikes), and
- test the robustness of decomposition against common real-life variable conditions.

3.2 Approach and Work Programme

To achieve the above-mentioned project goals, we consider a part of the neuromuscular system consisting of motor neurons, their recruitment properties, and a skeletal muscle that is surrounded by a skin-fat layer. The computational framework of the project P2-4a is then used to generate rich artificial but realistic EMG signals together with the corresponding motor unit excitation pulse trains. These data are used to train a deep neural network in a supervised way to perform the decomposition. We plan to use the conditional generative adversarial network (cGAN), sometimes called the coolest thing in deep learning, for this EMG to motor unit excitation translation task. It is the first time that the EMG decomposition task is addressed by a supervised deep learning algorithm. This work builds on our recent successful experiences in [P3, P4, P5].

WP 1: Create a rich, synthetic dataset comprising hundreds of neurons firing in different conditions and different geometries (Lead: O. Röhrle)

Task B1.1 - Interaction with PN2-4a: It defines the experimental setup, the number of selected motor units, the number and arrangement of the EMG electrodes, the skin-fat layer etc. EMG signals and motor unit excitation trains are simulated and recorded synchronously under various conditions.

WP 2: Design and training of a cGAN for EMG decomposition (Lead: B. Yang)

Task B2.1 - Design of the cGAN architecture: A cGAN consists of a generator G and a discriminator D. G has the task to generate fake but realistic motor unit excitation pulse trains as output from the conditional input, the multichannel EMG measurement. D tries to distinguish between real (recorded) motor unit excitation trains and generated fake ones. By backpropagation during training, G continuously improves his faking technique to further fool D, while D tries to find new differences between real and generated motor unit excitation trains to avoid to be fooled. The result of this continuous competition between G and D is that the generated motor unit excitation pulse trains are indistinguishable from the real ones at the end. This is mathematically a minimax optimization problem (game theory). For both G and D, we plan to study two different types of neural network: 1D convolutional neural network (CNN) and 1D recurrent neural network (RNN) with long-short term memory (LSTM) neurons. The former is feedforward and relatively easy to train, while the latter has feedback and thus a longer memory to capture the temporal correlation of an excitation pulse train. By using this general setup, any input-output-relationship (linear or nonlinear, under- or overdetermined) can be learned from examples without any model.

Task B2.2 – Design of a suitable loss function and training: One special constraint of the excitation pulse unit is its sparsity in the time domain. This has to be considered during the end-to-end training by choosing a suitable loss function to optimize the model parameters of the cGAN. L1-norm and regularization are two feasible approaches. Then the designed cGAN will be trained by using the loss function to optimize the model parameters of the cGAN.

Task B2.3 – Variable number of motor units: Any deep neural network up to now has a fixed number of input and output channels. The number of the motor units, however, is unknown in advance and time varying depending on the force to be achieved. Given a fixed number of output channels of the trained cGAN, a way has to be found to deal with a varying number of motor units. A recursive interference cancellation may be a feasible approach.

WP 3: Test the accuracy and robustness of decomposition against common real-life variable conditions (Lead: O. Röhrle/B. Yang)

The developed new decomposition algorithm has to be validated on both generated data and real recorded EMG signals. The former is relative simple due to the availability of the ground truth, the motor unit excitation pulse trains used as input in the EMG simulation. Care must be taken by using suitable validation metrics in order to take both false positive and false negative into account. In the latter case, a validation is difficult because the input unit excitation pulse trains are unknown. Two approaches are possible to facilitate this problem: a) Using intramuscular EMG and expensive manual annotation of the excitation pulse trains. B) Using existing decomposition algorithms as “gold standard”.

4 Relevance for the Project Network and the Cluster

4.1 Relation to the Focus Challenges and Goals of the Project Network

The proposed project aims to address two focus challenges in data-integrated simulation science: (i) bridging data-poor and data-rich scales and (ii) merging physics- and data-based modelling. Both focus challenges will be simultaneously addressed within PN2-4 by developing novel multi-scale simulations predicting the electro-physiological state during (non-)isometric contractions. This is essential to train, analyze, and validate the proposed novel motor unit decomposition method. The challenge is to bridge data-poor scales, i.e. the input to or the output from the motor neuron pool (recruitment), with the data-rich scale, i.e. detailed spatial and temporal information about the electro-physiological and mechanical state of (parts of) the musculoskeletal system, to gain more information about the behavior of the neuromuscular system. One key challenge will be to validate the proposed machine-learning based decomposition algorithms. While simulated cases provide excellent test and training data, the challenge will be to apply these methods to real data and overcome the inter-subject variability of biological systems. This challenge also addresses the “Individualization” research question posed within this project network. Furthermore, by extending the newly developed methods to non-isometric cases will require efficient and resource-limited simulations – a further research question of this project network.

4.2 Cooperation in ExC 2075

PN2 links and collaborates with the following projects (ordered by its intensity of collaboration):

PN2-3: One of the research focuses of PN2-3 is to use EMG data to link sensory feedback and motor command strategies with EMG. While PN2-3 benefits from our novel decomposition algorithms, PN2-4 utilises the experimental setup to obtain EMG measurements.

PN7-1: The idea of PN7-1 is to enable complex musculoskeletal models in a pervasive computing environment. PN7-1 aims to use a hierarchy of recruitment models to drive the system. One of the recruitment models can be EMG measurements. For that reliable and fast decomposition methods are needed.

PN5-7: Profs Haasdonk and Pflüger focus in PN5-7 on physics- and data-based surrogate models for mechanical systems for UQ and beyond. Based on previous collaborations with both PN5-7 PIs, collaborations between PN2-4 and PN5-7 will benefit from surrogate models developed in PN5-7 to eventually realise model-based approaches to decompose motor unit activity under non-isometric conditions.

PN4-4: A long-term collaboration will be with Profs Eberhard und Allgöwer and their project PN4-4 on “Theoretical Guarantees for Predictive Control in Multi-Agent Robotics Applications”. The distributed control approach could potentially be translated to models of muscular recruitment, i.e. developing novel motor unit pool models for muscular recruitment.

4.3 Approval by the Project Network Board

The key focus of PN2-4 is on utilising multi-X models and machine-learning tools for developing novel motor unit decomposition methods in order to investigate aspects of the system response, i.e. the neuromuscular system. Project PN2-4 contributes to two focus challenges identified by the Cluster (FC2, FC3) and two research questions identified by the project network (RQ2, RQ5). Moreover, PN2-4 links to PN2-3 and significantly contributes to the SimTech’s vision of the Digital Human Model.

Therefore, the Project Network Board approves this project proposal.

5 Literature

[L1] De Luca, C.J., Adam, A., Wotiz, R., Gilmore, L.D. and Nawab, S.H., 2006. Decomposition of surface EMG signals. *Journal of neurophysiology*, *96*(3), pp.1646-1657, 2006.

[L2] Holobar, A. and Zazula, D.: Multichannel blind source separation using convolution Kernel compensation. IEEE Transactions on Signal Processing 55, 4487–4496, 2007.

[L3] Merletti, R.; Holobar, A. and Farina, D.: Analysis of motor units with high-density surface electromyography. Journal of Electromyography and Kinesiology 18, 2008.

[L4] Holobar, A.; Minetto, M. A.; Botter, A. and Negro, F.: Experimental Analysis of Accuracy in the Identification of Motor Unit Spike Trains. Transactions on Neural Systems and Rehabilitation Engineering 18, 2010.

[L5] Holobar, A.; Minetto, M. A. and Farina, D.: Accurate identification of motor unit discharge patterns from high-density surface EMG and validation with a novel signal-based performance metric. Journal of Neural Engineering 11, 2014.

[L6] Negro, F.; Muceli, S.; Castronovo A.; Holobar A. and Farina D.: Multi-channel intramuscular and surface EMG decomposition by convolutive blind source separation. Journal of Neural Engineering, 2016

6 Funds Requested and justification of additional funds

6.1 Standard funding

This project applies for the following standard package of funding:

	1st year	2nd year	3rd year	4th year	Total
Doctoral Position (TV-L 13)	0.5	0.5	0.5	0.25	1.75 years
PostDoc Position (TV-L 13)	-	-	-	-	0 years
HiWi hours (10 h/week)	0.5	0.5	0.5	0.25	1.75 years
Consumables	1.000 €	1.000 €	1.000 €	500€	3.500 €
Travel	0 €	1.000 €	2.000 €	2.000 €	5.000 €
Investments	750 €	750 €	750 €	0 €	2.250 €
Total	**1.750 €**	**2.750 €**	**3.750 €**	**2.500 €**	**10.750 €**

This project is ideal for a PhD student with a background in machine learning. It provides him with unique aspects to become an expert in the field of data-driven modelling and understanding of neuromechanics. The PhD student will closely engage with the PhD student of PN2-4a.

The travel cost above has been budgeted such that the PhD student can attend one conference within Year 2-4. The investment is planned for an extension of the ISS GPU server for this computationally demanding study.

6.2 Extra funding for specific instrumentation and consumables (if applicable)

None

6.3 Total funding requested

Standard funding (without personnel)	1.750 €	2.750 €	3.750 €	2.500 €	10.750 €
Extra funding	0 €	0 €	0 €	0€	0 €
Total	**1.750 €**	**2.750 €**	**3.750 €**	**2.500 €**	**10.750 €**