Inter-personal variability in muscle synergies for gait control

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Human gait control allows people to walk in diverse and quickly-changing environments that require adaptation to changes in external (*i.e.* slope, evenness) and internal (*i.e.* movement range, lesions) conditions. This is facilitated by a feedback loop between the central nervous system (CNS), which sends out motor commands, and the muscles in the periphery, which execute said commands and send sensory information back to the CNS. This sensory information is then integrated to modify future motor commands. Understanding how this sensory-motor feedback loop leads to fast and flexibly adaptive motor behavior would enable us to design better prosthetic and robotic controllers.

Motor and sensory signals live in a high-dimensional space, roughly determined by the amount of muscles in the body. Trying to implement a controller in those dimensions would require a very high computational cost, and would make its implementation impractical. However, it has been reported repeatedly that the brain works in lower dimensions to simplify the control problem [1, 2]. We call these lower-dimensional signals *motor* and *sensory synergies*. While motor synergies can be easily obtained through dimension-reduction techniques using non-invasive muscle activation data, sensory synergies are mostly a hypothesis due to experimental limitations [2].

In this project, we want to calculate muscle synergies in different walking conditions, and use the changes in muscle activation to estimate the dynamics of sensory signals, calculate their synergies, and close the control loop with neuro-inspired decision-making models [3]. A first result is the calculation of motor synergies with classical tools like principal component analysis (PCA) or non-negative matrix factorization (NMF). These synergies can then be compared across activities and subjects to determine their similarity, *i.e.* how similar the solutions to the motor problems are. As expected, synergies are similar across tasks, showing that a person uses similar strategies to walk in similar conditions, instead of learning entirely different ways to walk. However, comparing across subjects we can see that muscle synergies also differ significantly [4], indicating that different people reach different solutions for locomotion, due to either different exercise habits, body capacity, or chance.

Understanding how motor synergies vary not only across tasks but also across subjects allows us to better understand the control of gait, but also renders classical techniques like PCA and NMF impractical. In order to understand this variation fully, we need to separate the effects of different variables before doing the analysis of these “marginalized” traces. The analysis with demixed PCA (dPCA) [5] allows us to do just that. Figure 1 shows the activity of two muscles recorded on three subjects during one step (left column), and the isolation of different sources of variance. In the second column, we see the variance associated to time, *i.e.* an average step, and in column three, the variance associated to each person, *i.e.* how much the personal activity varies with respect to the average step. Dimension reduction can then be performed on each demixed signal to understand how muscle activation and synergies vary across different variables.

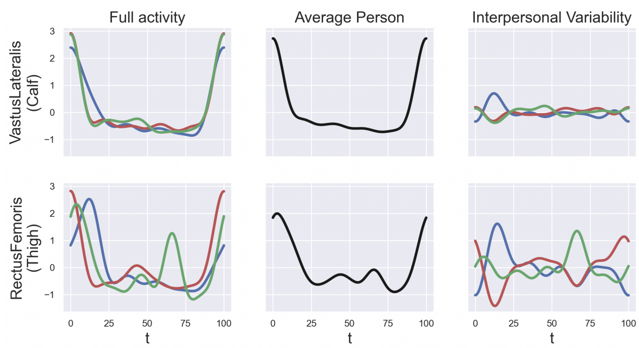

Figure 1: Marginalization of the data according to time and subject. Each row represents a muscle. Each column represents different contributions to the overall activity (first column). Most importantly, the last column shows the individual variation with respect to an average step.

References

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