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# Assessing the Relationship Between Gesture Intuitiveness and Muscle Network Efficiency: A Comparison of NMF and Inter-Muscular Coherence Analysis Methods †

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**Abstract**

This pilot study investigates the relationship between gesture intuitiveness and muscle network efficiency in human–machine interactions (HMIs), emphasizing objective neurophysiological measures. EMG signals from 16 muscles were analyzed to construct muscle networks based on synergies derived from non-negative matrix factorization (NMF) and intermuscular coherence (IMC) across three frequency bands. Metrics such as weighted global efficiency (WGE) and effective average strength (EAS) were correlated with gesture intuitiveness levels. Preliminary results suggest that WGE and EAS in synergy-based muscle networks, particularly in the Gamma 1 band, may be associated with perceived gesture intuitiveness ($p$ = 0.10 and 0.05, respectively). These findings suggest the potential utility of neurophysiological metrics to support the assessment of intuitive gestures, warranting further investigation with broader samples.

**Keywords:** gesture intuitiveness; muscle network efficiency; human–machine interaction; non-negative matrix factorization; intermuscular coherence; synergy-based muscle networks; coherence-based muscle networks; weighted global efficiency; effective average strength; gesture-based interfaces

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## 1. Introduction

Human–machine interaction (HMI) has gained significant attention as the demand for more natural and intuitive interfaces grows. With advancements in technology, gesture-based interfaces have emerged as a promising solution to enhance user engagement and simplify interactions with smart devices [1]. However, a persistent challenge in HMI research is the objective assessment of gesture intuitiveness—a key factor in determining how quickly and easily a gesture can be understood and used without prior training or

explanation. In this context, it is important to distinguish intuitiveness from naturalness. While intuitiveness refers to the user's immediate ability to infer the meaning or purpose of a gesture based on its design or context, naturalness concerns how closely a gesture resembles familiar actions from daily life or cultural conventions. A gesture can be intuitive without being natural, and vice versa. Clarifying this distinction is essential for developing and evaluating effective gesture-based interfaces [2]. Recent systematic reviews, such as that by Villarreal-Narvaez et al. (2020), highlight the complexities of gesture elicitation and the ongoing need for robust evaluation methods [1]. Traditional approaches often rely on subjective assessments through questionnaires, which, while useful, may lack reliability and consistency. In response, neurophysiological indicators, particularly those related to muscle synergy and coordination, offer a more objective and quantifiable approach to measuring intuitiveness. Specifically, features extracted from the muscle network (MN) provide valuable insights into the muscle synergies involved in movement execution [3,4].

Oscillatory activity in specific frequency bands plays a fundamental role in the organization and modulation of motor behavior. In the context of motor control, different rhythms are believed to support distinct functional demands, including movement preparation, execution, and feedback processing. Among these, Beta (13–30 Hz) and Gamma (30–80 Hz) oscillations have been consistently implicated in corticomuscular integration. Beta activity has been linked to the maintenance of steady motor output, motor inhibition, and the integration of sensory feedback during sustained or isometric contractions [5–7]. Gamma-band activity, in contrast, is more prominent during dynamic or phasic movements, where it supports rapid sensorimotor updates and the coordination of multi-joint actions [8–10]. Additionally, both bands show task-dependent modulation: for instance, Beta oscillations are influenced by visual feedback [11] and show transient suppression during movement initiation [12]. In this sense, Beta and Gamma frequency bands have been used to capture the neural underpinnings of muscle activity.

This study investigates whether improved coordination within MNs constructed using synergies derived from non-negative matrix factorization (NMF) and intermuscular coherence (IMC) can serve as a reliable indicator of gesture intuitiveness, shedding light on the efficiency of muscle activity and its relationship to natural gesture production.

The remainder of this paper is organized as follows. Section 2, 'Methods,' details the experimental setup, data acquisition, and methodologies employed for constructing muscle networks using NMF and IMC analysis. Section 3, 'Results and Discussion,' presents the findings regarding the relationship between muscle network efficiency metrics and gesture intuitiveness, along with a comprehensive discussion of these results. Finally, Section 4, 'Conclusions and Future Work,' summarizes the key findings of this study and outlines directions for future research.

## 2. Methods

One healthy left-handed male participant (25 years old, no neuromuscular disorders) performed seven FOLLOW ME-related gestures in response to verbal instructions. Each gesture was repeated six times in a randomized order, with 5-second intervals and 3-minute breaks between series (Figure 1).

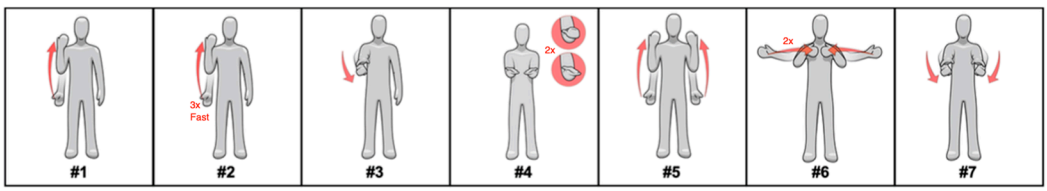



**Figure 1.** Schematic representation of the seven gestures performed by the participant.

The active movement phase for each gesture was defined from the onset of limb movement until the return to the initial position. A linear position transducer attached to both forearms was used to obtain motion data. Electromyography (EMG) data were collected from eight muscles per upper limb to capture muscle activity associated with each gesture. Skin surface preparation and electrode placement were performed according to the SENIAM guidelines (Figure 2). The EMG signals underwent filtering using a fifth-order Butterworth filter with a bandpass range of 13–90 Hz and a band-stop between 49 and 51 Hz to eliminate noise.

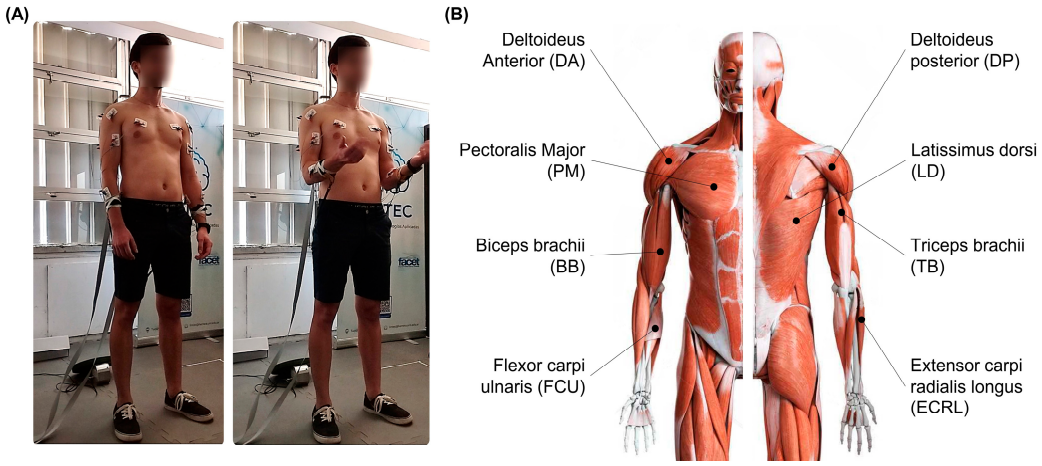



**Figure 2.** (**A**) Experimental setup: on the left, the subject observes the instructions; on the right, the subject performs gesture #4. (**B**) Schematic layout of muscle sensors on the front and back of the subject's body.

Non-negative matrix factorization (NMF) is a computational technique used to assess muscle synergy by decomposing EMG signals into simpler, non-negative components [13]. It separates EMG data into two matrices: the synergy matrix (W), which represents the activation patterns of individual muscle synergies, and the activation matrix (H), which describes the time-varying contributions of these synergies to overall muscle activity. This decomposition, expressed as $EMG \approx W \cdot H$, enables the analysis of how muscles coordinate and how these synergies are modulated over time. The synergy analysis was performed on EMG data filtered into three frequency bands: Beta (15–29 Hz), Gamma 1 (31–49 Hz), and Gamma 2 (51–80 Hz).

Intermuscular coherence (IMC) was calculated for 120 comparisons between muscle pairs for the same three frequency bands. This process followed five steps, as proposed in Bigot et al. [14]: auto-spectrum and cross-correlation analysis, mean auto-spectrum computation, magnitude-squared coherence estimation, and identification of statistically significant coherence regions.

Muscle networks (MNs) were then constructed using graph theory for each gesture. In these networks, each node represents a muscle, and edges indicate the connectivity strength between muscles, derived from both synergy and coherence data. A connectivity matrix quantifies these connections, with each value representing the strength of interaction between two muscles. This matrix serves as the foundation for building MNs, allowing for the analysis of muscle coordination patterns.

Connectivity matrices for synergies were obtained by calculating the outer product of each column in the synergy matrix W, where each element represents the weighted co-occurrence of two muscles within the same synergy [4]. The connectivity matrices for all synergies were averaged to create a single connectivity matrix representing the synergy-

based muscle network (SMN) for each gesture within each frequency band. We obtained 21 SMNs (7 gestures × 3 frequency bands).

For the IMC, connectivity matrices were constructed by assigning the IMC values of each muscle pair to their corresponding positions in the matrix. A coherence-based muscle network (CMN) was created for each gesture within each frequency band. Again, 21 CMNs were obtained (7 gestures × 3 frequency bands).

Finally, the SMNs and CMNs were analyzed to assess their spatial connectivity patterns. Quantitative evaluation employed metrics such as weighted global efficiency (WGE) [15] and effective average strength (EAS) [16] to characterize the network efficiency.

While WGE provides a comprehensive measure of integration across the entire muscle network, its sensitivity to gesture-specific muscle recruitment and dependence on network size may limit its ability to fully capture intuitive motor patterns, particularly in asymmetric or unilateral movements. In contrast, the EAS metric focuses exclusively on the functional pairs of muscles engaged in each gesture, mitigating the confounding influence of inactive nodes and offering a more task-relevant assessment of gesture execution [16]. Unlike other metrics, such as the clustering coefficient, which emphasizes localized connectivity and modularity, EAS better reflects the distributed, coordinated muscle activations underlying intuitive gestures. The clustering coefficient quantifies the tendency of nodes to form tightly interconnected subgroups, a feature that could be less informative in muscle networks, where functional coordination often relies on long-range interactions rather than localized clustering. Given our focus on efficiency and asymmetry in whole-limb gestures, metrics like the clustering coefficient offer limited insight into the dynamic, task-specific synergies that define intuitiveness. Thus, by analyzing the correlation between WGE and EAS with the intuitiveness level, we propose an exploratory analytical approach that balances system-wide connectivity with functional relevance, offering preliminary insights into the evaluation of gesture intuitiveness in HMI.

Correlations between these metrics and the intuitiveness level (IL) [2] associated with each gesture were analyzed to investigate the relationship between network efficiency and gesture intuitiveness.

To evaluate the association between muscle network metrics and gesture intuitiveness, Kendall's Tau-b correlation coefficients were computed. This non-parametric statistic was chosen due to the ordinal nature of the intuitiveness level (IL) and the small sample size ($n = 7$), which may violate the assumptions of normality required for parametric correlation tests, such as Pearson's $r$. Also, Tau-b is particularly suited for data with tied ranks, which can occur in gesture ratings.

The overall procedure is depicted in Figure 3.

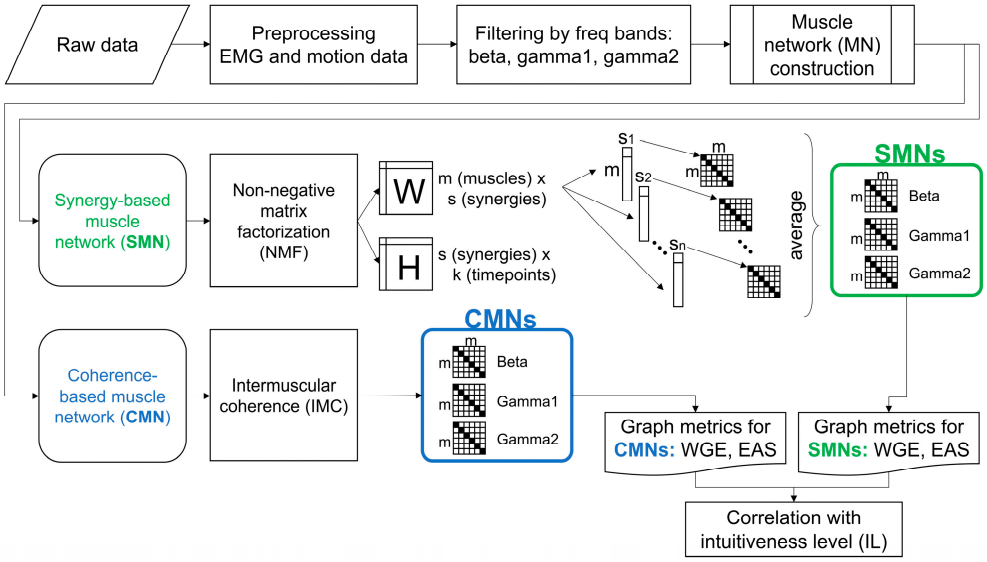



**Figure 3.** Processing flowchart showing the steps from raw data to muscle network construction. The top row illustrates the pre-processing stages applied to raw data, the middle row depicts SMN construction (green) via NMF, and the bottom row shows CMN construction (blue) using IMC analysis. The bottom-right corner highlights the extraction of graph features and the statistical correlation analysis.

## 3. Results and Discussion

The analysis of synergy-based muscle networks (SMNs) revealed a markedly higher connectivity compared to coherence-based muscle networks (CMNs), for the three frequency bands, as illustrated in Figure 4.

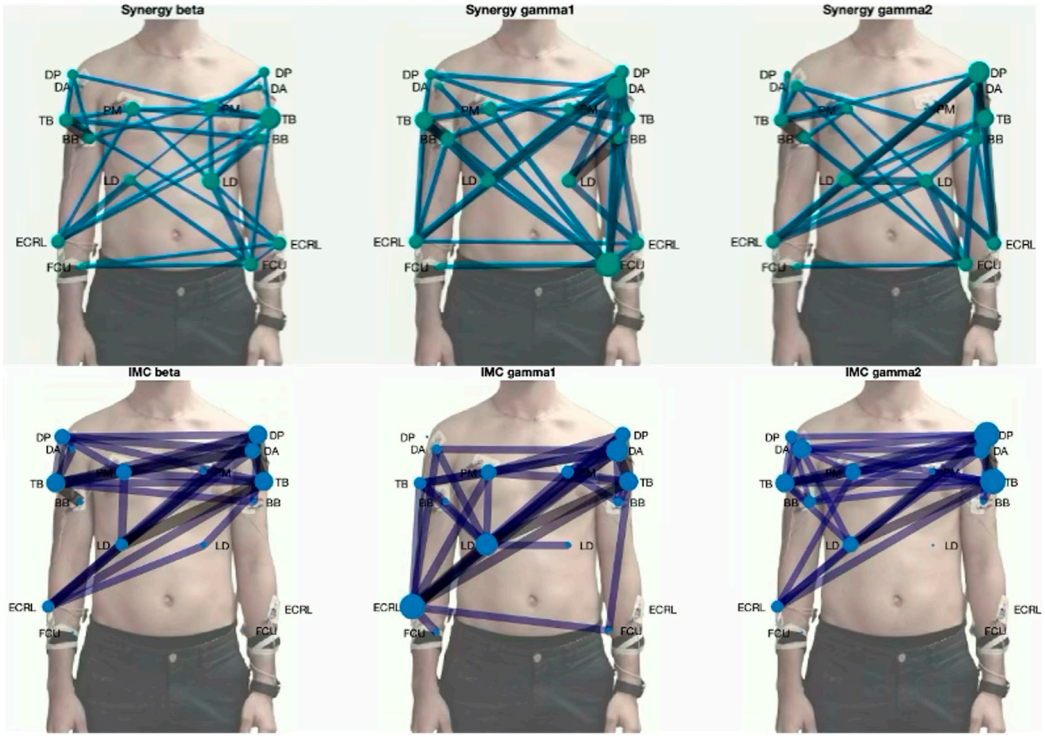



**Figure 4.** Example muscle networks (MNs) for gesture #4 across the Beta, Gamma 1, and Gamma 2 frequency bands. The first row displays synergy-based MNs (green) constructed using the non-negative matrix factorization method. The second row shows coherence-based MNs (blue) constructed using intermuscular coherence analysis.

The intuitiveness level (IL) of the seven most intuitive gestures, identified through the methodology described by Canuto et al. [2], is presented in Table 1. These gestures achieved the highest IL values among participants, highlighting their ease of recognition and natural association with the FOLLOW ME command. The IL metric serves as a quantitative indicator of how effectively each gesture aligns with user expectations, making it a suitable indicator for assessing the applicability of gestures in gesture-based human–machine interaction systems.

**Table 1.** The intuitiveness level (IL) of the seven gestures evaluated in this study.

| Gesture | #1 | #2 | #3 | #4 | #5 | #6 | #7 |
|---|---|---|---|---|---|---|---|
| IL | 1.0000 | 0.0965 | 0.3533 | 0.4657 | 0.3916 | 0.0491 | 0.1962 |

The weighted global efficiency (WGE) and effective average strength (EAS) metrics for different gestures across the Beta, Gamma 1, and Gamma 2 frequency bands, calculated from both SMNs and CMNs, are presented in Table 2. It is important to note that, due to the fundamental differences in their construction (synergy-based via NMF vs. coherence-based via IMC), the absolute connectivity values (WGE and EAS) derived from SMNs and CMNs are not directly comparable in magnitude, but rather provide insights into distinct aspects of muscle coordination. Visual inspection of Table 2 suggests that SMNs generally exhibit higher absolute WGE and EAS values across gestures and frequency bands compared to CMNs, reflecting the nature of synergy-based network metrics.

**Table 2.** Weighted global efficiency (WGE) and effective average strength (EAS) metrics for different gestures across three frequency bands (i.e., Beta, Gamma 1, Gamma 2), calculated from both synergy-based muscle networks (SMNs) and coherence-based muscle networks (CMNs).

| Gesture | Metric | Beta | | Gamma 1 | | Gamma 2 | |
|---|---|---|---|---|---|---|---|
| | | SMN | CMN | SMN | CMN | SMN | CMN |
| #1 | WGE | 0.1133 | 0.0472 | 0.0855 | 0.0357 | 0.0846 | 0.0529 |
| #2 | | 0.1287 | 0.0531 | 0.0665 | 0.0290 | 0.1156 | 0.0489 |
| #3 | | 0.1037 | 0.0691 | 0.0893 | 0.0510 | 0.0699 | 0.0674 |
| #4 | | 0.0506 | 0.0652 | 0.0916 | 0.0550 | 0.0770 | 0.0523 |
| #5 | | 0.0704 | 0.0779 | 0.0972 | 0.0610 | 0.0739 | 0.0391 |
| #6 | | 0.0719 | 0.0612 | 0.0347 | 0.0525 | 0.0974 | 0.0501 |
| #7 | | 0.0609 | 0.0611 | 0.0461 | 0.0549 | 0.0518 | 0.0434 |
| #1 | EAS | 0.4628 | 0.2250 | 0.4179 | 0.1736 | 0.4174 | 0.2542 |
| #2 | | 0.5423 | 0.2829 | 0.3351 | 0.1804 | 0.5584 | 0.2153 |
| #3 | | 0.4237 | 0.3809 | 0.4193 | 0.2525 | 0.3719 | 0.3707 |
| #4 | | 0.2617 | 0.3635 | 0.4062 | 0.2428 | 0.4278 | 0.2587 |
| #5 | | 0.3489 | 0.2788 | 0.3633 | 0.2288 | 0.4098 | 0.1976 |
| #6 | | 0.3200 | 0.2978 | 0.2218 | 0.2077 | 0.4524 | 0.2001 |
| #7 | | 0.3607 | 0.3136 | 0.2226 | 0.2040 | 0.3089 | 0.1868 |

Table 3 illustrates the Kendall's Tau-b correlation coefficients between the IL and the WGE and EAS metrics, computed using both SMNs and CMNs across the Beta, Gamma 1, and Gamma 2 frequency bands. Significantly, the metrics of WGE and EAS for the SMN in the Gamma 1 band demonstrated a positive correlation with IL.

**Table 3.** Kendall's Tau correlation between intuitiveness level (IL) and WGE/EAS metrics across Beta, Gamma 1, and Gamma 2 frequency bands for IMC and muscle synergy data.

| Metric | Beta | | Gamma 1 | | Gamma 2 | |
|---|---|---|---|---|---|---|
| | **SMN** | **CMN** | **SMN** | **CMN** | **SMN** | **CMN** |
| WGE | −0.143 | 0.048 | 0.524 * | 0.143 | 0.048 | 0.143 |
| EAS | −0.048 | −0.143 | 0.619 ** | 0.048 | −0.048 | 0.238 |

* $p < 0.1$ ** $p < 0.05$.

The Kendall's Tau-b correlation coefficients for WGE and EAS in the SMN on the Gamma 1 band were statistically significant at the $p = 0.1$ and $p = 0.05$ levels, respectively. These preliminary results suggest that gestures associated with higher connectivity and strength in muscle networks tend to be perceived as more intuitive. This supports the hypothesis that enhanced muscle coordination may serve as a physiological indicator of gesture intuitiveness and underscores the potential of synergy-based neurophysiological metrics to inform the design and evaluation of gesture-based interfaces in human–machine interaction.

These findings can be further contextualized within broader theoretical frameworks of motor control and embodied cognition. The sensorimotor system, which includes brain regions responsible for perceiving, simulating, and executing actions, underpins how conceptual knowledge is formed and accessed [17]. Intuitive gestures tend to activate well-established motor patterns that require minimal cognitive effort or adaptation [18,19]. Such gestures draw on familiar movements and motor primitives, which are grounded in everyday experience, enabling fluid execution and quick interpretation. According to embodied cognition theories, intuitive understanding emerges when interactions align with the body's natural movement tendencies and sensorimotor history [20]. From this perspective, the structure and efficiency of muscle networks (MNs) can serve as physiological markers of how naturally and intuitively a gesture is performed. By quantifying these properties through metrics such as EAS, the study sheds new light on the embodied foundations of gesture intuitiveness and supports the development of interaction systems that are more attuned to human motor and cognitive processes.

Moreover, our results are consistent with the principle of motor efficiency from the optimal feedback control framework in motor neuroscience, which postulates that effective movements minimize effort and variability while achieving task goals [21]. In our single-subject data, gestures with higher intuitiveness levels (ILs) tended to show stronger and more coherent muscle coordination, which may reflect the engagement of pre-established motor schemas. These exploratory results support the notion that intuitive gestures may rely not only on cognitive associations but also on embodied motor patterns developed through experience.

Although based on a limited sample, these initial findings may have implications for the design of gesture-based interfaces. Identifying gestures that are associated with more efficient muscle coordination—as measured by WGE and EAS—could help inform the development of interaction strategies that are not only perceived as intuitive but also physiologically aligned with natural movement patterns. Such dual considerations may contribute to improving user experience in specific applications such as rehabilitation, assistive technologies, or robotics. Further studies with broader populations are needed to validate this potential.

## 4. Conclusions and Future Work

This pilot study explored the potential relationship between gesture intuitiveness and muscle network (MN) efficiency using neurophysiological metrics derived from non-

negative matrix factorization (NMF) and intermuscular coherence (IMC). Preliminary results suggest that gestures associated with higher intuitiveness levels tended to exhibit greater network connectivity and efficiency, particularly in synergy-based muscle networks in the Gamma 1 frequency band.

While these findings are promising, they must be interpreted with caution due to the exploratory nature of the study and the limited sample size (a single participant). As such, the results should be considered indicative rather than conclusive.

Future research will aim to expand the sample to include a more diverse group of participants and a broader range of gesture types, including less intuitive ones. This will help improve the generalizability and robustness of the results and allow for a more comprehensive understanding of how muscle synergies relate to gesture intuitiveness. Ultimately, such insights could contribute to the development of more natural and effective gesture-based interaction systems.

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