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To cite this article: Andrea Gigli et al 2023 J. Neural Eng. 20 066016

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26 October 2023

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PUBLISHED 24 November 2023

23 May 2023

Journal of Neural Engineering

PAPER

Progressive unsupervised control of myoelectric upper limbs

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Keywords: coadaptive myocontrol, unsupervised myocontrol, muscle synergies, surface electromyography, motor skill learning Supplementary material for this article is available online

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e. Abstract

Objective. Unsupervised myocontrol methods aim to create control models for myoelectric prostheses while avoiding the complications of acquiring reliable, regular, and sufficient labeled training data. A limitation of current unsupervised methods is that they fix the number of controlled prosthetic functions a priori, thus requiring an initial assessment of the user's motor skills and neglecting the development of novel motor skills over time. Approach. We developed a progressive unsupervised myocontrol (PUM) paradigm in which the user and the control model coadaptively identify distinct muscle synergies, which are then used to control arbitrarily associated myocontrol functions, each corresponding to a hand or wrist movement. The interaction starts with learning a single function and the user may request additional functions after mastering the available ones, which aligns the evolution of their motor skills with an increment in system complexity. We conducted a multi-session user study to evaluate PUM and compare it against a state-of-the-art non-progressive unsupervised alternative. Two participants with congenital upper-limb differences tested PUM, while ten non-disabled control participants tested either PUM or the non-progressive baseline. All participants engaged in myoelectric control of a virtual hand and wrist. Main results. PUM enabled autonomous learning of three myocontrol functions for participants with limb differences, and of all four available functions for non-disabled subjects, using both existing or newly identified muscle synergies. Participants with limb differences achieved similar success rates to non-disabled ones on myocontrol tests, but faced greater difficulties in internalizing new motor skills and exhibited slightly inferior movement quality. The performance was comparable with either PUM or the non-progressive baseline for the group of non-disabled participants. Significance. The PUM paradigm enables users to autonomously learn to operate the myocontrol system, adapts to the users' varied preexisting motor skills, and supports the further development of those skills throughout practice.

1. Introduction

Myoelectric prosthetic hands can restore or enhance independence for individuals with limb differences, enabling them to perform various activities of daily living [1, 2]. Machine learning-based myocontrol approaches offer intuitive control of advanced prostheses [3] and are currently available in commercial systems [4, 5]. Classification techniques enable control over multiple grasp types by defining an association between muscular activity and the desired grasp [6, 7], while regression methods establish a continuous mapping between the user's muscle activations and motor commands for the degrees of freedom (DoFs) of the prosthesis [8, 9]. These techniques typically learn the myocontrol model in a supervised way, meaning that surface electromyography (sEMG) measurements of the forearm's muscles are associated with prescribed motor commands during a calibration phase.

Supervised myocontrol relies on the assumptions that the distribution of the control signal remains

consistent between training and testing conditions, and that training samples are accurately labeled [10]. However, meeting these assumptions in a realistic setting poses methodological challenges. The characteristics of sEMG signals can change over time due to factors like muscle fatigue, limb position, and electrode displacement [11, 12]. Common approaches to reduce this distribution shift involve capturing more of the signal variability in the training data [13, 14] or iteratively recalibrating the system with additional data over time [15, 16]. These methods come therefore at the cost of an increased burden on users by prolonging the data acquisition process. Additionally, accurately labeling samples can be difficult for individuals with limited residual muscle control, such as those with limb differences. Extensive preprosthetic user training is often required to generate muscle signals that are sufficiently distinguishable, stable, and repeatable for myocontrol. This typically includes mental practice, emulation of specific gestures using the phantom limb, and sEMG visualization using biofeedback [17, 18]. However, such training can be demanding and requires supervision from healthcare professionals. The requirement for expert guidance typically confines preprosthetic training to clinical facilities, which increases the associated costs, limits the user's exposure to training, and potentially slows down the adoption of the myocontrol technology [18].

Unsupervised myocontrol is a desirable alternative to supervised myocontrol, as it eliminates the need for hard-to-obtain labeled training data. Existing unsupervised myocontrol approaches derive lowdimensional approximations of the muscular input, corresponding to distinct muscle coactivation patterns, and employ them as control commands for the kinematic or kinetic variables of interest [19-22]. This is based on the neuromotor control principle that the human nervous system efficiently realizes movement by recruiting and coordinating nonredundant muscle synergies [23-25]. In this context, the nervous system treats the activations of each muscle synergy as high-level motor commands that can be combined to generate the muscular activity necessary to accomplish the desired movement. This also entails that information about the synergies' structure and coactivation is encoded into multichannel sEMG measurements of the muscular activity [24].

Nonnegative matrix factorization (NMF) algorithms are commonly utilized to extract muscle synergies from sEMG signals. The advantage of this specific factorization is that it decomposes signals into linear nonnegative combinations of nonnegative components, which mirrors the central nervous system's approach of combining nonnegative antagonistic muscle activations [24–26]. In addition, using these components as control inputs for prosthetic

devices enables users to naturally control multiple prosthetic functions at once and adjust their intensity proportionally. However, standard NMF solutions can be ill-posed, and they therefore need particular training procedures or formulations to enforce the identification of minimally overlapping components that could serve as reasonable proxies for muscle synergies [19, 26].

Jiang *et al* [19] proposed a minimally supervised approach for simultaneous and proportional (SP) myocontrol of a virtual cursor using muscle synergies related to wrist movements. To identify these synergies, they developed a DoF-wise calibration of the myocontrol system, which involved concatenating partial NMF models trained on sEMG data of antagonistic movement pairs, taking advantage of the distinct muscle activation patterns each pair generated. This method reduced supervision compared to traditional approaches, but still required users to perform specific movements in a predefined order, potentially posing challenges for individuals with limb differences.

Building on this work, Lin *et al* [20] developed an extension that imposed sparsity constraints on NMF to allow for a more flexible calibration procedure. During this calibration, participants were allowed to perform random wrist movements, engaging multiple DoFs of the wrist simultaneously. The sparse NMF formulation encouraged the extraction of minimally overlapping components, which were then manually associated with the control of the desired cursor directions. This manual association was performed to ensure an intuitive correspondence between muscle synergies and cursor directions but required direct supervision during the process. Moreover, their calibration procedure explicitly excluded finger movements, which could hinder the identification of potentially more effective muscle commands and could prove challenging for individuals who struggle to isolate wrist and hand movements.

Yeung et al [21] designed an adaptive version of the paradigm by Lin et al [20], in which the factorization model was automatically updated during operation to account for changes in muscle synergies caused by the nonstationarity of sEMG and the user's adaptation to the myocontrol system. The same quasi-unsupervised calibration procedure was followed to build a myocontrol model for a prosthetic wrist, which involved performing specific actions in an unstructured manner and manually defining a biomimetic motor mapping between muscle synergies and wrist actions. The myocontrol system automatically updated the factorization model when it detected model degradation, characterized by increased coactivation of antagonistic muscle synergies. Model updates were made possible by adopting an incremental NMF approach with sparsity constraints and **IOP** Publishing

a forgetting mechanism to gradually reduce the influence of older data. Even though this incremental NMF formulation allowed for fully unsupervised model updates, the paradigm still relied on a partially supervised and constrained calibration procedure to create a biomimetic motor mapping for myocontrol in the first place.

Other approaches have also attempted to reduce the amount of supervision necessary for defining biomimetic motor mappings. This includes methods that identify relationships between muscular activity and kinematic variables in a shared latent space [27, 28], or those leveraging musculoskeletal models to estimate forearm muscle forces directly from electromyographic recordings [29]. However, these strategies still require a loosely supervised calibration phase, involving synchronized acquisition of sEMG and ground truth data for the estimated kinematic variable.

As an alternative to biomimetic mappings, abstract motor mappings can be adopted to implement fully unsupervised myocontrol. This type of mapping, commonly used in supervised myocontrol approaches, links muscle activations to hand gestures without requiring a direct physiological relationship between them [30, 31]. Research shows that humans can learn such arbitrary mappings, including muscle synergy-based ones, through closed-loop interaction with a myocontrol system, making them a viable approach for prosthetic control [24, 32]. Abstract motor mappings based on muscle synergies provide flexibility and robustness, enabling users to control complex hand actions with comfortable, reliable, and stable muscle activations [22, 33], while also being more resistant to variations in myoelectric signals due to the muscle synergies' focus on underlying muscle coactivation structures [24].

Gigli et al [22] used abstract motor mappings to devise a fully unsupervised coadaptive simultaneous and proportional myocontrol paradigm for hand and wrist actions. Similarly to the method from Yeung et al [21], this also originated as an adaptive extension of the work of Lin et al [20]. However, this approach completely eliminated the need for initial model calibration and allowed users to identify viable muscle inputs autonomously. This was achieved through a combination of adaptive NMF, an abstract motor mapping, and a straightforward interaction strategy. An adaptive sparse NMF formulation was devised to extract muscle synergies from the user's sEMG in realtime. An abstract motor mapping was established by arbitrarily associating the extracted muscle synergies with predefined hand actions of the myocontrolled hand. As users interacted with the system and discovered action-triggering muscle

patterns, the synergies were continuously refined for enhanced control. This approach provided an adaptive and low-dimensional visualization of the muscle space, enabling users to discover complex muscle coactivation patterns, including those difficult to discern with standard biofeedback methods. Moreover, the approach demonstrated performance comparable to state-of-the-art supervised adaptive myocontrol approaches.

A limitation of all existing unsupervised myocontrol paradigms that rely on NMF, is that the number of components for sEMG factorization must be set to match the preexisting number of independent muscle synergies that the user can generate. Specifically, allowing too many NMF components might lead the factorization model to identify components unrelated to physiological muscle synergies, potentially resulting in unintended activations of the myocontrolled hand. Determining how many independent and stable muscle synergies the user can elicit is challenging. First, the amount of sensors used by the sEMG measurement system limits the number of detectable synergies [34]. Second, the individual's preexisting motor capacities can significantly impact the number of synergies elicited [25, 35]. Lastly, the number of distinct synergies may increase over time as the individual progressively familiarizes themselves with more motor tasks [25, 36]. In practice, determining the number of independent muscle synergies often requires extensive collaboration between the user and a clinician, making more autonomous methods for identifying and refining available synergies desirable.

An alternative approach is to use a progressive learning strategy for myocontrol functions, where users begin with a single function and gradually 'unlock' additional functions as they master existing ones. This method mirrors the progressive nature of human motor development, which involves the ongoing expansion and refinement of motor functions [25, 37, 38]. Throughout an individual's life, innate reflexes are integrated with newly acquired rudimentary motor skills, which are then refined and combined to form more advanced and specialized skills. This progression is connected to the development of muscle synergies, as new motor skills are achieved by adapting preexisting muscle synergies to meet the demands of tasks and efficiency [25, 38]. Moreover, the challenge point framework theory suggests that a progressive motor learning approach would support the acquisition of new motor functions. In fact, adapting the task difficulty to an individual's current skill level has proven helpful to regulate the learning workload and ultimately accelerate motor learning [39–41].

A sequential NMF formulation could be employed to implement a progressive motor learning procedure [42, 43]. This algorithm learns the factorization model by adding one component at a time, ensuring the stability of existing components when new ones are introduced. However, existing sequential NMF methods are not suitable for incremental settings as they are based on iterative warm reinitialization of progressively larger models and retraining on historical data to preserve the continuity of the existing components. Simply discarding the historical data when attempting online sequential NMF is unlikely to be successful, as the lack of context may lead to a loss of continuity in the existing components. Therefore, there is a need for an online factorization method that maintains component continuity without requiring the storage of historical data.

In this work, we introduce progressive unsupervised myocontrol (PUM), a fully unsupervised and coadaptive paradigm inspired by the progressive nature of human motor learning. PUM enables users to autonomously learn to control the functions of a myocontrolled hand one at a time. These functions are implemented through an abstract mapping between the users' muscle synergies and the desired actions of the hand and wrist. Users refine muscle synergies for myocontrol autonomously while familiarizing themselves with the system and request to unlock new functions as they become proficient with the existing ones. The result is a coevolving and coadaptive interaction dynamics between the user and the system. To achieve this, we extend the adaptive NMF from [22] with an algorithmic procedure to increase the number of components while preserving the existing ones without explicitly storing historical data. Moreover, we adjust the loss function to reduce the overlap between the identified components and to improve their stability over time.

In a multi-session user study, we evaluate how effectively PUM enables users and the myocontrol system to synergistically learn a control model in a completely unsupervised manner. We specifically investigate the performance of individuals with limb differences (LD), who stand to benefit the most from an unsupervised myocontrol paradigm, in comparison to non-disabled (ND) participants, who represent the best-case scenario for myocontrol due to their more extensive motor skills. Moreover, we examine how PUM compares to a non-progressive unsupervised myocontrol (UM) paradigm, based on that of [22], which serves as a baseline for identifying potential advantages and limitations of our approach. Our assessments and comparisons are based on the workload associated with the progressive learning of motor skills, as well as the evolution and retention of myocontrol performance in a series of target achievement control (TAC) tests involving a virtual hand.

The paper is structured as follows. In section 2, we detail the methods employed for the PUM paradigm.

Section 3 presents the study's findings, followed by a discussion of their implications in section 4. The appendix includes mathematical derivations of the factorization algorithm utilized in the myocontrol paradigms.

2. Methods

In this section, we introduce the PUM paradigm and discuss its relation to the non-progressive UM paradigm adapted from Gigli *et al* [22]. We then outline a multi-session study where we assess the effectiveness of PUM in enabling participants to progressively learn, refine, and retain control of a virtual hand's functions, and compare its performance to that of UM.

2.1. PUM

The PUM paradigm is inspired by the way humans progressively develop their motor skills when learning new tasks. The system factorizes muscular inputs into muscle synergies and arbitrarily maps them to functions of the myocontrolled virtual hand, while users learn the motor mapping by interacting with the system. Upon user request, the system adapts the number of synergies to accommodate an increasing number of functions, while aiming for minimal disruption to previously learned synergies. A schematic overview of the control paradigm is presented in figure 1.

2.1.1. Progressive incremental sEMG factorization

We introduce progressive incremental sparse nonnegative matrix factorization (P-ISNMF), an algorithm that adaptively computes an NMF model and enables online identification of additional components while preserving existing ones without model retraining. It builds upon incremental sparse nonnegative matrix factorization (ISNMF) [22], an adaptive NMF variant with sparsity constraints and a forgetting mechanism to discount outdated information. In addition to incorporating a progressive mechanism, our proposed approach features an improved objective function that results in sparser and more stable components.

NMF approximates a nonnegative matrix V of size $n \times s$ as the product of nonnegative factors W of size $n \times r$ and H of size $r \times s$, that is, $V \approx WH$ [44]. When the columns of V represent a series of s *n*-dimensional data samples, the columns of W represent a set of r basis vectors and those of H a series of s *r*-dimensional encoding coefficients that indicate the relative contribution of the bases to each data sample. In the context of myoelectric control, where data samples correspond to positive envelopes of the myoelectric signal, the bases and encoding coefficients can be loosely interpreted as muscle synergies and their activations.



myocontrol functions, the factorization model refines the identified muscle synergies by conducting periodic unsupervised model updates. Myoelectric control is achieved by factorizing muscle activity into muscle synergies and arbitrarily mapping the encoding coefficients to predefined myocontrol functions, obtaining motor commands for the orange myocontrolled hand. Users progressively unlock more myocontrol functions on demand. This scheme evolves to accommodate user skill evolution and allows the user and system to coadaptively refine control over new motor functions. A gray virtual hand serves as a reference during performance evaluation, presenting the users with functions to replicate in realtime with the myocontrolled hand.

Algorithm 1. ISNMF. © 2022 IEEE. Reprinted, with permission, from [22].

Input stream *S* of *n*-dim nonnegative samples **Parameter** r, β , γ , μ , ϵ , t_{max} $\mathbf{1} \ m \leftarrow 0$ $\mathbf{2}\,\mathbf{A}^0 \leftarrow \left[\mathbf{0}\right]_{n \times r}$ $\mathbf{3} \mathbf{B}^0 \leftarrow [\mathbf{0}]_{r \times r}$ 4 while true do 5 $m \leftarrow m + 1$ $V_m \leftarrow n \times k$ matrix with k new samples from S 6 7 If m = 1 then $W^m \leftarrow n \times r$ positive random matrix 8 9 else $\boldsymbol{W}^m \leftarrow \boldsymbol{W}^{m-1}$ 10 11 end 12 $H_m^m \leftarrow r \times k$ positive random matrix 13 $e_0 \leftarrow \| \boldsymbol{V}_m - \boldsymbol{W}^m \boldsymbol{H}_m^m \|_F^2$ 14 $t \leftarrow 0$ 15 repeat 16 $t \gets t + 1$ $\boldsymbol{W}^{m} \leftarrow \boldsymbol{W}^{m} \circ \frac{\mu \boldsymbol{A}^{m-1} + \boldsymbol{V}_{m} \boldsymbol{H}_{m}^{\mathsf{m}\mathsf{T}}}{\mu \boldsymbol{W}^{m} \boldsymbol{B}^{m-1} + \boldsymbol{W}^{m} \boldsymbol{H}_{m}^{m} \boldsymbol{H}_{m}^{\mathsf{m}\mathsf{T}} + \frac{\mu(1-\mu^{m})}{1-\mu} \beta \boldsymbol{W}^{m}}$ 17 $\boldsymbol{W}^{m} \leftarrow \max\left(\boldsymbol{W}^{m}, \boldsymbol{\epsilon}\right)$ $\boldsymbol{H}_{m}^{m} \leftarrow \boldsymbol{H}_{m}^{m} \circ \frac{\boldsymbol{W}^{m^{\mathsf{T}}} \boldsymbol{V}_{m}}{\boldsymbol{W}^{m^{\mathsf{T}}} \boldsymbol{W}^{m} \boldsymbol{H}_{m}^{m} + \gamma\left(\boldsymbol{H}_{m}^{m}\right)^{-0.5}}$ 18 19 $\boldsymbol{H}_{m}^{m} \leftarrow \max\left(\boldsymbol{H}_{m}^{m},\epsilon\right)$ 20 $e_t \leftarrow \| \boldsymbol{V}_m - \boldsymbol{W}^m \boldsymbol{H}_m^m \|_F^2$ 21 22 **until** $|e_t - e_{t-1}| / e_0 < \epsilon$ **or** $t > t_{max}$ $A^m \leftarrow \mu A^{m-1} + V_m H_m^m$ 23 $\boldsymbol{B}^m \leftarrow \mu \boldsymbol{B}^{m-1} + \boldsymbol{H}_m^m \boldsymbol{H}_m^m$ 24 25 end

ISNMF [22] is an incremental solution to the NMF problem that updates the factorization model with new data while discounting the contribution of previous data, without the need for storing it. We present a refined version of this algorithm that features an improved objective function for a sparser factorization and increased stability, and we provide a complete derivation in the appendix. In the following, we employ block notation for matrices, with subscripts identifying specific matrix blocks and superscripts representing the matrix status at particular updates. For instance, V_j denotes the data samples received during the *j*th update, W^m indicates the bases values at the *m*th update, and H_j^m corresponds to the encoding coefficients computed during the *m*th update for the block of data samples collected at the *j*th incremental update (with $m \ge j$ for obvious reasons). Furthermore, all product, division, or power operators applied to matrices in the update rules are understood to be elementwise. At the *m*th update, the algorithm refines the factorization model by minimizing the following objective function that incorporates new data and discounts past contributions

$$F^{m} = \sum_{j=1}^{m} \mu^{m-j} \left(\frac{1}{2} \left\| \mathbf{V}_{j} - \mathbf{W}^{m} \mathbf{H}_{j}^{m} \right\|_{F}^{2} + \frac{\beta}{2} \left\| \mathbf{W}^{m} \right\|_{F}^{2} + 2\gamma \left\| \mathbf{H}_{j}^{m} \right\|_{0.5}^{0.5} \right) .$$
(1)

The forgetting factor $\mu \in (0, 1]$ diminishes the influence of old data exponentially via μ^{m-j} , ensuring the model adapts without excessive reliance on historical data. $\|\cdot\|_F$ and $\|\cdot\|_{0.5}$ denote the Frobenius and the elementwise $L_{0.5}$ norms respectively. The scalars $\beta \ge 0$ and $\gamma \ge 0$ determine the regularization strength for the bases and encoding matrices.

The new objective function improves the one from the original method [22] by also scaling the regularizer of the bases with the exponential forgetting factor. The motivation for this change is to ensure that all three terms are balanced identically, regardless of the number of block updates⁵. Furthermore, the new objective function replaces L_1 regularization for

⁵ Note that the scaling factor $s(m) = \sum_{j=1}^{m} \mu^{m-j}$ starts at s(1) = 1and converges to $\lim_{m \to \infty} s(m) = \frac{1}{1-\mu}$. the encoding coefficients H with a sparser $L_{0.5}$ regularizer. A preliminary empirical validation confirmed that both modifications had the desired effect on stability and sparsity.

An incremental solution to this problem based on multiplicative updates is given in algorithm 1. The derivation of the incremental algorithm, found in the appendix, relies on the assumption that the model undergoes small changes in each update, meaning that old encodings remain practically unchanged when new data arrives. As a result, they no longer have to be optimized and past data samples and encoding coefficients can be aggregated into fixedsize history matrices rather than being stored explicitly. This, in turn, leads to a significant reduction in the computational and memory complexities of an incremental update, which are now constant in the number of updates [45, 46]. The hyperparameter r specifies the number of NMF components and is chosen to be lower than the data dimension. The tolerance $\epsilon > 0$ and the maximum number of iterations $t_{\text{max}} > 0$ establish the stopping condition for the iterative minimization of the objective function within each model update. The elements of W^1 and H_m^m are initialized to strictly positive random values sampled from max $(0, \mathcal{N}(\bar{V}^{m}, 1))$, where \mathcal{N} denotes the normal distribution and \bar{V}^m represents the historical average value of the data samples computed online.

Algorithm 2. Adding one component to the ISNMF model.

input r, W, A, B

1 $\tilde{w} \leftarrow n \times 1$ positive random vector	
$2 W \leftarrow [W \tilde{w}]$	
$3\tilde{\mathbf{a}} \leftarrow [0]_{n \times 1}$	
$4\mathbf{A} \leftarrow [\mathbf{A} \tilde{\mathbf{a}}]$	
$5 \tilde{\boldsymbol{b}} \leftarrow [0]_{r \times 1}$	
$6 \mathbf{B} \leftarrow \begin{bmatrix} \mathbf{B} & \tilde{\mathbf{b}} \\ \tilde{\mathbf{b}}^{T} & 0 \end{bmatrix}$	
$7 r \leftarrow r+1$	

The P-ISNMF method extends ISNMF to enable increasing the number of components r progressively without disrupting existing ones, while avoiding the need to store and retrain the model on past data. It achieves this by appropriately expanding the history matrices, which subsequently inform the model updates. The foundation of this method is the observation that the bases W, encoding coefficients H, and history matrices A and B encode componentspecific information in designated columns and rows. Specifically, W and A keep information about the rth component in their rth columns, H in its rth row, and **B** in both its rth row and column. Building on this observation, components can be introduced by extending W with strictly positive random values, sampled from the previously described distribution $\max(0, \mathcal{N}(\bar{\boldsymbol{V}}^m, 1))$. A similar extension of the old data encoding matrix *H* is possible but practically unnecessary as the incremental update rules only involve new data encodings, which are initialized at the appropriate size at the beginning of each update (line 12 in algorithm 1). Accordingly, history matrices *A* and *B* are augmented through zero padding to accommodate the lack of historical information for the new component, ensuring that the data related to existing components remain unaffected. This procedure is outlined in algorithm 2.

After incorporating the additional components, the model update process resumes, utilizing the history matrices to maintain the stability of existing components, as shown in algorithm 1. Despite not providing theoretical guarantees that this method preserves the stability of existing components, extensive preliminary analyses conducted on synthetic data have confirmed this.

2.1.2. Motor mapping and learning

Muscular input signals are periodically encoded into the synergy space using the rule in line 19 of algorithm 1 and subsequently used for position control of the virtual hand. The process involves establishing an abstract motor mapping that assigns the available muscle synergies, in the order of extraction, to predefined myocontrol functions. The mapping is arbitrary because the muscle synergy extraction process depends on the subject's physiology, the movements they performed, and the random initialization of bases and encodings. The encoding coefficients are scaled to consistent magnitudes by dividing them by their historical 95th percentile computed incrementally and then clipping them within the range [0,1]. These scaled coefficients are interpreted as the activation values for their corresponding functions. Specifically, since myocontrol functions are intended to be hand and wrist actions, the activation of each function is translated into the position command that realizes the corresponding action. A full activation executes the action completely, while a zero activation brings the hand to a rest position. Finally, given the graded nature of the coefficients and the possibility of activating multiple coefficients simultaneously, our system supports SP myocontrol.

Subjects learn to control the virtual hand one function at a time by practicing with the myocontrol system without expert supervision. Initially, subjects are introduced to the set of basic functions that the hand can perform and are informed that these functions may be controlled by muscular activations that are not necessarily physiologically related. During practice, subjects learn to control each function by isolating the associated muscle synergy. Once they feel confident in their command over a function, they can request unlocking another one and continue practicing, ensuring that they retain control over the previously learned functions. This procedure defines **IOP** Publishing

a coevolving and coadapting myocontrol paradigm. Coevolving refers to progressively increasing the number of myocontrol functions to mirror the development of the user's skills. Coadaptive refers to a synergistic adaptation process where the user produces increasingly distinctive muscle synergies while the system optimizes the sparsity of the identified synergies.

2.1.3. Comparison to UM

We compare the PUM paradigm with its nonprogressive counterpart based on the ISNMF algorithm detailed in algorithm 1. The difference is that in UM all basic functions are learned simultaneously rather than sequentially.

2.2. Experiment

We designed a multi-session user study to compare the realtime performance of myocontrol models obtained with PUM and UM, to track their evolution over time, and to assess the retention of performance after a period of non-use of the myocontrol system.

2.2.1. Participants

Ten ND subjects and two subjects with a unilateral upper-limb differences participated in the study. The ND participants, aged 27 to 33, had no previous experience with unsupervised myocontrol. Half of the ND participants tested PUM, and the other half tested UM. The participants with limb differences are denoted LD1 and LD2 in this paper. LD1, 35 years old, had a trans-radial congenital difference in the right arm. They could activate only two distinct muscle groups before the experiment, corresponding to forearm extensors and flexors. They were not a prosthetic user and had limited experience with myoelectric hands, having tested them for a few months at the ages of 5 and 20. LD2, 22 years old, had a transcarpal congenital difference in the left hand. They could perform visible wrist flexion, extension, and adduction at the time of the experiment. They were not a prosthesis user and had no experience with myoelectric control. Both LD participants tested PUM, because insightful comparisons between the two paradigms with only two LD subjects would have been unattainable. The study was conducted following the WMA Declaration of Helsinki and approved by the Ethics committee of Friedrich-Alexander Universität (No. 22-275-S). All participants gave written informed consent to participate in the study.

2.2.2. Experimental Setup

A Myo armband by Thalmic Labs provided 200 Hz, 8channel sEMG measurements of the forearm muscles on the subjects' dominant or different arm. The sEMG armband was positioned over the widest part of the forearm with the first sensor aligning with the brachioradialis muscle. This placement was done as precisely as possible to minimize electrode displacement across subjects and sessions. ND subjects and LD2 wore a resting hand orthotic splint and suitable padding to restrict hand or wrist movements and were instructed to avoid wrist rotations during the experiment. This requirement aimed at promoting isometric muscle contractions and has been found effective in making the sEMG of ND subjects more similar to that of individuals with upperlimb differences [47]. As indicated in figure 1, a monitor displayed an orange virtual hand visualizing the predictions of the myocontrol model and a gray hand serving as a reference during the experiment. Our experimental setup mirrored that of [22], who compared a state-of-the-art supervised myocontrol approach with an unsupervised myocontrol method analogous to our baseline paradigm, UM. This design was intended to facilitate an indirect comparison of the merits of our PUM paradigm with those of a standard supervised one.

2.2.3. Myoelectric control

The sEMG measurements were band-pass filtered online and in realtime using a second-order Butterworth filter with cutoff frequencies at 10 Hz and 90 Hz. The root mean square envelope of each channel was then computed over the last 300 ms and utilized as input for both myocontrol paradigms. The factorization algorithm used by both PUM and UM had hyperparameters of r = 4, $\beta = \gamma = 32$, $\mu = 0.8$, $\epsilon = 1 \cdot 10^{-5}$, and $t_{max} = 200$. The factorization model was updated at 0.2 Hz, while muscular encodings were computed at 20 Hz, normalized within the [0, 1] range, low-pass filtered online and in realtime with a fourth-order Butterworth filter with a 2 Hz cutoff frequency, and used as motor controls for the myocontrol functions arbitrarily associated to them.

Drawing from the work of Gigli et al [22], we limited the maximum number of myocontrol functions to four, as learning more functions with our setup would prove excessively demanding, even for ND subjects. For this study, we represented the four control functions with a power grasp, index finger pointing, wrist flexion, and wrist extension. This selection facilitates the evaluation of myocontrol performance on both individual and combined functions, as combinations of hand and wrist actions are usually more discernible than those of two hand actions, for example. Throughout this paper, we refer to these functions and their combinations as 'basic' and 'combined', respectively. Since our system implements position control, the myocontrolled hand automatically returns to a rest configuration when none of the functions is activated. Importantly, different control functions could be chosen without actually influencing the user's control strategy or the model performance. This is because our abstract motor mapping does not require a physiological association between muscle synergies and controlled functions.

	TRNF (retention)	TAC (retention)	Coadaptation	TRNF	TAC	Time since previous session
S1	_		х	х	x	_
S2	_	_	х	х	x	24 h–72 h
S3	х	х	х	х	x	24 h–72 h
S4		_	х	х	х	24 h–72 h
S5	х	х	х	х	х	7–10 d

 Table 1. Structure of the multisession experiment. The experiment consists of five sessions held on distinct days. This table outlines the temporal organization and the specific exercises featured in each session.

2.2.4. Experimental protocol

The experiment, detailed in table 1, included five sessions across different days. The initial four sessions were scheduled at least 24 h apart from each other and completed within two weeks, while the fifth session occurred about one week after the fourth. Each session included a coadaptation phase in which the system and participant synergistically refined the myocontrol model, along with two tests to assess myocontrol performance. One test was conducted without visual feedback and is referred to as target reaching with no feedback (TRNF), while the other featured visual feedback and is referred to as target achievement control (TAC). The myocontrol model was randomly initialized at the beginning of the first session and updated in later sessions to account for the participant's motor skills evolution and for the sEMG armband repositioning.

During the coadaptation phase, participants learned to control the four basic myocontrol functions while the myocontrol model was refined. This phase lasted 3 to 15 min but could be terminated early upon proficiently controlling all four basic functions. In the PUM paradigm, basic functions were learned progressively, with participants requesting to unlock a new function when confident in their control of the existing ones. To maintain consistency across participants, the experimenter verified that each function could be controlled stably and independently before unlocking the next one. The functions were always unlocked in the same order: power grasp, index pointing, wrist flexion and wrist extension. The chosen order held no specific significance and could in principle be tailored to different requirements or preferences. If the participant did not unlock all functions within the coadaptation phase duration, the subsequent myocontrol tests would only focus on the functions that the subject had unlocked so far.

In certain situations, the sparsity constraint in P-ISNMF may drive a component to zero if it is not considered essential for the reconstruction of new or historical data. Newly introduced components are particularly susceptible to this effect, as there is only a small amount of data available to reliably determine their added value to the model. Once the basis of a component has shrunk to zero, it becomes locked in this deactivated state due to the multiplicative update rule, and the corresponding myocontrol function is permanently inhibited. For this reason, this problem is referred to as zero-locking [48]. To counteract this zero-locking issue, we set the bases' lower limit to a small positive threshold, as shown on line 18 and line 20 of algorithm 1. Even with this thresholding mechanism, however, new components remain prone to re-suppression because their contribution to the data reconstruction is limited due to their small magnitude. Consequently, during the experiment, bases suspected to be zero-locked were reset to their initial values. This adjustment was made when a participant reported that a new function was consistently inactive or initiated by the experimenter if such inactivity remained unreported for over one minute.

In the TRNF test, the gray virtual hand displayed a sequence of reference functions and participants had to mimic those gestures without receiving visual feedback from the orange hand. The reference functions included only the basic functions unlocked so far and were presented in a randomized sequence repeated three times. This test assessed the participant's internalization of motor skills by focusing on feedforward control and eliminating reliance on visual feedback for instantaneous error compensation.

In the TAC test, participants controlled the orange hand to match reference functions displayed by the gray hand, using visual feedback. The reference functions were presented three times in random order. These included basic functions at full and halfactivation levels, and combined functions pairing one hand action with one wrist action both at halfactivation levels. Therefore, our tests assessed proportional control of up to four distinct functions and simultaneous control of two functions. This test design reflects the typical functional capabilities of modern myocontrol solutions, as simultaneous control of three functions has only been achieved in a few studies with more advanced setups for measuring muscle signals [49, 50]. A task was deemed successful if the myocontrol error stayed continuously below a threshold $d \leq 0.18$ for at least 2s before the maximum task duration of 10s. This error was computed as the maximum component of the elementwise absolute difference between the predicted function and the target function. Since the system's predictions represent position commands between 0 and

1, an error threshold below 0.18 means that we tolerate a deviation of up to 18% of the full activation range between the predicted and target functions.

Retention of myocontrol performance was evaluated at the beginning of the third and fifth sessions by administering TRNF and TAC tests using the model from the previous sessions, without conducting a preliminary coadaptation phase. These tests, referred to as s3r and s5r, assessed short and long-term retention respectively. By comparing short-term retention, where sensor replacement is arguably the main cause of performance degradation, with long-term retention, we aimed to understand to which extent performance degradation over time is caused by a loss of motor skill.

2.2.5. Performance evaluation

The workload during the coadaptation exercise represented the effort made to learn and refine motor skills based on muscle synergies by interacting with the myocontrol system. Participants reported their workload using the NASA-TLX questionnaire [51], which assessed mental, physical, and temporal demands, as well as perceived performance, effort, and frustration on visual analog scales ranging from very low, 0%, to very high, 100%. The overall workload was calculated as a weighted sum of these six dimensions, with participant-specific weighting coefficients determined through a pairwise comparison process [51].

Myocontrol performance in TRNF and TAC tests was assessed in terms of overall success and by evaluating the movement quality achieved during the gross and fine parts of the movement. The distinction between gross and fine movement serves to partition the task execution before and after the target function was first approached by the myocontrolled hand [52]. The overall performance was measured based on the myocontrol error in the TRNF tests, and the success rate and the completion time for TAC tests. For both test types, the gross movement was characterized in terms of duration and path efficiency, while the fine movement was characterized by the mean and standard deviation of the myocontrol error. The success rate was determined as the proportion of successful TAC tasks to the total attempted tasks, and the task completion time recorded the duration of successful tasks. Path efficiency denoted the ratio between the minimum required distance and the actual distance traveled along each independent DoF of the controlled hand to reach the target hand configuration. Importantly, all TAC metrics were calculated solely based on successful tasks, with the exception of the success rate itself.

These metrics were averaged across tasks for each combination of subject, session, and paradigm. Statistical tests were conducted on data from ND subjects to assess significant differences in workload and performance across sessions and between paradigms. Mixed ANOVA with the session as a within-subject factor and the myocontrol paradigm as a between-subject factor was used, and multiple post-hoc t-tests were performed when necessary to identify significant differences between sessions. The Benjamini–Hochberg method was applied to control the false discovery rate due to multiple comparisons [53]. These tests were chosen because the assumptions of normality and homoscedasticity were verified for the tested data subsets. The two LD subjects were analyzed individually without statistical tests, comparing their performances to those of other subjects.

3. Results

The results of the study are organized and presented reflecting the experimental protocol. We first report the participants' workload during the coadaptation phase, we then analyze the myocontrol performance for both TRNF and TAC tests, and we finally evaluate the retention of the learned motor skills. Throughout the section, our focus is on comparing the performance of LD and ND participants using PUM, as well as comparing the performance that ND participants achieved with the two myocontrol paradigms, UM and PUM.

Figure 2 displays the participants' workload during the coadaptation phase, as reported in the NASA-TLX questionnaire. LD and ND participants reported similar overall weighted workloads of around 50% in the first session, as shown in figure 2(a). The workload of ND participants was comparable for the two myocontrol paradigms and decreased significantly to 30% by the third session. A mixed ANOVA confirmed that the reported workload was significantly affected by the session number $(F_{4,32}, p < 0.001)$ but not by the control paradigm. Subsequent pairwise t-tests detected significant differences in workload between the initial two sessions and the subsequent ones, as depicted in figure 2(b). Conversely, LD participants maintained a consistently high workload, which may indicate that their adaptation to the myocontrol system was ongoing throughout the experiment. Figures 2(c) and (g) show that their mental demand and effort levels remained around 60% even in the final session.

The duration of each coadaptation phase appears to relate to the reported workload. This connection is expected due to the study design, as participants could request the termination of this phase when they felt in control of all the available myocontrol functions. ND subjects typically completed the coadaptation exercise in about 800s initially, with this duration reducing to about 300s for UM and 210s for PUM by the last session. LD 2 always used 900s, the maximum allowed time, while LD 1 took 900s until the third session and then progressively less, reaching around 750s in the final one.



The number of tasks in each TRNF and TAC test varied depending on the myocontrol paradigm, with UM consistently allowing control of four functions, and PUM potentially fewer than four. All ND participants who tested PUM achieved control of all four functions in the first session, except one, marked with a square symbol, who unlocked the last function in the second session. Both LD participants were evaluated on three functions in every session. LD1, represented by a hexagon, unlocked three functions within the first session but only learned to control the third one by the end of the third session. This achievement was particularly remarkable because this participant could only control two muscle synergies before the experiment, and they autonomously isolated a previously unknown muscle synergy using PUM. To allow further familiarization with the newly learned skill and in light of the significant achievement already made, the experimenters decided not to enable the fourth function. LD2, marked with a cross, initially achieved limited control of three functions and reached proficiency in the third session. Despite managing to unlock the fourth function, the participant was unable to activate it because the factorization algorithm did not identify additional activation patterns in the muscular signal and repeatedly set the magnitude of the fourth model component to zero. Consequently, myocontrol performance was not evaluated for the fourth function.

The performance in TRNF tests, as seen in figure 3(a), indicates that LD participants performed poorly when deprived of visual feedback, obtaining mean errors above 0.4 and fine mean errors above 0.3 throughout the entire experiment. Conversely, ND participants performed well in the absence

of visual feedback using both control paradigms across all sessions, achieving a final mean error of about 0.2. For them, a mixed ANOVA test revealed significant changes in mean error across sessions ($F_{6,48} = 6.08, p = 0.002$) but not between control paradigms, and pairwise t-tests detected significantly lower mean errors in sessions three to five compared to the first one, as reported in figure 3(b). Finally, the PUM paradigm enabled ND participants to approach the target more quickly and efficiently than UM, as indicated by the significantly lower gross motion time (by 0.6 s, p = 0.003) and higher gross path efficiency (by 0.1, p = 0.004) in figures 3(b) and (c).

Figure 4(a) presents the success rate achieved in the TAC test. In the first session, ND participants succeeded in approximately half the tasks, whereas LD participants achieved less than 25% success rate due to only being able to control two out of three functions. The performance of both groups reached equivalent success rates of 60% in the final session. Further analysis revealed that all participants controlled basic functions considerably better than combined functions, with success rates of 80% and 25%in the final session. The supplementary materials offer a visual breakdown of these success rates for basic and combined functions. The success rates of ND participants were comparable for both myocontrol paradigms and increased significantly across sessions. A mixed ANOVA test confirmed that the success rate changed significantly across sessions ($F_{6,48} =$ 6.88, p < 0.001), but was not influenced by the myocontrol paradigm. Pairwise t-tests, summarized in figure 4(b), indicated that the success rate increased significantly between the first and third sessions and



Figure 3. *Performance in the myocontrol test without visual feedback (TRNF).* (a) Mean myocontrol error per participant and session. (b) Corrected p-values for statistical tests comparing mean errors between sessions for ND participants. (c)–(f) Movement quality metrics during the gross and fine portions of the task in the final session. Markers represent the mean value of a statistic for a participant across all trials in a session. ND participants were evaluated on four myocontrol functions while LD participants on three. The ND participant marked with a square symbol had three actions assessed in the first session and four in subsequent sessions. Short and long-term retention exercises are highlighted with a yellow background. Asterisks indicate statistically significant differences between group means (*: p < 0.05, **: p < 0.01, ***: p < 0.001).





remained stable afterward. The success rate of LD participants also improved over time, although less uniformly. It remained below 25% during the first two sessions, markedly improved to above 50% in the third session when the participants learned to control the third function, and reached the level of ND participants in the final session.

Figures 4(c)-(g) focus on the successful TAC tasks in the final session. LD participants achieved a comparatively lower movement quality than ND

participants, requiring between 0.5s and 1s longer to complete the TAC tasks. This seemed to stem primarily from uncertainty in reaching the target hand configuration, rather than from inadequate control stability in the target's vicinity. Indeed, they demonstrated similar fine motion time and error as ND participants, but longer gross motion time or much lower gross path efficiency. ND participants attained similar movement quality with both myocontrol paradigms. They completed the successful tasks with either paradigm in approximately 4s. They executed the gross part of the movement significantly faster with PUM (gross motion time was about 0.4s lower, p < 0.001) while demonstrating similar motion time and myocontrol error in the fine part of the movement with both control paradigms.

The evolution of movement quality across sessions, visually detailed in the supplementary materials, offers further insights into participants' motor skill development. Although subjects both with and without limb differences experienced increased success rates, only the latter group demonstrated concurrent improvement in movement quality. In fact, LD participants displayed fluctuations in movement quality across sessions, indicating slower motor skill development.

Upon examining the failed TAC tasks in the last session, it became apparent that the main cause of failure was the difficulty to maintain the controlled hand near the target configuration. Even though participants reached the target configuration in at least 80% of failed tasks, they could not sustain it, resulting in average configuration errors substantially above the TAC success threshold of 0.18 (0.3 for ND participants and 0.45 for LD participants). A thorough visualization of performance during failed TAC tasks can be found in the supplementary materials.

Short and long-term motor skill retention were assessed by comparing performance differences between sessions s2 and s3r, and between s4 and s5r, respectively. Retention sessions are highlighted in yellow in figures 3(a) and 4(a). For these assessments, the mean error from the TRNF test and the success rate from the TAC test served as performance metrics. LD participants displayed comparable retention trends with and without visual feedback. Participant LD 2, marked with a cross, exhibited consistent motor skill retention in both the short and long term, while LD 1, marked with a hexagon, maintained performance in the short term but not in the long-term retention test. This participant reported having forgotten how to control the motor skill they most recently acquired but recovered it during the subsequent coadaptation session. For ND participants, mixed ANOVA results revealed that neither TRNF nor TAC performances were significantly affected by the myocontrol paradigm or its interaction with the session number. Therefore, performance retention was analyzed using pooled data from both myocontrol paradigms. In TRNF tests, no significant performance degradation was observed during retention sessions. For the TAC, while a decrease in the average pooled success rate was observable in the short-term retention, this was not statistically significant. However, a statistically significant decline was observed in the long term (by about 20%, p = 0.03), as reported in figure 4(b). Performance levels were restored however by the subsequent model update.

4. Discussion and conclusions

We discuss the performance of PUM for individuals with limb differences and compare it to the nonprogressive UM paradigm on a group of non-disabled participants. Our evaluation takes into account the workload experienced by participants while learning myocontrol skills, as well as the subsequent evolution and retention of myocontrol performance.

4.1. Evaluating PUM for users with LD

The study primarily evaluates the experiences of participants with limb differences with PUM and compares them to those of ND subjects. Understanding the experience of LD participants with PUM enables us to better identify their unique needs and challenges in adopting the technology. Meanwhile, ND participants serve as a best-case scenario for myocontrol in light of their wider range of motor skills.

Using the PUM paradigm, participants demonstrated proficient proportional control of multiple myocontrol functions, with LD participants controlling three functions and ND participants managing four. By the final session, LD participants achieved success rates similar to those of ND subjects in TACt tests, albeit with a comparatively lower movement quality. The average success rates were around 80% for tasks involving basic functions and 25% for those requiring combinations of two basic functions. The success rate for basic functions indicates a satisfactory level of performance and is consistent with findings from other studies on SP myocontrol [22, 49, 54]. While all participants were also able to control combinations of two functions, the corresponding success rates were considerably lower than those achieved on basic functions and below those reported in studies with similar experimental protocols [49]. This underlines a current limitation of our approach and identifies an area for future research. In any case, it should be noted that comparisons between studies on realtime myoelectric control are generally challenging due to differences in experimental setups, subjects characteristics, and tests being performed. A more detailed discussion about such comparisons will follow in section 4.2.

The internalization process of the learned myocontrol functions differed between the two subject groups. LD participants exhibited a consistently high workload during the coadaptation phase and a strong reliance on visual feedback during the tests, suggesting that they were continuously learning and adapting to the system. Conversely, ND participants adapted at a faster pace, reporting decreased workloads across sessions and showing better control without visual feedback in TRNF tests.

The long-term retention of newly acquired motor skills also varied among participants. LD 1 reportedly forgot how to control the most recently learned motor

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skill, although this ability was regained during subsequent coadaptation. In contrast, LD 2 exhibited no performance degradation, indicating good skill retention. Given the empirical evidence that LD individuals often require extended practice to learn new motor skills, even under expert guidance [55], it appears reasonable to speculate that LD 1 could have better internalized the new motor skill if allowed more practice sessions. Among ND subjects, the average TAC success rate during short-term retention tests exhibited a decrease that was not statistically significant. However, the performance degradation was more pronounced and reached statistical significance in the long-term retention tests. This result seems consistent with our expectation that confounding factors such as sensor displacement cause a minor degradation in both short- and long-term tests, whereas skill forgetting causes degradation that increases with time.

A noteworthy result of our study is that PUM not only enables LD users to autonomously learn myocontrol functions but also supports them in discovering previously unexpressed motor skills. For instance, LD 1, who could only control two muscle groups in their affected limb before the experiment, managed to identify a novel muscle synergy and learned to control three myocontrol functions in complete autonomy. We attribute this successful outcome largely to the unique design of the PUM paradigm. One key feature of this design is introducing one new function at a time. This helps maintaining the complexity of the motor learning process at a more manageable level, preventing the user from getting overwhelmed or frustrated. At the same time, this process continuously balances the learning difficulty with the user's evolving skill level, supporting the user to explore their muscular space and to discover new muscle synergies for control. Another distinct feature of PUM is to provide a rich yet intuitive biofeedback of the muscular activity. The paradigm associates each function of the myocontrolled hand to one distinct muscle synergy, effectively translating complex coactivation patterns into more understandable hand movements. In contrast, traditional sEMG biofeedback systems often provide separate feedback for each sEMG channel [56, 57], and this can be challenging to interpret for multi-channel systems [58].

The satisfactory realtime myocontrol performance of the two LD participants in basic functions and the fact that one of them discovered a new muscle synergy underline the practical value of the proposed PUM approach. These achievements gain further significance when considering that PUM does not demand preliminary assessment of the user's motor skills or professionally guided preprosthetic signal training used in traditional myocontrol approaches [17, 18]. Normally, a healthcare professional must assess how many distinct muscle activations the user can elicit to set up the number of myocontrol functions accordingly. In addition, the user often needs coaching to learn to generate muscle signals that are reliable and stable enough to initially calibrate the myocontrol system. Conversely, PUM only requires a brief instructional overview of the system. Then, it encapsulates motor skills assessment and signal training in an unsupervised coadaptive and coevolving learning process, thereby supporting a more autonomous engagement with myoelectric control. While learning new myocontrol functions, the user gradually generates more distinct muscle synergies and the system simultaneously improves the sparsity of the factorization model. Moreover, the system allows the user to unlock additional functions upon mastering the existing ones, which effectively tailors the number of functions to the user's current motor skills and reflects the progressive development of those skills through practice.

It seems logical to speculate that certain user's characteristics may influence the number of myocontrol functions they would be able to control. One such characteristic is the proximity of the limb difference. Transhumeral limb differences, for example, are associated with a lower amount of residual musculature compared to more distal ones, which potentially reduces the range of muscle synergies that can be generated with the residual limb [34]. Yet, it has been found that some individuals with transhumeral amputations who still experience phantom hand movements can elicit muscle signals with their residual musculature consistent with those movements [59, 60]. This unexpected ability, attributed to a preserved phantom limb neural representation and spontaneous neuronal reorganization or reinnervation, suggests that the potential for myoelectric control may not solely depend on the residual musculature. Regardless, the functional restoration of more proximal limb differences would involve control over an extended set of DoFs, possibly complicating the motor mapping. In conclusion, the influence of the limb difference proximity on the controllable myocontrol functions is not obvious and merits further research.

Another aspect that may influence the learning experience with unsupervised myocontrol paradigms such as PUM is the person's previous exposure to myoelectric control. Users with previous experience controlling a myoelectric prosthesis, or even a virtual hand, might rapidly gain control over new functions by drawing on their already refined repertoire of motor skills. In contrast, people without myocontrol experience might display more varied learning progressions. One contributing factor to this variability is that inexperienced users must not only learn new motor functions but also develop fundamental competences for myocontrol. These competences include, among others, modulating muscular contractions, actively relaxing muscles, and coordinating muscular activity with visual feedback of the controlled hand [61]. Even though none of the participants in our study voiced confusion pertaining these competences, it is reasonable to assume that some effort has gone into their development. Exactly delineating these two learning processes, however, is not possible in our experiment given that, during the coadaptation phases, participants were implicitly familiarizing themselves with myocontrol while concurrently learning new myocontrol functions.

People new to myocontrol may also face challenges determined by the nature of their limb differences. It appears plausible that amputees, drawing from their past experience with motor control on their now-absent limb, could have an advantage in identifying distinct muscle synergies. On the other hand, individuals with congenital limb differences might struggle more with this task, as they may need to concurrently form a new mental representation of the missing limb. As this aspect was not directly investigated in our study, we recommend it as an area for further exploration.

4.2. Comparing PUM to UM

We continue our evaluation by examining the performance of the PUM paradigm and its nonprogressive counterpart, UM, focusing on ND participants. Participants with limb differences were not included in this comparison because none of them tested the UM paradigm. The main objectives of this comparison are to determine if PUM distributes workload more effectively than UM, leading to a lower initial workload, and to verify if the models learned with both approaches achieve equivalent performance.

Contrary to our expectations, ND participants reported similar workloads for both paradigms. This outcome might have been influenced by limiting the maximum number of myocontrol functions to four, which appeared to be the practical limit of functions learnable with our setup according to preliminary tests and a previous study [22]. This limit, however, may have unintentionally oversimplified the motor learning task for ND participants, allowing them to learn all functions more easily than expected. The benefits of PUM in reducing the learning workload could have been more pronounced by enabling an increased number of functions. This argument seems to be supported by previous studies showing that ND participants often elicit five or more different muscle synergies during grasping [35]. Moreover, conducting the workload assessment at the end of each session could have led to underestimating the difficulties experienced during the initial stages of learning with UM. In fact, participants managed to learn

all functions at the beginning of the first coadaptation session using UM and first reported their workload in a questionnaire at the end of that session, potentially overlooking the challenges faced earlier.

PUM allowed ND subjects to reach equivalent myocontrol performance to its non-progressive counterpart either with or without visual feedback. Regardless of learning myocontrol functions progressively or simultaneously, participants also demonstrated a similar evolution and retention of performance. While it is difficult to compare our results with those of other studies because of the different experimental designs, we may attempt some useful comparisons. Our study design shares similarities with that of Gigli et al [22], where analogous TAC tests were used to compare a standard supervised myocontrol approach to an unsupervised myocontrol method that was equivalent to our baseline UM. The results of that study revealed that ND users achieved equivalent success rates with both methods. Although speculative, this equivalence appears to suggest that our progressive myocontrol approach, PUM, might perform comparably to a state-of-the-art supervised one, as both displayed equivalent performance to two similar unsupervised approaches. This line of comparison is further substantiated by the work of Nowak et al [49], who also used similarly designed TAC tests to evaluate another supervised myocontrol approach. A person with limb differences reportedly achieved success rates on basic actions similar to those observed in our study. While the success rates they observed for combined functions were higher, this might be attributed to using a more advanced high-density sEMG system. These comparisons provide preliminary indications that our PUM approach could perform similarly to supervised ones, even for users with limb differences. Nonetheless, these indications should be treated with caution until a direct comparison, possibly using a more advanced setup than the current one, is made through further research.

The results of this comparison indicate that both the PUM and UM paradigms resulted in equivalent learning workloads and myocontrol performance for ND participants. Speculation on how these results would translate to LD subjects could better define advantages and limitations of our PUM approach. We argue that the learning workload for each myocontrol paradigm depends on the relation between an individual's current motor skills and the number of functions they need to learn. In line with our findings for ND participants, we expect that both paradigms demand comparable learning workloads as long as the number of functions is similar to the number of distinct muscle synergies the person can elicit. Conversely, we contend that PUM might prove especially beneficial when the number of functions to be learned considerably exceeds the number of available

muscle synergies. In this scenario, PUM could limit the learning workload by allowing the discovery of new muscle synergies one at a time. As opposed to that, an unsupervised myocontrol paradigm that requires simultaneous identification of multiple new synergies would be obviously more challenging for the user. In this case, moreover, the factorization algorithm could approximate a single muscle synergy generated by the user as multiple redundant components, thus activating several functions at once. This redundancy could skew the visual feedback from the myocontrolled hand, limit the understanding of the control model, and ultimately, impede learning. In terms of myocontrol performance, we expect both control paradigms to yield the same performance also for LD users, provided that the same number of myocontrol functions had been already learned. This is because the difference between UM and PUM lies in the learning process, not in their implementation of myocontrol. While informed by preliminary tests, these speculations need further validation through future studies that directly compare PUM and UM on LD subjects.

4.3. Limitations and remarks

Due to challenges in recruiting participants with limb differences, only two individuals with congenital limb differences participated in the study. This implied that, although a qualitative analysis of their experiences provided insights into the effectiveness of PUM, those insights lacked statistical significance. Moreover, both limb-different participants had to be assigned the PUM paradigm. This decision was made to ensure a more comprehensive assessment of PUM's characteristics, as assigning the participants to different paradigms would have not yielded meaningful insights, due to their varied physiological characteristics and preexisting motor capacities. However, since no LD participants tested the UM paradigm, our study cannot confirm whether PUM can effectively distribute and limit the workload compared to UM. Despite our hypothesis that PUM may prove beneficial under certain conditions, discussed in section 4.2, further research is warranted to confirm this speculation.

The performance of LD participants was evaluated on three functions instead of four, reflecting their progress during the experiment. LD 1 notably learned to control three myocontrol functions by discovering a new muscle synergy that was different from the two synergies they had controlled throughout their life. However, this new function was not learned until the end of the third session. To give LD 1 sufficient time to consolidate the newly learned ability and avoid potential confusion that could affect long-term retention, the experimenters decided not to introduce an additional fourth function at this stage. LD 2 learned three myocontrol functions early in the experiment, unlocked the remaining one at the beginning of the third session, but never managed to activate it as the corresponding basis remained consistently zero-locked. Nevertheless, we argue that LD participants might have autonomously learned additional functions if the experiment had lasted longer and included more sessions. This possibility aligns not only with the experience of LD 1, who identified a previously unknown muscle synergy when given enough time, but also with the findings of [55] where an LD subject gained progressive mastery of novel functions across multiple supervised experimental sessions extending over many months. Yet, practical system designs should offer users the flexibility to manage their learning pace. Users should not only be enabled to start practicing new functions, but also to suspend or withdraw from practice when desired.

PUM employs P-ISNMF to progressively increase the number of components in the factorization model without compromising the stability of the existing ones. This prevents users from needing to repeatedly relearn myocontrol functions when new components are introduced, thereby maintaining performance efficiency. Although we do not provide theoretical guarantees for the stability of existing components, practical evidence from our experiment suggests that incorporating new components does not adversely impact the performance of previously learned myocontrol functions. This evidence also aligns with the results of preliminary tests on synthetic sEMG data. These tests assessed the ability of NMF, ISNMF, and P-ISNMF to reconstruct physiologically plausible muscle synergies that were used to generate the synthetic data. The tests showed that P-ISNMF introduces and learns components progressively without disrupting existing ones, and that it performs comparably to other NMF variants in identifying and reconstructing muscle synergies.

5. Conclusion

We developed a PUM paradigm to address the limitations of an existing unsupervised myocontrol approach [22]. Unlike the previous approach, PUM does not require a preliminary assessment of the user's motor capacities to set up the number of myocontrol functions of the system, and also accommodates for the evolution of new motor skills over time. This is achieved through a user-driven interactive process in which additional myocontrol functions

are introduced progressively and refined in an unsupervised way as the user gains proficiency with the system.

We tested the effectiveness of PUM in a multisession experiment with both congenital LD participants and ND ones, and compared it to a nonprogressive counterpart based on [22]. All participants successfully learned to control multiple myocontrol functions simultaneously and proportionally. LD participants completed the myocontrol tasks with comparable success rates to ND participants, despite showing a marginally lower movement quality and requiring a greater learning effort. Remarkably, one LD participant even learned a previously unexpressed muscle synergy and used it for myocontrol in complete autonomy. Finally, ND participants achieved similar performance with both PUM and its non-progressive baseline, which had already proved comparable to a supervised adaptive state-ofthe-art myocontrol system.

Ultimately, the PUM paradigm represents a significant advancement in adaptive unsupervised myoelectric control, as it offers a user-friendly and flexible system that supports autonomous learning of myocontrol functions. By catering to users with diverse motor abilities, the coevolving system not only supports but also promotes the development and enhancement of motor skills for myocontrol, ultimately enabling effective control of dexterous prosthetic devices.

Data availability statement

The data cannot be made publicly available upon publication because the cost of preparing, depositing and hosting the data would be prohibitive within the terms of this research project. The data that support the findings of this study are available upon reasonable request from the authors.

Acknowledgments

We thank Mr Fabio Egle for his assistance in recruiting participants with limb differences and his support during the experiments. Our appreciation also goes to Dr Bernhard Weber for the insightful discussions on how to plan our statistical analyses. Finally, we extend our gratitude to all the participants for their time and commitment to this study.

This research was funded by the German Aerospace Center (DLR).

Appendix. Derivation of the multiplicative update rules

This appendix details the derivation of the multiplicative update rules on line 17 and line 19 of algorithm 1, which are used to incrementally update the NMF factorization model with the data received during the *m*th update.

The incremental formulation of NMF is rendered here using superscripts and subscripts for matrices. Superscripts indicate the value of bases and encoding matrices at a specific update, while subscripts specify blocks in the data and encoding matrices. For example, V_i indicates the data samples received during the *j*th update, W^m represents the bases values at the *m*th update, H_i^m denotes the encoding coefficients computed during the *m*th update for the data samples received during the *j*th update. Specific subsets of blocks are indicated using a colon, as in $\boldsymbol{H}_{1:j}^m = [\boldsymbol{H}_1^m \cdots \boldsymbol{H}_j^m]$, while omitting the subscript implies the inclusion of all matrix blocks up to the current update, for example $\mathbf{H}^m = [\mathbf{H}_1^m \cdots \mathbf{H}_m^m]$ at the mth update. Since a data block V_m is never altered by the algorithm, that is $V_m^m = V_m^j$ $\forall j \ge m$, we omit the superscript notation for matrix $\mathbf{V} = [\mathbf{V}_1 \cdots \mathbf{V}_m]$. The multiplicative update rules use the elementwise product, division, and power operations, which are denoted by the circle operator, the fraction symbol, and the power operator respectively. When superscripts are applied to scalars, they indicate a standard power operation.

The rules correspond to performing alternating gradient descent minimization of the loss function in equation (1) with respect to the bases W and encoding coefficients H with step sizes set so to guarantee nonnegative updates. Both rules are calculated based on the assumption that the factorization model undergoes only minimal changes in each update. Specifically, it follows that the updated encodings for previous data blocks

$$\boldsymbol{H}_{1:m-1}^{m} \approx \boldsymbol{H}^{m-1} \tag{2}$$

and the solution can therefore be approximated by only calculating the encodings H_m^m corresponding to the new data block V_m at update m. Since the previous encodings $H_{1:m-1}^m$ remain unchanged, they no longer influence the gradient of the loss function in each update, meaning that in our approximation $\frac{\partial F^m}{\partial H^m} = \frac{\partial F^m}{\partial H_m^m}$.

The multiplicative update rule for the encoding coefficients H in line 19 is derived from gradient descent minimization

$$\begin{split} \boldsymbol{H}_{m}^{m} &\leftarrow \boldsymbol{H}_{m}^{m} - \Lambda_{H} \circ \frac{\partial F^{m}}{\partial \boldsymbol{H}_{m}^{m}} \\ &= \boldsymbol{H}_{m}^{m} - \Lambda_{H} \circ \left(-\boldsymbol{W}^{m \mathsf{T}} \boldsymbol{V}_{m} + \boldsymbol{W}^{m \mathsf{T}} \boldsymbol{W}^{m} \boldsymbol{H}_{m}^{m} + \gamma \left(\boldsymbol{H}_{m}^{m} \right)^{-0.5} \right) \end{split}$$

by simply setting the step size to

$$\Lambda_{H} = \frac{\boldsymbol{H}_{m}^{m}}{\boldsymbol{W}^{m \mathsf{T}} \boldsymbol{W}^{m} \boldsymbol{H}_{m}^{m} + \gamma \left(\boldsymbol{H}_{m}^{m}\right)^{-0.5}}$$

The multiplicative update rule for the model's bases W in line 17 also derives from gradient descent minimization

$$\boldsymbol{W}^{m} \leftarrow \boldsymbol{W}^{m} - \Lambda_{W} \circ \frac{\partial F^{m}}{\partial \boldsymbol{W}^{m}}$$

= $\boldsymbol{W}^{m} - \Lambda_{W} \circ \left(-\sum_{j=1}^{m} \mu^{m-j} \left(\boldsymbol{V}_{j} \boldsymbol{H}_{j}^{m^{\mathsf{T}}} + \boldsymbol{W}^{m} \boldsymbol{H}_{j}^{m} \boldsymbol{H}_{j}^{m^{\mathsf{T}}} + \beta \boldsymbol{W}^{m} \right) \right)$

by setting the step size to

$$\Lambda_W = \frac{\boldsymbol{W}^m}{\sum_{j=1}^m \mu^{m-j} \boldsymbol{W}^m \boldsymbol{H}_j^m \boldsymbol{H}_j^{m^{\mathsf{T}}} + \beta \boldsymbol{W}^m}$$

and simplifying the formulas as follows

$$W^{m} \leftarrow W^{m} \circ \frac{\sum_{j=1}^{m} \mu^{m-j} V_{j} H_{j}^{m^{\mathsf{T}}}}{\sum_{j=1}^{m} \mu^{m-j} W^{m} H_{j}^{m} H_{j}^{m^{\mathsf{T}}} + \sum_{j=1}^{m} \mu^{m-j} \beta W^{m}}$$

$$= W^{m} \circ \frac{\sum_{j=1}^{m} \mu^{m-j} V_{j} H_{j}^{m^{\mathsf{T}}}}{W^{m} \sum_{j=1}^{m} \mu^{m-j} H_{j}^{m} H_{j}^{m^{\mathsf{T}}} + \frac{1-\mu^{m}}{1-\mu} \beta W^{m}}$$

$$= W^{m} \circ \frac{\sum_{j=1}^{m-1} \mu^{m-j} V_{j} H_{j}^{m^{\mathsf{T}}} + V_{m} H_{m}^{m^{\mathsf{T}}}}{W^{m} \sum_{j=1}^{m-1} \mu^{m-j} H_{j}^{m} H_{j}^{m^{\mathsf{T}}} + W^{m} H_{m}^{m} H_{m}^{m^{\mathsf{T}}} + \frac{1-\mu^{m}}{1-\mu} \beta W^{m}}$$

$$= W^{m} \circ \frac{\mu \sum_{j=1}^{m-1} \mu^{m-1-j} V_{j} H_{j}^{m^{\mathsf{T}}} + V_{m} H_{m}^{m^{\mathsf{T}}}}{W^{m} \mu \sum_{j=1}^{m-1} \mu^{m-1-j} H_{j}^{m} H_{j}^{m^{\mathsf{T}}} + W^{m} H_{m}^{m} H_{m}^{m^{\mathsf{T}}} + \frac{1-\mu^{m}}{1-\mu} \beta W^{m}}$$

$$\approx W^{m} \circ \frac{\mu \sum_{j=1}^{m-1} \mu^{m-1-j} H_{j}^{m-1-j} H_{j}^{m-1^{\mathsf{T}}} + W^{m} H_{m}^{m} H_{m}^{m^{\mathsf{T}}} + \frac{1-\mu^{m}}{1-\mu} \beta W^{m}}$$

$$(3)$$

$$= W^{m} \circ \frac{\mu A^{m-1} + V_{m} H_{m}^{m^{\mathsf{T}}}}{W^{m} \mu B^{m-1} + W^{m} H_{m}^{m} H_{m}^{m^{\mathsf{T}}} + \frac{1-\mu^{m}}{1-\mu} \beta W^{m}},$$

$$(4)$$

where the approximation of equation (3) is possible under the assumption equation (2). The history matrices $A^{m-1} := \sum_{j=1}^{m-1} \mu^{m-1-j} V_j H_j^{m-1^{\mathsf{T}}}$ and $B^m := \sum_{j=1}^{m-1} \mu^{m-1-j} H_j^{m-1} H_j^{m-1^{\mathsf{T}}}$ introduced in equation (4) are used to store information about the past data samples and the corresponding coefficients. They can be recursively computed at the end of each update as $A^m = \mu A^{m-1} + V_m H^{m\mathsf{T}}$ and $B^m = \mu B^{m-1} + H_m^m H_m^m{\mathsf{T}}$, where the recursion is completed by setting A^0 and B^0 to zero matrices of sizes $n \times r$ and $r \times r$ respectively. This removes the need

to explicitly store past data, thereby enabling incremental model updates and maintaining the computational complexity of each update constant.

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