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RESEARCH ARTICLE

Control of Movement

A primitive-based representation of dance: modulations by experience and perceptual validity

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Abstract

The generation of complex movements such as dance might be possible due to the utilization of movement building blocks, i.e., movement primitives. However, it is largely unexplored how the temporal structure of a movement sequence and the recruitment of these primitives change with experience. Therefore, we obtained a representation of primitives with the temporal movement primitive model from the motion capture data of dancers with varying experiences, both for improvised and choreographed movements (elements from contemporary/modern/jazz) with different qualitative expressions. We analyzed differences between movement conditions regarding the number of temporal segments and the number of primitives, as well as their association with dance experience. Especially for the choreography with a neutral expression, the results indicate a negative association between experience and the number of segments and a positive association between experience and the number of primitives. The variation in the recruitment of these primitives suggests an increased consistency of modular control with experience, particularly for improvised dance. A prerequisite for the meaningful interpretation of these results regarding human movement production is that the model can generate perceptually valid dance movements. This was confirmed in a subsequent experiment, although the validity was slightly impaired for improvised movements. Overall, the results of the choreographed movement sequences suggest that experience is associated with an increase in motor repertoire that might facilitate fewer and longer temporal segments.

NEW & NOTEWORTHY This study demonstrates that a temporal movement primitive model, trained with movements performed by dancers with different levels of experience, is able to generate natural-looking dance movements. The results suggest that motor experience in dance is associated not only with fewer temporal segments but also with an increase in the number of underlying movement building blocks. The recruitment of these primitives, which might be used to simplify movement production, additionally seems to become more consistent with experience.

biological movement perception; dance experience; dimensionality reduction; event segmentation; movement primitives

INTRODUCTION

As humans, we are capable of producing a wide variety of movements with apparent ease and additionally adapt these to different environmental constraints. This is not trivial, as the human body is a complex system comprising numerous degrees of freedom (DoF), i.e., elements that can vary independently and thus need to be controlled given a specific movement goal (1). According to previous studies, the central nervous system may simplify the control of this complex system by using a pool of fundamental movement building blocks, i.e., movement primitives, and flexibly combining these according to the task at hand (2, 3). However, it remains unclear how such primitives and their composition change over the course of skill acquisition. According to the coordination development model by Bernstein (1), the acquisition of novel motor skills is accompanied by an initial "freezing" of DoF to constrain the motor system and thus reduce the complexity of a novel movement, which is then followed by an "unfreezing" of DoF over the course of further practice of the respective skill.

Previous findings suggest that learning and expertise are associated with changes in the primitive structure of movements;

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Haar et al. (4) applied PCA to the movement data of billiard shots and observed an increase in the number of principal components that explained more than 1% of the movement variance. Thus, in support of Bernstein's original hypothesis, the authors concluded that individuals use more DoF with practice. In line with this, Matsunaga and Kaneoka (5) analyzed the muscle activation patterns in the badminton smash shot and found that the activation patterns of advanced players were best represented by an increased number of motor primitives as compared with the activation patterns of novice players. Sawers et al. (6) also analyzed muscle activations and found an increase in motor primitives and a greater generalization of primitive function across tasks (beam vs. overground walking) with expertise. Contrary to the findings reviewed so far, studies focusing on artistic movements indicate an inverse relationship between experience and the number of primitives estimated to be used in movement execution; Bronner and Shippen (7) showed that the movements of expert dancers were better explained by fewer movement primitives in comparison to intermediate dancers when performing the Développé Arabesque. Similarly, Chang et al. (8) found a reduction in the number of movement primitives with skill progression in a Cha-Cha-Cha dance sequence. The lower number of primitives observed in experienced individuals is interpreted as an increase in the organization of primitives by the motor control system (7, 8). A commonality of both of these dance studies is that predetermined, short movement sequences were analyzed.

The differing results described so far could be due to differences in the overall temporal structure of the movements analyzed in these studies. None of them took the sequential order of movement elements within a sequence into account while computing the primitive representation. Although both the billiard shot (4) and the badminton smash (5) are of such a short duration that a temporal segmentation might be unnecessary, the analyzed dance sequences (7, 8), although having been of relatively short duration, contained multiple subparts. On a perceptual level, the segmentation of action streams may facilitate memory encoding and learning (9, 10), with movement speed identified as a relevant kinematic cue for segmentation (11, 12). The perceptual segmentation of action sequences, however, is influenced not only by low-level kinematic features of the observed movement but also by prior knowledge of the observer (12–14). Specifically, it has been shown that long-term motor experience of several years was associated with longer perceptual movement segments in both martial arts (12) and dance (13, 14). Even short-term motor experience had this effect, as amateur dancers perceived fewer segmentation boundaries after learning to dance the sequence to be segmented (13). Such perceived segmentation boundaries are believed to reflect internal action representations used to parse the observed action stream into meaningful parts (9). Based on psychological theories that postulate a common representational medium of perception and action, such as the theory of event coding and the common coding hypothesis, these internal representations are not only pertinent to the perception of movement, but they also reflect representations that pertain to the production of movement (15–19). Regarding the latter, segment boundaries indicated by neural state transitions in the primary motor cortex of primates during movement production were closely linked to the kinematic output in a reaching task, specifically the speed extrema of the end-effector (20). This shows the relevance of speed as a kinematic feature not only for the perceptual segmentation of a movement sequence (11, 12) but also for segmentation during movement production (20).

Considering the existence of a shared representational domain for the perception and production of movement (15–19), it seems plausible to assume that if sensorimotor experience resulted in fewer perceived segment boundaries in an observed movement sequence, motor experience might also lead to a reduction of movement segments during movement execution. Such a practice-related reduction should be less conspicuous in the ballistic aiming movements analyzed by Matsunaga and Kaneoka (5) and Haar et al. (4), simply because there might only be one segment. If movement segments were lengthening with practice and thus became reduced in number within a given movement sequence, one could expect such lengthening to require the development of appropriate primitives to cover longer segments. Indeed, previous work indicates that a smaller number of segments was associated with a more complex representation of primitives (21). In that study, an algorithm implementing a temporal primitive framework was used to segment a taekwondo sequence. The resulting segmentation boundaries were in good agreement with perceptual boundaries identified by human observers. Movement primitives can be seen as fundamental units utilized to construct the movement between these boundaries (22, 23). Although such an inverse relationship between movement segments and movement primitives might play a larger role in multipart movements such as dance sequences, it should not matter much for very rapid, ballistic movements such as a billiard shot or badminton smash.

The present study aims to test this hypothesized relationship between movement segments and movement primitives as a function of expertise. Since previous studies have mainly used stereotyped dance sequences (7, 8) and to allow for more variability in segment lengths, we chose to also target unconstrained movements and to focus on the dance styles contemporary, modern, and jazz. Furthermore, we also use different expressive qualities of movement to elicit additional variation in the temporal structure of the movement sequence and to assess the consistency of expertise effects.

As highlighted by Cross et al. (24), the versatility of dance and its high demands on multijoint coordination make this skill particularly suitable for the investigation of the development of expertise and analysis of coupling mechanisms between action and perception. Dance differs from other complex movements such as walking, as it can be categorized under artistic movements (25). In contrast to functional movements, these types of movements rather display exaggerated affective expressions, for example through an emphasis on timing and dynamics. In addition, these types of movements do not necessarily occur in daily life and are usually not object directed. Thus, while dance is a skill like many others in that it contains movements that can range from very simple to highly complex, it is special in that it enables the analysis of movements generated merely for movement's sake, also called "pure" movements (24).

To test the hypothesized relationship between expertise-dependent segment length and the number of movement primitives, we chose to use a temporal movement primitive

(TMP) model. Changes in the construction of movement can generally be assessed by decomposing the kinematic data or the underlying muscle activity and analyzing changes in the number, shape, and recruitment of the obtained representation of movement primitives, i.e., the movement's building blocks. Primitives differ regarding the dimension on which the extracted primitives are represented, i.e., spatial, temporal, or both, depending on the applied decomposition method. Various unsupervised learning algorithms have been implemented to obtain this lower-dimensional representation (26). Common techniques are principal component analysis (PCA), independent component analysis or nonnegative matrix factorization (27). Knopp et al. (28) showed that a perceptually valid representation of movement primitives can be obtained with a variationally trained TMP model, a specific type of Bayesian generative model. In that study, the perceptual validity was assessed by asking human participants to discriminate between video displays of the original and the model-generated movement. The confusion rate was used as a dependent variable to indicate how well the model is able to "confuse" the participant. More specifically, a confusion rate approaching 0.5 would indicate that the participant is not able to discriminate between the original and model-generated movements. The results from Knopp et al. (28) showed that the TMP model was the perceptually most valid (even hyperrealistic with a confusion rate above 0.5) for gait movements. However, so far, the perceptual validity of the TMP model has not been assessed for more complex movements, such as those produced by experienced dancers.

In *experiment 1*, the TMP model was used to evaluate the influence of dance expertise on the modular and temporal construction of a movement sequence. The resulting model parameters of this experiment can only be interpreted reasonably in relation to human movement production if the output of the generative model emulates the actual data to a sufficient degree [analysis-by-synthesis; e.g., Giese and Poggio (29)], indicating that the quality of the model is adequate for the types of movements analyzed in this experiment. Since the perceptual validity of the model has not yet been tested for dance movements, it was essential to also evaluate the model's validity for these types of movements. Therefore, in *experiment 2*, we examined if the utilization of the TMP model to generate choreographed and unconstrained dance movements would result in perceptually valid movements. Moreover, we assessed whether the performer's or the observing participant's dance experience affects the perceptual validity. Regarding the former, both general and specific experiences in contemporary/modern/jazz could lead to an increase in the complexity of the generated movements, possibly reducing the quality of the model and thus the confusion rate. On the part of the observers, higher levels of general and specific experience might improve their ability to distinguish between the original and model-generated movements, thereby reducing the confusion rate, and thus the perceptual validity of the model.

EXPERIMENT 1

In this experiment, the effect of motor experience in dance on modular structures during movement production was assessed.

Methods

Participants.

Twenty-one female dancers (mean age = 22.6 yr, SD = 3.0 yr) participated in the experiment after replying to an advertisement of the experiment posted on the university mailing list. Participants either received course credit or 18€ for their participation. The overall dance experience of the participants ranged from 2 to 18 yr, with 67% of participants reporting experience with dance improvisation. Exclusion criteria were disorders of the musculoskeletal system, abnormal vision, and an experience below 1 year in contemporary, modern, and jazz dance. The study was approved by the local ethics committee and all participants gave written informed consent to the experiment. The study was conducted in accordance with the ethical standards of the Declaration of Helsinki, except that we did not preregister the study.

Procedure.

The three-dimensional (3-D) positions of 39 passively reflecting markers were captured with a 28-camera VICON motion capture system (VICON, Oxford, UK) at a sampling rate of 120 Hz. Before the acquisition, participants were asked to wear tight-fitting clothes to ensure a secure marker placement. After an initial warm-up, anthropometric measurements were taken and the markers were placed according to the Vicon Plug-in Gait marker set. Participants were given the opportunity to get accustomed to moving with the attached markers and they were instructed that they could take as many breaks as necessary between motion captures.

In the first part of data acquisition, three-movement sequences (30-s duration each) of improvised dance were captured. Participants were specifically instructed to improvise, i.e., to not consciously plan their movements, and to "dance as if nobody is watching." The experimenter and participant were separated visually by a screen. In the second part of the acquisition, participants practiced a dance sequence that was choreographed by a professional dance teacher and contained elements from contemporary, modern, and jazz. The choreography was composed considering the following: *1*) it should be learnable by beginners, *2*) have a duration of approximately half a minute, and *3*) contain no floor movements (performing movements in close proximity to the ground posed a risk of unintentional marker detachment). Participants were instructed to practice the choreography until they felt secure in performing the sequence (no time limit was given). A prerecorded video of the dance sequence was shown on a projector screen and repeated automatically. After participants reported being capable of performing without the video display, the video was turned off. Participants were instructed to perform the dance sequence and the experimenter visually checked for deviations from the dance choreography displayed in the video. In the case of deviations, the subject was made aware of these and given the opportunity to rewatch the video and practice the dance sequence further.

Three movement sequences were captured in which the participants were instructed to perform the choreography as displayed in the video ("neutral" condition). Subsequently, participants were instructed to perform the choreography according to different expressive movement qualities, in a pseudorandomized order. These were the factors time and flow of the effort category of the Laban movement analysis (30), a comprehensive method used to describe human movement. Regarding the factor time, participants were instructed to perform the sequence quick (urgent, fleeting) and sustained (leisurely, lingering). Regarding the factor flow, participants were instructed to perform the sequence free, i.e., unconstrained, difficult to stop in the course of the movement, and constrained, i.e., controlled, able to stop the movement anytime. Three movement sequences were captured for each of these four conditions. All in all, three-movement sequences were captured of each of the six-movement conditions (improvised, neutral, time-quick, time-sustained, flow-free, and flow-constrained).

Data processing.

The 3-D marker trajectories were labeled and gaps were filled with algorithms implemented in Vicon Nexus (v2.11). The trajectories were low-pass filtered with a fourth-order Butterworth filter (6-Hz cut-off frequency). One participant and four additional movement sequences were excluded due to marker occlusion. An 18-joint hierarchical kinematic body model was fitted to the 3-D marker trajectories with a custom skeleton estimation software to compute joint angle trajectories. The .bvh-files containing the joint angle trajectories were visually checked for abnormalities in Blender (32). One participant and 2.4% of the remaining movement sequences were excluded due to artifacts (anatomically impossible joint-angle configurations). The joint angles of each movement sequence were partitioned into segments in the temporal dimension. The boundaries used to partition each movement sequence were computed by determining the minima of the summed speed of the wrist and foot markers (LWRA, RWRA, LTOE, RTOE), limited to a minimum distance of 160 ms between boundaries (Fig. 1, *A* and *B*).

Temporal primitive model.

The TMP model was used as a generative model for the joint angle trajectories (in exponential map representation). In the model, the data X of a joint j over time t in a segment are a weighted sum of m movement primitives MP (Fig. 1, *C* and *D*), with additive Gaussian noise $\epsilon \sim \mathcal{N}(0, \sigma_\epsilon^2)$, with $\sigma_e = 0.03$ (*Eq. 1*). Similarly, there is a Gaussian prior on the weights $W \sim \mathcal{N}(0, \sigma_w^2)$, with σ_w set to $\sigma_w = 1$ (joint angles overall ranged from approximately -2 to 2 rad). Finally, a Gaussian process prior was used for the movement primitives, $MP(t) \sim (0, \Sigma)$, with an RBF kernel (*Eq. 2*) for Σ. The variance and autocorrelation of the data were used to respectively estimate σ_m^2 and γ of the kernel. The data were decomposed via PCA to initialize the model parameters (MP and W).

$$X_{jt} = \sum_m W_{jm} MP_m(t) + \epsilon \qquad (1)$$

$$k(t, t') = \sigma^2 exp\left(-\gamma(t, t')^2\right) \qquad (2)$$

The optimal number of primitives and segments for each subject, condition, and repetition was estimated. To this end, the data were partitioned into varying number of segments (ranging from 10 to 40, in steps of 2), and the models were additionally trained with a varying number of primitives (ranging from 3 to 16). The model parameters, i.e., the weights and primitives, were optimized jointly with maximum-a-posteriori inference by maximizing the log joint probability of the data and the model parameters (*Eq. 3*) given the segment boundaries. The posterior distribution of the number of primitives was estimated with the model evidence, i.e., the marginal likelihood of each model, approximated via Laplace approximation [LAP (33)]. The model with the highest posterior probability regarding the number of primitives was identified for each dancer, condition, and repetition (Fig. 2*A*). The number of primitives and segments of these models were used in subsequent analyses.

$$\begin{aligned} &log(p(X, W, MP(t)) = log(p(X|W, MP(t)\, p(W)\, p(MP(t))) \\ &= log(p(X|W, MP(t)) + log(p(W)) + log(p(MP(t))) \end{aligned} \qquad (3)$$

An adjusted version of the TMP model was implemented to analyze modulations in the weighting of the primitives by experience. In the adjusted version σ_w was not set to 1 but given a Gamma prior, $\sigma_{w_{j,MP}} \sim Gamma(0.08, 1.5)$. This enabled us to

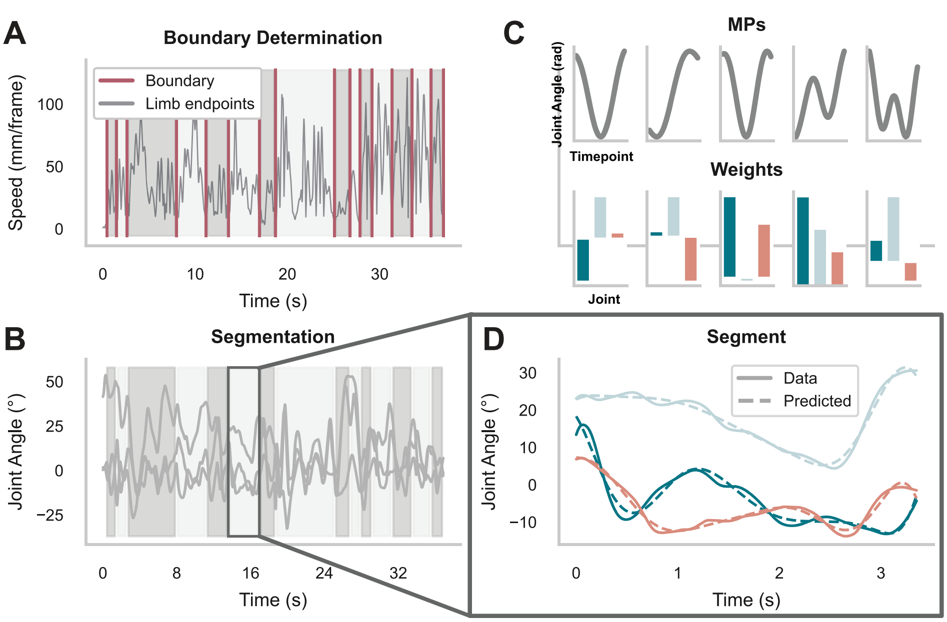

Figure 1. Example of the determination of boundaries for the temporal segmentation of the movement sequence, based on the summed speed of the limb endpoint markers (*A*), the segmented joint angle trajectories (*B*), movement primitives (MPs) and weights for the generation of joint angle trajectories (*C*), and the predicted and original joint angle trajectories of one segment (*D*).

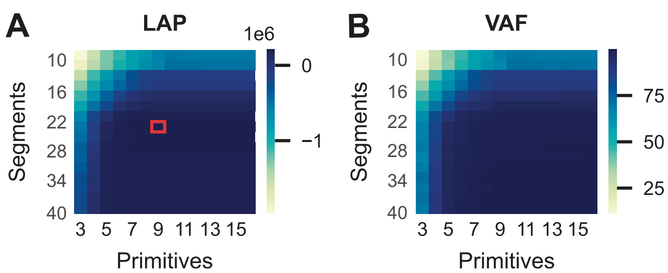

Figure 2. Example of LAP-scores (*A*) and Variance accounted for (VAF; *B*) for models with various number of primitives and segments. The red rectangle in *A* marks the maximum model evidence for this particular subject and condition. LAP, Laplace approximation.

learn the variance of the weights for each *j* and *MP*. The parameters of the Gamma hyperprior were estimated with the previously learned weights. The adjusted TMP model was trained for each dancer with the movement data of the third repetition of the improvised and neutral choreography condition. The learned log weight variance was extracted from the model with the highest model evidence and used to analyze differences in the weight variance by experience.

Data analysis.

We analyzed the data using Bayesian inference. The posteriors were computed with Markov Chain Monte Carlo, using the No-U-Turn sampler implemented in the Python library PyMC3 [v3.11.2 (34)]. To summarize the posteriors, we report 95% highest density intervals (HDIs).

We were interested in both the association with experience and the difference between performance modes (improvisation vs. choreography) and movement expression conditions. In addition, we wanted to check for an effect of repetition and a possible interaction between condition and repetition. Therefore, we applied a model that is analogous to a classical analysis of covariance (ANCOVA) (35). The factors condition (neutral choreography, quick, sustained, free, constrained, and improvisation), repetition (1, 2, 3), and condition × repetition were included and dance experience in years was used as a covariate x_{cov}.

As dependent variables, we separately analyzed movement smoothness as well as the number of primitives and segments. Movement smoothness was assessed to confirm the effect of the instruction regarding movement expression. As a measure of smoothness, we computed the mean squared jerk (36) with the acquired 3-D positions x of the hand markers LFIN and RFIN across time t (*Eq. 4*):

$$Mean\ squared\ jerk = \frac{1}{t_2 - t_1}\int_{t_1}^{t_2} \dddot{x}(t)^2\,dx. \tag{4}$$

The number of primitives and segments of the model with the highest model evidence regarding the number of primitives was determined for each dancer, condition c, and repetition r and also used as a dependent variable y.

Each element of the dependent variable y_i was assumed to be distributed as a Student t distribution, to account for outliers (*Eq. 5*). The location μ_i is a weighted sum of predictors P (*Eq. 6*). Zero-centered Gaussian priors were used for the overall baseline α_0 (*Eq. 7*) and the weights α_p, representing the main and interaction effects. For the latter, a standard deviation for the prior of σ_{α_p} was used (*Eq. 8*). This was given a Gamma prior, that was weakly informed on the scale of the data by using the standard deviation of the dependent variable σ_y, and setting the mode of the before $\frac{\sigma_y}{2}$ and the standard deviation to $2\sigma_y$. The condition-dependent metric predictor β_c was also given a zero-centered Gaussian prior (*Eq. 9*). The scales $\sigma_{c,r}$ of the Student t distribution were assumed to be Gamma distributed. The corresponding mode and standard deviation of these Gamma priors were given vague Gamma priors. To specify these weakly informed priors the data were grouped by Condition and Repetition and the standard deviation of y was computed for each group σ_{y_g}. The mode of the Gamma priors was set to the median of σ_{y_g} (when the dependent variable was segmented, the mode of the Gamma priors was divided by half to improve sampling), and the standard deviation of the Gamma priors was set to twice the standard deviation of σ_{y_g}. Finally, the degrees of freedom ν were given a broad exponential prior (*Eq. 10*):

$$y_i \sim Student\,t(\mu_i, \nu, \sigma_{c,r}) \tag{5}$$

$$\mu_i = \alpha_0 + \sum_c \alpha_{1,c}\, x_{1,c}(i) + \sum_r \alpha_{2,r}\, x_{2,r}(i) + \sum_{c,r} \alpha_{1\times 2,c,r}\, x_{1\times 2,c,r}(i) + \beta_c\, x_{cov}(i) \tag{6}$$

$$\alpha_0 \sim \mathcal{N}(0, 5\,\sigma_y) \tag{7}$$

$$\alpha_{1,c}, \alpha_{2,r}, \alpha_{1\times 2,c,r} \sim \mathcal{N}(0, \sigma_{\alpha_p}) \tag{8}$$

$$\beta_c \sim \mathcal{N}\left(0, \frac{2\,\sigma_y}{\sigma_{x_{cov}}}\right) \tag{9}$$

$$\nu \sim Exp\left(\frac{1}{30}\right). \tag{10}$$

Finally, we analyzed modulations by experience in terms of the weighting of the primitives. To this end, the log weight variance was used as a dependent variable and estimated for the factors joint, MP, and condition (improvised vs. choreography), with dance experience as a covariate.

Results

Kinematics.

The HDIs of the posteriors for the condition main effect contrasts show that the mean squared jerk is smaller in the Sustained than the quick condition (HDI of sustained-quick: $[-7.88 \times 10^{10};\ -5.54 \times 10^{10}]\ L^2/T^6$) and also smaller in the constrained than in the free condition (HDI of constrained-free: $[-2.08 \times 10^{10};\ -9.66 \times 10^{9}]\ L^2/T^6$). The posteriors do not indicate a difference in jerk between the Improvised and Neutral condition (HDI of improvisation-neutral: $[-6.62 \times 10^{10};\ -4.14 \times 10^{9}]\ L^2/T^6$).

The HDIs of the posteriors of the repetition main effect contrasts and of the interaction contrasts (condition × repetition) all contain zero. Thus, there does not appear to be a main effect of repetition nor an interaction effect.

The HDIs of the posteriors of the slope-parameter β_c (Fig. 3B) do not indicate an association between jerk and experience for any condition, except for the condition free. Specifically, the slope for the condition free indicates a positive association between mean squared jerk and experience (β_{Free}: $M = 1.05 \times 10^9$).

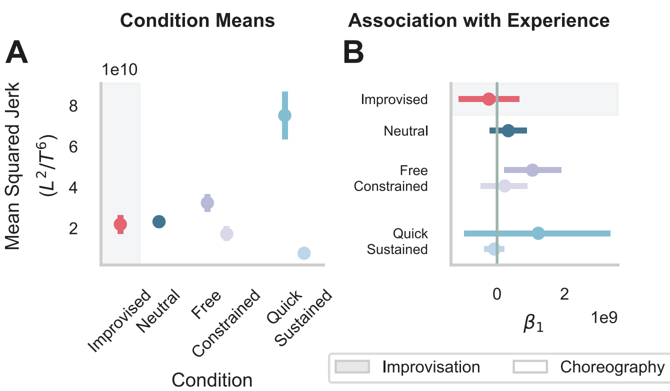

Figure 3. Mean and highest density interval (HDI) of posterior samples of α_c (*A*) and β_c (*B*) corresponding to the mean squared jerk of the hand markers and the association with experience (L, length; T, time).

Primitives.

The HDIs of the posteriors for the condition main effect contrasts show that the number of primitives (Fig. 4*A*) is larger in the sustained than the quick condition (HDI of sustained-quick: [0.13; 1.26]), whereas there is neither a difference between the constrained and free condition (HDI of constrained-free: [−0.76; 0.19]) nor the improvised and neutral condition (HDI of improvisation-neutral: [−0.70; 0.15]).

A positive association between the number of primitives and dance experience (Fig. 4*B*) is indicated by the nonzero HDI of the slope parameter (β_c) for the neutral condition ($\beta_{Neutral}$: M = 0.07), whereas the HDI of the improvised condition indicates no association with experience. The HDIs of the other conditions show a tendency for a positive association with experience, however, these HDIs also show credibility for a slope of zero, since (given the observed data) zero is within the HDI and values within the HDI have a higher probability than values outside.

The number of segments (Fig. 4*C*) appears to be larger in the improvised than in the neutral condition (HDI of improvised-neutral: [1.59; 5.47]) and also larger in the sustained than in the quick condition (HDI of sustained-quick: [0.57; 4.58]). There is no difference between the constrained and free conditions (HDI of constrained-free: [−1.51; 2.37]).

Regarding the association between the number of segments and dance experience (Fig. 4*D*), the slope parameter (β_c) for the neutral condition shows a negative association ($\beta_{Neutral}$: M = −0.35). In contrast, the HDI of the slope parameter of the improvised condition shows credibility for a slope of zero. This is also the case for the remaining conditions, except for the quick condition, where the HDI marginally does not indicate that a zero slope is credible (β_{Quick}: M = −0.28).

For both the number of primitives and the number of segments, the corresponding posteriors do not indicate a main effect of repetition nor an interaction effect (condition × repetition), since the HDIs of all contrasts show a high credibility for a zero difference.

A negative association between the number of segments and the number of primitives (Fig. 5) is shown to be credible for the improvised condition ($\beta_{Improvised}$: M = −0.09). Similarly, a negative association is also credible for the other conditions with the mean of β_c ranging from −0.14 (sustained) to −0.19 (free).

Weighting of primitives.

The learned weights and movement primitives for the first six primitives are displayed in Fig. 6. The weights are smaller for certain primitives (MP 2, 4, and 6, Fig. 6*A*). However, the resulting primitives appear to be quite consistent across subjects, regardless of the underlying experience level (Fig. 6*B*).

The log weight variance is smaller in the choreography condition than in the improvised condition (Fig. 7*A*; HDI of improvised-choreography: [0.51; 0.63]). Furthermore, the weight variance appears to decrease with increasing dance experience (Fig. 7*B*). This is the case for the improvised state (HDI of slope: [−0.02; −0.007]) and to a lesser extent for the choreography (HDI of slope: [−0.009; −0.002]).

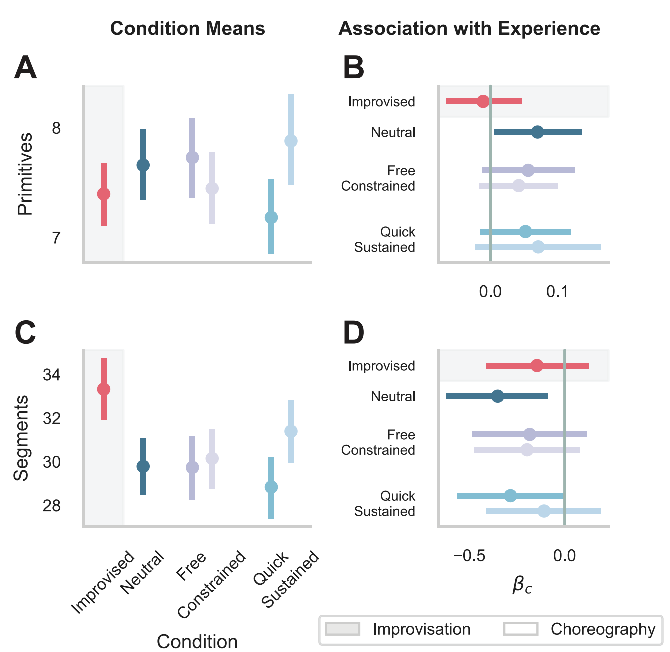

Figure 4. Mean and highest density interval (HDI) of posterior samples of α_c (*A* and *C*) and β_c (*B* and *D*) representing the number of primitives (*A*) and the association with experience (*B*) and the number of segments (*C*) and the association with experience (*D*).

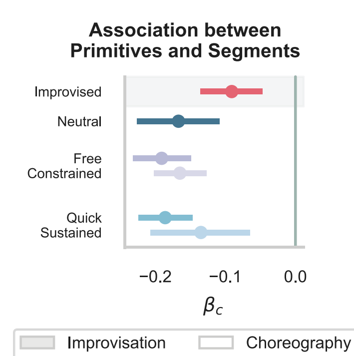

Figure 5. Mean and highest density interval (HDI) of posterior samples of the slope-parameters β_c, representing the association between the number of primitives and segments.

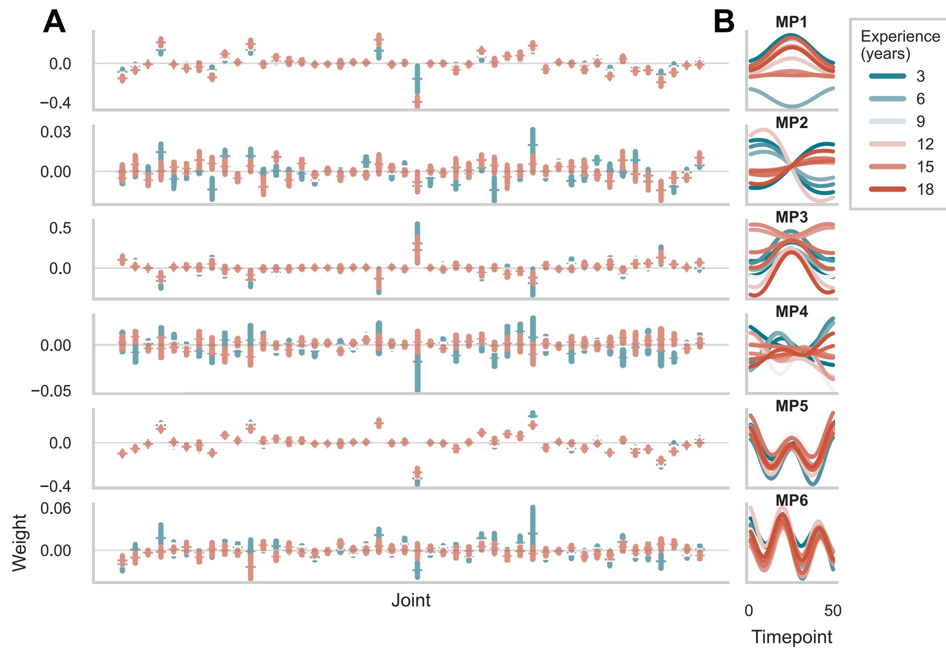

Figure 6. Means and standard deviation of subjects' median weights, grouped by dance experience (above or below 12 yr), across conditions and repetitions (*A*) and corresponding movement primitives (MP) 1 to 6 (*B*).

EXPERIMENT 2

In this experiment, the perceptual validity of the TMP model applied to dance movements was assessed with an online perception experiment, using the JavaScript library jsPsych (37).

Methods

Participants.

A participant management system (SONA system) was used to collect the data of 102 psychology students in the perception experiment (duration around 40 min). Of these, 18 participants were excluded due to not completing the experiment, 11 participants were excluded due to an accuracy below 60% in the attention checks, and furthermore, 1 participant was excluded due to an implausible median reaction time (132 ms). The data of the remaining 72 participants were analyzed (23 males; mean age = 22.7 yr, SD = 4.5 yr). All participants gave written informed consent to the experiment and received course credits for their participation. Participation requirements were an age above 18 yr and normal or corrected-to-normal vision.

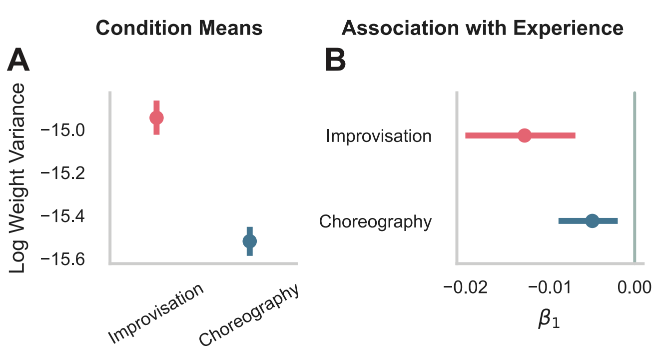

Figure 7. Mean and highest density interval (HDI) of posterior samples of α_c denoting the estimated log weight variance (*A*) and β_c denoting the association with experience (*B*).

Stimuli.

The third, i.e., last, repetition of the improvisation and choreography condition (neutral expression) of each dancer from *experiment 1* was used as stimuli in the perception experiment. The model-generated movements were created using the model with the highest evidence for each dancer and condition. The standard deviation of the noise prior σ_e was reduced exponentially over the five data points next to a segment boundary (from 0.03 to 0.005) to further enable smooth segment transitions for these models. Specifically, the reduction should facilitate that the predicted joint angles of a segment during weight inference match the data even more. This ensures that the end of a segment is approximately equal to the beginning of the next segment. Consequently, as the reconstructed segments were concatenated, thereafter, the predicted joint angles closely matched at the boundaries. The segments of each movement sequence were concatenated to obtain a minimum stimulus duration of 3.0 s. Thus, every stimulus is characterized by the condition (improvisation or choreography) and the variables in Table 1.

The resulting 288 movement sequences were displayed at veridical speed with stick figures (16 lines) on a canvas (1,250 × 600 pixels) rendered in webGL (Fig. 8*A*).

Task.

The task was a two-alternative forced-choice task. In each trial, the original and model-generated movement sequences were shown side-by-side and the display was repeated once. The participant was instructed to choose the movement sequence that appeared the more natural. The choice could be indicated with the corresponding arrow key on the keyboard (left or right) as soon as the repetition, i.e., the second display of the stimulus, started. Attention checks (n = 10) were evenly distributed across the time span of the experiment. These checks consisted of two static stick figures in different shades of gray displayed side-by-side (Fig. 8*B*). The participant was instructed to always choose the darker stick

Table 1. *Variables describing the stimuli used in the perception experiment*

Variable	Min	Max
Duration, ms	3,017	6,250
Variance accounted for, %	97.5	99.9
Segments	2	7
Primitives	5	11
General experience of the dancer, yr	2	18
Style-specific experience of the dancer, yr	2	18

figure. The age, gender, and general dance experience of the participant, as well as experience with specific dance styles (contemporary/modern/jazz among others), were obtained before the presentation of the stimuli.

Data analysis.

As in *experiment 1*, we analyzed the data using Bayesian inference and summarize the posteriors by reporting 95% highest density intervals (HDIs).

The perceptual validity of the TMP model was assessed with the confusion rate, θ, which indicates to which degree the model is able to "confuse" the participant. The confusion rate is calculated with the rating k of each trial i, relative to the total number of trials n (*Eq. 11*). Specifically, $k_i = 1$ if the participant chose the original movement sequence and $k_i = 0$ if the participant chose the model-generated movement sequence. Hence, a confusion rate of 0.5 would indicate that the participant is not able to distinguish between the original and model-generated movement. The lower the confusion rate, the less the participant was "confused" by the model-generated movements, i.e., chose the original movement sequence:

$$\theta = \frac{N - \sum_i k_i}{N}. \tag{11}$$

The modal confusion rate of each stimulus condition c (improvised dancing, choreographed dancing) was estimated with a hierarchical Beta–Bernoulli model using the rating data D. Due to the model's hierarchical structure, the confusion rate was also estimated for each stimulus s. The rating k of each trial and stimulus was assumed to be Bernoulli-distributed with a probability of confusion θ_s (*Eq. 12*), which was given a Beta-prior (*Eq. 13*).

$$k_{i,s} \sim Bernoulli(\theta_s) \tag{12}$$

$$\theta_s \sim Beta(\omega_c(\kappa_c - 2) + 1, (1 - \omega_c)(\kappa_c - 2) + 1) \tag{13}$$

$$\omega_c = \frac{1}{1 + exp^{-a_c}} \tag{14}$$

$$a_c \sim \mathcal{N}\left(0, \tau = \frac{1}{\sigma^2}\right) \tag{15}$$

$$\sigma \sim Gamma(1.64, 0.32) \tag{16}$$

$$\kappa_c = \kappa_{c-2} + 2 \tag{17}$$

$$\kappa_{c-2} \sim Gamma(0.01, 0.01) \tag{18}$$

The condition-specific modes of the Beta-distribution are denoted with ω_c, that is the output of a logistic function of a_c (*Eq. 14*), constraining the range of possible modes to the interval [0, 1]. A Gaussian prior was used for a_c (*Eq. 15*), representing a wide range ([0, 1]) of plausible values for ω_c. To this end, the standard deviation of the Gaussian prior was given a Gamma prior, with shape and rate settings corresponding to a mode of two and a standard deviation of four (*Eq. 16*). The condition-specific concentration parameter of the Beta-distribution is denoted with κ_c and governs the dispersion of stimuli confusion rates around the modal confusion rate of each condition. To ensure $\kappa_c > 2$ we compute κ_c from κ_{c-2} (*Eq. 17*), which was given a vague Gamma prior (*Eq. 18*). Overall, this yields the following chain of dependencies:

$$p(\theta, \omega, \kappa, \sigma|D) \propto p(D|\theta) \times p(\theta|\omega, \kappa) \times p(\omega|\sigma) \times p(\kappa) \times p(\sigma). \tag{19}$$

We additionally assessed whether the confusion rate differed by the dance experience of the observer. To this end, we grouped the observers by experience and implemented the same hierarchical model. However, in this case, s represents the participant and c the experience group. The participants were assigned the following groups: *1*) no experience, *2*) general (any) dance experience, *3*) specific experience (over 1 year of experience with the specific dance styles displayed in the stimuli, i.e., contemporary/modern/jazz).

A Bayesian logistic regression model (*Eqs. 20* and *21*) was implemented to estimate the dependence of the confusion rate on the predictors p, consisting of stimulus duration, variance accounted for, the number of segments, and the number of underlying primitives. In this case, the slope β_p of the logistic regression model is a measure of the influence of the explanatory variable x_p on the confusion rate:

$$k \sim Bernoulli(\theta) \tag{20}$$

$$\theta = \frac{1}{1 + exp\left(-(\alpha + \sum_p \beta_p x_p)\right)}. \tag{21}$$

Similarly, the effect of the performers' experience on the confusion rate was also assessed with a logistic regression model, where p consisted of the performers' general and specific dance experience. The parameters of the model were given weakly informed Gaussian priors.

Results

The results from the hierarchical model regarding the experience of the participant (Fig. 9A) show that the means of the posteriors of the corresponding parameters approach a confusion rate of 0.5 for all experience groups ($M = 0.47$). The increased HDI of the group with specific experience is due to the reduced number of participants in this group

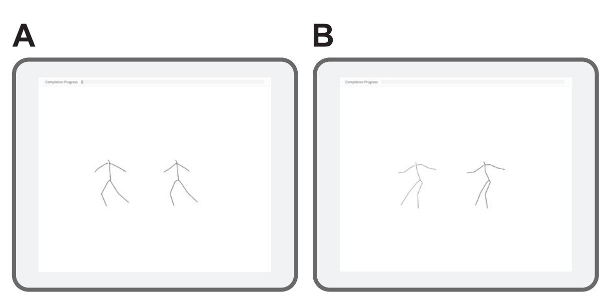

Figure 8. Screenshot of the online experiment (*A*) and the implemented attention checks (*B*).

resulting in a low precision of the estimate. The results suggest that participants, regardless of their level of dance experience, were hardly able to distinguish between the original and model-generated movements.

The mean of the stimuli containing choreographed dance movements also approaches a confusion rate of 0.5 (M = 0.48), as well as the mean for stimuli containing improvised movements (M = 0.45), although lower (Fig. 9*B*). The 95% HDI for the difference in the posterior estimates of the condition-specific ω, i.e., $\omega_{c=improvisation} - \omega_{c=choreography}$, was [−0.049, −0.006], suggesting that the confusion rate is lower for improvised than choreographed dance sequences.

The mean and 95% HDI of the posteriors from the slope parameters of the logistic regression models are displayed in Table 2. Both the performers' general and specific dance experiences do not seem to affect the confusion rate, since both means of the slope parameter are near zero.

Of the variables characterizing the stimuli, the variance accounted for seems to have a substantial effect on the confusion rate. The mean positive slope of 0.298 denotes that a higher variance accounted for is associated with a higher confusion rate, i.e., the ability to discriminate between the original and model-generated movements is reduced. The confusion rate does not appear to depend on the duration of the stimulus or the number of transitions (segments − 1) in the movement sequence. In addition, there does not seem to be a dependence on the number of underlying primitives, as the 95% HDI of the corresponding slope parameter indicates that a zero slope is credible.

DISCUSSION

In this study, the TMP model was applied to the motion capture data of choreographed dance sequences, with different movement quality expressions. We additionally applied the model to fully improvised, unconstrained dance movements. We explored whether and how the temporal structure of a dance sequence and the underlying movement primitives are modulated by experience. Results show an interdependence between temporal segments and movement primitives, while also suggesting an association with dance experience for certain movement conditions, i.e., primarily

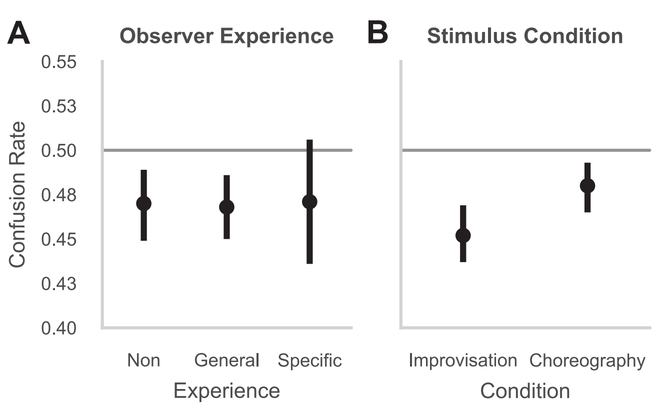

Figure 9. Mean and highest density interval (HDI) of posterior samples of the ω_c-parameters from the hierarchical Beta–Bernoulli models that were used to estimate the confusion rate for different experience groups (*A*) and stimulus conditions (*B*).

Table 2. *Mean and HDI of posterior samples of the slope-parameters (β_p) from the logistic regression models*

Predictor, *P*	Mean (β_p)	95% HDI
Performers' experience		
General experience	0.001	−0.005, 0.007
Specific experience	−0.001	−0.007, 0.006
Stimulus descriptors		
Duration	0.014	−0.034, 0.063
VAF	0.298	0.172, 0.426
Transitions	−0.023	−0.049, 0.003
Primitives	0.019	−0.007, 0.045

HDI, highest density interval; VAF, variance accounted for.

for the choreography performed with a neutral expression. Furthermore, the perceptual validity of the model was evaluated in a second experiment. In general, the results show that the model is capable of generating movements that are basically indistinguishable from the original movements.

The analysis of movement smoothness confirmed the effect of the instruction regarding various movement expressions. An association between smoothness and dance experience was solely found for the movement expression Free. In this case, movement smoothness was negatively (jerk positively) associated with the dance experience. This is in contrast to the results of prior studies, for instance showing a positive association between specifically dimensionless jerk and experience in a traditional Korean dance motion (38). However, the fact that no association was found for all remaining conditions overall supports previous findings, showing no association between jerk-based measures and dance experience (7, 38).

Analyzing the underlying components in conjunction with a temporal movement segmentation reveals a consistent trade-off between the two; the fewer the movement segments the greater the requirement for the number of underlying primitives to obtain a sufficient representation of the movement. Thus, this is in line with previous findings from taekwondo movements (21), showing that higher polynomial orders result in fewer segmentation boundaries. However, the segmentation boundaries in a taekwondo sequence are presumably more salient than those in dance. In general, there is a tendency for a positive association between the number of primitives and experience for choreographed, but not for improvised dance. The most prominent association is found for the neutral expression of the choreography. The results suggest an increase in the utilization of DoF and movement complexity with experience. An increase in motor primitives has also been demonstrated in the course of motor development (39) and with long-term ballet training in beam walking (6). Although prior studies have indicated that experience is associated with fewer components when analyzing dance sequences of shorter duration (7, 8), the application of a decomposition method to longer movement sequences thus suggests a reverse pattern.

In particular, for the neutral condition, there seems to be an association between experience and the number of temporal segments. This data-driven approach therefore is in line with previous perceptual studies, indicating that dance experience might lead to a broader representation of movement (13). Overall these results suggest that with increases in movement experience, there is a tendency for an increase in movement repertoire which might enable longer movement segments. Thus, an increase in primitives might facilitate a different temporal structure used by neural control mechanisms for more efficient production of coordinative movement. Previous studies have not incorporated consideration for the serial elements of a movement sequence and primarily represented primitives on the spatial dimension (5–7). However, according to Event Segmentation Theory, the identification of temporal boundaries is crucial for prediction, memory encoding, and learning (9, 10). According to the results of this study, experience is associated with the partitioning of a full-body coordinated movement sequence into fewer and larger elements.

Beyond an analysis of the number of primitives and segments, we further assessed modulations in the weighting of the primitives by experience. The results indicate that the variance of the weights decreases with experience for both improvised and choreographed movements, suggesting an increased consistency of modular control with experience. Furthermore, the weight variance is smaller in choreographed than in improvised dancing. This is likely due to the versatility of movements in improvised movements resulting in in a requirement for a greater diversification of weights.

The different movement expression qualities (factors time and flow) were based on the effort category of the Laban movement analysis, since this category characterizes the dynamic qualities of movement. The system has been applied in various movement-related fields, e.g., the effort category has been used as a basis for the semantic, automatic segmentation of motion capture data (40) and the Kinetography Laban system has been used to notate and analyze complex humanoid robot movements (41). The Labanotation is also applied in Laban movement analysis and uses body parts, space, duration, and beginning and end of a movement as factors to describe movement. Regarding the start and end points of an action, the temporal primitives can be viewed as basic modules used to construct the movement in between. Due to the temporal scalability of TMPs, a similar number of temporal segments could have been expected for the two opposite polarities of the factor time; the quick and sustained condition. Based on the difference in the number of primitives between the conditions sustained and quick, a straightforward scaling of primitives to prolonged segments, that encompass the same movement, is not feasible for the type of movement sequences used in this study. The modulation of the qualitative expression in line with the sustained condition of the effort category might have had the secondary effect of introducing more submovements to the movement sequence. Consequently, a scaling of temporal primitives does not turn a quick movement into a sustained one in this case, because the sustained condition might require more temporal segments. However, this may be feasible if the scaling factor is closer to one, e.g., for more uniform movements (42). The polarity constrained of the factor flow describes a bound and rigid motion. With respect to the DoF, this condition should be associated with a freezing of the DoF. On the other hand, the polarity free, characterized by being unable to stop in the course of movement, should consequently have the opposite effect. A difference in the number of primitives with the modulation of the factor flow was not found. Hence, this indicates that simply modifying the expressive quality regarding a constrained or free state is not sufficient to induce a modulation in the use of DoF.

A limitation of the current study is its cross-sectional nature and the range of dance experience included. Specifically, the dance experience analyzed only had a range of 16 yr and no professional dancers were included. Consequently, it would be interesting to replicate these analyses with a wider range of dance experience. The chosen segmentation method is a further limitation, due to its heuristic nature and lack of an obvious relation to the movement primitive model. With the applied version of the TMP model, the segmentation of the movement sequence has been implemented as a reasonable preprocessing step, to avoid having to temporally scale the primitives to the full length of the movement sequence (in this case ∼30 s). It is also implausible that movement primitives used during movement production would correspond to the full length of the sequences used. The segmentation method implemented in this study partitions the sequence based on the minima in the speed of the hands and feet. Although speed has been used as a kinematic feature by observers to segment movement sequences (11, 12), it was merely one of several segmentation criteria reported by observers, also varying depending on experience level (12, 13). Thus, it would be interesting to test other segmentation techniques as well. Moreover, it would be advisable to apply a more sophisticated segmentation method overall. However, the development of such a method is beyond the scope of this paper. This method should automatically determine the optimal number and length of segments given the implemented observation model with Bayesian model selection. To this end, the likelihood of the data given the model parameters (weights and MPs) would need to be computed for all possible segment boundary configurations for each plausible model complexity (number of segments and MPs). Although the computational effort required is a limiting factor, an unsupervised segmentation algorithm based on Bayesian Binning would be appropriate for this task (21).

The results from the perceptual validation experiment overall confirm that the TMP model is suitable for generating natural, full-body dance movements. This is supported by several factors. First, the confusion rate is independent of the performers' dance experience. Thus, the perceptual quality of the model is consistent regardless of the skill level underlying the production of the movements. In addition, the confusion rate does not seem to be modulated by the experience of the participant, i.e., participants with dance experience did not show an increased ability to detect deviations from what would be predicted to be a natural human-generated movement sequence, manifesting itself in lower confusion rates. Hence, the perceptual quality of the movements generated with the model seems to be independent of the participants' acquired knowledge and specific representation of the movement skill displayed. Furthermore, the confusion rate seems to be independent of the number of transitions in the movement sequence. This indicates that the model is able to produce naturally appearing movement sequences regardless of the number of segments needed. Lastly, there was no influence of the optimal number of underlying primitives on the confusion rate. This highlights the efficiency of the model-selection procedure, i.e., depending on the motion capture data a different number of parameters is required for a sufficient representation of the data, but the selection procedure results in the same perceptual validity nonetheless.

Certain factors seem to curtail the perceptual validity. If the TMP model was a valid movement representation under all conditions, there should be no difference between stimuli showing improvised and choreographed dance movements. However, the conditions under which the dance movements were performed resulted in different confusion rates. A lower confusion rate is observed for stimuli displaying improvised dancing in contrast to choreographed movement sequences. This might be due to an increased diversity and complexity of movements captured in the improvised condition, perhaps resulting in reduced model quality. Second, and possibly related, the confusion rate is dependent on the variance accounted for. This result is in partial agreement with findings by Knopp et al. (43). Although Knopp et al. (43) found no effect of the mean squared error on the perceptual performance of the TMP model in an online experiment, a lab-based version of the experiment showed that a smaller error was associated with a higher confusion rate. The latter is also in line with previous results by Knopp et al. (28).

Conclusions

The TMP model was applied to the motion capture data of improvised and choreographed dance sequences with differing movement expressions. The results show an interdependence between the number of temporal segments and movement primitives, as one would expect. In the case of a choreography performed with a neutral expression, the former seems to be negatively associated, whereas the latter indicates a positive association with dance experience. In addition, the perceptual validity of the model was assessed, showing that it is sufficient for choreographed and to a lesser extent for improvised dance movements. Furthermore, the model performance is a crucial predictor of the perceived naturalness of the model-generated movements. Overall, these findings indicate that an increase in experience is associated with an increase in motor repertoire together with fewer and longer temporal segments and that a representation of dance movements with the TMP model is feasible.

DATA AVAILABILITY

Source data and analysis code are openly available at the institutional repository of the Justus Liebig University Giessen (http://dx.doi.org/10.22029/jlupub-15651).

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DISCLOSURES

No conflicts of interest, financial or otherwise, are declared by the authors.

AUTHOR CONTRIBUTIONS

A.L. and M.H. conceived and designed research; A.L. performed experiments; A.L. and D.E. analyzed data; A.L., D.E., and M.H. interpreted results of experiments; A.L. prepared figures; A.L. drafted manuscript; A.L., D.E., and M.H. edited and revised manuscript; A.L., D.E., and M.H. approved final version of manuscript.

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