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Modularity in dance: Effects of expertise on the production and perception of full-body movements through the use of a Bayesian generative model based on temporal movement primitives

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Abstract

Dance can be viewed as a form of full-body art that has been practiced by humans for thousands of years in various social contexts. However, the relationship between the configuration of these expressive movements and the aesthetic qualities they elicit in observers is still unclear. According to current understanding, humans may be able to generate a variety of movement by relying on movement primitives: a pool of fundamental movement building blocks that can be flexibly combined to produce diverse movements. Years of sensorimotor experience might modulate these types of primitives, resulting in the motor skills observed in professional dancers today and their aesthetic performance.

The main objective of this thesis was to enhance our understanding of how the aesthetic perception of dance movements relates to their modular composition. To this end, a generative model based on movement primitives was implemented, its viability as a tool for perceptual experiments was tested, and finally applied to the aesthetic evaluation of artificially generated dance movements. All in all, four experiments were conducted. The first experiment examined the temporal segmentation of dance sequences, as this is a necessary pre-processing step for the implemented model, showing that using simple kinematic features is a viable approach for segmenting dance sequences up to a certain degree of fluidity. The second experiment focused on the perceptual validation of the model for dance movements, as this had not yet been evaluated. The findings indicate that the model is perceptually valid and robust to a range of factors, although its validity may be limited when movement complexity reaches a certain level. The third experiment goes beyond methodological assessments to explore how the modular composition of dance movements relates to sensorimotor dance experience. The results suggest that sensorimotor dance experience is associated with a more movement primitives, but fewer temporal segments. Finally, the fourth experiment assessed the aesthetic perception of dance movements based on their composition. Interestingly, movements based on a greater number of primitives also received higher aesthetic evaluations, which contrasts with previous studies on the aesthetic perception of dance. An exception to this pattern was observed, suggesting an uncanny valley phenomenon for artificial full-body movements.

Overall, this thesis addressed both methodological and conceptual aspects of dance movement production and perception within a modular framework, identifying limitations and offering directions for future research on the generation and appreciation of full-body artistic movement.

Contents

1 Background

Dance has existed since the time of ancient civilizations and may have even deeper prehistoric roots (Garfinkel, 2014). According to Garfinkel (2018), humans have likely been dancing for tens of thousands of years, possibly as far back as 40,000 years ago, or even earlier, though direct evidence is scarce. Dance has been practiced in a wide range of social contexts, from small-scale hunter-gatherer bands to large, urban societies (Garfinkel, 2018). Dance has also ranged in skill level and function, from amateur, lay participation in rituals, ceremonies, and courtship, to the emergence of professional dancers in modern times. Dance movements are characterized by their full-body involvement and intricate coordination, that is refined through practice. These kinds of artistic movements are often not object-oriented, and rather serve the expression of affective states in the form of non-verbal communication. Depending on the configuration of these expressive movements, they can elicit a certain emotional quality in the observer, such as pleasure, disgust, happiness of aesthetic appreciation. However, it can take years of practice to obtain the motor skills required to deliver a performance with a high aesthetic quality, in contrast to many everyday activities such as gait, where humans generally are experts in. It is still unclear what the constituents of this type of full-body artwork are that result in an aesthetic experience of the observer.

The human body is made up of over 600 muscles and 300 joints, all of which must be coordinated and controlled in order to generate coherent movement. Movement variations can be obtained through the use of different trajectories, speeds and accelerations. Hence, there are a considerable number of entities that need to be finely tuned to generate full-body movement, known as the degrees of freedom problem (Bernstein, 1967). Multiple solutions to this problem have been proposed (Latash et al., 2007). However, the predominant explanation for how humans are able to produce versatile and complex movements is the presence of a modular control architecture (D'Avella et al., 2015). According to this hypothesis, the CNS can simplify the control of degrees of freedom by using basic movement building blocks (Bizzi & Cheung, 2013; Giszter, 2015). These fundamental building blocks can be flexibly combined to generate full-body movement, even the complex movement sequences observed in dance. According to a wide range of theories, the production of movement and the perception of movement are closely linked (Friston, 2010; Hommel et al., 2001; Prinz, 1997; Shin et al., 2010; Wolpert et al., 2003). Thus, sensorimotor representations that are relevant to the production of movement may also play a role, to some extent, in the perception of movement.

Hence, if modularity is a strategy of vertebrates for the production of movement, it is plausible that the modularity of movement is also is relevant for its perception. However, there is barely any research on the composition of movement based on these fundamental movement building blocks and how it relates to the aesthetic quality of movement in dance and its perception.

1.1 Movement primitives for motor control

The presumed building blocks underlying full-body movement have been referred to as *motor primitives* when describing primitives at the muscular level (Giszter, 2015). Motor primitives, also known as muscle synergies, have been defined as "the coordinated activations of groups of muscles with specific time-varying profiles" (d'Avella et al., 2006) and describe how muscles are activated in relation to one another. On the other hand, *movement primitives* have been described as primitives at a kinematic level (Giszter, 2015) and can for example represent patterns of joint angles over time. Although movement primitives can in principle be seen as derived from motor primitives, a unified framework regarding the correspondence between these different types of primitives is lacking (Giszter, 2015). It is important to note that various terms have been used in the motor control literature to refer to these fundamental building blocks, including primitive (Giszter, 2015), synergy (D'Avella et al., 2015), module (Clark et al., 2010a), and coordinative structure (Wang et al., 2013). This diversity of terminology highlights the need for careful consideration within the field (Bruton & O'Dwyer, 2018).

The hypothesis of modularity as a key element of the motor control architecture is supported by a large body of findings on the intrinsic dimensionality of movements. Biological movements usually result in high-dimensional spatio-temporal data. For instance, if the 3D joint angles of 18 joints are captured with a sampling frequency of 100 Hz during a jump in the air lasting 4 seconds, this short movement already results in 21 600 datapoints (18 joints x 3 angles x 4 s x 100 Hz). However, many movements exhibit rather stereotypical spatio-temporal patterns, even cyclical in the case of for instance walking. Indeed, only four patterns can already account for about 90% of the variance in gait (Dominici et al., 2011), allowing for a representation with a much lower dimensionality. These low-dimensional representations have not just been found in human locomotion (Cappellini et al., 2006; Dominici et al., 2011; Ivanenko et al., 2004), but also in other movements, such as reaching (for a review, see d'Avella and Lacquaniti, 2013). However, as pointed out by Tresch and Jarc (2009), the ability to represent behavioral data in fewer dimensions does not necessarily provide strong support for the use of primitives in motor control. Observed low-dimensional patterns in movement output may not imply a motor control strategy based on fundamental movement building blocks, but might merely be a byproduct of task constraints and optimization (D'Avella et al., 2015; Tresch & Jarc, 2009). Indeed, even if each muscle is assumed to be controlled independently, these patterns could be observed emerging from the mechanical and physical properties of the body and thus would not represent biologically meaningful entities (Kutch & Valero-Cuevas, 2012).

Consequently, there has also been increasing interest in the encoding of motor primitives within the CNS and their neural basis (Cheung & Seki, 2021; Tresch & Jarc, 2009). Several findings from this area provide evidence for the neural basis of primitives. For example, co-stimulation of two spinal sites results in vector summation of the endpoint forces generated by each site separately (Mussa-Ivaldi et al., 1994). Similar features have been observed for primitives identified using motor cortical activations and those identified using muscle activations (Overduin et al., 2015). Additionally, modifications to muscle synergies have been observed in human stroke patients. Comparing the affected and unaffected arms showed that the degree of motor impairment correlates with the extent to which synergies merge, whereas the duration since the stroke correlates with the extent to which synergies become fragmented (Cheung et al., 2012). Lastly, a VR experiment with myographic controls showed that adaptation is faster after synergy-compatible than synergy-incompatible virtual surgeries, providing evidence for a modular controller (Berger et al., 2013).

Overall, low-dimensional patterns have been observed at different levels of the motor control hierarchy, including the motor cortex (e.g. Overduin et al., 2015), spinal interneurons (e.g. Hart & Giszter, 2010), motor neurons (e.g. d'Avella et al., 2003) and at the level of motor output (e.g. De Marchis et al., 2018; Endres et al., 2013). The use of a modular control strategy may be a general strategy employed by vertebrates to simplify motor control (Bizzi et al., 2008). It is plausible that a common ancestral network exists, as patterns similar to those observed in the lumbosacral motoneurons during the locomotion of toddlers have been found in other species, including rats, cats, macaques and guinea fowl (Dominici et al., 2011).

1.2 The identification and representation of primitives

Various methodological approaches have been implemented to represent primitives. Examples of factorization techniques applied include principal component analysis (PCA), non-negative matrix factorization and tensor decomposition (Takiyama et al., 2020). However, the type of technique implemented might be less relevant for the interpretation of findings, as different techniques yield similar results (Dominici et al., 2011; Tresch et al., 2006). The type of data used to obtain primitives is relevant, as it determines the type of primitives that are assessed. For the assessment of motor primitives, data are usually obtained from muscle activity measured by electromyography (EMG). Movement primitives, on the other hand, represent modularity at the kinematic level and are obtained via the measurement of joint angles.

Primitives can be represented in several domains. For instance, a primitive in the spatial domain would represent a pattern that characterizes the relationship between the activation of different muscles or joints. From a computational perspective, to generate a movement, the weights at each time point could be learned to specify the degree of recruitment of each primitive at each time point. Temporal primitives, on the other hand, would represent a temporal pattern, specifying relative activation over time. In this case, the weights of each muscle or joint could be learned, specifying the level of recruitment required for each temporal primitive. Depending on the duration of movement sequences, a temporal segmentation may be required as a pre-processing step in order to obtain several shorter segments for the modeling of temporal primitives. Finally, spatio-temporal primitives are represented in both the spatial and temporal domains, requiring fewer weights to be learned overall.

This work is concerned with temporal movement primitives learned with a Bayesian generative model from data representing joint angles during dance sequences. Due to the longer duration of movement sequences assessed, the sequences were partitioned into smaller segments. The model implemented in this thesis represented movements as a weighted sum, with weights W learned for each segment s, of M movement primitives MP, with additive noise ϵ, in order to generate data X of a joint j over time t in each segment (Eq. 1).

$$X_{jt} = \sum_{m}^{M} W_{jm} MP_m(t) + \epsilon \tag{1}$$

Models based on temporal movement primitives have been shown to be perceptually valid for walking movements (Knopp et al., 2019), i.e., human observers were not able to distinguish between the model-generated and the original movement. This type of model has even been employed to generate the walking sequences of a humanoid robot (Clever et al., 2017). The validation of the model used to represent movement is a critical requirement for any further assessment of the parameters of a trained model, for example in relation to various movement characteristics. However, the temporal movement primitive model has not yet been validated for dance movements, i.e. it is unclear whether the model would be able to generate naturally appearing dance movements. Considering that the temporal coherence of model-generated movements is more important for the perception of naturalness than single-frame poses (Knopp et al., 2019), a validation of the model specifically for dance movements is particularly crucial, as these types of movements should exhibit an even higher degree of movement dynamic complexity. In addition, and this aspect is less relevant for walking movements, as these are standard human movements performed in everyday life, the perception of the naturalness of model-generated movements should consider the degree of prior sensorimotor experience of the observer. It is plausible that experienced observers, possibly due to a higher discrimination ability (Aglioti et al., 2008; Calvo-Merino et al., 2005; Cross et al., 2013), might differ in their perception of movement naturalness compared to naive observers with no prior dance experience. Furthermore, the quality of the movements generated by the model might differ depending on the sensorimotor experience and skill level of the dancer who performed the movements used to train the model. For example, it is plausible that the movements of experienced performers may have more complex kinematics that are more difficult to capture in the model. Therefore, the experience of the performer should be taken into account when assessing the performance capabilities of the model.

1.3 Modulation of primitives by learning

If the underlying structure of complex human movement can be characterized as a modular composition of discrete movement primitives, this raises the question of whether, and how, these fundamental components are altered through the development of skills, potentially enabling the advanced motor coordination and aesthetic quality seen in expert dancers. The flexibility of modular control is still a matter of debate, but in principle it could involve modulation of factors such as primitive weighing, number, shape, or a combination of these. Humans may be born with as few as two primitives for locomotion, which are maintained throughout development as new ones are added (Dominici et al., 2011), that are more consistently activated (Hinnekens et al., 2023). Interestingly, primitives of toddlers appear similar to those of other species, but then diverge for humans later in development, possibly to allow for more human-specific movements (Dominici et al., 2011). It has also been suggested that technological innovation and the use of new tools may lead to new primitives in humans in the future (Giszter, 2015).

A study by Torricelli et al. (2020) showed that using visual EMG biofeedback during short-term learning can refine muscle activation and the organization of underlying muscle synergies to some degree. On the other hand, a high degree of preservation of muscle synergy shapes has been observed in stroke patients, despite impaired motor performance (Cheung et al., 2009). A less complex pattern of coordination after a stroke is associated with a smaller number of modules, and these appear to be merged versions of the modules observed in healthy people (Clark et al., 2010b).

Although functional movements are associated with an increase in motor primitives, both with long-term experience (Matsunaga & Kaneoka, 2018; Sawers et al., 2015) and short-term practice (Haar et al., 2020), research on artistic movements indicates an opposite pattern. Specifically, a reduced number of primitives was found in short dance sequences of experienced dancers in comparison to novices (Bronner & Shippen, 2015; Chang et al., 2020). However, in the category of artistic movements, the movement sequences evaluated in relation to a modulation of primitives have been relatively short and predetermined, i.e. improvised dance has not yet been evaluated in this context.

1.4 Effects of expertise and modularity on the perception of dance

A reduction in the dimensionality of movement inevitably removes parts of the movement. However, depending on the performance of the decomposition algorithm used, the removed part might merely represent noise and the dimensionality reduction might thus not affect the essential components of movement. Indeed, model-generated movements based on movement primitives have been found to be hyper-realistic, i.e., observers judged the model-generated movement to be more natural than the original walking movement (Knopp et al., 2019). On the other hand, model-generated stimuli have also shown different patterns of effects. Specifically, a phenomenon known as the Uncanny Valley refers to a sharp decrease in the appeal of model-generated stimuli as they approach human-like naturalness but do not quite achieve it (Mori, 1970; Mori et al., 2012). However, previous research on walking and simple everyday movements does not support the existence of the Uncanny Valley effect for model-generated movements (Piwek et al., 2014; Thompson et al., 2011), despite studies indicating its presence under certain conditions for model-generated character appearances (for a review, see Kätsyri et al., 2015).

In relation to the perception of dance, it is not only the perception of the naturalness of movement that is relevant, but also its aesthetic quality. Findings from Bronner and Shippen (2015) suggest that an increase in perceived movement aesthetics is indeed based on some sort of chunking or simplification of movement components. In detail, they found that the movement of expert dancers was associated with a higher aesthetic proficiency rating and fewer principal components. Additionally, there was a correlation between the rated aesthetic proficiency and the number of principal components, suggesting, "that perceptual chunking could explain aesthetic perception" (Bronner & Shippen, 2015). Similarly, Schmidhuber's theory of beauty posits that the aesthetic value of an object arises from the observer's ability to achieve an efficient internal compression of the information it conveys (Schmidhuber, 2009). In the context of dance, such perceptual compression may be facilitated by representing movements using the minimal number of components or primitives necessary to preserve the essential structure of the movement.

Lastly, observers with a higher degree of sensorimotor experience may have a greater discrimination ability (Cross et al., 2013) and therefore perceive movements with varying degrees of modularity differently than naive observers. Therefore, subjective characteristics relating to the observer should also be considered when evaluating the aesthetic perception of dance, in addition to objective characteristics related to the stimulus itself, such as its dimensionality.

2 Research aims

The preceding sections have outlined how modularity may be a strategy used by vertebrates to produce movements and how the dimensionality of movements may also be relevant for their aesthetic perception. For both movement production and perception, the sensorimotor experience respectively of the performer or observer may influence these processes. So far, these types of interactions have not been extensively studied, especially regarding artistic movement types, such as dance. However, an understanding of the modular composition of dance movements can provide insights into the fundamental mechanisms of motor control and how these are refined through practice. These practice-related refinements leading to skill progression can further our understanding of the changes in modular composition that might enable the generation of aesthetically refined dance movements. In turn, these insights can be utilized to improve our comprehension of how the composition of underlying movement primitives affects processes of aesthetic appraisal.

The overarching aim of this thesis is to further our understanding of the aesthetic evaluation of artistic movements in the domain of dance, in terms of the modular composition of movement. To achieve this objective, dance movements were decomposed and analyzed using a movement production model based on movement primitives. Firstly, this thesis presents an assessment of the segmentation of dance sequences as a pre-processing step prior to model training. The objective of this study is to ascertain the viability of employing basic kinematic characteristics for the segmentation of heterogeneous motion capture dance data. Secondly, the perceptual validity of the temporal movement primitive model applied to dance movements was evaluated, as this is a prerequisite for analyzing the trained model parameters, such as the movement primitives. The aim of this study is to assess the capability of the model to generate dance movements that appear natural and are indistinguishable from the original movement. Thirdly, the use of movement primitives in dance production was explored in relation to sensorimotor experience, and how this is related to the movement segments in a dance sequence. Finally, the aesthetic perception of dance movements based on a modular framework was assessed. Specifically, a perception experiment was conducted to evaluate how dance movements with varying dimensionality are perceived in terms of aesthetic appraisal, and whether this evaluation is modulated by the observer's level of dance expertise.

3 On the association between kinematic features and the perceptual segmentation of movement sequences by dancers and novices

This chapter is represented in the form of an unpublished manuscript.

Unpublished manuscript

On the association between kinematic features and the perceptual segmentation of movement sequences by dancers and novices

Abstract

The perceptual segmentation of continuous sensory information into meaningful events is a fundamental process of human cognition. Since dance can exhibit movement sequences of high complexity and fluidity, posing increased challenges to this perceptual process, the association between kinematic features and the perceptual segmentation of dance sequences by dancers and novices was assessed. Stimuli with different kinematic properties were created from motion capture data of a professional dancer. Participants navigated through these sequences to set segmentation boundaries. The results indicate that both groups rely on kinematic cues, specifically speed minima, for segmentation. However, the extent of this reliance varied with the characteristics of the movement sequence, and was limited for movement sequences with high fluid characteristics. In particular, ground contact events emerged as potentially significant cues for segmentation. While slightly higher agreements with speed minima were obtained with the segmentation points of dancers, no significant difference in segmentation frequency was found between the groups, and both groups show similar patterns of results across sequences with different kinematic characteristics. Overall, these results demonstrate the relevance of speed minima in perceptual segmentation, highlight the importance of contact events, and show the limitations of segmentations based on simple kinematic features such as speed.

Keywords: event segmentation, dance, motor expertise, motion capture, biological movement perception

1. Introduction

Humans need to encode and derive meaning from a continuous stream of sensory information in order to take appropriate actions and predict upcoming information. The perceptual system may rely on segmentation, i.e. dividing the stream into subsets by setting boundaries between events, to obtain a meaningful structure of the incoming information stream and reduce processing costs (Zacks et al., 2001). Changes in perceptual (e.g. motion parameters) or conceptual features (e.g. goals or causes) can make it more difficult to predict incoming information. According to Event Segmentation Theory (Zacks & Swallow, 2007), the resulting increase in prediction error leads to an update of so-called ”event models”, where the update corresponds to an event boundary.

Behavioural and neurophysiological evidence supports the notion that segmentation is a relevant process of the perceptual system and for memory encoding. For example, readers slow down at perceived event boundaries (Speer & Zacks, 2005; Speer et al., n.d.), suggesting additional processing (Kurby & Zacks, 2008). From a neurophysiological perspective, the activity of several brain regions changes at perceived event boundaries, e.g. while watching movies of everyday activities (Zacks et al., 2001) or reading (Speer et al., 2007). Furthermore, objective event boundaries in music (transitions between movements in a symphony) are also associated with changes in neural activity (Sridharan et al., 2007). Finally, there is evidence that event boundaries may be relevant for working memory updating and may serve as anchors for long-term memory encoding (for a review see Kurby and Zacks, 2008).

Segmentation is not only relevant for human perceptual processing, but is also an important step in certain computational methods, such as motion processing. For example, certain research objectives could require a computational method with a segmentation performance similar to how the human perceptual system would segment an incoming stream of information. There are several techniques for segmenting motion streams into subsets. There are both approaches using standard kinematic features (e.g. speed; Fod et al., 2002; Shiratori et al., 2003; Zhao and Badler, 2005), and more sophisticated statistical techniques, such as PCA or clustering (Barbič et al., 2004). In addition, approaches that use semantic content information exist, e.g. a notation system such as the Laban Movement Analysis used in dance (Bouchard & Badler, 2007), and methods related to theories pertaining movement production. An example of the latter is Bayesian Binning (Endres & Foldiak, 2005), an unsupervised algorithm that can be based on the framework of modularity, i.e. utilizing movement primitives as fundamental movement building blocks for movement production (Endres et al., 2011). The algorithm is able to identify segmentation boundaries in taekwondo sequences that are in agreement with boundaries identified by human observers (Endres et al., 2011). However, other skills might yield movement sequences with less salient boundaries than those in taekwondo. This might be especially pronounced in dance, where movements may have a more fluid quality and external movement goals may be less obvious, as movement may be generated just for the sake of movement.

Both bottom-up and top-down processes seem to be relevant for human perceptual segmentation. Regarding the former, certain movement features are relevant for movement segmentation. In particular, speed is correlated with the perceived segmentation boundaries of several everyday activities (Zacks et al., 2009). Furthermore, cortical activity is associated with changes in speed and perceived segmentation boundaries of moving point objects (Zacks et al., 2006). Transitions in neural activity (M1) in primates also coincide with speed extremes during the execution of arm movements (Kadmon Harpaz et al., 2019). On the other hand, top-down processes influenced by prior knowledge and expectations are also relevant. Previous studies show that experts select fewer segmentation boundaries when observing a dance sequence (Bläsing, 2015) and agree more on detected events in a figure skating routine (Levine et al., 2017). However, these effects of expertise were only partially found in other studies (Di Nota et al., 2020; Newberry et al., 2021). A possible methodological issue may be that the perceived segmentation boundaries in previous studies were obtained with key-presses while repeatedly observing the sequence at veridical speed (Bläsing, 2015; Levine et al., 2017), as these obtained boundaries may also be influenced by visual familiarity with the sequence and anticipatory processes.

Given the importance of understanding segmentation processes and the identified relevance of certain kinematic cues, the aim of this study is to assess the significance of specific kinematic cues for the perceptual segmentation of dance, as this type of movement can entail relatively complex kinematic characteristics. Previous studies show mixed results regarding the effect of dance expertise on perceptual segmentation. Therefore, a further aim is to investigate differences in segmentation behavior based on motor dance expertise. A different methodological approach than previous studies is implemented. Specifically, participants use a computer interface to navigate through the sequence, with unlimited time to set perceived segmentation boundaries. The focus is on dance sequences with contemporary/modern/jazz elements, as these types of sequences tend to have a high fluid quality, often without obvious segmentation boundaries. Overall, the aim is to assess how the perceived segmentation boundaries of dance experts and novices correspond to kinematic features of the sequences, and whether kinematic cues differ in their relevance depending on prior sensorimotor dance experience. In this regard, speed extrema are analyzed as a kinematic cue, as this feature has been found to be particularly relevant for human segmentation in previous studies (Zacks et al., 2009; Zacks et al., 2006). Finally, the effect on the perceived boundaries of dance novices and experts is assessed by analysing several dance sequences with different characteristics regarding the saliency of kinematic cues.

Stimulus	Sequence	Characteristic	Duration (s)
1	1	Fluid	15.9
2	2	Fluid	17.4
3	3	Salient	16.5
4	4	Salient	14.2
5	5	Neutral	13.8
6	5	Uniform	14.5
7	5	Varied	13.6
8	5	Floor contact	16.5

Table 1. Properties of the eight stimuli displayed in the experiment.

2. Methods

2.1 Participants

Informed written consent in accordance with the Declaration of Helsinki and data from 34 individuals (5 male; $M_{age} = 24.4$ years, $SD = 4.1$) were obtained. Participants with more than 10 years of formal dance training in contemporary, modern or jazz were assigned to the 'dancers' group (N = 16), while the remaining participants had less than one year of formal dance training and were assigned to the 'novices' group (N = 18). Musculoskeletal disorders, abnormal vision or age under 18 years were exclusion criteria. Participants received course credits for taking part in the experiment or 8€/hour. The local ethics committee approved the study.

2.2 Stimuli

The motion of a professional male dancer from the Staatsballett Berlin was captured in order to create the stimuli. The Xsens MVN Link system (Xsens Technologies BV, Enschede, The Netherlands) with 17 inertial measurement units was used to capture the kinematic data at 240 Hz in order to obtain joint angles using the Xsens MVN Analyze software (version 2022.0.0; Schepers et al., 2018). Prior to the export of the angles in the Euler angle representation, the data were downsampled to 60 Hz.

The motion capture data used to create the stimuli consisted of five movement sequences performed with different expressions, resulting in a total of eight stimuli (see Table 1). The first four movement sequences were characterized by being either fluid in motion, i.e., having few salient moments of acceleration and pause, or salient, i.e., characterised by a high number of instances of stillness. The fifth movement sequence was previously utilized in a study by Orlandi et al. (2020) and contained extracts from the choreography *Duo* by William Forsythe. The kinematic characteristics of the fifth sequence were varied by means of different instructions regarding speed as in Orlandi et al. (2020). The dancer was instructed to perform the sequence in four different ways: a) *neutral*, b) maintaining a constant speed throughout the entire sequence (*uniform*), c) emphasizing dynamic changes in movement speed (*varied*), and d) maintaining constant floor contact with the feet throughout the entire sequence (*floor contact*). The condition Varied should result in the occurrence of more salient moments of acceleration and pause, as in sequences 3 and 4. In contrast, the conditions Uniform and Floor contact should result in fewer salient moments that could be cues for segmentation events, as in sequences 1 and 2.

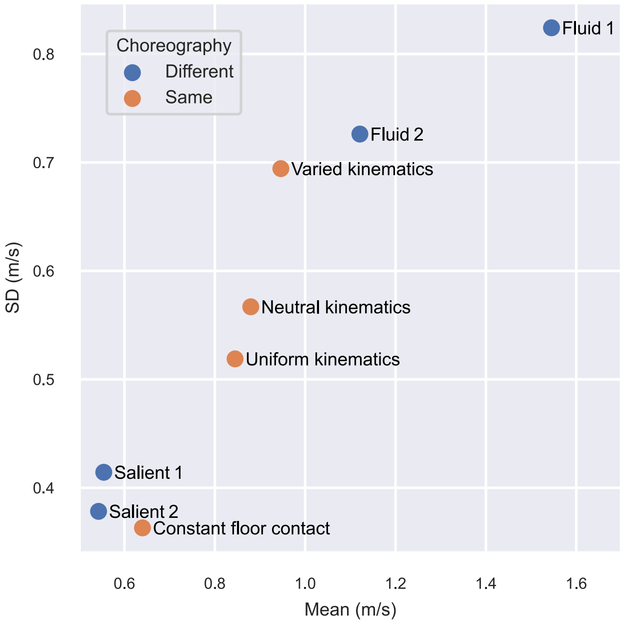

Figure 1. Mean and standard deviation of the mean speed of the hands and feet of the stimuli displayed in the experiment.

Figure 1 depicts the mean and standard deviation of the movement speed of the stimuli and shows that the sequences do indeed have different kinematic characteristics. The fluid sequences have a higher and more variable movement speed compared to the salient sequences. For the sequences with the same choreography, the sequence with Varied kinematics has a more variable movement speed compared to the sequence with Neutral kinematics, while the sequence with Uniform kinematics has a less variable movement speed compared to the sequence with Neutral kinematics.

Stick figures consisting of 27 lines were used to display the movement sequences. The figures had a width of approximately 7 cm and a height of 10 cm. The coordinates of the start and endpoint of the lines were calculated from the exported joint angles. The lines of the figures were rendered using OpenGL, with a line width of 4. They were displayed using PsychoPy (version 2022.2.4; Peirce et al., 2019) at veridical speed. The viewing distance of the participants from the 27-inch monitor (BenQ ZOWIE XL2740) was approximately 60 cm.

2.3 Procedure

The eight movement sequences used as stimuli were presented in a randomized order. During each display of a movement sequence, the participant could navigate back and forth through the sequence utilizing a set of keys on the keyboard. The experimenter demonstrated the navigation with the keys on a test sequence (not part of the stimulus set), and the participant was given the opportunity to test the navigation on this sequence before the display of the actual stimulus set. Furthermore, a handout was visible on the wall throughout the entire experiment, providing information about the navigation keys and their effect. The participant was instructed to set a boundary at every point judged to be the endpoint of a single, separable movement. Additionally, it was emphasized that there are no right or wrong entries in this task, and that the boundaries should be placed as perceived. Upon the placement of a boundary, this was indicated by a green vertical line on a timeline situated towards the lower portion of the screen. The participant had the option to restart, i.e., remove all previously set boundaries, during the segmentation of each movement sequence. Furthermore, the participant was requested to confirm the final boundaries before progressing to the subsequent movement sequence. No time constraint was imposed. The experiment lasted approximately 20 minutes and was conducted in a soundproof room.

2.4 Data analysis

The number of boundaries placed by each participant in each sequence was divided by the duration of the sequence to obtain the segmentation frequency (boundaries per second). The frequencies for the two salient and fluid sequences were averaged for each participant. A Bayesian independent t-test was performed to test for a difference between groups in the total time taken to complete the segmentation task. A 6 x 2 Bayesian mixed ANOVA was performed to test the effect of condition (characteristic of the segmented sequences) and group (dancers, novices) on segmentation frequency. The frequency data were log-transformed beforehand due to the skewness of the data. Statistical tests were performed using JASP (version 0.17.1; JASP Team, 2023).

In order to analyze if there is a general association between the speed of the sequences and the segmentation behavior of the participants, the mean speed of different body parts (hands, feet and both, i.e., "Effectors") for each sequence and the density of human segmentation points for each group were assessed. The stationarity of the time series was assessed using the Augmented Dickey-Fuller test (Dickey & Fuller, 1979). The time series were differenced to achieve stationarity and the correlation between the density of human segmentation points and the speed of the different body parts was computed using Pearson's correlation coefficient.

The agreement of human segmentation points and the minima in speed was assessed using a modified ROC analysis. To this end, human segmentation points with a high agreement between participants were extracted for each group using a threshold of the 70th percentile of segmentation point densities. The speed minima were identified by finding local minima in the speed time series. These were identified by implementing a prominence of at least 0.3 (Virtanen et al., 2020). In addition, the analysis was repeated using different thresholds for the maximum speed values that would allow a minimum to be identified. This was implemented due to the very different distributions of speed values between the sequences. Only sets of identified speed minima, i.e. for a given threshold, with a similar number of segmentation points to the number of human segmentation points, were further evaluated. Specifically, a maximum deviation of 1 was allowed between the number of kinematic and human segmentation points.

The hit rate was computed by evaluating each speed minima that occurred within 100 ms of a human segmentation point as a hit, if no other speed minima hat already been assigned to that human segmentation point. The remaining human segmentation points were categorized as false negatives. The sampling frequency of the data resulted in a large number of true negatives. Therefore, the false positive rate was calculated per second. The set of speed minima with the highest scores were extracted for each sequence, body part and group, where the score was calculated by subtracting the false positive rate from the hit rate. Finally, for contextual reasons, a line of no discrimination was calculated by sampling random segmentation points using a Poisson distribution and calculating the corresponding hit and false positive rates.

3. Results

3.1 Frequency of behavioral segmentation

A Bayesian Independent T-test shows anecdotal evidence ($BF_{10} = 1.8$) for a difference in the total time taken to complete the segmentation of the eight sequences, with dancers taking more time ($M = 23.6$ minutes, $95\% - CI = [17.5, 29.7]$) than novices ($M = 16.9$ minutes, $95\% - CI = [13.7, 20.1]$).

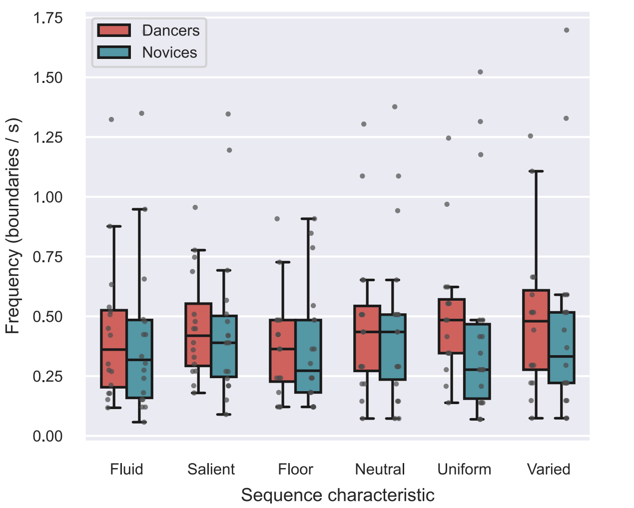

Figure 2. Frequency of human segmentation boundaries indicated for sequences with different characteristics by each group (individual data points displayed as points).

A 6 x 2 Bayesian mixed ANOVA with the factors condition (characteristic of the segmented sequences) and group (dancers, novices) shows that segmentation frequency (Figure 2) is best represented by a model including only the factor condition (BF_{10} = 3.2), followed by a model additionally including the factor group (BF_{10} = 2.0). However, there is anecdotal evidence favouring the null hypothesis compared to the model including only the factor group (BF_{01} = 1.6). Post-hoc tests for the factor condition show evidence of differences from the condition Floor (median segmentation frequency of only 0.33 boundaries/s), with extreme evidence for Salient (BF_{10} = 529.0), moderate evidence for Neutral (BF_{10} = 8.0), and anecdotal evidence for Uniform (BF_{10} = 2.9) and Varied (BF_{10} = 1.3). Additionally, there is anecdotal evidence for a difference (BF_{10} = 1.5) between the conditions Fluid (median frequency = 0.31 boundaries/s) and Salient (median frequency = 0.39 boundaries/s).

3.2 Movement speed and segmentation density

The correlation coefficients for the association between movement speed and human segmentation density for each group are shown in Figure 3. Overall, the heatmaps show a low to moderate correlation between the speed of different body parts and the density of segmentation points perceived by humans. The correlation coefficients are higher for the speed of the feet in almost all sequences, suggesting that human observers rely particularly on the kinematic properties of the feet for segmentation. This is especially evident for the choreographed sequences, where the results show up to moderate correlations for the speed of the feet. Furthermore, for the one sequence in which the feet were in constant contact with the ground and thus provided less prominent information, the associations between foot speed and human segmentation density are lower and similar for hands and feet. The apparent pattern of weighting the sensory information of the feet higher than that of the hands is similar for both groups, suggesting no difference in this regard.

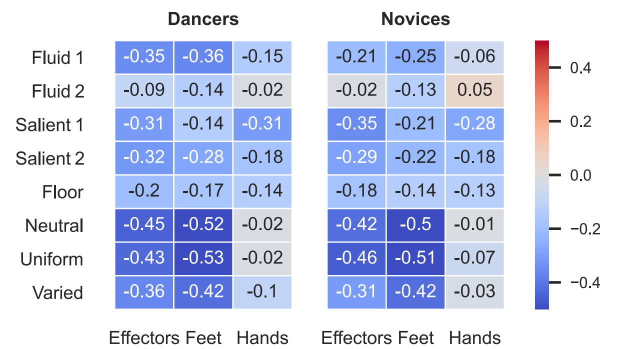

Figure 3. Heatmaps for the group dancers and the group novices, showing the correlation coefficients between the speed of different body parts (effectors include both hands and feet) and the density of segmentation points perceived by humans.

3.3 Agreement between speed minima and human segmentation points

The density of human segmentation points over time for each sequence, along with the corresponding speed profiles and minima of the effectors are displayed in Figure 4. Higher densities represent greater agreement among participants. The coloured points above the densities indicate where participants in each group were in high agreement, and thus correspond to the identified human segmentation points. On a descriptive level, the number of segmentation points with high inter-participant agreement was greater for dancers than for novices in all but three sequences (equal for Salient 1 and Neutral kinematics and lower for Varied kinematics).

The best hit rates and false positive rates for the speed minima and human segmentation points for each group are shown in Figure 5. For the dancers, the Fluid sequences and the sequence with Constant floor contact resulted in the lowest overall scores. The highest hit rates were obtained for the the sequences Salient 1 (effectors) and Neutral kinematics (effectors and feet), with a hit rate of 0.85 obtained for the latter, followed by the sequences Uniform and Varied kinematics. A similar, though less distinct, pattern is observed for the novices, with a maximum hit rate of 0.78 and lower scores than the dancers for the majority of the sequences. However, the performance of the Constant floor contact sequence is comparable to that of the Uniform and Varied kinematics for this group. For both groups, the speed minima of the hands lead to the lowest performance, whereas the performance obtained with the speed minima of the effectors is only slightly higher than that of the feet. Importantly, almost all sequences have scores above the line of no discrimination, indicating that the speed minima are generally informative for the segmentation task.

4. Discussion

In this study the relationship between kinematic features, in particular the speed of different body parts, and the perceptual segmentation of dance sequences by dancers and novices was analyzed. The results indicate that both groups rely to a certain degree on kinematic cues, specifically speed minima, for segmentation. However, the extent to which these cues are available and can be used for perceptual segmentation varies depending on the characteristics of the movement sequence.

Fewer human segmentation points were set for the sequence with constant floor contact than the same choreographed sequence with varying floor contacts and the sequence with a salient speed profile. This indicates that ground contacts are important cues for perceptual segmentation. However, no difference in the number of human segmentation points were found between the Salient and Fluid movement sequence. In addition, no difference was found between the groups in terms of segmentation frequency. This is in contrast to a study by Bläsing (2015), where fewer segmentation points were found for dance experts. However, it is in line with the mixed results on this subject reported in several other studies (Di Nota et al.,

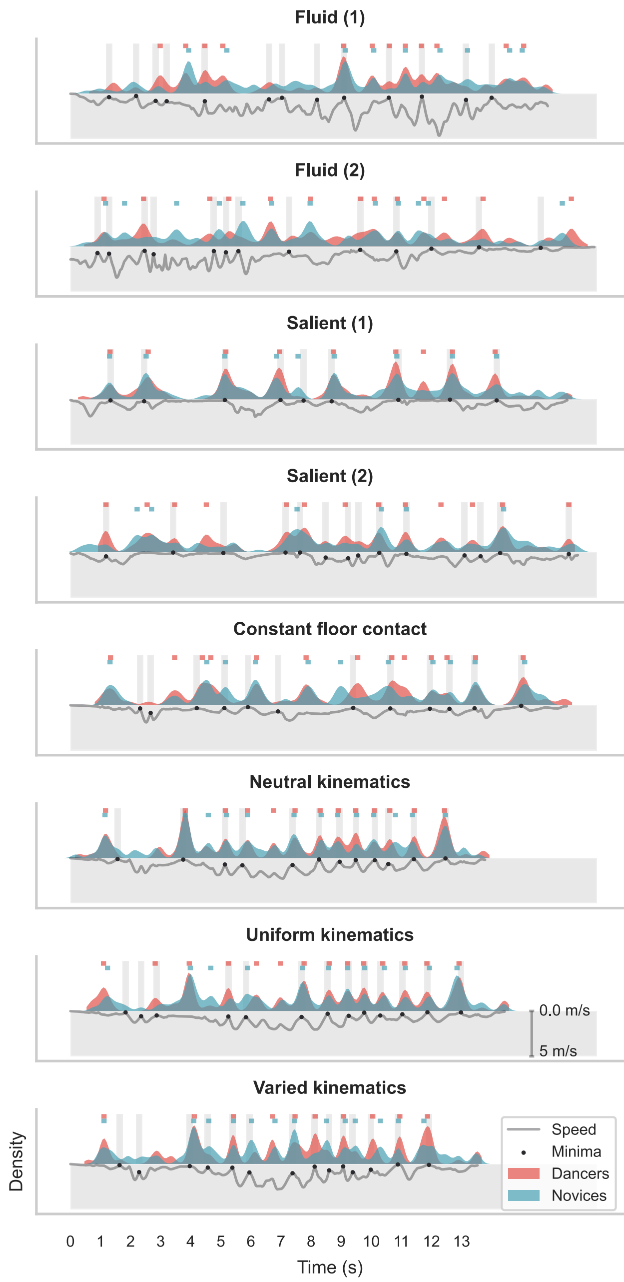

Figure 4. Human segmentation densities for each sequence and segmentation points where participants were in high agreement (points above the densities) for each group. Below the densities, the speed of the effectors is shown (note the inverted y-axis), along with the minima that resulted in the highest agreement with the human segmentation points (minima with the highest agreement for the dancers are shown for all sequences except Varied kinematics, as the dancers had more or the same number of agreed segmentation points for all sequences except this one). The grey areas above the speed minima indicate the 200 ms range that needed to overlap with the human segmentation point to be considered a hit.

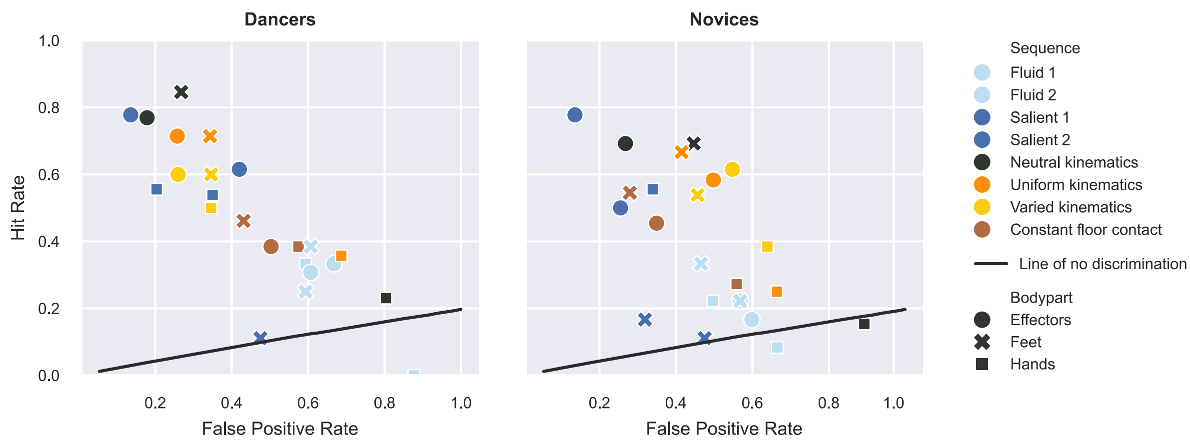

Figure 5. Best hit rate and false positive rate (per second) obtained for each sequence using the speed minima of the hands, feet or effectors and human segmentation points of dancers and novices. The line of no discrimination indicates the expected hit rate and false positive rate for random segmentation points.

2020; Newberry et al., 2021), despite the implementation of a different methodological approach in the current study, i.e. the use of a computer interface that allowed forwards and backwards navigation and unlimited time to set segmentation boundaries.

The finding that ground contact provides significant information for the perception of movement sequences is further supported by the result that, especially for the choregraphed sequences, the speed of the feet shows a higher correlation with the density of human segmentation points than the speed of the hands. Last but not least, the hit rate analysis also confirms this finding, as the hit rates obtained with the speed minima of the hands are lower than those obtained with the minima of the feet.

Overall, the values obtained from the hit rate analysis are predominantly above the level indicating random segmentation, with hit rates above 0.8 obtained using speed minima. This shows that speed minima are important cues for human perceptual segmentation. However, the extent to which speed minima are used as cues seems to depend on the characteristics of the motion sequence. For example, the sequences with constant ground contact and with a fluid motion resulted in lower hit rates, specifically a maximum hit rate of 0.4 for the sequences with a fluid motion, compared to the sequences with salient motion characteristics. This indicates that the presence of more pronounced kinematic features facilitates the perceptual segmentation process.

Regarding the effect of sensorimotor expertise, the descriptive results show a higher number of segmentation points with high inter-participant agreement for dancers than for novices. This is consistent with findings for figure skating, which also found higher inter-participant agreement for experts (Levine et al., 2017). However, there is no difference in the number of individual human segmentation points between the groups. In addition, although participants with no dance experience show descriptively lower hit rates than dancers, both groups exhibit similar patterns in the association between the movement speed of different body parts and the human segmentation density, as well as in the performance obtained with the hit rate analysis.

In summary, the results show the significance of floor contact events for human perceptual segmentation. The findings emphasize the usefulness of segmenting movement sequences based on changes in the position of body parts (as opposed to segmenting by joint angles, for example). However, the limitations of this approach become apparent when kinematic complexity is high, such as in certain dance movement sequences with less salient perceptual information. This highlights the need for more sophisticated movement segmentation methods. Additional kinematic features should be further explored and more advanced computational methods should be developed to better capture the complexity of movement sequences. This could involve the use of machine learning algorithms or the integration of multiple kinematic features to improve the accuracy and reliability of motion segmentation in different contexts.

5. Conclusions

The findings suggest that bottom-up kinematic cues are more relevant than top-down expertise for human perceptual segmentation, and that reliance on specific kinematic features such as speed minima varies depending on the complexity and characteristics of the movement sequence. Furthermore, the results highlight the importance of contact events for perceptual segmentation of movement sequences. The interplay between these factors should be investigated further and additional kinematic features that may contribute to perceptual segmentation in different contexts should be explored.

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

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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*).

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

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

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.

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

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

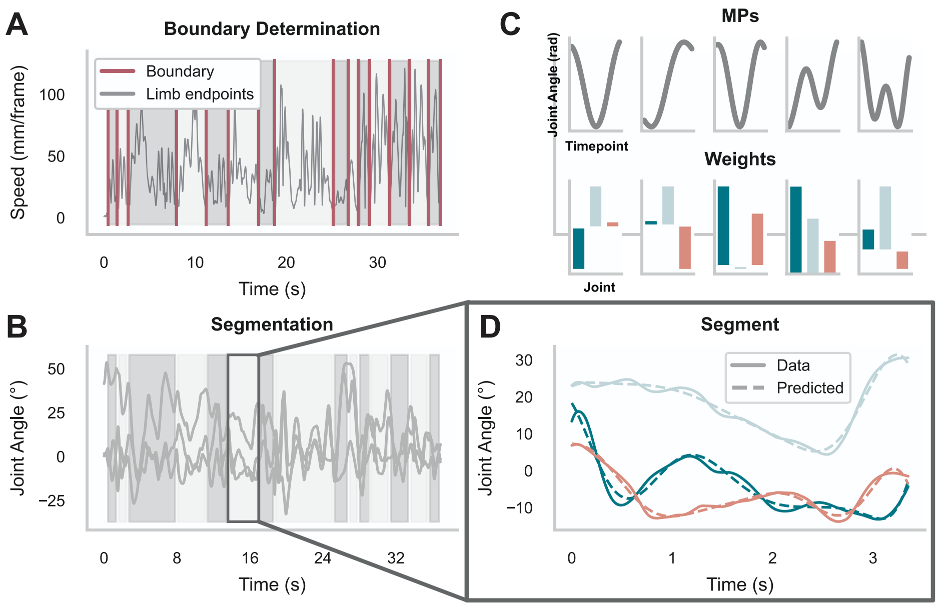

Figure 1. Example of the determination of boundaries for the temporal segmentation of the movement sequence, based on the summed speed of the limb endpoint markers (*A*), the segmented joint angle trajectories (*B*), movement primitives (MPs) and weights for the generation of joint angle trajectories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

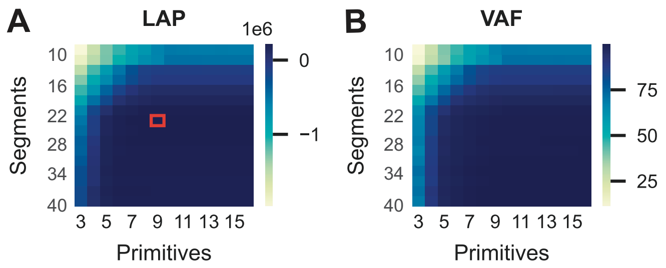

Figure 2. Example of LAP-scores (*A*) and Variance accounted for (VAF; *B*) for models with various number of primitives and segments. The red rectangle in *A* marks the maximum model evidence for this particular subject and condition. LAP, Laplace approximation.

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. 3*B*) 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}: $M = 1.05 \times 10^{9}$).

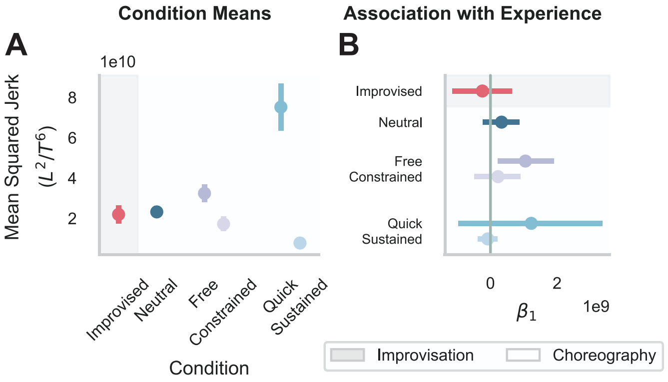

Figure 3. Mean and highest density interval (HDI) of posterior samples of α_c (*A*) and β_c (*B*) corresponding to the mean squared jerk of the hand markers and the association with experience (L, length; T, time).

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]).

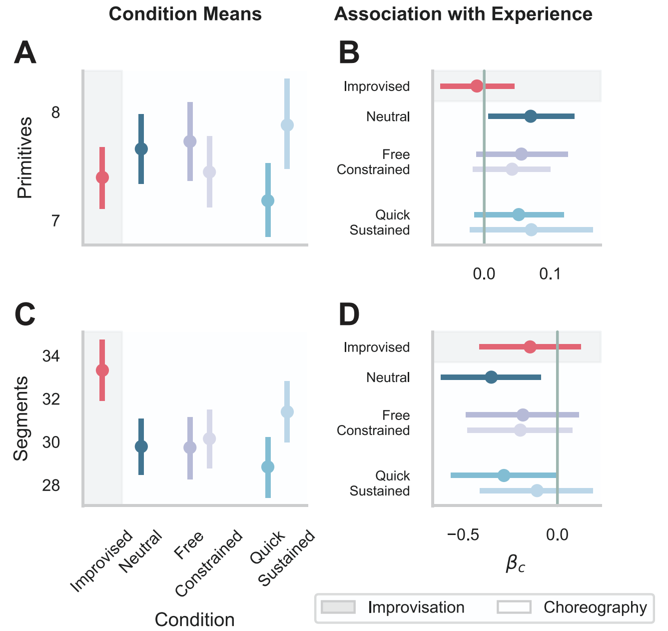

Figure 4. Mean and highest density interval (HDI) of posterior samples of α_c (*A* and *C*) and β_c (*B* and *D*) representing the number of primitives (*A*) and the association with experience (*B*) and the number of segments (*C*) and the association with experience (*D*).

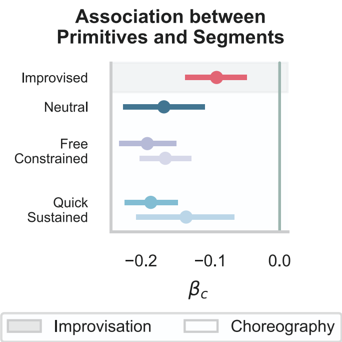

Figure 5. Mean and highest density interval (HDI) of posterior samples of the slope-parameters β_c, representing the association between the number of primitives and segments.

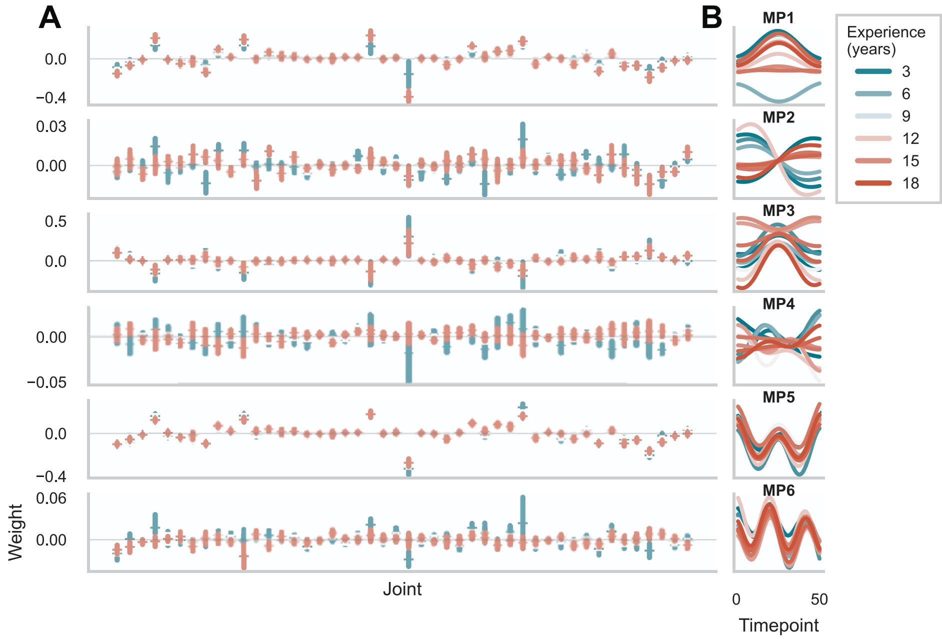

Figure 6. Means and standard deviation of subjects' median weights, grouped by dance experience (above or below 12 yr), across conditions and repetitions (*A*) and corresponding movement primitives (MP) 1 to 6 (*B*).

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.

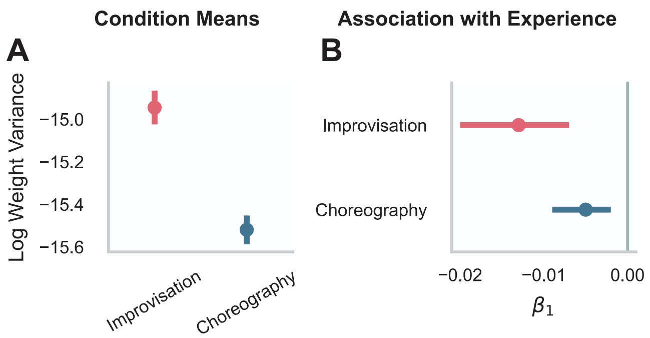

Figure 7. Mean and highest density interval (HDI) of posterior samples of α_c denoting the estimated log weight variance (*A*) and β_c denoting the association with experience (*B*).

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:

$$k \sim B\,ernoulli(\theta) \tag{20}$$

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

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. 9*A*) 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

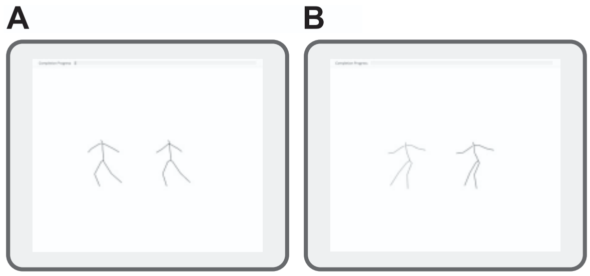

Figure 8. Screenshot of the online experiment (*A*) and the implemented attention checks (*B*).

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.

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.

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 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.

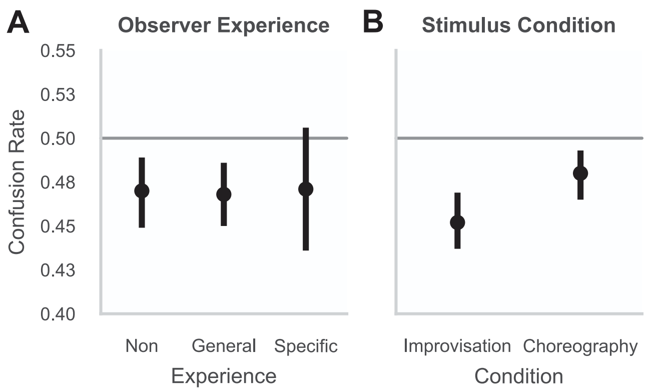

Figure 9. Mean and highest density interval (HDI) of posterior samples of the ω_c-parameters from the hierarchical Beta–Bernoulli models that were used to estimate the confusion rate for different experience groups (*A*) and stimulus conditions (*B*).

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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5 Dancing through the uncanny valley: On the likeability of model-generated dance movements

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Dancing through the Uncanny Valley: On the likeability of model-generated dance movements

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Abstract
The aesthetic perception of model-generated dance movements was analyzed by varying the human-likeness of the observed movements through the implementation of a model based on movement primitives. Likeability ratings and electrodermal activity in response to these model-generated movements varying in the number of underlying primitives were acquired for dancers and dance-novices. The results show that movements with a high degree of human-likeness were generally associated with higher aesthetic valuations. In dance experts, however, results show an uncanny valley effect in that likeability dropped for the most human-like model-generated kinematics. Additionally, the motion energy of the movement sequences also shows a remarkable association with aesthetic responses, although to a lower degree for dancers than novices. Overall, these results extend the perceptual phenomenon known as the uncanny valley to the aesthetic perception of model-generated movement kinematics, but also emphasize the relevance of sensorimotor experience for the aesthetic perception of expressive movements.

Keywords
movement aesthetics, motor experience, movement primitives, biological movement perception, uncanny valley

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1. Introduction

It remains unclear what inspired René Descartes to construct an intricate automaton in the likeness of a young girl. However, it is documented that when he brought it aboard a ship in 1646 to journey to Sweden, the captain and crew, unnerved by its mechanical, seemingly soulless movements, shattered it and cast its remnants overboard (Kang, 2016). Replicating the refined control humans possess over their bodies continues to challenge today's roboticists. Studying the algorithms that drive the control of complex bodily movements, however, does not need to be postponed until the creation of biomimetic robots. Considering that Descartes passed away merely four years after the tragic fate of his humanoid creation, it might be prudent for movement science to develop computational methods for generating complex motor behavior even in the absence of perfect biomimetic robots and test them in advance in simulations involving virtual agents. This ensures that when the appropriate robots are ready, the algorithms to control their bodies in producing natural movements will be ready as well and no roboticist will have to endure a similar fate as René Descartes.

Within the development of such algorithms for controlling the many degrees of freedom of full-body movements, one approach is centered around the idea of modularity: complex movements are decomposed into simpler movement primitives (D'Avella et al., 2015). These movement primitives are conceived as basic building blocks that can be flexibly combined to enable the central nervous system to generate complex movements according to different environmental constraints (for a review, see Giszter, 2015). With respect to studies on the perception of artificial movements, such a model-based approach offers the possibility to generate variations of the same movements, which is in contrast to a simple replay of the recorded motion. This allows the investigation of how different types of movement composition affect the perception of the generated movement. In comparison to neural networks used to generate complex movements (McCormick et al., 2015; Qi et al., 2019; Tang et al., 2018), the advantage of primitive-based generative models is that their parameters have a higher degree of meaningfulness, enabling a straightforward and target-oriented modulation of components used for movement production. We have recently reported a model based on temporal movement primitives (MP) that is able to generate dance movements that appear as natural as human-generated movements (Leh et al., 2023). For the artificial creation of expressive movement sequences such as used in dance, naturalness, however, is only a starting point. As dance has unique aesthetic qualities, it is yet to be demonstrated if such qualities can also be elicited through movements generated by a temporal movement primitive model.

The aesthetic experience that can be elicited by a dance performance is defined as a psychological state in the form of sensuous delights (Goldman, 2001), that is evoked by certain (not necessarily art-related) stimuli (Calvo-Merino et al., 2008). There are two main perspectives in the field of aesthetics on what induces such an experience. The objective theory of aesthetics holds that a universal impression of beauty is evoked by certain objective features, for example the compositional arrangement of stimulus elements, and that the response evoked by these stimulus properties should therefore have some degree of generality, i.e., be subject-independent (Jacobsen et al., 2004; Jacobsen & Höfel, 2002). In contrast, the subjective account of aesthetics asserts that aesthetic judgments depend on the beholder and focuses, for example, on the effect of prior experiences (Höfel & Jacobsen, 2007).

Although movements of experienced performers are perceived as being more aesthetic than movements of less experienced performers (Bronner & Shippen, 2015; Zamparo et al., 2015), it is still unclear which objective movement features contribute to this increase in the perceived aesthetic quality of movements. Findings from Bronner and Shippen (2015) suggest that an increase in movement aesthetics is based on some sort of chunking or simplification of movement components. In detail, they found that the movement of expert dancers, when performing the dance sequence développé arabesque, could be represented with fewer principal components, i.e., a reduced dimensionality, and was also given a higher aesthetic proficiency rating by trained dancers than the movement of dancers with only an intermediate skill level. Additionally, there was an association between the number of principal components and the rated aesthetic proficiency, suggesting, "that perceptual chunking could explain aesthetic perception" (Bronner & Shippen, 2015). A similar understanding of subjective beauty has previously been put forth by Schmidhuber in a formal theory of creativity, fun and intrinsic motivation (Schmidhuber, 2009); Therein, he proposed that subjective beauty depends on the ability to compress the incoming sensory signals, i.e., of several otherwise comparable patterns, the one with the simplest description (most compact representation) should be preferred. According to Processing Fluency Theory (Reber et al., 2004), this preference may be due to the ease with which these types of stimuli can be processed, as high processing fluency should result in a positive subjective experience. Most interestingly, processing fluency has been suggested to depend on the interaction between the observer and the observed: Beauty, on that account, arises from the processing experience of the observer (taking into account his or her sensorimotor, cognitive, and affective state) in combination with objective properties of the observed (such as goodness of form, symmetry, etc.). Analogously, it has also been suggested by Schmidhuber (2009) that perceived beauty should be modulated by the observer's prior knowledge, as experienced individuals can use previously learned compression encodings to better identify regularities in a novel movement. Generally, the mere repeated exposure to specific movement types might increase positive affective judgments (Zajonc, 1968), possibly due to an increase in perceptual fluency. With regard to the movement primitive framework, a more compact representation with a lower dimensionality can be obtained by utilizing fewer primitives to generate the movement. As this represents a type of movement compression, the use of too few primitives will compress the movement considerably, reducing the human-likeness of the generated movement.

In addition to compressibility, another important aspect regarding the generation of artificial human-like movements is the "uncanny valley" (Mori et al., 2012). This phenomenon describes an association between an artificial agent becoming increasingly human-like and the evoked response; an initial increase in likeability is postulated to be followed by a drastic decrease and a feeling of eeriness as human naturalness is approached, but not quite reached. Likeability only increases with a further increase in realism (Mori, 1970). Studies on the effect have mostly focused on static stimuli (see Kätsyri et al., 2015 for a review) or on the effect of a mismatch between sensory cues as a potential cause for the phenomenon (Saygin et al., 2012). Although movement was originally assumed to amplify the effect of agent appearance, i.e., deepen the valley (Mori et al., 2012), the effect has actually been found to be diminished by movement (Piwek et al., 2014). Movement was originally only described as a moderator regarding the effect of character appearance. However, it has been proposed that the effect could also exist only within the movement dimension, i.e., being driven solely by variations in how human-like the movements of the same character appear (Kätsyri et al., 2015). So far, there is no evidence for this. Rather, at least in the case of gait, an increasing human-likeness of walking movements is accompanied by a a monotonic decrease in eeriness (Thompson et al., 2011).

Besides objective movement features, several studies have also explored subjective features in regard to the aesthetic perception of whole-body movement, in particular dance (see Christensen and Calvo-Merino, 2013 for a review). These studies have shown effects of visual and especially motor familiarity with an action (Kirsch et al., 2015; Kirsch et al., 2013). Accordingly, familiar movements that are represented in the motor repertoire of the observer should yield higher aesthetic judgments than unfamiliar movements (Orgs et al., 2016). On the other hand, movements that are considered physically difficult to perform have been rated more aesthetic as well (Cross et al., 2011). Stimulus familiarity also has an effect on implicit measures of arousal, based on findings that the electrodermal activity (EDA) only differs between expressive dance movements for observers with art experience (Christensen et al., 2021) and for dancers only in the forward presentation, i.e., the familiar presentation (Christensen et al., 2016). Similarly, the observation of affect-evoking stimuli only revealed a relationship between facial muscle activity and explicit affective judgments for dancers, but not for non-dancers (Kirsch et al., 2016). Overall, the current state of the research suggests that familiarity with the observed action is a crucial factor for aesthetic perception. Motor familiarity might modulate the ability to simulate the observed movement based on the present motor repertoire (Calvo-Merino et al., 2005; Calvo-Merino et al., 2006). Observers with prior sensorimotor experience may also be able to use previously learned encodings to better compress the displayed movement, thereby leading to an increase in perceived subjective beauty (Schmidhuber, 2009).

The aims of this study were threefold: (1) We sought to test whether our model based on MP could also be used to not only generate dance movements that appear natural but also similarly likeable to human observers as the movements of a professional dancer; (2) Furthermore, by experimentally modulating the human-likeness of the movement, through the number of MP used for movement generation, we sought to examine the effects of how human-like the generated movements were on their likeability; (3) By including expert and non-expert dancers, we aimed to elucidate the role of sensorimotor expertise in the perception of model-generated dance movements as such expertise has been shown to be a major determinant of aesthetic perception. In order to obtain components for movement generation, we applied a temporal movement primitive model to the motion capture data of a professional dancer, thereby ensuring a certain aesthetic quality in the movement data used to train the model. Furthermore, we decided to extend the assessment of the aesthetic perception of the observed model-generated movements beyond explicit subjective ratings by also assessing EDA as an indicator of implicit affective responses.

To our knowledge, the effect of human-likeness of model-generated movements on aesthetic perception and its modulation by the expertise of the observer has not yet been examined. Based on previous findings, we expect the likeability judgements to differ with the experience of the observer (Kirsch et al., 2015; Kirsch et al., 2013) and to be higher for human-like movements (Orgs et al., 2016). For observers with no prior sensorimotor experience, the observed movements by a professional dancer might be low in familiarity and/or more difficult to compress cf. Schmidhuber, 2009 irrespective of the degree of additional artificial decreases in human-likeness. However, for observers that are generally familiar with the observed actions, also on a motor level, the effect of reducing human-likeness through a reduction of movement components on perceptual aesthetics might be much more pronounced. On the other hand, an uncanny valley effect could be observed instead of a monotonic increase in perceived likeability with increases in the number of MP, in case model-generated movements that are highly human-like evoke a negative response.

2. Methods

2.1 Participants

36 individuals (6 men) participated in the experiment after providing written, informed consent in accordance with the Declaration of Helsinki. Two participants were excluded, due to communication issues during the data acquisition. Of the remaining participants ($M_{age} = 24.4$ years, $SD = 4.1$), 18 participants had less than a year experience in formal dance training (group "novices") and 16 participants had at least 10 years of formal dance training in the styles contemporary, modern or jazz (group "dancers"). Participants either received course credits or 8 €/hour for taking part in the experiment. Exclusion criteria were disorders of the musculoskeletal system, abnormal vision or an age below 18 years. The study was approved by the local ethics committee.

2.2 Stimuli

The kinematic data of a professional dancer from the Staatsballett Berlin was captured at 240 Hz during improvised dancing with 17 inertial measurement units using the Xsens MVN Link-System (Xsens Technologies BV, Enschede, The Netherlands). Joint angles were computed, downsampled to 60 Hz and exported in Euler angle representation with the software Xsens MVN Analyze (version 2022.0.0; Schepers et al., 2018).

The joint angle trajectories (in axis-angle representation) were modelled with a temporal movement primitive model. As a pre-processing step, the motion-capture data (overall duration of approx. 9 minutes) were partitioned into segments with a minimum duration of 600 ms. The boundaries of the segments were determined by computing the minima (with a minimum prominence of 0.5 m/s) of the mean speed of the hands and feet. In cases were the resulting segments exceeded 3 seconds, additional minima were computed within these longer segments (minimum duration between minima of 1000 ms and a minimum prominence of 0.05 m/s).

In the temporal movement primitive model, the data X of a joint j over time t are a weighted sum of M movement primitives MP, with additive Gaussian noise $\varepsilon \sim \mathcal{N}(0, 0.03)$ (Eq. 1). A Gaussian prior was used for the weights $W \sim \mathcal{N}(0,1)$, which specify how much each MP is recruited for each joint. To facilitate smooth MP, a Gaussian process prior with a RBF kernel (Eq. 2) was used for the primitives, $MP \sim \mathcal{N}(\mu(t), k(t,t'))$.

$$X_{jt} = \sum_{m}^{M} W_{jm} MP_m(t) + \varepsilon \tag{1}$$

$$k(t,t') = \sigma^2 exp(-\gamma(t-t')^2) \tag{2}$$

The MP and weights were learned by optimizing the log joint probability of the data and the model parameters. We trained models with 3 to 23 MP and estimated the model evidence via Laplace approximation (LAP; Endres et al., 2013). The variance accounted for and model evidence of the trained models are displayed in Figure 1. The model with 15 MP yielded the largest model evidence. See Figure 1c for the learned primitives of this model and an example of their weightings.

The segments were concatenated to obtain a minimum stimulus duration of 5 seconds. Of the resulting 96 movement sequences ($M_{duration} = 5.6s, SD = 0.5s$), 20 were randomly selected for the experiment in order to limit the duration of the experiment and prevent participant fatigue. Each movement sequence was displayed in its natural form (replay of the collected motion-capture data) as well as in six different MP representations (with 3, 6, 9, 12, 15 and 18 MP). Examples of the stimuli can be found in the supplementary material.

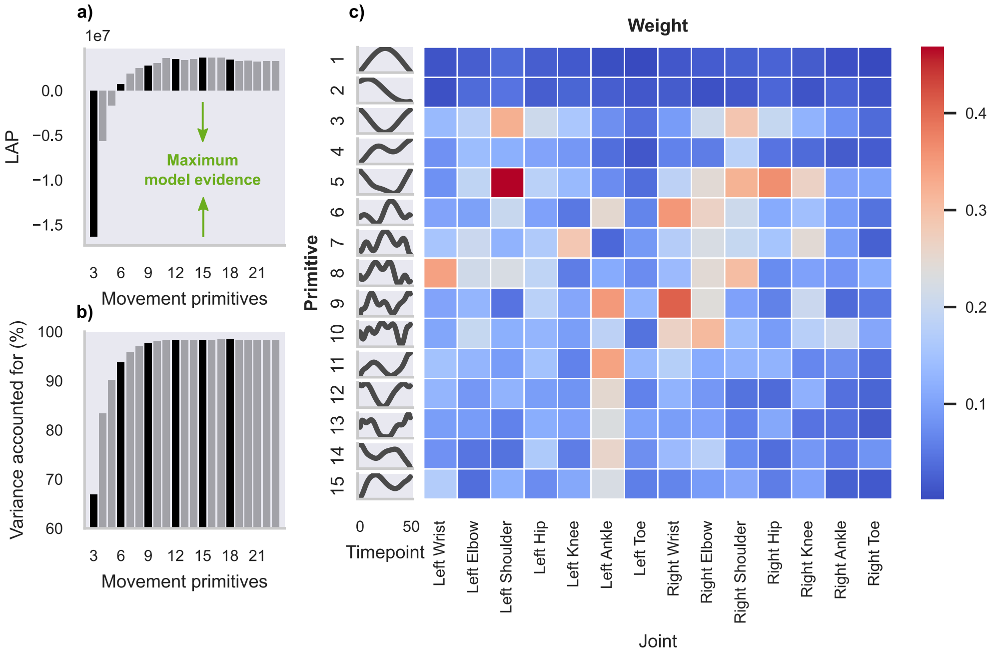

Figure 1. Model evidence, estimated via Laplace approximation (LAP; a), and variance explained (b) of all models trained. The models that were used to generate the stimuli for the experiment are marked in black. The primitives of the model with 15 primitives and an example of the corresponding weights of each primitive and joint of a movement sequence (c).

Furthermore, eight additional stimuli of dance sequences (not included in the main stimulus set and only displayed in its natural form) were randomly interspersed throughout the experiment to check participant attention (see Procedure). All movements were presented as stick-figures (covering a screen area of approximately 7 cm in width and 10 cm in height). The stick-figures consisted of 27 lines that were rendered with openGL (glLineWidth set to 4) and displayed on a 27”-Monitor (BenQ ZOWIE XL2740, refresh rate 240Hz; viewing distance $\sim$ 60 cm) at veridical speed using PsychoPy (version 2022.2.4; Peirce et al., 2019).

2.3 Procedure

In order to measure EDA to assess an individual’s arousal, participants were asked to wash their hands (without soap). Two Ag-AgCl electrodes (EL507A) were filled with isotonic electrode paste (GEL101A) and attached to the thenar and hypothenar eminence of the left hand. A minimum preparation period of 10 minutes was then set prior to recording the EDA signal in order for the electrode connection and the signal to stabilize.

During this preparation period, the participants filled out a questionnaire for a detailed assessment of their dance experience. To check the EDA signal, the participant was asked to take and hold a deep breath and to do an arithmetic task. The participant was instructed to minimize coughing, deep sighs, bodily movements and speaking throughout the measurements. A 2-min baseline was recorded while participants looked at a gray screen. Participants carried out a test trial to familiarize themselves with the task. Subsequently, the participants were asked to find a comfortable sitting position and to breath slowly and regularly for the recording of another baseline (1 min) directly prior to the start of the stimulus presentations.

Stimuli were presented in a random order. A white fixation cross (1.5 x 1.5 cm) was presented before (1500 ms) and after (1000 ms) each stimulus. To minimize surprise, the movement stimulus was faded in and out. After each stimulus presentation, the participant was asked to rate (self-paced) how much they liked the movement using a 7-point Likert-scale ranging from 1 (”Liked very little”, in German: ”Sehr wenig gefallen”) to 7 (”Liked very much”; in German: ”Sehr gut gefallen”). The response was given by pressing the corresponding key on the keyboard with the right hand. The elements of a trial are displayed in Figure 2. In the eight trials used to check attention, participants were asked a yes/no question regarding the movement in the displayed sequence (e.g. ”Did the dancer raise his arms?”) and could respond with the keys 3 or 5. The experiment consisted of 140 trials (20 sequences x 7 sequence presentations). The total duration of the experiment was approximately 45 minutes.

Triggers were sent from the computer running the stimulus presentation software to the computer recording the EDA signal to mark the start and end of each movement stimulus in the EDA trace. The EDA signal was recorded with the software Biopac Student Lab (version 4.1.1) at 2kHz with a BIOPAC MP36 data acquisition unit (BIOPAC Systems, Inc., Goleta, CA) and a SS57LA lead set. The measurements took place in a soundproof room and the room temperature was kept constant at ∼22°.

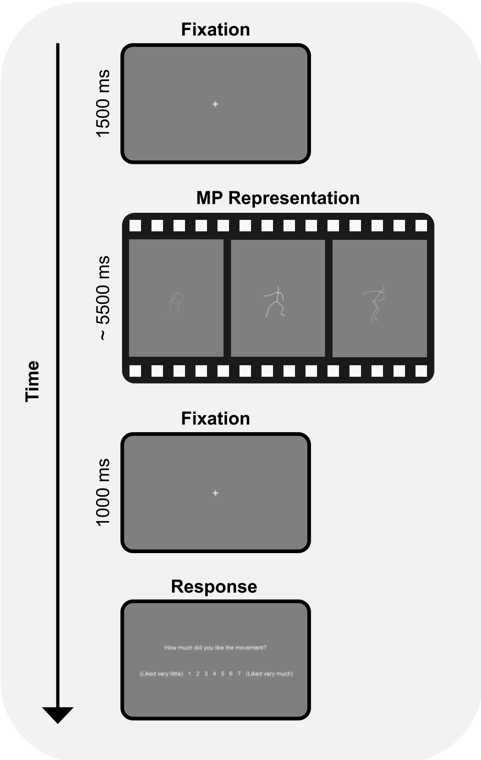

Figure 2. Elements of a trial including representative stimuli used in the experiment. After a fixation cross the movement sequence was displayed in various movement primitive (MP) representations (3-18 primitives or natural representation). The stick-figure was faded in at the beginning and faded out at the end of the sequence, in order to minimize surprise. After another fixation cross following the movement stimuli, the participant was asked ”How much did you like the movement?” and asked to rate the sequence from ”Liked very little” to ”Liked very much” on a scale from 1 to 7.

2.4 Data analysis

2.4.1 Behavioral data

The data of one participant were excluded from the analysis due to the participant responding incorrectly in more than two of the eight attention check trials. The mean rating of each MP representation (across sequences) was computed for each participant. Likewise the mean rating of each sequence (across MP representations) was computed for each participant to analyze the effect of movement sequence.

2.4.2 Psychophysiological data

The EDA signal was smoothed with a 4th-order Butterworth low-pass filter with a cutoff frequency of 3Hz. Then, the phasic component of the signal was extracted using a 2nd-order Butterworth high-pass filter (as in e.g. Biopacs AcqKnowledge Software) with a cutoff frequency of 0.05Hz (Bach et al., 2013). The EDA signal was downsampled to 20 Hz and the signal trace of each trial was extracted. Specifically, the signal trace from stimulus onset to one second after stimulus offset was extracted, due to a typical latency of the EDA response of about 1 to 3 seconds (Lim et al., 2003).

The signal amplitude of each trial was obtained by first finding the peaks in the signal trace with a minimum width of 20 data points (i.e., 1 second). In cases where only one peak was found in the signal trace of a trial (56.3% of trials), the amplitude was obtained by computing the minimum signal value between stimulus onset and that peak and subsequently the difference in the signal between the minimum and the peak. In cases where more than one peak was found (4.9% of trials), the minimum signal value between the first and last peak was computed. Subsequently, the amplitude was obtained by computing the signal difference between the minimum and the last peak. The last peak was used due to the mentioned latency of the signal (see above). Lastly, if no peaks were found (38.8% of trials), the amplitude was obtained by computing the difference between the minimum value in the entire signal trace and the end value. In trials where the signal just decreased or remained stable, this last method would result in an amplitude close to zero. An example of EDA traces is shown in Figure 3.

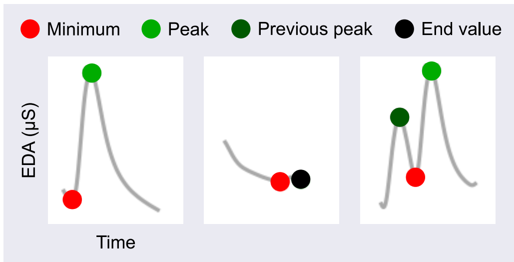

Figure 3. Example electrodermal activity (EDA) traces from three trials.

To enable inter-individual comparisons the amplitudes of each participant were standardized by dividing the amplitudes of each participant with the median amplitude of that participant. Then, the amplitudes were normalized by applying a log transformation (log(amplitude + 1). To analyze the effects on EDA amplitudes, the median EDA amplitude of each MP representation and sequence was computed for each participant.

2.4.3 Statistical analysis

JASP (version 0.17.1; JASP Team, 2023) was used for the statistical analysis of the data. Two 7 x 2 Bayesian mixed ANOVAs were performed to test the effect of movement representation (original + six MP representations) and group (dancers, novices) on ratings and EDA amplitudes. Similarly, Bayesian mixed ANOVAs were performed to test the effect of the factors sequence, repetitions (the repeated display of a sequence, but with a different MP representation) and group on ratings and EDA amplitudes.

2.4.4 Model comparison

The data of both group were further analyzed with regard to an uncanny valley pattern (Mori et al., 2012), i.e., showing an increase in ratings, followed by a dip and a subsequent increase close to the natural display. To this end, three models were fitted to the data of each group. Each individual's difference in rating between "neighboring" MP representations was computed, i.e., difference between representation with 3 and 6 MP, 6 and 9 MP and so on. According to the uncanny valley, a decrease in likeability should be observed with MP representations closely approaching but not reaching the natural human movement, which in this case would imply a negative difference value between 15 and 18 MP followed by positive difference value between 18 MP and the original human movement stimulus.

The difference values of each contrasted MP representation i were assumed to be normally distributed (Eq. 3), with Gaussian priors for μ_i and a Half-Student-t distributed prior for σ_μ, which depended on the sample group size N (Eq. 4). Different bounds and locations were implemented for μ in the three models, however all with $\sigma_\beta = 1$. The model "Increase" (Eq. 8) only contained changes between MP representations that were bounded to be positive, β_+ (Eq. 8). This was compared to a model, termed "Valley" (Eq. 9), also containing positively constrained change parameters, however with the second to last change parameter bounded to be negative, β_- (Eq. 6), conforming to an uncanny valley pattern. Lastly, we compared these to a third model ("Unbound", Eq. 10) with no bounds on the change parameter, β (Eq. 7). The posteriors were computed with the No-U-Turn Sampler using the Python library PyMC (v5.6.0; Salvatier et al., 2016).

$$y_i \sim \mathcal{N}(\mu_i, \sigma_\mu) \tag{3}$$
$$\sigma_\mu \sim HalfStudent\,t(\sigma = 1, \nu = N-1) \tag{4}$$
$$\beta_+ \sim \mathcal{N}(0.1, \sigma_\beta),\ \beta_+ \in [0, \infty] \tag{5}$$
$$\beta_- \sim \mathcal{N}(-0.1, \sigma_\beta),\ \beta_- \in [-\infty, 0] \tag{6}$$
$$\beta \sim \mathcal{N}(0.1, \sigma_\beta) \tag{7}$$
$$\mu_{increase} = [\beta_+ \beta_+ \beta_+ \beta_+ \beta_+ \beta_+] \tag{8}$$
$$\mu_{valley} = [\beta_+ \beta_+ \beta_+ \beta_+ \beta_- \beta_+] \tag{9}$$
$$\mu_{unbound} = [\beta\ \beta\ \beta\ \beta\ \beta\ \beta] \tag{10}$$

3. Results

3.1 Behavioral responses

Overall, the likeability ratings of novices (M = 3.73, SD = 0.40) were lower than the ratings of dancers (M = 4.06, SD = 0.59). A 7 x 2 Bayesian mixed ANOVA with the factors movement representation (original + six MP representations) and group (dancers, novices) shows that the ratings (Figure 4a) are best represented by a model including the factors MP and group. The Bayes factor (BF_{10} = 9.21×10^{12}) indicates decisive evidence in favor of this model compared to the null model. There is strong evidence ($BF_{10} = 18.3$) for the best model over the model that additionally includes the interaction effect. This means the data are 18.3 times more likely under the best model than the model that includes the interaction effect on top of the two main effects. Post-hoc tests for the factor MP show decisive evidence for a difference in ratings between 3 MP and more (range of $BF_{10} : 548.0 - 15189.9$) and up to strong evidence between 6 MP and more (max $BF_{10} = 12.7$). Additionally, there is moderate evidence for a difference in ratings between 18 MP and the natural representation ($BF_{10} = 3.1$).

A 7 x 2 Bayesian mixed ANOVA with likeability ratings as the dependent variable and the factors repetition and group shows no evidence for any model including repetition as a factor (all $BF_{10} < 1$; Figure 4b).

Regarding the effect of movement sequence on rating (Figure 4d), the best model includes the factors sequence and group, as well as the interaction effect. There is decisive evidence for this model over the null model (BF_{10} = 9.3×10^{50}). The sequences that had a high mean rating were more dynamic (e.g. including turns and jumps) in comparison to the sequences with low ratings. To further elucidate the substantial rating differences between the sequences, we computed the motion energy of each sequence by computing the average of the summed inter-frame Euclidean displacements of each body segment. Group-wise Pearson correlations to test the association between the motion energy of the sequences and their mean rating (Figure 4c) shows decisive evidence ($BF_{10} = 2982.1$) for a correlation between the ratings of novices and motion energy ($r = 0.82, 95\% - CI = [0.55, 0.92]$). Similarly, although to a lower degree, there is evidence ($BF_{10} = 74.3$) for an association between the ratings of the dancers and motion energy ($r = 0.70, 95\% - CI = [0.34, 0.86]$).

The difference in the likeability ratings of the dancers between MP representations, with model estimates of μ, are shown in Figure 5a. Of the models tested, the model Valley is the best model according to the expected log pointwise predictive density (Figure 5b), which is a measure of a model's predictive accuracy for expected new data points, i.e. higher values indicate a better out-of-sample predictive fit. This model receives a weight of 0.91, where the weight (ranging from 0 to 1) can be interpreted as the probability of the model being true among the models tested given the data. The other two models, Unbound and Increase, received weights of 0 and 0.09 respectively. For the novice data (Figure 5c), the difference in model weights (Figure 5d) is less pronounced, with the Unbound model also receiving a weight of 0, while the Increase and Valley models receive weights of 0.39 and 0.61 respectively.

3.2 Psychophysiological responses

The EDA amplitudes elicited during the display of the MP representations are shown in Figure 6a. A 7 x 2 Bayesian mixed ANOVA with the factors movement representation and group shows moderate evidence for the null model, i.e., the

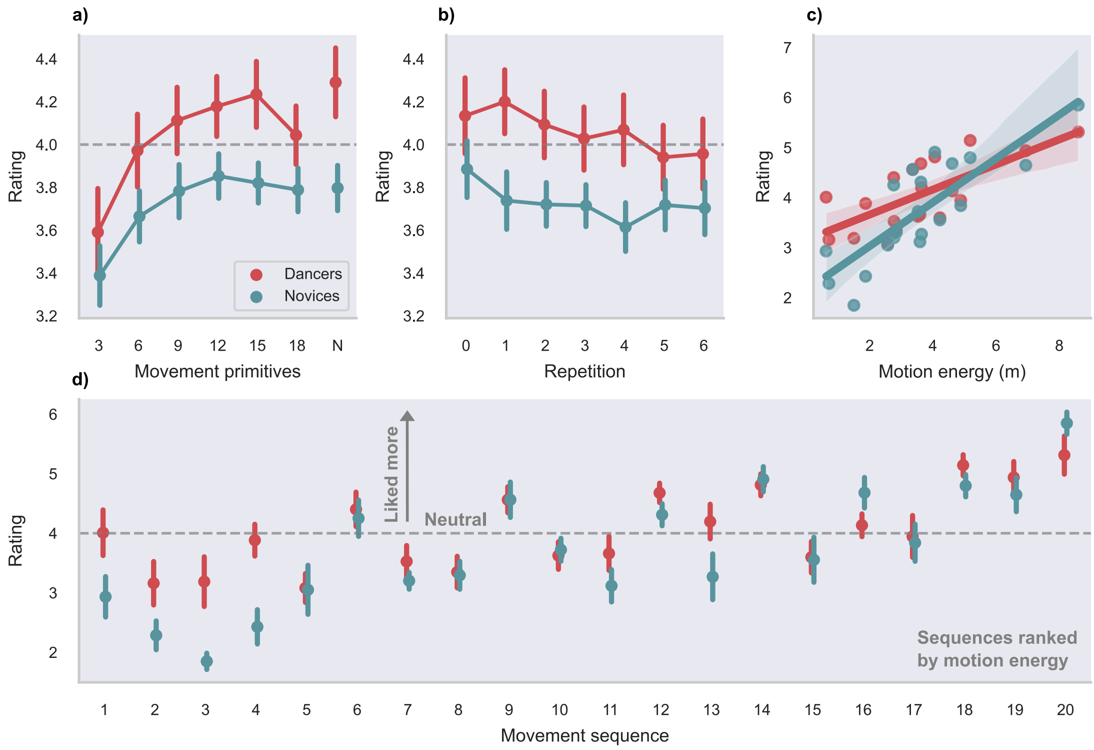

Figure 4. Ratings of movement primitive representations (a; N: natural display) and repeatedly displayed sequences (b), as well as the association between sequence ratings and sequence motion energy (c) and the ratings of each movement sequence (d). Errorbars show standard errors.

data are 5.4 times more likely under the null model than the second best model including the factor group. This suggests that the physiological arousal while observing the movement sequences was not influenced by the degree of human-likeness of the observed movement.

A 7 x 2 Bayesian mixed ANOVA with the factors repetition and group shows that the amplitudes are best represented by a model including the factor repetition. The Bayes factor indicates decisive evidence in favor of this model compared to the null model ($BF_{10} = 2.21 \times 10^{12}$). Implicit affective responses to the same movement sequence were elevated on the first displays and then decreased as the sequence was repeated (Figure 6b). There is moderate evidence for the model including the factor repetition over the model additionally including the factor group ($BF_{01} = 3.4$).

4. Discussion

In this study explicit and implicit responses of dancers and non-dancers to movements varying in human-likeness were analyzed. Overall, results indicate that while model-generated dance movements can indeed evoke positive aesthetic responses in human observers, both subjective and objective measures seem to be relevant for the aesthetic perception of dance sequences generated by a temporal movement primitives model. Model-generated movements that contained fewer MP resulting in a less human-like appearance were found to elicit diminished likeability judgments. This was the case both for individuals with and without prior experience in dance. However, subjective likeability was overall higher for individuals that had prior experience in dance. The attenuated aesthetic responses for observed movements with fewer MP and for individuals lacking skill-specific motor representations shows that aesthetic responses are reduced when familiarity with the observed action is low. Thus, not only is the presence of corresponding action representations in the human observer relevant for aesthetic perception, but additionally the degree to which these representations might be activated or utilized due to how human-like the observed movement is. This is in line with previous finding on the effects of sensorimotor familiarity on the aesthetic perception of dance (Kirsch et al., 2015; Kirsch et al., 2013). Furthermore, the results corroborate previous findings concerning other art-related skills. Chamberlain et al. (2022), for example, recently showed that human-like, computer-generated drawing movements were perceived as more aesthetically pleasing than unnatural drawing actions, while this perception was, similar to the results of the present study, dependent on the observers' artistic expertise.

Interestingly, a deviation from the general pattern of greater likeability with more human-like movements emerged when dancers observed model-generated sequences approaching human-likeness. For these individuals with prior motor experience, the highest likeability rating for the model-generated

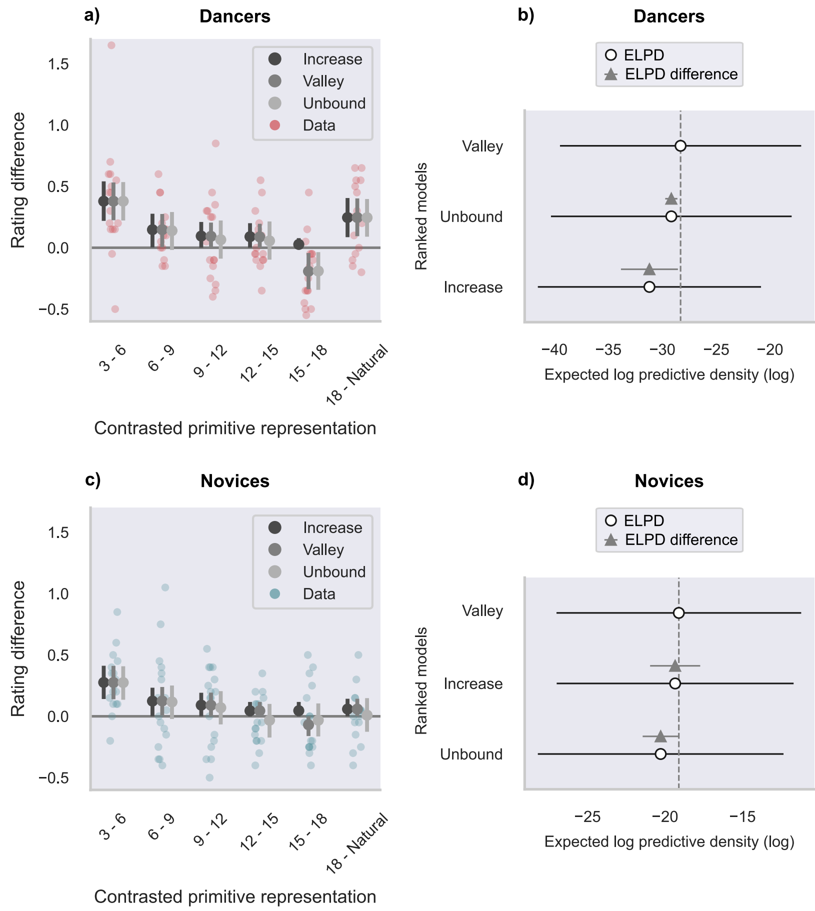

Figure 5. Observed data and model estimates (μ with 95%-HDIs) for the dancers (a) and novices (c). The leave-one-out expected log pointwise predictive density (ELPD) as a measure of each model's predictive fit for the data of the dancers (b) and novices (d). The dotted line marks the ELPD of the best estimated model.

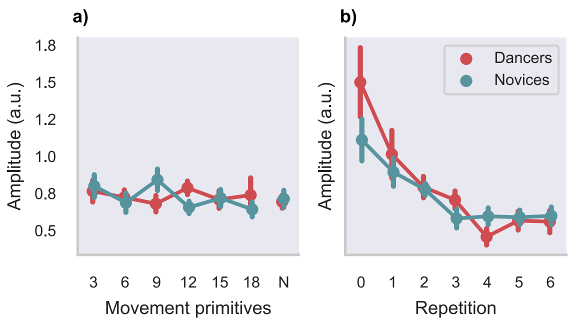

Figure 6. Amplitudes of the electrodermal activity for movement primitive representations (a; N: natural display) and repetitions (b). Errorbars show standard errors.

movements was found for the temporal movement primitive model also deemed optimal by Bayesian model selection, that is the model with 15 MP, whereas likeability dropped considerably for the movements generated by the model with 18 MPs. A subsequent comparison of three models used to assess the relationship between MP representations and likeability ratings showed that a model representing a valley pattern is the best one for the dancers' ratings. Conversely, the model displaying only an elevation in ratings with an increase in human-likeness performs the worst. This can be taken to suggest that an uncanny valley effect can be found in the movement domain as well, i.e., as a result of movement kinematics and irrespective of character appearance, which was the same for all presented stimuli. The underlying cause might be a better discrimination ability for observers with prior experience in producing the movement patterns displayed.

Although a previous study by Bronner and Shippen (2015) found that aesthetic evaluations are higher for whole-body movements that are characterised by fewer principal components, our results do not suggest that aesthetic perception could be based on a reduced dimensionality of components in the observed movement. Except for dancer's reduced aesthetic evaluation of model-generated movements with 18 MP, we did not find that evaluations differ in terms of the number of underlying movement building blocks given a similar quality of movement reconstruction, i.e., variance accounted for. The model with e.g. 9 primitives clearly offers a more compact description of the movement than models with more primitives, while having a comparable reconstruction quality, but the movements generated with this model did not receive the highest aesthetic ratings. Thus, the results obtained by varying the number of components underlying the movement do not support a compression account of beauty (Schmidhuber, 2009). However, the higher subjective ratings observed in the group with prior experience in dance would align with the proposed notion that experienced individuals can use previously acquired encodings to better compress incoming sensory signals, leading to an increased perception of beauty.

The movement sequence itself has a higher effect on perceived aesthetics, than the representation regarding human-likeness. The motion energy shows a strong association with behavioral responses, consistent with previous work showing that aesthetic ratings are related to certain kinematic characteristics (Neave et al., 2011; Torrents et al., 2013; Torrents et al., 2015). Interestingly, the association between ratings and this objective stimulus property is stronger for non-dancers, indicating that simple objective kinematic features play a larger role in evoking aesthetic responses in observers without specific prior motor experience in the skill displayed. Although individuals with prior motor experience are influenced by this kinematic feature to some degree as well, higher-level features, for example related to pose configurations and multi-joint movement dynamics, might be of more relevance for the aesthetic perception of these individuals. This is supported by the finding that when "less is happening" in the sequence (low motion energy), the difference between the group ratings is largest, i.e., dancers still gave these sequences a rating approaching a neutral liking, although they were less dynamic. This indicates that in assessing aesthetic evaluations of dancers, factors other than standard kinematic metrics may be of greater importance.

Our results confirm that stimulus familiarity has an effect on implicit measures of arousal. However, in contrast to previous studies finding a difference in skin conductance levels during stimulus observation due to long-term experience (Christensen et al., 2021; Christensen et al., 2016), our results indicate a fairly short-term effect. On a psychophysiological level, the subconscious affective response to a movement sequence decreased and then plateaued within a couple of repeated displays of a sequence. This habituation effect has been observed for simpler stimuli as well, such as electrical stimuli and sound clicks (Lim et al., 2003). This shows that despite of the complexity of the stimuli and general interest in the skill displayed, evidenced by investing years in learning the skill, autonomic sympathetic arousal appears to still saturate quite rapidly when novelty is reduced.

The higher aesthetic responses of dancers compared to novices that were observed in this study might be due to the presence of motor representations related to the observed actions for the dancers. On the other hand, they could also be due to visual familiarity with the stimuli displayed. An argument for the former is that increased aesthetic preferences have primarily been observed due to the physical practice of a dance sequence (Kirsch et al., 2015; Kirsch et al., 2013). Obtaining motor experience in a skill might increase the ability to simulate observed movements, which has been postulated as an embodied simulation account of aesthetics (Kirsch et al., 2015). Motor simulation has been associated with the activity of certain brain areas, therefore termed action observation network (Buccino et al., 2001), which also is increased when observing dance actions that are part of the observer's own motor repertoire (Calvo-Merino et al., 2005; Calvo-Merino et al., 2006; Cross et al., 2006). The increased activation of this network when observing certain actions has also been shown to be predominantly due to motor familiarity, and not visual familiarity with the observed movement (Calvo-Merino et al., 2006). Since also artificial movements of objects can activate this network of brain areas, although to a lesser degree than biological hand movements (Engel et al., 2008), it would be of interest to assess the activity of this network during the observation of model-generated movements varying in human-likeness in future studies. Moreover, primitive-based models could offer an approach to test the extent of embodiment for movement aesthetics, for example by extracting MP from multiple subjects' movement data and assessing the aesthetic evaluation of movements generated with self-based and other-based primitives by the same subjects.

5. Conclusion

In this study, we used a model-based approach relying on movement primitives to generate artificial dance movements. We find that higher explicit aesthetic responses are elicited by movements with a high degree of human-likeness and also for individuals with prior motor experience in dance. For the latter, however, the results suggest an uncanny valley effect, indicating that expert dancers are able to detect the artificial in the seemingly natural. Furthermore, we find that the motion energy of the movement sequences is positively associated with the likeability ratings, more so for novices than dancers, leading us to speculate that dance experts may be able to discover beauty in presumably less interesting movements. Such speculation aside, the findings clearly highlight the enhanced perceptual abilities associated with sensorimotor dance experience. In summary, the effects regarding human-likeness support the role of familiarity for movement aesthetics and show the relevance of both top-down and bottom-up processes for the aesthetic perception of whole-body movement.

6. Data availability

Source data and analysis code related to this manuscript can be found at the institutional repository of the Justus Liebig University Giessen (http://dx.doi.org/10.22029/jlupub-17926).

7. Acknowledgments

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9. Disclosures

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

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6 General discussion

In this thesis a generative movement model based on temporal movement primitives was applied to assess how motor control structures during dance generation are modulated by learning. Furthermore, the aesthetic perception of model-generated movements with varying dimensionality and its association with the observer's sensorimotor experience in dance was examined. In terms of research method validation, the perceptual validity of the model was analyzed specifically for dance. Additionally, the temporal segmentation of dance sequences based on kinematic features was evaluated using human segmentation boundaries from a perception experiment.

6.1 Summaries

6.1.1 Temporal movement segmentation based on kinematic features

The feasibility of movement segmentation based on simple kinematic features was evaluated. Of interest was whether a sequence segmented using the minima of the speeds of different body parts would correspond to segments perceived by humans. This could indicate that this type of segmentation would also be suitable as a pre-processing step for a model such as the temporal primitive model, which is utilized to generate movement based on a framework of human movement production. Since the correspondence between sequences segmented using kinematic features and the segments perceived by humans might differ depending on the sensorimotor experience of the observer, both dancers and novices were analyzed. Sequences with different kinematic features obtained from motion capture of a professional dancer were segmented by both groups. The results show that, for both groups, the perceived segments corresponded quite closely to the segments obtained with speed minima for dance sequences with pronounced moments of stillness. On the other hand, the sequences with a very fluid character showed a relatively low agreement with human segmentation points. In particular, the motion profile of the feet, potentially as an indicator of ground contact events, emerged as a crucial source of sensory information for segmentation. The agreement between kinematic and human segmentation points for the different sequences was similar for both groups. Furthermore, the number of segmentation points observed did not differ between groups. Overall, this suggests that while speed minima may be a useful indicator for segmenting certain types of dance sequences, it may not be as effective for more fluid movements. Hence, additional kinematic features or more sophisticated segmentation methods may be required to more appropriately segment the full range of dance sequences.

6.1.2 Perceptual validation of the model for dance movements

Experiment 2 in Leh et al. (2023) was conducted to assess the perceptual validity of the implemented model for dance movements. In this experiment, participants were shown model-generated movements side-by-side with the original movement and asked to indicate which of the two movements shown was more natural. The results indicate that participants were basically unable to distinguish between the two movements. Furthermore, the ability to discriminate between the two was not affected by several stimulus-related factors, such as stimulus duration, the experience of the dancer performing the movement, and the number of underlying primitives and temporal segments. However, the explained variance of the model, i.e. how well the model was able to replicate the original movement, had a considerable effect, in that participants perceived the original movement as more natural when the explained variance of the model used to generate the stimulus was low. This is consistent with previous studies on the perceptual validity of the temporal movement primitive model (Knopp et al., 2019, 2020). Additionally, the perceptual validity was lower for improvised than for choreographed dance movements, perhaps due to a lower degree of movement complexity in the latter. Subjective characteristics, particularly the observers' dance experience, had no effect on the ability to discriminate between the model-generated and the original movement. Overall, this suggests that the validity of the model is quite robust to a variety of object- and subject-related features. Thus, the temporal movement primitive model is a viable candidate as a movement model for further studies on motor control in dance.

6.1.3 Effects of sensorimotor experience on movement primitives and temporal segments in dance production

The modulation of motor control structures by sensorimotor experience in dance was explored. The results of Experiment 1 in Leh et al. (2023) indicate that a higher degree of sensorimotor experience is associated with more movement primitives but fewer temporal segments, specifically for choreographed dance performed with a neutral expression. This is consistent with previous research on non-artistic skills (Haar et al., 2020; Matsunaga & Kaneoka, 2018; Sawers et al., 2015) and may suggest that more degrees of freedom are utilized with skill progression.

Longer movement segments may be facilitated by this increase in movement building blocks. Furthermore, the findings suggest that experienced dancers exhibit a more consistent form of modular control, resulting in greater precision, as would be expected with increased proficiency in a given skill. Interestingly, the shape of the temporal primitives obtained is quite similar across dancers with varying levels of experience, at least on a descriptive level.

The finding of an increase in primitives with motor experience contrasts with previous findings in dance, where the decomposition methods implemented showed a reduction in the number of primitives with experience (Bronner & Shippen, 2015; Chang et al., 2020). In comparison, longer movement segments were implemented and improvised dance was also investigated in addition to choreographed dance in Leh et al. (2023). The dance sequences examined were not only longer, but also non-cyclic in nature. A temporal segmentation preceded the training of the models, and the consideration of these temporal segments and their association with movement primitives sets the study apart from previous studies on modular structures during dance production.

6.1.4 Effects of movement dimensionality and sensorimotor experience on aesthetic perception

In Leh et al. (2025), the aesthetic perception of dance movements was assessed based on a modular framework. The results show that model-generated movements can lead to positive aesthetic evaluations, i.e. the model is able to generate not only natural but also aesthetic movements. In general, model-generated movements incorporating a greater number of primitives resulted in higher explicit subjective aesthetic responses, as indicated by keypresses. However, no difference in implicit affective responses, measured by electrodermal activity, was found for different degrees of movement modularity. Not only objective features of the movement, i.e. its dimensionality, were relevant for the aesthetic perception of movement, but also subjective features, specifically the sensorimotor experience of the observer. The aesthetic responses were generally lower for individuals without prior dance experience. Furthermore, there was a strong correlation between motion energy and explicit responses for this group, which was less pronounced in the case of dancers. Thus, individuals without prior sensorimotor experience may be more susceptible to simple kinematic features regarding their aesthetic perception than individuals with experience. It is particularly noteworthy that the likability valuations of dancers was found to decline in response to model-generated movements with the highest dimensionality, which were presumed to be the most human-like. This suggests an uncanny valley effect and extends this perceptual phenomenon to model-generated dance movements.

6.2 Limitations and future directions

Whilst there have been several findings from the studies in this thesis, there are some limitations that should be addressed in future research. Overall, the studies are cross-sectional in nature. Future studies could adopt a longitudinal approach to track changes in the modular composition of movement and how it is perceived over time as individuals gain dance experience. Furthermore, a limitation is the range of dance experience of the participants whose movements were captured and used for model validation. Incorporating a wider range of experience levels, including professional dancers, could provide a more comprehensive understanding of how expertise influences modularity in movement production and the perception of model-generated movements in terms of their validity. Additionally, the perceptual validity of more complex movement sequences should be further assessed based on the results of the perceptual validation study regarding improvised dance. Nevertheless, the ability of the model to produce aesthetic movements using data from a professional dancer strengthens its validity.

Finally, the segmentation method based on speed minima, while reasonable for certain types of dance sequences, may not be suitable for more fluid movements. Future research should explore more sophisticated segmentation methods that can account for the diverse kinematic characteristics of dance sequences. One promising approach could be the use of the Bayesian Binner algorithm, which has been shown to have relatively good agreement with human segmentation points for martial arts sequences (Endres et al., 2011), and which can incorporate the movement primitive model as part of the segmentation point selection algorithm. This method could potentially provide a more accurate segmentation of fluid dance sequences. Future studies could investigate the application of the Bayesian Binner Algorithm to dance sequences and compare its performance with simpler segmentation methods, such as speed minima, to determine its effectiveness in capturing the complex dynamics of dance movements. If movement primitives are used for movement production, and the representation of movement primitives can be appropriately incorporated into the Bayesian Binner algorithm, then the resulting boundaries of the algorithm might be expected to more closely coincide with the boundaries perceived by individuals with sensorimotor experience of the skill represented in the segmented sequences.

This thesis builds upon a wide range of studies on the use of primitives for movement production (Bizzi et al., 2008; Giszter, 2015). The majority of studies have focused on primitives extracted from muscle activity or kinetic data. In this work, however, primitives at the kinematic level were analyzed and the relationship between modules at different levels (e.g. motor or kinematic) is still unclear (D'Avella et al., 2015; Giszter, 2015). In particular, it is uncertain how kinematic movement primitives are related to the underlying muscle activity and whether they have any real functional relevance, or whether they are simply an efficient way of describing movement. Accordingly, more research is required regarding the relation of modules at different levels of the motor hierarchy. On the other hand, even if the model merely functions as a compression algorithm, it provides insight into the composition of movement, as the parts that would be omitted by compression are clearly not relevant for a movement to be considered natural or aesthetic, and thus may represent redundant information.

Since the model is shown to be valid for both improvised and choreographed dance, and to be able to generate aesthetically pleasing movements, it offers unique opportunities to study certain topics that might otherwise be difficult to investigate. An example is the degree of embodiment for movement aesthetics. Specifically, movement primitives of dancers could be extracted and used to generate movements. The aesthetic evaluation of these movements could then be assessed by the same dancers. This approach could help determine whether dancers find movements generated from their own primitives more aesthetically pleasing compared to those generated from others' primitives. Such studies could provide insights into the relationship between motor control strategies and aesthetic perception, and how individual sensorimotor experiences influence the appreciation of movement aesthetics. On the other hand, it is remarkable how similar the movement primitives extracted from the movements of dancers with different sensorimotor experience are, using the specific temporal movement primitive model implemented. As a consequence, the movements produced by the model may not differ significantly due to a similar library of underlying primitives. In this regard, it should also be noted that the results of this thesis are based on a specific movement generation model that is not able to generate new movements per se, i.e. completely new movements that were not part of the training set. Rather, after successful model training, the model is able to reproduce the originally captured movement with relatively low error.

Based on the findings of this thesis, future research on the uncanny valley in the movement domain should consider sensorimotor experience as a factor in perceptual studies. The modulation of human-likeness in this particular study was operationalized by utilizing a varying number of underlying movement primitives to produce the model-generated movement. This does represent a type of compression and could be linked to Schmidhuber's theory of beauty (Schmidhuber, 2009). According to the theory, the aesthetic value of an object is related to the observer's ability to compress the information it contains. Future research could investigate whether the degree of compression, as operationalized by the number of movement primitives, correlates with aesthetic evaluations of model-generated movements. This specific compression hypothesis was not explicitly tested in this thesis, although it could have been tested for completeness. On a descriptive level, however, there was no evidence of a pattern consistent with this hypothesis, but rather the opposite. Nevertheless, it is unclear whether the compression obtained with the movement primitive model is the type of compression that should lead to a higher aesthetic evaluation according to Schmidhuber's theory of beauty. In light of this theory, a key point to consider regarding the fourth experiment presented in this thesis is that most of the stimuli had already been compressed prior to presentation. This pre-compression may have limited the ability of the human perceptual system to further reduce the stimulus to a more compact internal representation. The findings of this thesis confirm that original human dance movements can indeed be represented in a lower-dimensional space. However, with respect to aesthetic perception, the findings indicate that an already compressed stimulus does not facilitate an aesthetic experience. This may be because such stimuli arguably offer reduced potential for further compression. Instead, aesthetic pleasure may primarily arise from the perceptual system's ability to transform a stimulus containing noise or redundancy into a more compressed internal representation (Schmidhuber, 2009). The results of this thesis appear to support this latter interpretation. The naturally occurring reduction in movement dimensionality observed in experienced dancers in previous studies (Bronner & Shippen, 2015; Chang et al., 2020), and which was shown to be associated with enhanced movement aesthetics, cannot be artificially reproduced by the movement primitive model implemented in this thesis. Further research is therefore needed to develop a more nuanced understanding of the forms of compression that may accompany sensorimotor learning in dance.

Overall, this thesis provides insights into the modularity of dance production and perception, but further research is needed to address the aforementioned limitations and build upon the findings.

7 Conclusions

This thesis explored modular control structures in dance production and dance perception and their relationship with sensorimotor experience in dance. It extended previous research by also focusing on improvised dance and the temporal segments in dance sequences. On a methodological level, this thesis provides evidence that the temporal movement primitive model is sufficiently valid for dance movements and that a temporal segmentation of dance sequences based on speed minima is reasonable to a certain extent. The findings indicate that, under certain conditions, the number of temporal segments and movement building blocks are modulated by dance experience. Finally, it shows that sensorimotor experience in dance is also relevant to the aesthetic perception of movement sequences with varying degrees of modularity. Interestingly, the results suggest that there may be an uncanny valley effect in the movement domain (irrespective of character appearance) for observers with sensorimotor experience in dance.

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