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SEE HOW IT FEELS TO MOVE: RELATIONSHIPS BETWEEN MOVEMENT CHARACTERISTICS AND PERCEPTION OF EMOTIONS IN DANCE

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Abstract: *Music makes humans move in ways found to relate to, for instance, musical characteristics, personality, or emotional content of the music. In this study, we investigated associations between embodiments of musical emotions and the perception thereof. After collecting motion capture data of dancers moving to emotionally distinct musical stimuli, silent stick-figure animations were rated by a set of observers regarding perceived discrete emotions, while 10 movement features were computationally extracted from the motion capture data. Results indicate kinematic profiles—emotion-specific sets of movement characteristics—that furthermore conform with dimensional models of valence and arousal, suggesting that observers rated the emotions consistently according to distinct movement features prevalent in the animations. Outcomes show commonalities and differences to a previous study that linked these movement features to auditory perception of musical emotion, providing insights into how emotional expression of music-induced movement could be conveyed and understood through auditory and visual channels, respectively.*

Keywords: *music-induced movement, emotion, perception, computational movement feature extraction.*

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INTRODUCTION

Oftentimes, listening to music makes humans move, and it can even be difficult to avoid spontaneous bodily responses, ranging from foot tapping or head nodding to full-body dance movement (Keller & Rieger, 2009; Lesaffre et al., 2008). Such movements usually are spontaneous and not choreographed; however, most often these responses are regular and organized, for instance, synchronized with the pulse of the music or mimicking instrumentalists' gestures (Leman & Godøy, 2010). Several factors have been found to affect music-induced movement characteristics: music-intrinsic features such as beat strength and pulse clarity (Burger, Thompson, Luck, Saarikallio, & Toiviainen, 2013; van Dyck, Moelants, et al., 2013), individual features such as personality and music preference (Luck, Saarikallio, Burger, Thompson, & Toiviainen, 2010) or mood (Saarikallio, Luck, Burger, Thompson, & Toiviainen, 2013), and the emotional content of the music (Burger, Saarikallio, Luck, Thompson, & Toiviainen, 2013; van Dyck, Maes, Hargreaves, Lesaffre, & Leman, 2013).

Such involvement and utilization of the body have contributed to the notion of embodied (music) cognition, which claims that human cognition and intelligent behavior require goal-directed interaction between the mind/brain, sensorimotor capabilities, body, and environment—a coupling of action and perception, rather than merely passive perception (e.g., Varela, Thompson, & Rosch, 1991). Musical involvement in this framework can be seen then as linking the perception of music to body movements, in that body movements reflect, imitate, and help listeners parse and understand musical elements (Leman, 2007). Leman suggested several (coexisting) components of corporeal articulations, differing in the degree of musical involvement and the kind of action–perception couplings employed. Synchronization constitutes the fundamental component and relates to entraining and predicting the beat structure. Embodied Attuning refers to linking body movement to musical features more complex than basic beat structure (e.g., melody, harmony, timbre, or rhythm). Finally, Empathy is seen as the component that links musical features to expressivity and social functions of music, including emotional expression.

As research on emotions and nonverbal behavior has shown, it is possible to successfully express and communicate emotional states to observers through body movements. Already in 1872, Darwin assigned certain body movements and postures quite specifically to emotional states; joyful movements, for example, were described as jumping, stamping, body thrown backwards and shaking, and upright torso and head, whereas anger was characterized by trembling body, shaking fist, erected head, and expanded chest. Sad movements were described as passive, motionless, and a downward directed head. Wallbott (1998) conducted a study in which he used a scenario-based approach with professional actors finding distinctive movement features for each emotion category; for instance, sadness was expressed with a collapsed body, whereas joy and anger were associated with an upright torso. Anger was the most active emotion, followed by joy and sadness. Lateral arm movement and dynamics/power related mostly to anger, less for joy, and even less for sadness. Spatially expansive movements typically represented anger and joy, whereas sad movements covered less space. De Meijer (1989) used actors performing several movement characteristics instead of emotions. These movements differed in general features, such as trunk or arm movement, velocity, and spatial direction. In a subsequent step, observers attributed emotional characteristics to the movements. The results suggested that fast, active, open, light, and upward directed movements with raised arms and a stretched trunk were perceived as happy, whereas strong and fast movements with a bowed torso and a high force were perceived as angry. In contrast, sad movements were described as slow, light, downward directed, with arms close to the body. Coulson (2004) used pictures of static body postures of computer-generated figures that he manipulated systematically in several parameters. Observers associated anger with a forward bent body having hands in front of the chest and bent elbows, whereas a forward-leaning and downward crouched body with downward-directed hands related to sadness. A backwards bent body with upraised arms and hands characterized as happy. Halovic and Kroos (2018) investigated emotion recognition in gait and found that a bouncing gait and increased arm movement portrayed happiness, whereas a slow and slouching gait suggested sadness, and a fast and stomping gait characterized anger.

Moreover, emotions are an essential component of musical engagement and experiences (e.g., Juslin & Sloboda, 2010; in particular, Gabrielsson, 2010; Juslin & Västfjäll, 2008) with strong influences, for instance, on the listener's mood (e.g., Saarikallio, 2011), as well as being one of the most important reasons for many to listen to music (Krumhansl, 2002). Various perceptual experiments have shown that listeners are able to recognize emotion in music (e.g., Eerola & Vuoskoski, 2011). Various approaches to categorizing emotions have been proposed: discrete emotions (e.g., Balkwill & Thompson, 1999), domain-specific emotion models (such as the GEMS model, see Zentner, Grandjean, & Scherer, 2008), or dimensional models (Ilie & Thompson, 2006). The discrete model described emotions as unidimensional, independent from each other, and derived from a limited number of universal basic emotions, such as happiness, anger, or sadness. An advantage of using this approach is the possibility to name the emotions in clear terms. However, a disadvantage is that they can be mixed and confused with other emotions, and the terms might be too generic for all possible emotions elicited by music. Domain-specific models, such as the GEMS (Geneva Emotion Music Scale), have been developed based on this approach to create a repertoire of emotions being highly music-related; however, these models might still bear the above-mentioned disadvantage. A dimensional approach could reduce this challenge. In such models, emotions are represented as a combination of two (usually valence and arousal) or three (valence, arousal, and tension) mutually independent dimensions, often illustrated as a two-(or three-) dimensional space with valence on the horizontal axis and arousal on the vertical axis (tension would form the third axis, yielding a cubical design). In such a model, happiness would be represented as an emotion high on arousal and high on valence, for instance, whereas sadness would be judged low on arousal and low on valence, and thus located opposite to happiness in a two-dimensional space. Anger, high on arousal and low on valence, thus, would be next to happiness and on top of sadness. Tenderness, commonly judged as low on arousal and high on valence, thus would be located below happiness and next to sadness (see Figure 1 for an illustration). Examples of such approaches are the circumplex models of affect by Russell (1980) and Schlossberg (1954). Eerola and Vuoskoski (2011) compared the different models and found that discrete and dimensional models performed similarly well in unambiguous, easily identifiable emotions, while the dimensional model outperformed the discrete model in case of ambiguous emotions.

Despite emotions and emotional impact being an essential component of music experiences, and emotions showing relationships to nonverbal behavior and movement, studies that link emotions with music-related movement are relatively rare. A few studies have been conducted in the field of music performance. Dahl and Friberg (2007), for instance, recorded

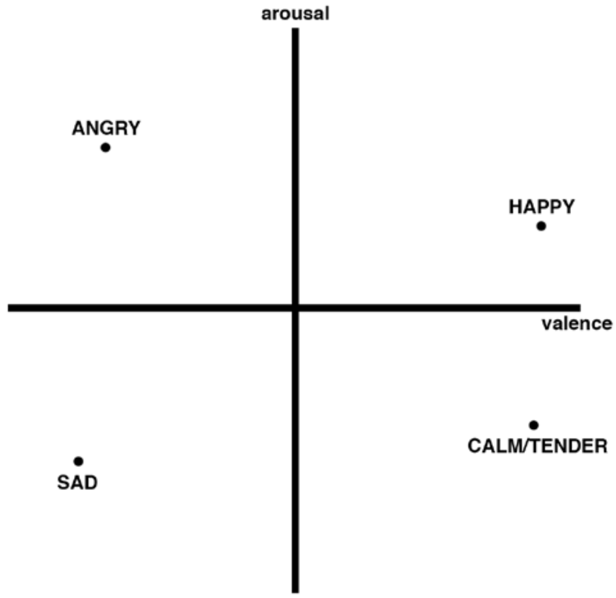

Figure 1. Locations of discrete emotions in a two-dimensional model as a combination of valence and arousal (based on the circumplex model of affect by Russell, 1980).

players of the marimba, bassoon, and saxophone performing with different emotional intentions (happy, angry, sad, and fearful) and had observers evaluate the emotion perceived in the movements and indicate movement cues conveying these emotions. Observers could identify successfully happy, angry, and sad performances (although they failed for fear) and indicated distinct cues: happy performances were communicated using medium regularity and fluency, high speed, and high amount of movement, while anger was conveyed with medium regularity, low fluency, high speed, and medium-to-high amount of movement. Sad performances were communicated with very regular and fluid movement, low speed, and small amount of movement. Based on these findings, Burger and Bresin (2010) developed a small mobile robot displaying these three emotions using a limited set of movements: happiness, for instance, reflected large, fluid, and circular movements; anger presented large, irregular, and jerky movements; whereas sadness was conveyed through slow, regular, and reduced movements. Their subsequent perceptual experiment demonstrated that subjects successfully recognized the emotions.

Camurri, Lagerlöf, and Volpe (2003) adopted a similar approach as Dahl and Friberg (2007) when asking professional dancers to perform the same dance in four different emotional characters. In their qualitative approach, they identified happiness as performed with frequent tempo changes with longer stops, dynamic movements, and changes between high and low tension; associated anger with short movements with short stops between, frequent tempo changes, as well as dynamic and tense movements; and portrayed sadness with long and smooth movements, few tempo changes, and low tension. Using a video-based analysis tool, Castellano, Villalba, and Camurri (2007) found two main movement characteristics that differentiated happy, angry, sad, and pleasurable dance gestures: The “Quantity of Motion” (QoM), that is, the overall amount of detected movement, and “Contraction Index” (CI), the contraction and expansion of the body, were measured in a two-dimensional space. QoM referred to the difference between high and low arousal (happiness and anger would be high, sadness and pleasure low on QoM), whereas CI to the difference between positive and negative emotions (happiness and pleasure high, anger and sadness low on CI). Boone and Cunningham (1998) found in a dance study in which actors displayed basic emotions that happiness was characterized by upward arm movements, angry movement by high tempo changes of the torso, sad movements by low tension, and fearful movements as rigid and upright.

In case of emotions in spontaneous movement induced by music (for an overview, see van Dyck, Burger, & Orlandatou, 2017), van Dyck, Maes et al. (2013) conducted a motion-capture study in which participants underwent an emotion induction task to feel either happy or sad and were subsequently asked to dance to an emotionally neutral piece of music. When induced to feel happy, participants moved faster and more accelerated, as well as more expanded and impulsive, as compared to when feeling sad. In a subsequent perceptual experiment (van Dyck, Vansteenkiste, Lenoir, Lesaffre, & Leman, 2014), observers successfully recognized the emotional state of the dancers to a high degree and paid most attention to movement of the dancers' chests. Burger, Saarikallio et al. (2013) conducted a study on perceived emotions in which they collected motion-capture data of spontaneous dancing, computationally extracted movement features from these data, and linked these to ratings of emotions perceived in the stimuli presented to the dancers. They found distinct movement feature combinations for each emotion. Happiness was linked to small foot distance as well as rotating and complex movements; anger was related to jerky and nonrotational, straight movements; sadness was associated with low movement complexity; and tenderness was linked to low head and hand acceleration, fluid movements, and a forward-bent posture.

In summary, emotions can be recognized in posture (e.g., Coulson, 2004), movement (e.g., de Meijer, 1989), gait (e.g., Halovic & Kroos, 2018), music performance (e.g., Dahl & Friberg, 2007), as well as the gestures of professional dancers (e.g., Camurri et al., 2003). Emotion perception in spontaneous dance/music-induced movement has been investigated much less frequently—with the exception of van Dyck et al. (2014), who used only happy and sad stimuli—despite the fact that visual information has a significant effect on how music is perceived (Tsay, 2013; Vuoskoski, Thompson, Clarke, & Spence, 2014). Therefore, in this study, we aimed to investigate emotion perception in music-induced movement. Increased knowledge on this topic is necessary to understand the multimodality of emotion perception—not only within dance and music contexts, but also more generally in human movement behavior.

The present investigation extends a previous study (Burger, Saarikallio et al., 2013) that investigated the relation between movement kinematics and emotions perceived in music (auditory domain) by exploring how subjective ratings of emotions displayed in video-only motion-capture animations (visual domain) related to movement kinematics. To this end, we drew on this earlier motion-capture study, in which participants freely moved to different musical stimuli, as a foundation for a perceptual experiment, in which a different set of participants evaluated motion-capture animations selected from the motion-capture dataset according to perceived emotions. For this analysis, we chose discrete emotion ratings (happiness, anger, sadness, and tenderness), as have been used in previous studies (in particular, movement-related ones), and set them in relation to the dimensional model. These discrete emotions were assumed to be more concrete and rather easily distinguishable and recognizable in dance movements, especially compared to the two axes of valence and arousal in the dimensional model or the more specific emotions in the GEMS model (Zenter et al., 2008). We chose video-only stimuli to prevent any influence of auditory input on participants' evaluations of movement. Moreover, we selected the same set of movement features used in Burger, Saarikallio et al. (2013) for comparability reasons.

We asked the following three research questions:

1. What are the relations between perceived emotions and the movement features of dance-like movement presented as motion-capture animations?
2. How do these movement features link to movement features found earlier related to emotion ratings of the audio stimuli?
3. How do the results for the discrete emotions relate to the dimensional model of valence and arousal (Russell, 1980)?

Based on the studies mentioned above, we predicted that each emotion would link to a specific set of movement characteristics, following and extending the results of Burger, Saarikallio et al. (2013). Thus, we expected that movements high on rotation and complexity, as well as having small foot distance, would be evaluated as happy, jerky movements without rotation as angry, movement of low complexity as sad, and smooth movement with low acceleration and forward tilted torso as tender. We further hypothesized that locating the discrete emotion results in a two-dimensional space would be consistent with the circumplex model of valence and arousal (Russell, 1980).

METHODS

The following section describes the methods that we used in this study. We drew on previously collected motion capture data that we subsequently utilized in a perceptual study to investigate relationships between embodiments of musical emotions and the perception thereof. The results of the motion capture study are published in Burger, Saarikallio et al. (2013) and will be used as references in the current analysis.

Motion Capture Data Collection

Participants and Stimuli

Sixty participants (43 female, 17 male; average age 23.92 years; *SD* = 3.27) took part in the underlying motion-capture study, recruited from the University of Jyväskylä’s general student population. Six participants had received formal music education, although 30 reported playing a musical instrument. Four participants had a formal background in dance, and 27 had received some kind of dance tuition during their lives. Fifty-one participants reported liking to dance to music. All participants expressed engaging in some kind of sports activity. Participation was rewarded with a cinema voucher. All participants gave their informed consent prior to their inclusion in the study and were free to discontinue the experiment at any point. Ethical permission for this study was not needed, according to the guidelines stated by the University of Jyväskylä’s (Finland) ethical board.

We presented participants with 30 musical excerpts of various popular music genres (techno, pop, rock, Latin, funk, and jazz). All stimuli were naturalistic (existing music) to make the experiment as ecologically valid as possible. The thirty stimuli provided participants with a wide range of music genres and emotional expression and catered to preferences and familiarities among the participants. A team of music researchers at the University of Jyväskylä selected the music based on these characteristics and the following: All stimuli were nonvocal, in 4/4 time, differed in their pulse clarity and rhythmic complexity (i.e., all with a perceivable beat), and had a tempo range of 82 to 140 BPM. We used a length of 30 seconds per song: This stimulus length kept the experiment sufficiently short while providing stimuli long enough to induce movement.

Apparatus and Procedure

Participants' movements were recorded using an eight-camera optical motion capture system (Qualisys ProReflex), tracking the three-dimensional positions of 28 reflective markers attached to each participant at a frame rate of 120 Hz. Figure 2 presents the locations of the markers. The location of the markers were as follows: (L = left, R = right, F = front, B = back): 1: LF head; 2: RF head; 3: LB head; 4: RB head; 5: L shoulder; 6: R shoulder; 7: sternum; 8: spine (T5); 9: LF hip; 10: RF hip; 11: LB hip; 12: RB hip; 13: L elbow; 14: R elbow; 15: L wrist/radius; 16: L wrist/ulna; 17: R wrist/radius; 18: R wrist/ulna; 19: L middle finger; 20: R middle finger; 21: L knee; 22: R knee; 23: L ankle; 24: R ankle; 25: L heel; 26: R heel; 27: L big toe; 28: R big toe. The musical stimuli were played via a pair of Genelec 8030A loudspeakers using a Max/MSP patch running on an Apple computer. We recorded the room sound with two overhead microphones positioned at a height of approximately 2.5 m. This microphone input, the direct audio signal of the playback, and the synchronization pulse transmitted by the Qualisys cameras when recording, were recorded using ProTools software in order to synchronize the motion capture data with the musical stimulus afterwards.

Participants were recorded individually and asked to move to the presented stimuli in a way that felt natural. Additionally, they were encouraged to dance if they wished but were requested to remain in the center of the capture space indicated by a 115 x 200 cm mat.

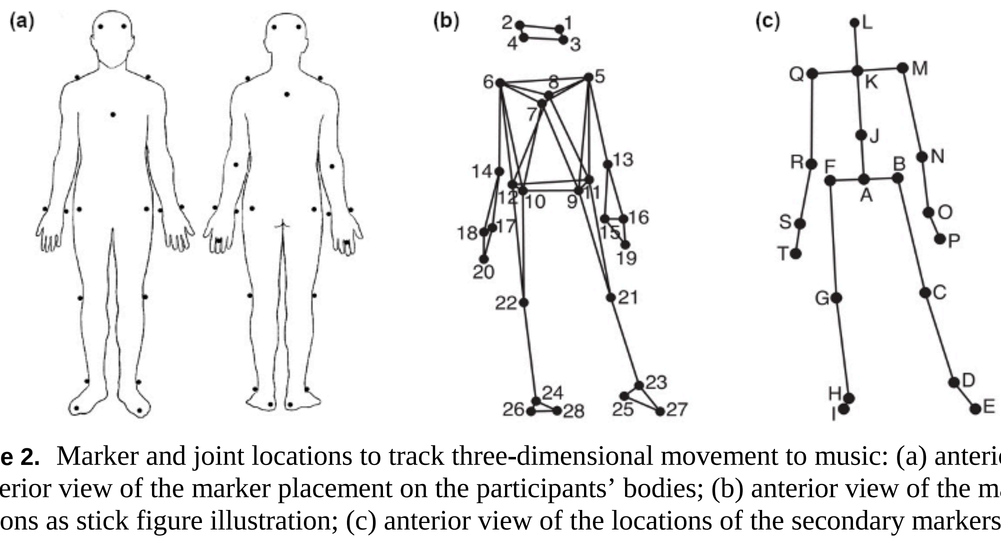

Figure 2. Marker and joint locations to track three-dimensional movement to music: (a) anterior and posterior view of the marker placement on the participants' bodies; (b) anterior view of the marker locations as stick figure illustration; (c) anterior view of the locations of the secondary markers/joints used in the animations and analysis.

Motion-Capture Data Preprocessing

After labeling the motion-capture (mocap) data in the Qualisys Track Manager software, we used the MATLAB Motion Capture Toolbox (Burger & Toiviainen, 2013) to further process the data in creating the stick figure animations and for analysis purposes. First, we edited the recordings to provide only the duration of each musical stimulus. Following this, we derived a set of 20 secondary markers—subsequently referred to as joints—from the original 28 markers by creating virtual joints (where one cannot place a mocap marker) and removing redundant markers as well as to receive an easily perceivable stick figure representation. The locations of these 20 joints are depicted in Figure 2c. The locations of joints C, D, E, G, H, I, M, N, P, Q, R, and T are identical to the locations of one of the original markers; the locations of the remaining joints were obtained by averaging the locations of two or more markers; joint A: midpoint of the four hip markers; B: midpoint of markers 9 and 11 (left hip); F: midpoint of markers 10 and 12 (right hip); J: midpoint of breastbone, spine, and the hip markers (mid-torso); K: midpoint of shoulder markers (manubrium), L: midpoint of the four head markers (head); O: midpoint of the two left wrist markers (left wrist); S: mid-point of the two right wrist markers (right wrist).

Perceptual Study

Stimulus Creation/Stimuli

The visual stimuli used in this experiment were selected from the pool of the above described motion capture study. Based on results of a rating experiment conducted within a previous study, in which 30 independent raters rated the audio stimuli regarding perceived happiness, anger, sadness, and tenderness (see Burger, Saarikallio et al., 2013), we identified four musical excerpts that most clearly conveyed one of the following emotions: happiness, anger, sadness, and tenderness (see Table 1). We chose four songs to keep the experiment sufficiently short. Subsequently, to present observers with as representative, yet variable, examples as possible, we chose two female and two male participants (from now on referred to as “dancers”). We selected these dancers based on their movement characteristics (i.e., dancers whose performances received

Table 1. Overview of the Stimuli for the Target Emotions, Including Artist, Song, Tempo, and Average Rating of 30 Independent Observers of the Respective Target Emotion (Rating Scale 1–7).

Target emotion	Artist	Song	Tempo	Average rating
Happiness	Dave Weckl (1994) (track 2, 0:10-0:41)	“Mercy, Mercy, Mercy”	105	5.15
Anger	In Flames (2006) (track 5, 0:00-0:30)	“Scream”	100	6.26
Sadness	Johanna Kurkela (2005) (track 2, 3:22-3:52)	“Hetki hiljaa”	122	5.18
Tenderness	The Rippingtons (1992) (track 1, 1:13-1:42)	“Weekend in Monaco”	113	4.53

the highest values regarding several movement features—such as speed, acceleration, area covered, or complexity—that Burger, Saarikallio et al., 2013, found significant for each emotion in their previous analysis). The four chosen dancers moderately liked the stimuli (ratings between 3 and 4.25 on a scale from 1 to 5) and were moderately familiar with them (ratings between 3 and 4 on a scale from 1 to 5). We then created stick figure animations of these movements via the MATLAB Motion Capture Toolbox using the joint configuration described above (see also Figure 2c). The animations were trimmed to the mid-20 s of each original performance, yielding 16 (4 dancers x 4 stimuli) combinations of stick-figure dance performances shown to the observing participants.

The four musical stimuli the dancers moved to were of different tempi (100 bpm, 105 bpm, 113 bpm, 122 bpm). In order to avoid issues that might arise from stimuli of different tempi, we time-shifted the movement data using the MATLAB Motion Capture Toolbox and adjusted their tempi to 113 bpm (corresponding approximately to the mean tempo, with keeping one at the original tempo). In addition, we rotated the movement data on the stick figures to be visible from the front with respect to the average locations of the hip markers. In all videos, the stick figures were plotted in black on a white background.

Participants

Eighty university students (from now on referred to as “observers”), aged 19–36 years, participated in the study (53 females; average age: 24.74; *SD* of age: 3.42). None of the observers participated in the preceding motion-capture experiment. We recruited observers from the University of Jyväskylä’s general student population. In this group, 35 observers had not received any musical training, 23 had received between 1 and 5 years of musical training, and the remaining 22 had received more than 5 years of musical training. Fifty-two observers had taken some type of dance lessons; 75 observers reported liking movement-related activities, such as dance and sports. None of the participants was a professional musician, dancer, or athlete. Thirty-seven observers reported going out to dance more than once a month. Observers were rewarded with a movie ticket for participating in the study.

Apparatus

To gather the perceptual ratings, a custom patch was created in Max/MSP 5, a graphical programming environment, running on Max OS X on an Apple iMac computer (see Figure 3). The patch used QuickTime Player 7 to play back the video material in a separate window. The setup enabled the observers to repeat excerpts as often as they wished, to move forward at their own speed, and take breaks at any moment of the experiment.

Procedure

Observers accomplished the experiment individually in a soundproof room. They were instructed to rate the emotions expressed in the clips (perceived emotions) on seven-step scales (from *not at all* to *very much*) for Happiness, Anger, Sadness, and Tenderness. The 16 silent video clips were presented in randomized order. Prior to the experiment, observers completed a short questionnaire regarding their gender, age, musical and dance training, and movement and dance activity. We also provided observers with a practice example so that they became

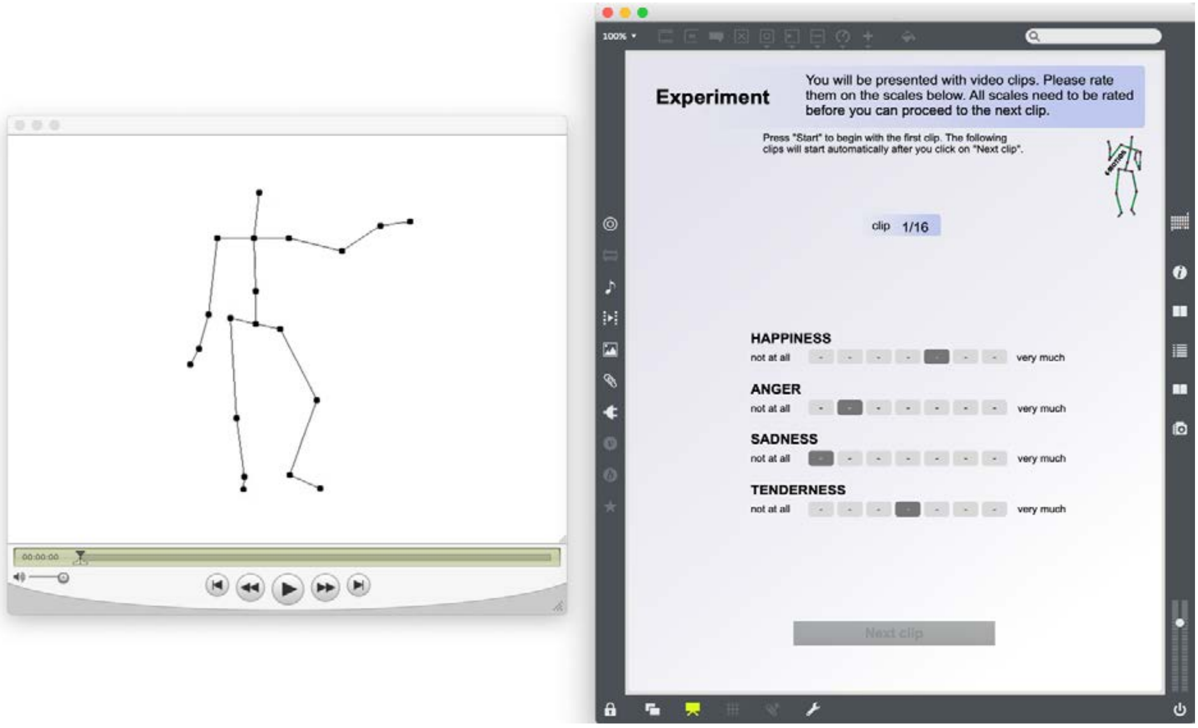

Figure 3. Screenshot of the Max/MSP patch used to collect the emotional perceptual ratings of the stick figure animations.

familiar with the interface, the type of stimuli, and the rating scales used. At the start of the experiment, we explicitly instructed participants to rate according to what emotion they thought the dancers wanted to express in the clip and not what they might feel when watching the clip. The participants were advised to take breaks in during the experiment if they felt like it. The experiment took between 10 and 25 minutes depending on the participants' rating speed.

Movement Feature Extraction and Analysis

Following the analysis process performed in Burger, Saarikallio et al. (2013), we extracted 10 movement features from the motion capture data. As a preparatory step, the instantaneous velocity and acceleration were estimated from the three-dimensional joint position data using numerical differentiation and a Savitzky-Golay smoothing FIR filter (Savitzky & Golay, 1964) with a window length of seven samples and a polynomial order of two. These values were found to provide an optimal combination of precision and smoothness in the time derivatives. Furthermore, to express the data relative to the center of the body with defined directions of the body axes, we transformed the data from a global to a local coordinate system by firstly rotating them on a frame-by-frame basis. As a result, the hip joints (A, B, and F) were aligned to be parallel to the x-axis and the origin of the coordinate system was shifted to the mid-point of the hip (Joint A). This procedure is visualized using position data in Figure 4. Most features, unless noted otherwise below, were calculated using the local coordinate system.

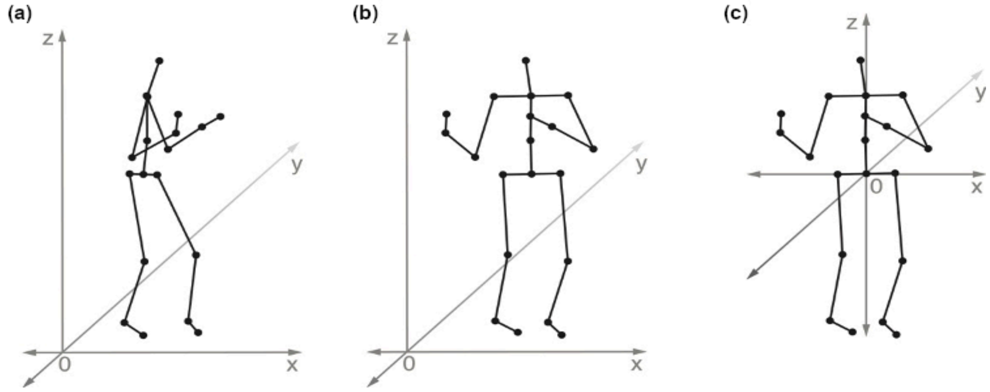

Figure 4. Transformation from global to local coordinate system exemplified with one frame of position data: (a) Original position data; (b) rotation on a frame-by-frame basis so that the hip markers are aligned parallel to the x-axis; (c) shift of the origin of the coordinate system to the midpoint of the hip to represent the data relative to this point.

The following features were used:

- Postural features
  - Torso Tilt: vertical tilt of the torso (Joints A–K), positive tilt related to bending forward.
  - Hand Distance: distance between hands (Joints P and T).
  - Foot Distance: distance between feet (Joints E and I).
- Local kinematics
  - magnitude of Head Acceleration (Joint L).
  - magnitude of Hand Acceleration (Joints P and T).
  - magnitude of Foot Acceleration (Joints E and I).
- Global kinematics
  - Area of Movement: The smallest rectangle that contains the projection of the trajectory of the Center of Mass (Joint A) on the horizontal plane (i.e., floor), averaged across a 4 s analysis windows with a 2 s overlap. This feature was calculated based on the global coordinate system.
  - Fluidity: Overall movement, fluidity/smoothness measure based on the ratio of velocity to acceleration. The combination of high velocity and low acceleration reflects fluid movement, whereas the combination of low velocity and high acceleration reflects nonfluid movement.
  - Rotation Range: Amount of rotation of the body (Joints M and Q) around the vertical axis.
  - Movement Complexity: Based on Principal Components Analysis (PCA) of the position data (all joints), in this case, can be understood as a decomposition into distinct (independent) movement components. The more principal components required to explain the movement, the more dimensions are present in the movement and thus the more complex the movement has been. The feature is quantified by taking the cumulative sum of the variance that could be explained by the first five principal components. A more extensive description of this feature can be found in Burger, Saarikallio et al. (2013).

Subsequently, we averaged the instantaneous time–series values of each variable across the dancers for each stimulus presentation to receive one value per observer per emotion stimulus. These values were used in the statistical analysis presented below.

RESULTS

Movement Features

Figure 5 shows the distribution of movement features per emotion/stimulus averaged across the four dancers. Dancers altered their movements considerably when dancing to the different stimuli. We did not perform inferential statistics on these data, as there were only four dancers.

Next, we correlated the movement features with each other to assess relationships among them. In our aim of using unique and independent features in the analysis, an uncorrelated feature

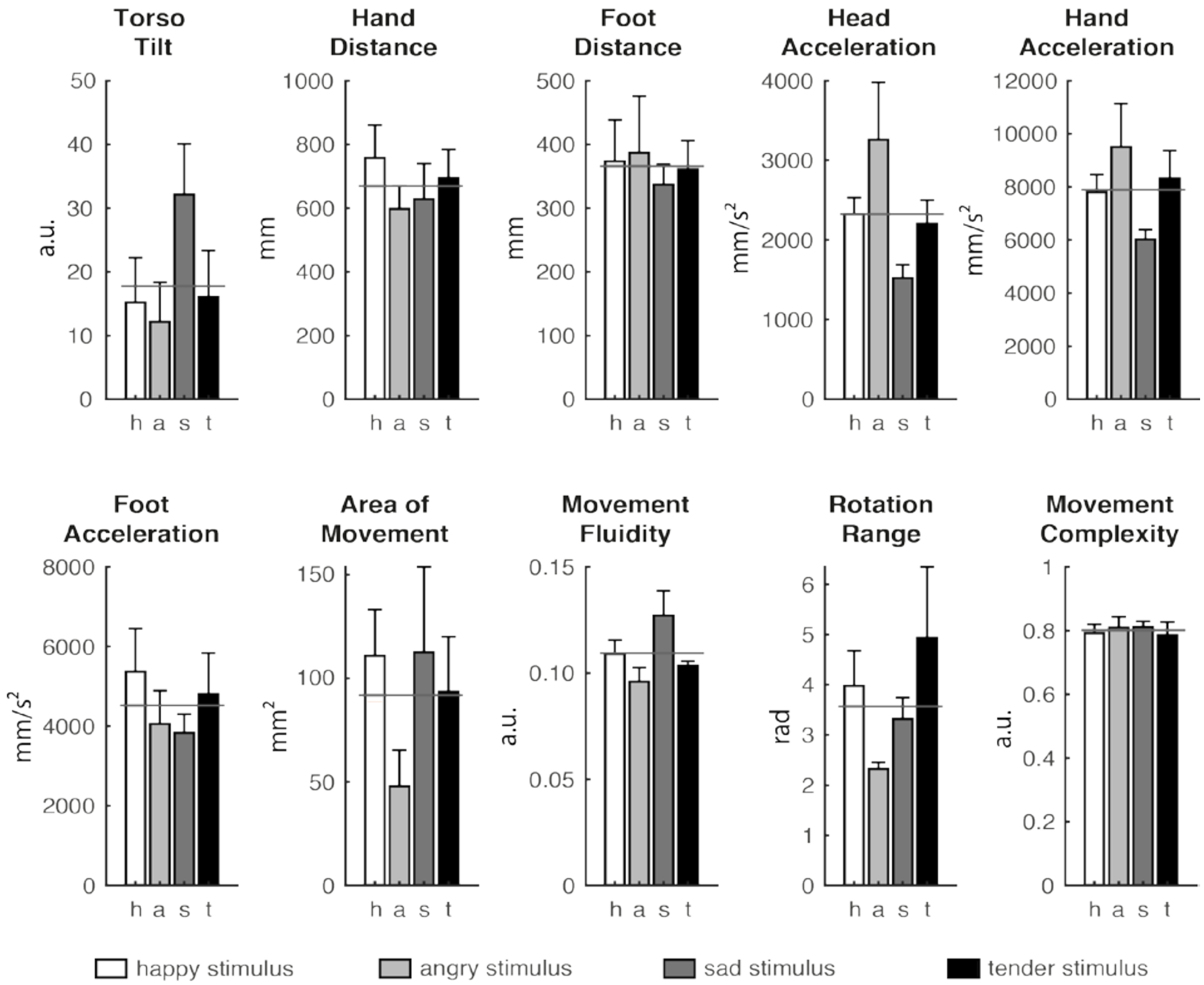

Figure 5. Distribution of movement features per emotion/stimulus averaged across the four dancers. The horizontal line in each subplot indicates the mean across the stimuli. Error bars indicate the standard error. *Mm* refers to millimeters, *s* to seconds, *rad* to radian, and *a.u.* to arbitrary unit.

set is desired; however, because the features are based on markers placed on the same person, it is likely that the selected features displayed some degree of dependence. Indeed, features based on similar markers or calculations correlated significantly, such as Foot Acceleration, Complexity and Area of Movement, as well as Head and Hand Acceleration. Table 2 provides the full correlation matrix.

Perceptual Ratings

We correlated the perceptual ratings with each other using Spearman correlations (as the rating data were considered ordinal) and found significant negative correlations between Happiness and Sadness ratings and between Anger and Tenderness ratings. The full correlation results are displayed in Table 3. The results suggest that observers were able to distinguish meaningfully between the emotions, aligning them as suggested in Russell's dimensional model of valence and arousal (Russell, 1980).

In order to verify whether the 80 observers could recognize the target emotions when watching the movements, we conducted repeated measures ANOVAs. For the Happiness ratings,

Table 2. Pearson Correlations (N = 16 video stimuli) of Movement Features; Significant Correlations are Indicated in Bold (*** $p < .001$, ** $p < .01$, and * $p < .05$).

	To Ti	Ha Di	Fo Di	He Ac	He Ac	Fo Ac	Area	Fluid	Rot
Ha Di	-.29								
Fo Di	.23	-.44							
He Ac	**.75*** **	-.16	**.65****						
Ha Ac	**.61****	-.21	.38	**.75*****					
Fo Ac	.44	-.43	.31	.33	.48				
Area	-.01	-.26	.14	-.09	-.04	**.70****			
Fluid	-.33	**.51***	-.23	-.37	**-.54***	-.34	.15		
Rot	-.08	.05	.10	-.03	.17	.43	.33	.17	
Comp	-.24	**.61***	-.45	-.24	-.41	**-.71****	**-.53***	.23	-.47

Note. To Ti–Torso Tilt; Ha Di–Hand Distance; Fo Di–Foot Distance; He Ac–Head Acceleration; Ha Ac–Hand Acceleration; Fo Ac–Foot Acceleration; Area–Area of Movement; Fluid–Fluidity; Rot–Rotation Range; Comp–Complexity.

Table 3. Spearman Correlations (N = 16 video stimuli) of Emotion Ratings; Significant Correlations are Indicated in Bold (*** $p < .001$).

	Happiness	Anger	Sadness
Anger	-.38		
Sadness	**-.84*****	-.14	
Tenderness	.26	**-.83*****	.43

the happy stimuli received the highest ratings on average (*M* = 4.51, *SD* = 0.88), followed by tender (*M* = 4.23, *SD* = 0.97), angry (*M* = 3.52, *SD* = 0.94), and sad (*M* = 3.11, *SD* = 0.86). The repeated measures ANOVA showed a significant main effect, $F(3, 237) = 81.61$, $p < .001$, $\eta_{\mathrm{p}}^2 = .51$. Follow-up pairwise comparisons using Bonferroni correction for multiple comparisons revealed significant differences between the happy and the other three stimuli (*p* between .000 and .01, levels indicated in Figure 6), indicating that observers rated the happy stimuli significantly higher on the Happiness scale than the other stimuli. For the Anger ratings, the angry stimuli received the highest ratings on average (*M* = 2.54, *SD* = 0.97), followed by happy (*M* = 1.48, *SD* = 0.69), tender (*M* = 1.38, *SD* = 0.62), and sad (*M* = 1.33, *SD* = 0.60). The repeated measures ANOVA showed a significant main effect, $F(1.54, 121.64) = 99.15$, $p < .001$, $\eta_p^2 = .56$ (Greenhouse-Geisser correction due to violation of sphericity). Follow-up pairwise comparisons revealed significant differences between the angry and the other three stimuli (all $p < .001$, see Figure 6), indicating that observers rated the angry stimuli significantly higher on the Anger scale than the other stimuli. Noteworthy though are the lower averages overall compared to the Happiness ratings. For the Sadness ratings, the sad stimuli received the highest ratings on average (*M* = 3.03, *SD* = 1.13), followed by tender (*M* = 1.95, *SD* = 0.81), angry (*M* = 1.90, *SD* = 0.76), and happy (*M* = 1.75, *SD* = 0.71). The repeated measures ANOVA showed a significant main effect, $F(2.12, 167.28) = 95.94$, $p < .001$, $\eta_p^2 = .55$ (Greenhouse-Geisser correction due to violation of sphericity). Follow-up pairwise comparisons revealed significant differences between the sad and the other three stimuli (all $p < .001$, see Figure 6), indicating that observers rated the sad stimuli significantly higher on the Sadness scale than the other stimuli. For the Tenderness ratings, the sad stimuli received the highest ratings on average (*M* = 4.09, *SD* = 1.01),

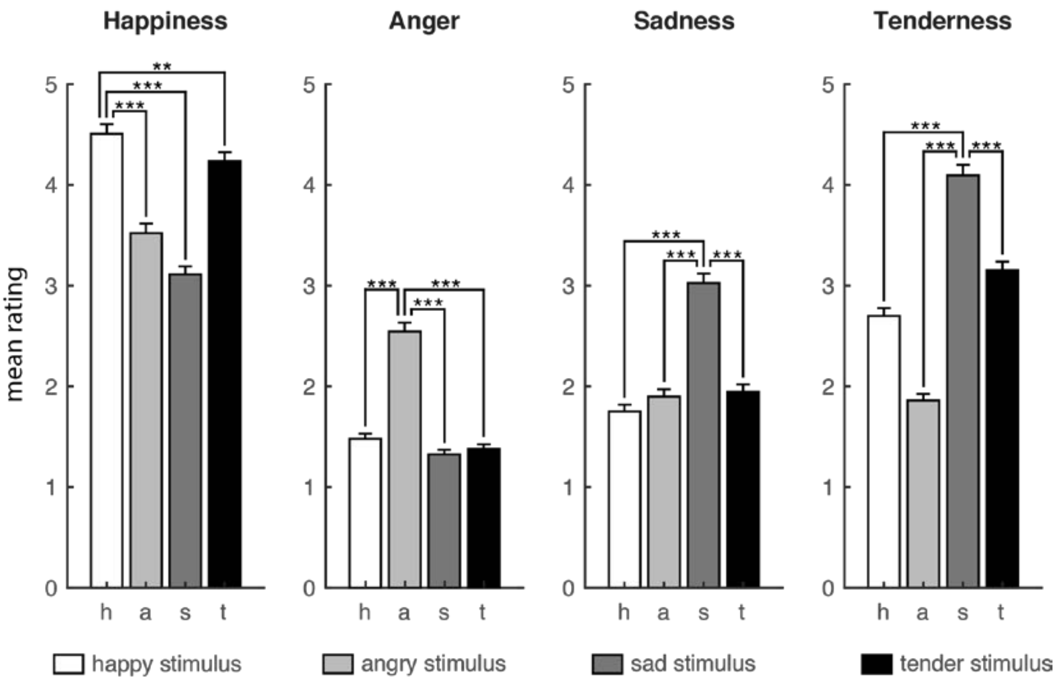

Figure 6. Overview of the emotion ratings. Significant differences only indicated related to the emotion that received highest rating (*** $p < .001$ and ** $p < .01$).

followed by tender (M = 3.15, SD = 1.12), happy (M = 2.70, SD = 1.08), and angry (M = 0.86, SD = 0.87). The repeated measures ANOVA showed a significant main effect, $F(2.36, 186.31) = 147.70$, $p < .001$, $\eta_p^2 = .69$ (Greenhouse-Geisser correction due to violation of sphericity). Follow-up pairwise comparisons revealed significant differences between all stimuli ($p < .001$, see Figure 6); however, the tender stimuli were not rated highest on the Tenderness but on the Sadness scale, indicating a confusion between these target emotions.

Linking Movement Features and Perceptual Ratings

In order to identify relationships between movement characteristics and the emotion ratings of the video animations, we conducted Spearman correlations. Due to the large number of correlations (40), we controlled the false discovery rate by applying the Benjamini-Hochberg procedure (see Benjamini & Hochberg, 1995) at a significance level of $p < .05$. The full results can be found in Table 4.

Happiness ratings correlated significantly with Head and Foot Acceleration, Area of Movement, and Complexity (all positive apart from Complexity); thus observers rated stick figure videos high on happiness when dancers had elevated head and foot acceleration, covered a large area, and had low-dimensional movement complexity. Anger ratings showed significant negative correlations with Area of Movement and Rotation Range, suggesting that observers rated stick figure clips as angry when dancers used a small area and did not rotate. Sadness ratings showed significant negative correlations with Head, Hand, and Foot Acceleration and positive correlations with Torso Tilt, Fluidity, and Complexity. Hence, observers rated stick figure videos high on sadness when dancers showed limited head, hand, and foot acceleration; were upright;

Table 4. Spearman Correlations (N = 16 video stimuli) Between Movement Features and Emotion Ratings; Significant Correlations are Indicated in Bold (*** $p < .001$, ** $p < .01$, and * $p < .05$ after FDR correction).

		Perceptual ratings			
		Happiness	**Anger**	**Sadness**	**Tenderness**
Movement features	**Torso Tilt**	.38	.24	**-.60***	-.27
	Hand Distance	-.49	.15	.39	-.21
	Foot Distance	.55	-.12	-.54	.18
	Head Acceleration	**.60***	.20	**-.78*****	-.32
	Hand Acceleration	.47	.23	**-.69****	-.46
	Foot Acceleration	**.84*****	-.41	**-.71****	.19
	Area of Movement	**.67****	**-.76*****	-.29	**.62****
	Fluidity	-.46	-.35	**.68****	.32
	Rotation Range	.53	**-.67****	-.19	.44
	Complexity	**-.83*****	.47	**.56***	-.39

and presented highly fluid and complex movement. Tenderness ratings correlated significantly with Area of Movement, suggesting that observers rated stick figure clips as tender when dancers used a large amount of space.

In order to relate our correlational results to Russell's (1980) circumplex model of valence and arousal, we followed Russell's approach, using multidimensional scaling (MDS) to achieve a representation of the data in a two-dimensional space. First, we correlated the columns of the correlation matrix of Table 4 (subsequently referred to as the kinematic profiles of the respective emotions) with each other using Spearman correlation to obtain an emotion similarity matrix based on their dependence on the kinematics. Next, we created a full dissimilarity matrix as a distance matrix required for the multidimensional scaling by subtracting the correlation values from 1 (to obtain zeros along the diagonal and otherwise positive elements only). Subsequently, MDS was performed on this dissimilarity matrix (using *cmdscale* in MATLAB). As the rotational configuration of the MDS solution is arbitrary, the initial solution was rotated by 65° counterclockwise in order to better line up with the placement of discrete emotions in the circumplex model (Russell, 1980). The graphical depiction is shown in Figure 7. For reference, we added Russell's discrete emotion locations to the plot. As can be seen, the locations align well, with an amplification of the arousal axis, suggesting that relationships between movement features and perceived emotions are consistent and fit well with this model.

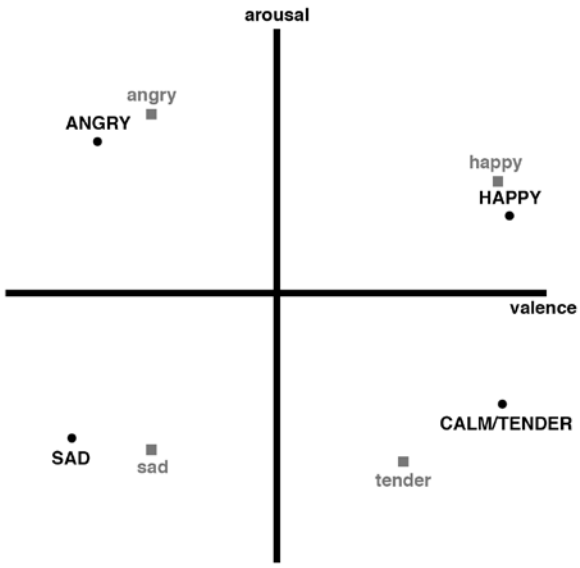

Figure 7. Multidimensional scaling solution of the emotion rating/movement feature correlations (indicated by the squares, gray font, and lowercase letters), together with Russell's (1980) multidimensional scaling solution for emotion terms according to the valence/arousal axes (indicated by the circles, black font, and uppercase letters).

DISCUSSION

In this study, we related the kinematics of music-induced movement to visual perception of emotions in corresponding silent motion capture animations, aiming to investigate the relationships between embodied responses to music and human perceptual evaluations of these responses. Each emotion could be linked to a specific set of movement characteristics, resulting in kinematic profiles, suggesting that observers rated the emotions consistently according to distinct movement features prevalent in the animations. Furthermore, the movement–emotion links conformed well to the location of discrete emotions in the circumplex model of emotions (Russell, 1980), indicating high consistency and unambiguousness in how observers perceived emotional expression in music-induced dance movements. This investigation forms an illustrative example of embodied music cognition (Leman, 2007) and provides support for Leman's notion of empathy, where music conveys emotional qualities that can be embodied and expressed via movement. The results furthermore provide insights into the multimodality of emotion perception of movement.

Earlier studies often employed professional actors or dancers asked to portray specific emotions (e.g., Camurri et al., 2003; Castellano et al., 2007). Such an approach yields stylized movements that might be very representative for a certain emotion, but might lack naturalness. However, the stimuli used in the current study derived from quasispontaneous movement to music, which potentially lacked emotion-specific qualities because the dancers were not instructed specifically to express certain emotions via their movements. Despite the dancers being unaware of any connections to emotions, they still moved in ways that observers linked to emotional expressions. Furthermore, our choosing such quasispontaneous movements, as opposed to using staged movements, in combination with existing music and nonprofessional dancers, increased the ecological validity of the study, in that such movements occurred naturally.

The musical stimuli corresponding to the four discrete emotions showed mutual differences in the ways the four dancers, used later as stick figure animations, expressed them. Noticeably, happy-sounding music let dancers move with higher foot acceleration and using a larger area, whereas moving to an angry-sounding musical stimulus increased head acceleration and decreased fluidity (e.g., head banging). Fluidity and head acceleration were found highest for sad-sounding excerpts; tender-sounding stimuli showed the highest amount of rotation. Although the analysis of these characteristics is not the focus of this paper (as our research aim was to connect these features with perceptual evaluations), the results are in line with the results of the larger data set to which the four dancers selected for this study belong (see Burger, Saarikallio et al., 2013). Thus, this research provides an adequate representation of movement features communicating emotional expressions useful in perceptual experiments. The results furthermore are in line with the characteristics found in studies on dance movement (e.g., Camurri et al., 2003; Castellano et al., 2007), as well as general movement studies (e.g., Coulson, 2004; de Meijer, 1989; Wallbott, 1998).

As expected, the selected movement features correlated to some extent with each other. Because the human body is coupled, and thus also are the related motion-capture data, movement features of the same or adjacent body parts (e.g., feet or hand and elbow), as well as movement features of the same kind (e.g., acceleration features of various body parts), often correlate significantly. This is the case in the present findings as well, such as Acceleration of Head and Hands, Fluidity and Acceleration of Hands, or Foot Acceleration and Area of Movement. However, the features still cover different movement qualities and characteristics (e.g., Area of Movement and Complexity or Head Acceleration and Foot Distance), thus we decided to keep these variables in further analyses.

The emotion ratings provided by the observers in the perceptual experiment resulted in significant negative correlations for Happiness and Sadness as well as for Anger and Tenderness. These findings align with research on the relations between discrete emotions

(Eerola & Vuoskoski, 2011; Russell, 1980; Vieillard et al., 2008), and indicate both an opposite/adverse perception of these emotion pairs and a coherent and consistent rating behavior of the observers overall.

Observers were able to identify successfully the target emotions in case of Happiness, Anger, and Sadness (i.e., rated the respective stimuli significantly higher on the intended emotion scale than the other stimuli). Interesting to note is that ratings for Anger and Sadness were much lower than for the other two emotions (see Figure 6). This could indicate difficulties in portraying negative emotions via spontaneous dance movements, as observers would more commonly connect dance with positive feelings, pleasure, and fun. Acted portrayal of emotions, as used in previous studies (e.g., Camurri et al., 2003), might have resulted in clearer outcomes.

In case of Tenderness, however, observers rated Sadness highest, indicating a confusion between the two low arousal emotions. Music expressing either sadness or tenderness could have elicited similar movements, for instance, fluid movement as indicated in Burger, Saarikallio et al. (2013) and Dahl and Friberg (2007). Thus, when watching the animations without sound, movements could have been similarly mistaken for sadness rather than tenderness. Such confusion relates to the communication of tenderness that has been found previously in both music and movement-related research (e.g., Eerola & Vuoskoski, 2011; Gross, Crane, & Fredrickson, 2010; Pollick, Paterson, Bruderlin, & Sanford, 2001). Interestingly, the Tender stimuli rated as Sad happened much more often than the Sad stimuli rated as Tender. It could be posited that the nature of the stimuli and their acoustic features serve as explanatory factors, in that the prerequisite for the stimuli selection was having some regular beat structure to induce movement responses. However, it is difficult—if not impossible—to find musical stimuli that express either tenderness or sadness and simultaneously feature a perceivable beat, as a stronger beat and higher onset rate would increase the arousal level of the stimuli and thus be rated towards happiness or anger/fear respectively (Grekow, 2018; Laurier, Lartillot, Eerola, & Toiviainen, 2009). Consequently, movements to Tender stimuli might exhibit similar characteristics as movements to sad-sounding music, both being on a low arousal level. As the observers rated the movements without being able to listen to the music perceived by the dancers, the movements might have appeared more towards the sad than the tender side.

By bringing movement features and emotion ratings together, we were able to identify several relationships—kinematic profiles—between kinematics and emotion evaluations, illuminating how observers might base emotional judgments on movement characteristics when viewing silent dance animations. Observers rated clips as happy when dancers used high acceleration of head and feet, showed low-dimensional movement, and covered a large area, thus overall active movement using a large area. Moreover, we found a moderate correlation for rotation that was close to being significant (i.e., nonsignificant after adjusting the significance levels). This result is in line with the result obtained in Burger, Saarikallio et al. (2013) that found rotation related to happiness presented in the audio stimuli. The correlation values are indeed very close to each other (.53 in this analysis and .55 in Burger, Saarikallio et al., 2013), suggesting that participants also linked rotating movements with happiness when perceiving the videos. Due to the different sample size—30 in the previous analysis and 16 in the current one—however, the threshold of the correlation values to be flagged significant was higher in this analysis, marking the correlation as nonsignificant. Yet, we could not replicate the significant positive correlation between movement complexity and Happiness ratings of the audio examples. This result seems counterintuitive, as it could be expected that happiness—as an active emotion—would be embodied using complex movement as well. Moreover, combined with the positive values for acceleration and rotation, one could assume a positive relationship with complexity, too. However, this result could have emerged due to the larger sample size (60 dancers, 30 stimuli) in Burger, Saarikallio et al. (2013), so that the reduced sample (four dancers, four musical stimuli) used in the current study might not have offered the same variability. Thus, the four dancers might have moved in complex ways for all four stimuli, explaining the rather similar values of this movement feature (see Figure 5—the average for the Happy stimulus is slightly lower as compared to the other three stimuli). Furthermore, this analysis found significant relationships that the previous analysis did not find, although these correlations (acceleration features and area of movement) were in the same direction and highlight the relation between active movement and happiness. These results are in line as well with previous findings, for instance, by Burger and Bresin (2010), Dahl and Friberg (2007), and De Meijer (1989).

Observers perceived anger in movements covering small areas and without rotation, which means dancers were standing mainly in one spot and were neither moving nor turning around. This is very much in line with results described in Burger, Saarikallio et al. (2013), where significant negative correlations were found between fluidity and rotation and the angry-sounding music stimuli. Fluidity also correlated negatively (not significant) in the current analysis, while area correlated negatively (not significant) in the previous analysis, corroborating the results. Previous research, such as Dahl and Friberg (2007), Camurri et al. (2003), and Boone and Cunningham (1998), found similar relationships between nonfluent, nonrotational movement and anger.

Observers rated clips as sad when dancers' head, hand, and foot acceleration was low, and movements were bent forward, fluid, and complex. This pattern is opposite to the results for the Happiness rating, further indicating consistent rating behavior of the participants. This result pattern overall suggests that observers rated a video as sad when movements were smooth and of low activity (low acceleration). The results are somewhat in line with Burger, Saarikallio et al. (2013), particularly when comparing the correlations for acceleration and fluidity (same direction, but not significant). Again surprising is the result for complexity, as one would expect sad movements to be less complex (e.g., Camurri et al., 2003; Dahl & Friberg, 2007), which would fit to the negative correlations with the acceleration features. However, it again could be due to the dancer and stimulus reduction, choice of one specific stimulus representing sadness, and the low variability in the complexity values.

Observers associated tenderness with dancers that covered a large area, probably dancers stepping or walking. This result is to some extent in line with Burger, Saarikallio et al. (2013). In this previous analysis, tender music was embodied with a forward-bent body, low acceleration of the head and hands, and fluid movement. In the current analysis, all these features correlated in the same direction, although not significantly. It could have been that observers focused primarily on the space used by the dancers and only marginally paid attention to other features.

In order to connect the current results to emotion models, we used multidimensional scaling to locate the emotions in a two-dimensional space. These locations match up very well with locations suggested by the Burger, Saarikallio et al. (2013) study that displayed the emotion audio-ratings based on polar angles in a two-dimensional space. Furthermore, the solution fits well with the locations of discrete emotions in the circumplex model of emotions (Russell, 1980), indicating high consistency and unambiguousness in how observers perceived emotional expression in music-induced dance movements. Compared to Russell's solution, the locations of all four emotion ratings appear amplified on the arousal axis. This could suggest that arousal or activity is perceptually more salient in the movement than valence. Sadness and tenderness were located closer to each other than to anger or happiness, which could explain the confusion between sadness and tenderness.

This study gathered only observers' ratings, which could be conceptualized as a conscious, overt decision of their underlying perception, expressed in and potentially restricted to given categories (rating scales) provided by the researcher. Thus, adding physiological measurements, such as galvanic skin conductance, could reveal insights into observers' own emotional states and provide access to a covert perception of emotional content. Furthermore, eye-tracking technology could be used to measure where observers visually focused when making the rating decision. This might yield a more precise identification of movement features and body parts being characteristic for expressing emotions in dance movement. Additionally, in future studies, researchers could ask observers to name specific body parts or movement characteristics they paid attention to and found relevant for providing the rating.

This study involved only video excerpts without sound, as we were interested in the communication of emotional expression solely via movement. However, it would likewise be interesting to investigate audio–video stimuli in studying the multimodal integration that occurs when audio presents a second means of communicating emotional expression. Such research could involve both congruent and incongruent combinations (i.e., clips that show either a matching combination of stimulus/emotion and exhibited movements or a mismatched combination of both). Interesting questions that could arise, then, are whether audio–video clips would be evaluated differently than when audio is not present, whether different movement features would turn out significant, and whether one of the domains would influence the perception of observers more than the other. Moreover, we used only four stimuli—one per emotion (resulting in 16 clips overall)—to keep the experiment sufficiently short. However, future study could include more or different stimuli to validate further these results.

It could be argued that time-shifting the movement data could have changed some of the emotional characteristics of the dance movements. However, taken that the time-shifting was relatively moderate (7% for the happy and sad stimulus, 13% for the angry one), we assume that these changes did not affect emotion perception. Furthermore, body movement could have been impacted not only by the emotional connotation of the music, but also by the underlying musical characteristics of the chosen stimuli, and dancers could have moved simply in relation to the musical characteristics without taking emotion into account, particularly because they were instructed to move only as they felt natural. However, given that emotional connotations arise from certain combinations of musical characteristics (e.g., Grekow, 2018; Laurier et al., 2009; Saari, Eerola, & Lartillot, 2011), those cannot be disentangled fully, which is evident also from the high prediction rate of music emotion recognition models that predict perceived emotion from musical/audio features (e.g., Kim et al., 2010; Vempala & Russo, 2018). That the movement analysis presented in Burger, Saarikallio et al. (2013) aligns well with the perceptual results presented here, we feel confident that the dancers were able to convey emotions in their movement. Furthermore, the approach of asking people to dance without a concrete emotional instruction is a more ecologically valid approach than asking them, for instance, to portray specific emotions, and thus such an approach might say more about spontaneous human behavior.

The perceptual data collection involved a larger percentage of female than male observers. It could be that women are better at recognizing emotions in others, as research suggests that women tend to be higher in empathy than men are (e.g., Lennon & Eisenberg, 1987; Schieman & van Gundy, 2000). However, due to the skewed gender distribution in the data set, we did not include an analysis of gender here. Thus, future data collections could aim at a more balanced gender distribution to investigate whether gender affects emotion recognition in dance movement. Furthermore, we did not analyze our data with respect to music or dance expertise. Although previous research, for instance, suggests that professional musicians rate emotions with higher accuracy (Castro & Lima, 2014), our sample did not include professional musicians or dancers. Thus, further research could investigate the influence of professional expertise by specific participant recruiting.

The current study used animations in two dimensions that might have lacked characteristics visible when seen with more depth information (i.e., using three-dimensional projection techniques or presenting the two-dimensional animations from various angles). Future perceptual studies could therefore include animations with more depth information or use, instead of stick figure, a more naturalistic-looking avatar to provide an increased set of human features.

This study used animations of dancers who had been instructed to dance or move as it felt natural to them. A future motion-capture study could explicitly instruct dancers to portray the emotion they perceive or feel in the music or portray an emotion specified by the experimenter. Additionally, the musical stimuli could be selected based on their emotional characters to express the target emotions more clearly than the current set of stimuli. This might provide a more controlled, coherent, and systematic dataset, containing more emotion-stereotypical movement, which might be more readily perceivable by observers. Such stimuli might be useful even for target groups having challenges understanding and expressing emotions (e.g., people on the alexithymia or autism spectrum).

The present study provided profound insights into the perception of dance movements, establishing links between kinematics of music-induced movement responses and the evaluations of independent observers regarding emotions expressed in these movements (visual domain). This investigation follows up a motion-capture study (Burger, Saarikallio et al., 2013) that connected kinematics of music-induced movement with emotional characteristics of music (auditory domain). Based on the current and 2013 studies, we have found significant congruence in auditory and visual perception of emotions in music-related activities. Significant kinematic profiles for each emotion indicate commonalities and differences between both studies, providing insights into how emotional expression of music-induced movement could be conveyed and understood through auditory and visual channels.

IMPLICATIONS FOR RESEARCH, APPLICATION, OR POLICY

This investigation forms a contribution to the theory of embodied music cognition and provides support for Leman's (2007) notion of empathy. The results additionally provide insights into emotion perception of movement as a multimodal phenomenon that not only contributes to dance and music contexts, but also to understanding expression and expressivity in general human movement. Furthermore, this research could have implications on brain functionality studies, in particular to notions regarding the common coding theory (Prinz, 1984) that claims that perceiving an action activates brain areas associated with producing the action and vice versa. Specifically, our research could be viewed as support for arguments that the common coding theory would apply not only to overt actions but also to covert capacities like emotion, suggesting observers understand others' emotions in movements by internally mirroring the movement themselves. In addition to these theoretical implications, our research might have implications on practical level, for instance in a (music) therapy context, using music and movement to express and better understand one's own emotions.

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