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BODY, SPACE, AND EMOTION: A PERCEPTUAL STUDY

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Abstract: *The present study aims at providing a systematic account of emotion perception applied to expressive full-body movement. Within the framework of the lens model, we identified the decoding process underlying one's capacity to categorize emotions while watching others' behaviors. We considered the application of Laban movement analysis, a method focusing on qualitative aspects of movement. An original*

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experimental setup used a contemporary choreography interpreted by four expert dancers in an environment that restricted their movement to their peripersonal space. Each performance consisted of a subtle or intense emotional interpretation of the choreography (e.g., happiness, anger, surprise, fear, and sadness). Results showed that emotions being expressed in this confined environment could still be identified, categorized, and associated with a profile of movement qualities and specific body parts.

Keywords: *nonverbal expressive movement, emotion, peripersonal space, lens model, Laban movement analysis, dance, choreography.*

INTRODUCTION: BODY, SPACE AND EMOTIONS

The body is a tool of unparalleled power for expressing emotion beyond the use of verbal utterances, and this issue has been the focus of numerous research studies (e.g., de Gelder, 2013; Glowinski et al., 2011; Wallbott, 1998). However, the relationship between space and the body's emotion expression powers has been far less studied. This is due in part to prior difficulties in exploring and recording human interaction or body expression with a high degree of precision and flexibility. Most of the performances recorded for scientific experiments take place within a laboratory setting to allow absolute control over lighting conditions that otherwise might affect the robustness of the tracking. In fact, far fewer studies engage the natural setting of the performance (e.g., open-air performance and theatre). The role of space, and specifically the impact of a small space, on the progression of movement, particularly on the full-body expression of an individual's emotion, remains to be clarified. A better insight into such relationships is valuable for a wide range of domains, including psychological research on emotional and aesthetical expression or the field of human–computer interaction (Pantic, Pentland, Nijholt, & Huang, 2007).

In a context that combines psychological, aesthetic, and human–computer interaction research, studies focusing on emotion and space often refer to boundary conditions, extreme situations (e.g., flight space), or phobias (e.g., claustrophobia; see Palinkas, 2001). To address the space–emotion relationship, we present a case study of a dance choreography that was performed by professional dancers conveying various expressive emotional intents. This experimental method drew upon previous work by Camurri, Lagerlöf, and Volpe (2003). What characterizes these performances, and distinguishes the novelty of our contribution, is that the space made available to each dancer corresponded to their peripersonal space. This peripersonal space has been approximated by the kinesphere in dance theory as the environmental sphere surrounding the body whose periphery can be easily reached by extending a limb (Laban & Lawrence, 1947; Sutil, 2013). We are interested in understanding how external observers can discriminate the expressed emotions based on the expressive behavior of the dancer within the boundaries of his/her peripersonal space. Our contribution integrated the Laban movement analysis (LMA) categories, used to describe qualitative movement, to fit the decoding process underlying such observers' emotional categorizations. We also were interested in evaluating other factors' impact on the emotion recognition process: (a) the observers' expertise (e.g., does being a trained dancer augment sensitivity to emotion expression?), (b) the performance expressive intensity (e.g., are emotions better recognized when expressed in an emphatic manner?), and (c) the potential role of body parts in emotion recognition (e.g., are there specific relationships between expressed emotions and body parts?). This paper is organized in the following manner. We first review the existing approaches in the literature that attempt to recognize emotions through body postures and movements with a specific focus on dance as a test case. Next, we present the developed experimental framework, which includes the steps dedicated to the recording and presentation of the stimuli and details related to the statistical analysis methods applied to the participants' answers. This is followed by the presentation of our results: how emotions are recognized and how they can be described in terms of the LMA categories. In the Discussion section, we examine the impact of the participants' expertise, the intensity of the stimuli, and the relationship between specific emotions and identified body parts. Finally, we conclude this paper by addressing future research directions.

Body as a Source of Emotional Expressivity

The body is a key source of information for emotion recognition. An increasing trend in research relates to facial and vocal expression, gesture, and dynamic body motion recognition (e.g., Glowinski et al., 2011). The recent development of low-cost digital image recording equipment, together with the advent of professional motion-capture technologies, has enabled a close analysis of nonverbal modalities in human communication of emotions and, in particular, bodily behavior (Wallbott, 1998). Recently, affective computing, along with the wide range of related application areas, has led the way to meet an increasing demand for the creation of natural, intelligent, adaptive, and personalized multimodal environments (Vinciarelli et al., 2012).

Until the turn of the 21st century, various coding systems were proposed by psychologists. The main focus has been on emotional facial expression due in part to the pioneering work of Ekman, who offered a systematic account for facilitating explicit coding and categorization (FACS; Ekman & Friesen, 1978). A realm of new standards is emerging in this domain, opening opportunities for commercial applications of automatic emotion recognition. Furthermore, alternative approaches have been developed more in recent decades. Research results in psychology suggest, in particular, that body movements do constitute a significant source of affective information (Wallbott, 1998). For example, body gesture, as a complement to facial expressions, can help disambiguate emotional information (de Gelder, 2006; Todorov, Baron, & Oosterhof, 2008). Yet, the vast number and combination of body postures and gestures offers a higher degree of freedom for expressions that can be difficult to easily manage during analysis. No standard body-movement coding scheme equivalent to the FACS for facial expressions exists to facilitate decomposing bodily expression into elementary components. Various systems have been suggested by psychologists (e.g., Bobick, 1997; Dael, Goudbeek, & Scherer, 2013) but none has reached the consensus achieved by the Ekman's system (Ekman & Friesen, 1978) for facial expression analysis.

Alternative approaches have been developed to fill this need. For instance, research on upper body expressivity took advantage of the clear conceptualization of sign language (e.g., Gunes & Piccardi, 2009). The world's many sign languages, now being extensively documented, have become a resource for emotion recognition. In sign language, signs made with the hands work in complex coordination with signs made with the face, head movements, torso shifts, gaze, gestures, and mimetic moves. As upper-body movements also correspond to what can be captured easily through a Webcam in the typical working environment (i.e., where people sit in front of their desktop computer), the recognition of such movements has stimulated a realm of applications in this domain. Yet, with the advent of wearable computing, that is, devices worn on the body giving the potential for digital interaction, particular attention is now being devoted to specific limb expressivity (e.g., arms, fingers; see Velloso, Bulling, & Gellersen, 2013). In this context, the lack of systematic coding has been successfully compensated for through a promising alternative approach developed by Caramiaux (2014). Caramiaux, Montecchio, Tanaka and Bevilacqua (2014) investigated and demonstrated how the variability of the body behavior itself can stand as a central cue for capturing expressivity. However, other than the seminal work by Pollick, Paterson, Bruderlin, and Sanford (2001) on motion of knocking, very few experiments have investigated emotional communication through specific limb variations. The key issue in recognition of affective bodily expression is to consider the level of information that determines the quality of movement. The view the body as a whole represents a complete source of affective information is now receiving increased attention in the scientific literature. The recent interest into full-body emotion expressivity can be related to the diffusion of advanced motion capture systems (e.g., Vicon) and especially to the larger dissemination of RGB-depth cameras (e.g., Kinect) that allow for an affordable and relatively fine-tuned tracking of an individual's body movement.

Existing studies on full-body movement have used coarse-grained posture features (e.g., leaning forward or slumping back) or low-level physical features of movements (i.e., kinematics, see, for example, Bianchi-Berthouze, Cairns, Cox, Jennett, & Kim, 2006). Other approaches have exploited the dynamics of gestures, referring to psychological studies reporting that temporal dynamics play an important role in interpreting emotional displays (e.g., Kapur, Kapur, Virji-Babul, Tzanetakis, & Driessen, 2005).

Towards a Unified Approach

One may note the disparity between the different approaches and, as pointed out earlier, the lack of broader and systematic view to address emotion recognition based on full-body expressivity. A few attempts have drawn inspiration from dance notation and theories (Camurri et al., 2003; Laban & Ullmann, 1971). The key issue is to consider the level of information that determines the quality of movement, that is to say the general characteristics about the way a movement is performed (e.g., the effort dimensions of LMA described below). This level of information may lie between the low-level features (e.g., position of and derivatives in a limb's trajectory that report a mere displacement and inform about a specific gesture or motion activity) and a high level of information related to the emotional categories that people may use to infer emotional attitudes through observation (Glowinski et al., 2011). In this context, Laban's (1947) conceptualization has proved useful in modeling what could be an intermediate level of information representing qualitative properties of movement where expressivity is embedded and conveyed. Emotion recognition may ultimately rely on the specific combination of these qualitative properties of movement (Glowinski et al., 2011). Since the pioneering work led by Zhang et al. (2006), an increasing number of computational implementations have been suggested but much more needs to be done on the perceptual side. Thus, our study aims to tackle this aspect by focusing on the perception of emotions expressed through full-body movement in a restricted environment (i.e., the performer's peripersonal space).

Our specific goal is to provide a systematic account of the decoding process underlying such bodily emotion recognition and observe the respective impact of the observer's expertise, the intensity of the performance expressivity, and role of body parts in this process. In particular, we are interested in understanding whether an intermediate level of emotional information discernment related to the perception of movement qualities based on the LMA conceptual framework (Laban & Ullmann, 1971) could help in tying the low and high levels of emotional information. We expect this study will shed light on to which level of information may be decisive in researchers' understanding of the perceptual processes underlying emotion classification.

The research approach to the expression of emotion employed in this study relies on the lens model initially developed by Brunswik (1956), adapted to the performing arts by Juslin and Laukka (2003), and recently reviewed by Glowinski et al. (2014; see Figure 1). According to this model, the analysis of emotion expression must take into account both the sender's (e.g., the performer) and the receiver's (e.g., the observer) perspectives. Two types of processes are thus considered: emotion expression/communication through body behavior (e.g., the proximal cues exhibited by a performer) and emotion recognition (e.g., the observer inferences based on the behavioral cues of that performer).

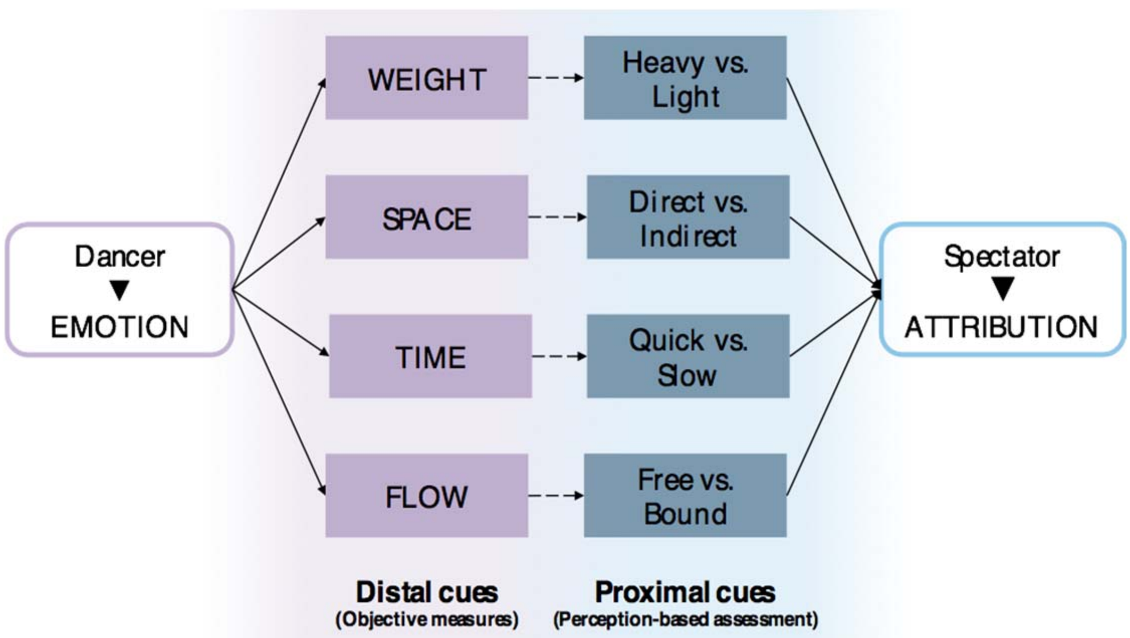

Figure 1. An illustration of the revisited lens model (Brunswik, 1956) integrating the effort dimensions (i.e., factors and elements) of Laban movement analysis (Laban & Lawrence, 1947). This conceptual framework includes both the point of view of the sender (e.g., the dancer) and of the receiver (e.g., spectator). The respective encoding and decoding processes of emotion expression through body components can be analyzed in a systematic way. In particular, the attribution of a specific emotion category during the recognition phase of the movement can be related to the way a spectator combines bodily, effort-based, features of the dancer's performance.

Perceptual Evaluation in Terms of Movement Qualities

An analysis in terms of movement qualities helps identify the differences between the perspective of the person expressing the movement (i.e., the sender) and that of the person observing the same movement (i.e., the receiver). According to Laban (as cited by Sutil, 2013), movement can be experienced intuitively as a continuum, an indivisible flux of changes. Alternatively, movement can be rationalized as a series of snapshots that can be ordered, structured, and formalized as the building blocks of a representation (Glowinski, Camurri, Chiorri, Mazzarino, & Volpe, 2007). This conceptual framework facilitates investigating and understanding the implicit or explicit strategies an observer applies in manipulating the collected snapshots of movement in building up a complete, sensitive, and yet subjective representation of the (performer's) sequence. Supported by a profound dualistic approach, Laban's key movement concepts come in pairs of opposites (Laban & Lawrence, 1947). The theory of efforts developed by Laban aims at characterizing such dynamism in relation to four basic properties (effort factors): weight, space, time, and flow (Laban & Lawrence, 1947). Each of these factors is in turn divided into opposed subcategories known as effort elements (heavy–light, direct–indirect, quick–slow, and free–bound). These effort elements allow researchers to understand the fundamental qualitative differences in human movement. As stated by Sutil (2013, p. 5), "The difference between punching someone in anger and reaching for a glass is slight in terms of body organization—both rely on extension of the arm and the same spatial direction of the movement. The weight of the movement and the intensity of the movement are very different, though."

In this study, the Laban elements (Laban & Lawrence, 1947) are operationalized via measurable descriptions, described as follows:

1. The weight element considers the individual's movements in relationship to gravity and may describe its vigorousness. The two subcategories associated are heavy (i.e., powerful) and light (i.e., delicate).
2. The space element here considers the individual's movements related to his/her peripersonal space. The two subcategories associated are direct and indirect. Indirect motion is interrupted and roundabout, and direct motion proceeds along a mostly straight line without deviation.
3. The time element is a measure of movement activity speed. The two associated subcategories are quick (i.e., sudden and urgent) and slow (i.e., sustained, continuous, and time stretching).
4. The flow element characterizes the continuity of the movement. The two associated subcategories with this element are free (i.e., a fluid and released movement) and bound (i.e., a controlled or contained movement).

Emotion Categories, Peripersonal Space, and Laban's Effort Dimensions

Based on the qualitative approach of movement expressivity, recent computational studies have investigated how emotion could be rendered by integrating the effort dimensions (i.e., factors and elements) of Laban movement analysis (Laban & Lawrence, 1947). Initially, the objective in this domain was not to access perceptual processes only but also to create complementary strategies to organize and classify large databases on motion that included more subtle aspects of expressions relating to emotion. A first attempt by Wakayama, Okajima, Takano, and Okada (2010), then Okajima, Wakayama, and Okada (2012), showed that motion retrieval can benefit from the use of a subset of LMA dimensions, especially when searching for data (indications, instances) on body movement in large research databases (Kapadia, Chiang, Thomas, Badler, & Kider, 2013). Recently, Aristidou, Charalambous, and Chrysanthou (2015) inspected the similarities among various emotional states classified according to the arousal and valence of Russell's (1980) circumplex model and a subset of features that encode stylistic characteristics of motion based on the LMA. Overall, previous experimental results, based on video processing or body limbs' trajectory dynamics, show that these features can be extracted using the LMA dimensions and thus allow researchers to encode body posture differences depicting emotion expression. The pertinence of Laban's (Laban & Ullman, 1971) dimensions as descriptors for motion expressivity can be attested further by their use in avatar animation. Since the seminal work of Chi, Costa, Zhao, and Badler (2000), various studies have demonstrated that LMA-derived dimensions can be exploited efficiently in motion parameterization and expression (Zhao & Badler, 2005).

Unfortunately, few studies have considered the application of Laban-based analysis in understanding perceptual processes during emotion recognition. Levy and Duke (2003) used LMA dimensions to score the capacity of nonprofessional dancers to improvise sequences of expressive movement. Correlation analyses in emotion recognition revealed relationships among the emotional states of depression and anxiety and certain movement qualities. Focusing on the specific case of walking, Crane and Gross (2013) explicitly instructed participants to use LMA-based analysis to classify the observed nuances of emotions. Sadness, anger, contempt, and joy were decoded with accuracy that ranged from 74% to 32 %, respectively; for most of the targeted emotions, decoding accuracy was related to the four effort factors (Serino, Annella, & Avenanti, 2009).

Peripersonal Space, Kinesphere, and Emotions

Peripersonal space has been defined in contrast to general space in a way similar to how space is defined in geometry or topology (Serino et al., 2009). In dance theory, this peripersonal space has been approximated further by a kinesphere, which refers to the space occupied by an outreaching body without it moving from one spatial location (Laban, 1966). Specifically, it can be represented as an area within reach of the body's extended limbs which, when projected in all directions from the body's center, can be conceived as a totality of movement or a sphere of movement (Sutil, 2013). Therefore, the kinesphere gives an operationalized way to analyze peripersonal space (see Figure 2) and how each individual might explore the surrounding environment to express emotion and, in turn, how such peripersonal space may reciprocally impact on emotional expression.

Dance as a Test Case

Dance appears as an ideal test case to study emotion in relation to movement expressivity. It condenses within a minimal amount of space and time the human capacity to express emotional information. Aesthetically, it is possible to create a minimally expressive dance or a dance that

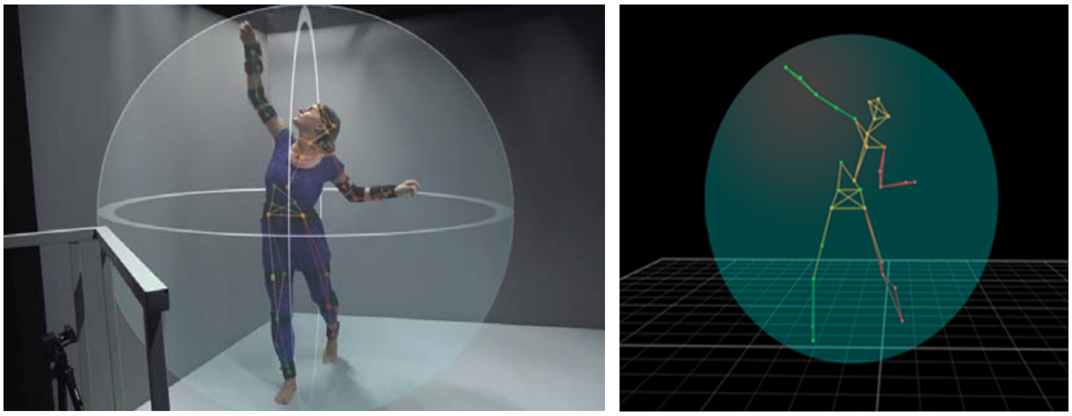

Figure 2. Illustration of the peripersonal space as operationalized by the concept of kinesphere (Laban, 1966). The figure on the right represents the motion capture of the dancer's movement (on the left) that was used in the perceptual experiment presented in this paper.

unfolds slowly. Typically, dance provides no functional or utilitarian use of the space (i.e., related to a practical task achievement, such as opening a door or typing on a keyboard), but rather to express oneself. In contemporary Western dance art, however, the aesthetics have turned into quite everyday activities; therefore objects and space may be interrelated in very functional ways. Dance as a test case allows the experimenter to observe movement of an undetermined wide range of complexity that can vary according to the level of the dancer's expertise (e.g., from beginner to accomplished dancer) as well as according to the choreography. Specific to our research interest, dance also can reveal exceptional and evolved ways of exploiting the surrounding space. By focusing on the expression of emotion, through movement in a limited space or constrained environment, we sought to observe how a dancer faces this challenge: Specifically, we were interested in how the dancer could transform a source of what could appear to most people as a stress or difficulty into a positive experience. Therefore, we experimentally defined a limiting condition where the performer was bounded by a choreography that limited the variety of possible movements within a further, restricted environment that constrained the dancer's displacement within his/her personal space. As a consequence, we expected that this challenging situation could impact the performer's creative capacity in expressing emotion through the only dance component that remained freely available: body expressivity. We explored this issue by assessing how external observers perceived such emotional body expression.

Laban Movement Analysis and Dance

The LMA is widely used in dance, either to annotate and generate choreography or to train dancers. With the advent of new systems for motion capture, dancers have shown an increased interest in using these new forms of interaction to map in real-time their expressive body movements to audio or visual feedback. The LMA dimensions have resurfaced as a source of inspiration in capturing key expressive variations in dance performance and for improving the "naturalness" during interaction with automatic systems (Mancas, Glowinski, Volpe, Coletta, & Camurri, 2010). Drawing upon Laban's approach, Camurri et al. (2003), and Van Dyck, Vansteenkiste, Lenoir, Lesaffre, and Leman (2014) developed a qualitative approach to human full-body movement for emotion recognition. In this study, LMA dimensions were approximated through a combination of low-level physical features to allow for a coarse description of an encoding process of emotion through body behaviors (e.g., emotion arousal revealed by acceleration peaks). Based on a more explicit computational modeling of Effort-Shape features, Alaoui, Caramiaux, Serrano, and Bevilacqua (2012) developed an interactive augmented dance performance that extracts movement qualities (energy, kick, jump/drop, verticality/height and stillness) to generate a visual simulation.

However, these previous works overlooked the experiences that can be gained through perceptual studies based on the LMA. For dance examples, it is useful to consider the key conceptual distinctiveness embodied in this art form. Dance can be considered a specific case of stylized body movements in which the entirety of movement encodes a particular emotion. Stylized motions usually originate in laboratory settings, where subjects are asked to freely act on an emotion without any constraints. Another key distinction may refer to the propositional and nonpropositional aspects of movement (Boone & Cunningham, 1998). Raising one’s hand to indicate stop, for example, may be considered a propositional movement that constitutes established signs to transmit shared meaning. As stated in Camurri et al. (2003), emotions can be expressed through propositional movement (e.g. a clenched fist to show anger or raised arms to demonstrate joy), whereas nonpropositional movements are embodied not in discrete, easily segmented motions but rather through a subtle combination of movement qualities (e.g., lightness or heaviness). From the point of view of a perceiver, this distinction could be interpreted as a shift in attentional focus, whether on the configurational aspects (e.g., gesture as an explicit, well-delimited code) or the dynamic itself (i.e., how one expresses emotional intent). In this study, we focused on the nonpropositional style of movements as represented by dance sequences.

In our research, we considered how external observers combine body movement based on the LMA to recognize the emotional intent of contemporary dancers during their performance. Specifically, we focused on assessing the significance of the time, weight, space, and flow factors featured in emotion recognition by external observers.

METHODS

Participants

Dancers

Two female (D1 and D2) and two male (D3 and D4) professional contemporary dancers were recruited for this study. Their average age was 28 years, and they were remunerated 100 CHF for their participation. All participants provided signed informed consent prior to study participation. The protocol for this study was approved by the University of Geneva, Switzerland, at the Faculty of Psychology and Educational Sciences. Dancers were asked to wear tight clothes, their hair was tied up, and all jewelry and accessories were removed for the recordings.

Observers

Forty-eight observers, recruited through social networks, participated in the experiment (17 males; age *M* = 27.77 years, *SD* = 10.77). Among them, 38 were following or had followed dance classes and 10 never practiced dance. We followed the standard of the Geneva education system in dance to categorize our research participants: The experts in our study (*n* = 22) were dancers with 8 or more years of practice; those with 1 to 7 years of dance experience were considered novices (*n* = 16). Individuals with a year or less of dance practice were grouped into the nonexpert condition (*n* = 10). All observers were competent in French, the language used to collect the data.

Stimuli Recording

MoCap (motion capture) optical reflectors (markers) were positioned on dancers' body to record their movement (see Figure 3). Each dancer had an equal number of reflectors attached to the left and right halves of their body. However, these reflectors were not symmetrically positioned to allow them to be distinguished more easily by the camera system and to facilitate offline postprocessing of data. Eight Bonita 3 Vicon cameras were used to record dancers' movements. The motion-capture system sampled the data at 120 frames per second. This material allowed us to record in three dimensions the position of the 30 markers placed on the dancers' body. By using a body model, the state (orientation and position, where applicable) of each body part was estimated.

Katrin Blantar, a professional choreographer, designed specific sequences of stylistic movements that excluded stereotyped postures that could be perceived as expression of a basic emotion (e.g., upward movements expressing anger). This 30-second microdance (see Glowinski

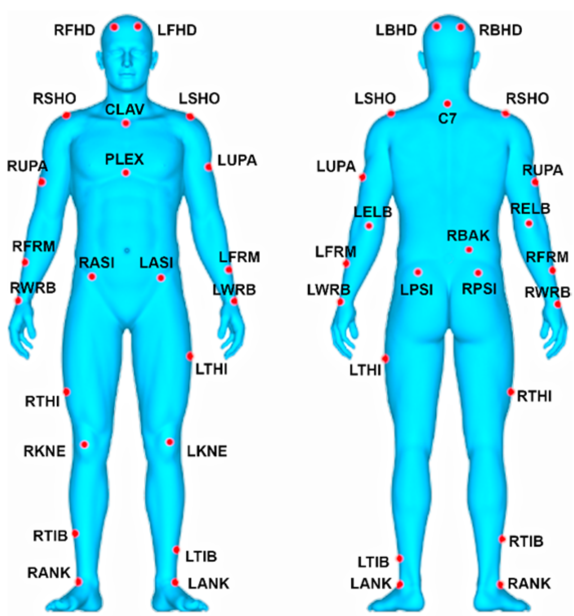

Figure 3. Disposition of the motion capture optical reflectors on the dancers' bodies.

et al., 2007) was performed in a controlled environment of 3 x 3 m that strictly enclosed the dancer's kinesphere.

This choreography was first learned by the dancers in a formal way without emotional engagement. Then, during the experiment, each dancer explicitly addressed a scenario for each emotion, meaning that they reviewed the proposed definitions (see Table 1) before integrating that into their expression of the choreography. Each dancer performed each emotional expression twice, at two levels of intensity: first in a subtle way (i.e., low-intensity condition) and then with a more emphasized and demonstrative manner (i.e., high-intensity condition). This distinction was based upon a paradigm used in music to distinguish between levels of expressivity (Davidson, 1993). Dancers were asked not to modify the choreography, but no instructions were given concerning how emotions should be expressed through their dancing that choreography. By the completion of the recording process, each dancer performed a set choreography six times: one that contained no emotional expressivity (neutral, danced twice) and versions that expressed the five emotions (i.e., happiness, anger, surprise, fear and sadness) in both low and high intensity. Thus a total of 12 performances per dancer were recorded, resulting in, overall, about 5 hours of recordings.

Stimuli Preparation

The Vicon Nexus software program[1] was used to reconstruct and label the data. At the end of the processing, the reflectors were linked to each other to simulate the head, chest, pelvis, arms, and legs (see Figure 4). To create the video stimuli (i.e., the various choreographies performed in abstract representations), we displayed the linked markers through the Vicon Nexus view, using Camtasia software[2] (see Figure 5).

Table 1. Definitions of the Five Emotions Used as the Basis for Expressive Choreography and Observer Perceptions (based on Banziger & Scherer, 2007).

Emotion	Definition
Anger	Feel violent discontent caused by an action deemed stupid or malicious.
Happiness	Feel transported by a wonderful event happening in a more or less unpredictable way.
Fear	Feel threatened by an imminent danger that could affect one's survival or physical or mental integrity.
Surprise	Feel confronted, often abruptly, with an unexpected or unusual event (without a positive or negative connotation).
Sadness	Feel depressed and discouraged by the loss of a relative, an object, or a familiar environment.

Note. The definitions were used by the dancers in creating the emotional expressiveness of the choreography versions for the stimuli preparation; the observers then employed the definitions during the emotion recognition task.

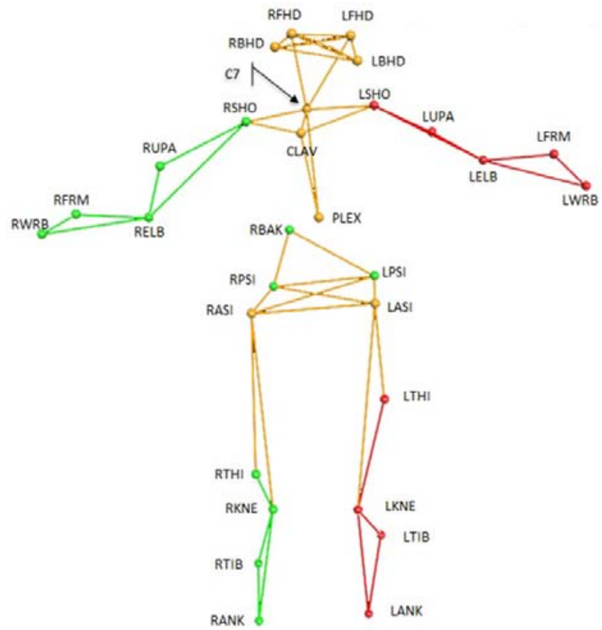

Figure 4. A silhouette of a dancer at the end of the Vicon Nexus processing, created through connecting the data collected via optical reflectors on a dancer's body.

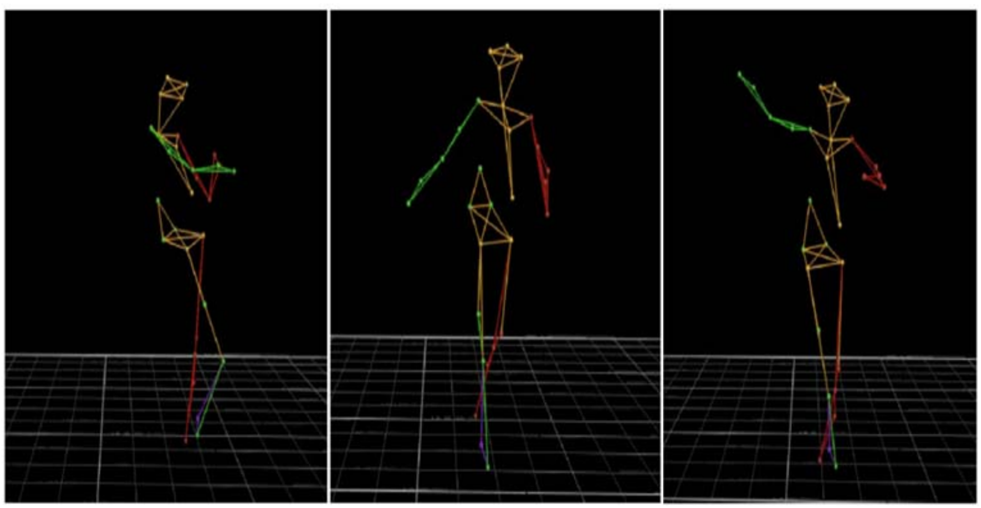

Figure 5. Screenshot examples of movement sequences of the choreography expressing happiness, as performed by dancer D1.

Questionnaires

The Qualtrics software program[3] was used to create the online questionnaires. Four questionnaires, each containing videos of two dancers, a man and a woman, were created. They were written in French and checked by all authors of the study; all English translations provided for this paper were conducted by the authors. The first questionnaire displayed the performances of dancers D1 and D3, the second of D1 and D4, the third of D2 and D3, and the fourth of D2 and D4. Two videos of D1 expressing sadness were lost due to a technical problem. Thus, the first and second questionnaire presented 22 videos, whereas the other two contained 24 (each video of each of the two selected dancer). All videos were presented, in 428 x 1027 cm format. In each questionnaire, the videos were presented randomly. The observers completed only one of the four questionnaires in order to reduce the duration of the experiment.

The questionnaire was administered in a lab. Observers were asked to complete information regarding their age, gender, and diploma or study degree. Questions followed concerning their dance training (i.e., “Have you already followed dance classes?” “Which kind of dance did you practice?” “How many hours per month?” “How many years of practice?”) and contemporary dance familiarity (i.e., “How frequently do you watch contemporary dance performances?”). Before presenting the videos, the observers were asked to carefully read the definitions of the five emotions they would use in the questionnaire to judge the performances (see Table 1). The neutral condition was simply presented as a performance without clear emotional engagement.

Depending on the questionnaire, 22 or 24 videos were then randomly displayed to each participant. For each video, the participants did not identify the perceived emotions directly but rather by following Dael’s method (Dael et al., 2013), that is, rating the intensity they perceived of each emotional expression from 0 (*low intensity*) to 100 (*high intensity*). This 100-point scale enabled a fine-tuned evaluation of participants’ responses and to distinguish better how they recognized emotion. Participants were then instructed, via a forced-choice question, to indicate which body part most captured their attention during the performance, choosing between the head, shoulders, arms, pelvis, or legs. Then, four scales were displayed, ranging from 0 to 100, to measure the various elements of the Laban theory of effort (Laban & Lawrence, 1947): weight (0 = *heavy*, 100 = *light*), space (0 = *direct*, 100 = *indirect*), time (0 = *quick*, 100 = *slow*), and flow (0 = *free*, 100 = *bound*). The observers were asked to select these elements intuitively and without overthinking. The questionnaire was completed by the participants in 40 minutes, on average. Figure 6 provides an overview of the experimental protocol adopted in this study.

Statistical Analyses

To analyze the data regarding the participants’ emotion recognition in the performances, their evaluations of the Laban dimensions among the emotions, and their responses regarding emotions and their intensity, and the body parts capturing attention, we used the generalized linear mixed models (GLMMs) statistical method. GLMMs combine the properties of linear mixed models, which incorporate random effects, and generalized linear models, which handle nonnormal data by allowing the researchers to specify different distributions, such as Poisson or binomial (Bolker et al., 2009). By using GLMMs, we could also control for the interindividual variability random effect.

To investigate the contribution of each variable and its interactions, we compared different models, from the most simple (i.e., with one unique variable) to the most complex (i.e., all combinations of variables). Statistical differences were evaluated through Chi-square difference tests. Our fixed effects comprised the specific emotions expressed by the dancers in individual

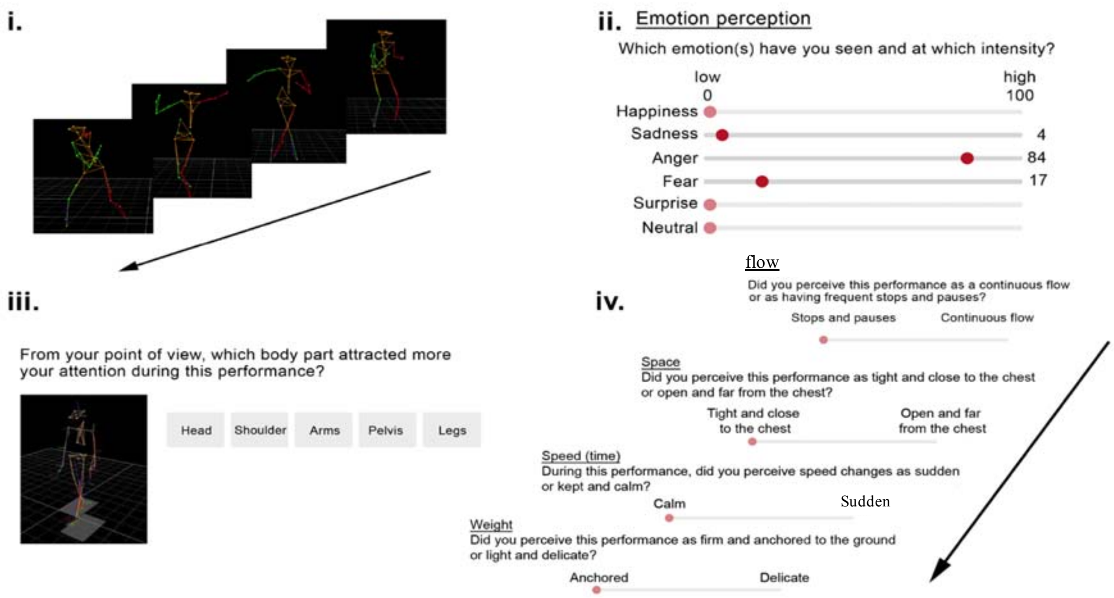

Figure 6. An overview of the experimental protocol adopted in this study, comprising (a) the microdance sequence of emotionally expressive choreography by professional dancers using motion-capture technology to create the stimuli, and observers' perception regarding (b) the rating of the perceived emotions, (c) the body part of the dancer's representation that drew the participant's attention during the dance, and (d) the questions regarding the performance qualities and expressivity (LMA elements).

videos (i.e., happiness vs. surprise vs. sadness vs. anger vs. fear vs. neutral), the intensity of the dances (low vs. high), and the dance expertise of the observers (nonexpert vs. novice vs. expert). Our random effect consisted of the interindividual differences of ratings between the observers. Our dependent variables were the observers' perception responses on the emotional scales (happiness, surprise, sadness, anger, fear, and neutral) that we transformed into binomial variables 1 (*the emotion with the relative highest rating*) or 0 (*for all other emotions that scored under this maximum value*) for each trial. Four other dependent variables were the Laban factors (flow, space, time and weight), which were continuous variables ranging from 0 to 100. Finally, five binomial variables concerned the body part (head, shoulders, arms, pelvis, or legs) that captured the most participants' attention during each performance.

RESULTS

Emotion Recognition, Influence of Expertise, and Relations Between Emotion and Laban's Dimensions

The dancers' intended emotion showed a significant main effect in all emotional scales, as displayed in Figure 7: happiness, $\chi2(5, N = 48) = 92.15$, $p < .001$; sadness, $\chi2(5, N = 48) = 192.81$, $p < .001$; anger, $\chi2(5, N = 48) = 52.02$, $p < .001$; fear, $\chi2(5, N = 48) = 82.47$, $p < .001$); surprise, $\chi2(5, N = 48) = 28.36$, $p < .001$); and neutral, $\chi2(5, N = 48) = 30.65$, $p < .001$). As shown

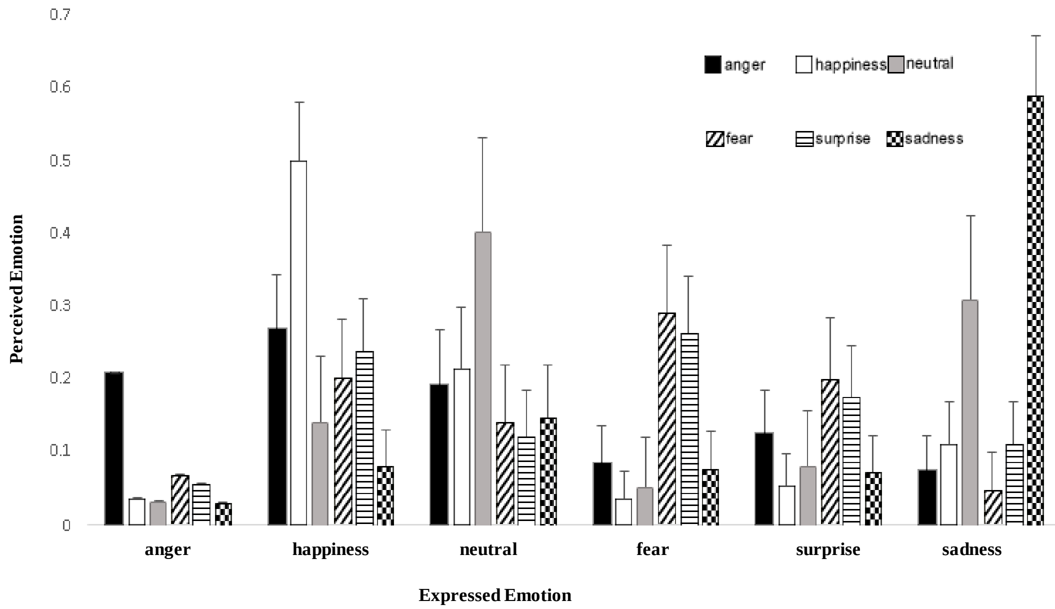

Figure 7. Histogram representing on the horizontal axis the emotions expressed by the dancers and on the vertical axis the emotions rated by the observers ($N = 48$). Vertical bars denote a 95% confidence interval.

by contrast analysis, observers perceived significantly more happy, sad, angry, and neutral expressions when the dancers expressed happy, sad, angry and neutral expressions, respectively, than the other emotions: happiness, $\chi 2(1, N = 48) = 69.08, p < .001$); sadness, $\chi 2(1, N = 48) = 31.81, p < .001$); anger, $\chi 2(1, N = 48) = 62.19, p < .001$); and neutral, $\chi 2(1, N = 48) = 25.23, p < .001$).

Data did not show any difference in emotion recognition based on level of expertise. No significant interaction between emotion and expertise was observed in the emotional scales: (happiness, $\chi^2(10, N = 48) = 4.52, p = .92$; sadness, $\chi^2(10, N = 48) = 11.98, p = .29$; anger, $\chi^2(10, N = 48) = 4.40, p = .93$; fear, $\chi^2(10, N = 48) = 10.91, p = .36$; surprise, $\chi^2(10, N = 48) = 16.96, p = .75$); and neutral, $\chi^2(10, N = 48) = 5.14, p = .88$).

Data showed that the fear emotion was recognized differently according to the level of intensity (low vs high intensity), $\chi 2(4, N = 48) = 13.13, p < .05$ (see Figure 8). As shown by a simple effect, an expressed fear was significantly more frequently perceived as fear when it was expressed with low intensity rather than high intensity ($\chi 2(1, N = 48) = 20.09, p < .001$). No other significant interaction was found for the other emotions: happiness, $\chi 2(4, N = 48) = 7.36, p = .12$; sadness, $\chi 2(4, N = 48) = 3.97, p = .41$; anger, $\chi 2(4, N = 48) = 5.69, p = .22$); and surprise, $\chi 2(4, N = 48) = 8.77, p = .07$.

Emotion showed a significant main effect in all Laban's factors: time, $\chi 2(5, N = 48) = 220.32, p < .001$; weight, $\chi 2(5, N = 48) = 62.50, p < .001$; space, $\chi 2(5, N = 48) = 107.93, p < .001$; and flow, $\chi 2(5, N = 48) = 51.51, p < .001$). These results are displayed in Figure 9.

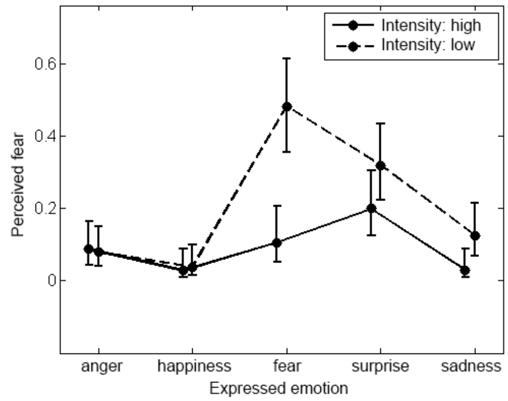

Figure 8. Plot of the interaction between the emotion expressed by the dancers and the observers' perceived intensity of the dances in the fear scale. Vertical bars denote a 95% confidence interval.

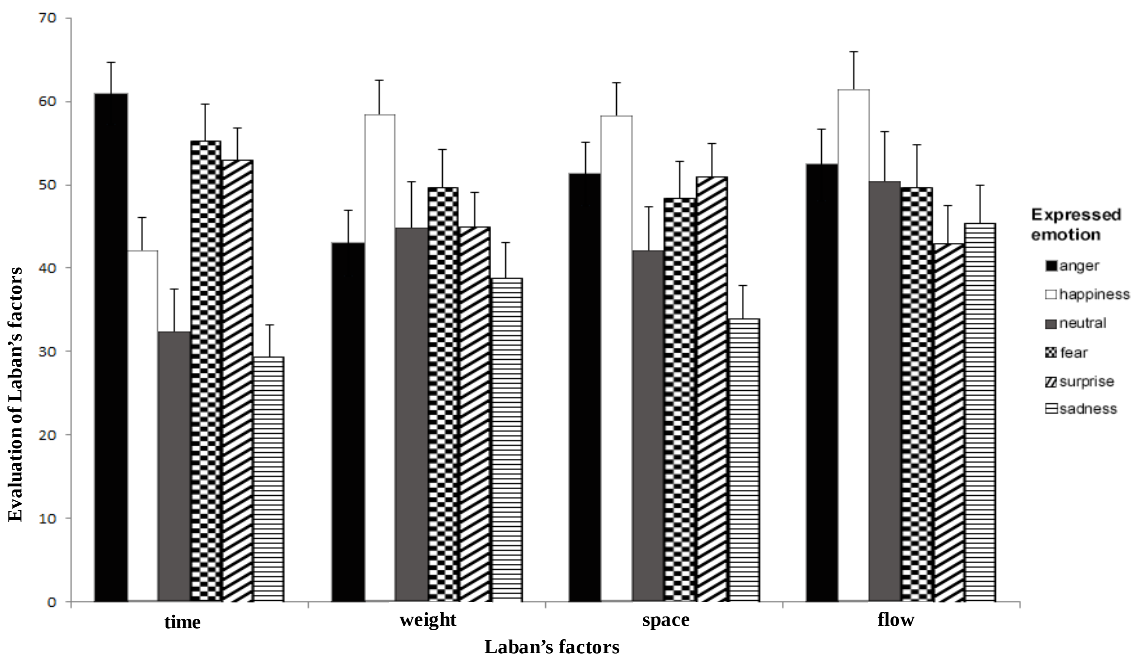

Figure 9. Histogram representing differences in Laban's criteria evaluation (speed, weight, extension and flow) between each expressed emotion (anger, happiness, neutral, fear, surprise and sadness; $N = 48$). Vertical bars denote a 95% confidence interval.

Time Factor

As shown by the comparisons, anger was rated as significantly quicker, representing sudden and urgent movement, $\chi2(1, N = 48) = 99.65$, $p < .001$, than the other emotions. Moreover, fear and surprise were rated as significantly quicker, $\chi2(1, N = 48) = 127.29$, $p < .001$, than the happy, neutral, and sad expressions. Neutral and sad expressions were rated significantly slower than happiness, $\chi 2(1, N = 48) = 24.92$, $p < .001$. However, no significant difference was observed between neutral and sad expressions, $\chi 2(1, N = 48) = 1.03$, $p = .31$, or between fearful and surprise expressions, $\chi 2(1, N = 48) = 0.86$, $p = .36$.

Weight Factor

Happiness was rated as significantly lighter than the other emotions, $\chi 2(1, N = 48) = 4.56$, $p < .05$. Conversely, sadness was rated as significantly more anchored and heavier than the other emotions, $\chi 2(1, N = 48) = 19.50$, $p < .001$. No significant difference was observed between anger and neutral, $\chi 2(1, N = 48) = 0.32$, $p = .57$, or anger and surprise, $\chi 2(1, N = 48) = 0.59$, $p = .44$) expressions. However, anger was recognized as significantly more anchored than fear, $\chi 2(1, N = 48) = 5.66$, $p < .05$. No significant difference was obtained between the expressions of neutral and fear, $\chi 2(1, N = 48) = 1.99$, $p = .16$, neutral and surprise, $\chi 2(1, N = 48) = 0.002$, $p = .96$, or fear and surprise, $\chi 2(1, N = 48) = 2.71$, $p = .10$.

Space Factor

Sadness was rated as significantly more indirect than the other emotions, $\chi 2(1, N = 48) = 70.25$, $p < .001$. Anger and happiness were rated as significantly more direct than neutral, fear, or surprise expressions, $\chi 2(1, N = 48) = 19.99$, $p < .001$. Between these two groups, happiness was rated as significantly more direct than anger, $\chi 2(1, N = 48) = 8.58$, $p < .01$, and neutral was considered significantly more indirect than the fear or surprise expressions, $\chi 2(1, N = 48) = 7.45$, $p < .01$. However, no significant difference was observed between fear and surprise, $\chi 2(1, N = 48) = 0.99$, $p = .32$.

Flow Factor

Happiness was rated as significantly more fluid, that is, referring to a free, relaxed, and uncontrolled movement, than the other emotions, $\chi 2(1, N = 48) = 36$, $p < .001$. By contrast, surprise and sadness were the two emotions recognized as the most bounded, $\chi 2(1, N = 48) = 26.22$, $p < .001$. No significant difference was observed between them, $\chi 2(1, N = 48) = 0.74$, $p = .39$. Moreover, anger was rated no differently than the neutral or fear expressions, $\chi 2(1, N = 48) = 0.34$, $p = .56$ and $\chi 2(1, N = 48) = 0.78$, $p = .38$, respectively, which were also not significantly different, $\chi 2(1, N = 48) = 0.03$, $p = .86$.

Relationships Among Expressed Emotions and Body Parts

Emotion showed a significant main effect on the dependent variables: the head, $\chi 2(5, N = 48) = 71.23$, $p < .001$; arms, $\chi 2(5, N = 48) = 12.23$, $p < .05$; shoulders, $\chi 2(5, N = 48) = 11.23$, $p < .05$; and pelvis, $\chi 2(5, N = 48) = 12.01$, $p < .05$. However, no significant difference was observed in the legs variable, $\chi 2(5, N = 48) = 6.42$, $p = .27$.

For sake of clarity, we developed a visualization procedure to illustrate how each perceived emotion could be systematically related to a specific body area. Based on the analysis of the contrasts, we individuated three levels of gray-scale intensities (light grey, dark grey, and black) to designate the level of explicit attention the observers noted regarding the head, shoulders, arms, pelvis, and legs with respect to the emotion expressed (see Figure 10). Black indicates the highest significant correlation between an emotion and the observed body part; a light gray code indicates the lowest one. The other body parts, for which correlation was neither the highest nor the lowest, were colored in dark gray. We report in the following the results of the contrast analyses. The observers noted the head as the focus during dances involving fear in comparison to neutral condition: $\chi2(1, N = 48) = 20.21, p < .001$); shoulders (sadness in comparison to surprise: $\chi2(1, N = 48) = 7.37, p < .01$); arms (anger in comparison to fear: $\chi2(1, N = 48) = 9.47, p < .01$); pelvis (happiness in comparison to fear: $\chi2(1, N = 48) = 8.49, p < .01$); legs (anger in comparison to sadness: $\chi2(1, N = 48) = 3.61, p = .06$).

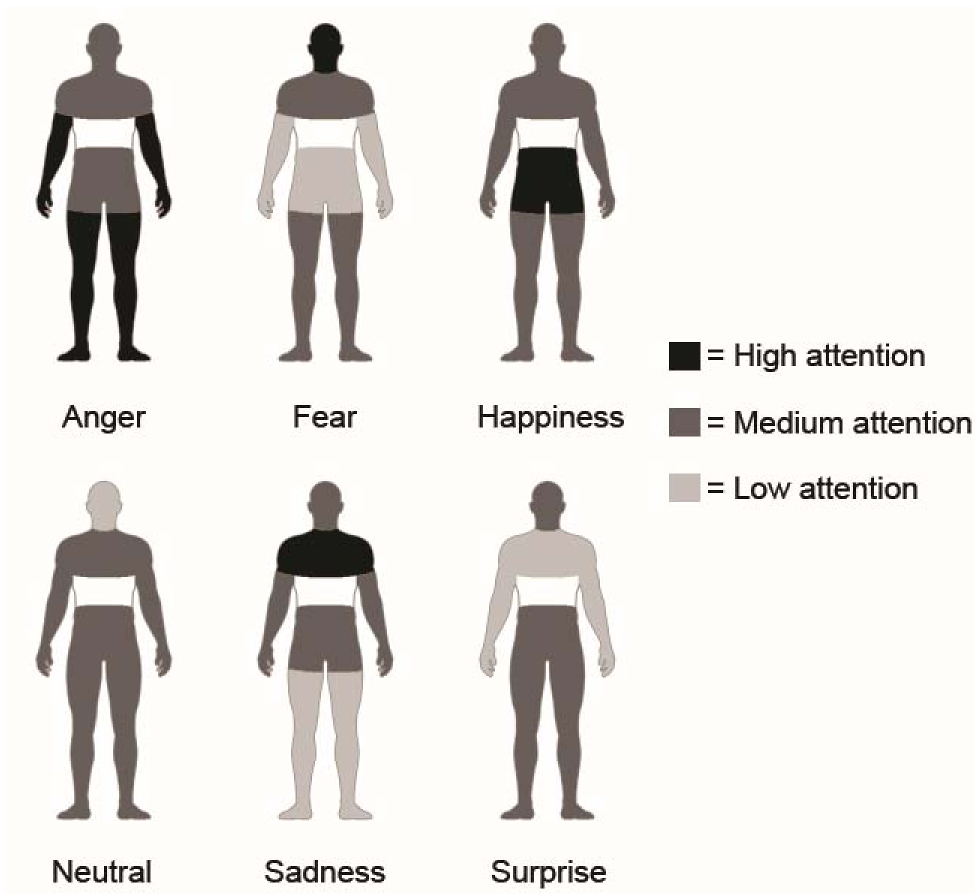

Figure 10. Degree of reported observers' attention to the different body areas depending on emotions expressed by the dancers. Neutral and Surprise did not appear to have a clear consensus regarding which body part most observers observed. Rather, the observers had responses across multiple body areas.

DISCUSSION

In agreement with the literature (Camurri et al., 2003; Crane & Gross, 2013; Shikanai, Sawada, & Ishii, 2013), our results show that the emotions of happiness, anger, and sadness are typically identified correctly by the observers. Of the three, sadness is recognized most often, followed by happiness. This partially reproduces the results of the studies by Camurri et al. (2003) and Dittrich, Troscianko, Lea, and Morgan (1996), in which the highest recognition rate was obtained for sadness, followed by anger and joy. For the neutral performance, in which no emotion was expressed, observers also predominantly perceived it correctly. However, when the dancers expressed fear or surprise, these two emotions were not readily distinguished. This perceptual confusion finds support from two prior studies. In the seminal study by Ekman and Friesen (1974) on emotional facial expressions and in the study of a full-body behavior in a daily life scenario by Meijer (1989), expressions of surprise tended to be recognized as fear. In our study, the perceived expressions of fear and surprise shared most of the Laban factors: time, space, and weight. For the Laban elements associated with time, for example, speed changes were seen as particularly fast for these two emotions and for the weight factor, the performance was perceived as moderately anchored to the ground and light and delicate.

Contrary to our expectations based on earlier studies (e.g., Bläsing et al., 2012; Broughton & Davidson, 2014; Cross, Kirsch, Ticini, & Schütz-Bosbach, 2011), the expertise of the observers had little influence on the emotion recognition in this study. Overall, our results suggest that the affective components of body expression are less driven by expertise in dance; we saw broadly consistent responses across observers, in line with van Paasschen, Bacci, & Melcher (2015). However, the use of a point-light display based on MoCap recordings could have diminished the impact of expertise. This type of minimalistic display transmits a sufficient amount of gestural information for emotion recognition when deployed in a restricted environment, and perhaps even those without dance experience were able to recognize the emotional expressions from these images. It is possible that additional physical evidence (e.g., facial expression and skin texture) may have allowed for one's dance expertise to become more apparent.

These findings also could be explained by the fact that the criterion chosen to classify our group (i.e., novice, expert, and nonexpert) was not sufficient enough to differentiate the levels of expertise. Our criterion for expertise was based on the standard levels of training period (8 years of regular practice) that Swiss dance institutions suggest to their most motivated students who are preparing for a professional career. Among the 22 experts who participated in our study, only four were dancing professionally. In future studies, we plan to include a larger number of experts, specifically professional dancers, to test whether sensorimotor expertise or aesthetic familiarity may impact emotion recognition in the specific context of this study (see also Bläsing et al., 2012).

Results confirmed that emotions expressed in the high intensity condition (i.e., with a higher emphasis and demonstrative manner) during performances are better recognized than in the low emotional intensity, where emotion would be more subtlety expressed (Burger, Saarikallio, Luck, Thompson, & Toiviainen, 2013). Our results show a statistically significant and a marginal difference, respectively, for fear and surprise in that the emotion recognition was higher in the low intensity condition. However, anger, joy, and sadness were perceived in a similar way for both intensities. This result goes against our expectations based on the literature and the results obtained by Hill and Pollick (2000). These authors showed that a particular increase in the expressive intensity of movements produced a better recognition of joy and anger. In their study, however, the differences between the expressive conditions were achieved through offline manipulation of the recorded point-light display used to render the dancers' performances.

More noteworthy is that fear was recognized by the observers as a more intense conveyed movement in our context of investigating the body gestures and movements. One can argue that, in real-life conditions, the experience of fear might be related to reduced motion in body parts in order to be less detectable by dangerous animals or conspecifics in a threatening situation. Such fear-related body movement might have been integrated as an internal representation of fear by dancers and spectators, explaining our results.

Results showed that Laban's effort dimensions can inform on an intermediate level of perceptual processing underlying the emotion recognition. They revealed that the movement qualities can be discriminated in a statistically significant way and be significantly associated with emotion portrayals, thus highlighting their expressive pertinence. Considering the time factor, the anger, fear, and surprise emotions were positively related to quicker element ratings in comparison to the sad and neutral conditions. This is in line with the results in the scientific literature (Camurri et al., 2003; Crane & Gross, 2013; Meijer, 1989). As previous research has shown, fear and surprise cannot be distinguished based on the time factor alone. Concerning the weight factor, performances expressing joy turned out to be lighter and delicate whereas those expressing sadness were seen as firmer and anchored to the ground. However, this single criterion may not be sufficient to discriminate between surprise, anger, and fear. For the space factor, the movement underlying the joy and anger emotions was considered as more direct than those of sadness, confirming recent studies on this specific issue (Crane & Gross, 2013; Shikanai et al., 2013). This factor alone, however, did not allow for any distinction between fear and sadness. Finally, the flow factor was positively rated in the happiness emotion, displaying the LMA elements of relaxed, free, and uncontrolled movement, whereas surprise and sadness seemed to include bound, tense, and controlled types of movement.

These results replicate the findings in Camurri et al. (2003). In addition, our results show that the surprise and fear emotions, which prior search has found are typically confused by observers, could be distinguished on the flow factor: The movement related to fear was rated as more uncontrolled than that of surprise (see also Wallbott, 1998). These findings, in totality, are consistent with Crane and Gross's observations that emotions displayed by dancers affect movement style in distinctive ways that could be described consistently with a specific combination of the effort dimensions (Crane & Gross, 2013).

An original finding of this study concerns the how various body parts attract the attention of observers according to which emotions they perceive expressed by the dancers. It extends and confirms an original approach developed by Nummenmaa, Glerean, Hari, and Hietanen (2014) to observe how emotions may be preferentially related to specific body parts. Our results concerning the upper body parts (i.e., head, shoulders, arms) and the pelvis—and the absence of any significant effect concerning the legs—are confirmed partially by Sawada, Suda, & Ishii (2003) and by empirical observation from early contemporary dance. In this period, expressions and movements were confined essentially to the upper body, particularly the chest. Legs were less used. In the mid-20th century, choreographer Ted Shawn stated, “The torso must become the most sensitive and expressive part of the body” (Shawn, 1963, p. 63). Our results, however, show that the head attracted more observers’ attention when watching dance performances expressing happiness, anger, or no emotion (the neutral condition) than fear, surprise, or sadness. Arms were primarily observed during performances expressing anger; dances expressing sadness attracted less attention to the arms. Concerning the shoulders, the happy, sad, and neutral conditions attracted the participants’ attention to this area of the body, whereas performances expressing surprise did significantly less. Finally, the pelvis was considered the most salient when watching happy and neutral performances and the least when sad dances were presented. Our results provide a further detailed insight on how differentiated emotion recognition is associated with specific body parts.

The use of peripersonal space (Cléry, Guipponi, Wardak, & Ben Hamed, 2015; Serino et al., 2009) as an environmental restriction to constrain dancers’ expressive movement also is a unique component of this study. It allowed us to evaluate whether expressed motion within a limited environment could still be recognized by observers.

Our findings showed that angry, fearful, happy, surprised, and sad emotions can still be well discriminated in constrained movement. In addition, our findings highlight that not only space-related features but also complementary movement qualities (e.g., flow, weight, and time) characterize the decoding process of emotion expression in a systematic manner within this specific context (see also Taffou & Viaud-Delmon, 2014). To better understand how emotion recognition may vary in relation to a space representation, a future experimental protocol could include systematic manipulation of the space rendering during the stimuli presentation. The same point-light displays could be presented in a virtual environment that differs in terms of space extension (e.g., either strictly matching an individual’s peripersonal space or placing a dancer’s rendered movement within a larger neutral space). On the other hand, these results reveal the dancer’s potential for exploiting his/her peripersonal space for emotion expression. According to Cléry et al. (2015), not only is the type of action performed in the representation of peripersonal space key, but also the emotional consequences of the actions can dynamically modify it. A computational analysis of the Laban effort dimensions may help clarify the encoding processes of emotion through expressive body behavior. Of specific interest will be the relationship among the expressed emotions, the exploration of the confined space, and the qualitative features of movement. An experimental manipulation also could consider the dance performance within a wider variety of environments (e.g., restricted to peripersonal space or to a larger space, such as a theater stage). Finally, this study reveals the potential of using dance as test case for investigating emotion expression and peripersonal space representation.

CONCLUSIONS

As novel digital environments increase the degree of freedom in movement expression, ongoing research would benefit from a conceptual framework and set of methodological procedures to consider the implicit effects of the space factor on emotion expressivity and perception. Using dance as a test case and a choreographed performance with a variety of emotional variations, we systematically considered the decoding processes underlying a spectator’s identification of the emotion expressed within the performer’s peripersonal space.

Within the integrated conceptual apparatus of the lens model and the LMA, we contribute by offering a better insight into the qualitative features of body expression on which external observers may rely. We further reveal commonalities in perceptual strategies developed by dance experts and nonexperts.

This study sets the agenda for future developments in the thriving and quickly evolving field of motion analysis and on nonverbal communication in technologically mediated environments. Future work includes (a) extending and replicating with a greater number of participants the correlations observed so far, and (b) establishing relationships within the encoding process (i.e., those implemented by the dancers through their body behavior). The computational modeling of LMA features may be exploited in this perspective.

IMPLICATIONS FOR THEORY OR APPLICATION

Our study is advancing the technological breakthrough in the analysis of full-body expressivity but also acknowledges the embodied turn toward cognition research, confirming the prominent role of emotion and embodiment as essential components of cognitive processes. We used dance as a test case and bound the dancer's movements to his/her peripersonal space in order to better study the crucial impact of space constraints on emotional body expressivity and observers' perception of emotions expressed within those constraints. Drawing upon the Laban movement analysis framework seems an efficient approach for recognizing emotions and revealed underlying perceptual process. Used in a Brunswik's (1956) lens model, we believe those qualities categorized along the Laban's effort dimensions are intermediate-level key components in emotion recognition. This study could help advance a new generation of digital environments, allowing for natural and emotionally vivid interactions. Equally, this line of research could facilitate better automated recognition of emotion from bodily movement. In addition, it suggests how dance research can influence a wide variety of disciplines also interested in exploring the perception and interpretation of emotional conveyance.

ENDNOTES

1. More information on the Nexus software is available at http://www.vicon.com/products/software/nexus
2. More information on the video capture software used to display the motion capture video https://www.techsmith.com/camtasia.html
3. More information on the software used to develop the online questionnaire at http://www.qualtrics.com

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