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Impact of elicited mood on movement expressivity during a fitness task

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ABSTRACT

The purpose of the present study was to evaluate the impact of four mood conditions (control, positive, negative, aroused) on movement expressivity during a fitness task. Motion capture data from twenty individuals were recorded as they performed a predefined motion sequence. Moods were elicited using task-specific scenarii to keep a valid context. Movement qualities inspired by Effort-Shape framework (Laban & Ullmann, 1971) were computed (i.e., Impulsiveness, Energy, Directness, Jerkiness and Expansiveness). A reduced number of computed features from each movement quality was selected via Principal Component Analyses. Analyses of variance and Generalized Linear Mixed Models were used to identify movement characteristics discriminating the four mood conditions. The aroused mood condition was strongly associated with increased mean Energy compared to the three other conditions. The positive and negative mood conditions showed more subtle differences interpreted as a result of their moderate activation level. Positive mood was associated with more impulsive movements and negative mood was associated with more tense movements (i.e., reduced variability and increased Jerkiness). Findings evidence the key role of movement qualities in capturing motion signatures of moods and highlight the importance of task context in their interpretations.

1. Introduction

The complex relation between human movements and affects was already acknowledged more than hundred and forty years ago by Charles Darwin (Darwin, 1955). During the last ten years, pushed by the progress of embodied cognitive sciences (Clark, 1999), this topic has received a renewed interest from various research domains such as Psychology (Niedenthal, Barsalou, Winkielman, Krauth-Gruber, & Ric, 2005), Neurosciences (De Gelder, 2009) and Computer sciences (Kleinsmith & Bianchi-Berthouze, 2013). In this paper, we present a study which investigated how affects elicited within the context of a fitness task impact movement expressivities of a fitness coach.

Movement can be defined as position variations of body parts in space and time characterized by kinematic parameters (e.g., amplitude, velocity, Hess, 1943). One intrinsic property of human movement is its variability: comparisons of human movements collected in the same task inevitably reveal differences. Various factors are at the origin of these human move-

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ment fluctuations. One major source of intra-individual variability in human movement is affect. Several researchers have considered body expressions in a discrete manner proposing coding schemes for hand gestures (McNeill, 2008) or full body postures (Bull, 1987; Dael, Mortillaro, & Scherer, 2012). However, movement variations induced by affect as continuous changes have received less attention (Gross, Crane, & Fredrickson, 2010).

An affect is a relatively brief multicomponent episode (cognitive, motor, physiological, and phenomenological) which facilitates a response to an event of significance for the organism (Davidson, Scherer (Klaus Rainer), & Goldsmith, 2003). Emotions, moods and affects are concepts often used interchangeably and some authors advocate for a sharper discrimination. For example, for Davidson et al. (2003) moods last longer and have lower intensities than emotions and affect is a more global encompassing term. Affects are studied through a wide variety of conceptual frameworks. Discrete approaches consider affects as separate states: Ekman (1971) identifies six basic emotions (i.e., happy, sadness, surprise, fear, disgust, and anger), and Jack, Garrod, and Schyns (2014) propose a four basic emotions model (i.e., happy, sad, fear/surprise and disgust/anger). Dimensional approaches define them according to several continuous axes (Coan & Allen, 2007), valence and arousal being two major dimensions. Dominance as a third dimension is often considered (Mehrabian, 1996). Although the discrete framework of affect is the dominant approach (more in accordance with the study of discrete facial expressions), body expressions of affects have been meaningfully interpreted through the use of affective dimensions (Kleinsmith & Bianchi-Berthouze, 2013). Going more continuous in the analysis of affects and behaviors appears more in line with theoretical interpretations based on emotions' action tendencies components (Frijda, 1987) or the description of affects as dynamic changing states (Sheets-Johnstone, 2010).

The joint analysis of affects and body movements necessitates to consider methodological aspects related to affect elicitation (Coan & Allen, 2007). The first issue is to decide about the way to enact an affective episode in a controlled setup. Some authors collect affective expressions portrayed either by professional actors (Omlor & Giese, 2007; Pollick, Paterson, Bruderlin, & Sanford, 2001) or non-professional actors (Bernhardt & Robinson, 2007). Alternatively, experimental procedures have been designed to induce more spontaneous affective phenomena (James A. Coan & Allen, 2007) such as the Velten mood induction procedure (i.e., reading and trying to feel the suggested affect using sixty sentences, Velten, 1968), the use of music (Van Dyck, Maes, Hargreaves, Lesaffre, & Leman, 2012), film clip (Rottenberg, Ray, & Gross, 2007), autobiographical recall (Brewer & Doughtie, 1980), hypnosis (Bower, 1981), gifts (Nummenmaa & Niemi, 2004), pictures (Ito, Cacioppo, & Lang, 1998) and odors (Ehrlichman & Halpern, 1988). Overall, positive affects appear to be more difficult to induce than negative affects (Westermann, Spies, Stahl, & Hesse, 1996). With the specific aim of studying movement variations instead of discrete static expressions, studies have less focused on stimulus-response type procedures with the use of the autobiographical memories paradigm (Barliya, Omlor, Giese, Berthoz, & Flash, 2013; Crane, Gross, & Rothman, 2009; Gross et al., 2010; Kang & Gross, 2011), music (Michalak et al., 2009; Van Dyck et al., 2012) and video games (Savva & Bianchi-Berthouze, 2012). Illustrating the importance of felt affects in movement variations, Kang and Gross (2011) observe that participants' kinematics are different between trials in which affects are felt. The notion of felt affects should be distinguished from other common dichotomies of elicitation protocols such as acted versus non-acted conditions or portrayed versus natural protocols: these distinctions suggest that acting intentionally an affective episode is artificial proposing a somehow false affective expression while spontaneity would be related to true and authentic affects (Scherer, 2013). However, everyday affective episodes in social situations are subject to regulatory processes in order to manage impressions (Goffman, 1959). As a result, an affective expression is always a trade-off between push effects (i.e., internal factors which are reactive and related to adaptive behaviors) and pull effects (i.e., external factors which are constraining and related to cultural expectations) (Scherer, 2013). In this perspective, a voluntary affective expression is considered as an affective episode with a dominant pull effect where the affect can be felt.

The circular causality existing between movements and affects is also an element to acknowledge when making the choice of the experimental induction task to elicit affects. Studies demonstrating the one-sided influence of affect on motion are numerous (Kleinsmith & Bianchi-Berthouze, 2013), revealing that the experience of an affective episode involves perceptual, somatovisceral and motor feedback aspects (Bosse, Jonker, & Treur, 2008; Niedenthal, 2007). Conversely, in accordance with the James-Lange theory, the impact of movement on experienced affects has been evidenced through various protocols (Laird & Lacasse, 2014): motor actions influence the evaluation of affective stimuli (Dru & Cretenet, 2008) or the remembering of affective memories (Casasanto & Dijkstra, 2010). Hence, the nature of the movement performed during the experimental task should be considered according to the research purpose. A common approach to control movement influences on a participant's affective state is to use functional tasks where movement has an ordinary purpose. Such actions are, for example, walking (Barliya et al., 2013; Crane et al., 2009; Karg et al., 2009; Omlor & Giese, 2007; Roether, Omlor, Christensen, & Giese, 2009; Venture, 2010), knocking (Bernhardt & Robinson, 2007; Gross et al., 2010) or drinking (Pollick et al., 2001).

Body movements are characterized in a high dimensional configuration space with many interrelated degrees of freedom. Defining the level of analysis to characterize these motions impacts results and their interpretability. A low level approach to movement provides objective measures of kinematic features (e.g., joints angles, segments positions, joints and segments velocities and accelerations). Precise and continuous in essence, their collection is demanding (high cost of motion capture systems) as well as difficult to interpret due to the complexity of human movement. A high level analysis is more qualitative and requires videos and observers for manual coding. Observers can provide subjective annotations of different features (e.g., types and frequencies of behaviors). Subtle variations of positions, velocities or orientations (taken in isolation or combined) can be misperceived but are closer to the human perceptual realm facilitating interpretations. Several authors have introduced the notion of movement qualities (Wallbott, 1998) which can be considered to be located at an intermediate level of analysis: they are inherently subjective (i.e., they can be annotated by observers, Wallbott, 1998) and some recent works propose automatic quantifications of these movement qualities (Piana, Stagliano, Camurri, & Odone, 2013). This ambivalence is made possible by the dual nature of these expressivities: movement qualities are subjective descriptions of motion dynamics based on kinematic information. The Labanotation system (Laban & Ullmann, 1971) is used to analyze dance movements and provides a framework for analyzing body movements and shapes with a systematic movement quality approach. Related specifically to this framework, some authors propose four dimensional equations to compute time-series originating from the Effort-Shape space (Kapadia, Chiang, Thomas, Badler, & Kider, 2013; Samadani, Burton, Gorbet, & Kulic, 2013). One advantage of using the Effort-Shape analysis is to provide a comprehensive and systematic approach to describe qualitative and quantitative characteristics of movements. It allows summarizing and interpreting movements with a small set of parameters.

Recent interests in affectively induced movement variations provide valuable results useful to form hypotheses for the present study. In gait analysis, Crane et al. (2009) note that the amount of motion increases when the affective arousal level increases. The highest variability is observed with anger, which is an affect featuring a high arousal level. Gross, Crane, and Fredrickson (2012) observe the influence of five target affects on walking movements. Their results suggest three different movement styles corresponding to different arousal levels. High arousal affects (i.e., joy and anger) share the same features for most of the Effort-Shape qualities. Control and content are associated with another group of shared qualities. Low arousal affects (i.e., sadness) are associated with the third group. Overall, the association between high affective arousal and a combination of high velocity, energy, force, directness and expansiveness is a recurrent finding (Gross et al., 2010, 2012; Montepare, Koff, Zaitchik, & Albert, 1999; Wallbott, 1998; Dael, Goudbeek, & Scherer, 2013; Crane and Gross, 2013). This is attributed to the physical effort mobilization or the state of readiness to act provoked by a high arousal level (Frijda, 1987). Discrimination of affects according to valence is less consistent across studies. Glowinski et al. (2011) find that in cases of high arousal, smoothness enables to distinguish between negative and positive affects. Even if the clustering algorithm defined by these authors performed well, the pattern is less distinctive for low arousal affects. When affects are induced in dancers, happiness-related expressions are observed to be more expanded and are more impulsive than expressions of sadness (Van Dyck et al., 2012). When interpreting valence in the framework of action tendencies, a negative feeling is hypothesized to be associated with the tendency to flee, whereas a positive feeling is related to free activation (Frijda, 1987). The latter is a non-specific motor response, and it probably participates to the difficulty in recognizing it (Fredrickson, 1998). Another possible reason for this lack of valence discrimination in movements is the interaction between valence and arousal: valenced bodily expressions are different under low versus high arousal affects, with high arousal affects being easier to discriminate than low arousal affects.

The present paper aims at studying the intra-individual variability of human movement under different and induced moods. We designed a short and simple fitness movement to avoid any impact of learning during the experiment. The main advantage of using a predefined fitness movement sequence is that it reduces the automaticity present in everyday tasks (e.g., walking) that could alleviate the behavioral variability induced by different affective contexts. Another aspect of this research study is the focus on contextually valid mood conditions: to avoid using traditional eliciting procedures that might not fit with the fitness coach scenario, we chose to adopt a more ecological approach that could elicit commonly encountered moods in a fitness coach's daily life. Because we did not find in the existing literature any appropriate existing protocol for eliciting full-body expressions of moods for a fitness coach, we defined a new protocol. The impact of different audience types (observation only, supportive or adversial) on performances is studied in various sports (Law, Masters, Bray, Eves, & Bardswell, 2003). Overall, being observed by an audience is considered as a stressful condition impairing performances for novel skills. Alternatively, humor (inducing positive moods) appears to be a useful mood regulation strategy before a performance in different sports as in (Tamminen & Crocker, 2013). Lastly, encouragement and motivation conveyed by coaches are now recognized as essential for the development of athletes motivations (Black and Weiss, 1992). These three aspects of a coach life are the basis for our three affective conditions: a fitness coach can be stressed by his/her audience, amused and happy, and/or motivated to perform a session challenging the audience. Because we are interested in the one-sided influence of affect on movement variation, we avoided choosing movements composed of metaphoric, emblematic or iconic gestures that might be affectively connoted.

A dimensional approach of emotions seems to be relevant for studying body expressions of emotions and for enabling comparison with previous works. Thus, we analyzed our data in terms of valence and arousal. Happiness, stressed and motivated conditions corresponds respectively to positively valenced, negatively valenced and highly aroused mood conditions. Additionally, the highly aroused mood conditions of challenging the audience is driven in majority by the intention to communicate a motivated state and can be considered as a voluntary affective episode. In contrast, the positively and negatively valenced moods induce a more reactive state (push effects) which is better understood as spontaneous affective episode. The assessment of the influence of affective contexts on the individual affective experience was achieved thanks to the combination of self-report questionnaires and physiological measures.

Movement kinematic features were analyzed using the Effort-Shape analysis model. Five time-series (i.e., Impulsiveness, Energy, Directness, Jerkiness and Expansiveness) were computed from kinematic data to assess movement qualities related to effort and shape qualities from the Labanotation system. We chose multiple temporal and frequency features to characterize these five time-series (e.g., mean, mean peak frequencies). From this set of dependent variables, we assessed the impact of mood conditions on the variability of fitness movements characterized by motion qualities. We hypothesize that we can better discriminate conditions with different levels of arousal than the conditions with different levels of valence. The

Energy quality should enable the discrimination between conditions with different arousal levels. We chose two moods opposed in valence with the same arousal level to avoid comparing manifold aspects of affective states at the same time. We do not expect to see much variability between the stressed and happiness conditions because they have both moderate levels of arousal. In the negatively valenced condition, we hypothesize that the movement should be less expanded (i.e., low Expansiveness) and more sudden and jerkier (i.e., high Impulsiveness and Jerkiness) compared to the positively valenced condition. Moreover, the control condition is expected to induce less expressive movements than all other conditions.

2. Method

2.1. Participants

Twenty French sports sciences students between 20 and 25 years old (11 females; Mage = 21.3, SD = 1.7) took part in the study after signing a statement of informed consent pertaining to the experimental procedure as required by the Helsinki declaration and the EA 4532 local Ethics Committee. We selected participants in this limited age range as it is acknowledged that regulation after mood induction depends on age (Larcom & Isaacowitz, 2009). The average duration of weekly sport activities of participants was 7.3 h (SD = 3.4). The participants were free of sensory, perceptual, and motor (shoulder, elbow, hip, knee and ankle) disorders and naïve about the purpose of the experiment.

2.2. Task

We sent to the participants a video of the choreography to perform one week before data collection. Participants were asked to watch the video and learn the fitness choreography to be able to reproduce it on the day of data collection. The experiment was designed as a repeated-measure protocol to evaluate changes in movement characteristics at the intra-individual level. The choreography was composed of two different foot movements (i.e., step, mounted knee), repeated twice for each side, two different arm movements (i.e., waved arm, uppercut) repeated twice for each side, and two combinations of each previous foot and arm movement (i.e., step/wave, mounted knee/uppercut) repeated twice for each side (Fig. 1 shows

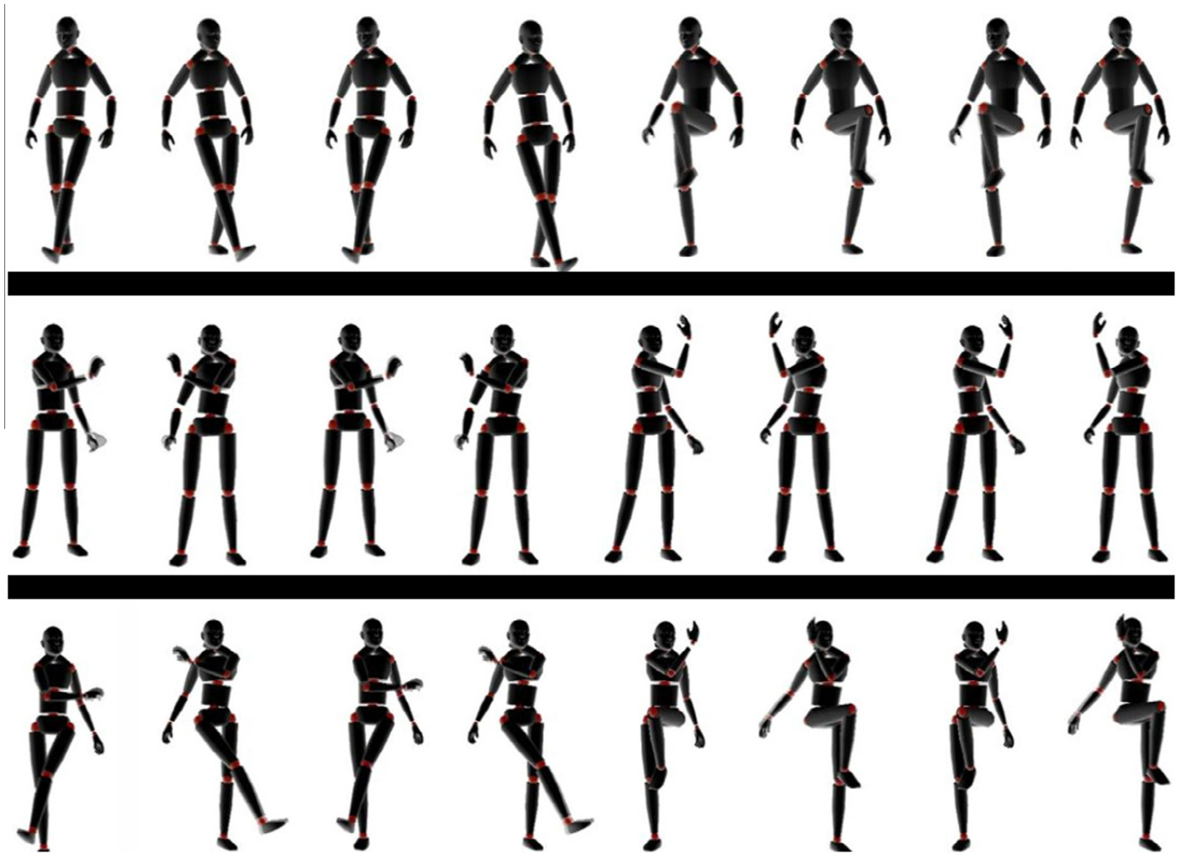

Fig. 1. Key frames of one recorded motion sequence for one participant, one frame per movement.

key frames of the motion sequence recorded for a participant). The movement sequence composed of the four elements previously described was repeated three times per condition.

2.3. Procedure

Participants were not paid for the study. Participants' movements were collected using a full body motion capture system: the experiment room was equipped with 10 infrared cameras (S250e Optitrack system, frequency: 120 Hz, resolution: 832 * 832). All data collected from these devices were post-synchronized. Participants wore a QSensor device to record electro-dermal activity. To estimate the mood state of participants, we combined physiological measures through electro dermal activity (EDA) and self-report questionnaires (Ouss, Carton, Jouvent, & Widloêcher, 1990). Upon arrival, participants were given a consent form, the partial description of our research aims (i.e., to study fitness movement from fitness coaches without any mention of movement qualities or mood) and a description of the task (i.e., to repeat the previously learned choreography four times). A control (low arousal, neutral valence, C) condition started the experiment. The general instruction was to perform the choreography in the "best way." This instruction was repeated before each condition. Then, positively (P) and negatively (N) valenced conditions were counterbalanced across participants. The P condition consisted of performing the choreography after receiving a reward (i.e., hardware and sweetmeat) and watching a 1:30 min mash-up of funny videos. The N condition consisted of performing the choreography after the experimenter explained that the live video of the participant's performance was going to be displayed in real-time at a remote lecture hall in front of hundreds of students (which was simulated using a fake video display). Finally, in the highly aroused (M) condition, the participant had to imagine her/himself as a fitness trainer who had to motivate her/his audience. This last condition was less spontaneous than the other conditions. It aimed at collecting more voluntary expressions with a high arousal level for comparison with the two more spontaneous conditions (P and N). Between each conditions, participants completed affective self-report questionnaires (e.g., differential emotion state; DES) and performed a distraction task (i.e., memory words). The EDA was revealed to be higher (i.e., increased arousal) for the P (*Mdn* = 1.8 (10.2)) and N (*Mdn* = 2.2, (10.9)) conditions compared to the C (*Mdn* = 0.42 (5.1)) condition, ($z = -4.37$, $p < 0.001$) and ($z = -4.18$, $p < 0.001$), respectively. The EDA was higher for the M condition (*Mdn* = 2.4 (10.1)) compared to the P and N conditions, ($z = -4.37$, $p < 0.001$) and ($z = -4.23$, $p < 0.001$), respectively. The DES report for the negative affective scale revealed a decrease between the N and P conditions ($Z = -2.18$, $P = 0.029$) (Giraud et al., 2014). These results confirmed the validity of our eliciting procedure.

2.4. Collected features

Participants wore a suit combination of a jacket, a trouser and a cap with 36 markers attached according to the Arena software marker-set (Fig. 2). We exported three dimensional kinematic data into MATLAB corresponding to X, Y and Z positions of each marker across time according to the global coordinate system. We used three dimensional markers coordinates (i.e., positions of colored markers in Fig. 2) to compute kinematic time-series of upper and lower segments (left and right), hip, torso and head corresponding to a motion quality from the Labanotation system (see Table 1). The computation of these

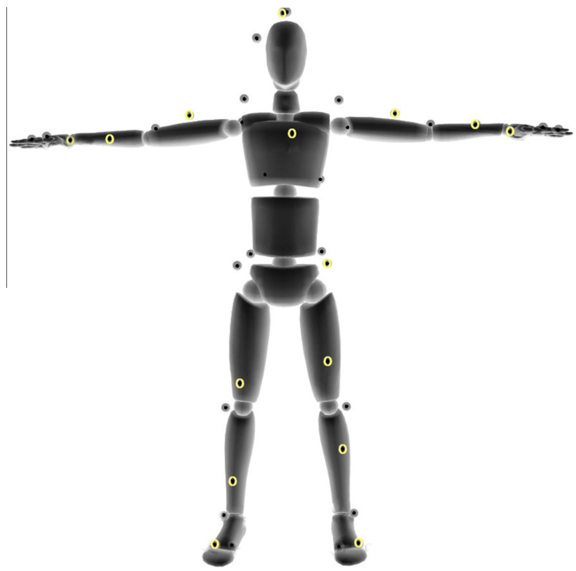

Fig. 2. Optitrack marker-set and markers used (surrounded in yellow) for time-series computation of upper and lower limbs (left and right), hip, torso and head.

Table 1
Descriptions and equations of time-series according to Effort and Shape qualities.

Effort and shape qualities	Times series – descriptions	Equation
Time-effort	**Impulsiveness**. Time effort can be determined as the net acceleration at the body parts over time. Large values of net acceleration indicate sudden movements characterized by a high Impulsiveness	Eq. (A.1) $I_{member} = \frac{\lvert V(t_i) - V(t_{i-1}) \rvert}{t_i - t_{i-1}}$ $Vi(t)$, velocity of the segment
Weight-effort	**Energy**. Weight effort can be determined as energy at each instant (t) over time. m_{member} is the approximation of the mass of each segment according to the Winter table (Winter, 2004). Large values of Energy indicate strong movements.	Eq. (A.2) $E_{member} = \frac{1}{2} m_{member} * Vi(t)^2$
Space-effort	**Directness**. Space effort is computed as the inner product of chest and segment displacement (i.e., right hand, left hand, right foot, left foot) trajectories. Direct movements are thus usually characterized by a small number of peaks.	Eq. (A.3) $D_{member} = \vec{V}_{chest} * \vec{V}_{member} = (V_{chest\ X} \quad V_{chest\ y} \quad V_{chest\ z}) * \begin{pmatrix} V_{member\ X} \\ V_{member\ Y} \\ V_{member\ Z} \end{pmatrix}$
Flow-effort	**Jerkiness**. Flow effort is determined as the 3D curvature for each segment for each time. The curvature is a rapport between velocity and acceleration. Computation of curvature gives small values for smooth movements and high values for jerky movements.	Eq. (A.4) $J_{member} = \frac{\sqrt{(v_{xi}*a_{yi} - v_{yi}*a_{xi})^2 + (v_{zi}*a_{xi} - v_{xi}*a_{zi})^2 + (v_{yi}*a_{zi} - v_{zi}*a_{yi})^2}}{(v_{xi}{}^2 + v_{yi}{}^2 + v_{zi}{}^2)^{\frac{3}{2}}}$ v_{xi} *and* a_{xi} indicate the first and second derivatives of the segment position at frame i, respectively
Shape-qualities	**Expansiveness**. Shape Qualities describe the way the body is changing toward space. Expansiveness is associated to the position of each segment according to the center of mass at each time. Values of Expansiveness are close to zero for dense movements and are high for expanded movements.	Eq. (A.5) $Ex = 3/4 * \pi DI_x * DI_y * DI_z$ $DIx = \frac{1}{n}\sum_{m=1}^{n}\sqrt{(x_{mi} - x_{ci})^2}$ $DIy = \frac{1}{n}\sum_{m=1}^{n}\sqrt{(y_{mi} - y_{ci})^2}$ $DIz = \frac{1}{n}\sum_{m=1}^{n}\sqrt{(z_{mi} - z_{ci})^2}$ DIx, DIy, DIz are the sum of distances between the mass center coordinate (x_{ci}, y_{ci}, z_{ci}) and the n-th segment coordinate (x_{mi}, y_{mi}, z_{mi}) at frame i

different time-series was inspired and adapted from previous studies (Glowinski et al., 2011; Samadani et al., 2013; Camurri, Lagerlöf, & Volpe, 2003; Chen, Lin, Tsai, & Dai, 2011). For Impulsiveness, Energy and Jerkiness, we first computed one time-series for each of the fourteen segments and add them to have three full body Impulsiveness, Energy and Jerkiness time-series. Time effort was computed like Chen et al. (2011) by deriving marker position to obtain the net acceleration. Energy and Jerkiness was computed like Glowinski et al. (2011), respectively as the kinetic energy according to segment velocities and specific rapport between acceleration and velocity of segments. We computed directness time-series in the same way that Samadani et al. (2013) as tangents of hand and foot trajectory according to torso trajectory. Finally we used the formula of density index of Camurri et al. (2003) to compute Expansiveness time-series. This time-series was not used in previous works authors preferring to employ bounding box formula to compute Expansiveness despite density index is more informative because taking account all segments.

This procedure gives us five full-body time-series (i.e., Impulsiveness, Energy, Directness, Jerkiness, and Expansiveness) according to five Effort-Shape qualities (i.e., Time effort, Weight effort, Space effort, Flow effort, and Shape qualities), respectively. Seven temporal features and three frequency features are defined from each full-body time-series and are computed for each movement sequence. We used a particular set of feature to better cover the temporal (minimum, maximum, mean, standard deviation) and frequential (mean frequency, peak frequency and 80 power frequency) domains. We also computed index of dispersion and entropy to have information about distribution and predictability.

2.5. Data analysis

Analyses were conducted for the (C-M), the (C-P), and the (C-N) pairs of conditions. We chose to perform a statistical analysis separating the pairs of conditions because we make a distinction between the voluntary condition (i.e., M) and spontaneous conditions (i.e., P and N). The statistical procedure is the same for both. First, we applied a standardized Z-score transformation on the data (separately on data from the control and motivation conditions together and on data from the control, positive and negative mood conditions together). To keep only meaningful variables (representing most of the variance in the data) and avoid multicollinearity in our predictive models, and because we had no assumptions on which specific features were relevant, we performed a data reduction analysis with a principal component analysis procedure (PCA) on each movement quality separately. After choosing the best model, we kept variables that best accounted for the explained variance of the quality (higher loadings). From this set of variables, we performed a univariate analysis: repeated-measures Friedman and post hoc Wilcoxon to assess the importance of each separate variable in condition comparisons. Then, a multivariate approach is proposed: we built a predictive model with a generalized linear mixed model procedure.

3. Results

3.1. Dimensional reduction

The applied PCA on each movement quality across the C, N, and P conditions is presented in Table 2. We used the cumulative 80% amount of variance method to choose the optimal number of components. Across movement qualities, the first three principal components enable to reach the 80% of variance explained by the model.

Across the different movement quality models, a common pattern emerged grouping the variables in a systematic manner. The first component explaining most of the variance (51.2% in average) correspond to the temporal properties of the signal (i.e., minimum, maximum, mean, standard deviation and energy). This strong shared variance highlights a high level of redundancy justifying the selection of one of these variables (i.e., the mean) for each movement quality. The second component explaining a significant part of the variance (21.6% in average) correspond to the properties of the signal in the frequency domain (i.e., peak frequency, mean frequency and 80 power frequency). As for the first component, collinearity in subsequent analysis is avoided by selecting one of these three variables (i.e., mean frequency) for each movement quality. The last component includes two variables (i.e., index of dispersion and entropy) which characterize the time-series distribution within the temporal domain (12.3% in average). However, the entropy variable is less consistently correlated with the index of dispersion across movement qualities. When exploring the potential of four component models, the fourth component was recurrently composed of the entropy variable highlighting its complementarity relatively to the index of dispersion. Both variables were kept for subsequent analyses. Thus, we systematically kept the temporal and frequency

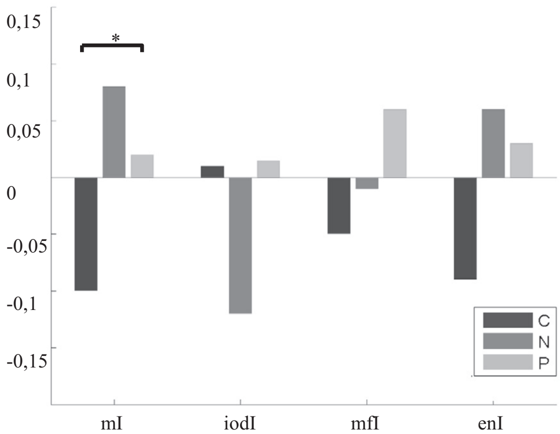

Fig. 3.1. Effort qualities – Impulsiveness. Medians (of standardized scores) for relevant features plotted according to C, N and P conditions. Asterisks indicate significant differences between conditions: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. Positive values mean sudden movements. Variables: Mean (mI), Index of dispersion (iodI), Mean frequency (mfI) and Entropy (enI) of Impulsivity.

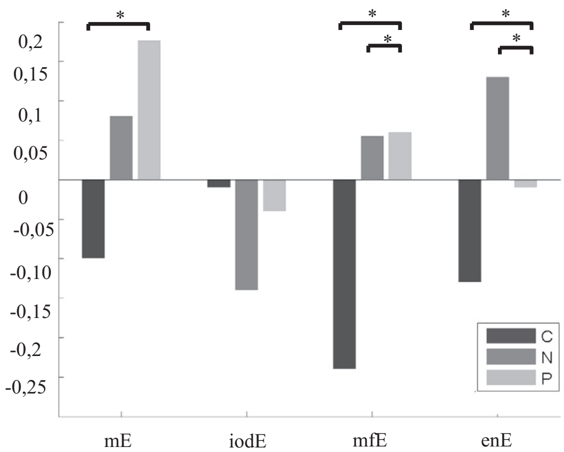

Fig. 3.2. Effort qualities – Energy. Medians (of standardized scores) for relevant features plotted according to C, N and P conditions. Asterisks indicate significant differences between conditions: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. Positive values mean energetic movements. Variables: Mean (mE), Index of dispersion (iodE), Mean frequency (mfE) and Entropy (enE) of Energy.

Table 2
Components loadings for the three component models of PCA for each movement quality.

Time-series	Impulsiveness			Energy			Directness			Jjerkiness			Expansiveness		
Components	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Features															
Minimum	.84	.24	-.47	.29	.37	.73	-.89	-.57	-.61	.19	.11	.94	.86	-.2	.06
Maximum	.81	.16	.36	.77	.48	-.29	.83	.63	.55	.88	.32	.19	.92	-.3	.67
Mean	**.97**	.16	-.31	**.91**	.44	.54	**.94**	.37	-.26	**.94**	.28	.19	**.98**	-.22	.45
Standard Deviation	.96	.04	-.01	.9	.44	.54	.91	.41	.16	.91	.34	.23	.86	-.31	.83
Energy	.87	.07	-.21	.86	.05	.33	.89	.17	.01	.93	.27	.19	.83	-.61	.54
Peak frequency	.57	-.18	-.34	-.05	.47	.2	.03	.42	-.03	-.53	.09	.28	-.21	.86	-.35
Mean frequency	.23	**.96**	-.17	.6	**.91**	.24	.51	**.93**	.51	.15	**.96**	.17	-.29	**.94**	-.29
80 power frequency	-.02	.92	-.34	.35	.9	.16	.62	.89	.51	.18	.95	.17	-.29	.9	-.2
Index of dispersion	-.25	-.26	**.9**	-.08	-.01	**-.92**	-.07	0	**.85**	.49	.7	**-.44**	.33	-.31	**.97**
Entropy	0	.9	**-.41**	0.45	.48	**.079**	.23	.76	**-.05**	-.68	-.11	**-.12**	-.25	.91	**-.4**
Cumulative percent of variance explained for the first three components: 1	46			47			51			47			55		
2	74			67			69			67			78		
3	87			80			83			77			90		

Note: Rotation Method: Promax with Kaiser Normalization. Grey lines indicate selected variables for the following analyses and surrounded cells in bold highlight the recurring pattern of components.

means, the index of dispersion and the entropy index of each movement quality, reducing the number of variables from 50 to 20 (4 features for each time-series × 5 time-series).

As the choreography was repeated three times per condition, we averaged the twenty variables over the three blocks for each participant to obtain mean scores for the twenty variables for each condition (C, N, P, M) and observation (20 participants).

3.2. Univariate analysis

To examine the impact of the mood induction procedures on selected variables, we first performed repeated-measure comparisons using Friedman and post hoc Wilcoxon tests on the spontaneous conditions (P and N condition) compared to the C condition. As these tests are based on rank transformation, results are presented with medians (Mdn) instead of means. Figs. 3.1–3.4 shows the results of this analysis. To examine the impact of the high arousal induction on our set of selected variables, we performed the same analysis. Figs. 4.1–4.5 shows features that are significantly different between the voluntary M condition and the control C condition.

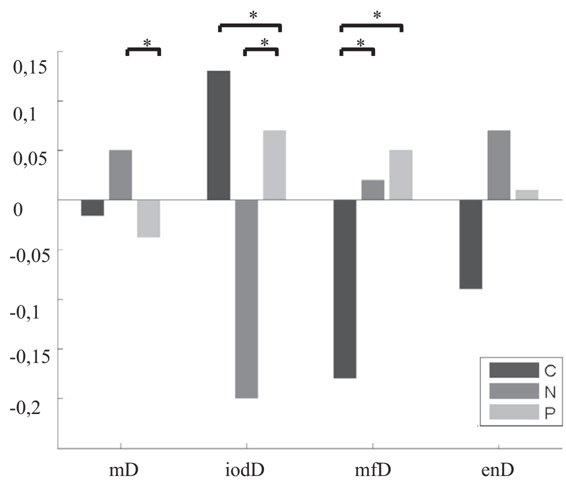

Fig. 3.3. Effort qualities – Directness. Medians (of standardized scores) for relevant features plotted according to C, N and P conditions. Asterisks indicate significant differences between conditions: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. Positive values mean indirect movements. Variables: Mean (mD), Index of dispersion (iodD), Mean frequency (mfD) and Entropy (enD) of Directness.

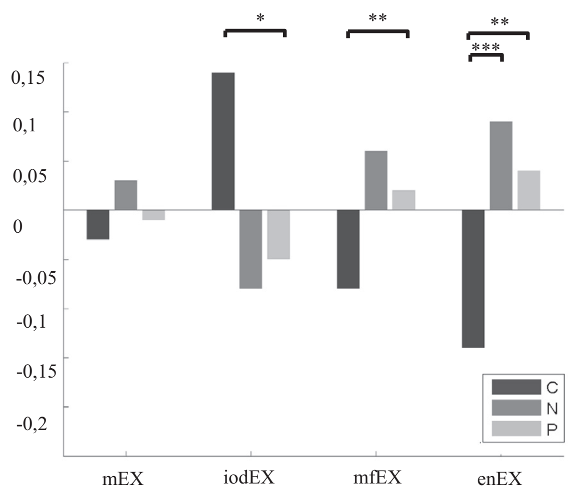

Fig. 3.4. Shape qualities – Expansiveness. Medians (of standardized scores) for relevant features plotted according to C, N and P conditions. Asterisks indicate significant differences between conditions: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. Positive values mean movements which take more space (away from the mass center). Variables: Mean (mEX), Index of dispersion (iodEX), Mean frequency (mfEX) and Entropy (enEX) of Expansiveness.

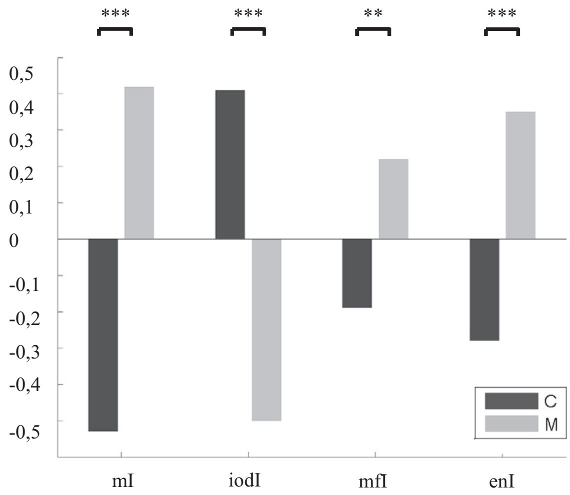

Fig. 4.1. Effort qualities – Impulsiveness. Medians (of standardized scores) for relevant features plotted according to C and M conditions. Asterisks indicate significant differences between conditions: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Positive values mean sudden movements. Variables: Mean (mI), Index of dispersion (iodI), Mean frequency (mfI) and Entropy (enI) of Impulsivity.

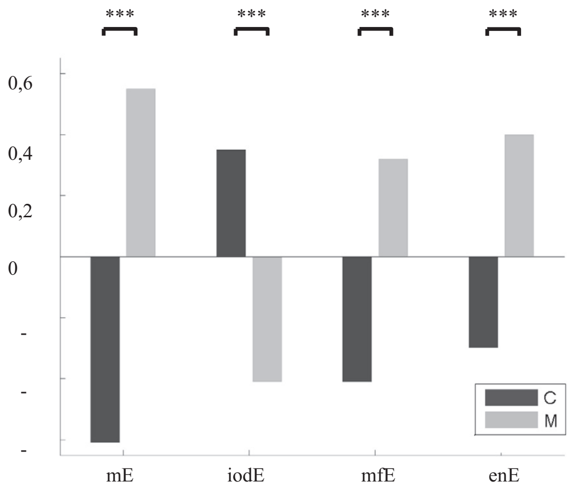

Fig. 4.2. Effort qualities – Energy. Medians (of standardized scores) for relevant features plotted according to C and M conditions. Asterisks indicate significant differences between conditions: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Positive values mean energetic movements. Variables: Mean (mE), Index of dispersion (iodE), Mean frequency (mfE) and Entropy (enE) of Energy.

Overall, several features were significantly different between the four conditions. No features from the movement quality of Jerkiness appeared to be significant when comparing the C, N and P conditions.

3.2.1. Control versus Negative mood condition (C-N)

Regarding the frequency means (the overall representation of the variation according to the frequency domain), the influence of the negative mood conditions compared to the control condition was characterized by the presence of lower frequencies in the Energy time-series ($Z = -3.46$, $p = 0.001$) and presence of higher frequencies in the Directness time-series ($Z = -2.29$, $p = 0.022$). The Expansiveness time-series were less regular and predictable in the negative mood conditions compared to the control condition ($z = -2.65$, $p = 0.008$).

3.2.2. Control versus Positive mood condition (C-P)

The influences of the positive mood condition compared to the control condition were characterized by an increase in mean of Impulsiveness ($Z = -3.09$, $p = 0.02$) and Energy ($Z = -2.49$, $p = 0.013$), presence of lower frequencies in the Energy time-series ($Z = -3.05$, $p = 0.002$), higher frequencies in the Directness time-series ($Z = -2.09$, $p = 0.036$), higher frequencies and more dispersed in the Expansiveness time-series, respectively ($Z = -2.57$, $p = 0.01$) and ($z = -2.21$, $p = 0.027$). For

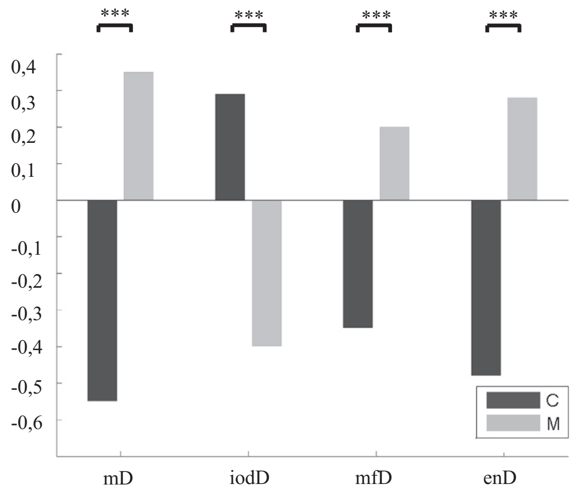

Fig. 4.3. Effort qualities – Directness. Medians (of standardized scores) for relevant features plotted according to C and M conditions. Asterisks indicate significant differences between conditions: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Positive values mean indirect movements. Variables: Mean (mD), Index of dispersion (iodD), Mean frequency (mfD) and Entropy (enD) of Directness.

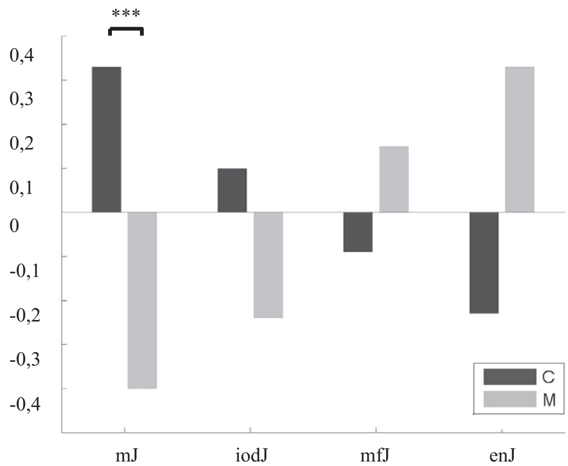

Fig. 4.4. Effort qualities – Jerkiness. Medians (of standardized scores) for relevant features plotted according to C and M conditions. Asterisks indicate significant differences between conditions: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Positive values mean Jerky movements. Variables: Mean (mJ), Index of dispersion (iodJ), Mean frequency (mfJ) and Entropy (enJ) of Jerkiness.

entropy (the representation of the regularity and predictability of the time-series), the Energy time-series and Expansiveness time-series were less regular and predictable in the positive mood conditions compared to the control conditions, respectively ($z = -3.05$, $p = 0.002$) and ($z = -2.65$, $p = 0.008$). The index of dispersion (the index measuring the distribution dispersion of the time-series) in the Directness time-series were less dispersed in the positive mood condition compared to the control conditions, ($z = -2.29$, $p = 0.022$).

3.2.3. Positive versus Negative mood condition (P-N)

Regarding the means, the influences of the negative mood compared to the positive mood condition were characterized by a decrease in Directness ($Z = -2.09$, $p = 0.036$) and a more dispersed Directness time-series ($z = -2.33$, $p = 0.02$). The Energy time-series were less regular and predictable in the positive mood conditions compared to the negative conditions ($z = -3.05$, $p = 0.002$).

3.2.4. Control versus Motivated mood condition (C-M)

Regarding the means, the influences of the high arousal condition compared to the control condition were characterized by an increase in Impulsiveness ($Z = -3.88$, $p < 0.001$), Energy ($Z = -3.92$, $p < 0.001$), Directness ($Z = -3.92$, $p < 0.001$), and

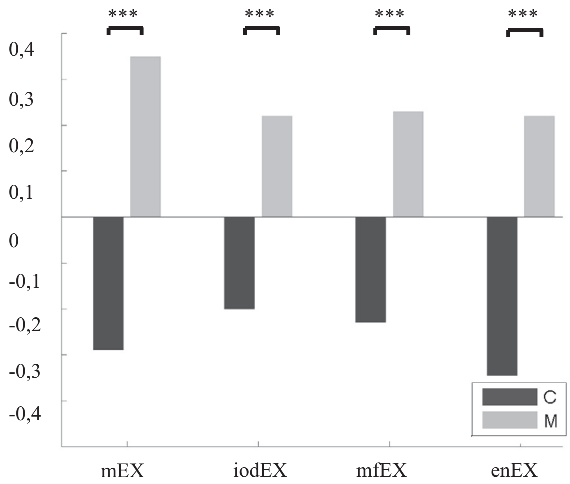

Fig. 4.5. Shape qualities – Expansiveness. Medians (of standardized scores) for relevant features plotted according to C and M conditions. Asterisks indicate significant differences between conditions: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Positive values mean movements which take more space (away from the mass center). Variables: Mean (mEX), Index of dispersion (iodEX), Mean frequency (mfEX) and Entropy (enEX) of Expansiveness.

Expansiveness ($Z = -3.92$, $p < 0.001$) and a decrease in Jerkiness ($Z = -3.88$, $p < 0.001$). Regarding the frequency means, the influences of the high arousal compared to the control condition were characterized by the presence of higher frequencies in the Impulsiveness time-series ($Z = -3.09$, $p = 0.002$), Energy time-series ($Z = -3.54$, $p < 0.001$), Directness time-series ($Z = -3.24$, $p = 0.001$) and Expansiveness time-series ($Z = -2.57$, $p = 0.01$). Regarding entropy, Impulsiveness, Energy, Directness and Expansiveness time-series were less regular and predictable in the high arousal condition compared to the control condition, ($z = -3.77$, $p < 0.001$), ($z = -3.65$, $p < 0.001$), ($z = -3.65$, $p < 0.001$) and ($z = -3.92$, $p < 0.001$), respectively. Regarding the index of dispersion, Impulsiveness, Energy and Directness were less dispersed, whereas the Expansiveness time-series were more dispersed in the high arousal condition compared to the control condition, ($z = -3.69$, $p < 0.001$), ($z = -3.65$, $p < 0.001$), ($z = -3.92$, $p < 0.001$), (-2.53, $p = 0.01$), respectively. Almost all selected features were significant with Jerkiness as the least represented quality.

3.3. Multivariate analysis

To complement this univariate approach, we performed a multivariate analysis based on Generalized Linear Mixed Models (GLMM). We applied this supervised learning method to create a model classifying conditions according to a set of selected variables. For this analysis, the experimental conditions which were the independent variables in the univariate analysis become the dependent variables. The set of independent variables (predictors) is composed of twenty variables: temporal and frequency means, index of dispersion and entropy index for each time-series. GLMMs extend linear models in that the dependent variable (criterion variable) can be non-normally distributed, and observations are not required to be independent. A link function enables to specify the nature of the association between predictors and the criterion. In our case, the distribution of the dependent variable was binomial (i.e., two conditions to discriminate). Because our experiment was based on a repeated measure design, there was a strong assumption that measures across one participant were correlated (which can be accounted by the random effect of the mixed model). Hereafter, we compare different models for both C-M voluntary and C-P – C-N spontaneous conditions. The process of building a mixed-model is characterized by four elements: the maximum model, the random effect structure, predictors selection strategy and a model selection strategy (Cheng, Edwards, Maldonado-Molina, Komro, & Muller, 2010). The maximum models include the twenty variables selected with the PCA. Subject only were entered as random intercept effects with a variance component correlation structure because there was no assumption of variability across blocks within conditions. To select a parsimonious set of predictors (reduced number of variables without significant loss of variance explained), we applied a backward elimination strategy. The selection of the best model was based on the -2 log pseudo likelihood criterion. Table 3 provides statistical information about global model fit for the C-N, C-P, and C-M models and Table 4 provides details about significant predictors for each selected model.

For the two spontaneous conditions when compared to the control condition (C-N and C-P), almost all predictors (i.e., all except those from the Impulsiveness movement quality) had to be included in the model to make it converge. Yet, the models were not significant. The classification rates were also less important (i.e., minus 20%) than for the C-M model. The model of direct comparison of the two spontaneous conditions (P-N) did not converge. Hereafter, only significant results are described.

Table 3
Summary of GLMM analysis.

	Information on models			
	F	P	−2LPL	Classification rate (%)
C-M	32.05	***	738.4	97.5
C-P	1.54	0.08	518.1	78.9
C-N	1.48	0.10	534.7	78.1
P-N	Does not converge			

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 4
Parameter estimates for fixed effects and random effects for the three GLMMs as a function of mood prediction.

Parameter		Model C-M	Model C-P	Model C-N
			Fixed effects	
Impulsiveness	mI		3.36*(1.8)	
	mE	5.8***(1.02)		
Energy	iodE			−1.66*(0.69)
	fmE			2.15**(0.7)
Directness	mD		−3.3*(1.38)	−2.73**(0.82)
Jerkiness	mJ			0.99*(0.42)
Expansiveness	mEX		1.47*(0.67)	1.33**(0.43)
			Random effects	
Intercept		14.29*(7.4)		

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

3.3.1. Control versus Negative mood condition (C-N)

The C-N model revealed that the negative mood condition was characterized by a decrease in the dispersion, an increase in high frequencies in the Energy time-series, an increase in Jerkiness means, a decrease in Directness means and an increase in Expansiveness means compared to the control condition.

3.3.2. Control versus Positive mood condition (C-P)

We found an increase in Impulsiveness means for the positive mood condition, a decrease in Directness means and an increase in Expansiveness means compared to the control condition (last two features are common for CN and CP models).

3.3.3. Positive versus Negative mood condition (P-N)

Additionally, even if some selected features for the C-N model were significant while not for the C-P model, the selected features and their signs were nevertheless identical. This common pattern might explain the impossibility to discriminate directly the positive and negative mood conditions (i.e., P-N model does not converge).

3.3.4. Control versus Motivated mood condition (C-M)

Looking at the C-M model, only one variable (mE) was necessary to make the model converge and to be significant with a high percentage of classification rates. The mean of Energy was the best feature that characterizes changes between the control condition and the high arousal condition. To investigate the role of inter-individual differences, we compared the model with and without random intercepts. The results (not presented here) showed that the classification rate decreased about 20 percent due to inter-subject variability, which provided evidence of the importance of taking into account the idiosyncratic aspect that affected all responses from the same subject: all participants increased their Energy in the high arousal condition but with different intercepts (i.e., levels).

4. Discussion

In this paper, we described the study of spontaneous movement expressivities (i.e., movement qualities) of elicited moods within different context of a fitness coach task. To do so, we designed a short and simple fitness movement sequence in order to reduce behavior configural variabilities (i.e., variations in form) that emerge during free voluntary expressive movements. Our fitness movement can be considered as a trade off by avoiding too automatic and rigid pattern of motor coordination (e.g., walking) and thereby to maximize the probability of catching motor signatures of mood.

The focus of the study was on elicited moods in a specified context: we chose to elicit commonly encountered moods in a fitness coach's daily life and defined a new protocol eliciting three moody states (i.e., happy, stressed and motivated) interpreted in a dimensional approach of affect. DES and EDA were used to validate the effectiveness of our protocol conditions in eliciting these different valence and arousal levels. Negative valence (stressed), positive valence (happiness) and high arousal (motivation) conditions were compared to a control condition. Time-series inspired by the Laban Effort-Shape framework were computed and post-processed with appropriate statistical procedures in which features covariance were considered (via principal component analysis) to reduce dimensionality. This framework enabled us to precisely characterize movements whilst keeping a high degree of interpretability.

In line with other studies exploring the influence of affects on body movements, we expected to find differences between mood conditions, especially in the motivated condition (M) where EDA was observed to be higher compared to the other conditions. We assumed that the positively (P) vs the negatively (N) valenced mood conditions would be more difficult to discriminate given the inconsistencies in the literature. Energy was hypothesized to discriminate the low arousal condition (control condition C) from the high arousal condition (M). In line with the literature, we expected variables from Expansiveness, Impulsiveness and Jerkiness to discriminate the P condition from the N condition (valence discrimination).

4.1. Voluntary versus spontaneous conditions: differences due to arousal levels

In both univariate and multivariate analyses, the kinematic features computed from the fitness choreography were differentially involved in the discrimination of arousal related conditions (M vs. P, N and C) and valence related conditions (P, N vs. C). Also in line with our expectations, the positive (P) and the negative (N) mood conditions were less strongly discriminated from the control condition (C) and from each other (P versus N) than the motivated condition (M) was from the control condition: at the multivariate level the C-P and the C-N models were not significant and the P-N model did not converge whereas the C-M model was highly significant requiring only one variable to converge. Additionally, both the C-P model and the C-N model required almost all variables to be included in the model to converge and fewer variables appeared to be significant at the univariate level. We interpreted this lack of differentiation of the P and N conditions compared to the M conditions as being a result of the moderate and similar level of activation induced by these two conditions. In past researches, Gross et al. (2012) observed similar results for time, space and weight qualities for the Angry and Joyful conditions. Authors concluded that the similar level of arousal between those affects might have accounted for the lack of significant differences. In accordance with this interpretation, Glowinski et al. (2011) observed more difficulties in discriminating differently valenced affects with low arousal levels compared to high arousal levels. Hence our protocol might have induced subtle differentially valenced moods limiting the emergence of prototypical patterns for the happy and stressed conditions.

4.2. Spontaneous conditions: similarities and subtle differences of positive and negative moods compared to control

4.2.1. Similarities between positive and negative moods

The univariate analysis for the C-P and the C-N conditions revealed the exact similar pattern of significant differences when compared to the control condition. At this univariate level, both the P and N conditions were associated with increased Energy mean frequencies and reduced Expansiveness predictability compared to the control condition. One conclusion is that these conditions were characterized by faster cyclical sequences which could be interpreted as resulting from increased mood activation (independently from valence). One limitation of such interpretation is that mean Energy (the variable related to the motivated condition assumed high in arousal) was not involved in both the P and N conditions. As explained previously, the type of mood activation was different in the M condition (i.e., included an intentional aspect) from the P and N conditions which were more spontaneous. Thus, the pattern of more spontaneous arousal could have been different in nature as well, having a less direct influence on the movement signature. The multivariate models provided a slightly different picture: Energy mean frequencies were still increased for both conditions but without being significant for C-P and Expansiveness predictability was not included in the C-P model. Instead, other similarities emerged: the P and N conditions shared a significant decrease in mean Directness and an increase in mean Expansiveness. The increase in Expansiveness was still coherent with an interpretation based on the idea that the P and N conditions shared a level of spontaneous mood activation (i.e., arousal). However, the decrease in Directness was less coherent with past literatures which associated high arousal with more Energy, Expansiveness and Directness (Gross et al., 2012). Again, this discrepancy can be interpreted by considering the specific nature of our task. A better performance in such a fitness task can be characterized by enhanced Energy expenditure, but also by better movement form realization (e.g., making well curved arm waves). As our movement sequence included several curved movements, participants might have attempted to perform better resulting in more curved movement (i.e., a decrease in Directness).

4.2.2. Specificities of the negative mood

Regarding what was specific to the negative mood condition (compared to the control condition), the C-N multivariate model evidenced a decrease in Energy dispersion and an increase in mean Jerkiness. Although in appearance these two results seemed contradictory (i.e., smoother movement are often associated with more regular movement), the specific nature of our negative mood condition can help disambiguate these findings. In the N condition, participants were told to being watched by a full theatre, inducing a feeling of being judged by others. Under this ego threat, participant might have put more effort in the control of their movements, leading to a more rigid signature. Thus, the Energy of the sequence had a smaller range and variability, but was also more tense (i.e., increasing Jerkiness). Such a contextual interpretation explains also the discrepancies with past literature showing lower Jerkiness for negative affects. For example, Montepare et al. (1999) found negative and positive correlations associated with the angry condition (jerky movement) and the neutral condition (smooth movement), respectively. More in line with our results, Gross et al. (2012) found tense movements for anger and joy compared to the neutral condition. One limitation of this analysis was that it did not account for individual differences in the appraisal of the situation. This condition of ego threat in a demonstrating task was not necessarily perceived as negative by athletes (Oudejans, Kuijpers, Kooijman, & Bakker, 2011). Some of the sports students might have put themselves in a stimulant state and have conducted the task in the best way they could. Future works could consider these individual differences to better distinguish felt experience induced by such a protocol.

4.2.3. Specificities of the positive mood

Regarding what was specific to the positive mood condition, the multivariate approach revealed a simple pattern with an increase in mean impulsivity. The result was also present in the univariate approach but other differences appeared to be significant: the positive condition was also associated with more Energy, less dispersed Directness and Expansiveness, higher frequencies in Expansiveness and increased entropy in Energy and Expansiveness. Although Impulsivity and Energy have already been associated with positive affects (Gross et al., 2012; Montepare et al., 1999; Van Dyck et al., 2012), the decrease in dispersion (for Directness and Expansiveness) was difficult to interpret. The increase in entropy is an interesting result as it is in accordance with Frijda (1987), who described action tendencies as "growing vague when emotions are positive" (i.e., joy). Motor activity is "non-specific" and less constrained within positive affect which might lead to less predictive movement patterns.

4.3. Voluntary condition: intentionally energetic but smooth movements

As hypothesized, the M condition was the most clearly discriminated condition. At the univariate level, almost all movement features were significantly different from the control condition. For Impulsiveness, Energy, Directness and Expansiveness, the expressivity level in the M condition was higher in quantity (mean) and frequency (mean frequency), with a reduced variability (index of dispersion) and reduced predictability (higher entropy). This common pattern is characteristic of highly expressive behaviors which are faster, more energetic, direct and less dispersed (Wallbott, 1998). When looking at the multivariate discriminant analysis for the C-M model, the inclusion of the mean Energy (mE) alone provided the best parsimonious model, with a classification rate of approximately 97.5 percent. This result is consistent with similar studies where arousal was consistently associated with body movement quantity and Energy (Gross et al., 2012; Pollick et al., 2001). For example, in the study by Glowinski et al. (2011), regardless of affective valence, high and low arousal are characterized respectively by a high and low amount of activity, the quantity of movements being very close to movement Energy. These results highlighting the clear discriminant pattern of the M condition across all movement qualities might not only be due to the highly aroused nature of the task. Asked to purposely motivate an audience, the movement expressivity pattern can be interpreted as a result of the expressed motivation to be conveyed (by contagion). A future work could attempt to distinguish the movement signature of a more spontaneous motivation (i.e., intrinsic) to perform energetic fitness choreography from its more voluntary signature (i.e., extrinsic) evidenced here.

Lastly, the decrease in overall quantity (mean) of Jerkiness at the univariate level can be interpreted by considering the nature of the condition: coaches were asked to entrain an imagined audience. In this fictitious scenario, participants might have adapted their movement to facilitate interpersonal coordination. Such an adaptation is associated with strategies to make oneself more predictable (Vesper, van der Wel, Knoblich, & Sebanz, 2011) and mobilize "coordination smoothers" (Sacheli, Tidoni, Pavone, Aglioti, & Candidi, 2013). The decrease in mean Jerkiness as well as the reduction in dispersion (index of) of the four other movement qualities might be part of these strategies. Yet, this literature on interpersonal predictability of movements is emerging and more work is required to better understand the various possible strategies.

4.4. Limitations

Overall these results are partially coherent with past literatures whilst highlighting the more subtle nature of spontaneous versus voluntary moods movement signatures. The framework of computed movement qualities inspired by the Labanotation system (Laban & Ullmann, 1971) combined with a dimensionality reduction method enabled to provide an interpretable framework. Whilst most of the discrepancies in our results have been explained by the specificity of the fitness coaching situation, a remaining research question is to whether findings in the literature based on movement qualities observations are comparable with kinematics based movement qualities. In an extension of the Brunswikian lens model (Brunswik, 1956), Scherer (1978) formalized this issue as the question of the perceptual representation: studying how distal cues (measured and quantified cues) are related to proximal percepts (evaluation of cues). A very recent perceptual study with non-expert observers based on the same task attempted to provide this comparison (blinded). Firstly, intercorrelations of observed movement qualities were high revealing a halo effect centered on the Energy quality. Secondly, only the Energy quality was coherently correlated to the Energy quality computed based on kinematics data: observed Expansiveness was only partially related to computed Expansiveness and the other qualities were unrelated. Conversely, the only alternative research work which proposed such an analysis compared computed movement qualities with observations from a certified movement annotator on acted arm movements and revealed a high agreement across the Effort-Shape space (Samadani et al., 2013). These results highlight how observed and computed movement qualities are not simply interchangeable: the type of movement and the observer expertise modulate this relation.

One issue with physiological evaluations of mood induction protocols is that they are inherently related to the physical activity of the participant. It is not an issue in calm perceptual experimental setup, but it does in sport-oriented experiment such as in our study. The question of the baseline is therefore essential: the control condition (performing the movement sequence without any specific mood induction protocol) is a better baseline than the traditional quiet waiting phase. Future research could investigate how to integrate such measures in affect-oriented movement task protocol.

Lastly, the use of GLMM as our multivariate approach highlighted two limitations. The differences in results between the univariate and multivariate approaches indicate the potential presence of multicollinearity. In our post processing approach, we reduced the dimensionality and multicollinearity at the movement quality level in order to keep the essence and interpretability of the computed expressivities. Future works could investigate in more details the definition and computation of movement qualities in order to provide more discriminated dimensions. Additionally, the importance of random intercepts in our multivariate approach calls for more considerations of individual differences in such protocols. Individuals have different behavioral styles as well as different ways to appraise demanding situations. Personality variables could help disambiguate such variations and interpret those differences in intercept.

5. Conclusion

In the presented, twenty participants performed a predefined fitness motion sequence within a motion capture setup under four conditions: stressed by the observation of an audience (i.e., negative mood), amused by a video and gifts (positive mood), motivated to perform a session challenging a fictitious audience (i.e., aroused mood) and a control condition. Kinematics variations were analyzed via movement qualities (i.e., Impulsiveness, Energy, Directness, Jerkiness and Expansiveness) inspired by Effort-Shape framework (Laban & Ullmann, 1971). A reduced set of variables was selected via a dimensionality reduction technics to keep results interpretable and attempting to bridge the gap between quantitative motion analyses and qualitative observer evaluation. The aroused mood condition was strongly associated with increased mean Energy compared to the three other conditions. The positive and negative mood conditions showed more subtle differences interpreted as a result of their moderate activation level. Positive mood was associated with more impulsive movements and negative mood was associated with more tense movements (i.e., reduced variability and increased Jerkiness). These findings confirm only partially past researches highlighting the importance of task contexts for the analysis of affects. In addition, the difficulty to match univariate and multivariate analyses as well as the uncertainty about how perceptual cues (i.e., kinematics information) are used to form observer evaluations are two issues to deal with in future researches. The database recorded during this experiment is available for download and can be used by other researchers willing to conduct additional analyses.

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