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Biomechanical metrics of aesthetic perception in dance

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Abstract

The brain may be tuned to evaluate aesthetic perception through perceptual chunking when we observe the grace of the dancer. We modelled biomechanical metrics to explain biological determinants of aesthetic perception in dance. Eighteen expert (EXP) and intermediate (INT) dancers performed *développé arabesque* in three conditions: i) slow tempo, ii) slow tempo with relevé, and iii) fast tempo. To compare organizational metrics of kinematic data, we calculated intra-excursion variability, principal component analysis (PCA), and dimensionless jerk for the gesture limb. Observers, all trained dancers, viewed motion capture stick figures of the trials and ranked each for i) aesthetic proficiency and ii) movement smoothness. Statistical analyses included group by condition repeated measures ANOVA for metric data; Mann-Whitney U rank and Friedman's rank tests for non-parametric rank data; Spearman's rho correlations to compare aesthetic rankings and metrics; and linear regression to examine which metric best quantified observers' aesthetic rankings, $p<0.05$. The goodness of fit of the proposed models were determined using Akaike Information Criteria (AIC). Aesthetic and smoothness rankings of the dance movements revealed differences between groups and condition, $p<0.0001$. EXP were rated more aesthetically proficient than INT dancers. The slow and fast conditions were judged more aesthetically proficient than slow with relevé ($p<0.0001$). Of the metrics, PCA best captured the differences due to group and condition. PCA also provided the most parsimoneous model to explain aesthetic rankings. By permitting organization of large data sets into simpler groupings, PCA may mirror the phenomenon of chunking in which the brain combines sensory-motor elements into integrated units of behavior. In this representation the chunk of information which is remembered, and to which the observer reacts, is the elemental mode shape of the motion rather than physical displacements. This suggests that reduction of redundant information to a simplistic dimensionality is related to the experienced observer's aesthetic perception.

Key words: Akaike Information Criteria, chunking, dimensionless jerk, principal component analysis, variability

INTRODUCTION

In 1623, the astronomer Galileo Galilei observed that the universe "is written in the language of mathematics" (Tegmark, 2008). More recently, Max Tegmark wrote “our external physical reality is a mathematical structure” (Tegmark, 2008). Perception of dance (visual) or music (auditory) is perception of reoccurring shapes and patterns. These shapes and patterns, in the abstract, are based on numerical relationships, which are expressions of space and time. In movement analysis, we employ biomechanical mathematics to describe and analyze movement. Here, we ask, is there an biomechanical metric that relates to our aesthetic perception of the dancer?

Aesthetic perception

When two dancers perform the same movement, a movement practiced multiple times on a daily basis, how does the viewer intuitively know that one dancer embodies greater aesthetic proficiency or is more pleasing (Calvo-Merino, Ehrenberg, Leung, & Haggard, 2010; Calvo-Merino, Jola, Glaser, & Haggard, 2008; E. S. Cross, Kirsch, Ticini, & Schutz-Bosbach, 2011)? Dance (and music) has been a medium for communities to interrelate since primitive societies (I. Cross, 2012; Kraus, Hilsendager, & Gottschild, 1991). As dance moved to the performance venue, it became removed from group communal interaction to one of observer – performer or audience and dancers. This assumes there are aesthetic properties to dance movement and that the audience experiences an aesthetic response of some sort (Bläsing et al., 2012). Depending upon their movement experience, observers may evaluate their aesthetic experience in several ways; through cognitive judgement or affective appreciation (valence) of dance movement based upon qualities such as movement amplitude, velocity, difficulty, or control; while others may include their own familiarity and physical ability in their aesthetic appreciation (Chatterjee, 2003; E. S. Cross, Kirsch, Ticini, & Schütz-Bosbach, 2011; Leder, Belke, Oeberst, & Augustin, 2004; Montero, 2012; Torrents, Castaner, Jofre, Morey, & Reverter, 2013). The information-processing model presented by Leder at al. (2004) suggests that there are two types of output in aesthetic processing: aesthetic emotion and aesthetic judgement (Leder et al., 2004). To date, the majority of research on dance aesthetics has focused on emotional liking: the observers’ perception of affect and affective reponse to dance (Calvo-Merino et al., 2008; Christensen, Nadal, & Cela-Conde, 2014; Kirsch, Drommelschmidt, & Cross, 2013; Orgs, Hagura, & Haggard, 2013). The cognitive aesthetic evaluation of technical proficiency such as control, accuracy, and fluidity, the focus of this study, has been less studied.

With no external goal to quantify a score, can we quantify the difference in the viewer's aesthetic judgement of these two dancers performing the same movement? What is the relationship between this perception of dance, in this case a ballet sequence, and its biomechanical organization? Does the observer perceive dance movement with some organizational strategy for recall? Does the concept of chunking for the purpose of extracting meaningful event features, while suppressing extraneous information, relate to a kinematic metric?

Linear and nonlinear metrics in human movement

A dynamic systems approach offers determination of coordinative patterns that may be overlooked in more traditional linear kinematic measures organized around measures of centrality. Movement patterns in high and low skilled subjects or those with dysfunction can be considered adaptations to the constraints of mechanics, environment, and task. Most movements, such as walking, display stereotypical spatial-temporal patterns, which suggests that human movements organize degrees of freedom into functional coupled relationships to achieve the task. These constraints, resulting from what are apparently complex motions, consist of significantly less active degrees of freedom than an unconstrained system. These degrees of freedom are patterns of joint movements rather than individual articulations. Because motor behavior is also inherently variable, the challenge is to identify coordination patterns that may distinguish different groups of subjects, with greater skill or disability, or between conditions of differing levels of difficulty. A widely applied method in structural dynamics is to describe complicated movements in terms of a small number of underlying modes of vibration (e.g. principal component analysis). Could principal component analysis (PCA) also be related to the manner in which elements are chunked into larger combinations as as part of the aesthetic perception of movement?

Coordination variability can be assessed by approaches such as angle-angle plots, PCA, vector coding, and entropy. Seemingly contradictory research findings suggests that there is an 'optimal' coordination variability in healthy, skilled subjects, no matter what the movement, that is necessary to permit adaptation to mechanical, environmental, and task constraints (Chow, Davids, Button, & Koh, 2008; Pollard, Heiderscheit, van Emmerik, & Hamill, 2005; Stergiou & Decker, 2011; Wagner, Pfusterschmied, Klous, von Duvillard, & Muller, 2012). This lies between the higher and lower variability reported in populations with less skill or neurologic and musculoskeletal dysfunction (Hamill, van Emmerik, Heiderscheit, & Li, 1999; Hein et al., 2012;

Kiefer et al., 2013). The majority of analyses, to date, have focused on sports activities that have an end goal such as speed or accuracy.

Patterns of variability (e.g. simple v. complex skills, injured v. healthy subjects) may not be generalizable and may differ depending on the movement to be analyzed (e.g. basketball dunk v. ballet movement). To date, dynamic systems approaches have been applied to the analyses of dance movements in only limited fashion (Hollands, Wing, & Daffertshofer, 2004; Reeve, Hopper, Elliott, & Ackland, 2013; Smith, Siemienski, Popovich, & Kulig, 2012; Torrents et al., 2013; Vincs & Barbour, 2014). Are certain metrics sensitive to determine differences due to skill level or condition difficulty in ballet movement?

Maximum smoothness theory introduced the jerk metric, the third time derivative of position, as a quantitative principle of motor control as well as a way to characterize the smooth gracefulness of natural movements (Hogan & Flash, 1987). This brings dance immediately to mind. A number of jerk measures have been used to quantify smoothness and coordination in studies that examine changes due to neurologic impairment and rehabilitation (Rohrer et al., 2002; Teulings, Contreras-Vidal, Stelmach, & Adler, 1997; Yan & Dick, 2006). It has been used less frequently to examine differences in skill level (Hreljac, 1993). Jerk may provide a metric for the objective quantification of smoothness of motion and, by extension, to the skill level of the practicioner. Recently, Hogan and Sternad (Hogan & Sternad, 2009) described the inability of numerous measures of jerk to correlate with a *subjective* assessment of smoothness of movement. These jerk measures, depending on their individual formulation, had dimensions of time and position to appropriate powers. They proposed a dimensionless measure of jerk which was found to be insensitive to periods of inactivity and more accurately reflected divergence from smooth and coordinated movement. Does dimensionless jerk correlate with subjective smoothness when assessed by trained dance observers?

Aesthetic criterion of dance

In ballet, the goal of movement is to meet an technical aesthetic criterion, that includes specific timing and spatial relationships of upper and lower extremity placement, while making it appear effortless (Autere, 2013; Cohen, 1997; Hagendoorn 2005). Previous researchers, examining frequently performed ballet movements such as the *développé arabesque* and *grand rond de jambe en l'air,* reported similar movement organization and timing across various levels of expertise (e.g. expert, advanced, and intermediate dancers) (Bronner, 2012; Kwon, Wilson, & Ryu, 2007; M. Wilson, Lim, & Kim, 2004). In these studies there were no differences in limb angular displacement and velocity. Only kinematic control of the pelvis (e.g. three-dimensional

(3-D) peak angular displacement) appeared to differentiate skill level. However, the prescribed timing and spatial directives may have constrained these biomechanics findings. If there is no difference between the two dancers in the general shape and timing kinematics of the dance movement (e.g. peak angular displacement and velocity), alternative approaches are called for. Could this be due to stability (e.g. less variability), a cost function, or some other set of kinematic parameters such as dimensionless jerk or nonlinear variability algorithms such as principal component analysis? Furthermore, does differentiation of skill and condition by a kinematic metric relate to observer perception?

The purpose of this study was three-fold. The first aim was to apply linear and nonlinear dynamic systems approaches to determine the sensitivity of these metrics to differentiate skill level and condition in a complex ballet sequence, the développé arabesque. The second aim was to determine whether experienced observer rankings of the performers' *développé arabesque*, viewing abstracted motion capture stick figures, for technical aesthetic proficiency and movement smoothness can also differentiate skill level and condition. Finally, the third aim was to compare these biomechanical metrics to the experienced observer rankings for aesthetics and smoothness to determine which metric best quantified observer perceptions of the dancers' *développé* arabesque sequence.

2. **METHODS**

Subjects

<u>Dancers</u>

Eighteen healthy adult dancers (12 female, 8 male), recruited from internationally recognized professional dance companies and affiliated pre-professional training programs, volunteered for this study. Each dancer was assigned to one of two groups with distinct levels of dance expertise: i) expert and ii) intermediate. The expert (EXP) group was based on employment in a professional company. The intermediate (INT) group, comprised of student dancers, was determined by ballet class placement by dance faculty. During auditions, students are placed into ballet technique classes that ranged from beginning to advanced levels (Ballet 1-7); we selected students placed into Ballet 4 and 5, or intermediate level classes. Inclusion criteria was the ability to attain the criterion dance sequence, *développé arabesque*, at a height of 90º (e.g. gesture limb perpendicular to the stance limb and parallel to the floor) and exclusion was a history of lower extremity injury during the previous six months that caused a dancer to stop dancing for one week or more. We did not include naïve or beginner participants in this study because naïve and beginner dancers were not able to meet the inclusion criteria. The university Institutional Review Board approved this study. A power analysis of sample size for a two group repeated measures with three conditions (2 X 3) study, with a large effect size (f=0.80), power=0.95, and $\alpha = 0.05$, determined a sample size of 8 was necessary. Therefore, the selected sample size of 18 subjects was more than sufficient. Participant demographics were collected at intake.

The ratio of female to male dancers was the same within each group (5 females, 4 males). Comparison of group demographics was performed using a paired t-test for independent samples. There were differences between groups in age (EXP = 25.8 ± 2.6 and INT = 20.4 ± 1.5 years, $p<0.0001$) and years of dance experience (EXP = 15.22 ± 6.68 and INT = 5.50 ± 5.15 years, $p=0.003$), but no difference in height (1.71 ± 0.076 m), mass (62.20 ± 8.67 kg), leg length (0.92 ± 0.05 m), or starting first position turnout (107.94 ± 11.89º).

<u>Observers</u>

Previous research has reported differences in the aesthetic experience of viewers with differing levels of expertise in performing the observed movements (Calvo-Merino et al., 2010; E. S. Cross, Kirsch, Ticini, & Schutz-Bosbach, 2011; Kirsch et al., 2013). Therefore, we selected trained dancers to act as observers of the arabesque sequences. Experienced dancers are able to rapidly process movement, developed as part of their training, and may use ‘schematic expectancies’ to maximize their short-term memory (C. Stevens et al., 2010). Twenty seven different dancers, recruited from international caliber professional dance companies and affiliated pre-professional training programs, volunteered to evaluate the arabesque data for i) aesthetic proficiency and ii) smoothness. Observers included nine professional and 18 advanced or intermediate pre-professional dancers (22 female, 5 male), They had a broad span of dance experience from 4 to 40 (mean 15 ± 9) years and ranged from 18 to 55 (mean 28 ±12) years of age.

Experimental Protocol

<u>Motion capture</u>

The dance-specific task, *développé arabesque*, was a sequential, multi-joint movement that required intra and inter-segmental coordination of lower and upper extremity movement with changes from bipedal to unipedal postural control. It is practiced in every ballet class, and consequently was well known to each subject. Each dancer’s preferred *1st position* foot placement (heels touching with lower extremities externally rotated) was marked on the floor, measured (Bronner, 2012), and used as the starting position (Fig. 1).

Insert Fig. 1 here

A tape recording of a metronome with voice instruction overlay provided the tempo of the movement sequence (40 or 90 beats·min-1). Dancers practiced the *développé arabesque* sequence (Fig. 1A – D) for three conditions prior to data acquisition to synchronize their movements with the metronome. The dancers were instructed to emphasize spatial and temporal precision. From the starting posture (1st position), the gesture lower extremity passed through *passé* (hip and knee flexion, with ankle plantar flexion), and extended posteriorly to *arabesque* (gesture hip and knee extension with ankle plantar flexion), where it was held for one count, followed by return to the initial *1st position*. Dancers performed six consecutive 'excursions' (or repetitions of the *développé arabesque* sequence) within one trial with the right lower extremity as gesture limb. This was followed by six consecutive 'excursions' with the left lower extremity as gesture limb.

The *developpé arabesque* sequence was performed in three conditions to reflect differing tempo and balance constraints. For Condition 1, the *developpé arabesque* was performed on flat foot at a tempo of 40 beats·min-1 (Slow-flat). For Condition 2 using the same 40 beats·min-1 tempo, dancers were asked to *relevé* (rise up onto the toes of the stance limb and hold) (Slow-bal) during the arabesque phase of the sequence. For Condition 3, the *développé arabesque* was performed on flat foot at a tempo of 90 beats·min-1 (Fast). The excursions lasted approximately 40s in length for Conditions 1 and 2, and 18s for Condition 3.

Kinematic data were collected at a sampling rate of 120 Hz, with a 5-camera motion analysis system (Vicon 250, Oxford Metrics Ltd, Oxford, UK). A full body marker set comprised of 29 reflective, spherical markers in the Plug-In gait marker set was used to create an 11-segment model. Attire for all subjects consisted of a dark colored unitard to maximize contrast of reflective markers.

Kinematic data were reconstructed using a Vicon Bodybuilder model (Oxford Metrics Ltd, Oxford, UK). Kinematic data were filtered with a 4th order 20Hz order low pass FIR filter. Dance movements may require movement of three or more limbs; four in the case of a jeté or leap. Both upper extremities and one lower extremity are moving in the *développé arabesque*, In ballet, the gestural foot is often considered an expressive focal point. Therefore, we focused our analysis on the gestural lower extremity.

<u>Observer rankings</u>

We defined *aesthetic proficiency* as the technical accuracy of timing, dynamics, and shape as performed by each dancer. We defined *smoothness* as the fluid trajectory of the lower extremity gesture limb. The ranking numbers 1-18 were selected for the total number of subjects, with 1 for most to 18 for least in: i) aesthetic technical proficiency, and ii) movement smoothness. Aesthetic proficiency and smoothness rankings were conducted in separate sessions. Ranking was selected, rather than rating, in order to compare each dancer to the others within a given condition. Observers evaluated the abstracted motion capture stick figure data for the left and right lower extremity as gesture limb of all subjects on a laptop computer within one condition in a single viewing (add youtube movie example of stick figures). Group assignment was unknown to the observers. There were six consecutive 'excursions' within one trial per gesture limb. Observers were permitted to view a trial again if needed as they reorganized the ranking numbers of a given condition.

Data analysis

Observer rankings

Mean aesthetic and smoothness observer rankings were calculated for each dancer trial in each condition. For the aesthetic and smoothness rank data, the non-parametric Mann-Whitney U rank test for two independent samples was used to determine group differences. The non-parametric Friedman two-way ANOVA rank test (K-related samples) was used to determine condition differences. Statistical significance was set at $p \leq 0.05$ for both the Mann-Whitney and Friedman tests. If significance was determined in the Friedman test, post hoc pairwise comparisons were conducted using the Wilcoxon signed-rank test with a Bonferroni correction (0.05/3 = 0.017). The assumption of homogeneity of variance was checked for aesthetic and smoothness rank data using Levene's test for non-parametric ranked data.

Three-D pelvis-hip angle-angle and toe displacement variability

Intra-excursion variability for the pelvis-hip, an important control area (Bronner, 2012), was calculated on the angle-angle phase plane for all three cardinal planes. For the 3-D angle-angle analysis, pelvis inclination was defined as the included angle between the normal to the right anterior iliac spine (RASIS), left anterior iliac spine (LASIS), sacrum plane and global vertical. The hip articulation angle was defined as the included angle between the femur proximal to distal axis and the normal to the RASIS, LASIS, sacrum plane. Each trial was decomposed into its constituent excursions (six per trial). The excursion commenced when the toe marker on the gesture leg exceeded an altitude of 190mm and ended when the marker descended below 190mm.

The 3-D angle of the pelvis and hip angle between the normal of the pelvis and the proximal/distal axis of the gesture femur were calculated. The standard deviation across the excursions of the pelvis and hip angles were calculated as a fractional basis of the excursions. The pelvis-hip MSD was the mean of these standard deviations.

We did not normalize the temporal component of the data of these excursions as this process can distort the spatial relationship between trials (Hamill, McDermott, & Haddad, 2000), which was a parameter of interest. Furthermore, dancers have been found to be extremely consistent when performing movements to an external tempo (Reeve et al., 2013).

Three-D angle-angle plots were constructed of the pelvis and hip for the three conditions and an MSD value was calculated for each subject. Similarly, MSD was calculated for the 3-D toe displacement using the same decomposition into its constituent excursions (six per trial) and onset and offset criteria. The mean and standard deviation of the gesture toe was calculated along its 3-D trajectory. The toe MSD was the mean of the standard deviation along the trajectory.

Because each excursion had a discrete onset and offset, circular statistics were not necessary. To compare pelvis-hip and toe variability for left and right gesture limbs, separate 2 (group) X 3 (condition) repeated measures ANOVA comparisons were conducted, with pairwise comparisons. Statistical significance was set at $p \leq 0.05$ for all tests.

<u>Principal component analysis</u>

PCA is a data reduction technique for the compression of large data sets (Jolliffe, 2002) and has been shown to be appropriate for feature extraction in human movement analysis (Daffertshofer, Lamoth, Meijer, & Beek, 2004). PCA was used to quantify 3-D kinematic patterns using the full data set. The joint angle time histories were calculated from the motion data. A 15-element state vector was defined for each time instant of each trial from the angular position of the pelvis (3 degrees of freedom (DOF) in a rotation sequence about the P-A axis, followed by rotation about the lateral axis, followed by rotation about the S-I axis) together with the joint articulations of the hip (3 DOF in a rotation sequence about the abduction/adduction axis, followed by rotation about the flexion/extension axis, followed by rotation about the internal/external rotation axis), knee flexion (1 DOF) and ankle dorsi/plantar flexion and internal/external rotation (2 DOF) of the stance and gesture limbs. Knee flexion was defined as the angle between the line from the knee joint centre to the hip joint centre and the line from the knee joint centre to the ankle joint centre in the plane defined by these two lines. These variables were selected as elements in the state vector as they span the domain of possible lower limb motion with the exception of knee varus/valgus and ankle abduction/adduction which were considered trivial.

The principal components were calculated for the matrix of the above vector for each time in the trial. The matrix was initialized normalized, so that they have zero mean and unity variance. Principal components that contributed less than 2% to the total variance in the data set were eliminated. Mean dimensionality of the non-redundant state manifold count was calculated for each group and condition and compared with a 2 X 3 repeated measures ANOVA, with pairwise comparisons, p≤0.05.

<u>Jerk</u>

Dimensionless jerk as described by Hogan and Sternad (2009), was calculated for 3-D linear displacement of the gesture toe as:

$$\mathrm{Jerk}_{\mathrm{dimensionless}} = \frac{D^3 \int_{t_1}^{t_2} \dddot{x}(t)^2 dt}{v_{mean}^{2}}$$

where D = duration of the trial

x(t) = position variable

v = first time derivative of the position variable

and for 3-D angular displacment of the gesture hip as:

$\mathrm{Jerk}_{\mathrm{dimensionless}}$ =

$$D^5 \int_{t_1}^{t_2} \dddot{\theta}^2 dt$$

where θ = angular displacement

Separate 2 (group) X 3 (condition) repeated measures ANOVA comparisons for the i) 3-D linear displacement of the gesture toe; and ii) 3-D angular displacment of the gesture hip were conducted, with pairwise comparisons. Statistical significance was set at the $p \leq 0.05$ for all tests.

Correlation of observer rankings and biomechanical variables

Aesthetic rankings were compared to smoothness rankings, MSD for 3-D pelvis-hip angle-angle and toe displacement variability, PCA, and dimensionless jerk for 3-D hip angle and toe displacement using Spearman's rho correlations for nonparametric variables, $p \leq 0.05$.

Modeling rankings and movement metrics

We employed mixed model linear regression analysis to examine which variables, MSD, PCA, and jerk, were good predictors of each observer's aesthetic and smoothness perception. Separate regression analyses approximated the i) aesthetic; and ii) smoothness ranking data with regressors that consisted of the following:

Model 1) 5 predictors: PCA, jerk (hip and toe), and MSD (3-D pelvis-hip and toe);
Model 2) 1 predictor: PCA;
Model 3) 2 predictors: jerk (hip and toe);
Model 4) 1 predictor: toe jerk;
Model 5) 2 predictors: MSD (pelvis-hip and toe); and
Model 6) 1 predictor: MSD toe.

The goodness of fit of the proposed models were determined using Akaike Information Criteria (AIC), with the least AIC value, indicating the best fit. The AIC value is

$$\mathrm{AIC} = 2k - 2\ln(L),$$

Where k is the number of parameters in the model, and L is the maximized likelihood function for the model. The corrected AIC value (AICc) for finite sample size where

$$AICc = AIC + 2k(k+1)/(n-k-1)$$

was selected for comparison of the models. All statistics were conducted using SPSS (SPSS v. 21, IBM Corp, Armonk, NY).

RESULTS

Observer rankings

The Mann-Whitney U test for group indicated that aesthetic rankings were lower for EXP dancers (median = 4.10, interquartile range (IQR) = 2.20-6.20) compared to INT dancers (median = 10.20, IQR = 8.20-12.00) [U=88.00, $p<0.0001$]. A non-parametric Friedman test of differences among repeated measures for condition was conducted, rendering a Chi-square test value of 15.267, $p<0.0001$. Post hoc Wilcoxon signed-rank test indicated that Slow-flat aesthetic rankings (median = 7.75, IQR = 4.88-10.13) were significantly lower than Slow-bal (median = 8.30, IQR = 5.17-12.00) [z = 2.109, p=0.017]; Fast rankings (median = 7.90, IQR = 2.20-11.20) were also lower than Slow-bal [z = 3.570, $p<0.0001$]; and Slow-flat was lower than Fast [z = 2.233, p=0.012]. [Note, lower rank indicated greater excellence in aesthetic proficiency rankings. For smoothness results see Supplement.]

Insert Fig. 2 here

Three-D pelvis-hip angle-angle and toe displacement variability

Three-D gesture limb pelvis-hip angle-angle plots for a representative subject from each group performing six excursions during each condition are seen in Fig. 3. The MSD seen in the six plots demonstrate variability around the mean. Comparisons found a significant difference between groups [$F(34,1)=6.532$, p=0.015] (Fig. 4A), with EXP displaying lower pelvis-hip angle-angle MSD than INT dancers. There were no differences between conditions.

There were group differences in 3-D toe displacement MSD [$F(34,1)=12.406$, p=0.001] with EXP reflecting lower toe MSD than INT, and for condition [$F(34,1)=5.277$, p=0.028]. Fast condtion 3-D toe MSD was lower than the Slow-bal condition (p=0.014). There was an interaction between group and condition [$F(34,1)=4.254$, p=0.047] (Table 1, Fig. 4B). Three-D toe MSD was lower in EXP compared to INT dancers in the Slow-flat (p=0.047) and Slow-bal conditions ($p=0.004$).

Insert Figs. 3 and 4 here

Principal component analysis

The PCA analysis had three effects: (1) it orthogonalized the components of the input vectors so that they were uncorrelated with each other; (2) it ordered the resulting orthogonal components (principal components) so that those with the largest variation came first; and (3) it eliminated those components that contributed the least to the variation in the data set. The PCA dimensionality of the movement reported indicates the number of mode shapes which were required to account for 98% of the total variance of the motion data captured during the arabesque excursions.

Figure 5A shows an example of five principal modes calculated for a representative INT dancer. The first mode, and hence the mode contributing the most variance to the movement, was predominantly a hip flexion/extension motion. The second mode was mainly a hip abduction/adduction. The third mode was associated with knee flexion/extension of the support limb, the fourth mode was support limb ankle internal/external rotation, and the fifth mode was associated with gesture limb ankle internal/external rotation. The combination of these five modes accounted for 98% of the variance of the trial.

Insert Fig. 5 here

Figure 5B shows an example of the four principal modes calculated for a representative EXP dancer. The first mode consists of hip flexion/extension motion, similar to the intermediate dancer. The second mode for the expert dancer was also mainly a hip abduction/adduction, however the third mode was dominated by support limb ankle internal/external rotation. The fourth mode was primarily support limb knee flexion/extension. These four modes accounted for 98% of the variance of the trial.

The mean dimensionality of the state manifold accounting for 98% of the variance for EXP dancers was significantly lower than the mean dimensionality for INT dancers for group [$F(34,1)=25.339$, $p<0.0001$] and condition [$F(34,1)=14.876$, $p<0.0001$] (Fig.6A and B). Post hoc pairwise comparisons for condition indicated there were differences between Slow-bal and Slow-flat ($p=0.008$) as well as Slow-bal and Fast ($p<0.0001$), with Slow-flat and Fast less than Slow-bal.

Insert Fig. 6 here

Dimensionless jerk

Comparisons of 3-D toe jerk found differences between conditions [F(34,1)=81.420, p<0.0001] but not for group (Fig. 7B). Pairwise condition comparisons were not significant. Similarly, for 3-D hip angular jerk, there were differences between conditions [F(34,1)=24.649, p<0.0001] but not for group (Fig. 7A). Pairwise condition comparisons found jerk was lower for the Fast condition than the Slow-flat or Slow-bal conditions (p<0.0001 and p=0.002, respectively).

Insert Fig. 7 here

Relationships between aesthetics and biomechanical *variables*

Rankings for aesthetics and smoothness were highly correlated (r=0.817 p<0.0001). [See Supplement for additional smoothness correlations]. There were significant correlations between aesthetics rankings and PCA (r=0.620, p<0.0001), 3-D hip angular jerk (r=0.460, p<0.0001), 3-D toe jerk (r=0.258, p=0.014), pelvis-hip angle-angle MSD (r=0.460, p<0.0001), and toe MSD (r=0.447, p<0.0001).

Modeling rankings and movement metrics

Among the models, model 2, which used a single predictor of PCA, demonstrated the least AICc value for aesthetic ranking responses of the observers (Table 1).

Insert Table 1 here

DISCUSSION

In general, observer aesthetic and smoothness rankings and biomechanical parameters were capable of distinguishing between group and condition, with the exception of 3-D toe jerk and pelvis-hip angle-angle MSD metrics. In discrimination between groups, kinematic metrics revealed that the movement of EXP dancers was smoother (e.g. lower jerk), more consistent (e.g. lower MSD), and displayed lower organizational parameters (fewer principal components) across all conditions. Differences between groups were generally greater in the Slow-flat and Slow-bal conditions compared to the Fast condition. In discerning differences between conditions for both groups, there was generally an inverted horseshoe trendline to the data, with Slow-bal reflecting higher rankings for aesthetics (e.g. less aesthetic proficiency) and smoothness (e.g. less smooth), higher MSD, higher dimensional components, and higher jerk. In contrast, the Fast condition reflected the lowest number of principal components and lowest jerk. PCA provided the most parsimoneous model to explain observer rankings. Each of the variables are discussed further in the sections below.

Observer rankings

We chose dancer-observers who were well trained in the movements that they ranked for aesthetics and smoothness. Evidence suggests that cortical regions involved in the action-observation network respond more strongly when the observer sees a kinesthetically familiar movement compared to one that the observer has never performed (Bläsing et al., 2012; Calvo-Merino, Glaser, Grezes, Passingham, & Haggard, 2005; E. S. Cross, Hamilton, & Grafton, 2006). Aesthetic judgement has been linked to both action and processing fluency (Hayes, Paul, Beuger, & Tipper, 2008; Reber, Schwarz, & Winkielman, 2004). Experienced dancers compared to naïve observers judge the motor perceptual experience of precision, fluidity, and control differently. Therefore, we selected dancers to perform the observer rankings with the expectation that this expertise refines their observation of the technical aesthetic qualities of dance (Montero, 2012). In this study, despite reviewing the motion capture stick figures on separate occasions to rank for aesthetic proficiency or smoothness, rankings for aesthetic proficiency and smoothness were highly correlated. This suggests that movement fluidity may be an important component of cognitive aesthetic perception.

Several groups have developed dance-specific aesthetic competance evaluation measures that focus on the cognitive aspects of aesthetics such as technique accuracy, dynamics, and control (Angioi, Metsios, Twitchett, Koutedakis, & Wyon, 2009; Chatfield & Byrnes, 1990; Krasnow & Chatfield, 2009). Each group demonstrated excellent repeatability between judges in their respective measures, with sensitivity to determine change with training or due to expertise. Similar judgement of competancy is also used in sports competitions such as diving, gymnastics and figure skating (Díaz-Pereira, Gómez-Conde, Escalona, & Olivieri, 2014; Looney, 2004; Pajek, Cuk, Pajek, Kovac, & Leskosek, 2013; Young & Reinkensmeyer, 2014). We chose to rank aesthetic judgement specific to each dancer's ballet technique for this reason. Aesthetic valience may be more variable across individuals due to personal taste (Leder et al., 2004).

Researchers have employed several ways of displaying dance movement in order to study the aesthetic perception of dance. Observers have viewed dance as point light displays (Sevdalis & Keller, 2011), motion capture stick figures (Sato, Nunome, & Ikegami, 2014; Torrents et al., 2013), static stick figures (Daprati, Iosa, & Haggard, 2009), video (Calvo-Merino et al., 2008; E. S. Cross, Kirsch, Ticini, & Schütz-Bosbach, 2011; Jola & Grosbras, 2013; Miura et al., 2010), and live performance (Angioi et al., 2009; Stevens et al., 2009). Observation of live and video performances are most ecologically valid and may be important to study aesthetic valence. In contrast, abstraction of the dancer's movement in point-light or motion capture stick figure representation allows the observer to focus on form and fluidity to make technical aesthetic judgements without distraction by costumes, sets, or music.

Observers were able to distinguish between groups and conditions with both aesthetic proficiency and smoothness rankings. It is possible that these dancer-observers were able to accomplish this due to their specialized training in recognizing movement configurations, encoding them (in the case of ballet, this may include verbal encoding as it has a set vocabulary), and then extracting key information as part of the process of learning new choreography (C. Stevens et al., 2010; Stevens, Ginsborg, & Lester, 2010). In this study, the *développé arabesque* was a relatively short, well-learned phrase, enabling the observers to focus on differences between the performers.

Relationships between observer rankings and biomechanical variables

Our results found that aesthetic rankings and all variables were significantly correlated. The highest correlation between aesthetic proficiency and biomechanical metrics was to PCA (r=0.620, greater than that of smoothness to PCA, r=0.479, see Supplement). Recently, multiple factor analysis (MFA), an extension of PCA to handle multiple data tables that measure sets of variables collected on the same observations, was applied to four dance movements: (1) *arabesque penchée* requiring balance; (2) *tour en dehors* or turn; (3) *brisé volé en arriére en tournant* or skater's jump; and (4) a forward fall, performed by expert dancers (Torrents et al., 2013). Non-expert observers rated motion capture stick figures performing each of the movements for aesthetic 'beauty.' Movement amplitude was the basic parameter used in judging positive aesthetics, followed by turning velocity, and the length of time that balance was maintained. In other studies, greater difficulty or faster movements were more appealing to naïve oservers (Calvo-Merino et al., 2008; E. S. Cross, Kirsch, Ticini, & Schütz-Bosbach, 2011). These findings correspond to the lower aesthetic and smoothness rankings we found for the Fast condition (lower ranking of aesthetic proficiency and smoothness indicated greater excellence). However, we found that aesthetic and smoothness rankings were highest for the

Slow-bal condition, the more difficult of the conditions. The expertise of these observers did not rank balance itself with positive aesthetics. It is likely, they perceived technical problems in the performers' achievement of that condition.

Sato et al. (Sato et al., 2014) investigated the relatonship of aesthetic competance to variability of amplitude, velocity and shape in hip hop dance. Three groups of dancers with differing skill levels performed the wave. Similar to this study, motion capture stick figures were rated by experienced judges. Aesthetic judgement discriminated successfully between experts, non-expert, and novice dancers and correlated highly with smoothness propogation of the wave. Components of aesthetic technical proficiency include control, accuracy, and fluidity. Therefore, it is possible that the movement smoothness is a subset of aesthetic technical proficiency, explaining the high correlation (r=0.817) between the two parameters in our analysis.

There were also correlations between smoothness rankings and all variables with the exception of pelvis-hip angle-angle MSD. Again, the highest correlation was to PCA. Dancers' training focuses on timing and the dynamic quality of movment. Therefore, the observers, all trained dancers, may have been particularly attuned to the smoothness perception parameter as it relates to fluidity.

Three-D pelvis-hip angle-angle and toe displacement variability

Angle-angle MSD analyses demonstrate variability in coodination patterns during 3-D joint coupling. This variability may decrease or increase with expertise depending on the task, offering flexibility to achieve certain goals (Wagner et al., 2012; C. Wilson, Simpson, van Emmerik, & Hamill, 2008).

In dance, the aesthetic shape and timing goals may dictate the coordination patterns. Researchers have reported more stable joint coordination in dancers compared to non-dancers during a rhythmic coordination task (Kiefer et al., 2011). Greater variability in pelvic motion in the *développé arabesque*, measured by the coefficient of variability (CV), differentiated between intermediate and expert dancers in all three planes (Bronner, 2012). The greatest variability was found in intermediate dancers in the transverse plane. Similar differences for end segment 3-D toe and finger CV differentiated skill level in the same study. Other dance researchers reported that CV was able to distinguish between experts and novice hip hop dancers in several kinematic measures (Sato et al., 2014). Both pelvis-hip angle-angle and 3-D toe MSD findings in this study were similarly able to differentiate differences between skill in this study.

The effect that altered speed and balance constraints have on angle-angle variability is less clear. One study comparing pelvis-trunk coordination and variability in walking and running found no changes in variability due to speed (Seay, Van Emmerik, & Hamill, 2011). In this study only 3-D toe MSD distinguished differences between conditions. Pelvis-hip control of the center of mass may be a critical control parameter, particularly when the participant must stand on one limb. This may explain our finding of no differences between conditions in pelvis-hip angle-angle MSD.

Principal component analysis

PCA is a technique which reduces complex data sets into smaller set of principal components which are capable of repoducing the original movement the as a linear superposition of these modes and hence is an efficient data compression method. The technique also has the effect of associating noise in the motion with components which add little variance and hence can often be eliminated from the analysis.. We found that our more skilled EXP dancers demonstrated lower dimensional components when compared to the INT dancers. Previously, a different intra-limb organizational strategy was found in the temporal kinematics of the *développé arabesque* in EXP compared to INT dancers (Bronner, 2012). This difference may be reflected in the lower number of PCA nodes seen here in the EXP group.

Differences due to skill or practice have been reported by other researchers (Ko, Challis, & Newell, 2003). In 2-D analyses, these researchers reported a shift to lower dimensional components with learning, represented by two principal components (Ko et al., 2003). In a 3-D learning study, Hong and Newell reported no change in the number of three principal components that explained 90% of the variance (Hong & Newell, 2006). However, the movement was a relatively constrained one on a ski-simulator. In a simple 3-D pointing movement with an accuracy constraint, researchers reported more than 95% of the variance was included in one principal component, representing ten joint angles from shoulder to wrist (Tseng, Scholz, Schoner, & Hotchkiss, 2003). Using a 32 marker set and motion capture, Hollands et al. (Hollands et al., 2004) reported that only a small number of principal components were sufficient to describe a 15s movement phrase performed by two professional dancers. Nine modes represented the dataset, with 82% of the variance represented in the first three PCAs. However, the movement phrase was not described nor was any difference found between the two dancers.

In this study, dance skill (e.g. group) had a direct effect on the number of active modes of coordination. Given the complexity of the *développé arabesque* with gesture and stance limbs, requiring changes in stability, balance and speed, results demonstrated a surprisingly low dimensionaility, ranging from four to seven dimensions in EXP and INT dancers respectively. The Slow-bal condition in EXP dancers was primarily reflected in the 5th component, while the Fast condition was reflected in the 3rd and 4th components. In contrast in INT dancers, Slow-flat and Slow-bal were reflected in the higher 5th, 6th, and 7th components while the Fast condition was primarily reflected in the 5th and 6th components. Unfortunately, there is no standard way to analyze or report PCA, therefore it is not possible to directly compare our results to those previously conducted on dance-related movements.

Singular value decomposition (SVD) is similar to PCA in pairing a large number of features into a smaller subset of major movement structures (Land, Volchenkov, Blasing, & Schack, 2013; Volchenkov & Bläsing, 2013; Volchenkov, Bläsing, & Schack, 2014). This method was able to discern the level of movement expertise in both ballet dancers and golfers.

Our results found PCA was also able to discriminate between conditions, with Fast and Slow-flat demonstrating lower dimensionality than Slow-bal. In contrast, using accelerometry, PCA was not able to differentiate between conditions in walking at slow, preferred, and fast speeds (Kavanagh, 2009).

Dimensionless jerk

We employed the dimensionless measure of jerk to eliminate differences between the conditions due to movement duration or extent (Hogan & Sternad, 2009). We observed an inverted horseshoe in hip and toe jerk histographs for both groups, with the Fast condition reflecting the greatest smoothness (lower jerk) and Slow-bal condition reflecting the least smoothness (higher jerk).

Minimal jerk theory was initially proposed to explain planning of hand movements in space. It assumed that movment is based on a kinematic endpoint path trajectory, predicting straight line paths and bell-shaped velocity curves with a dynamic optimization criterion to maximize smoothness (Flash & Hogan, 1985). The majority of jerk research has focused on arm movements based on the endpoint path trajectory. Alternatively, to explain subsequent observations of the linear relationship of joint velocities when joints move in a coordinated way and trajectories that are not necessarily straight lines, an optimization-based minimum angular jerk model was proposed (Friedman & Flash, 2009). Subsequent comparison of this model using a two-joint index finger a grasping movement to other optimzation models reported that the best fit was the angular jerk model.

Researchers have demonstrated a decrease in jerk metrics with training or expertise (Hreljac, 1993, 2000; Schneider & Zernicke, 1989) and increased jerk metrics with increased gait speed when comparing walking and running (Hreljac, 2000). However, none of these studies utilized dimensionless jerk. As described by Hogan and Sternad (Hogan & Sternad, 2009), the dimensionless jerk measure indicates the number of velocity fluctuations but is independent of movement duration.

Due to the computational complexity of performing a single limb balance while moving the leg (and torso) at various speeds, durations, and balance constraints, we chose to investigate dimensionless minimal jerk optimization for both endpoint and angular jerk variables of the gesture limb. Our results found that both angular and endpoint jerk metrics were sensitive discriminators between conditions (tempo and balance), but not to discriminate differences in expertise (group) in this experimental paradigm. Recently, a novel measure for quantifying movement smoothness, *spectral arc-length* metric, has been proposed to overcome shortcomings in existing metrics (Balasubramanian, Melendez-Calderon, & Burdet, 2012). This metric warrants further investigation.

Interestingly, the Fast condition revealed lower rankings in both aesthetic proficiency and smoothness, fewer principle components, lower 3-D toe MSD, and lower jerk. Although we manipulated the arabesque sequence with speed and balance constraints, the Fast condition was not performed at a maximal speed but was metronome controlled. The Fast condition may have minimized demand on pelvis-hip coordination with subsequent reduction in 3-D toe MSD due to diminished time in single limb weight bearing. Increased tempo may also have resulted in reduced sub-movements and lower jerk.

Modeling rankings and movement metrics

For aesthetic rankings, model 2 received the least AICc value, indicating that this was the most parsimonious model for the data. Model 2 modeled aesthetic ranking on the PCA predictor variable. For smoothness rankings, model 2 again received the least AICc value, signifying the best fitting model for the data (supplemental data).

AIC tells us what variables are important and which are not in establishing a model. If a variable appears in a model that has a higher AICc score compared to a model that does not contain that variable, then that variable can be ignored. In the case of both aesthetic and smoothness rankings, the model with the least AICc value, PCA, corresponded with the highest correlation values.

PCA, which permits the organization of large data sets into simpler groupings, may reflect how the brain organizes huge amounts of sensory input into chunks (Chen, Penhune, & Zatorre, 2008; Janata & Grafton, 2003), or, in the case of dance, what is known as phrases.

Chunking is thought to be the way in which the brain combines sensory-motor elements into integrated units of behavior during motor learning. Chunking, in a dynamic process, emerges spontaneously: as we learn to read, we focus on individual letters and then quickly combine them into words, leading to groups of words and then whole sentences. A similar process is thought to occur in both music and dance: we begin with notes or steps, which then become chunked into short phrases or elemental components which can be linearly, or non-linearly, combined to recreate a representation of the original experience whilts retaining minimal information. Sequences become organized into fewer but larger chunks, decreasing the need for cognitive control with a shift to other neural areas such as those related to motor execution and ultimately, with expertise, automaticity (Sakai, Hikosaka, & Nakamura, 2004).

Orgs et al. (Orgs et al., 2013) suggested a hierarchical model of aesthetic perception of dance movement: postures, movements, and the larger units of phrases. They suggest that observer experience may affect how observers weight these hierarchical levels, with dance experts focusing more on phrasing or larger chunks. Similarly, Bläsing (Blasing, 2014) reported dance expertise reduced perceived segment boundaries, with, subsequently, longer phrases. In competitive diving, PCA was applied to kinematic data to predict judges' technical scores, reporting a high correlation between predicted and actual scores (Young & Reinkensmeyer, 2014). We ask, are the judges extracting fundamental patterns of coordination that reflect these PCA results?

Various motor control theories have attempted to explain how we organize the complexity of movement with its multiple degrees of freedom. Just as we may use a minimization cost function of some sort to perform a motor act, the brain may seek to organize what it perceives to be the simplest mode. Similarly, aesthetic perception may utilize chunking to assess complex movement. PCA may provide an organizational structure of pattern recognition to explain this phenomenon. PCA can reveal hidden structure within a complex data set while simultaneously filtering out noise. The efficiency of smooth movement, minimization of effort, and clear lines found in the expert dancer were reflected in lower PCA components.

Limitations

Perhaps ranking was not the optimal metric for aesthetic or smoothness perception. In the future, we will investigate the effectiveness of Likert scales for multiple components of aesthetic perception (e.g. both cognitive technical judgement and valience) that observers can apply to each dancer trial separately. This does not require them to hold in their memory how the other dancers performed within a given condition.

No movement kinetics were included in our models or analyses. Given the important contribution of dynamics to the quality of dance movement, future investigation will investigate whether kinematics and/or kinetic metrics are preferred determinants of aesthetic perception.

Conclusion

Our examination of a number of biomechanical metrics in a complex dance sequence with shape, timing, and balance constraints found that PCA best captured the differences due to expertise and condition. Further comparison between these biomechanical metrics and movement aesthetic rankings found that PCA provided the most parsimoneous model to explain these observer rankings. If the grace of a dancer is a component reflected in aesthetic perception, it was not well captured quantitatively by jerk metrics. Perhaps the way our brain perceives and the way we view movement is that which simplifies the movement into the fewest organizational groupings; in this case, PCA. A movement with a low PCA dimensionality is highly constrained and possesses significantly fewer generalized degrees of freedom than joint variables. The experienced dancers revealed lower PCA dimensionality, and it was these dancers that were most ranked as most aesthetically proficient. This suggests that reduction of redundant information, a simplistic dimensionality, may be an important part of observer perception. Our model of the biological determinant of aesthetics suggests that the brain is tuned to value movement grace, clarity, fluidity, and efficiency of intent, that is found in the beauty of dance.

In a study employing linear and nonlinear metrics to analyze a complex movement, we found that the nonlinear PCA was the most promising tool for the quantification of this art form. Further study of dance biomechanics using PCA may provide insight into motor learning, motor control, and neuro-aesthetics.

Acknowledgments

We thank the participating dancers and other volunteers.

Conflict of Interest

The authors declare that they have no conflict of interest.

Table 1. AICc models of aesthetic rankings

Model	Predictors	Parameters	AICc	ΔAICc	F	df	p
1	5	PCA	542.475	86.556	25.734	84,1	<0.0001
		hip ang jerk			1.736	84,1	0.191
		toe jerk			1.006	84,1	0.319
		MSD pelvis-hip			0.01	84,1	0.92
		MSD toe			7.967	84,1	0.006
2	**1**	**PCA**	**455.919**	**0**	**46.367**	**88,1**	**<0.0001**
3	3	hip ang jerk	572.012	116.093	1.357	87,1	0.247
		toe jerk			5.063	87,1	0.027
4	1	toe jerk	520.174	64.255	8.743	88,1	0.004
5	2	MSD pelvis-hip	483.974	28.055	4.451	87,1	0.038
		MSD toe			10.978	87,1	0.001
6	1	MSD toe	485.193	29.274	17.748	88,1	<0.0001

Abbreviations: AICc, Akaike Information Criteria corrected; ΔAICc, change in AIC; PCA, principal component analysis; ang, angular; MSD, mean standard deviation.

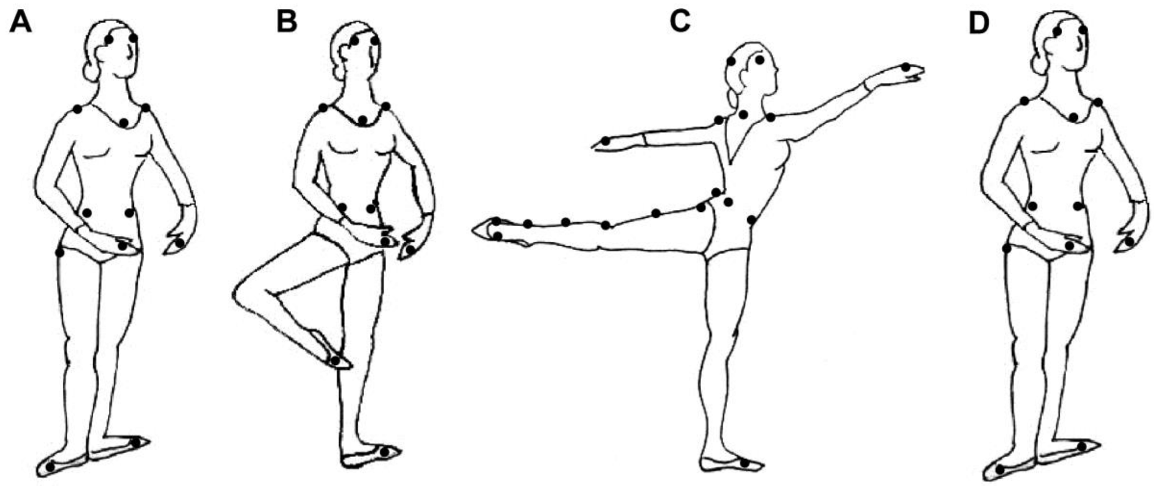


Fig. 1 Arabesque sequence for the Slow-flat and Fast conditions: A) First position, B) Passé, C) Arabesque, D) First position. In the Slow-bal condition, the dancers rises onto their forefoot during the arabesque and briefly holds it before returning to first position.

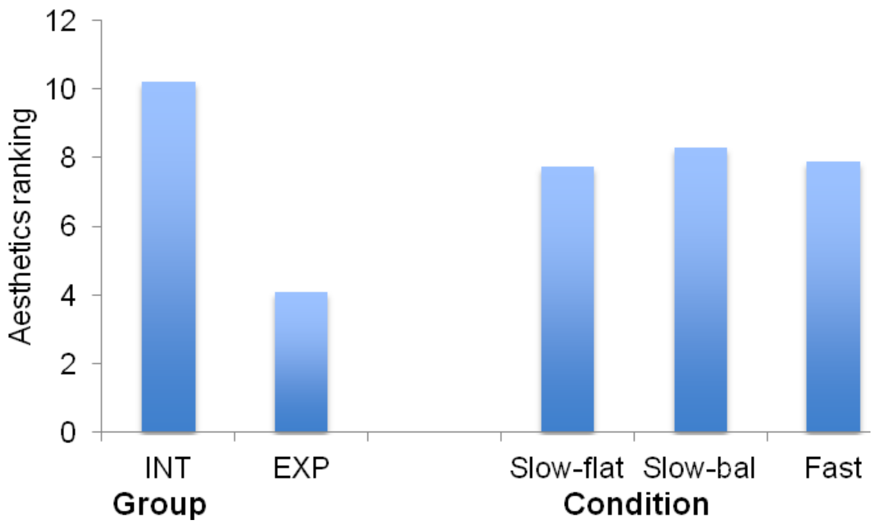


Fig. 2 Aesthetic proficiency ranking. Median for Group and Condition. Note: lower ranking denotes greater aesthetic excellence.

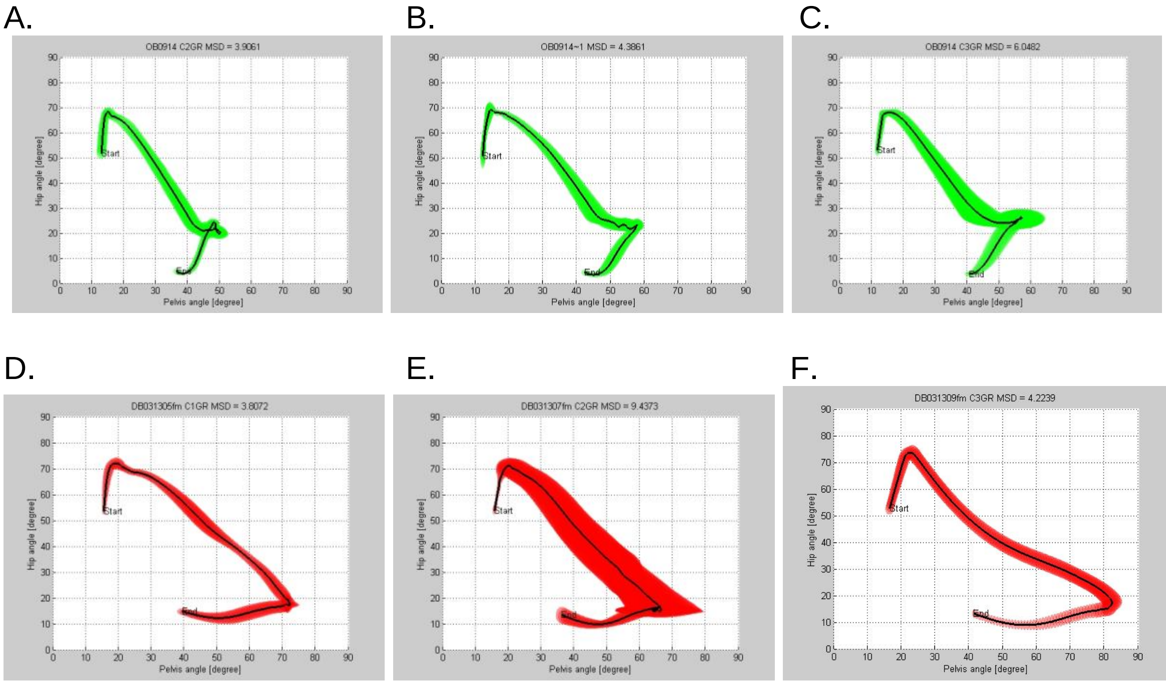
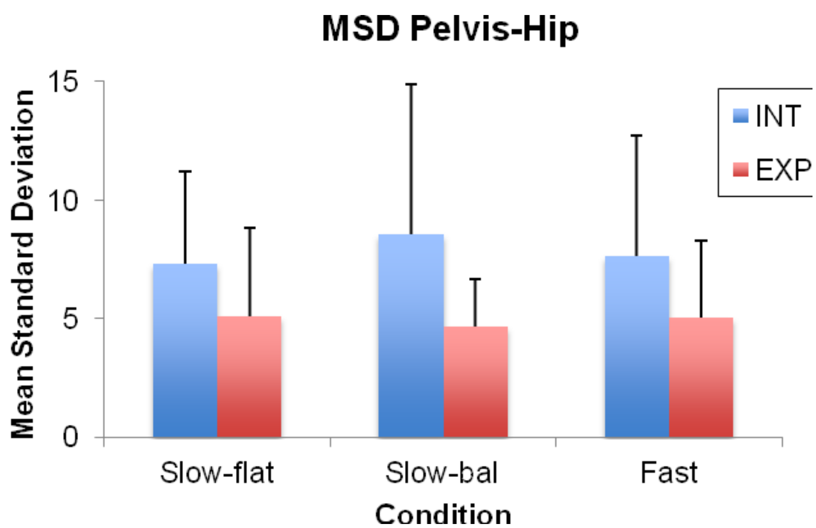


Fig. 3 Mean standard deviation (MSD) 3-D pelvis-hip angle-angle plots of representative subjects. The pelvis is on the x-axis and hip is on the y-axis, the EXP subject is seen in green and INT subject is in red. A-C. The trial was decomposed into its constituent excursions (six per trial). On each plot is a line which represents the mean of the excursions together with an envelope which indicates ±1 standard deviation of the excursion trajectories. The colour of the envelope is red for the INT and green for the EXP dancer. A-C. Representative EXP subject performing six excursions of the three conditions: A) Slow-flat, B) Slow-bal, and C) Fast. D-F. Representative INT subject performing six excursions of the three conditions: D) Slow-flat, E) Slow-bal, and F) Fast.

A.



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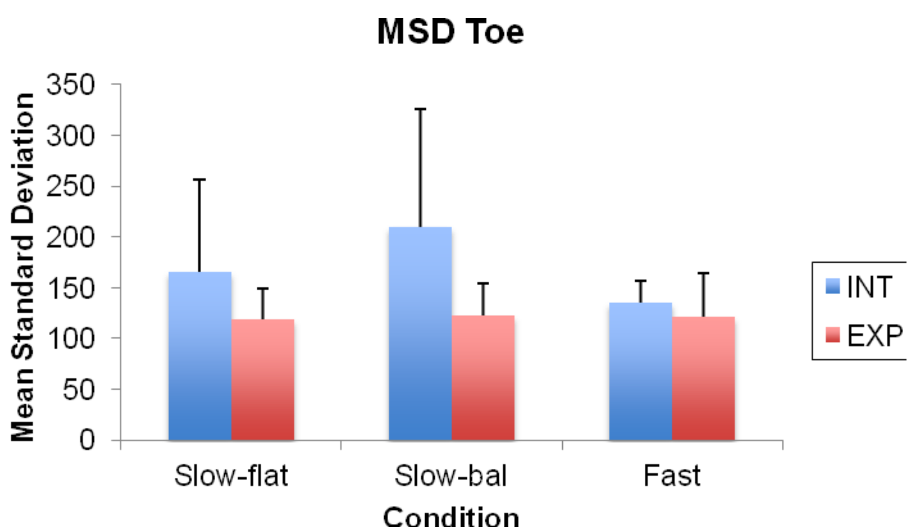
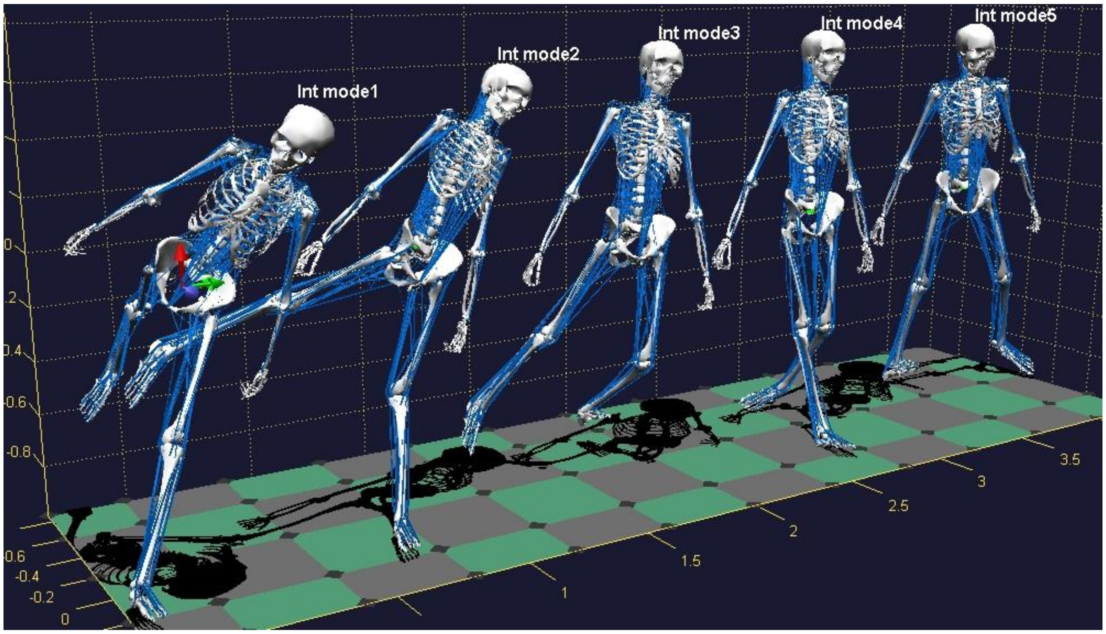


Fig. 4 Mean standard deviation (MSD) (SD) for 3-D segmental coordination. A) 3-D pelvis-hip angle-angle; and B) 3-D toe displacement (INT group blue, EXP group red).

A.



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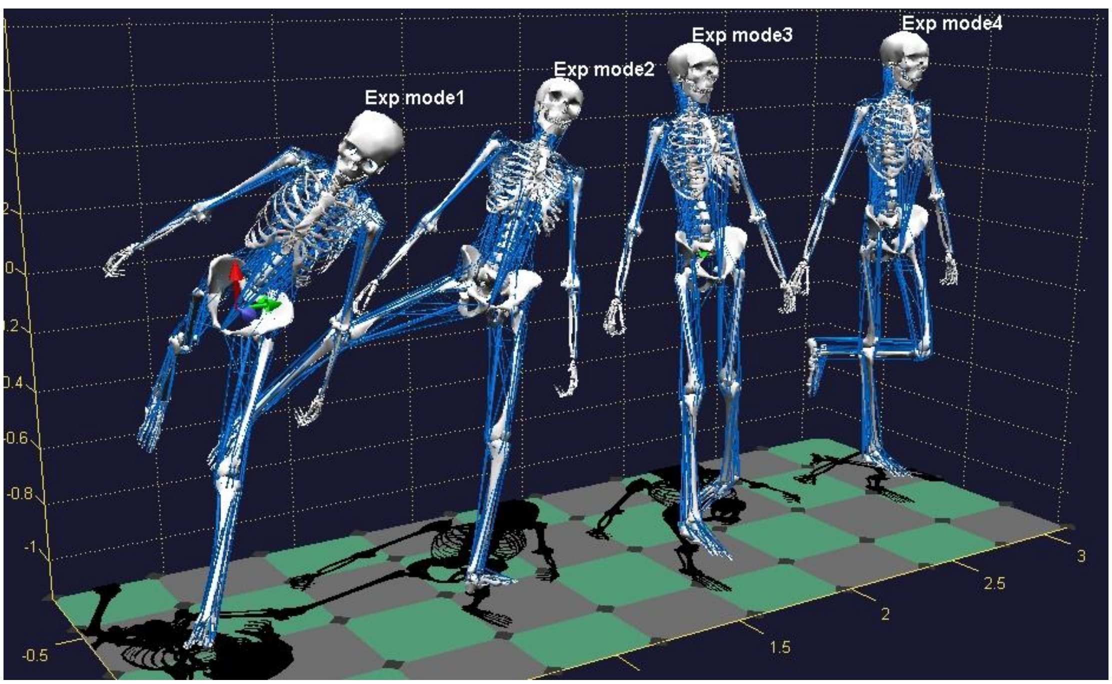


Fig. 5 Principal components. A) Examples of the five modes which accounted for 98% of the variability of the motion of an INT dancer. B) Examples of the four modes which accounted for 98% of the variability of the motion of an EXP dancer.

A.

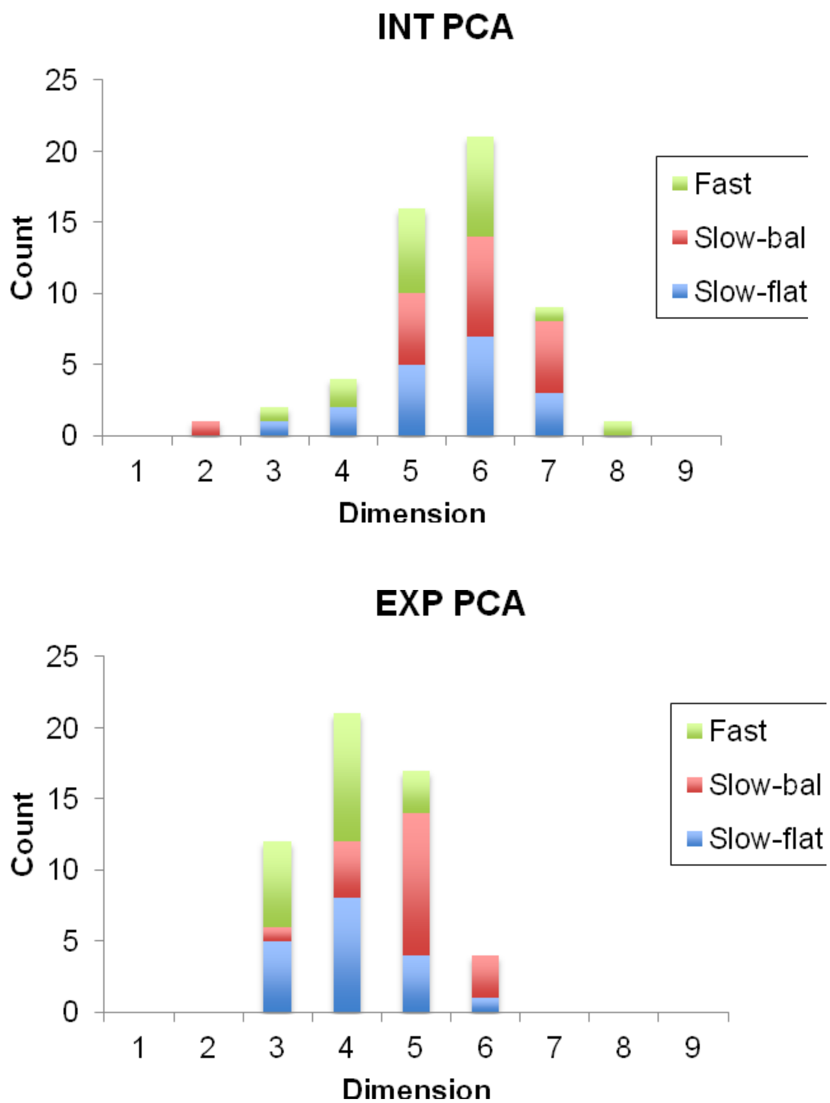
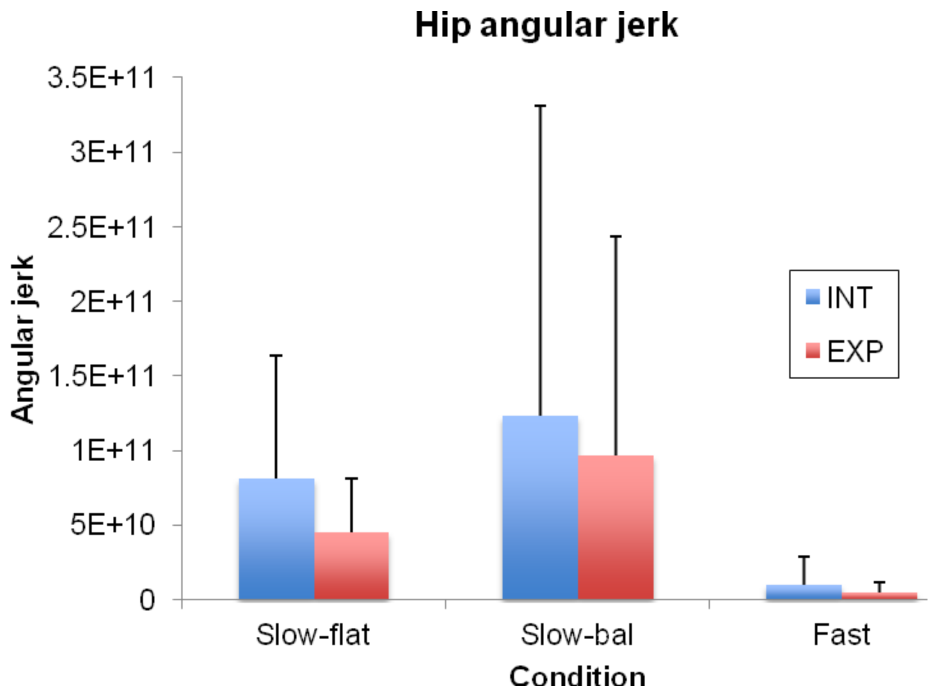


Fig. 6 Principal component analysis. A) Mean dimensionality of the state manifold for the INT group; B) Mean dimension for the EXP group (Blue is Slow-flat, Red is Slow-bal, and Green is Fast condition).

A.



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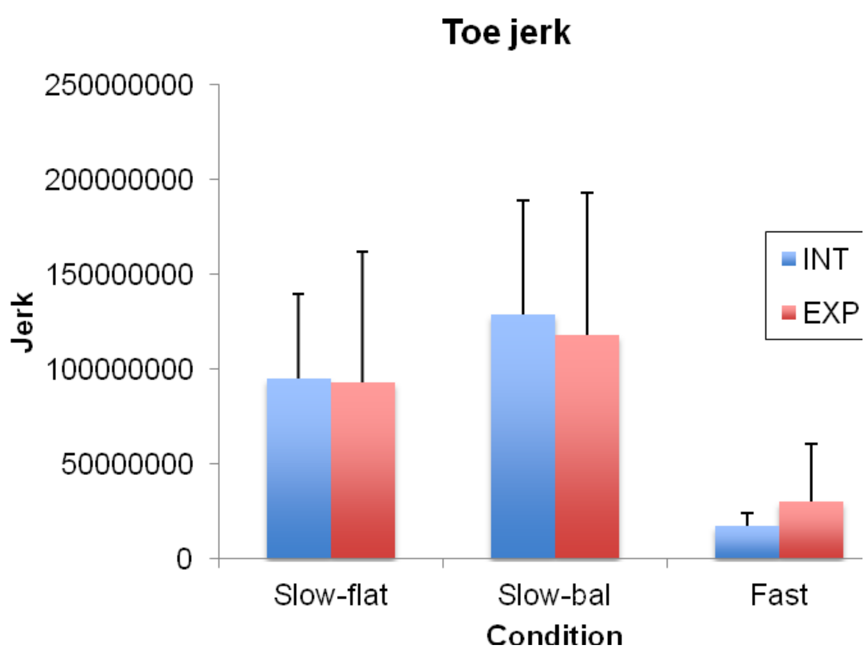

Fig. 7 Mean (SD) dimensionless jerk. A) Sagittal plane gesture hip angular jerk; B) 3-D gesture toe jerk (INT group blue, EXP group red).

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