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INFLUENCE OF MUSICAL FEATURES ON CHARACTERISTICS OF MUSIC-INDUCED MOVEMENTS

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ABSTRACT

Music has a close connection to both sound and movement. These relations have been more extensively investigated with respect to music production than for music perception. In particular, there is a lack of research on how musical features affect the characteristics of music-induced body movements. This study aims at investigating this relationship by analyzing these kinds of movements in relation to the musical stimuli that induced the movements. Participants were presented with 30 short excerpts of popular music and were asked to move to the music. Their movements were recorded with an optical motion capture system. Subsequently, 55 movement and 44 musical features were extracted from the respective data. We performed Principal Component Analysis on the movement data to reduce the number of relevant features and correlated the resulting five Principal Components scores with the musical features. The outcome of this analysis suggests that a clear pulse in the music tends to increase the overall amount of movement, as it might be encouraging to move to. Music with a clear rhythmic structure in the low frequency range seems to make people move much on the spot, while a less clear structure in this frequency range rather tends to let people wander around, as if they were "searching for the beat". The outcome of this study indicates that musical features influence bodily movement to a great extent.

1. INTRODUCTION

Music seems to have a tight link not only to acoustic but also to body-related features, as stated in the embodied music cognition approach (e.g. Leman, 2007). Body movements are a crucial part in the production of music since they are required in order to play an instrument, but instrumentalists also perform additional movements that are not needed for the actual sound production, for instance movements that support emotional expressivity (Wanderley et al., 2005; Thompson & Luck, 2008). However, it seems that body movements also play a decisive role when humans experience (i.e. listen to) music as there is the observation that music can induce movement also when listening to music (e.g. Keller & Rieger, 2009). Though not making the music by themselves, people tend to move in an organized way to music, e.g. by mimicking instrumentalist's gestures or rhythmically synchronizing with the pulse. One could postulate that our bodily movements might help parse the structure of the music.

A large body of research has been conducted on listeners' abilities to synchronize to musical (or beat) stimuli through finger or foot tapping (for a review see Repp, 2005). Zentner and Eerola (2010) have been investigating toddler's abilities to bodily synchronize with musical stimuli. Toiviainen et al. (in press) investigated how music-induced movement exhibited pulsations on different metrical levels, finding that eigenmovements of different body parts were synchronized with different metric levels of the stimulus. Dance is as well taken into account; Stevens et al. (2009), for example, studied movements of professional dancers. However, there seems to be a lack of research performed on people, who do not have a professional musical or dance background but still listen, experience and react to music by using (spontaneous) whole body movements. Luck et al. (2009) started by investigating the influence of individual factors such as personality traits on musically induced movements, but the influence of musical features seems to have been disregarded so far. Although people might exhibit different movements to the same musical stimulus, some commonalities in the movement characteristics might still be observed.

This study aims at investigating the relationship between musical features and features of music-induced movement to music. It is hypothesized that certain musical features, in particular beat-related ones, have an effect on the characteristics of the movements that people perform when listening to music.

2. METHOD

A total of 64 participants took part in the study. Four participants were excluded from further analysis due to being seated or leaving the capture space while recording. Thus, 60 participants remained for subsequent analysis (43 female, 17 male, average age: 24, std. of age: 3.3). All of these participants were students from the different faculties of the University of Jyväskylä, 58 participants were of Finnish nationality. Six participants had a formal background in music education, while four participants had a formal background in dance education. Participation was rewarded with a movie voucher.

They were presented with 30 musical stimuli of different popular music genres including Techno, Pop, Rock, Latin, Funk, and Jazz. All stimuli were 30 seconds long, non-vocal, in 4/4 meter, but differed in their rhythmic complexity, pulse clarity and tempo (82-199 bpm, mean: 130 bpm). The stimuli were presented in random order for each participant.

The participants' movements were recorded using an eight-camera optical motion capture system (Qualisys ProReflex) tracking at a frame rate of 120 Hz the locations of reflective markers attached to each participant. This technique produces a highly accurate, 3-dimensional representation of the performed movements. The musical stimuli were played back via a pair of Genelec

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loudspeakers using a Max/MSP patch running on an Apple computer. The room sound was recorded with two microphones hanging above the participants at approximately 2.5m. This microphone input, the direct audio signal of the playback, and the TTL pulse transmitted by the Qualisys cameras when recording, were recorded using ProTools software in order to synchronize the motion capture data with the musical stimulus afterwards. Four Sony video cameras were used to record the sessions for reference purposes.

The participants were equipped with 28 reflective markers. The locations of the markers can be seen in Figure 1a. After attaching the markers, we ensured that they were not inhibiting the participants' mobility, and that the participants were comfortable with the apparatus and setting. The participants were asked to remain in the centre of the capture space indicated by a 115 x 200 cm carpet.

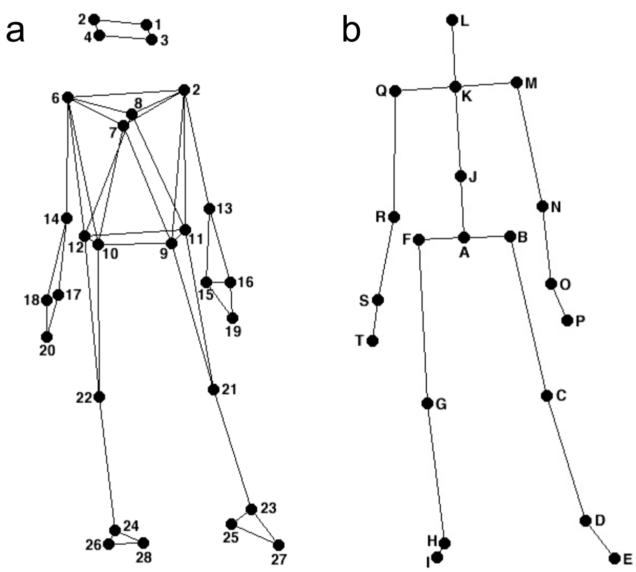

Figure 1: a) Anterior view of the location of the markers attached to the participants' bodies. **b)** Anterior view of the locations of the secondary markers/joints used in the analysis.

The participants were asked to move in a way that felt natural to the stimuli presented. Additionally, they were encouraged to dance if they wanted to. Each participant was recorded individually. After the recording session, the participants were asked to fill in a questionnaire about their current mood, affect, and emotional state, and about their background concerning music, dance and sport activities.

3. RESULTS

The first step of the data processing was to extract the relevant movement data, disregarding all movement that was performed when no music was playing. This was done by trimming the movement data using MATLAB based on the relation of TTL pulse and audio recording. In order to extract various kinematic features, using the MATLAB Motion Capture (MoCap) Toolbox (Toiviainen 2008) a set of 20 secondary markers, subsequently referred to as joints, was derived from the original 28 markers. The locations of these 20 joints are depicted in Figure 1b. The locations of joints C, D, G, H, M, N, P, Q, R, S, and T are identical to the locations of one of the original markers, while the locations of the remaining joints were obtained by averaging the locations of two or more markers. Subsequently, the data was transformed to a local coordinate system, in which the location of the each joint was expressed in relation to the location of the midpoint of the hips (Joints B and F).

Kinematic variables such as instantaneous velocity, acceleration, and jerk of various body parts were estimated from the joint location data using numerical differentiation. Additionally, instantaneous kinetic energy was estimated using body-segment modeling (see Toiviainen et al., in press). Subsequently, the instantaneous values of each variable were averaged for each stimulus presentation. This yielded a total of 55 postural, kinematic, or kinetic features for each of the 60 participants and 30 stimuli.

To the feature matrix, we applied Principal Component Analysis to reduce the number of relevant features and to group them. Using the Kaiser's criterion, we ended up with five Principal Components (PCs), which contained a total of 90.3% of the variance. Table 1 presents a characterization of the kinematic features that appeared to have a high influence on each of these PCs.

PC No.	Component Characterization	Variance
1	Amount of Local Movement	74.6%
2	Amount of Global Movement	6.8%
3	Hand Flux	4.0%
4	Head Speed	2.6%
5	Hand Distance	2.1%

Table 1: Characterization of the five Principal Components obtained from the kinematic variables.

The first Principal Component explains a great amount of variance. Nearly all the kinematic features (highest loadings of features containing acceleration and jerk of different body parts) contributed to this component, so we called it Amount of Local Movement. The second PC had high loadings from features that characterize the area covered by the movements and was thus named Amount of Global Movement. For the third PC, the hand related speed, acceleration, and jerk features were most dominant, so we labeled it Hand Flux. The fourth PC was related to the Head Speed, and the fifth component received Hand Distance as the most pertinent feature. Figure 2 displays three-second movement traces for the performances that received the highest score for each Principal Component.

Subsequently, 44 musical features related to tempo, pulse clarity, spectral flux, attack, timbre, and pitch were extracted from the stimuli using the MATLAB MIRToolbox (Lartillot & Toiviainen, 2007), again resulting in one averaged value for each feature per stimulus.

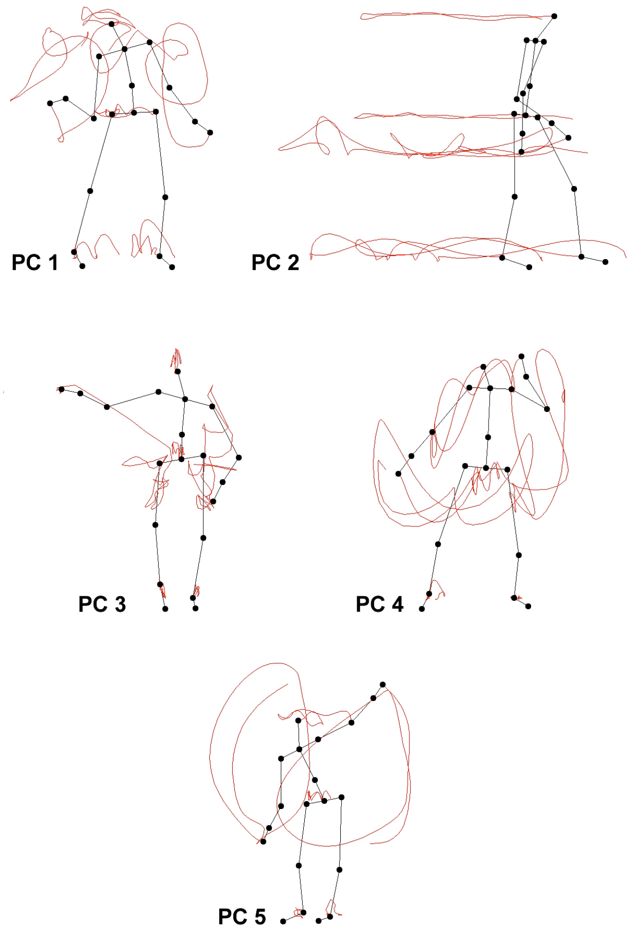

Figure 2: Three-second movement traces for the performances that received the highest score for each Principal Component. The following joints were taken to visualize the traces: L (head), A (center of mass), P/T (fingers), and I/E (feet).

We continued the data analysis by correlating the scores of the five PCs, averaged across participants, with each of the 44 musical features. The musical features that appeared to have the highest correlation with each PC are shown in Table 2.

PC No.	Musical Feature
1	Fluctuation Entropy (r = -.61)***
2	Sub-Band 2 Flux (r = -.63)***
3	Fluctuation Entropy (r = .56)**
4	Mode (r = .57)***
5	Maximum Key Strength (r = .61)***

Table 2: Highest correlation of each PC with musical features. (*** p<.001, ** p<.01)

The first Principal Component showed the highest (negative) correlation with a feature called Fluctuation Entropy. The Fluctuation (Pampalk et al. 2002) describes the strengths of rhythmic periodicities contained in the signal. By calculating the entropy of this distribution, a measure for metric “disorder” of the signal is obtained. Thus, the higher the entropy, the more periodicities are present in the signal. Accordingly, the lower the entropy, the clearer the periodicity is and the easier it is to perceive the beat. The negative correlation indicates that the participants moved their whole body significantly more, faster, and jerkier when the periodicity of the signal was clear.

The second PC has the highest correlation with the Spectral Flux of the second Sub-Band (Alluri & Toiviainen, 2009). In order to extract this feature, the stimulus is divided into 10 frequency bands, each band containing one octave in the range of 0 to 22050 Hz. For each of these ten bands, the spectral flux was calculated as the Euclidean distance between the corresponding sub-spectra of successive frames of the signal. For a more detailed description of the feature see Alluri & Toiviainen (2009). The second sub-band corresponds to the frequency range of 50-100 Hz, which is basically the frequency region of kick drum and low bass guitar, i.e. of the “rhythm section”. The negative correlation of Flux of Sub-Band No. 2 and Principal Component 2 – Amount of Global Movement – suggests that the participants moved faster and used more space when the stimulus did not contain much spectrotemporal change in this sub-band and vice versa.

Principal Component 3, the Flux of Hands, was again found to correlate highest with Fluctuation Entropy, though this time positively and less strongly than the highest correlations of PC 1 and 2 with their respective features. Thus, participants tended to move their hands more, especially in a more accelerated and jerky fashion, when the pulse was not clear.

Principal Component 4 exhibits the highest correlation with the Mode of the stimulus. More specifically, the stronger the major characteristic of the stimulus, the faster the participants moved their heads.

Finally, the fifth Principal Component – the Hand Distance – achieved the highest correlation with the musical feature Maximum Key Strength. The Key Strength estimates the probability of each key to be the key of the given stimulus. The maximum value is then taken to retrieve the most probable key candidate. The higher this value is, the stronger/clearer the key is distinguishable. The positive correlation with PC 5 suggests that the clearer the key is, the wider the hands are apart from each other.

4. DISCUSSION

We investigated the influence of musical features on music-induced movements. Participants were asked to move to 30 short excerpts of popular music while being recorded with an optical motion capture system. Subsequently, 55 movement and 44 musical features were extracted from the respective data. We performed Principal Component Analysis on the movement data and correlated the Principal Components with the musical features. The results indicate that certain musical features influence features of music-induced movements to a great extent.

Stimuli containing low Fluctuation Entropy tended to increase people’s Amount of Local Movement, meaning acceleration, jerk, and speed of various body parts in all three dimensions, which suggests that music with few periodicities, i.e. a clear beat that is easy to recognize, makes people move their limbs. Music with high Fluctuation Entropy, containing many periodicities, caused the participants to move less accentually as the rhythmic complexity deterred their ability to perceive a clear beat.

Moreover, the amount of variation in the frequency range of 50-100 Hz (Sub-Band No. 2 Flux) appeared to influence the Amount of Global Movement. Music that varied a lot in this frequency range, i.e. having a strong and eventful rhythm, tended to let participants move slower and more on the spot than music with less variation in the low Sub-Bands. In the latter case, the participants were more wandering around and using the whole capture space, as if they were "searching for the beat".

The positive correlation between Hand Flux and Fluctuation Entropy suggests that, in the absence of a clear beat, the participants made wider and more irregular movements. It can be speculated that the participants were trying to find or identify the beat with their hands when they could not perceive one single clear beat.

The correlation of Head Speed and mode is an interesting one, for which we could not find any convincing explanation yet. Stimuli with a more major character seem to make the head move faster. This feature, however, needs more detailed analysis before any conclusions can be drawn.

The correlation of Hand Distance and Maximum Key Strength is interesting as well. The clearer the key the wider the hands, thus it might be the case that participants used their hands more when the key was clear, whereas kept them closer and fixed to the body when the key was less clear.

This study proposes several relations of musical features and music-induced movements. In particular, it suggests that a clear beat seems to increase the amount of movement of limbs, and high changeability in the low frequency range seems to make people move more on the spot. These features could excite (specific) movements, as it might be more stimulating to move or easier to synchronize to the music. However, these relations still require more profound analysis, both investigating more thoroughly the correlation structure between the musical features and the Principal Components. Rhythm and synchronization aspects should be taken into account as well to find out more about influence of Fluctuation Entropy and low Sub-Band Flux.

5. AUTHORS' NOTE

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