Dance Tempo Estimation Using a 3D MEMS Accelerometer

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***Abstract*— Being an engaging physical activity, creative dance requires high levels of particular skills and body motion control. Automatically detecting dancing tempo has the potential of supporting many practical applications, from assessing dance move timing and overall performance to monitoring progress in the learning process. In this article, we present and evaluate a dance tempo estimation methodology that resides on a single, orientation independent, leg-attached 3D MEMS accelerometer. As the solution avoids using video cameras or IR imaging sensors, it is computational efficient, user-friendly and applicable for a variety of dancing situations - when the dancer is dancing alone, in the crowd, or in front of an audience. We focus our attention on Solo jazz dancing. Initial validation performed for a professional dancer dancing at seven different tempos ranging from 120 to 240 bpm with a 20 bpm tempo increment showed that the methodology is accurate up to 0.5 bpm. Further investigation, including different professional and amateur dancers, dancing following actual jazz music and not only metronome tempo is necessary in order to fully evaluate the presented methodology.**

I. Introduction

As an engaging physical activity, also cultivating capacities for expression and communication, dancing requires a high level of particular skills and body motion control. While dancing, the dancer creatively chooses various moves to perform, following the musical rhythmic structure. It has already been reported that hobbyist dancers strongly benefit from various dance assistance technologies.

In particular, assessing dance move timing has the potential of supporting many practical applications, from monitoring progress in the learning process, and overall performance, to classifying individual style and observing differences when dancing alone, in pair or in the presence of an audience. It can benefit professional as well as hobbyist dancers.

In the area of human motion recognition, classification, and analysis research, over the last years, it has been consistently demonstrated that inertial microelectromechanical (MEMS) inertial sensors (accelerometers and gyroscopes) are an efficient tool. Unlike using video cameras or IR imaging sensors, solutions based on inertial sensors are computational efficient, easy-to-use, user-friendly and applicable for a variety of situations.

We formulate our research question as the following: how efficient are inertial sensors when used for estimating dancing tempo? Specifically, we want to provide a practical, user-friendly solution not interfering with the dance performance itself. We investigate a dance tempo estimation methodology that resides on a single, orientation independent, leg-attached 3D accelerometer. As the solution avoids using video cameras or IR imaging sensors, it is computational efficient, user-friendly and applicable for a variety of dancing situations - when the dancer is dancing alone, in the crowd, or in front of an audience; moreover, as the orientation of the sensor is arbitrary, it is easy to use by the end user on an every-day basis.

In particular, we focus our attention on Solo jazz moves. Solo jazz dance is a rhythmic and playful solo dance in which the dancer depicts jazz music through one's one movement. It evolved through the first half of the 20th century to include elements of both Africanist and European dance and is mainly characterised by improvisation, syncopated (deviating from the regular) steps and rhythms, call and response to music, all while featuring the vocabulary and steps of the vernacular jazz tradition.

The number of steps a dancer performs in minutes represents the dance tempo and is directly related to the musical tempo of the song. As a rule, each step is performed during one musical tatum period, i.e. the smallest time interval between successive notes in the musical rhythmic phrase, corresponding to the fastest tempo of the song.

As a rule, Solo jazz is danced to jazz music with tempo anywhere between 100 and 250 beats per minute [bpm]. Tempos between 130 and 160 bpm are considered medium. Tempos above 220 bpm are considered fast and usually involve contrasting Charleston moves to dragging steps and improvisations.

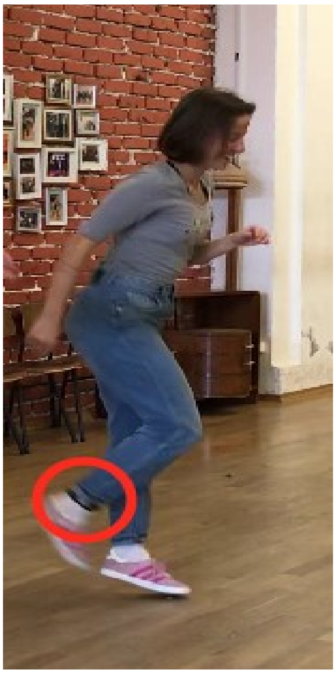

Figure 1. Position of the 3D MEMS accelerometer on the dancer's right leg ankle.

The variability of the eight included dancing steps brings to a pleiad of predefined authentic Solo jazz dance moves.

A. Related Work

One of the first wireless systems for capturing dance gestures were developed by the MIT Media Lab and have been mounted on the toe and heel [1][2]. In [1] authors present the design and implementation of expressive footwear capable of recording foot 3D acceleration and angular velocities at a sampling frequency 50 Hz. In [2] authors present a design of a wireless, wearable network of 6-axis inertial measurement units for interactive dance ensemble.

The Shadow dancer interface [3] is based on shoe-integrated force sensors that enable the dancer to interact with sounds and images.

In [4] authors present Saltate!, a wireless system that acquires data from force sensors mounted under the dancers' feet, detect steps, and compares their timing to the timing of beats in the music playing. For detected mistakes, the system emphasises the beats acoustically to help dancers stay in sync with the music.

In [5] authors present a prototype mobile app that tracks students' motion data whilst they practise dance exercises.

Accelerometers are used to assess postural sway in ballet dancers during first position, relevé, and sauté [6] and to assess performance of basic routines in classical ballet [7].

Additional approaches to dance motion capture and analysis avoid any body-worn hardware but rather exploit either computer vision, processing either video from one or more cameras watching the stage [8]-[12] or signals obtained from a Kinect system [13]-[18].

II. Methodology

Dancing tempo, denoted with υ, representing the number of steps a dancer performs in minutes, is directly related to the tempo of the song. As a rule, one dance step is performed during one musical tatum period, i.e. the smallest time interval between successive notes in a rhythmic phrase, corresponding to the fastest tempo of the song. Eight steps are combined into a full dance move and danced to the musical rhythmic phrase.

To capture dance motion, a 3D MEMS accelerometer is positioned just above the dancer's right ankle, as illustrated in Fig. 1. In particular, for our analysis, motion signals were acquired using a Metaware wearable device produced by mbientlab [19].

The micro- position and orientation of the sensor is arbitrary as it proved to not affect the results. The device itself is calibrated and the acquired signals are compensated for sensor inaccuracies including output bias drift, inaccurate sensitivities and alignments of the sensor sensitivity axes.

3D acceleration is captured with a sampling frequency f_s = 200 Hz, which proved to be sufficient for the problem at hand using empirical observations. Signals are obtained at equal equidistant time samples $T = 1/f_s = 0.005$ s. Signals acquired this way are further filtered using a low-pass filter with a cut-off frequency f_{co} = 20 Hz to remove motion artefacts.

Since the eight steps of a Solo jazz move are performed iteratively with the right and left leg the smallest inter step onset interval for a single leg is equal to half of the dancing tempo frequency. Measuring T_{step} in seconds, we can write:

$$\upsilon = \frac{120}{T_{step}} = 120 f_{step}. \quad (1)$$

For dancing tempos υ between 100 and 240 bpm, the basic frequency of the right leg step $T_{step} = 1/f_{step}$ is between 0.83 and 2 Hz.

For detecting the dancing tempo we use a comb feedback filter bank with the first peak of the frequency response f_{comb}, increasing uniformly from 0.83 to 2 Hz, representing the considered 100-240 bpm dance tempo range. Opting for the comb feedback filter is argumented by it's frequency response, which is f_{comb} periodic. This periodicity enables us to extract the dancing steps' basic frequency and the higher harmonics.

For each sequence of signals to be checked for dance moves, we normalize to zero mean all three acceleration signals. We feed each filter in the bank with these three normalized acceleration signals. We assign a fixed gain alpha to each filter in the bank. Overall best results were obtained with a gain factor of 0.7. For each filter in the bank, the energy of the output is computed cumulatively across all three acceleration signals. When the comb filter is tuned to the dancing tempo, i.e., when f_{comb} and f_{step} match, the energy of the comb filter output is the highest. Considering this, the dancing tempo is finally estimated as the frequency of the filter with the highest energy output response.

III. Results and Discussion

We performed initial validation of the presented methodology for a professional dancer dancing at seven different tempos ranging from 120 to 240 bpm with a 20 bpm tempo increment:

$$\upsilon_i = 120 \text{ bpm} + i\,20 \text{ bpm}; \quad 0 \le i < 7. \qquad (2)$$

The tempo was dictated by a metronome.

For each tempo, the dancer performed around 40 dance moves. The tempo obtained using the presented methodology

For all considered tempos υ_i, the result obtained using the presented methodology deviated from the metronome dictated tempo for less than 0.5 bpm.

Further investigation, including different professional and amateur dancers, dancing following actual jazz music and not only metronome tempo is necessary in order to fully evaluate the presented methodology.

ACKNOWLEDGMENT

This research was funded by Javna Agencija za Raziskovalno Dejavnost RS: P2-0246.

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