https://doi.org/10.1145/2968219.2968261

A System to Support the Learning of Movement Qualities in Dance: a Case Study on Dynamic Symmetry

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Ubicomp/ISWC'16 Adjunct , September 12-16, 2016, Heidelberg, Germany
ACM 978-1-4503-4462-3/16/09.
http://dx.doi.org/10.1145/2968219.2968261

Abstract
In this paper, we present (i) a computational model of Dynamic Symmetry of human movement, and (ii) a system to teach this movement quality (symmetry or asymmetry) by means of an interactive sonification exergame based on IMU sensors and the EyesWeb XMI software platform. The implemented system is available as a demo at the workshop.

Introduction
Recently we proposed a conceptual framework for the analysis of expressive qualities of movement, illustrated in Figure 1 and described in detail in [4]. It consists of four layers, ranging from physical signals to high-level qualities and addresses several aspects of movement analysis such as different spatial and temporal scales. In particular, the framework applies to dance performance. In the framework, features computed at lower layers and closer to physical aspects, contribute to the computation of the features at higher levels, that are usually related to perceptual and more abstract concepts. Furthermore, at Layer 2 low-level motion features are computed at a small time scale (i.e., observable frame by frame) whilst features at Layer 3 are usually extracted on groups of joints (or the whole body), and require longer time periods to be observed. The framework was developed within the EU-H2020 ICT

Project DANCE[1], which aims at analyzing the affective and relational qualities of body movement and at investigating how sound and music can represent and express them.
In this paper, we propose a computational model of Symmetry, a movement quality that is considered important in dance teaching [5], and in general in learning movement. Symmetry can be considered at two different levels of our conceptual framework. Low-level *Postural Symmetry* (Layer 2 in the framework) can be described in terms of the shape of the body silhouette with respect to an axis or plane (e.g., vertical). It can be computed from the dancer's silhouette in 2D or in 3D (including depth measurement from RGB-D sensors) or in terms of a cluster of body markers in a motion capture setting. Instead, if we take into account also the dynamic and temporal dimensions, we can define *Dynamic Symmetry* as a higher-level feature (Layer 3 in the framework) by considering the coordination and dynamics of parts of the body. *Dynamic Symmetry* is an important aspect of several physical activities for example in sport (e.g., synchronized swimming, rowing), and in motoric rehabilitation. In this paper, however, we focus on dance performance. The ability to maintain the dynamic symmetry (but also dynamic asymmetry) is a very important especially in contemporary dance.

The objective of this paper is twofold: (i) to present an algorithm based on data from Inertial Measurement Unit (IMUs) to extract in real-time Dynamic Symmetry in terms of movement, jerkiness and kinetic energy; (ii) to present the resulting implementation in a serious game to teach dynamic symmetry and asymmetry of limbs in dance.

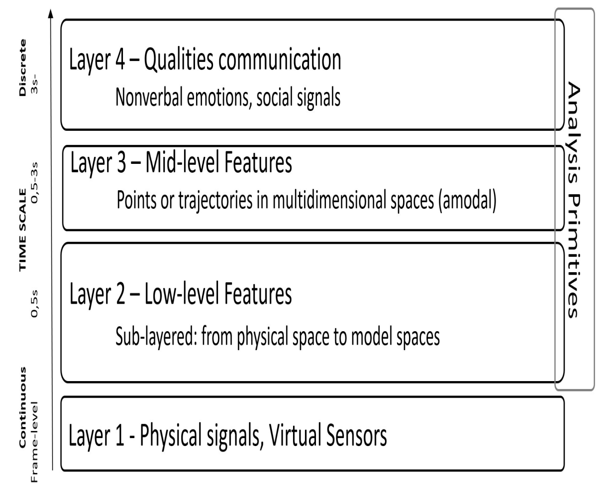

Figure 1. A conceptual framework for the analysis of movement expressive qualities.

IMU-based Dynamic Symmetry Algorithm

We compute Dynamic Symmetry from IMU data. The data can be extracted from sensors located on two different dancer's body parts (e.g., on the dancer's wrists, or ankles) or on two dancers (e.g., on the dancers' heads). We present an algorithm in which IMUs are placed on a single dancer's wrists.

We consider the two IMUs H^R and H^L, placed, respectively, on the dancer's right and left wrist. IMUs, embedded in mobile phones or other wi-fi devices like x-OSC [3], provide the linear accelerations $H^R_{Lin_{x,y,z}}$ and

1 http://dance.dibris.unige.it

$H^{L}_{Lin_{x,y,z}}$ of, respectively, the dancer's right and left hand along the *x*, *y*, and *z* axes. Linear acceleration corresponds to the acceleration detected by the device without gravity.

First, we compute two low-level movement features:

- *Jerkiness* – at time t, hands linear accelerations $H^{N}_{Lin_{x,y,z}}(t)$ with $N\epsilon\{R,L\}$ are read; we compute the squared jerk of the dancer's hands by deriving the linear acceleration components:

$$J^N = \left(\frac{\mathrm{d}H^N_{Lin_x}}{\mathrm{d}t}\right)^2 + \left(\frac{\mathrm{d}H^N_{Lin_y}}{\mathrm{d}t}\right)^2 + \left(\frac{\mathrm{d}H^N_{Lin_z}}{\mathrm{d}t}\right)^2$$

Then, we normalize J^N over a buffer of 20 values:

$$J^N_{tot} = \frac{\sum_{i=1}^{20} J^N_i}{Max(J^N_{tot})}$$

- *Kinetic Energy* – it is computed as the absolute kinetic energy of the dancer's hands (assuming that the mass of both hands is equal to 2, as we skip the 0.5 multiplicative factor in computing kinetic energy):

$$E^N = \left(\int H^N_{Lin_x}\right)^2 + \left(\int H^N_{Lin_y}\right)^2 + \left(\int H^N_{Lin_z}\right)^2$$

  By integrating the linear acceleration components we obtain the velocity components, necessary to compute kinetic energy. As before, we normalize the resulting value:

$$E^N_{tot} = E^N / Max(E^N_{tot})$$

Both the above-mentioned features belong to Layer 2 of the conceptual framework described in Figure 1 and [4].

In the second step, we compute Dynamic Symmetry of movement from the two above-mentioned features as follows:

- for each dancer's hand H^N with $N\epsilon\{R,L\}$:
  - read the value of $H^N_{Lin_{x,y,z}}$
  - compute absolute jerk J^N_{tot} and kinetic energy E^N_{tot}
  - compute the absolute difference of jerk and energy of the two hands:

$$D_J = |J^R_{tot} - J^L_{tot}|$$
$$D_E = |E^R_{tot} - E^L_{tot}|$$

Dynamic Symmetry DS is computed as the minimum between these two differences:

$$DS = Min(1 - D_J, 1 - D_E)$$

The whole algorithm was implemented in EyesWeb XMI [1][2].

An exercise to learn (A)Symmetry in dance

One of the skills a dancer has to learn is a full independence and control of different parts of the body. Full independent control of limbs is of particular interest in contemporary dance. We designed an exercise based on real-time measurement and interactive sonification of the level of Dynamic Symmetry as described in the previous section. This exercise is available in two versions: for an individual dancer and for a teacher-student dyad. We started from a version for 2 IMU sensors (e.g., the onboard IMU of two smartphones or two xOSC wearable sensors). In the individual version of the exercise, the dancer wears the two IMU sensors on her/his left and right wrists. In the teacher-student version, the student and the teacher wear one IMU sensor on the same (or mirrored) wrist: the aim, in this case, is to have the student imitating the teacher, not from the point of view of the exact trajectories of movement, but rather in terms of similarity/symmetry of jerkiness. The amount of Dynamic Symmetry between the two IMU sensors is computed, and this value is mapped to control the parameters of a sonification algorithm, to provide an auditory feedback (through musical rewarding) of the level of coordination, symmetry, and synchronization achieved with the arms.

The sonification mirrors on the auditory domain the degree of Dynamic Symmetry coming from movement analysis. Symmetries are repetitions in space as periodicities are repetitions in time. A way to convey Symmetry in the auditory channel is to spectrally stretch a harmonic spectra, which may be regarded as a symmetric entity in which its components are distributed at a distance of integer multiples of a fundamental. If we alter this relationship as if we were stretching an elastic body, we can break this spectral symmetry and partials will not fuse anymore in one single pitch with equally spaced components. A similar approach may be carried in the time domain, waving between a periodic sound and sounds with no or little periodicity, using complex ring modulations or using non NSS like Dynamic Stochastic Sound Synthesis Concatenations. Sonification aims at augmenting the proprioception of the level of Dynamic Symmetry (or asymmetry, according to the objectives of the learning experience) between arms (individual case), or the level of imitation of the quality (teacher-student).

Implementation

An EyesWeb XMI implementation of this exercise has been developed in the framework of the EU-H2020 ICT Project Wholodance. A demo will be available to be experimented and evaluated by workshop participants. In the future, we aim to carry out further evaluation studies involving external observers rating the level of dynamic symmetry they perceive in the student and teacher movements, comparing the human ratings with the output of the Dynamic Symmetry algorithm.

Acknowledgement

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement 688865 Wholodance.

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