Dance style analysis using Laban descriptors

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ABSTRACT
UPDATED—10 June 2020. Motion Capture (mocap) data from different dance styles (bachata, capoeira, reggaeton and salsa) will be analyzed using Laban movement analysis to study the unique characteristics that in fact, make a concrete dance belong to a particular dance style objectively speaking.

Author Keywords
Laban notation, analysis, MATLAB, Mocap, dance style

MOCO PAPER SUMMARY

This mini project is based on the MOCO paper *Folk Dance Evaluation Using Laban Movement Analysis* [1]. In it, motion capture technology is analyzed and a framework based on the principles of Laban Movement Analysis (LMA) aims to identify style qualities in dance motions. LABAN feature space plus kinematic descriptors can be subsequently used for motion comparison and evaluation. A user's movements are captured and compared to the folk-dance template motions to evaluate its dance performance.

INTRODUCTION

For the Laban analysis of dance styles, the Dance Motion Capture Database [2] was used extracting the dance styles that had more samples. Afterwards, the files were modified so MATLAB® Motion Capture Toolbox (Mocap) [3] were able to analyse them. Finally, kinematic and LABAN descriptors were applied on a set of joints to extract relevant data to differentiate each dance style and its further analysis and possible classification.

REVIEW OF RELEVANT LITERATURE

About dance style

In order to analyze styles of dance, we must clarify beforehand what we understand by "dance style". Style seems to refer to persistent patterning in ways of performing structure, from subtle qualities of energy to the use of body parts as recognized by people of a specific dance tradition [4]. Having this defined, the different dance styles that are going to be studied are assumed to present different patterns and movement qualities which make them unique.

LABAN Movement Analysis

The movement of the human body is complex and it is not possible to completely describe the hu- man movement language if rough simplifications in motion description are used or if motion has not been properly indexed from the outset. Laban Movement Analysis (LMA) (Maletić, 1987) is a multidisciplinary system which incorporates contributions from anatomy, kinesiology, and psychology and which draws on Rudolf Laban's theories to describe, interpret and document human movements; it is one of the most widely used systems of human movement analysis and has been extensively used to describe and document dance and choreographies over the last century [5].

LABAN and dance analysis methods

The LABAN systems' sound theorical base and its flexibility of application make it a significant method for dance analysis in research [6].

Also, LABAN has been used in many researches for quality motion recognition, used in combination with other non-linear systems for training and classification, such as Hidden Markov Models [7], recursive neural networks [8], random forests, Extremely Randomized Trees, Support Vector Machines [9]. Isomatic technic is also a popular method for this data visualization [10].

For linear classification, one of the most common linear projection methods is Principal Component Analysis (PCA). Linear methods, however, fail to capture important nonlinear structure in the data.

Non-linear/linear classification methods for classification are not developed due to the time limitations of this project.

About LABAN descriptors

There is no consensus on which descriptors characterize best motion quantities and qualities [11].

These descriptors can be defined at various temporal and spatial resolutions: the temporal resolution may be limited to a single frame or may cover a sequence of frames; the spatial resolution may represent one joint (e.g., end-effector joints), a set of joints (e.g., the hand-arm system) or the whole body (postures).

LABAN descriptors election

A subset of the LMA components and representative features that are indicative to capture the motion properties is elected. Due to time limitations, only Effort component and its subcategories are studied as considered one of the most relevant descriptors [11].

The EFFORT component describes the intention and the dynamic quality of the movement, texture, feeling tone, and how the energy is being used on each motion. It comprises four subcategories named EFFORT factors:

Space

Addresses the quality of active attention to the surroundings. It has two polarities: Direct (focused and specific) and Indirect (multi-focused and flexible attention).

Weight

Is a sensing factor, sensing the physical mass and its relationship with gravity. It is related to movement impact and has two dimensions: Strong (bold, forceful) and Light (delicate, sensitive).

Time

Is the inner attitude of the body towards the time, not the duration of the movement. Time polarities are Sudden (has a sense of urgent, staccato, unexpected, isolated) and Sustained (has a quality of stretching the time, legato, leisurely).

Flow

Is the continuity of the movement; it is related to feelings and progression. The Flow dimensions are Bound (controlled, careful, and restrained movement) and Free (released, outpouring, and fluid movement).

IMPLEMENTATION

Dance database

From the Dance Motion Capture Database [2], 2 samples from bachata, capoeira, reggaeton and salsa and 3 from salsa were analyzed. Each sample contains 38 markers in 3D. Each marker number were assigned to a joint and a specific name. Specific notation [markers] was elected for this purpose

# marke	marker name	Description	Group
0	FH	Head left	HEAD
1	RH	Head front	HEAD
2	BH	Head right	HEAD
3	LH	Head back	HEAD
4	CLAV	Clavicula	TORSO
5	esternon	Breastbone (esternór	TORSO
6	C7	Cervical vertebra	TORSO
7	T10	Toracic vertebra	TORSO
8	RBWT	Hip right back	HIP

Table 1. An extract from the markers and name assigned.

To see spatially which number correspond to each marker, Mokka [13] application was carefully employed.

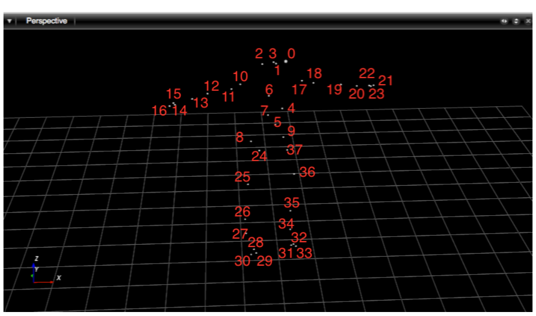

Figure 1. Positions of markers in Mokka

MoCap toolbox for analysis

Once the database is built, it has to be "understood" by MoCap Toolbox in order to execute specific data analysis included functions. Header of .tsv files were cautiously modified to fit the exigencies of the toolbox.

A pre-processing of data was carried out in the database as it has often "burst" errors where adjacent marker samples have null or "0 value". MoCap Toolbox functions were used for re-establishing values substituting these errors by interpolation method.

Body joints

Since the feature space is high dimensional (87 features), it is difficult to visualize the data and understand their properties. Rather than studying joint by joint (consider the high number of possible dimensions), a set of joints representing one body part are elected [1].

Kinematic descriptors

Low-level motion descriptors are either kinematic or dynamic quantities characterizing the evolution of the motion trajectories over time. Features such as velocity, acceleration or jerk are studies when it comes to dance analysis [14]. MoCap Toolbox functions were used for the computation of these descriptors.

LABAN effort

LABAN EFFORT and its subcategories were calculated over the different body parts comprised of various joints. Calculations were carried out following [11] indications for the equations in MATLAB.

RESULTS

Due to the high dimensionality of the results (and not having enough time for implementing an isomap visualization), the most remarkable data extracts from the different body parts are shown below:

Kinematic descriptors

Features such as acceleration, jerk, velocity, covered distance or phase, do not shed much light on to differentiating the dancing styles.

The most outstanding ones are shown below:

Autocorrelation matrix

The enhanced autocorrelation matrix can be plotted as an image to allow visual inspection of the time development of periodicity. The colors provide an indication of the regularity of periodic movement, with warm colors corresponding to regions of highly regular periodic movement. It is calculated on the 3 markers that constitute the body part.

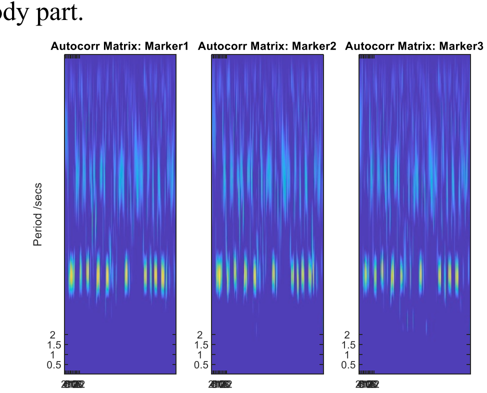

Figure 2. Hips reggaeton Stephanos

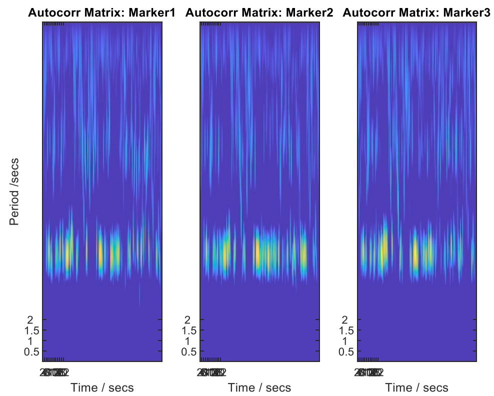

Figure 2. Head reggaeton Vasso

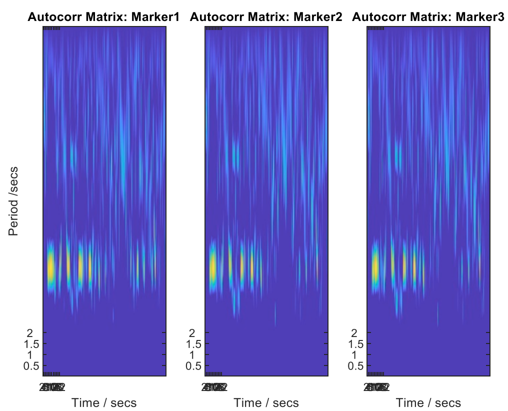

Figure 2. Hand reggaeton Stephanos

These autocorrelation matrices show that there is a great periodicity found in reggaeton genre present even in the different body parts. An autocorrelation that is more unevenly distributed through time in other dance styles.

Marker distances

They are calculated between first and the second joint that form the body part.

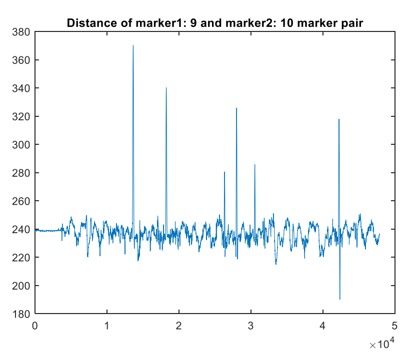

Figure 2. Capoeira 1 hips

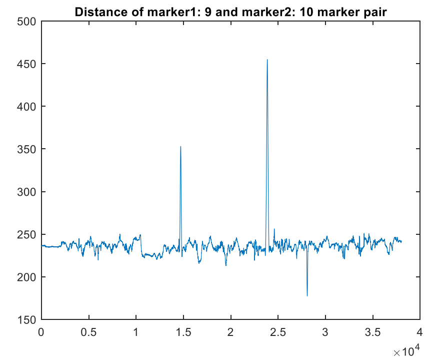

Figure 2. Capoeira 2 hips

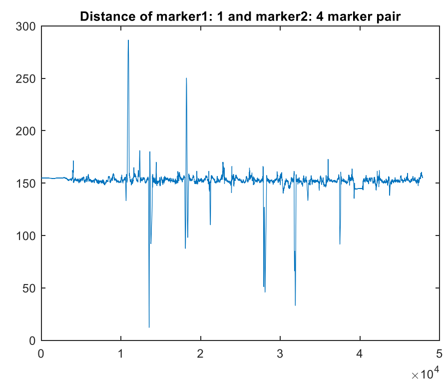

Figure 2. Capoeira 1 head

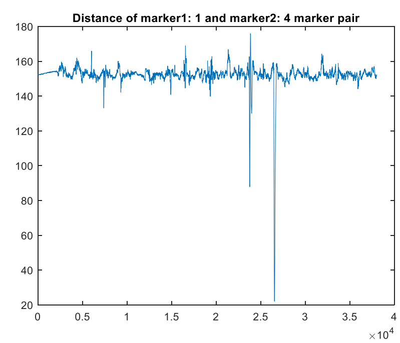

Figure 2. Capoeira 2 head

When it comes to markers distances, capoeira shows a low oscillating mean with big jumps in between. The other dance styles demonstrate a much higher oscillation rate in marker distances.

Periodicity

Estimation of the periodicity of the movement of the markers.

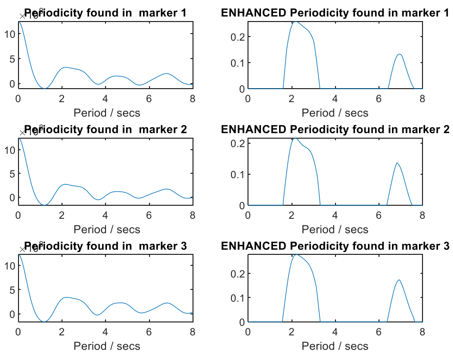

Figure 2. Reggaeton Stefanos head

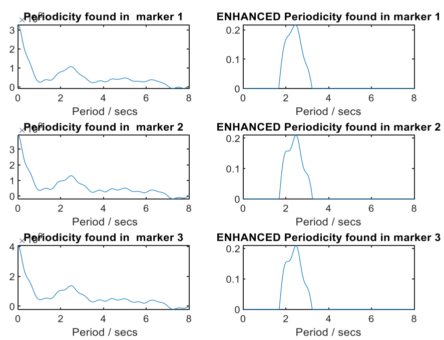

Figure 2. Reggaeton Stefanos hand

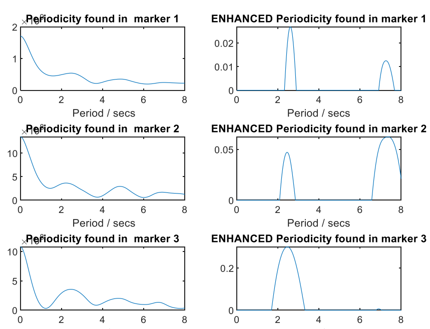

Figure 2. Reggaeton Stefanos hips

In reggaeton, periodicity of markers goes down to around 2s, in comparison with the other dance styles, that are around 4s.

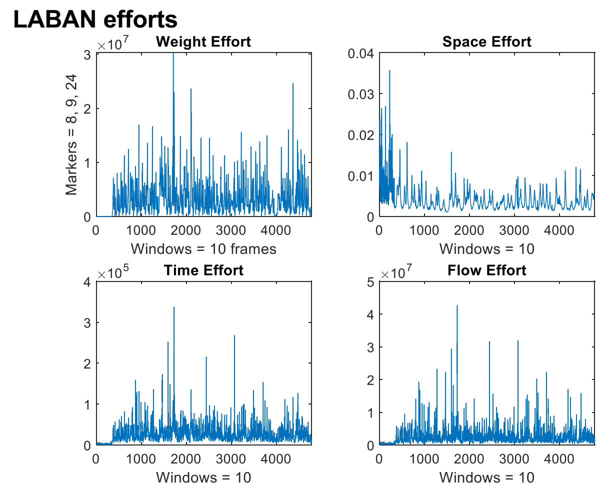

Figure 2. Hip Capoeira 1 efforts

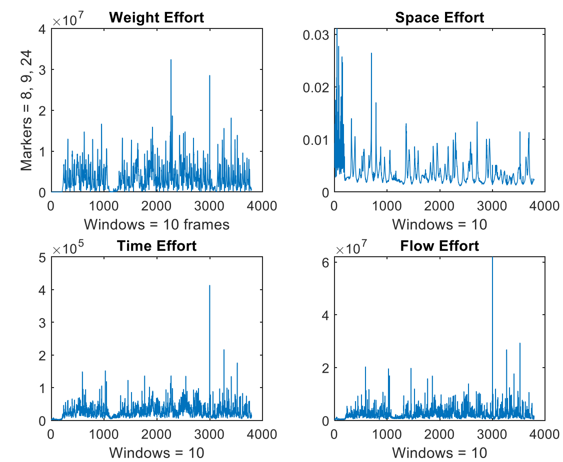

Figure 2. Hip Capoeira 2 efforts

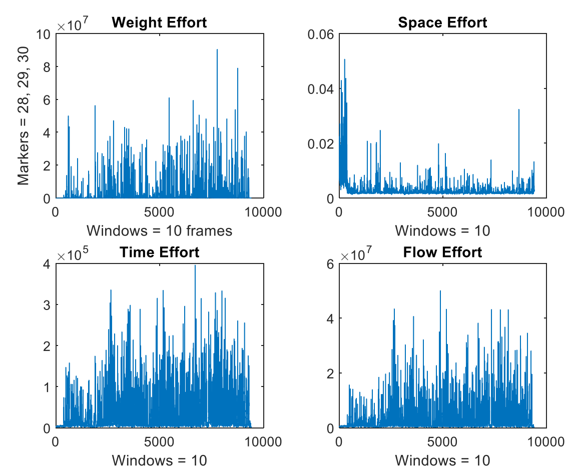

Figure 2. Thorax Salsa Stefanos efforts

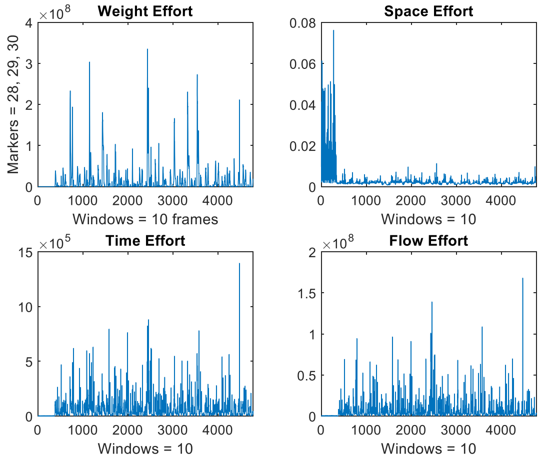

Figure 2. Foot Capoeira 1 efforts

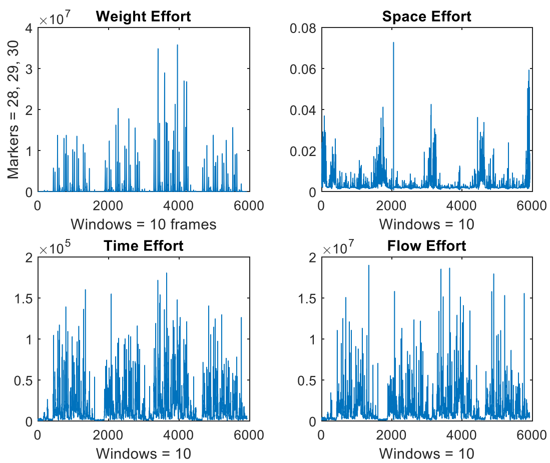

Figure 2. Foot Stefanos 2 Bachata efforts

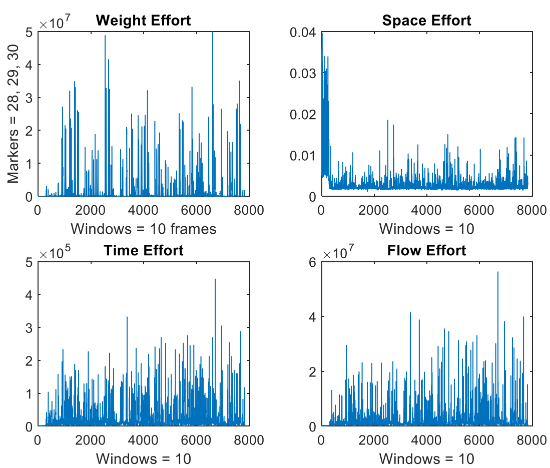

Figure 2. Foot Stefanos Reggaeton efforts

We can highlight some aspects of LABAN efforts: Capoeira time effort for thorax body part has periodic higher peaks than any other dance style. It also has one order more in weigh effort in the y-axis in any other body part. In comparison, salsa has a higher mean for flow effort, like the others dance styles. With respect to foot weigh effort, 2 samples of bachata reach a peak of 6, reggaeton samples reach 5 as maximum, and salsa samples record 10 as top.

DISCUSSION

Results are not showing a definitive difference among all dance styles so we can state a faithful classification of them. Some of the samples display movement qualities that are enough distinctive to differentiate them from other dance styles, such as capoeira, showing that there are clear patterns that we can regard for classification just by looking. However, others are not as clear at first glance.

This project has extracted 4 qualities for each MoCap record for each body part (4*8*6 = 192), which makes a total of 192 graphs. Without dimensionality reduction or isomap visualization this is not a task that a standard pair of eyes can extract the relevant features to distinguish dance styles.

Moreover, studying 3 or less samples (the only available on the database) for each dance style is not a confident way to extract reliable results. Even, some data seemed to be corrupted from the database…

CONCLUSION

Notably different dance styles in terms of LABAN effort (like capoeira can differ from reggaeton) can be distinguished easily at first glance by visualizing LABAN descriptors through time, like weigh or time effort, concluding that there are objective features which characterize movement qualities which are really important, special and unique for each dance style which allows classification and distinction.

The more similar movement qualities are among dance styles, the more difficult is to classify them in different genres (salsa and bachata, for example). Nevertheless, the savior election of movement qualities to analyze, relevant to the movements present in the dance, will improve the right classification.

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