A Novel Tool for Motion Capture Database Factor Statistical Exploration

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ABSTRACT
The recent arise of Motion Capture (MoCap) technologies provides new possibilities, but also new challenges in human motion analysis. Indeed, the analysis of a motion database is a complex task, due to the high dimensionality of motion data, and the number of independent factors that can affect movements. We addressed the first issue in some of our earlier work by developing *MotionMachine*, a framework helping to overcome the problem of motion data interpretation through feature extraction and interactive visualization [20]. In this paper, we address the question of the relations between movements and some of the various factors (social, psychological, physiological, etc.) that can influence them. To that end, we propose a tool for rapid factor analysis of a MoCap database. This tool allows statistical exploration of the effect of any factor of the database on motion features. As a use case of this work, we present the analysis of a database of improvised contemporary dance, showing the capabilities and interest of our tool.

Author Keywords
Movement Analysis; Motion Capture; Motion Feature; Factor Analysis; Statistical Software.

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous; I.4.8. Image Processing and Computer Vision: Scene Analysis: Motion; G.3. Probability and Statistics: Statistical software.

INTRODUCTION
Motion capture (MoCap) data analysis is an emerging field for research and development, which allows new prospects in many areas, including human computer interaction (HCI), entertainment, movement education (sport, music, etc.), and health movement analysis. However, the exploration and analysis of a motion dataset is a complex task, and requires proper tools to extract and interpret the relevant information contained in movements. This complexity is due to two main issues:

- Firstly, movements generate high-dimensional data, generally consisting of 3D trajectories of a large set of nodes forming a skeleton, which are difficult to interpret. Hence their processing is a necessary step in order to extract relevant features of fewer dimensionality, easier to analyze and interpret semantically. A few tools have been presented in the literature to address that issue. Among them, Burger and Toiviainen [6] proposed the *MoCap Toolbox*[1] for analysis and visualization of MoCap data in the Matlab environment. The recent *Mova*[2] platform developed by Alemi et al. [1] is an online movement analytics platform allowing investigation on several motion features on a single file. Finally, *MotionMachine*[3], proposed initially by Tilmanne and d'Alessandro [20], is a multi-purpose C++ framework developed for motion processing, interactive visualization, and for HCI applications design.

- Secondly, in a dataset of any type of movement performance, a large number of factors can influence the way a performer moves. Factors are the variables, intra- or inter-individual, which can have an effect on movements. Inter-individual factors may be of various types, including social factors (e.g., culture, education), psychological factors (e.g., personality, emotions, state of concentration), physiological factors (e.g., gender, age, morphology, force, suppleness), or psychophysiological factors (e.g., handedness, motor skills). On the other hand, intra-individual factors are related to the performance, independently of the performer, such as the type of dance, or the purpose of a particular exercise. Many specific researches on these factors have been conducted in different contexts, such

[1] *MoCap Toolbox*: https://www.jyu.fi/hum/laitokset/musiikki/en/research/coe/materials/mocaptoolbox

[2] *Mova*: http://www.sfu.ca/~oalemi/mova/

[3] *MotionMachine*: https://github.com/numediart/MotionMachine

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as clinical factor analysis on gait patterns [15, 25], or investigation of emotion factors effects on body action and posture [8], and on kinematics of locomotion [4], to mention a few.

All these factors may have different effects on motion features, effects which are generally very difficult to analyze separately. To address that issue, and thus reduce the complexity of motion data analysis, we developed a new tool for factor statistical analysis in the *MotionMachine* framework, to explore relations between any factor and any motion feature.

We start this paper by presenting the environment used for the development of our tool. We then present the statistical analysis module and its integration in the *MotionMachine* framework. Finally, we propose a factor analysis of a contemporary dance MoCap database conducted using the proposed tool.

MOTION PROCESSING FRAMEWORK

MotionMachine is a cross-platform and open source C++ framework developed for MoCap data manipulation, interactive visualization, and analysis. It independently inherits all the functionalities of two libraries from which it is built: *Armadillo*, a C++ library for linear algebra, and *openFrameworks*, a framework allowing the development of graphical and interactive applications [20].

General Structure

The architecture of the *MotionMachine* framework is composed of two independent modules. The first module, based on *Armadillo*, enables motion data representation, signal processing and analysis. This module allows the fast prototyping of features derived from raw motion data, providing higher level representations of the movement, and enabling new inputs for motion analysis and interpretation. The second module enables the interactive visualization of 3D motion data, and all the results of the processing module, including motion features and statistics. The visualization module of *MotionMachine* is divided in four layers, allowing superimposed visualization of the different results of the processing module:

- The **3D scene** allows visualization of the 3D motion data.
- The **2D figure scene** is used to display motion features extracted from the raw data.
- The **annotation layer** enables to label key frames of the visualized data, allowing data segmentation.
- The **user interface layer** displays graphical commands, allowing the user to control and interact with the application.

Each layer can be displayed in superimposition, or individually, allowing functional global visualization of the processing module results [20, 21].

Motion Features Set

A first aspect of the present work is the development of a set of motion features to incorporate in the statistical analysis module. Various motion features have been used in the literature for MoCap data analysis. Motion features can be classified in various categories, exploring different aspects of motion. First, low-level motion features categories, which directly describe motion trajectories, include raw data representations (e.g., joints positions, rotations), as well as kinematic and kinetic features. Then, these low-level features can be used as input for extraction of high-level features, which enable more direct semantic interpretation of the movement [13]. High-level motion features include expressive features [e.g., 3, 12, 17], ergonomic features [e.g., 2, 5], spectral and temporal features [e.g., 9, 14], relational features [e.g., 16, 20], and machine learning movement representations [e.g., 7, 11, 18, 22, 24].

Many of these features have been implemented in the *MotionMachine* framework, and a detailed presentation of the implemented features is under publication [21]. The list of the available motion features in *MotionMachine* includes:

- **Laban effort features** [12]: weight/time/space effort, kinetic energy, jerk
- **Laban space features**: travelled distance, covered area
- **Ergonomic features**: balance, postural load [2], Tai Chi related features (kinesphere)
- **Rhythm and periodicity**: auto-correlation, power spectral density, periodicity from peak
- **Relational features**: Müller features [16]

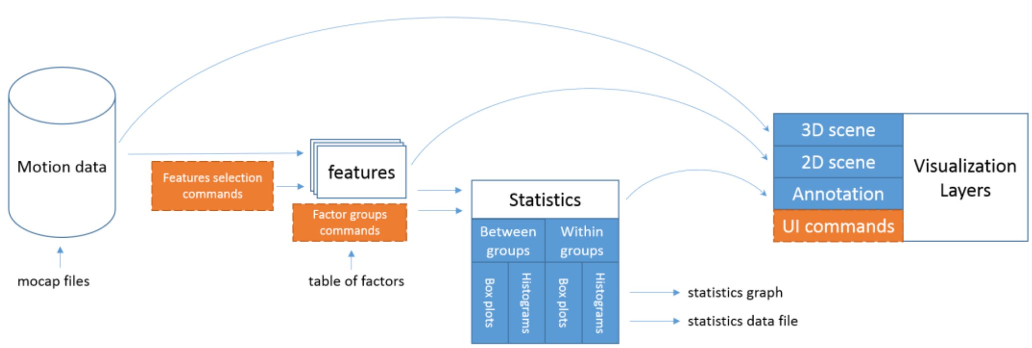

Figure 1 – Factor Statistical exploration module general block diagram

- **Machine learning representations**: Hidden Markov Model decoding [18], Dynamic Time Warping, Principal Component Analysis [23]

FACTOR STATISTICAL EXPLORATION MODULE

Motion features factor analysis allows to investigate how the different factors can independently influence the way a performer moves. For that purpose, we developed and incorporated a statistical analysis module in the *MotionMachine* framework.

In the remaining of this section, we first explain the general structure of the module. We then focus on three particular steps of the workflow: the factors classification, the features selection, and the statistical process. Finally, we briefly present the rendering and interaction functionalities we included in the module, additionally to the basic functionalities inherent to the *MotionMachine* framework.

General Structure

Figure 1 displays the general structure of the statistical exploration module. The input data required by the program are the MoCap data, and a table of factors. From the MoCap data, motion features are extracted, and are then processed by the statistical module. Firstly, the data are classified into groups according to the factor to analyze. From these groups, different statistics are then processed, and histograms and box plots are generated within groups, and between groups. Finally, the results are rendered in the annotation layer of the visualization module of the *MotionMachine* framework.

The control and interaction with the program are made easy and intuitive thanks to the user interface layer, consisting of graphical commands, allowing features and factors selection, statistical process configuration, and navigation between the different results.

Factors Classification

Within the dataset, each motion sequence can be characterized according to each intra- and inter-individual factor. E.g., a sequence i is rendered on a hip-hop choreography, on a sad and powerful music piece, by dancer α, of feminine gender, Chinese culture, small size, and left-handed.

The information about factors of each sequence of the dataset is provided to the program via the table of factors. This table, stored in a standard file format (*.csv* extension), can be read and edited in any standard spreadsheet editor. A table of factors example is presented in Table 1.

Each line corresponds to a sequence of the dataset, and each column to a factor. For each sequence, an index corresponding to the state of each factor is given, allowing automatic classification by the program. For instance, to analyze the first factor (i.e., gender, containing two states: woman, man), the program will create two groups, one containing all sequences rendered by a woman, and the other containing all sequences rendered by a man.

	Factor 1 Gender	Factor 2 Music	Factor 3 Experience	Factor 4 Culture	…
File 1	Woman	Rock	3 years	Occidental	…
File 2	Man	Rock	3 years	Occidental	…
File 3	Woman	Classic	10 years	Oriental	…
File 4	Man	Classic	10 years	Oriental	…
…	…	…	…	…	…

Table 1 – Table of factors: example

Features Selection

The module allows analysis of any motion feature implemented in the *MotionMachine* framework. According to the type of motion data, some features may be more relevant than others. For instance, Laban movement analysis was originally developed for dance gestures, and more broadly, expressive gestures. On the other hand, ergonomic features are generally used to analyze athletic gestures. In order for the user to choose which features to analyze, graphical user commands were embodied in the module.

Statistical Process

Motion features are defined in various measurement units and scales, and their direct comparison is irrelevant. Nonetheless, it is of great interest to know, for a specific factor, which feature allows better discrimination. To that end, each motion feature was normalized with the global mean and standard deviation of the database, resulting in new dimensionless motion features.

From the groups of data classified according to the selected factor, statistics are processed on the selected motion features. Usual statistical attributes are extracted from the continuous features, such as moments (mean, standard deviation), quartiles (median, 25%, 75%), extrema, and distribution estimation (histogram). These statistics are evaluated for each sequence within a group, as well as for the group as a whole, allowing comparisons within and between groups. Results can be visualized in the module under two usual representations: the box plot and the histogram.

The box plots and histograms visualization in the *MotionMachine* framework enables qualitative comparisons between groups and sequences, for different factors and different motion features, allowing an exploration of the effects of the different parameters. However, it can be valuable to extract an index from these box plots, in order to quantify these effects. To that end, a distance between statistical attributes for different states of the factor is proposed. This distance is computed as follows:

$$\Delta_{X,f_a f_b} = X_{f_a} - X_{f_b} \quad (1)$$

where f is the factor analyzed (e.g., the gender), f_a and f_b are two different states of the factor (e.g., female and male), X is a statistical attribute (mean, median, quartile 75, etc.), and $\Delta_{X,f_a f_b}$ is the distance between statistical attributes X of states f_a and f_b.

The maximal distance for a factor corresponds to the distance between the states providing the maximal and minimal statistical attributes. This maximal distance will be simply written as Δ_X in the rest of the document for notation simplicity:

$$\Delta_X = \max_{a,b}(\Delta_{X,f_a f_b}) \tag{2}$$

One maximal distance can be computed for each statistical attribute. For this analysis, the moments and quartiles were retained, and extrema were omitted. Indeed, In the case of the extrema, maxima and minima can be fully determined by any unusual peak in the feature, and hence do not globally represent the feature. As a final index to quantify factor effects, a mean of these distances was chosen:

$$\Delta = \frac{\Delta_{mean} + \Delta_{std} + \Delta_{median} + \Delta_{Q75} + \Delta_{Q25}}{5} \tag{3}$$

This index can be considered as a global distance between two box plots, taking moments and quartiles into account. It will be expressed in the rest of the paper as the "effect size". In comparison with a classic Cohen's distance (similar to Δ_{mean}), Δ is more robust to the non-normality of data distributions as it takes several statistical attributes into account.

As it is computed with standardized data, it is expressed as a ratio of the global standard deviation of the database (σ_{db}). For instance, $\Delta = 0.5$ means that the distance between box plots is $0.5 * \sigma_{db}$, i.e. half of the global standard deviation of the database. This effect size is thus an indication of the importance of the factor influence on a motion feature.

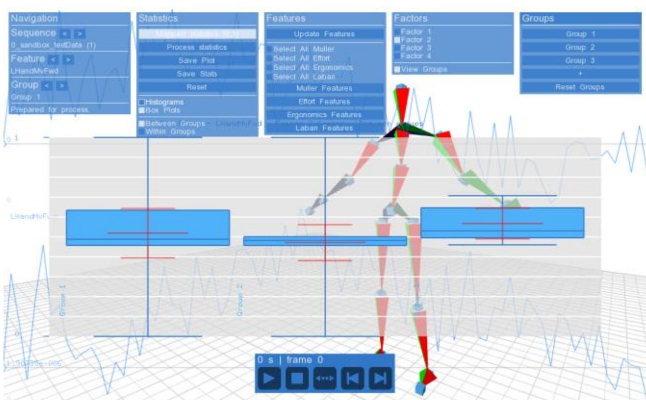

Figure 2 - Interface of the statistical exploration module. The four visualization layers are activated. First, the 3D scene displays the ground (gray grid) and the 3D skeleton at a given frame of a sequence. Secondly, the 2D figure scene displays continuous motion features (blue curves). Then, the third layer displays the box plots, and finally, graphical commands are displayed above all previous layers.

Interface

Figure 2 shows an example of the application graphical interface, where all the visualization layers are displayed. The interface encompasses intuitive graphical commands, allowing the control of the application workflow. These commands consist of four tabs: *Factors*, *Features*, *Statistics*, and *Navigation*; respectively allowing factor configuration, motion features selection, configuration of the statistical process, and navigation between the various results.

USE CASE: FACTOR ANALYSIS OF IMPROVISED CONTEMPORARY DANCE

As an example of the capabilities of the proposed tool, we present the factor analysis of a database of improvised contemporary dance. This database was recorded to explore relationships between music styles and a dancer's way of moving.

Methods

Database

Six professional dancers from the dance school P.A.R.T.S[4] were recorded with a motion capture system, while dancing on six different 45 second music excerpts. On these music excerpts, each dancer individually performed five improvisations, and a prepared choreography. The five music excerpts chosen for the improvisations were picked in an emotionally tagged music database. The tags of these music pieces were defined on two scales: arousal (calm to powerful), and valence (sad to happy) [19]. The five picked music pieces were chosen so that each one carries an extreme emotion on the valence-arousal diagram (see Figure 3).

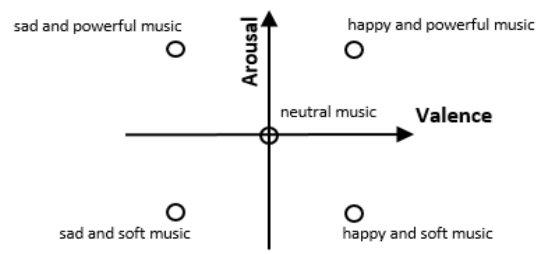

Figure 3 - Arousal-valence emotion diagram

All the data were recorded with the *Qualisys*[5] motion capture system, at a framerate of 177 FPS. For each session, a total of 68 reflective markers were placed on the entire body, and were captured with 11 infrared cameras. From these markers trajectories, 20 anatomical landmarks trajectories were extracted thanks to the *Visual3D*[6] software.

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[4] P.A.R.T.S : www.parts.be/en

[5] *Qualisys* Motion Capture Systems : http://www.qualisys.com/

[6] *Visual3D* (*C-Motion*) : http://www.c-motion.com/products/visual3d/

Factors

From this database of 36 sequences (6 performances rendered by 6 dancers), we established a table of factors including six factors:

- **Gender** (women – men)
- **Dancer id** (1 – 2 – 3 – 4 – 5 - 6)
- **Music id** (1 – 2 – 3 – 4 – 5 – 6)
- **Arousal** (positive – negative – neutral)
- **Valence** (positive – negative – neutral)
- **Improvisation** (yes – no)

Motion Features

Among all the possible motion features, a subset of features was selected for the analysis. First, three expressive motion features, extracted from Laban movement analysis theory [3], were chosen for the analysis:

- **Kinetic energy**: the kinetic energy of the whole body (E) is expressed as a sum of the kinetic energy of each body segment. As individual segments weights are not known, a model giving proportions of each segment weight in the whole body weight [10] is used. As these normalized weights are dimensionless, the unit of this feature is [J/kg]. The kinetic energy is computed through the following equation :

$$E(t_i) = \frac{1}{2} \sum_{k \in K} w_k v_k (t_i)^2 \qquad (4)$$

  where v_k and w_k are respectively the speed and normalized weight of the segment k.
- **Travelled distance**: this feature refers to the accumulated distance that is travelled on the ground over a period of time by the center of mass of the body.
- **Covered area**: it stands for the area that is covered on the ground over a period of time. It describes how widely the scene is explored by the center of mass of the body.

Then, among all the ergonomic features, three were selected:

- **Postural load**: the postural load of the whole body is a weighted sum of the stress of each body joint. The stress index of a joint is directly related to its orientation compared to its maximal amplitude of movement, on each of its degrees of freedom. Details are provided in [2].
- **Kinesphere expansion and deviation (Tai Chi)**: these features come from an ergonomic principle used in the art of Tai Chi. The center of the sphere corresponds to the center of mass of the body. Its radius is expressed as the mean distance of the body end-effectors (hands, feet and head) to the center, and gives the sphere expansion. The sphere deviation is given by the standard deviation of the aforementioned distances. Details are to be published in [21].

Results

For each factor and each motion feature, a statistical analysis was conducted through the module. Table 2 presents an overview of the effect sizes, as mentioned earlier, indicating possible influences of each factor on each motion feature.

In this table, we can observe that the maximum stands for the effect size of the music factor on the covered area ($\Delta = 1.81$). Figure 4 shows the corresponding inter-groups box plots. Each box plot corresponds to the distribution of covered area for each music, considering the renditions of all dancers. We can see that Music 1 has the highest results in terms of covered area. It is interesting to note that it corresponds to the choreographed piece. The lowest results correspond to Music 4 and 5, i.e. to the sad pieces (negative valence). Finally, the intermediate results correspond to Music 2, 3 and 6, the happy and neutral pieces. These results seem to show the influence of the valence, and improvisation status on the covered area. Their respective effects on covered area are indicated through the corresponding effect sizes: $\Delta_{valence} = 0.82$ and $\Delta_{impro} = 1.45$ (see Table 2). Concerning the arousal scale, the effect appears less pronounced as the corresponding index is only $\Delta_{arousal} = 0.4$. We can first deduce that dancers seem to travel more on the choreography than during any of the improvisations, probably because this specific choreography was thought and prepared to occupy the available space, unlike improvisation. Then, we deduce that dancers seem to naturally occupy more space on happy music than on sad music.

On the other hand, the minimum of the effect sizes in Table 2 stands for the effect of the music arousal level on the postural load ($\Delta = 0.07$). Figure 5 shows the corresponding groups box plots, which are similar for each arousal level. Consequently, the postural load seems independent of the arousal level, meaning that dancers make movements as stressful on powerful music as on soft music.

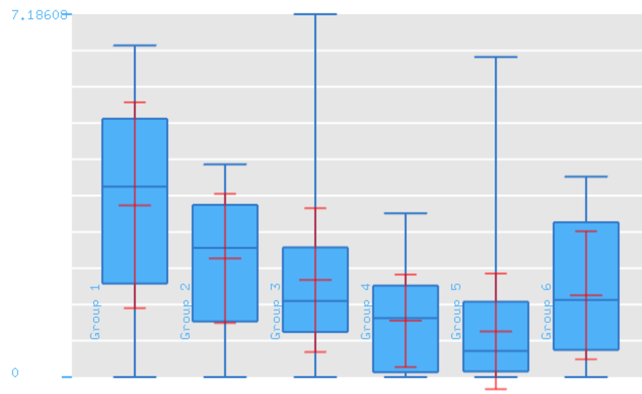

Figure 4 – Inter-groups box plots for the covered area feature and music id factor ([J/kg]). Ordered by Music 1 to 6: choreography; powerful-happy; soft-happy; powerful-sad; soft-sad; neutral-neutral. $\boldsymbol{\Delta = 1.81}$.

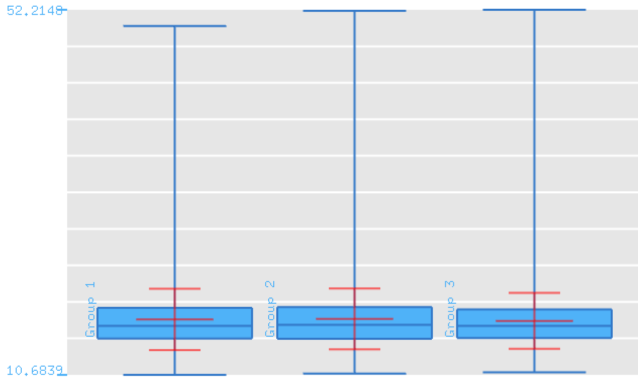

Figure 5 - Inter-groups box plots for the postural load feature and arousal factor (dimensionless unit). Order: positive, negative and neutral arousal. $\mathbf{\Delta = 0.07}$.

In Table 2, we chose two arbitrary thresholds in order to classify the different results. For effect sizes lower than $0.25 * \sigma_{db}$ ($\Delta < 0.25$), we consider that there is no factor effect on the considered motion feature. For indices higher than $0.25 * \sigma_{db}$ but lower than $0.5 * \sigma_{db}$, we consider that there is a small effect. Finally, for $\Delta > 0.5$, we consider that there is a big effect. In Table 2, results in red (bold and underlined) show big effects, and results in orange (bold) show small effects. Taking these into account, we can distinguish two categories of motion features. First, energy, travelled distance and covered area, are greatly influenced by four factors: dancers, music pieces, valence level, and improvisation status. There also seems to be a small effect of the arousal level. However, these three features seem to be independent of gender. On the opposite, postural load, kinesphere expansion and kinesphere deviation, are only greatly influenced by the dancers id, and they seem only slightly influenced by gender and music pieces. They are mostly independent of music emotions and improvisation status. It is interesting to note that the first category corresponds to Laban expressive features, and the second to ergonomic features. As Laban features were initially developed to analyze expressive gestures, it comes as no surprise that they have more dependence to the analyzed factors in the present use case.

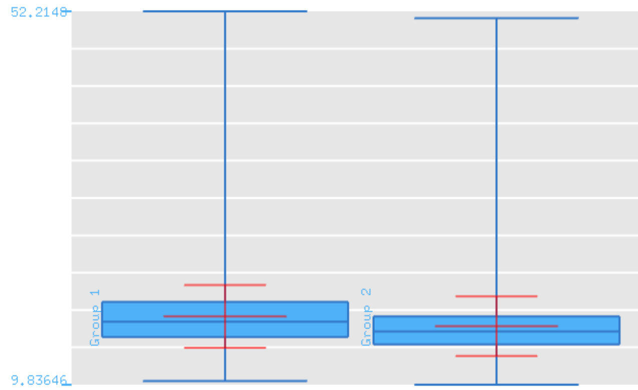

Figure 6 – Inter-groups box plots for the postural load feature and gender factor (dimensionless unit). Order: women, men. $\mathbf{\Delta = 0.32}$.

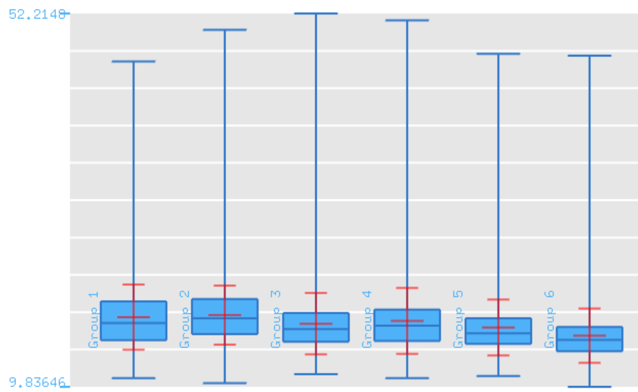

Figure 7 – Inter-groups box plots for the postural load feature and dancer id factor (dimensionless unit). Order: women left, men right. $\mathbf{\Delta = 0.73}$.

DISCUSSION

The proposed tool can be used for various applications, as the input data and parameters are highly flexible. First, the *MotionMachine* framework can read many different standard types of motion data files. Secondly, the most relevant motion features for a user-specific analysis can be selected. And finally, the table of factors is fully editable by the user, allowing her/him to define custom factors

Δ	Kinetic Energy	Travelled Distance	Covered Area	Postural Load	Kinesphere Expansion	Kinesphere Deviation
Gender	0.13	0.12	0.16	**0.32**	**0.27**	0.2
Dancer	**0.81**	**0.93**	**1.34**	**0.73**	**1.62**	**0.9**
Music	**1.07**	**1.17**	**1.81**	**0.29**	**0.36**	**0.36**
Arousal	**0.35**	**0.29**	**0.4**	0.07	0.23	0.14
Valence	**0.66**	**0.71**	**0.82**	**0.26**	0.2	0.13
Chore/Impro	**0.64**	**0.69**	**1.45**	0.12	0.19	0.24

Table 2 – Factor analysis of a contemporary dance database – Effect sizes. Legend: $\mathbf{\Delta > 0.5}$ in red (bold and underlined). $\mathbf{0.25 < \Delta < 0.5}$ in orange (bold).

according to her/his use case.

However, the results of the tool we developed are based on basic statistics, and confidence tests are lacking. More complex and thorough statistical analysis, such as a multivariate analysis of variance, should be the next step of its development. Aside from this, the proposed application is very user-friendly and allows fast exploration of statistical relations between factors and motion features. After an exploration step with this tool, an extended analysis can be conducted with a focus on the highlighted factors and features, through dedicated statistical analysis tools. To that end, the extracted motion features can easily be exported as binary or ascii files readable in any standard data analysis environment such as Matlab, Octave or R.

Additionally to the factor analysis capabilities, a real advantage, as an end-user, is found in the integration of all the steps of the analysis in a single standalone tool, including motion data parsing and visualization, annotations, feature extraction, statistical analysis, and the layered and interactive visualization of all the results, as well as exportation functionalities.

Concerning the programming aspect of the tool, high modularity and reusability is offered by the open source *MotionMachine* framework, based on the C++ programming language, and the *openFrameworks* and *Armadillo* libraries, allowing various development prospects. All the necessary tools for feature prototyping are integrated in the framework, and make it easy to implement new motion features for specific gestures analysis. Considering this, our tool can help to understand movements, and the factors that can influence them in general. Applications of this tool can be found in many areas, such as psychology and physiology, by analyzing motor control or impairments, or in sport, dance or musical education by investigating cultural differences, styles, or skills acquisition.

A use case was presented to illustrate the capabilities of the tool. A database of contemporary dance including 36 sequences was considered for the analysis. From this database, six factors and six features were analyzed through the statistical exploration tool, and various interesting results were extracted. These results are yet explorative and preliminary, because of the small number of sequences included in each factor group. For instance, each gender was represented by only three dancers, and each valence or arousal level was represented by only one or two music pieces, although rendered several times. These numbers are too low for general deductions. Nevertheless, this use case shows the interest of the presented tool. The overview presented in Table 2 shows the capabilities to synthesize the information present in the database, and Figure 4 to Figure 7 illustrate the interest of the visualization and navigation between graphical results, for complete statistical exploration.

CONCLUSION

In this paper, we addressed the problem of the complexity arising in the analysis of a motion database, by presenting a new tool for statistical exploration of relations between motion features and factors. We first introduced the environment used for its development: *MotionMachine*, a programming framework allowing the development of interactive applications for motion processing and analysis. The developed tool and its integration in the *MotionMachine* framework was then presented. As an illustration of the use of the presented tool, we conducted a factor analysis of a database of improvised contemporary dance. Several interesting results could be extracted from the analysis, showing the interest and capabilities of the proposed tool. Applications of this tool can be found in any area focusing on movement understanding, including psychology, physiology, and sport or musical education. Future work will include the integration of more advanced statistical processes, the implementation of new motion features, and the test of new use cases.

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