Motion Visualisation of Dancers' Performances

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ABSTRACT (ENGLISH)

The paper presents research on a large collection of audiovisual recordings of dance performances from the Prix de Lausanne archive, exploring how dancers' motion on stage could be visualised in alternative ways. Four Motion Visualisations (MVs) are automatically generated based on features extracted from monocular video, with each MV focusing on specific aspects of the performance. Namely, human positions and velocities, dancers' cutouts and depthmaps are computed and recombined in four modes: Analytics, Skeleton, Afterburn and Particles, through a scalable computational pipeline. Finally, the paper presents the results of a user's evaluation, highlighting a preference for Afterburn and confirming that both casual users and dance experts enjoy these alternative modes of motion visualisation.

Keywords: dance archive; motion visualisation; computational pipeline

ABSTRACT (ITALIANO)

Visualizzazioni di Movimento di Performance di Danza

L'articolo presenta una ricerca su un'ampia collezione di registrazioni audiovisive di spettacoli di danza appartenenti agli archivi del Prix de Lausanne, esplorando come il movimento dei ballerini sul palco possa essere visualizzato in modi alternativi. Quattro Visualizzazioni di Movimento (MV) sono state generate automaticamente sulla base di caratteristiche estratte da video monoculari, con ciascuna MV incentrata su aspetti specifici della performance. In particolare, le posizioni e le velocità dei ballerini, i loro ritagli e le mappe di profondità vengono calcolate e ricombinate in quattro modalità: Analytics, Skeleton, Afterburn e Particles, attraverso una pipeline semi-automatizzata. Infine, l'articolo presenta i risultati della valutazione degli utenti, evidenziando la preferenza per Afterburn e confermando che sia gli utenti occasionali sia gli esperti di danza apprezzano queste modalità alternative di visualizzazione del movimento.

Parole chiave: archivio di danza; visualizzazione del movimento; pipeline computazionale

1. INTRODUCTION

In the *Convention for the Safeguarding of the Intangible Cultural Heritage*, UNESCO recognizes the performing arts, such as music, dance and theatre, as part of Intangible Cultural Heritage (ICH), and the importance of preserving them, including measures on "promotion, enhancement, transmission [and] revitalization".[1] Based on these guidelines, this paper explores novel ways to visualise and represent the motion of dancers on stage. Certainly not a novel idea, the earliest attempts at visualising motion actually go back to the 19th century with the famous chronophotography experiments conducted by Étienne-Jules Marey, who sought to abstract the human body to "pure movement" (McCarren, 2003, p.29). In this research, we worked with the Prix de Lausanne archive, an audiovisual collection of 1500 performances on stage, capturing the finals of this world-famous dance competition for young dancers. Due to the scale of the dataset, it was necessary to develop a semi-automatic pipeline, where visual features are extracted with Artificial Intelligence (AI) models and recombined to generate four Motion Visualisations (MV), each focusing on different aspects of human bodies moving in and through space. A users' perception study, conducted during the week of the Prix de Lausanne 2024 in Lausanne, Switzerland, validates the MVs created and investigate the effect of dance knowledge on users' appreciation.

2. RESEARCH CONTEXT

Over the last decades, professionals of the sector and scholars alike have developed a variety of ways to preserve ICH, including the digital capture of performances (Hou et al., 2022). In the specific case of

[1] https://ich.unesco.org/en/convention#art2

dance practices, the *i-Treasures* initiative (2013-2017) embarked on a series of digitization endeavours aimed at immortalizing the living traditions encompassing folk dances (Dimitropoulos et al., 2014; Grammalidis & Dimitropoulos, 2015). In a parallel vein, famous choreographers have preserved their works through digital means. Wayne McGregor contributed with the Google Arts & Culture Lab to create *Living Archive*, a web-based platform to explore a digital landscape of all the human poses in its repertoire of performances.[2] Similarly, William Forsythe documented its practice with audiovisual recordings of rehearsals, performances, and installations since the 1970s, resulting in the *Performative Archive* (ZKM, 2023). He also co-created *Synchronous Objects*, a research investigation into how to transform dance into choreographic objects through data (Zuniga Shaw, 2014). Such practices are also present in other fields, like martial arts, with works such as *Kung Fu Motion Visualisation*, by media artist Tobias Gremmler.[3] Similarly, visual artists Quayola and Memo Akten won the Golden Nica at Ars Electronica Prix in 2013 for their series of animated movies *Forms*,[4] generated using 3D match-moving techniques, a common method in computer-generated (CG) pipelines, on footage of the Commonwealth Games.

3. DESIGNING MOTION VISUALISATIONS

The main goal of this research was to automatically create alternative ways to visualise dancers' motions from monocular video recordings of their performances on stage. The first step therefore involved extracting various features from the audiovisual footage. Namely, we employed MediaPipe BlazePose GHUM 3D model to compute human skeleton data from the monocular videos (Bazarevsky et al., 2020). This model outputs 33 keypoints in three-dimensional space, normalised to the frame size. From the skeleton positional data, velocity information for each keypoint was then computed. Moreover, the model also created a mask, used to obtain "cutouts" of the dancers by removing the background from the frames. Finally, we used the MiDaS model for monocular depth estimation to generate depth maps (Ranftl et al., 2022). For each frame, we thus ended up with keypoints positions and velocity, dancers' cutouts and depth maps. The latter two more "visual" features are demonstrated in Figure 1.

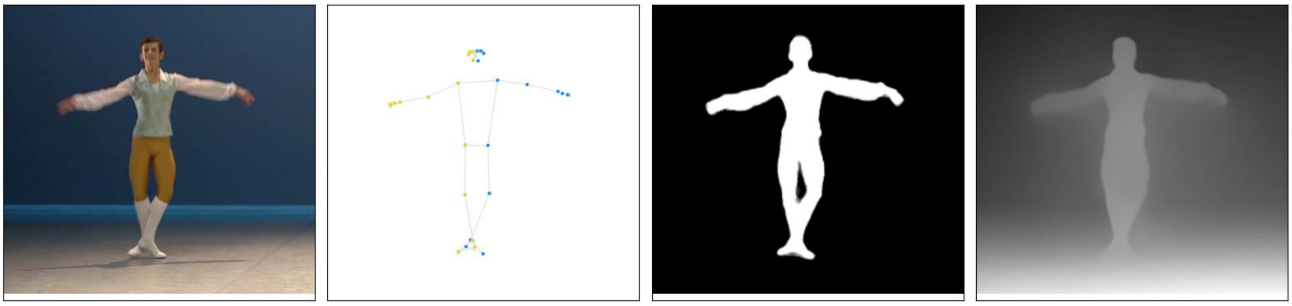

Figure 1. Visual features extracted. From left to right: original frame, keypoints, cutout and depthmap.

These elements were then combined to create four different Motion Visualisations, as illustrated in Figure 2. First, Analytics focuses on the dancers' hands and feet. It provides a simplified view of the full skeleton where only the head, the centre of the hips, the hands and the feet are visualised, tracing golden paths on a black background based on the interpolated positions. Three-dimensional boxes scale around each keypoint based on the corresponding velocity, visualising dancers' slower or faster movements in space. Second, Skeleton displays the full body of the dancers with a stick-like figure based on the keypoints extracted, inspired by Marey's early chronophotography experiments. Five positions at intervals of one second each are shown with decreasing alpha values, creating an effect of trace through time. Third, Afterburn also plays with the idea of tracing through time using this time the "cutout" of the dancers. Here as well the previous "cutouts" have temporarily increased transparency, creating an ethereal ghost-like effect that homages dance ephemeral value as a live performing art. For this MV in particular, we were inspired by Norman McLaren's 1968 experimental dance film *Pas de Deux*. Finally, Particles mixes the dancers' masks and the depthmaps with a particle simulation created in Unreal Engine where the particles

[2] *Living Archive*: https://experiments.withgoogle.com/living-archive-wayne-mcgregor

[3] *Kung Fu Visualisation*: https://www.youtube.com/watch?v=RwJG62tRjGU

[4] *Forms*: https://www.memo.tv/works/forms/

"falling" in the dancer cutout are brightly coloured while the others are in a deep blue. Furthermore, the camera is set to slowly rotate around the dancer, to recreate a more immersive feeling. This particular MV focuses therefore on the physical place that the dancer takes on stage. Due to the size of the collection, a Python script automatically process all the videos, computing the aforementioned visual features. The four MVs are then rendered in Python (Afterburn), Unity (Analytics and Skeleton) or Unreal Engine (Particles), due to technical requirements.

Figure 2. Examples of the four Motion Visualisations of dancers' performances. From left to right: Analytics, Skeleton, Afterburn, Particles.

4. EVALUATION

The four Motion Visualisations we created were showcased during the week of the Prix de Lausanne in February 2024, as part of an interactive installation whose goal was to let visitors explore the 1500 recordings of dance performances on a 4k touch screen (description of the full installation is outside the scope of this paper but interested readers can find more information in Alliata & Kenderdine (2024)). The interactive interface allowed visitors to freely switch between the original video and the four MVs. During the week, visitors were randomly approached and asked if they would answer a short survey about the MVs on an iPad, using the survey tool *muse* (Kocsis & Kenderdine, 2013).[5] Our objective was to answer the following research questions: which MV visitors have preferred and how are these MV rated in general in terms of attractiveness, confusion and interest overall (RQ1); and whether dance knowledge impact visitors' appreciation of the different MVs (RQ2).

Over the course of the week, 26 answers were collected, with a mean age of 40.2±3.6 years (ranging from 15 to 76 years old) and 73% of the respondents having identified as female. Dance knowledge was reported at 5.85±0.59 out of 10, although 8 persons indicated a 9/10, explained by the presence of many professionals in the dance field for this event. Table 1 reports the average visitors' scores for the seven Likert scale items. We observe that visitors rated positively all four of the MVs, with a preference for Afterburn and Particles. The watch times (in second) recorded by the application are consistent with the results from the survey insofar as people spent more time watching Afterburn (13.05±1.55) and Particles (15.54±3.17) than Analytics (10.74±1.25) and Skeleton (11.11±1.69). Table 1 also show that, overall, our MVs were rated highly interesting and attractive and only slightly confusing. We consider these results to be a clear indication that the MVs we designed were well received by the general public, answering RQ1, although it would seem that the Analytics one should be reworked.

To better understand these results, we conducted a correlation analysis between questions L1 to L4 and G1 to G3.[6] Figure 3 reports the results of the Spearman's computation. Note that we employed Benjamini-Hochberh correction to control the false discovery rate, due to conducting multiple comparisons. The

[5] Since the MVs were shown during a public exhibit, the requirements for the user survey were quite important. In particular, it had to be very short and could therefore not delve deeper into each of the four MV. The number of questions was kept to a minimum, with only ten questions in total: three on demographics (age, gender and dance knowledge) and the seven Likert scales items reported in Table 1.

6 This solution was preferred instead of directly asking the three questions G1 to G3 for each MV to keep the questionnaire as short as possible.

analysis reveals that the four MV could actually be split into two groups, based on their appreciation by visitors. Respectively, Skeleton highly correlates positively with Analytics ($r=0.64$, $p\text{-value}<0.05$) and Afterburn with Particles ($r=0.54$, $p\text{-value}<0.05$). Although the four MV were presented as a single group of four alternative modes of visualising dancers' motions, these results indicate that visitors were able to perceive the similarity between Analytics and Skeleton. The two MVs are indeed both focused on dancers' movements, with the first highlighting the velocity of key body parts while the second expresses the trace of the whole-body movement.

Furthermore, we note that Afterburn was significantly positively correlated with the "interesting" score ($r=0.47$, $p\text{-value}<0.05$), potentially explaining why it received the highest score. Conversely, Analytics was deemed the most confusing MV (although the result is not significant, $r=-0.32$, $p\text{-value}=1.00$), potentially explaining why it received the lowest score. This MV is indeed the most complex, with multiple layers of information being displayed between the positions of the selected keypoints and their corresponding velocities. Since these visualisations were shown without additional explanations, we can infer from these results that the Analytics MV was not intuitive enough and would therefore require a certain re-design. This claim is further supported by informal comments visitors expressed during the exhibit, asking more questions specifically on the Analytics MV. In particular, one visitor mentioned they would have found it easier to understand if shown alongside the original video. This is also in concordance with Afterburn being the most appreciated MV, since it is the only one showing the original dancer.

Moving on RQ2, we wanted to find out if people more knowledgeable about dance would appreciate more or less these MVs. Thus, we investigate the effect of self-reported dance knowledge on the seven scores by fitting a simple linear regression model. Table 1 however reveals that dance knowledge had no significant effect on any of the seven scores. Indeed, it explained at maximum 5.8% of the total variance (in the case of the "interesting" score G1), while it is below 1% for the majority of the individual scores L1 to L4. Although such results might seem inconclusive, we posit it actually indicates that the MV we designed can equally be well appreciated independently of dance knowledge, thus being effective at conveying dancers' motion for casual and expert users alike.

Question (Likert scale)	**Score**	**Fitted model**	**R2**	**F(1,24)**	**p-value**
How much do you like the Analytics visualization? (0-10)	6.73±0.39	6.2995+0.0738x	0.013	0.3092	0.585
How much do you like the Skeleton visualization? (0-10)	7.12±0.42	7.1036+0.0020x	0.000	0.0002	0.989
How much do you like the Afterburn visualization? (0-10)	7.96±0.33	8.2713-0.0530x	0.009	0.2262	0.639
How much do you like the Particles visualization? (0-10)	7.39±0.44	7.0651+0.0547x	0.005	0.1311	0.720
These alternative views of movements visualizations are interesting. (1-5)	4.35±0.15	4.6932-0.0594x	0.058	1.483	0.235
These alternative views of movements visualizations are attractive. (1-5)	4.23±0.15	4.5131-0.0483x	0.037	0.9117	0.349
These alternative views of movements visualizations are confusing. (1-5)	1.92±0.21	1.4467+0.0815x	0.055	1.389	0.250

Table 1. Quantitative questions and effect of dance knowledge on the corresponding scores, based on the results of a linear regression model. No significant effect was found.

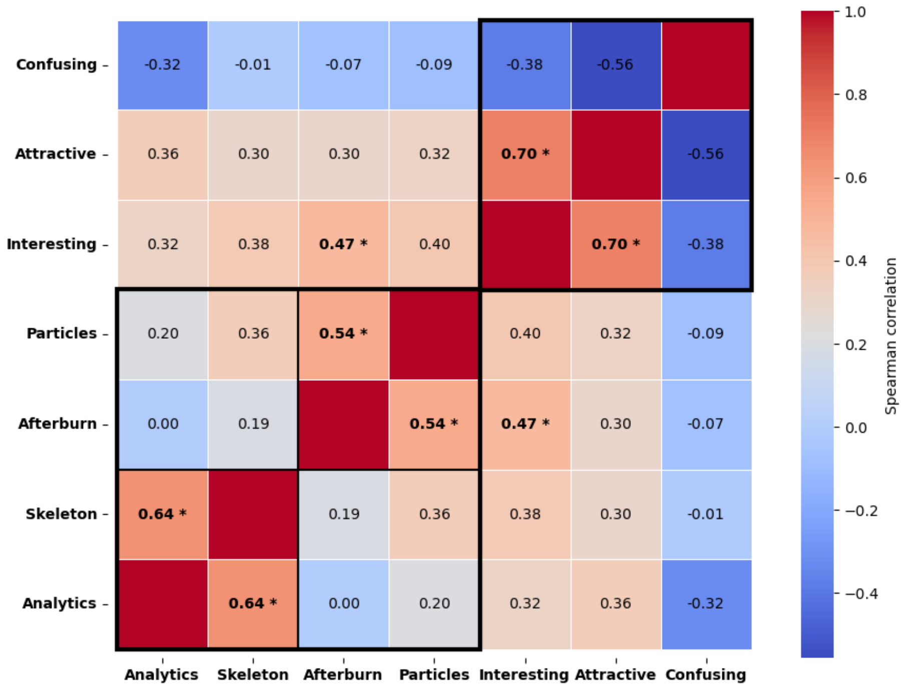

Figure 3. Spearman's correlation on the seven scales results with Benjamini-Hochberh correction. Significant values are marked in bold with an asterisk (at α=0.05).

5. KEY TAKEAWAYS ON VISUALISING MOTION

This research shows that it is possible to visualise motion in a variety of ways. The four MVs we have designed are indeed only a glimpse into an endless realm of possibilities but we believe they are sufficient to demonstrate the benefits of our approach. In particular, they show how computational approaches can be leveraged to generate these visualisations at scale, an important aspect given the politics of mass digitization of recent decades (Kenderdine et al., 2021). Motion can be operationalised by computing a variety of features even from simple monocular video recordings of dance performances (in contrast to the complex datasets generated by motion-capture technologies), and this wealth of new data can then be used to generate these "motion-as-data visualisations", hence Motion Visualisation. In comparison with the arguably greater artistic value of Gremmler's *Kung Fu visualisations* or *Forms* by Quayola and Memo Akten, our research therefore contributes an experiment at larger scales, better suited to face the challenges resulting from mass digitization.

Applying Artificial Intelligence (AI) to extract such features, however, is not a perfect process. There are inconsistencies in the results and missing data. We noticed for instance that the BlazePose model sometimes failed to detect the dancer on stage when the camera was too far away. Similarly, the dancers' cutouts and the depthmaps obtained with MiDaS are occasionally inexact because of more flowy costumes. These "errors" are then replicated in the MVs, with blanks where data is missing or unnatural shapes where dancers' bodies and costumes blend. The MVs we designed are thus a visualisation as much of dancers' motion as of the inaccuracies AI models produce. In our opinion, these "errors" should therefore not be treated as such but be considered as the kind of specificity that arises from the introduction of AI methods in these more artistic practices. It is however also important to note that new (and arguably) better models are released regularly, these errors should therefore be less and less present.

6. CONCLUSION

The four Motion Visualisations we have created are the result of a will to combine the wealth of digital archiving that has been produced with performing arts and the advances in computer vision enabling the extraction of a variety of features from audiovisual recordings. As shown in this paper, these alternative ways of visualising dancers' motions on stage can be efficiently generated at scale with computational methods to first extract relevant features and then combine them in different renderings.

We have furthermore validated that these Motion Visualisations are appreciated by casual and expert audiences alike, with a preference for Afterburn and Particles. We were particularly pleased to observe users did not find the MVs as confusing, although we note that Analytics was potentially too distracting and might benefit from a certain rework. The average watch times on the four MVs during the week were also consistent with the results of the survey, further strengthening our conclusions.

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