Safeguarding our Dance Cultural Heritage

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Abstract

Folk dancing is a key aspect of intangible cultural heritage that often reflects the socio-cultural and political influences prevailing in different periods and nations; each dance produces a meaning, a story with the help of music, costumes and dance moves. It has been transmitted from generation to generation, and to different countries, mainly due to movements of people carrying and disseminating their civilization. However, folk dancing, amongst other intangible heritage, is at high risk of disappearing due to wars, the moving of populations, economic crises, modernization, but most importantly, because these fragile creations have been modified over time through the process of collective recreation, and/or changes in the way of life. In this tutorial, we show how the European Project, SCHEDAR, exploited emerging technologies to digitize, analyze, and holistically document our intangible heritage creations, that is a critical necessity for the preservation and the continuity of our identity as Europeans.

CCS Concepts

• ***Computing methodologies*** → ***Computer graphics; Animation; Motion processing; Mixed / augmented reality; Virtual reality; Learning paradigms;***

1. A detailed outline of the tutorial

This tutorial presents the research outcomes and contributions of the transnational EU project, SCHEDAR (Safeguarding the Cultural Heritage of Dance through Augmented Reality), funded under the Joint Programming Initiative on Cultural Heritage. In particular, this tutorial deals with the digitization, analysis, and dissemination of dance heritage through Mixed Reality, aiming to devise groundbreaking advances that will refine the entire pipeline of dance cultural production in ways that were not possible in the past, helping it to grow and respond to the challenges of the new digital era.

Firstly, we present effective methods for dance 3D digitization that is accessible to everyone, by providing low-cost efficient solutions for motion and mesh capturing using vision or depth cameras. This is challenging for folk dance creation since dancers usually perform in groups, wearing large garments and using accessories. We present methods used to capture dynamic 3D scenes, showing that our method is more broadly applicable to other volumetric capture devices. In addition, we introduce effective methods for semantic and contextual analysis for motion indexing, and retrieval from large datasets, without the need of manual labelling and annotation of dance data. Contextual dance motion analysis, that is timescale and temporally order invariant, can be used to portray the chronological and geographical evolution of dance, and unveil potential cultural similarities between dances of neighboring countries, thus putting the foundations for the establishment of digital dance ethnography. Furthermore, we have leveraged motion analysis to devise unsupervised learning methods for identifying and retrieving dance motions from large datasets by providing an example motion as query; going beyond keyword searches. We present the architecture and design of the cloud-based platform for motion search and retrieval that we built on top of these ML models. We discuss how its programmable API can be utilized in third-party application development (e.g. dance games and VR applications). Finally, we devise a highly immersive Virtual/Augmented Reality platform for interactive dance teaching based on motion data reusability, holistic motion analysis, and advanced 3D character visualization.

One of the main novelties and impacts of our project is the use of emerging technologies, to digitize, analyze, and holistically document our intangible heritage creations, that is a critical necessity for the preservation and the continuity of our identity as Europeans. Safeguarding our dance heritage in digital forms also helps in the dissemination to the youngest generation. The straightforward nature of the systems developed facilitate, even the non-expert general public, to be able to engage intuitively with the dances, ensuring

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that it is widely accessible. Our project is expected to enable the design of digital dance libraries, and the development of learning applications through gamification, such as virtual dance museums.

1.1. Keywords

Motion Analysis, Intangible Cultural Heritage, Depth-based human reconstruction, Motion Signatures, Motion Indexing, Motion Search Engine, Dance in Mixed Reality.

1.2. Tutorial Type

We are targeting to a half-day tutorial (180 minutes)

2. Organizers and Presenters

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3. The proposed outline

A proposed outline of the tutorial is:

- **Digital Dance Ethnography, Motion analysis and large-scale data organization**; by *Andreas Aristidou, University of Cyprus.*

  Folk dances often reflect the socio-cultural influences prevailing in different periods and nations; each dance produces a meaning, a story with the help of music, costumes and dance moves. However, dances have no borders; they have been transmitted from generation to generation, along different countries, mainly due to movements of people carrying and disseminating their civilization. Studying the contextual correlation of dances along neighboring countries, unveils the evolution of this unique intangible heritage in time, and helps in understanding potential cultural similarities. However, the large diversity of motions, and their complexity, makes automatic motion indexing challenging, especially for highly dynamic, heterogeneous, and stylized motions, such as dancing. Most motion clustering techniques rely on motion skeletal [KGP02, KPZ*04, BCvdPP08] or relational [MRC05, KCT*13, RKW16] information, and fail to assess other important aspects of human action, such as synchronization and scaling. In fact, each performer's improvisation, experience, and talent may result in different variations of the same dance, while the same dance can vary in the temporal order, and duration, even if they are performed by the same dancer. This session of the tutorial presents a method for contextually motion analysis, capable of organizing dance data semantically, to form the first digital dance ethnography [ASC19]. The method is capable of exploiting the contextual correlation between dances, e.g., see Figure 1, and distinguishing fine-grained differences between semantically similar motions [ACOH*18]. It illustrates a number of different organization trees, and portrays the chronological and geographical evolution of dances.

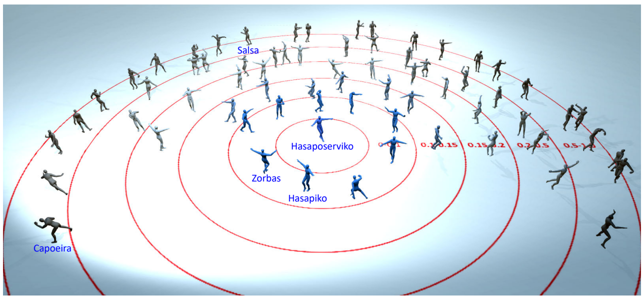

Figure 1: *This figure demonstrates, in a circular partition, the degree of similarity of the* Hasaposerviko *dances to other dances in the collection. Similar dances to the query dance are placed closer to the center circle. The similarity is also illustrated by different shades of blue; the numbers in red indicate the degree of dissimilarity for that partition. Refer to the supplementary video for an animated visualization of this demonstration.*

- **Recovering 3D human motion**; by *Cèline Loscos, University Reims Champagne-Ardenne,* and *Franck Multon, University Rennes 2 - Inria.*

  In this session of the tutorial, we address the problem of 3D motion reconstruction from depth sensors. We outline the challenges associated to folk dancing capture. Indeed, folk dancers usually perform in groups, wearing large garments and using accessories. We illustrate that it is possible to infer a 3D-parametric model out of a single depth image captured from an RGBD camera which is well adapted to the previously described conditions. The proposed approach is a two-step hybrid approach. First, we adapted double U-Net networks [RFB15] to perform body segmentation to identify limbs out of the depth image. Together with the body segmentation we search the dense correspondence between 3D surface points and vertices of a template human shape. Second, we adapt the shape and the pose of a template human model (SMPL) [LMR*15] to align the resulting labelled 3D points to the vertices of this template, using nonlinear optimization [BBLR15]. This proof of concept is yet to be extended on real capture data, but its initial results are promising to be well performing in the context of folk dancing capture. Compared to state-of-the-art methods based on either full deep learning [WXZ*20, JCZ19] or tracking methods. Figure 2 depicts the process and the results of this method on two different depth images.

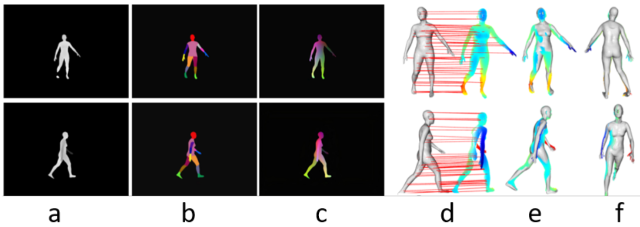

Figure 2: *Reconstruction of the 3D human shape+pose based on depth images. (a) input depth image, (b) body segmentation, (c) dense correspondence with color label, (d) 3D representation of the dense correspondence on a template character, (e) and (f) our results.*

- **Capturing Real 3D Scenes Using Multiple Volumetric Cameras**; by *Joseph E. Parkins and Alan Chalmers, University of Warwick*.

  Recent advances in depth-capturing technology, such as the Microsoft Kinect Azure [Kin21], and photogrammetric techniques, e.g. [NBSR20], have made it now possible to capture and subsequently display in great detail, volumetric videos (VVs); 3D volumes of dynamic activity. This tutorial session covers methods and challenges when capturing dynamic 3D scenes, including multiple dancers (Figure 3), using an array of Azure Kinects. To capture the required activities fully in 3D requires multiple devices. Temporal and spatial alignment are critical when combining dynamic scenes from these multiple devices. Spatial alignment can be achieved by ensuring there is a static reference object in the scene that can be seen by all devices. Temporal alignment for multiple Azures is straightforward as the official API supports simultaneous capture from multiple devices using a mechanical link cable and a hardware frame capture synchronisation is included. However, a major unsolved issue – to-date – is the lack of an officially supported cable of longer than 1m. Cables longer than this result in lost or corrupted frames, which have to be dealt with after the capturing process. In addition, despite having an array of 7 micro-phones on each device, there is currently no official means for accessing this data correctly, with only one audio feed per device being visible when using 3rd party libraries. Furthermore, although Microsoft say quite clearly in their documentation that the Kinect Azure includes a global shutter that enables the device to be used in any ambient lighting condition [Azu21]. This was simply not the case as was shown when we attempted to capture 3D data outside, even on a cloudy day. As Figure 4 shows, it is necessary to enclose the area of capture in a "tent" in order to reduce the ambient lighting to a level that will not saturate the IR camera and thus avoid highly noisy or even no depth data.

Figure 3: *This figure shows four Morris dancers being captured with the Kinect system and the resultant point cloud.*

Figure 4: *Coping with capturing outdoors*

- **Sifting through motion data**; by *Efstathios Stavrakis, Algolysis Ltd*.

  In this tutorial session, we present the underlying algorithms and architecture of moqap (`https://moqap.eu` - Figure 5), a cloud-based motion data search engine which leverages unsupervised learning (Variational Autoencoders) to provide state-of-the-art motion queries by example. While in the previous decade digitizing human motion has been a fundamental challenge for scientists, engineers and practitioners, with the advent of affordable motion capture hardware and the availability of advanced software techniques generating motion data is no longer considered a technological barrier. Instead, motion processing and retrieval are nowadays highly-sought, since it is only a matter of time until massive amounts of motion data become ubiquitous, similar to text, images and videos. Sifting through large motion capture datasets [ACOH*18, BDV*17, WN15, KCT*13, BWK*13, MBS09], identifying motions with certain characteristics and utilizing them in end-user applications are now gaining momentum, not only in the context of dance heritage, but in a broader scope [SEBZ21].

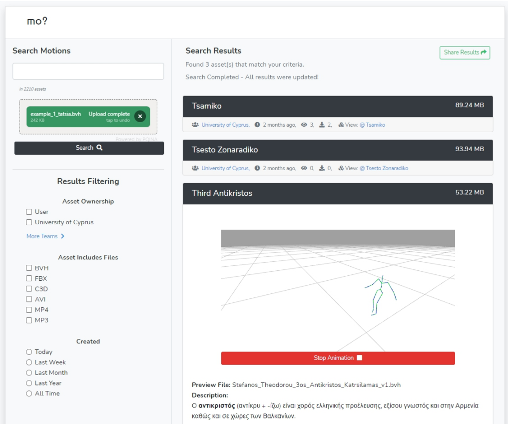

Figure 5: *Query-by-example in the* moqap *motion search engine.*

- **Mixed Reality challenges and advances in dance education**; by *Bhuvaneswari Sarupuri, University of Rennes 2*.

  Dance is an intangible expression of cultural heritage. Being able to teach dance to a wider population is as important as preserving the dance forms. Using interactive technologies such as Mixed Reality devices can be a solution in making learning dance more realistic, intuitive, engaging and enjoyable [CLTK11]. Different dance teaching experiences have been previously developed having different teaching goals in mind. However, there are still many challenges in transferring complex motor skills of dancing such as type and frequency of intervention, feedback modality, and dance skill retention. Also, even though the visual and audio information in Mixed Reality can be very realistic, there are still many challenges in terms of interaction [CDC*14]. This tutorial presents the current challenges in HCI in teaching dance [ERKI16]. As part of evaluating dance training, we developed a Virtual Reality dance training tool as shown in Figure 6. Further, we present the evaluation of usability, fun and engagement of participants in using our VR dance training application [SKAM22].

Figure 6: *VR dance studio setup in Unity. [Inset] A participant wearing HTC Vive Wireless HMD with additional foot and hand trackers for full body tracking.*

- **Virtual Dance Museum**; by *Andreas Aristidou, University of Cyprus*.

  This presentation introduces a virtual dance museum that has been developed to allow for widely educating the public, most specifically the youngest generations, about the story, costumes, music, and history of our dances. Over the last decade, great attention has been given in the use of digital technologies on-site from museums, or online in the form of websites; since 2002 the online visitors outnumbered that of physical museums, indicating that virtual museums have an important role to play in safeguarding and disseminating historical and cultural assets [BMS21]. However, most of the current efforts concern tangible cultural heritage and do not cover intangible assets, that are equally important and even more frangible. In that manner, we lay the grounds for the first publicly accessible virtual dance museum specifically dedicated to the preservation and documentation of intangible cultural heritage creations, which freely gives end-users the opportunity to explore folk dance creations through interactive technologies [AAC*21]. The museum acts as a complement to walled museums and offers the benefit of not having borders. It has been built upon an already collected dance database, the Dance Motion Capture Database `http://dancedb.eu/` [SAS*12], which consists of a range of Greek/Cypriot folk dances, among other dance performances. A specially designed relational database schema has been employed to holistically structure the information within the database, that is ideal for archiving, presenting, further analyzing, and reusing dance motion data. The users can view and interact with the archived data using advanced 3D character visualization in three ways: via an online 3D virtual environment; in virtual reality using headset; and in augmented reality, where the 3D characters can co-inhabit the real world (see Figure 7). The museum is publicly accessible via `http://dancemuseum.eu/`, and also enables motion data reusability, facilitating dance learning applications through gamification [ASC*15, SNAMT20].

Figure 7: *Two Greek/Cypriot dances as demonstrated in the main exhibition of our virtual dance museum. Dancers are dressed with garments that have been designed as digital equivalents to the traditional suits.The cloth has been physically simulated, to deform and react to the movement of the character in a natural way, and attached on the mesh of the wooden mannequin.*

4. Background and potential target audience

The targeted audience for this tutorial is the scientific community with interests in character animation, virtual and augmented reality; the gaming industry; as well as other companies that deal with human motion capturing, motion analysis, synthesis, serious games, dance gamification, and mixed reality; the media; as well as policy makers/authorities; folklore communities; and parties. For the body and shape reconstruction based on a single depth image, the audience should be knowledgeable on recent deep learning methods.

5. Presenter's resume

The presenter's resume in alphabetically order:

Andreas Aristidou is an Assistant Professor at the Department of Computer Science, University of Cyprus, and Research Fellow at CYENS, Centre of Excellence. He had been a Cambridge European Trust fellow at the University of Cambridge, where he obtained his PhD. Andreas has a BSc in Informatics and Telecommunications from the National and Kapodistrian University of Athens and he is an honor graduate of Kings College London. His main interests are focused on character animation, motion analysis, synthesis, and classification, and involve motion capture, inverse kinematics, deep and reinforcement learning, intangible cultural heritage, and applications of Conformal Geometric Algebra in graphics.

Alan Chalmers is a Professor of Visualisation at WMG, University of Warwick, UK and a former Royal Society Industrial Fellow. He has an MSc with distinction from Rhodes University, 1985 and a PhD from University of Bristol, 1991. He is Honorary President of Afrigraph and a former Vice President of ACM SIGGRAPH. Chalmers has published over 250 papers in journals and international conferences on HDR, high-fidelity virtual environments, multi-sensory perception, parallel processing and virtual archaeology and successfully supervised 50 PhD students. In addition, Chalmers is a UK representative on IST/37 considering standards within MPEG and a Town Councillor for Kenilworth where he lives.

Cèline Loscos has been a Professor of computer science at University of Reims Champagne-Ardenne since 2010. She obtained her PhD in computer science at Joseph Fourier University (Grenoble, France) in 1999. After a postdoctoral fellowship (2000-2001) at University College London, United Kingdom, she was appointed lecturer. In 2007, she joined the University of Girona, Spain. She conducts her research in the LICIIS laboratory. Her research topics focus on computational photography, 3D imaging, and virtual reality.

Franck Multon is a Professor of biomechanics and computer simulation at University Rennes2, France, and is leading the Inria MimeTIC team. He has a PhD in computer sciences in 1998 from University Rennes1. He is coordinating the national actions of Inria in applying digital sciences to sports. He published over 110 publications in multidisciplinary domains such as computer animation, virtual reality, biomechanics, ergonomics, sports sciences. His main research interest consists in coupling motion analysis and simulation to better measure, analyse, and simulate human motion.

Bhuvan Sarupuri is a postdoctoral researcher at M2S Lab, University of Rennes2 and MIMETIC, INRIA. She is currently working on ways to teach dance using virtual reality. She obtained her Ph.D. from HITLab NZ, University of Canterbury. Bhuvan has masters in human interface technology and Machine intelligence. Her main interests are skill transfer using mixed reality, locomotion in virtual reality, social VR, and Usability study design.

Efstathios Stavrakis is a co-founder and senior scientist at Algolysis Ltd, a Cyprus-based Research and Innovation SME. He has a PhD in Computer Science from the Vienna University of Technology (Austria) and has been conducting research in academia and the industry for over 15 years. His research interests are in the areas of computer graphics, animation, artistic rendering, virtual reality and games.

6. Previously presented tutorial

A similar tutorial has been successfully held during the 19th EUROGRAPHICS Workshop on Graphics and Cultural Heritage (EG GCH'21), in the University of Bournemouth premises, on 4th of November 2021, in a hybrid format. Approximately 50 people attended the tutorial. In this revised and extended version of the tutorial, in contrast to the former presented tutorial, which was limited only to people interested in cultural heritage, we are targeting to a larger audience, with a wider, multi-disciplinary background, who wish to initiate work in the domain of intangible cultural heritage; the emerging space of digitization, analysis, and visualization of performing arts; or to work in similar domains that could benefit from this research (e.g., physical activity training, serious games, exergames, etc.).

7. Acknowledgements

The work presented in this tutorial is part of the SCHEDAR project (`https://www.schedar.eu/`). The project was funded as part of the JPICH Call on Cultural heritage. Funding agencies are the *Cyprus Research & Innovation Foundation* (with protocol number P2P/JPICH_DH/0417/0052), the *Art and Humanities Research Council* (AHRC) and the *Agence National pour la Recherche* (Projet-ANR-17-JPCH-0004).

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