Echofluid: An Interface for Remote Choreography Learning and Co-creation Using Machine Learning Techniques

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ABSTRACT

Born from physical activities, dance carries beyond mere body movement. Choreographers interact with audiences' perceptions through the kinaesthetics, creativity, and expressivity of whole-body performance, inviting them to construct experience, emotion, culture, and meaning together. Computational choreography support can bring endless possibilities into this one of the most experiential and creative artistic forms. While various interactive and motion technologies have been developed and adopted to support creative choreographic processes, little work has been done in exploring incorporating machine learning in a choreographic system, and few remote dance teaching systems in particular have been suggested. In this exploratory work, we proposed Echofluid-a novel AI-based choreographic learning and support system that allows student dancers to compose their own AI models for learning, evaluation, exploration, and creation. In this poster, we present the design, development and ongoing validation process of Echofluid, and discuss the possibilities of applying machine learning in collaborative art and dance as well as the opportunities of augmenting interactive experiences between the performers and audiences with emerging technologies.

CCS CONCEPTS

• **Applied computing → Distance learning**; **Performing arts**; • **Computing methodologies → Reinforcement learning**; *Artificial intelligence.*

KEYWORDS

reinforcement learning; remote learning; creativity support tools; dance learning; choreography support

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1 INTRODUCTION

Dance, as one of the most experiential artistic forms, is one of the most challenging research topics among the third-wave shifts of HCI research[4]. Born from physical activities, dance carries beyond mere body movement. Choreographers interact with audiences' perceptions through the kinaesthetics, creativity, and expressivity of whole-body performance, inviting them to construct experience, emotion, culture, and meaning together[16]. Dance nurtures a wide range of human proclivities such as "precision, musicality, creativity, expression, mastering of space and time, and social awareness.[16]" With the HCI communities increasingly recognizing the human body not simply as a functional component but as the very foundation of our embodied cognition and every other extension, research on improving computational dance supports can have an ample range of inspiration in many HCI fields (e.g., interactive systems and AR/VR).

There have been numerous projects introducing state-of-the-art motion technology and artificial intelligence into choreography. Alaoui et al.[1] identified four categories of existing digital dancing tools: reflection tools, generation tools, interaction tools, and annotation tools. Meanwhile, technology that addresses dance learning and rehearsal is still fairly unexplored[13, 16, 18]. The use of technology in enabling remote dance education has been going on in the past two decades adopting movement analysis software such as Life Form[8], but most dance e-learning programs are limited to a simple video recording format[10, 12, 14, 15]. Raheb[17] summarizes a series of prototype systems designed to support dance learning through practices, annotation, quality analysis, and reflection such as SuperMirror, YouMove, and Just Follow me. These proposed systems not only demonstrate technical viability with satisfactory usability but also show potentials for distant dance learning where the physical presence of dance experts is not promised.

Although there have been arguments about whether the demonstration-reproduction method is the most effective method[5, 9], it remains one of the most common methods in dance teaching. Many existing dance learning systems adopted such mimicry workflow[2, 6, 7], leveraging motion capture and biomechanical visualizations for self-evaluation and reflection. They typically involve 4 phases: motion demonstrations, motion capture of the expert and student, gesture recognition, and quality evaluation. In motion demonstrations, it is not extensively addressed how much personalization students can have in selecting movement content[16] and many systems provide only partial decisions to the students such as YouMove[3]. Furthermore, because evaluating dance is a complex computational problem and can be done from numerous different aspects such as motion accuracy, shape, quality, and effort, in terms of dance evaluation, most systems elect to focus on providing one aspect, continuous or discrete feedback but not both. Students rarely have the freedom to choose their own mode of evaluation. Lastly, while AI and machine learning technology have great potential in digital dance support, movement recognition and personalized dance learning, tremendously few choreography systems have incorporated them into learning system.

In this project, we proposed Echofluid–a novel AI-based choreographic learning and support system that allows student dancers to compose their own AI models for learning, evaluation, exploration, and creation. Echofluid contributes to the computational support for choreographic and performing arts with the following key aspects:

- A proof of concept of a novel AI system that students and performers can use to construct their own model and can potentially be utilized for practice, rehearsal, reflection, exploration, and co-creation in a variety of settings
- A practical software program that allows for asynchronous dance teaching and self-contained dance learning
- A new application of AI in collaborative art and dance, and expanding the possibility of interactive experiences between the performers and audiences

2 DESIGN AND IMPLEMENTATION

During the Covid-19 pandemic, dance schools and choreographers across the country have had to completely stop working, teaching, and learning. To address dancers' need for remote dance technology, we worked with an interdisciplinary team from visual arts, performing arts, industrial and systems engineering, and computer science, and engineered Echofluid. Employing artificial intelligence and Azure motion technology, Echofluid allows dancers to train their own AI model with movement-evaluation mapping pairs of their own choice.

2.1 Use Cases

2.1.1 Echofluid for self-practice. Sarah has recently begun to learn dancing and she wants to practice a specific elbow movement. Due to social distancing, she can not physically meet her instructor. Prior to Echofluid, the only way she can receive feedback is video-recording her movements and sending it to her instructor for evaluation.

With Echofluid, she can now quickly train a model for self-evaluation. She can create a model for the elbow movement by inputting a series of movements-evaluation mapping, with elbow movements she can select from our computer vision database and with quality evaluation numbers she can upload by herself. She can train the model with our artificial neural network (ANN) engine and view the model training and performance statistics for any further parameter fine-tuning. With the complete model, she can now video-record her own movements using the provided Azure motion technology, and run it with Echofluid, and her model will produce a fairly accurate evaluation of her elbow movement quality. If she finds this quality evaluation is not sufficient, she can change to different evaluation mode and train new models with input-output mappings of her choice.

2.1.2 Echofluid for co-creation. This feature is what we envision with Echofluid. John and Alex are two dance professionals and want to use Echofluid to explore novel ways of performing dance while interacting with each other. They can train a model to predict Alex's movement based on John's movement, with model input being John's Azure movements recording and output being Alex's Azure movements recording. In a different model, Alex can build a sonification model where he maps his movements to a series of sound effects. During the live performance, they can deploy both models and with John leading the dance, the models are able to predict Alex's movement and project it onto John while generating music based on Alex's movement.

2.2 Interface

The interface primarily consists of model creation, model evaluation, and model deployment.

On the model creation page, dancers are asked to provide movement and label mapping pairs. In Figure 1, the top interface is the step where users will customize model overall settings such as the movement item in the input and the range of value in the output label (e.g., 100, 95, 75 or 0). Dancers can select movement item from our computer vision database, which consists of a list of items each with three linguistic identifiers: joint, action, and quality (e.g., elbow - arc - softly, or ankle - ripple - warmly). One of our investigators, a dancing professional, recorded movement items by performing them while tracked with a Microsoft Azure camera, creating a real-time virtual skeleton that represents his movements. Our current ANN engine supports both classification and evaluation, and thus, in the output label dancers can input either discrete or continuous values. Upon creating the overall settings, users can add individual data points, movement-label mappings by recording their movement and input their label value, as shown in the bottom interface in Figure1. Once all parameters are set up, dancers can begin training the model by clicking the start button.

The model evaluation page, as shown in Figure2, features a loss function plot and relevant data of model training. Because the ANN model can be trained better with hyper-parameters fine-tuning, this page provides a graphical user interface for dancers to select the best training parameters such as different types of machine learning model. On the model deployment page, users can deploy

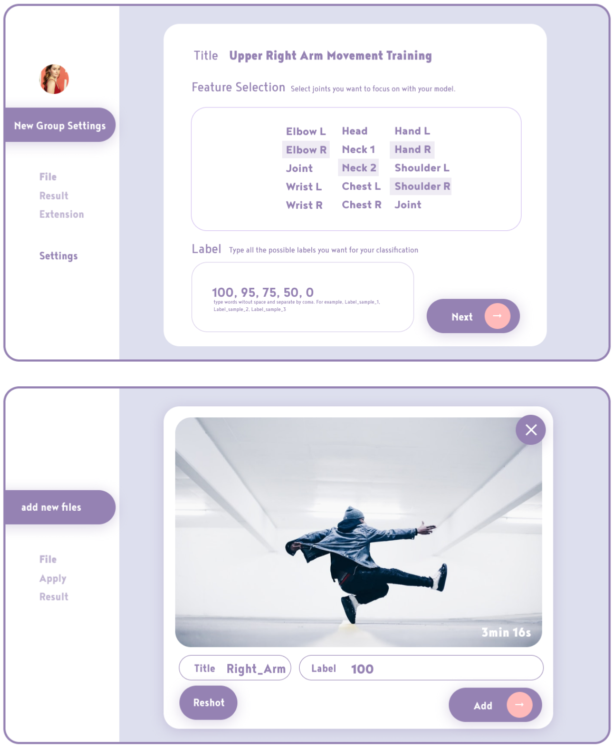

Figure 1: Echofluid Model Settings (top) and Data Recording (bottom). The top interface is the first model creation step where users will customize model overall settings. Upon creating the settings, users can then add individual data points through the bottom interface, movement-label mappings by recording their movement and input their label value.

the complete model for their own purpose. We currently support a simple self-evaluation where users can supply their own movement recording and use their models to evaluate their performance. The interface is implemented in Unity.

2.3 Algorithm

For rapid prototyping of the possibilities of machine learning on choreographic data, we used Unity's MLAgents package to stream motion data from the Unity software package to a Python application which implements PyTorch for reinforcement learning. Reinforcement learning is highly suitable for training agents in a real-time, interactive environment. It should be noted that for training outputs with a pre-recorded data set such as captured motion, it is unnecessarily slow. However, this implementation provides interesting future potential for training rewards to be adjusted in response to live motion feedback from a dancer. Our configuration used Proximal Policy Optimization, a learning rate of 5.0e-05, 3 epochs, a layers size of 256 and 2 hidden layers.

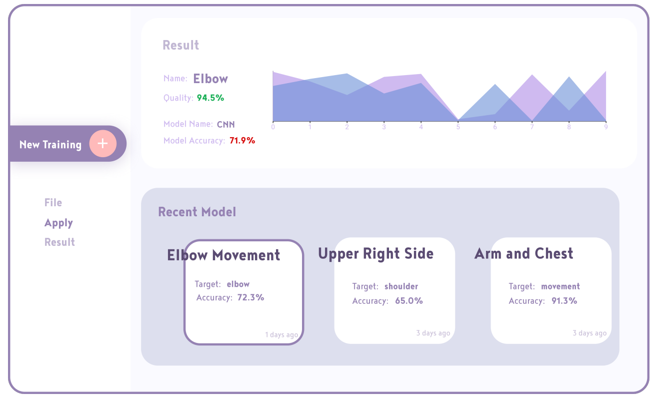

Figure 2: Echofluid Model Evaluation page provides a graphical user interface for dancers to select the best training parameters such as the iteration number of different type of machine learning model.

3 DISCUSSION AND FUTURE WORK

In this explorative work, we built Echofluid to provide dancers with the means to incorporate AI technology for their own movement practicing and learning. While we currently focus on building and optimizing the model training aspect of the software, in the next phase we plan to not only further expand the modality of media that can be trained in the model to include sound and movement skeleton but also focus on model deployment to enable other uses of AI model such as co-creation, sonification and real time performance. Also, validating user experience of the software is the next step. We plan to conduct user studies with dance learners and dance experts to evaluate both the general usability and how different levels of experts would adopt this software into their rehearsal and performance.

We envision Echofluid to be a system that can be used in a wide range of dance settings such as practice, rehearsal, and co-creation of dance emphasizing AI as the collaborative enabler. One future direction is model training for co-creation. Currently, Echofluid is limited to generating numerical results for evaluation purpose only. In the future it can support multimedia as the output. Dancers can, for instance, map movements to particular sound effects and create models that can generate music based on dancing movement[11]. Another direction is using Echofluid as a procedural choreographic generation tool. In rehearsal and performance, the software program can randomly generate an initial instruction. As the dancer performs the movement, the ANN will attempt to classify the joint, action, and quality performed and then, use its (imperfect) classification of the movement to generate the next instruction. In this way, the dancers and software system can be engaged in a collaborative feedback loop of instructions, performed gestures, computer vision identification, and computer anatomical feedback. In performance, the process of the interaction between performer and AI will be presented through an augmented reality environment (with AR glasses provided by LEVYdance) including the text of the movement instructions paired with procedurally generated virtual landscapes that represent the identifiers through topography.

There are also many opportunities for future performances of this hybridized physical/virtual performance model, such as stage + projection, stage + augmented reality, and/or remote virtual reality.

We hope the success of Echofluid can inspire other software of similar kind. Echofluid creates numerous possibilities for remote learning in dance, allowing instructors to pre-record entire movement sessions in 3D and submit those repertory materials to students anywhere in the world for self-practice. In choreography and composition courses, this system could allow for the creation of entire choreographic works without the necessity to be in-person in the studio. This type of choreographic "drafting" tool is also useful economically for professionals working in cities where rental prices make in-person studio time a premium - creating a choreographic structure beforehand would allow artists to create more efficiently with less time in the studio. Echofluid also presents interesting prospects for dance archiving, with the possibility of recording and organizing the movements and full works of historically or culturally important works of choreography in 3D, allowing for the preservation of repertory works for future performance, analysis and study, or historical preservation.

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