MoveFeel: Expressive Dance Movement Determination Through Video Analysis

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ABSTRACT

We propose MoveFeel, a movement computing framework that leverages vision-based analysis to compute meaningful metrics for assessing expressive dance movement. Our system is a multi-component workflow which extracts and collects dance movement images, processes and quantifies human pose skeletons, and computes attributes pertaining to dance movement that adhere to the movement methodologies based on "The Dynamics of Movement" by Rudolph Laban. We conduct a feasibility study to classify the expressive intentions of dance phrases encapsulated within a dance routine. We detail the interacting components of our system and discuss the interpretation and conversion of subjective dance principles into quantified metrics. MoveFeel demonstrates promise in generating metrics that can effectively distinguish dance phrases that are associated with positively or negatively expressed emotion. Our goal is to build upon these techniques and apply them to the movement arts (dance, theatre), medicine (therapy), and education.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing**.

KEYWORDS

movement computing, dance movement, pose estimation

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1 INTRODUCTION

The field of dance performance has been gradually adopting new approaches to producing, analyzing, and instructing dance content. For example, dance instructors and experts who previously relied solely on live performance to study and assess dance movement are utilizing remote learning and asynchronous teaching methods to supplement their processes [15]. Many performances are recorded on video and proliferated on the internet, allowing those outside of the immediate stage audience to view dance content at their choosing. Advancements in artificial intelligence (AI), machine learning, and computer vision (CV) have cultivated new techniques in the analysis of human-based movement in video and images. Video-based pose detection has found applications in industry and the arts, and dance is no exception. While AI has refined methods to determine *what* or *who* is detected within an image or video, the burden still lies on the human viewer to generate insights from the performance that is seen on screen. It is important to provide tools and frameworks that help experts, students, and performers understand movement that is not viewed in person, as recorded performances can require new ways of responding to contextual ideas and intent that the dancer is communicating to the audience.

Expressiveness is a crucial aspect of dance. Not only does it provide meaning to a performance, but it also serves as an indicator of attitude. It provides a deeper understanding of a performer's mindset and emotions. Laban Movement Analysis (LMA) provides a theoretical foundation to examine how movements can generate clear expression and purpose. LMA provides an interface that bridges the subjective experience of dance with the technical aspects of dance. Laban's Movement Factors are principles used to clarify specific intentions, action and environments that can be generated with different choices within the factors of movement: Flow, Time, Weight and Space. AI-leveraged detection of these movements can be useful to refine features of movement in the form of metrics.

We propose *MoveFeel*, which captures and articulates these metrics as "Effort" measurements within the LMA framework. Our goal is to provide a system that relies upon detection of human pose and movement within video to generate measurements that can be transformed into Laban based analyses to help dancers better distinguish, identify, and understand expressive movement. A primary challenge is the availability of ground truth. Dance movements are still largely analyzed subjectively, and therefore is no perfect movement to emotion mapping. To address this challenge, our system focuses on computing metrics that can be utilized in multiple ways, rather than designing an absolute movement-based emotion classification system. Previous studies that exclusively use pose estimation data from video concern themselves with identifying dance styles from performances [5] or attempt to verify the reliability of LMA altogether through subjective, human-based analyses [3]. To the best of our knowledge, our approach differs in that our system aims to provide a dance-genre agnostic system that

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solely determines dancer intentionality and attitude. In the following sections we present some information on the Laban Movement Efforts, followed by implementation details and early analysis from *MoveFeel*.

2 BACKGROUND

2.1 Laban Movement Efforts

Laban Movement Analysis (LMA) is a widely used system to observe, interpret, and describe human movement, developed by Rudolf Laban, a Movement Theorist. LMA is used in a number of professional, academic and artistic fields (Medicine, Kinesiology, Acting, etc.) and serves as a rubric for dance analysis and assessment. The LMA framework consists of four conceptual components, defined as **Body** (the decision factor), **Effort** (the intention factor), **Space** (the attention factor) and **Shape** (the emotional factor) [7].

Our work aims to provide measurements for LMA Efforts, as they are most associated with a dancer's conscientious attempts to perform technique and relay expression and dynamics of movement. The Effort component is further categorized into 4 dynamic factors:

- **Space**: Also referred to as "Focus", is the direction in which the body is moving.
- **Weight**: The body's movement as an expression of gravity.
- **Time**: The tempo of a body's movement.
- **Flow**: The openness of a body and its movement.

These efforts each lie within their own spectrum, and the permutations of these efforts can be manifested through various kinds of actions. The LMA Efforts reflect the mover's attitude toward investing energy and can operate as a rubric to frame or interpret a dancer's intentions and attitude [8]. The quality of the movements expressed through these efforts help instructors determine students' inner attitudes and action during movement phrases. Careful use of the dynamics of movement may equip instructors and dancers, an important means to evaluate their intentions and actions while dancing. Evaluation of these efforts can also help evaluators differentiate the mover's attitude in order to offer clear and direct feedback for dancers of different skill sets. Novice dancers tend to have difficulty expressing themselves through movement. Conversely, experienced dancers often have incorporated the investment of energy and thus convey stronger artistic intentions which will translate into specific emotional meanings, artistry, and personal experience within a performance.

2.2 Related Work

Dance movement can be measured and analyzed through multiple lenses; researchers can determine dance quality through highly direct means [1] (motion capture and IMUs) or indirect means [17] (ML-based detection). For example, a direct measurement approach features the use of accelerometers within smartphones [6] to detect dance rhythm through the body's changes in direction.

Laban Movement Analysis (LMA) is commonly used as a framework to generate semantic analyses from the various modalities produced from dance movement. El Raheb et al. devise a framework to analyze dance content, jointly utilizing LMA principles and consultation with dance experts from a wide array of genres [14]. They primarily use LMA as a reference, categorizing a set of intermediary dance qualities that can be applied to a broad set of dance styles and genres. Their conceptual model attempts to fill a gap between the highly-abstract definitions of dance movement defined by LMA and the granular measurements derived from measured dance content, and some elements of this conceptual model are used to guide our initial steps researching dance movement.

Alaoui et al [1]. use a multi-modal approach to capture Laban efforts, using motion capture sensors, accelerometers and EMG devices to derive direct measurements for Space, Time and Weight, respectively . Aristodou et al. [2] have a similar approach, capturing a set of mocap-derived properties that encapsulate all of the Laban principles, including LMA Efforts. They use feature analysis and PCA to determine if LMA efforts can differentiate dances of different styles, expressions and aptitudes. Both studies rely heavily upon multi-modal approaches to detecting and measuring dance movement. The scope of their research exists outside of the technical limitations that are enforced upon dance practitioners, who do not have access to motion capture equipment and IMUs. Often times, dancers rely on uni-modal (single camera video) or even bi-modal (video and music) manifestations of dance movement content and measurements. "Dancer in the Eye" designs a multi-layered interpretation system that analyzes dance movement and translates it to expressional qualities, but it is also subject to the inclusion of sensored measurements [4]. Earlier efforts on computing movement-derived metrics have focused primarily on exercise movements [10–13].

3 SYSTEM DESIGN

MoveFeel consists of three main components: a frame extractor, pose keypoint preprocessor, and the Laban Efforts Estimator (LEE). These components operate in a workflow-type configuration. Figure 1 shows the architecture for MoveFeel.

3.1 Frame Extractor

The Frame Extractor converts videos to image frames with an extraction rate of 30 frames/second. The conversion is initiated at the point of playback when the dancer is first seen on stage and performs their first movement. These frames are saved in PNG format.

3.2 Pre-Processor

The Pre-Processor consists of two main modules; the Pose Estimator and Movement Attributes (MA) module.

3.2.1 Pose Estimator. The Pose Estimator consists of a Python application that is a modification of the tf-pose-estimation library [16]. Tf-pose-estimation is a variant of the "OpenPose" Tensorflow algorithm developed by the CMU Perceptual Computing Lab [9]. Pose-Estimator runs the "mobilenet-thin" Tensorflow model, which balances trade-offs between computational effort and latency. Pose Estimator produces a vector of image coordinates that correspond to skeleton keypoints (nose, neck, right/left shoulder, right/left elbow, right/left hip, right/left eye, right/left ear, right/left knee, right/left wrist, right/left ankle) within a recognized human pose. Figure 2 shows a rendered skeleton detected from an image. Pose Estimator ingests a bundle of video frames from the Frame Extractor and outputs a time-series dataset of pose keypoints, with each skeleton

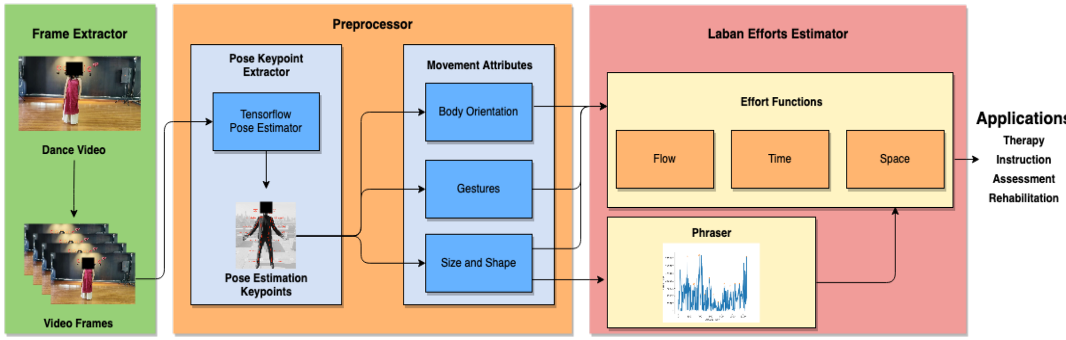

Figure 1: MoveFeel Architecture. It consists of three components: Frame Extractor, Preprocessor and Laban Efforts Estimator.

data object representing a detected pose from a video frame. The keypoint coordinates are normalized with respect to the frame size to account for variations in video resolution and person size.

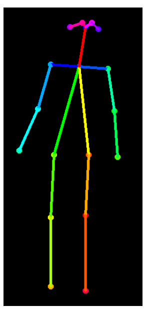

Figure 2: Skeleton keypoints from the Pose Estimator.

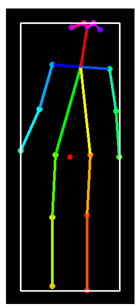

Figure 3: Bounding-boxed skeleton keypoints.

3.2.2 Movement Attributes Module. The Movement Attributes (MA) module contains functions that compute movement attributes captured from dance video. We focus on three primary attributes, as discussed below:

- **Body Orientation**: Body orientation is measured as the angular configuration of the dancer, characterized by the major joints of the arms and legs. Limb angles are bounded within 0 and 180 degrees; reflex angles are not measured. We measure angles in the acute sense because we are primarily concerned with the degree of bent of the limbs. This indicates how far/close a dancer's arms and legs extend with respect to their torso. We generate 3 pairs (left and right) of limb angle attributes: (1) angle between the shoulder and upper arm, (2) angle between the upper and lower arm, and (3) angles between the upper and lower leg. These angles collectively represent the body orientation.
- **Gestures**: Gestures refer to the velocity of limb and skeleton movement. Limb velocity is determined as the rate of change of position of shoulders, knees, ankles and wrists. The skeleton movement velocity is measured by computing the centroid for all keypoints in each frame. The centroid point is the center of the width and height of skeleton bounding box. The centroid's distance displacement from frame to frame is used to compute velocity. Velocity is measured in pixel distance per frame units.
- **Body Size and Shape**: We also compute the dimensions of the dancer in relation to their environment. We generate bounding boxes that surround the dancer skeleton. Bounding box dimensions are measured in pixels. We look at the area of the bounding box in the subsequent steps to understand how open or closed a user's body is. Figure 3 shows an example of a dancer whose pose is visually annotated with bounding box generated by the MA module.

3.3 Laban Efforts Estimator

The Laban Efforts Estimator (LEE) is the final module which infer Laban Efforts from the movement-derived attributes. LEE consists of two modules, the Phraser and Laban Efforts Functions.

3.3.1 Discretizing Dance Movement: The Phraser. The Phraser serves as a component that partitions the time-series movement data produced from our preprocessor into discrete, observable windows called "phrases". The purpose for this process is twofold: to convert our continuous time-series data into analyzable chunks which allows for feasible computation of Laban Effort metrics of different dance videos and to adhere with the established principles of dance theory.

Dance experts describe a dance phrase, or a *movement sequence*, as a section of a dance routine with a discernible beginning, middle, and end, similar to "sections" in a piece of music [18]. However, dance phrases are understood as subjective measurements that are determined by the performer or the audience, and phrases can transition to each other naturally or can be bridged by a transition movement. Phrases indicate moments within a dance routine that can communicate various states of intention and expression. The reasoning behind using phrases as the unit of computation was that LMA metrics cannot be encapsulated as a summation of an entire routine, since a performance can portray a wide array of expressions and thus it is difficult to derive discernible observations of a performer's state of mind. It is more feasible to compute and analyze Laban Efforts metrics in smaller windows and to understand patterns of the expressions produced from these windows to discern the overall expressiveness of a performance with time. As such, we develop an algorithm that approximates the measurement of dance phrases within time-series movement data.

The Phraser takes bounding box areas from the Movement Attributes module as input. It then runs a sliding window through the time series data. We pick a window size of 100 frames (3 seconds).

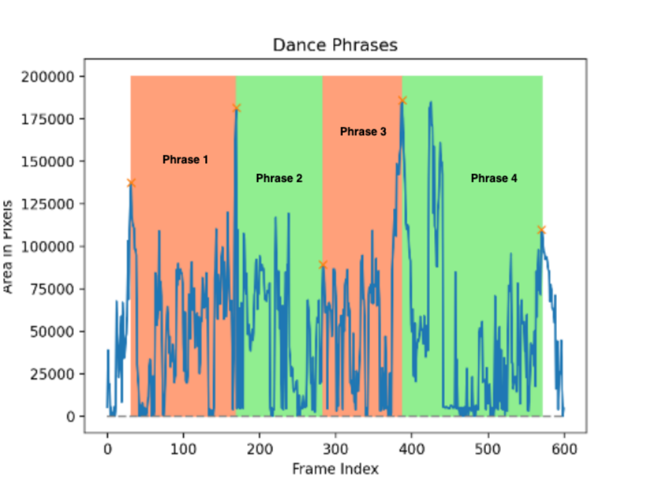

Figure 4: Dance phrases denoted by alternating-colored windows in a bounding box area graph.

There is no overlap between consecutive windows. Within each window, we detect the local maxima which denotes the boundary between two phrases. Intuitively, the local maxima represents poses in which a dancer opens their body. These poses often indicate the preparation and transition to another major movement within a dance performance. Thus, local maximas can represent viable delineations between dance phrases. The subsequent window starts at the frame after the detected local maxima. Figure 4 shows a graph measuring the bounding box area pose of a dance routine captured in 600 frames of video. Peaks detected within the sliding window partition the frames into phrases. An array of these phrases is then used as input for Laban Efforts Estimator.

3.3.2 Defining Laban Efforts Through Metrics: Laban Efforts Functions. The final phase of MoveFeel is concerned with ingesting the movement attributes from the MA and the frame indexes from the Phraser to compute metrics that can indicate Laban Movement Efforts. To help implement and verify these metrics, we consulted with a movement expert. Figure 7 shows a tree describing the Laban Efforts and their corresponding metrics. The *Weight* effort, used to describe the gravity or tension of a movement, was omitted from our implementation. Verified by our movement expert, *weight* is most associated with the mindset and thought process of the performer, so the characteristics and metrics that explain *weight* are difficult to measure without sensors or additional measurement modalities. We provide definitions for the metrics that constitute *Flow*, *Time* and *Space.*

Flow. Limb extension and the overall size of the body indicate the spectrum of "bounded" and "unbounded" movement. Performers who convey tight, focused emotion during a routine tend to constrict their bodies, generating bent limb angles and making themselves appear smaller. Unbounded dancers will extend their arms and legs, and will appear bigger. Figures 5 and 6 demonstrates the visual difference between these two effort styles.

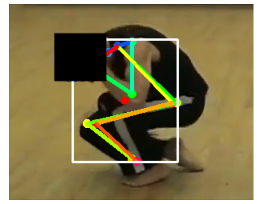

Figure 5: Bounded Flow Effort.

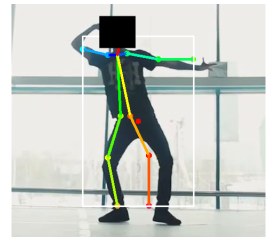

Figure 6: Unbounded Flow Effort.

Time. Movement velocity provides an adequate representation of the tempo of a dance phrase, but acceleration provides a greater factor of explanation. Sustained, smooth movements are represented by lower accelerations of limb and overall body movement, while sudden, jerky movements will have comparatively greater accelerations. We use accelerations as a reflection of the time effort.

Space. Efficient movement is dependent on the dancer's decision to move along in a direct or indirect manner. For example, a modern dancer may bound directly across a stage, while a ballet performer may conduct a series of spins and poses before reaching their destination. We characterize this effort as the distance traversed per phrase.

Table 1: The Laban Effort Metrics.

Effort	Metric
Flow	Right Shoulder Angle Variance
	Left Shoulder Angle Variance
	Right Elbow Angle Variance
	Left Elbow Angle Variance
	Bounding Box Height Variance
	Bounding Box Width Variance
Time	Average Right Wrist Acceleration
	Avg. Left Wrist Accel.
	Avg. Right Ankle Accel.
	Avg. Left Ankle Accel
	Avg. Centroid Accel.
Space	Centroid Velocity

Table 1 presents the Laban Efforts and their associated metrics.

4 EVALUATION

We evaluated the MoveFeel system on 10 different dance videos, all filmed with a single-camera and on-stage. The videos were downloaded from YouTube and were clipped at 1500 frames. The videos feature dance performances themed on a mode of expression, emotion or intention, either with a positive or negative emotional association. We also targeted dances with movements that could be analyzable within the context of LMA, and thus translatable to quantified Laban Effort Metrics.

Positive/Negative expression labels are generated in a supervised manner (human-labeled) and are binary (positive or negative) and non-probabilistic. Examples of positively expressed dance performances were those themed around joy, catharsis, and excitement, while negatively expressed performances contained themes of melancholy, somberness, or sadness. Positively-expressed dance

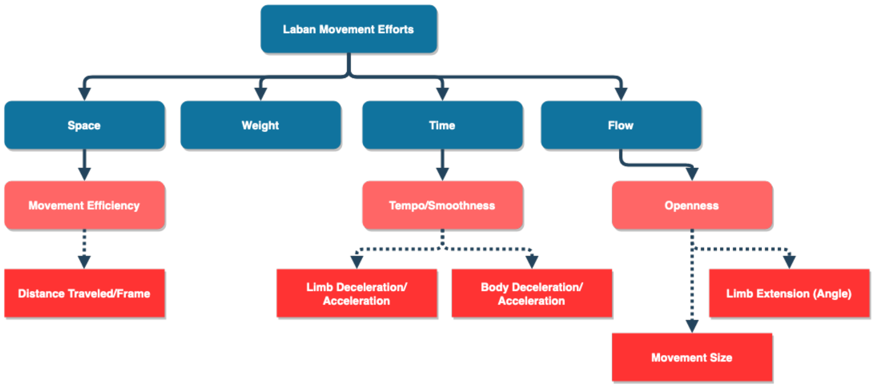

Figure 7: The Laban Efforts shown in a tree format. 2nd-level nodes represent intermediate representations of efforts and the leaf-level nodes denote metrics that explain the LM Efforts.

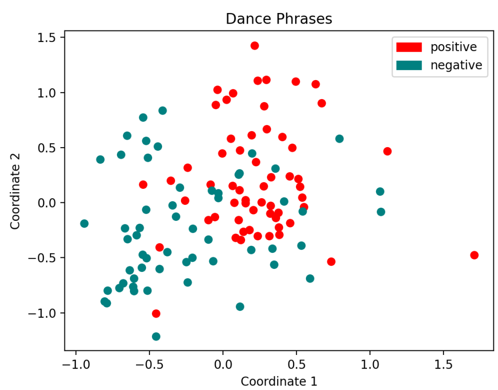

Figure 8: Multidimensional Scaling applied to expressive dance phrases. Red and green dots represent dance phrases associated with positive and negative expression, respectively.

videos featured performances from religious dance and Hip-Hop, while negatively-expressed dance videos consisted of modern and interpretive performances. Although we used data from performances from specific genres of dance, MoveFeel can be used on videos of any dance style. We processed 5 videos each from the previously described *positive* and *negative* categories and produced a feature set of the granular Laban Effort Metrics, where each data point representing a dance phrase.

Figure 8 presents a scatterplot of the analyzed dance phrases, with each phrase colored according to its assigned expression type. We applied Multidimensional Scaling based on Euclidean distance to the data set, and produced clusterings of phrase points based on feature similarity. The plot presents noticeable clustering and separation between positive and negative dance phrases. This observation indicates that our features can effectively distinguish dance movements of differing intention and emotion.

Figures 9, 10, 11 present Laban Effort metrics comparisons for Flow, Space and Time over a time-series of subsequent dance phrases, respectively. For the sake of clarity, we provide metrics that significantly explain the differences in Laban efforts between positively and negatively expressed dances. Figure 9 shows that Flow effort for a given positively expressed dance performance has a greater average standard variance (77.72) across a series of phrases than that of a negatively expressed performance (29.38). Space and Time show similar respective observations of positively expressed dance phrases generating higher average distance rates and average gesture acceleration (right wrist) than that of the negatively expressed dance phrases.

Future evaluations will consist of recruiting live dancers to submit expressive dance videos as test data to serve as ground truth for expressive dance identification. This data will validate system accuracy. We also plan on measuring MoveFeel's runtime speed as a means to improve the system's performance and to leverage it as a real-time application.

5 DISCUSSION

The results of our experimentation demonstrate a strong correlative relationship between the ranges of Laban Efforts and of the intended expressions of dance phrases. Positive dance phrases tend to feature quick, sudden movements, with the performer moving more across the stage within a phrase. They will also feature more varied size of movement and limb angles. Negative dance phrases will tend to exhibit features on the opposite ends of the spectrum for the three types of Laban Efforts. However, it should be noted that dance routines will not always have uniform modes of movement, and therefore one should not expect all dance phrases within a routine to be the same in terms of expression. For example, many performances themed around grief or anger will often contain dance phrases with jabs, stomps and open gestures, which could mistakenly indicate a joyful expression. Context is an important part of the interpretation of expression and that should be a contributing factor to our analyses and possibly to the input of our system.

6 APPLICATIONS

Dance and Theatre Instruction. MoveFeel can inform students of the quality of a phrase of movement in terms of how accurately the movement reflects the mover's attitude toward investment of energy, which is associated with change of mood and emotion, and

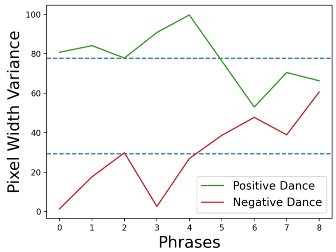

Figure 9: Flow comparisons between Positive/Negative dances represented by the bounding box width variance feature.

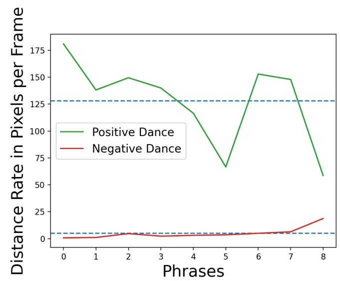

Figure 10: Space comparisons between Positive/Negative dances represented by the distance rate (pixels/frame) feature.

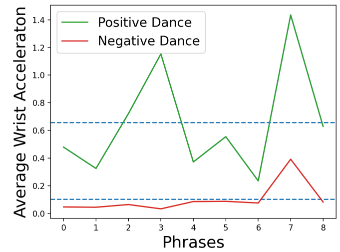

Figure 11: Time comparisons between Positive/Negative dances represented by the average wrist acceleration feature.

hence is an inroad to expressivity [8]. This leads into evaluations of whether or not they are conveying the "story" or "message" of their phrases effectively to their audience. Our movement expert posits that experienced dancers are more effective at demonstrating emotion and intention through their performance, as they are typically less concerned about technique and focus on themes inherent in their performance. Novice dancers normally struggle with conveying expression, as they tend to be more self-conscious and focus primarily on physical technique, instead of sensing the body as they dance. The proposed system provides a means to identify and correct dancers who may struggle with movement-based expression. In the future, we aim to extend the system to multiple dancers in the camera view. Theatre teachers also use the Laban Principles to help actors portray characters effectively; our system could relay feedback to an acting student of whether their audience is receiving the intended emotional tenor of the character they are attempting to portray. For example, MoveFeel can generate measurements on how calm or manic a character is intended to be. A calm character would remain still and take up less stage space during a performance, while a nervous character would do vice-versa. This action could be measured with the Space effort metric of our system.

Dance Therapy and Counseling. Dance therapy is commonly used to help patients recover from mental and emotional trauma through the use of movement. MoveFeel can serve as an effective tool to help therapists better assess the needs of their patients, who may not be able to verbally communicate their emotions. Therapists could use MoveFeel to detect changes in Laban Effort metrics measured between dance therapy sessions to determine if their patients' mental health is improving, and can preemptively prescribe modified therapeutic counseling if they're not. Our system could provide data that can assist therapists in implementing improved patient-specific therapy plans.

7 CONCLUSION

MoveFeel is an AI-based system that can detect, process, and analyze movement data from video and can effectively identify expression and intention through Laban-based Effort metrics. We present a multi-stage workflow model, and demonstrate our system's ability to effectively distinguish dance phrases of different expression types. In the future, we will focus on refining the metrics computed by our model, improving the run-time performance of the processing algorithms, and eventually conducting a user study to validate our system in real-time. Through this system, we aim to help artists, experts and students better understand and interpret dance movement through technology.

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