

# Expressive Virtual Modalities for Augmenting the Perception of Affective Movements

A. Clay<sup>1</sup>, M. Courgeon<sup>2</sup>, N. Couture<sup>1</sup>, E. Delord<sup>1</sup>, C. Clavel<sup>2</sup>, J.-C. Martin<sup>2</sup>

(1)

ESTIA, LaBRI,  
Université Bordeaux 1 CNRS  
Technopole Izabel, 64210 Bidart, France  
Telephone number, incl. country code  
{a.clay, n.couture, e.delord}@estia.fr

(2)

LIMSI-CNRS  
BP 133  
91403 Orsay Cedex, France  
Telephone number, incl. country code  
{courgeon, celine.clavel, martin}@limsi.fr

## ABSTRACT

Recent progress in augmented reality enables them to be integrated in performing arts applications. So-called “augmented performances” are set up around the world, providing the audience with a new experience. As artistic tools, augmentation elicits aesthetic emotions within the audience by conveying the artists' emotional intent. The emotional communicative power of augmented reality in a performance has however not yet been formally evaluated from a perception point of view. This paper reports an experiment about the emotionally communicative power of several virtual modalities. We first describe how we collected a set of emotionally-expressive dance sequences from a professional dancer. We explain how the emotion expressed in each sequence is recognized by computer automatic recognition techniques and human subjects. We explain how we generated for each sequence virtual elements that are animated according to the expressed emotion. The resulting augmented dance sequences are then evaluated by human judges in order to determine which augmentation better conveys the original emotion. Results report that complex emotions are harder to recognize than simple emotions in a dance context, but that augmentation might improve recognition of those complex emotions.

## Categories and Subject Descriptors

H5.2 [Information Interfaces and Presentation]: User Interfaces—Input devices and strategies, Interaction styles, User-centered design.

## General Terms

Performance, Experimentation, Human Factors.

## Keywords

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Augmented performances, emotion, virtual agent.

## 1. INTRODUCTION

Performing arts are relevant for studying the expression and perception of affects. Today, augmented reality can bring additional means of enhancing the experience of the audience, taking into account the level of expertise with respect to dance of people attending a ballet performance.

Our project [27] aims at exploring means of combining augmented reality and emotion for cultural applications including Ballet. The partners aim at developing a prototype in which the expressive movements of a dancer are motion-captured and recognized in terms of emotion. Several virtual modalities are then added for the audience. In this paper, we describe a first version of the system and how a preliminary perceptive test enabled to compare the augmenting modalities.

We rely on Scherer's definition of emotion as a specific category of affects. An emotion can be seen as “an episode of interrelated, synchronized changes in five components in response to an event of major significance to the organism” [22]. These five components are: the cognitive processing, the subjective feeling, the action tendencies, the physiological changes, and the motor expression. In [23], Scherer discriminates utilitarian emotions (elicited by every-day events) from aesthetic emotions (elicited by art). In this work we focus on utilitarian emotions, as they are the ones performers seek to communicate (while aesthetic emotions are experienced by the audience).

Ekman proposed a set of characteristics that distinguish basic emotions from other affective phenomena (distinctive universal signals, distinctive physiology, automatic appraisal, distinctive universals in antecedent events, distinctive appearance developmentally, presence in other primates, quick onset, brief duration, unbidden occurrence, distinctive thoughts, distinctive subjective experience) [10]. Different sets of basic emotions have been proposed such as Joy, Surprise, Fear, Anger, Sadness, Disgust and Contempt [9]. Izard [13] also considers Interest, Shame and Guilt. In everyday life, several emotions often occur at the same time resulting in the expressions of blends of emotions [21][8]. Independent and bipolar dimensions have also been

proposed for representing emotional states. Russell proposed a 2D circumplex model of affects using a pleasure-displeasure dimension and an arousal-sleep dimension [20]. Other additional dimensions are also proposed such as dominance-submissiveness [19] or unpredictability [11].

Mixed Reality [17] is an interaction paradigm born from the will to merge computers processing abilities and our physical environment, drawing computer abilities out from its case. The goal is to eliminate the limit between the computer and the physical world, in order to allow interweaving information from the real world and information from the virtual world. On the continuum of Mixed Reality, from real world to virtual world, the AR paradigm appears. AR consists in augmenting the real world with virtual elements such as images. Augmented reality sounds as a relevant tool in the context of a ballet since it might be helpful to better convey the choreographer message. Technology evolutions quickly become new tools for artists to experiment with. Virtual arts evolve with technology, including augmented performing arts. In this paper we describe how we implemented and evaluated the impact of several virtual modalities augmenting dance movements.

This paper is organized as follows. Section 2 surveys related work about emotionally expressive movement and augmented dance performances. Section 3 describes our platform for collecting expressive dance and for generating augmentative virtual modalities. Section 4 describes the results of a perception tests comparing how much various virtual modalities help subjects to recognize the emotion intended by the dancer.

## 2. RELATED WORK

### 2.1 Emotions and their bodily expressions

An emotion can be seen as an “episode of interrelated, synchronized changes in five components in response to an event of major significance to the organism”. These five components are: the subjective feeling, the motor expression, the action tendencies, the physiological changes, and the cognitive processing. Emotions can be distinguished from other affective states (e.g. mood, attitudes) : utilitarian emotions are “relatively brief episodes of synchronized response of all or most organismic subsystems in response to the evaluation of an external or internal event as being of major significance for personal goals and needs” [23]. Emotion do not always occur one at a time, but instead frequently involve blends in everyday situations [21][8][16].

There is a large literature about bodily expression of emotions. Darwin listed several body movements linked to different emotions. Similar studies were conducted on expressive body movements during acted data.

In 1989, De Meijer [7] identified and validated, through human evaluations of actor performances, affect-expressive movement cues, such as trunk curvature, position of hands or velocity of a movement. Later, in 1998, Wallbott [26] conducted a study in which actors were elicited with the following emotions: elated joy, happiness, sadness, despair, fear, terror, cold anger, hot anger, disgust, contempt, shame, guilt, pride, and boredom. Twelve drama students were asked to code the body movements and postures performed by these actors. Distinctive patterns of movement and postural behavior associated with some of the

emotions were observed (e.g. “arms crossed in front of chest” for the emotion of pride, or the number of self-manipulators for shame). A number of movement and posture categories distinguished between ‘active’ emotions (like hot anger or elated joy), and more ‘passive’ emotions. Movement and postural behavior when encoding different emotions were to some degree specific to some emotions. Wallbott’s work can be seen as complementary with the ones of de Meijer. The analysis of evaluation data enabled both of them to compute the weights of each movement cue in the expression of a set of particular emotions. Those results on the analysis of dynamic aspects of movements were extended in 2004, by Coulson [5] who worked on affective cues in static body postures. For his study, Coulson used computer-generated material to avoid actor bias. Posture cues were defined as vectors of angles between limbs, thus giving a formal, “computer-friendly” description.

Several other researchers experimentally studied postural expression of affective states and interpersonal attitudes (e.g. postural congruence as a sign of rapport). Bull describes a series of studies where he observed that there were distinctive postures associated both with interest/boredom and disagreement/agreement. Interpersonal attitudes are often described according to two dimensions: 1) friendly vs. hostile, and 2) dominant vs. submissive. These interpersonal attitudes are reflected in several multimodal behaviors such as posture or duration of gaze while speaking. Information about affective state was observed to be conveyed both by body movement and static posture.

Berthouze et al. [1][15] used motion capture to collect and build low-level description of affective postures using acted and spontaneous protocols . These models were used to recognize affective categories or dimensions.

Beatrice de Gelder et al. [25] propose a hierarchy of neural detectors, which can discriminate seven basic emotional states from static views of associated body poses. In one study, when face and body conveyed conflicting emotional information about basic emotions, judgment of facial expression was hampered and became biased toward the emotion expressed by the body.

### 2.2 Expressive movement and augmented performances

Laban’s Theory of Effort is a seminal work in the domain of expressive movements, conducted from the 1920’s to the 1950’s. Laban was a choreographer. His work was drawn from and applied to dance. The Theory of Effort was described and analyzed by Hodgson [12]. Laban divides human movement into four dimensions: body, effort, shape and space. These dimensions focus on describing the expressiveness of a gesture by identifying how a particular gesture is performed, as opposed to what gesture is performed.

In the field of computer science, the Infomus Lab in Genoa based their research on Laban’s theory to identify and validate formally-described cues for computer-based recognition. Their studies cover several artistic contexts such as dance [3] and piano performances [4]. Comparatively to research in the field of psychology, such Computer Science-based studies identify formally described movement cues, thus making them easier to

integrate in a emotion recognition computer system. The Plane [29] unified dance, theater and computer media in a duo between a dancer and his own image. The dancer had a wireless movement capture device that enabled him, through his movement, to trigger video and audio media. Several shows were set up mixing dance and augmented reality by enabling the dancer to have some control over the projection of virtual graphics and lights, and the playing of sounds and music. In such a configuration, the computer system is seen as an instrument of the show rather than a stage setup. Hand-Drawn Spaces [14] presented a 3D choreography of hand-drawn graphics, where the real dancer's movements were captured and applied to virtual characters. Motion capture was not performed in real time and only virtual dancers were on stage. This work, presented at SIGGRAPH in 1998, acts however as a landmark in the field of mixing dance and motion capture. In 2002 the same team furthers the exploration of motion capture in real time. In "The Jew of Malta" [30], virtual buildings architecture cuts and virtual dancer costumes were generated in real time, depending on the music and the opera singer's position on the stage. Each of those shows used technology as an instrument of the show. The artistic use of those technological tools implicitly elicited aesthetic emotions within the audience. The impact of technology on audience recognition of the expressed emotion was however not explicitly identified. The work presented in this paper hence aims at addressing this issue by identifying which augmentation or composition of virtual modalities is most successful in enabling emotions expressed by the dancer to be recognized by the audience.

### 3. SYSTEM ARCHITECTURE AND COMPONENTS

#### 3.1 System Architecture

Four applications (Moven, eMotion, Marc and Shadoz) are running on four computers (see figure 1). Applications communicate with each other in real time using UDP/IP protocol.

The Moven software by Xsens is bundled with the Moven motion capture suit. It delivers position and rotation coordinates for 23 segments of the human body, and is able to render the movement as a virtual skeleton moving over a plane. The eMotion application uses those coordinates to estimate an emotion label. The MARC software uses this emotion to animate a virtual face expressing emotion. Finally, the Shadoz application uses the movement information, the computed emotion and the rendered face to produce a virtual environment. The eMotion and Shadoz softwares were developed using TrollTech's Qt library, thus making the applications OS-independent. Finally MARC is using the Virtual Choreographer 3D engine, developed on multiplatform C++ libraries.

#### 3.2 eMotion

Our computer-based gestural emotion recognition system relies on 3 successive steps: acquiring data, extracting gestural and postural emotional cues, and interpreting them as an emotion. We do not focus on identifying new expressive movement cues for emotion recognition but instead considered characteristics proposed by de Meijer [7] in our emotion recognition system. Unlike Coulson's and Infomus lab's works, cues drawn from de Meijer are verbally described and have to be interpreted to be implemented in a

computer system. However, De Meijer's work provides cues that are easier to implement and the respective weight of each cue for interpreting an emotion.

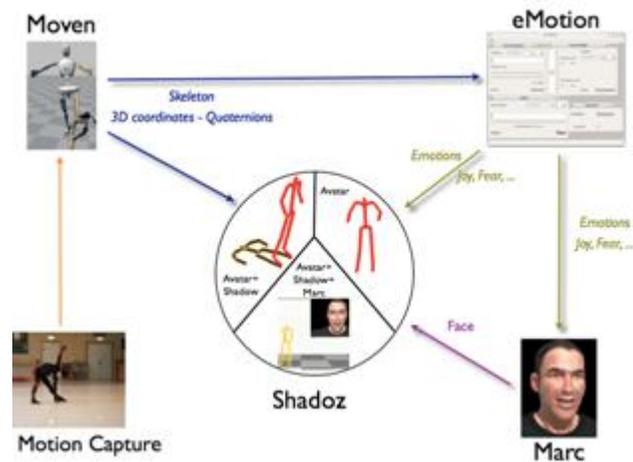


Figure 1. The integrated software architecture.

From the flow of coordinates provided by the Moven application, the eMotion software computes trunk and arm movement, vertical and sagittal directions, and velocity. Each features can take values in a discrete set. Trunk curvature ( $\{\text{stretched-bowed}\}$ ) is computed by the position of the spine comparatively to the plane formed by the basin and both shoulders. Arms expansion ( $\{\text{closed-open}\}$ ) is obtained by thresholding the distance between the wrists and the distance between the wrists and the spine. A speed vector of the basin is also computed at each frame. Thresholding its norm provides velocity ( $\{\text{fast-slow}\}$ ), thresholding its z-axis component provides the vertical direction of the movement ( $\{\text{upward, downward}\}$ ). Sagittal movement ( $\{\text{forward-backward}\}$ ) is obtained by computing the scalar product of the speed vector and the normal vector of the plane going through the basin and the shoulders. In this way, we consider the movement to go forward if the movement follows the direction of the torso. Interpretation is then made over the six basic emotions defined by Ekman [10]: joy, fear, anger, sadness, disgust, and surprise. We focused on these emotion categories as their bodily and facial expressions are already documented in the literature and we were willing to explore how the perception of their blend can be augmented with virtual modalities. Interpretation of the considered cues into the set of basic emotions is computed using a matrix of weights of each cue for each emotion. The weight of the matrix were drawn from the results of the analysis of those cues in [7]; no computer training was hence performed. An emotion was chosen as the maximum sum of weights of all the considered cues.

The eMotion software delivers an emotion label at each frame. Emotion over a period of time is computed as the maximum in the ratios between the number of frames detected as a particular emotion and the total number of frames. From an architecture point of view, the eMotion software is a component-based system that relies on the three levels of Capture (acquiring data from the world), Analysis (extracting emotionally-relevant cues) and

Interpretation (interpreting those cues to infer an emotion). Each atomic operation (data acquisition from a sensor, extraction of a feature, interpretation from a set of feature) is embedded in a pluggable/ unpluggable communicative component which allows easy modifications of the system

### 3.3 Shadoz

The Shadoz application, developed in C++ and QT, provides an extensible software base for augmenting a ballet stage, with plugins to handle emotions and graphical output. In the current version, Shadoz uses the coordinates from the Moven suit to create a virtual shadow that mimics the dancer's movement. Dancer's emotions are mapped to the virtual shadow, which changes size and color accordingly. Mapping between emotions and color and size ratio were drawn accordingly to Biren [2] and Valdez [24] studies:

Emotion	Color	Size
Joy	RGB(255,102,102) = Soft-Red	Real size * 3
Surprise	RGB(255,204,51) = Yellow-Brown	Real size * 3
Fear	RGB(0,0,0) = Black	Real size / 3
Sadness	RGB(148,0,211) = purple	Real size / 3

### 3.4 MARC

MARC is a real-time facial animation system. In this application, it uses eMotion's output to render and animate a high quality virtual face. MARC's animation is based on a MPEG4 [18] compliant animation system carried out using the Virtual Choreographer 3D engine [28] and performed in GPU. To increase visual realism, we simulate skin translucency (see figure 2.1) using latest techniques for real-time BSSRDF [6]. Realistic wrinkles are dynamically triggered from facial deformation. (see figure 2.2).

As MARC is capable of blending up to 8 different facial expressions with independent intensities, we developed a smoothing algorithm creating a progressive facial evolution from eMotion's binary outputs. The algorithm deals with six emotions intensity, corresponding with the six basic emotions detected in emotion. The intensity is either decreasing toward 0% or increasing toward 100%. Only the last detected emotion is increasing, and every other ones are decreasing. Increase and decrease speed depends on the repetition of detection. If an emotion A is detected, its intensity starts to increase slowly. Then, if A is detected repeatedly and successively, its intensity increase faster and faster. False detections are so absorbed, i.e. do not appears on the face, and repeated detections have a higher impact on facial animation.



Figure 2. MARC. Skin close-up (1) Smile wrinkles (2)

## 4. PERCEPTION STUDY

The goal of this perception study was to compare several augmenting modalities. Our initial hypothesis was that, due to individual differences in non-verbal perception and in dance expertise, these modalities would have different effects across people. In this experiment, we tested the augmentations that our system could offer, using the original video of each affective dance as a reference.

### 4.1 Collecting affective dance sequences

In order to design augmenting modalities and test the recognition of emotion by the eMotion module, we collected motion-captured movements of a dancer.

Dance sequences were performed by a single professional ballet dancer. Recordings were performed using the Moven capture suit, a firewire video camera and a camcorder. The artist clapped hands at the beginning of each sequence, thus allowing synchronizing the flow of coordinates and the two video flows. Each video sequence was of about 1'15" length.

Expressive dance improvisations were collected in two sessions. In the first one, the dancer was told a single emotion label from our chosen set {cold anger, hot anger, positive surprise, negative surprise, fear, sadness, disgust, sadness, joy}. Each affective state had to be performed three times. The 24 resulting sequences were randomly performed. The second session mixes the Ekman's six basic emotions. Seven pairs were studied and randomly performed: {fear+anger, sadness+fear, disgust+surprise, sadness+anger, joy+sadness, disgust+anger and joy+anger}. A scenario approach was used to communicate emotion pairs to the dancer. For example, the pair sadness+anger was expressed by "A motorist crushed your dog"

We then obtained 31 affective dance sequences as a collection of materials where it is possible to base experiments to determine the impacts of various expressive virtual modalities for augmenting the perception of affective movements.

### 4.2 Perception tests during collection

While we recorded the dancer's movements, we also performed a perception test with an audience of seven people. The goal was to evaluate of human subjects recognize the intended affective state. The seven people evaluated each performed sequence by picking

what they felt to be the expressed emotion among our sets of labels Recognition percentages for human recognition represents the ratio of people having recognized the expressed emotion.

For the purpose of this study, we first kept the sequences that were best recognized by the eMotion software (>70% of the frames in the sequence) with a human recognition higher than 50%. We completed the test set with sequences best recognized by the system, even if human recognition was low.

We hence kept five sequences for our tests, representing sadness, joy, sadness, negative surprise, and joy+sadness. The second "sadness" sequence has the particularity to have had a 42% human recognition rate, while the eMotion software recognized it sadness for 56% of its duration. As such we distinguished the two sadness sequence by calling them "sadness rH" (recognized by human) and "sadness nrH" (not recognized by human). We refer to these sequences as "affective dances".

### 4.3 Method

Five modalities were explored in this perceptive test. We used the five affective dance sequences kept from the initial recollection (see paragraph 4.1). For each affective dance, five video sequences were generated, each corresponding to a modality or a combination of modalities.

The first modality was the recorded video sequence of the affective dance. This was used as a reference stimulus in this test.

The second modality was a video sequence of the same movement and from the same point of view, but performed by a uniformly-black three-dimensional matchstick avatar (called "avatar" in the following sections). This modality was chosen to see the impact of a minimalist representation of the dancer on the emotional perceptive abilities of the test subjects.

The third modality was MARC's expressive and realistic 3D face. The eMotion software was used to recognize emotions over the affective dance sequence. The obtained corresponding sequence of emotions was then used to generate a video of MARC's face expressing this sequence of emotions.

The fourth modality was made using the Shadoz software. The 3D matchstick avatar was augmented with an expressive shadow that changed size and color according to the recognized emotion. The matchstick avatar also changed color accordingly.

The fifth and last modality combined Shadoz's matchstick avatar and expressive shadow and MARC's expressive face in a single video.

We hence had a total of 25 video sequences (5 emotions x 5 modalities). 25 sets of 5 video sequences each were semi randomly generated: each set featured one expression of a particular emotion, and one modality among the five tested modalities.

25 (10 females, 15 males) subjects voluntarily participated in the evaluation of the video sequences. Subjects were drawn from the universities staff and students, with age ranging from 23 to 62.

First, subjects had fill in their age, sex and profession before answering three multiple-choice questions: "How many dance shows have you ever seen?", "Would you say that you are

sensitive to other's behavior, on a daily basis?", and "How would you rate your empathy, that means your ability to recognize and understand someone's emotional state?"

Each subject was then presented a set of video sequences to evaluate on a laptop computer. A predefined speech was told them to explain them what to do.

For each video in the set, subjects could recognize up to three different emotions. They had to rank those three emotions on a forced-choice table, using "1" for the most intense recognized emotion and "3" for the least intense recognized emotion. Subject could rank several emotion ex-aequo in case of similar intensity. Subject could recognize and rank only one or two emotions.

Subjects were allowed to watch the video sequences several times. Subject did not have any time constraint to complete the evaluation.

### 4.4 Results

We first analyzed the results by considering all attributions made by the subjects and we conducted an analysis of Chi2. We first looked at whether the perception varies according to the emotional stimulus and the different presentation modalities. Finally, we focused on some individual characteristics such as gender and level of expertise in dance.

Results show that emotional perception significantly vary according to the emotional stimuli (Chi2=65,77 p<0.05).

From the "Joy" stimulus, subjects perceive 36% of Joy and 23% of Positive Surprise.

From the "Negative surprise" stimulus, subjects perceive 21% of Fear, 23% of Negative Surprise and 21% of Sadness.

From the "Sadness" stimuli, attributions are the same for the two stimuli. Subjects perceive 38% of Sadness for Sadness nrH and 32% of Sadness for Sadness rH.

From the complex emotion "Joy+Sadness", subjects perceive mainly 29% of Joy and 32% of Sadness.

We were willing to compare the recognition of "single emotions" (Sadness nrH, Sadness rH, Joy) vs. "complex emotions" (negative surprise, Joy+Sadness). We categorized the answers of subjects according to the expected results (correct answers, partly correct answers, incorrect answers). We rated the recognition of subjects as "correct / incorrect" for single emotions. For complex emotions (e.g. "negative surprise"), we rated the recognition as "partly correct" when the subject reported only one of the two emotions.

Table 1 provides the number of answers in each category. Chi2 analysis reveals that 1) single emotions are well recognized whatever the presentation modality, 2) complex emotions are not well recognized (Chi2=40,44 p<0.05 significant results).

We also compared the different presentation modalities (Table 2). In two presentation conditions (Video, avatar), complex emotions were not well recognized. In the three conditions (avatar+Shadoz, Marc, avatar+Shadoz+Marc), complex emotions were better recognized than in the two conditions (Video, avatar).

	<b>Correct</b>	<b>Partly correct</b>	<b>Not correct</b>
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Sadness nrH	21	0	4
Sadness rH	17	0	8
Joy	19	0	6
Negative surprise	12	4	9
Joy + Sadness	12	11	2

**Table 1. Number of answers by subjects for each emotion.**

As the whole sample, female subjects recognized the single emotions better than the two complex emotions (NegativeSurprise, JoySadness). For male subjects, NegativeSurprise was recognized as well as the single emotions.

We also compared subjects with respect to their expertise in dance (estimated by the number of shows they had attended). 15 subjects were rated with little expertise in dance (number of attended shows smaller than 5). 10 subjects were rated as having a stronger expertise in dance (number of attended shows greater than 5).

		Correct	Partly correct	Not correct
avatar+ Shadoz+ Marc 	Neg. surprise	4	0	1
	Sadness nrH	5	0	0
	Sadness rH	4	0	1
	Joy	4	0	1
	Joy+Sadness	3	2	0
Video 	Neg. surprise	3	0	2
	Sadness nrH	5	0	0
	Sadness rH	3	0	2
	Joy	3	0	2
	Joy+Sadness	1	4	0
avatar+ Shadoz 	Neg. surprise	1	2	2
	Sadness nrH	3	0	2
	Sadness rH	5	0	0
	Joy	4	0	1
	Joy+Sadness	4	0	1
avatar 	Neg. surprise	0	2	3
	Sadness nrH	4	0	1
	Sadness rH	2	0	3
	Joy	4	0	1
	Joy+Sadness	0	3	1
Marc 	Neg. surprise	4	0	1
	Sadness nrH	4	0	1
	Sadness rH	3	0	2
	Joy	4	0	1
	Joy+Sadness	3	2	0

**Table 2. Number of answers for each emotion in each modality.**

No intergroup difference was found whatever the emotion or the presentation modality. Nevertheless, an intragroup analysis revealed that for « low expert » subjects, the recognition of different emotions varies. These subjects recognize equally single emotions and negative surprise. From the stimulus JoySadness, subjects attributed only one emotion (either Joy or Sadness). The different presentation modalities do not impact the emotional recognition. Subjects with a stronger expertise in dance recognised NegativeSurprise less well than the other emotions (single emotions or JoySadness). Their perception was also affected by the presentation modalities: when subjects saw “avatar only”, their recognition rate was lower than for the other presentation modalities.

## 5. CONCLUSION AND FUTURE DIRECTIONS

In this paper we presented an experiment which aimed at being a first step toward determining which kind of augmentation or combination of augmentations, among the ones we had developed, helped audience to better recognize the emotion expressed by a ballet dancer, compared to a video of this dancer. To achieve this, we recorded dances using a video camera and a motion capture suit. A first set of human evaluators allowed us to pick five dances that best expressed the intended emotion. From these five dances, we performed computer-based emotion recognition at each frame. Recognized emotions were then used twice: to animate an expressive face and to modulate the size and color of an avatar's shadow.

Resulting testing material for impact of augmentations were normal video, avatar only, avatar + emotionally-reacting shadow, expressive face alone, and avatar + emotionally-reacting shadow + expressive face. Five semi-randomly picked video (normal or augmented) were shown to each of the twenty-five human evaluators.

The results reported above showed that complex emotions were more difficult to recognize than single emotions. Nevertheless, users might benefit from augmented modalities to improve the recognition of these complex emotions. As complex emotions seem more frequent in dance shows, these first results encourage us to continue such experiments with a larger sample of human subjects. Differences between levels of expertise in dance need further investigation such as how to evaluate such expertise with more detailed information than the number of attended shows (e.g. compare students of a dance school vs. students with a scientific curriculum).

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