I Am a Tree: Embodiment Using Physically Based Animation Driven by Expressive Descriptors of Motion

Caroline Larboulette
University of South Brittany
Vannes, France
caroline.larboulette@univ-ubs.fr

Sylvie Gibet
University of South Brittany
Vannes, France
sylvie.gibet@univ-ubs.fr

Figure 1. Physically based animation of 5 trees driven by expressive descriptors of human motion conveying 5 different emotions: from left to right: *Happy*, *Cool*, *Neutral*, *Stressed* and *Sad*.

ABSTRACT
Expressive representation of human movement has given rise to various static or dynamic artistic creations, whether they take into account specific postures or motion sequences. In this paper we are interested in the expressive qualities of motion and how these qualities influence the evolution of a $3D$ simulated system. The embodiment of this system takes the form of a non-anthropomorphic structure (non-human appearance) whose behavior expresses the emotional content of the original human motion. Expressive descriptors are extracted from a sequence of theatrical movements executed with different emotional states and used to dynamically control a mass-spring system coupled to a particle system as well as its rendering. The framework allows for the exploration of different sets of motion descriptors and mappings to the parameters of the $3D$ simulation. The resulting animations are discussed and evaluated through perceptual studies.

Author Keywords
Embodiment, expressive, animation, simulation, motion, descriptors, perception

ACM Classification Keywords
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INTRODUCTION
Historically, humans have sought to represent their expressive movements through artistic experiences and performances. These representations, which can take several forms, implicitly reflect the *intention* and the *feeling* that were involved when producing the movement. Through various means and materials, artists have thus attempted to translate an inner feeling whose intention and expression should be perceivable by others.

Over the last century, many studies in psychology have shown that body postures and movements convey observable features of emotional states. Thus, different emotions may be recognized from different body postures [26]. Recent studies have proven the relevance of dynamic information for detecting emotion in whole body movements [8, 10, 7]. Moreover, the recording of human motion has given the possibility to analyze and synthesize expressive movements for various affective computing applications, either applications that detect and recognize the emotions of the user, or that generate an expressive behavior through a virtual or physical entity [15]. In Human-Computer Interaction (HCI), to make the best use of human abilities, new sensor technologies are used to explore new ways of interacting with virtual or real systems. In Performing Arts, many studies have focused on dance or expressive movements, where the whole body motion is exploited to control (interactively or not) sound and visual outputs.

The notion of motion quality has recently emerged. It is defined as the way in which the movement is executed [1]. Laban Movement Analysis (LMA) theory [16, 2, 21] has proposed, through the Effort and Shape components, to describe the qualitative aspects of the movement. Different sets of motion qualities have been defined, with a few attempts proposing computable measures of these expressive qualities for captured motion [25, 14, 18].

The present work is motivated by the development of a simulated graphical framework which is sensitive to whole body motion and its expressive modulations. We will consider that the expressive modulations characterize the way the motion is performed, guided by the emotional context and the intent of the performer.

Moreover, although there is extensive work on producing expressiveness in anthropomorphic structures (virtual humans in particular), we are interested in this paper by non-anthropomorphic structures such as physical structures taking shapes and trajectories that do not resemble human postures or movements. We aim at producing behaviors that incorporate recognizable affective expressions. By coupling expressive features to parameters of the graphical simulation, we propose a way to explore the control of the simulated structure, and to find the best mapping from human perception and aesthetics points of view.

RELATED WORK

Using expressive motion to control or interact with simulated or real systems has given rise to various research work and applications, ranging from Computer Graphics or Human-Computer Interaction to artistic creations and performances.

Different kinds of embodiments which express affective states may be considered, among them, those represented by anthropomorphic structures. In particular, designing compelling characters capable of creating a more intuitive and engaging interaction with a user constitutes a challenge for the animation of expressive characters. To achieve animation of highly believable and stylistic characters, machine learning techniques can be used to capture style in motion and generate novel movements with variations in style [4, 12, 11, 13]. In these studies authors consider a low-level definition of style, in terms of variability observed among several realizations of the same gesture. However, it may be difficult to parameterize motion and to produce controllable and flexible behaviors in real-time. In addition, if many studies focus on controlling expressive virtual humans, little work has focused on the relationship between expressive behavior of non-anthropomorphic virtual structures and motion qualities.

Motion provides a powerful expressive modality for affective expression which has inspired research in computational graphics. In recent works, researchers have studied what properties of human motion influence affect. Observers generally attribute complex emotions to a set of animated geometric primitives [3]. Basic properties of $2D$ motion textures have proven their capacity to influence the affective ratings of valence, intensity and interest [20]. This latter work has been extended to $3D$ motion features and has shown that speed, direction, path curvature and shape strongly influence affective impressions (valence, comfort, urgency and intensity) [9].

Other gestural interaction studies have been developed for visual and performing arts [19]. For example, a full-body interaction is explored through the *Integrarte* artistic installation to make users interact with sound and image production [6]. Inspired by LMA's theory, Alaoui et al. propose to control a mass-spring system (MSS) using motion descriptors [1]. The MSS is considered as a graphical metaphor reflecting dancers' movement qualities. Their approach is implemented in the context of the installation proposed by the Emio Greco$|PC^c$ dance company, for 4 classes of movements: *Breathing*, *Jumping*, *Expanding* and *Reducing*. The movement qualities composing the recognized components of these movements are then mapped to the forces of the physical model.

Following this line of research, we also focus on motion qualities and propose a mapping of the expressive features to the parameters of a graphical dynamic system. We compute descriptors on $3D$ full-body motion sequences, performed with various emotional states, that we have recorded. We have chosen descriptors issued from the literature [18] that give a good and generic coverage of motion descriptors commonly used by computer scientists. They include a set of kinematic and geometric low-level descriptors as well as high-level descriptors (descriptors that may be interpreted by movement experts or perceptual evaluators and are optionally characterized by semantic labels or discrete variables), some of which are inspired from LMA classification. The aim of this work is not only to study how motion qualities interact with a physical $3D$ simulated system, through physical and kinematic parameters, but also to evaluate the influence of these parameters on the visual representation, in particular concerning the dynamical rendering and coloring effects.

SYSTEM

We have chosen a simplified tree to represent our entity. We have voluntarily chosen a non-realistic model for the tree and the leaves. As for a real tree, the trunk does not move. Three branches are attached to the trunk and are animated. Leaves are generated from the branches and fall down towards the floor.

Physically Based Animation System

Our physically based animation system is composed of a mass-spring system to animate the branches coupled with a particle system to simulate the leaves. The entire system is subject to external forces such as the wind or gravity although we did not map any parameter to those forces in the application described hereafter.

The mass-spring lattice is a reversed tetrahedron: the particles of the base are the tip of the branches and the top is attached to the trunk where the branches meet. There is an additional particle in the center to represent the center of mass of the tree and this particle is linked to the branches tips with 3 additional springs. Figure 2 shows the lattice we have used. For the spring restlengths, we have used the original distance between the particles so that if no effect is injected into the system, it is stable and remains undeformed. Note that we did not add gravity to the external forces as we want the deformations to be driven only by the expressiveness of the movement and nothing else.

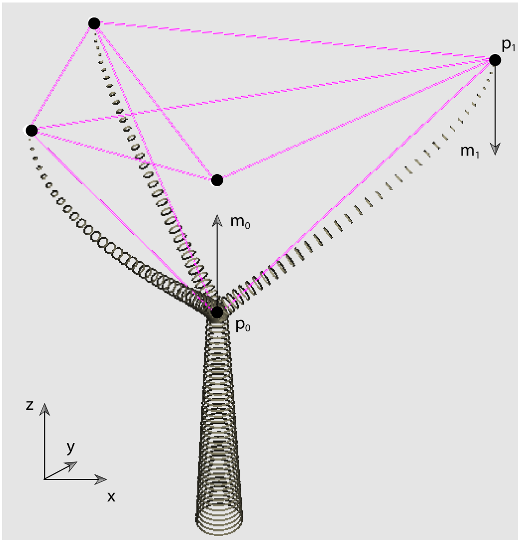

Figure 2. Mass-spring lattice: the masses (black dots) are connected through linear damped springs (colored segments). The branches are rendered as generalized cylinders constructed around a Hermite spline defined by $\mathbf{p}_0, \mathbf{p}_1, \mathbf{m}_0$ and $\mathbf{m}_1$.

At a given time t, the positions of the masses are integrated using a Runge-Kutta of order 4 numerical integration scheme from the forces generated by the springs.

To create the leaves, a particle emitter is attached to each end of each branch. The emitters emit particles around the tip of the branch with a random position and a unit velocity of $(0, 0, -1)$ so that the particles go down. The velocity $\mathbf{v}$ of emitted particles as well as the rate of emission of the particles are modulated according to the computed movement qualities as described in the following section. The position $\mathbf{x}$ of a particle at time $t+d_t$ is integrated as $\mathbf{x}_{t+d_t} = \mathbf{x}_t + \mathbf{v} * d_t$. Note that once emitted the velocity $\mathbf{v}$ of a given particle is constant.

Rendering

The tree is rendered as 4 generalized cylinders (see figure 2). The shape of the trunk is defined by a straight line and two radii. The shape of each branch is defined by a Hermite spline and two radii. The cylinders are generated along the line or spline using a linear interpolation of the radius.

On the unit interval $(0, 1)$, given a starting point $\mathbf{p}_0$ at $t = 0$ (here the trunk end point) and an ending point $\mathbf{p}_1$ at $t = 1$ (here the tip of the branch), with a starting tangent $\mathbf{m}_0$ at $t = 0$ and an ending tangent $\mathbf{m}_1$ at $t = 1$, the position $\mathbf{p}(t)$ on the Hermite spline can be expressed as:

$$\begin{aligned}\mathbf{p}(t) = \quad & (2t^3 - 3t^2 + 1)\mathbf{p}_0 + (t^3 - 2t^2 + t)\mathbf{m}_0 \\ & +(-2t^3 + 3t^2)\mathbf{p}_1 + (t^3 - t^2)\mathbf{m}_1\end{aligned} \tag{1}$$

For the branches, the end points $\mathbf{p}_1$ of the splines are driven by the mass-spring simulation. Note that the trunk end points $\mathbf{p}_0$ do not move. For each branch, the origin vector $\mathbf{m}_0$ is set to $(0, 0, 1)$ so that the branches come out of the trunk nicely and with a G^1 continuity. The end vector $\mathbf{m}_1$ is initially set to $(0, 0, -1)$ to obtain a nice shape. The $m_1.z$ coefficient is then modulated during animation to modify the shape of the tree according to the Shape Directional descriptor.

To render the leaves, we have used a leaf billboard. The size of a leaf depends on its lifetime: the older the smaller. After some time, the leaf disappears. This coincides more or less to when it touches the ground.

In addition, we have used the velocity of the leave to add a rotation effect. This is done by rotating the quad over which the leaf is painted around the viewing axis (eye to leaf). The angle of rotation is calculated as the dot product of the up-vector of the viewing axis and the leaf velocity.

The color of the tree, trunk plus branches, is fixed. The color of the leaves changes according to the mood of the movement as will be described in the following section. This is implemented through a GLSL shader.

MOTION DESCRIPTORS AND PARAMETERS MAPPING

To modulate the shape of the tree and the behavior and color of the leaves, we have computed several motion descriptors on 5 motion sequences. Each motion sequence lasts about 6000 frames at $200Hz$ and represents the same scenario played with one of the 5 emotions: *Cool*, *Happy*, *Neutral*, *Sad* or *Stressed*. The parameters mapping has been chosen based on common sense, meaning of the descriptors and trials.

The descriptors we have used as well as the corresponding equations used to compute them can be found in [18]. However, although we have used normalized equations to compute those descriptors, a scaling factor exists between different movements depending on the type of movement or more simply the scale of the character. There is no solution to date in the literature (see **DISCUSSION**) so we have clamped or linearly scaled the values with respect to the maximum and minimum values observed on the 5 sequences of motion we have used. We have thus been able to use the same scaling values for all 5 motions, but those scaling factors may have to be changed if applied to very different motions or characters different in size.

Tree Shape

Center of Mass

The particle representing the center of mass of the tree is constrained to move like the center of mass of the captured human. To remove the global motion of the character in the $3D$ space, we do not use the CoM position directly but we compute the distance between the Root joint and the CoM and we use this distance to displace the center of mass of the tree. As a result, the tree balances when the center of mass of the captured human moves.

Breathing

To make the tree breathe like a human-like entity, we have used the Bounding Volume descriptor of the original movement to modify the restlength of the springs. The breathing effect is obtained as the system expands or shrinks according to the volume of the bounding box. The more the volume of the bounding box, the more the expansion of the tree (see figure 3).

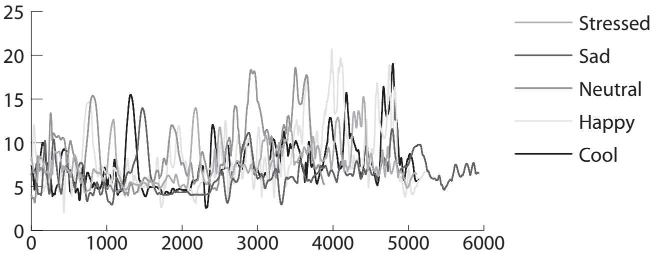

Figure 3. Bounding Volume for the 5 emotions computed on the bounding box of the character.

Curvature

The curvature of the branches is related to the Shape Directional descriptor. This descriptor describes the shape of a movement, whether it is *arc-like* or *spoke-like*. By modulating the end vectors $\mathbf{m}_1$ of the Hermite splines defining the shape of the branches, we can increase or decrease the curvature of a branch.

The Shape Directional value being a scalar value, we have opted to only scale the vector without modifying its direction. The $m_1.z$ value of the end vector of the spline is thus the opposite of the Shape Directional value that we have scaled to keep sensible values. We have computed the descriptor over a window of 10 frames to avoid flickering effects and then linearly interpolated the value over time (see figure 4).

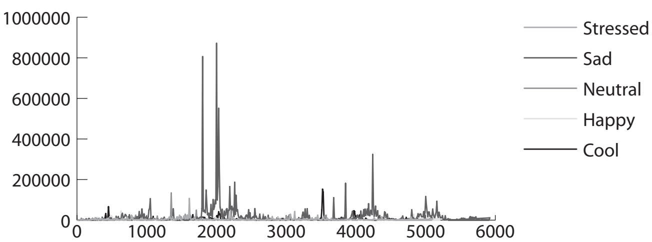

Figure 4. Shape Directional descriptor for the 5 emotions computed on a time window of 10 frames.

Fluidity

The fluidity of the movement is characterized by the Flow Effort descriptor. It describes whether the movement is *Free* or *Bound*. The way the tree is free or not to move is related to how stiff the mass-spring system is. We have thus used the Flow Effort descriptor to increase or decrease the stiffness and the damping of the springs. Starting with a stiffness of 10^{-3} and a damping of 10^{-3}, we have scaled those values by the Flow Effort value divided by 1000. Higher scaling factors lead to an unstable system. As a mass-spring simulation is very sensitive to stiffness and damping values, it can also not be changed too abruptly. We have thus used a time window of 20 frames for the descriptor computation to obtain a more stable and natural simulation (see figure 5).

Leaves

Velocity

The velocity of a given particle is constant once it is emitted. However, the velocity of each particle depends on the Time Effort and Space Effort movement qualities. The Time Effort descriptor represents the sense of urgency, whether a

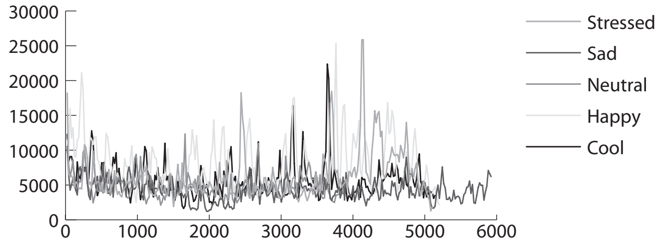

Figure 5. Flow Effort descriptor for the 5 emotions computed on a time window of 20 frames.

movement is *Sudden* or *Sustained*. We thus update the $v.z$ coefficient of the velocity according the opposite of the Time Effort value. We have used a time window of 10 to compute this descriptor (see figure 6).

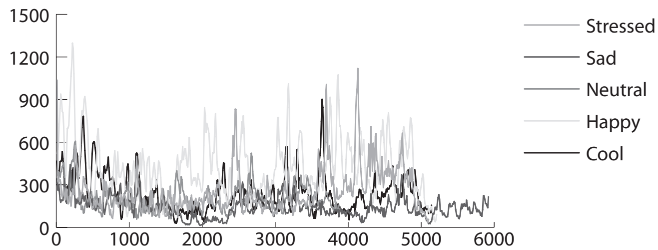

Figure 6. Time Effort descriptor for the 5 emotions computed on a time window of 10 frames.

The Space Effort descriptor defines the directness of the movement, whether it is *Direct* or *Indirect*. The higher the Space Effort value, the more multi-focused the movement. We have thus modulated the velocity of the particles on the x and y axis so that the particles spread more or less. The $v.x$ and $v.y$ values thus vary between -0.01 and 0.01, a value of 0 meaning the particle goes straight down. We have used a time window of 10 to compute this descriptor (see figure 7).

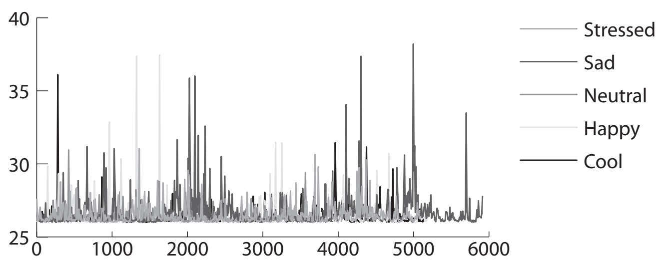

Figure 7. Space Effort descriptor for the 5 emotions computed on a time window of 10 frames.

Rate

The rate of emission of the particles is also related to the Time Effort descriptor. The higher the Time Effort value, the more particles will be emitted over a given period of time. On the contrary, a lower value of Time Effort yields a lower rate value making the production of the particles slower giving an impression of stretching time. The rate is thus proportional to the Time Effort value computed over a time window of 1 (see figure 6). A larger window would loose the subtleties of the movement.

Colors
To obtain aesthetic variations of colors, we have used the Munsell Color Order System [24] to select colors according to the Weight Effort value and the Extensiveness. In the Munsell color space, a color is defined by its hue (whether it is green, red, blue...), its saturation (vivid versus pale colors) and its brightness [23]. Any two neighbors in the Munsell color space have the same perceptual variation.

The advantage of this COS is that it can be ordered in $3D$: on the x axis, the saturation changes for a given hue and brightness; on the y axis, the brightness increases or decreases, and going into circles around the y axis changes the hue for a given saturation and brightness. As a result, any elliptic path in this space will result in an aesthetic change of color [22, 17] (see figure 8).

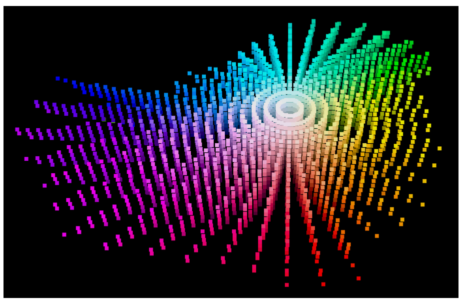

Figure 8. $3D$ **plot of the Munsell Color Order System.**

Hue
Extensiveness computes the normalized sum of the distances between end effectors (both hands, both feet, both shoulder and the head) and the Center of Mass of the body. It gives information on whether the movement is executed in confined space (when acting sad for example) or uses a wider volume (when acting joyful for example). We have thus used this descriptor to select the hue of the color (see figures 9 and 13).

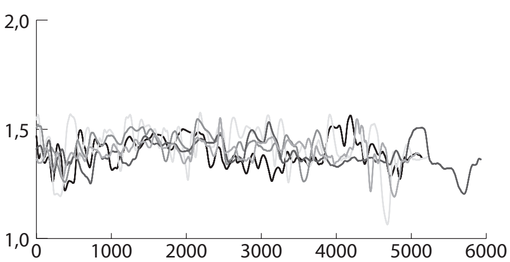

Figure 9. Extensiveness descriptor for the 5 **emotions.**

Brightness
The Weight Effort descriptor describes whether a movement is *Strong* or *Light*. We have used this descriptor to change the brightness of a given color (i.e. move up and down in the Munsell color space), a bright color depicting a light movement and a dark color representing a strong movement. To obtain smoother and more aesthetically pleasing colors, we have used the Weight Effort descriptor computed over a time window of 20 frames (see figures 10 and 13).

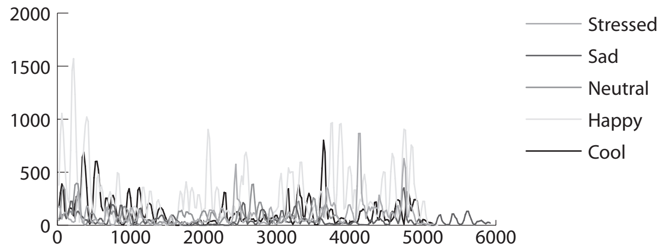

Figure 10. Weight Effort descriptor for the 5 **emotions computed on a time window of** 20 **frames.**

RESULTS AND EVALUATION
Performing arts (theater, pantomime, dance, magic, mime, etc.) provide good examples of full-body movements as a channel of expression. We have used a mime theatrical scenario for which feelings and emotions can be solely conveyed by bodily movement [5]. For the purpose of this study we only used one sequence of a magician trick, namely *The Disappearing Box*, enriched with emotional content. It is acted five times by the same performer with the following emotions: *Cool*, *Happy*, *Neutral*, *Sad* and *Stressed*.

The full-body high-definition motion is captured at $200Hz$ using 8 Oqus400 cameras and 64 passive markers placed on the body, face and hands. The motion is then reconstructed using the Qualisys software.

Mapping and Resulting Effects
A summary of the mappings used in our examples is shown on table 1. Note that the exact same mapping is used for the 5 animations.

Descriptor	Physical Parameter	Effect
CoM	p_{center} of the MSS	Bending of the tree
BVolume	restlength of springs	Breathing of the tree
ShapeD	$m_1.z$ of spline	Curvature of branches
Flow Effort	s & d of springs	Fluidity of branches
Time Effort	v_z of particles	How fast leaves fall
Space Effort	v_x & v_y of particles	How straight leaves fall
Time Effort	rate of particles	How fast leaves rise
Extensiveness	hue	Changing hue (leaves)
Weight Effort	brightness	Strong/Light color (leaves)

Table 1. Mapping of the movement descriptors to the physical parameters of the simulation and the effect obtained.

Breathing and Fluidity
Breathing of the tree and fluidity of the movement of the branches is obtained through changes in the parameters of the mass-spring system: restlength, stiffness and damping of the springs. Opposed emotions are *Happy* and *Stressed*. A happy movement will expand more and move more freely than a stressed movement. Figure 11 shows the tree at the beginning of the *incantations* action for those two emotions.

Curvature
The curvatures of the tree branches are obtained through changes of the Hermite splines tangents m_1. Opposed emotions are *Sad* and *Happy*. A sad movement is usually slower (so its curvature increases) and more stunted. Figure 12

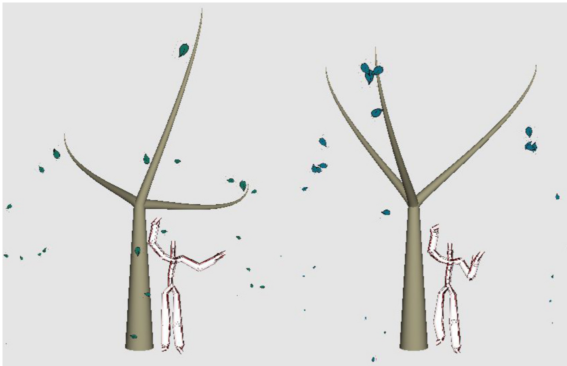

Figure 11. Effect of the restlength, stiffness and damping of the springs of the mass-spring system on the shape of the branches on the happy movement (left) and the stressed movement (right) at the beginning of the action *incantations*.

shows that this effect can be simulated through the Shape Directional descriptor.

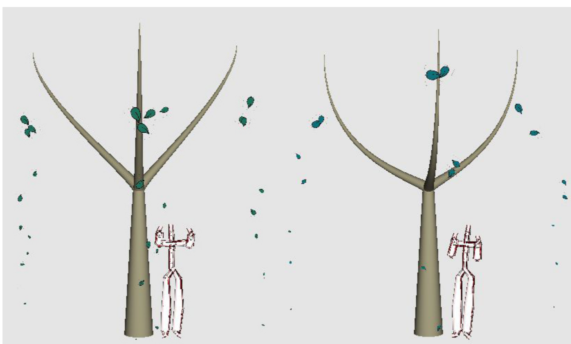

Figure 12. Curvature of the branches on the happy movement (left) and the sad movement (right) at the end of the action *grabbing the box*.

Colors

The color palette used for the leaves rendering is computed according to the Extensiveness and the Weight Effort descriptors: happy movements have more hue variations than other moods and also have brighter colors than sad movements. This is shown on figure 13 at the end of the *introduction bow* action.

Figure 13. Color of the leaves on the happy movement (left) and the sad movement (right) at the end of the *introduction bow* action.

We have illustrated some of the effects of the physically based simulation parameters. Note that in each of the examples, the character is in a very similar pose, that shows that the differences in the shape of the tree or color of the leaves is due to the dynamics of the system.

Validation

Baseline Experiment

To validate our results, we have first conducted an evaluation of the 5 tree animations produced on 17 subjects. They have been shown the videos and asked to qualify each video by one of the following adjectives: *Cool*, *Happy*, *Very Happy*, *Sad*, *Very Sad*, *Stressed*, *Calm*, *Soft* or *Neutral*.

Table 2 shows the confusion matrix obtained. *Happy* and *Very Happy* have been grouped as well as *Sad* and *Very Sad*. The other qualifying adjectives are debatable as *Calm* can be understood either as *Cool* or *Sad* (it's a low arousal movement). Same remark for *Soft* that can be confused with *Calm* and may qualify a *Cool* or *Sad* movement. Those additional adjectives have thus been removed from the confusion matrix.

What we have observed is that the *Neutral* video was graded as *Cool* by most people. The results were then shifted. The *Cool* video was graded as *Happy* and the *Happy* video as *Very Happy*.

Video Emotion	Cool	Happy	Neutral	Sad	Stressed
Cool	22.2%	6.5%	**35.9%**	3.4%	8%
Happy	**55.6%**	**61.3%**	32%	34.5%	22.7%
Neutral	3.7%	0%	5.7%	0%	16%
Sad	14.8%	9.7%	26.4%	**46.6%**	18.7%
Stressed	3.7%	22.6%	0%	15.5%	**34.7%**

Table 2. Confusion matrix of the results for the 5 emotions.

Except for the *Neutral* video that was clearly categorized as many different feelings, the other emotions were recognized with a score above chance ($> 20\%$) with a better identification of the *Happy* emotion. We thus concluded that our system did convey some emotion, however we needed to also evaluate the original movements to be able to draw actual conclusions.

Valence / Arousal Experiment

As the original sequences are very long (around 30 s), this might make the evaluation task too complex, therefore we have decided to evaluate the system for shorter actions performed with different expressions. For our second experiment, we have created 3 movement chunks of 5 seconds duration each from each original captured motion, those motion chunks being synchronized with actions found in the 5 original motions: *incantations*, *showing the result* and *final bow*. For each movement chunk, we have captured the original motion portrayed by a stick figure character, and the tree animation. We thus had a total of 3 movements x 5 emotions x 2 renderings, i.e. 30 videos. We asked the participants to first grade the *valence* of the motion, on a $1-7$ Lickert scale, 1 meaning *very negative / unpleasant* and 7 meaning *very positive / pleasant*. They were then showed the videos a second time and asked to grade the arousal on a $1-7$ Lickert scale, 1 meaning *very passive / calm* and 7 meaning *very active / aroused*. The videos were shown in a random order to account for any learning effect.

31 participants (24 men, 7 women), aged from 18 to 61 (24 on average) from various backgrounds took part to the experiment. As the scores are scaled between 1 and 7, the expected values for the 5 emotions are:
- *Happy*: positive (valence > 4) & energetic (arousal > 4)
- *Cool*: positive (valence > 4) & lethargic (arousal < 4)
- *Neutral*: valence $= 4$ & arousal $= 4$
- *Sad*: negative (valence < 4) & lethargic (arousal < 4)
- *Stressed*: negative (valence < 4) & energetic (arousal > 4)

Figure 14 shows the results obtained for the 3 videos of the *Happy* tree. Note that both the valence average value $(4,258)$ and the arousal average value $(5,731)$ are superior than 4 which means that the emotion is correctly identified. Figure 15 shows the results obtained for the 3 videos of the *Sad* tree. Again, the emotion is correctly identified as the average for both, valence and arousal are below 4.

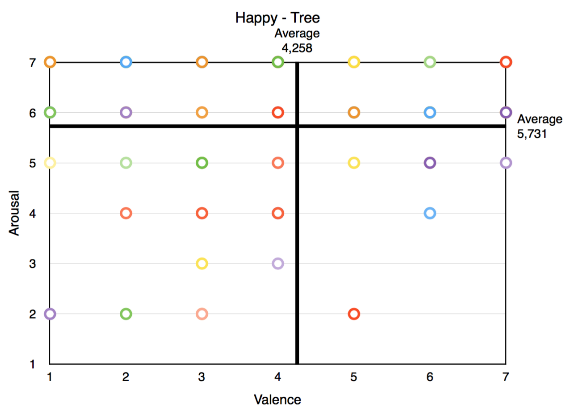

Figure 14. Valence/Arousal experiment results for the *Happy* tree videos, for the 31 participants.

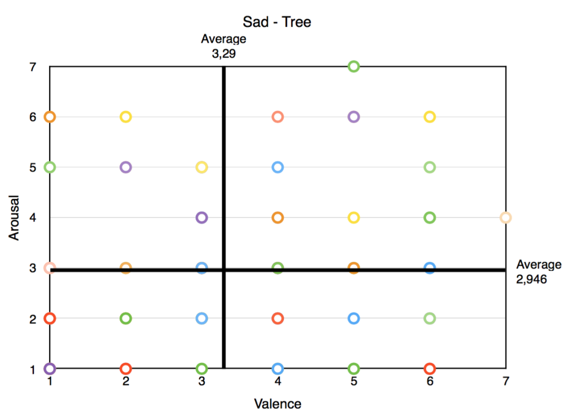

Figure 15. Valence/Arousal experiment results for the *Sad* tree videos, for the 31 participants.

Table 3 shows the average results obtained. The results are satisfactory. They confirm the ones obtained in the first perceptual evaluation. For the five emotions, the valence values are coherent for the Tree: (> 4) for *Happy*, close to 4 for *Cool* and *Neutral*, and (< 4) for *Sad* and *Stressed*, with an enhancement observed for the Tree values relatively to the Character ones for the negative values. Note that the *Stressed* emotion was badly rated for the Character.

Val./Ar.	Happy	Cool	Neutral	Sad	Stressed
Val. Char	**5,366**	**4,28**	4,71	**3,602**	4,559
Val. Tree	**4,258**	3,978	3,86	**3,29**	**3,559**
Val. All	**4,812**	**4,129**	4,285	**3,446**	4,059
Ar. Char	**5,258**	**3,796**	3,645	**2,312**	**4,914**
Ar. Tree	**5,731**	4,28	3,763	**2,946**	**4,602**
Ar. All	**5,495**	4,038	3,704	**2,629**	**4,758**

Table 3. Valence (Val.) and Arousal (Ar.) average values for the Tree videos, the original Character videos and All videos mixed.

Concerning the arousal, the values for the emotions *Happy* and *Stressed* are above 4 for both the Character and the Tree. For the emotions *Cool* and *Sad*, the arousal values are correct for the Character (< 4), but arousal is too high for *Cool* emotion for the Tree. Adjustments of the parameters should probably be considered in further experiments. Finally, the *Neutral* emotion, while not being exactly equal to 4 for valence and arousal is between the values of *Cool* and *Sad* for the Tree, which is coherent.

DISCUSSION AND FUTURE WORK

Our first experiments that consist of coupling expressive motion to visual outputs through a physical system shaping a tree are promising. Instead of using a direct mapping of raw motion descriptors (e.g., velocity, acceleration, jerk) to physical parameters, we opted for an indirect manipulation of motion cues that have already proven to be efficient to represent the expressive qualities of motion, and a $3D$ representation of a non-anthropomorphic physical system which provides a visual feedback of this expressiveness.

Generic and full-body motion descriptors commonly used in the literature have been adopted to provide a homogeneous and unified view of the motion qualities, usable for any motion data. However, results may significantly change according to the way the descriptors are computed. In particular, the effects are strongly dependent on the parts of the body (upper or lower body, hand-arm, head, etc.), on the choice of the time window (number of frames with a sliding window), and on the nature of the skeleton's structure on which the descriptors are computed. Although the descriptors are already normalized, we are convinced that it is necessary to make them adapt to more variations, including motion retargeting problems and spatio-temporal properties of the movement. For off-line applications, one way is to identify key-frames to determine relevant postures and actions, and re-compute the motion to be able to compare different actions of different length performed with different emotions. Splitting the body into sub-articulated chains or effectors, and applying weightings to these subparts for calculating the different descriptors, may also significantly modify the descriptors' computation.

We proposed a descriptors / physical parameters mapping for one sequence of theatrical motion played several times with different emotions. Our primary evaluation has shown some consistency between the effect of emotion on movement and on the animated physical system. Our second perceptual evaluation confirmed that the emotions were transferred from the original system to the simulated system but they might need some adjustments. For example, the tree is a little bit too aroused in cool movements but in the right range for the other emotions. However, such adjustments are difficult to make because too many parameters at different levels (on the motion analysis, on the parameters mapping and on the scaling for the physically based simulation) are involved at the same time. We find it necessary to apply our algorithms to more movements and physical structures, and to perceptually analyze the effect of specific mappings and renderings. We intend in particular to separately analyze (i) the perceptual effect of each parameter, (ii) the structure of the physical system by experiencing different anthropomorphic and non-anthropomorphic systems, (iii) the behavior of the particle system associated to the leaves, and (iv) the color variations. These partial evaluations could first be made interactively by watching the variation of a descriptor, a mapping or a physically based unitary simulation when performing some movement. Once a correct mapping is detected, it could be validated through perceptual experiments.

We also aim at building specific expressive motion databases with more subjects and more relevant emotion elicitation protocols, such as the use of sound or music.

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