# PERFORM: Perceptual Approach for Adding OCEAN Personality to Human Motion using Laban Movement Analysis

FUNDA DURUPINAR
University of Pennsylvania and Oregon Health & Science University
and MUBBASIR KAPADIA
Rutgers University
and SUSAN DEUTSCH
Drexel University
and MICHAEL NEFF
University of California Davis
and
NORMAN I. BADLER
University of Pennsylvania

A major goal of research on virtual humans is the animation of expressive characters that display distinct psychological attributes. Body motion is an effective way of portraying different personalities and differentiating characters. The purpose and contribution of this work is to describe a formal, broadly applicable, procedural, and empirically grounded association between personality and body motion and apply this association to modify a given virtual human body animation that can be represented by these formal concepts. Because the body movement of virtual characters may involve different choices of parameter sets depending on the context, situation or application, formulating a link from personality to body motion requires an intermediate step to assist generalization. For this intermediate step, we refer to Laban Movement Analysis, which is a movement analysis technique for systematically describing and evaluating human motion. We have developed an expressive human motion generation system with the help of movement experts and conducted a user study to explore how the psychologically validated OCEAN personality factors were perceived in motions with various Laban parameters. We have then applied our findings to procedurally animate expressive characters with personality, and validated the generalizability of our approach across different models and animations via another perception study.

CCS Concepts: •**Computing methodologies** → **Computer graphics;**

The research reported in this document was performed in connection with Contract Numbers W911NF-07-1-0216 and W911NF-10-2-0016 with the U.S. Army Research Laboratory. The views and conclusions contained in this document are those of the authors and should not be interpreted as presenting the official policies or position, either expressed or implied, of the U.S. Army Research Laboratory, or the U.S. Government unless so designated by other authorized documents. Citation of manufacturers or trade names does not constitute an official endorsement or approval of the use thereof. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation heron.


DOI: 0

Additional Key Words and Phrases: Laban movement analysis, OCEAN personality, character motion, perceptual study

**ACM Reference Format:**

F. Durupinar, M. Kapadia, S. Deutsch, M. Neff and Norman I. Badler. 2016. PERFORM: Perceptual Approach for Adding OCEAN Personality to Human Motion using Laban Movement Analysis. *ACM Trans. Graph.* 15 pages.
DOI: 0

## 1. INTRODUCTION

An important part of human communication involves the manifestation of personality. Research indicates that people convey features of their personalities in everyday contexts, and third parties can successfully recognize these features [Gosling et al. 2002; Mehl et al. 2006]. Personality allows us to evaluate and understand other individuals in terms of stable qualities, and therefore plays an important role in the assessment of our social environment. In order to achieve realism and believability, virtual worlds need virtual characters that can trigger desired perceptions and can be consistently distinguished from each other in terms of their behaviors. Personality is a central component of what defines a character: personality makes interactions interesting and meaningful. Our response to a game character, an educational virtual agent, a personal avatar, a simulated actor in a story environment or even an anthropomorphic robot will be highly shaped by their personality.

Human body motion conveys psychological content through subtle variations in the manner and extent of a given functional motion or gesture. Such variations therefore may express widely differing mental states of the character. Animators exploit this relationship to give visual insight into the characters's unseen personality. Research shows that the human body can be as communicative as the face; body cues are the first to be perceived, especially at a distance when people are approaching to initiate social interaction [Vinayagamoorthy et al. 2006]. Movement style is a broad concept that indicates the manner in which an action is performed. Actions with the same intent but different styles can often contribute

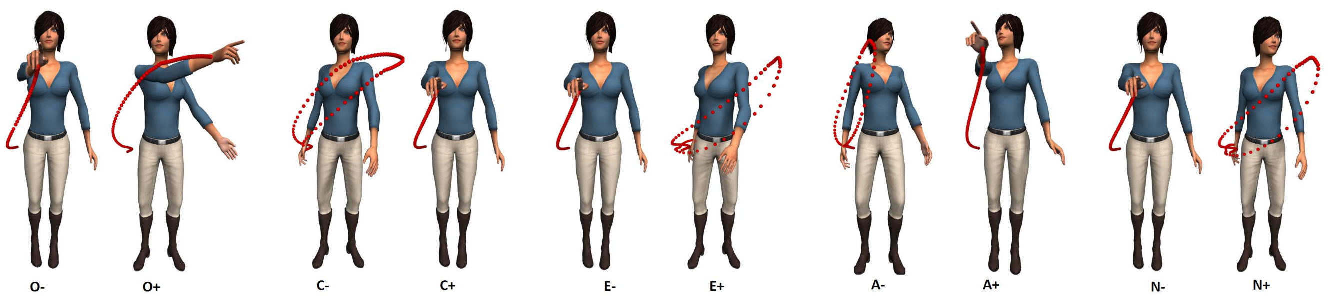



Fig. 1. Variations in pointing motion for different traits of the OCEAN Personality Model: (O)penness, (C)onscientiousness, (E)xtroversion, (A)greeableness, (N)euroticisim. Red lines illustrate the motion path of the character's hand. Screenshots are captured at the same time during the animation.

to our understanding of their performers' psychological states such as their personalities or emotions.

In this work, we aim to apply this knowledge to create variation in the motion styles of virtual humans in response to user-assigned personality traits. Automated motion variation through a high-level and intuitive authoring tool based on personality can be especially useful in scenarios with multiple agents. The animator may be spared the potentially painstaking process of authoring the behavior of each background character separately, and individual motion clips can be customized based on personality, allowing their reuse. Thus, movement diversity across the agents in a crowd will be achieved without limiting the animator to random choices, but allowing the agents to move with their individual styles consistently throughout the animation. Diversity can be parametrically varied even within personality types. In addition, such a high level parametric interface can be driven by event-driven or narrative requirements [Kapadia et al. 2013b].

A prerequisite to personality-driven motion synthesis is to gain an understanding of what aspects of the dynamics of human motion contribute to what factors of personality. There has been extensive research in the psychology literature that shows the influence of body movement on the attribution of personality [North 1972; Ekman et al. 1980; Knapp and Hall 1978]. However, because of the complexity of human physiological and biomechanical processes, the bodily manifestation of personality, although perceivable, is not easy to formulate. The main purpose of our work is to formally define the mapping between the characteristic parameters of human movement and different personality traits in an effort to synthesize motions with personality. In the computer graphics literature alone, a great deal of motion parameters have been defined [Bouchard and Badler 2007; Chi et al. 2000; Coulson 2004; Neff and Fiume 2005; Neff et al. 2010; Neff et al. 2011; Hartmann et al. 2006; Kobayashi and Ohya 2006; Mancini and Castellano 2007]. Countless combinations of these parameters are possible and different parameter sets may yield similar visual results depending on the implementation. Therefore some meaningful simplification or formalization is necessary in order to analyze their perceptual effect. To serve this purpose, we employ Laban Movement Analysis (LMA), which is a technique for systematically evaluating human motion. LMA acts as an intermediary language, an "Interlingua", to translate between low-level motion parameters and personality. A formal description of LMA parameters would facilitate the effective classification and formulation of qualitative human movement characteristics. Thus, it provides a convenient means to define a mapping between expressive movement qualities and personality. We use LMA as an intermediary instead of defining a direct mapping between motion parameters and personality to avoid arbitrary parameter selection decisions. Such a mapping substantially reduces the input dimension (from 39 motion parameters to 4 Efforts in our case). LMA is also independent of any particular motion representation, thus researchers can easily adopt Effort-personality mappings using different motion synthesis techniques. In addition, LMA parameters are more intuitive to interpret, especially by movement experts who are trained to qualitatively identify these quantities.

Our work is conducted in five steps:

(1) Mapping between Low-Level Motion Parameters and LMA Parameters: We conducted an expert study with 2 certified LMA experts[1] to define low-level parameters that effectively represent LMA elements and derive a mapping between these movement parameters and LMA factors (Section 4).

(2) Implementation of Low-Level Movement Parameters: We extended and improved the EMOTE system (Expressive MOTionEngine), introduced by Chi et al. [Chi et al. 2000] (Section 5).

(3) Mapping from LMA Parameters to Personality Factors: We performed a perceptual user study to derive a mapping between LMA Effort parameters and the five-factor OCEAN personality model, which consists of five orthogonal personality traits: openness, conscientiousness, extroversion, agreeableness and neuroticism. We thus generalized the representation of personality across various motions and virtual characters (Section 6).

(4) Personality-Driven Motion Synthesis: We used the mappings in (1) and (2) to formulate the link between motion parameters and OCEAN personality factors(Section 7.1).

(5) Validation: We conducted another user study to validate our findings (Section 7.2).

In Section 2, we provide background information highlighting the terms and models used. Next, we review related work in Section 3. We present our contribution in Sections 5-7, and sum up with discussions and future work in Section 8.

[1]We have collaborated with one Certified Movement Therapist (CMA) trained at the Laban Institute of Movement Studies in New York City and one Certified Laban/Bartenieff Movement Analyst (CLMA) trained at Integrated Movement Studies, giving us two independent LMA perspectives.

## 2. BACKGROUND

### 2.1 Laban Movement Analysis (LMA)

Laban Movement Analysis (LMA) is a technique created by Rudolf Laban to formally classify qualitative human movement characteristics which signify personal and cultural differences. LMA's Effort and Shape components specify a comprehensive parameter set for describing the dynamics[2] and the form of human movement. Effort characterizes the dynamic aspects of motion, describing one's inner attitude towards four bipolar factors: Space, Weight, Time and Flow. Each factor changes within the range of two extremes of *indulging* and *condensing*. Space (Indirect vs. Direct) describes attention to the environment; Weight (Light vs. Strong) is the sense of impact of one's movement; Time (Sustained vs. Sudden) is the attitude toward time with a sense or lack of urgency; and Flow (Free vs. Bound) encapsulates continuity, bodily tension and control.

Variation in Effort communicates the person's affective state and provides us with cues about personality. Formulating a direct mathematical link between Effort and personality is challenging because human beings usually exhibit more than one Effort factor in their movements. Using a single Effort factor is highly uncommon and appears only in extreme cases. Similarly, displaying all four Effort elements at the same time is uncommon. In our daily lives, we tend to use Effort in combinations of 2 (States) or 3 (Drives). States are more ordinary and common in everyday usage whereas Drives are reserved for extraordinary moments in life. We have more intense feelings in these distinctive moments; hence, they convey more information about our personality [Adrian 2002]. Therefore, we refer to Drives in order to derive the Effort-personality mapping.

The Shape component describes the body form related to movement. One aspect of Shape, Shape Quality, portrays the manner the body changes form in space and involves the three dimensions as: Enclosing/Spreading (horizontal), Sinking/Rising (vertical), Retreating/Advancing (sagittal). Some Effort factors have affinities with Shape Qualities. For instance, Strength has an affinity with Sinking, Lightness with Rising, Indirect with Spreading, Direct with Enclosing, Sustained with Advancing and Sudden with Retreating. Therefore, we exploit the Shape Qualities in order to strengthen the impact of Effort perception. Further information on LMA is provided in Appendix.

### 2.2 OCEAN Personality Model

Personality characterizes individual differences in patterns of thoughts, feelings and behaviors that are consistently exhibited over time. There are several personality theories such as type or trait-based, psychodynamic or behavioral theories. In our system, we represent personality by the OCEAN personality model [Goldberg 1990]. The OCEAN model, which is also known as the Five Factor Model (FFM), is the most commonly accepted personality theory with a substantial body of supporting research. It describes personality as a five dimensional space, which consists of openness, conscientiousness, extroversion, agreeableness and neuroticism. Each dimension is a continuum between two poles such as introversion and extroversion.

Openness is characterized by curiosity, imagination and a broad range of interests. Conscientiousness determines a person's self-discipline, impulse control, organizational skills and dependability. Extroversion is the sociability aspect. Agreeableness denotes how friendly, easy-going and kind a person is. Finally, neuroticism is the tendency to experience emotional instability. Orthogonality of each axis makes the OCEAN model a suitable candidate to represent the personalities of intelligent virtual characters, by minimizing redundancy and preventing the overlap of dimensions. Thus, the complexity of defining and validating the mathematical links between OCEAN dimensions and animation parameters is considerably alleviated.

[2] We use "dynamics" to mean general movement characteristics rather than a more restrictive "physics-based" sense.

## 3. RELATED WORK

**Data-Driven Approaches**

There is a wide array of work dedicated to data-driven motion synthesis. Existing approaches for synthesis of emotional movements parameterize animations for different emotion styles [Unuma et al. 1995; Egges et al. 2003] and explore techniques to model style components in motion [Brand and Hertzmann 2000; Shapiro et al. 2006]. Other data-driven approaches include gesture synthesis methods [Kipp et al. 2007; Levine et al. 2010], style transfer techniques [Hsu et al. 2005; Liu et al. 2005] and adding emotional styles directly to joint curves using signal processing [Amaya et al. 1996]. The main drawback of data-driven approaches is the difficulty of obtaining data that captures the vast array of personality, emotions, and styles of characters and providing adequate coverage of this very large space.

**Personality and Motion**

Neff *et al* [2010] evaluate how varying gesture rates and certain motion parameters affect the perception of extroversion, showing a positive correlation between gesture rate and performance changes with perceived extroversion. Neff *et al* [2011] later determine the correlation between gestures and perceived emotional stability. They show that non-signaling hand gestures significantly increase the perception of neuroticism and in later work [Liu et al. 2016], show that a set of movement variations also impact perceived neuroticism.

Chittaro and Serra [2004] use the FFM to model two aspects of motion with respect to personality: neuroticism influences speed of animations, while extroversion influences the interpersonal distance between characters.

Durupinar *et al.* [2011] examine the link between all the five factors of the OCEAN personality model and motion. Most of the parameters in that work involve agents' steering behaviors with respect to each other in a crowd. Only one parameter, gesturing amount, can be separated as it refers to individual motion styles rather than steering preferences. However, the gesturing parameter solely determines the number of clips animated on the virtual character. A similar work by Guy *et al.* [2011] introduces a system that derives a mapping between simulation parameters related to steering and personality traits of individuals within a crowd.

**Emotional Styles**

As well as personality, emotion can be conveyed through motion. Crane and Gross [2007] study the effect of different emotions on recorded motion and show that emotions affect postures, body and limb movements, and they can be perceived accurately by observers. Normoyle *et al*. [2013] show how changes in posture and dynamics affect the intensity and type of perceived emotion. Levy and Duke [2003] systematically examine the relationship between personality/emotion and Laban movement with human subjects. They report a relationship between emotion levels, personality characteristics and specific movement variables. For example, females are found to be less likely to change Effort if they are depressed and/or anxious. McDonnell et al [2008a] investigate the role of body shape on the perception of emotion and state that emotion identification is largely robust to change in body shape.

Also, a rich vocabulary of movement qualities indicates a more stable and social personality. This is consistent with the findings of North [1972] and Bartenieff [1980] who report that less Effort leads to less expressivity and more psychological distress.

**Laban Movement Analysis in Computer Graphics**

Laban Movement Analysis has been adopted in several character animation studies related to movement styles. The EMOTE system (Expressive MOTionEngine), introduced by Chi et al. [2000], facilitates the representation of several motion parameters that characterize expressive human movement, enabling the modification of an existing motion in terms of its style. EMOTE applies Laban Effort and Shape components to animation key frames to generate natural synthetic gestures using empirical mappings between Effort components and kinematic motion attributes such as the parameters that affect limb trajectories, timing and movements of torso and arm joints. Taking the EMOTE system a step further, Zhao *et al.* [2000] demonstrate how the LMA parameterization can be used to drive animations through natural language instructions. Our system is based on the EMOTE model. However, EMOTE mappings were not based on empirical studies and no associations with personality were attempted. Although a link between personality and Effort is hypothesized later [Allbeck and Badler 2002], these hypotheses have not been evaluated. We have improved the implementation, the parameter space and the empirical evaluation of the EMOTE model in our work. Besides, unlike the original EMOTE system, our implementation can be used with any humanoid skeletal structure.

Samadani *et al* [2013] derive physical measures of Effort and Shape components that facilitate computational analysis of expressive motion for hand and arm movements. LMA components also have applications in motion retrieval and synthesis [Chao et al. 2006; Kapadia et al. 2013a].

In general, capturing slight style differences using motion capture data is a challenging problem. Torresani *et al* [2007] introduce a method based on sample-based concatenation methods and parametric motion style learning algorithms in order to overcome this problem. They use LMA Effort factors to describe motion styles and automatically learn the mapping between LMA factors and animation parameters. Bouchard and Badler [2007] apply an LMA Effort classifier to automatically segment motion-capture data by analyzing movement styles.

**Movement Diversity in Crowds** Diversity of movement in crowds is important since people are remarkably good at detecting unnatural synchronies in crowd motions, such as everyone moving in lockstep or everyone exhibiting the same motion "style". A perception study by McDonnell *et al* [2008b] on crowd variety examines the effect of appearance and motion clones on the perceived variety of a crowd. They show that applying the same motion to different body shapes is easily detected. Gu and Deng [2011] focus on the creation of motion diversity across the simulated agents in a crowd. They use three principles to diversify agent motions: the motions of nearby agents should differ as much as possible, the crowd as a whole should exhibit as much diversity as the data (and motions needed) allow, and the individual characters should use motions consistently. This leverages human perception nicely: when one focuses on a particular cluster of people in the crowd they look (movement-wise) locally different, but if followed through the animation they individually move consistently.

## 4. EXPERT STUDY FOR LMA-DRIVEN MOTION SYNTHESIS

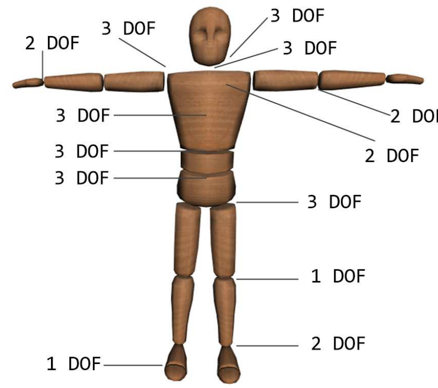



Fig. 2. The degrees of freedom for the wooden model.

Our animation framework employs the techniques introduced in the EMOTE model [Chi et al. 2000] to represent Effort and Shape qualities by customizing the timing, form and expression of movement characteristics. However, instead of adopting the LMA parameter settings in EMOTE, we use a new parameterization because the original was too rigidly bound to specific joint transformations. Since motion analysis requires formal training, we resorted to human expertise[1]. We have implemented a user interface for the movement experts to select motion parameters for LMA qualities (Figure 7 (a)).

The EMOTE model considers Effort qualities in isolation and does not provide a method to combine different Efforts. As mentioned in Section 2.1, Effort qualities are exhibited in combinations in real life. In order to build up our motion-parameter mapping framework, we chose to represent combinations of three Efforts, *Drives*, because of their intensity and distinctive nature. There are 32 Drive constellations, which are combinations of 3 Effort elements ($\binom{4}{3} * 2^3$).

The derivation of Drives is computationally challenging because the parameter combinations of several Effort factors are not linearly additive; the impact of an Effort factor on a particular motion parameter depends on the other Efforts that it is combined with. After many brainstorming sessions with our movement experts, we determined a total of 39 motion parameters that could adequately quantize each Drive constellation. The motion parameters and their implementation are detailed in Section 5 and Table IV. We went through several iterations of motion-parameter tuning sessions with both of our experts. We cooperated with the CMAs in parameter selection and system improvement until mutual satisfaction was achieved. In addition, we consulted 10 dance students (9F/1M, aged 18-20), who had experience with Laban Motion Analysis. They collaborated with our CMA and helped fine tune the motion parameters. Since LMA qualities are precise concepts, despite our experts having different backgrounds, the final results are objective in terms of the manifestation of these qualities.

For the Drive-quantization work, we utilized a wooden mannequin figure, which was intentionally preferred over a realistic-looking human model in order to avoid character-based preconceptions. Both the experts' and the dance students' preferences were to use a gender-neutral, expressionless (except motion) mannequin without any context information so that the focus would be only on motion, providing more accurate results. The wooden mannequin is an articulated figure with 21 joints (Figure 2).

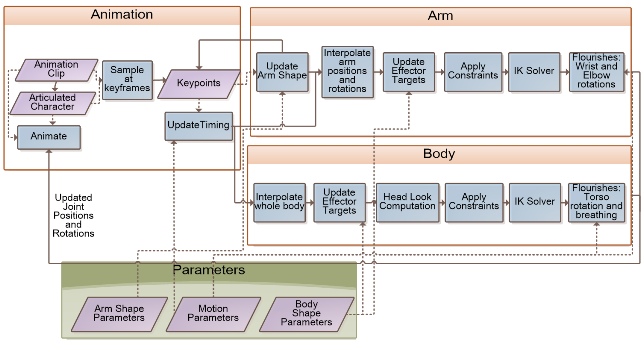



Fig. 3. Animation pipeline.

To conduct our study, we first recorded a set of representative human actions that were obtained via motion capture using a 12-camera optical Vicon system and post-processed in Vicon Nexus and Autodesk MotionBuilder. We worked with a single actor, but the animations were then edited in Autodesk Maya with the help of the CMA in order to eliminate conspicuous gestures that emphasized a particular Effort quality such as involuntary shoulder twitches. We recorded 9 motion clips that display the actor performing a variety of atomic actions. These actions are walking, pointing to a spot, knocking, throwing, waving, picking up a pillow, lifting a heavy object, pushing a heavy object and punching. Such atomic actions can be represented without any context information. They have everyday usage and they display variety in terms of physical strength as some of them require exerting force while others are purely stylistic. The motion capture clips were then converted to animation files and retargeted to the wooden model. The CMAs then selected motion parameters for each of the 32 Drives and 8 Shape forms as static postures. In order to promote differentiation, we focused on the extremes of the Drives, i.e. the Effort qualities comprising each Drive are not intermediate values, but the boundaries.

## 5. ANIMATING MOTION PARAMETERS

Our system operates primarily by adjusting an existing motion by changing key time and pose information. It also introduces some additional parameters that enhance the expressiveness of motion. The animation pipeline is depicted in Figure 3. The essential characteristics of our system are:

(1) Incorporating the motion of the whole body, not just arm movement and torso shape.
(2) Key frame manipulation including anticipation and overshoot effects.
(3) Shape timing parameters that define the transition between Shape Qualities.
(4) Introducing torso rotation and head look-at control for defining the character's attention.
(5) Implementing Drives, rather than single Effort elements, through collaboration with experts and input from user experiments.

### 5.1 Timing

Motion capture clips were converted to animation files and imported into Unity 3D, which extracts keyframes automatically. The system first samples the animation at keyframes to determine the keypoints at which the positions and rotations of all the joints in the body are set. Keypoints of end-effectors (wrists or feet in our case), are classified into *Goal* keys and *Via* keys as described in [Chi et al. 2000]. Both *Goal* and *Via* points determine the path of the motion. During an animation sequence, the end-effector stops at *Goal* points and passes through *Via* points without pausing. *Goal* frames include the first and the last frames of the animation in addition to the keyframes, where the end-effector velocities are close to zero. *Via* frames include the rest of the keyframes. The timing of these keypoints is updated according to motion parameters which are determined by Effort qualities. At each timestep $t_i$, we find the normalized time $\tilde{t}_i \in [0, 1]$ between previous and next *Goal* frames as:

$$\tilde{t}_i = \frac{t_i - t_i^p}{t_i^n - t_i^p} \tag{1}$$

where $t_i^p, t_i^n$ are the times of previous and next *Goal* frames with respect to $t_i$. We then apply a timing function $Q$, to achieve a new normalized time $\tilde{t}_i^*$ , and an updated time $t_i^*$ for the current frame. Figure 4 shows the graph of $dQ/d\tilde{t}$, the integral of which gives us the new normalized time, $\tilde{t}_i^*$:

$$\tilde{t}_i^* = Q(\tilde{t}_i) = \int_0^{\tilde{t}_i} Q' d\tilde{t} \tag{2}$$

The variables $V_A$, $V_O$, $T_A$, $T_{Inf}$ and $T_O$ are determined by the Effort parameters, and they control acceleration/deceleration pattern of movement. After computing the new normalized time $\tilde{t}_i^*$ we find the new time $t_i^*$ using the animation length $T$ as:

$$t_i^* = \frac{\tilde{t}_i^*(t_i^n - t_i^p) + t_i^p}{T} \tag{3}$$

We separate path control from timing control by applying a double interpolant method [Steketee and Badler 1985]. Figure 5 shows graphs of sample animation curves. We find the *Via* key number $k$ at $t_i^*$ (Figure 5 (a)). Using the keys $k$ and $k + 1$, and the local time between these keyframes according to $t_i^*$, we compute the positions and rotations of all the joints in the body by interpolation. Rotations are defined as quaternions and their intermediate values are computed by spherical linear interpolation. We then interpolate the target positions of the effectors between the keypoints $k$ and $k + 1$ using Kochanek-Bartels splines [Kochanek and Bartels 1984] (Figure 5 (b) and (c)). The reason we prefer Kochanek-Bartels splines is that they include tension and continuity parameters that determine path curvature, enabling the control of motion fluidity.

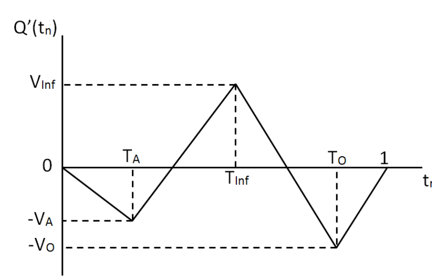



Fig. 4. Velocity of timing.

Anticipation and follow through (overshoot) are implemented by changing the timing of the animation. In order to account for anticipation and overshoot effects, where $t_i^* < 0$ and $t_i^* > 1$, we insert an imaginary key beyond the start and end frames and find the *Via* key at $-t_i^*$ and $2 - t_i^*$ respectively. Anticipation and overshoot implicitly affect the timing of body parts causing dragging and follow through effects. For instance, consider a very basic walking animation where the effectors are at the feet and the hips. The insertion of an imaginary key before the starting frame causes the hip and the swinging leg to move different distances for the same duration, yielding a dragging effect. Similarly, inserting an imaginary key beyond the end point causes the leading part (hip) to slow to a stop, while the swinging leg continues to move.

## 5.2 Shape

We utilize a full body inverse kinematics system [RootMotion 2015] where the effectors include hands, feet, shoulders and hips. The positions of effectors achieved via interpolation are updated according to Shape Qualities. For instance, Sinking Shape can be achieved by lowering the hips during the animation. This requires changing the positions of hips and hands before feeding them into the inverse kinematics solver. Figure 6 shows which Shape Quality affects which effectors. The black lines are translational changes whereas red curves show rotational changes. Enclosing Shape is exemplified by moving the hands and feet closer to the body and rotating the feet inwards, whereas Spreading Shape is depicted as moving the hands and feet away from the body and rotating the feet outwards. Sinking is represented by lowering the hips and hands whereas Rising is represented as rising the hips and hands as well as rotating the feet around the x axis in order to give a tiptoeing effect. Retreating involves taking a step back by moving the hands, hips and feet while Advancing implies taking a step forward. Note that changing the positions and rotations of end effectors, i.e. hands and feet, affects the positions and rotations of the arm and leg chains.

Because Shape is more than just a static body form, we represent it as a transition between different postures that are specified for the beginning, end, and an inflection time during the animation. For each Drive, our LMA experts determined the coefficients of these postures' contribution for the first and last frames of the animation, as well as at the inflection time. Coefficients of each Shape dimension take values in the range $[-1, 1]$, where -1 means a sunken posture and 1 means a rising posture in the vertical dimension. For example, in the Wring Action Drive (Indirect, Strong, Sustained) the character was given Sinking Shape in order to emphasize Strength. The character sinks slowly from the beginning of the animation to the inflection time and then straightens from the inflection time to the end of the animation.

The coefficients $\delta_t^d$ of Shape for horizontal, vertical and sagittal dimensions $d$ at time $t$ are interpolated as:

$$\delta_t^d = \begin{cases} \frac{t-t_0}{t_i-t_0}(\delta_{t_i}^d - \delta_{t_0}^d) + \delta_{t_0}^d & \text{if } t \in [t_0, t_i] \\ \frac{t-t_i}{t_1-t_i}(\delta_{t_1}^d - \delta_{t_i}^d) + \delta_{t_i}^d & \text{if } t \in [t_i, t_1] \end{cases} \quad (4)$$

where $d \in \{hor, ver, sag\}$ and $\delta_{t_0}^d, \delta_{t_i}^d, \delta_{t_1}^d \in [-1, 1]$ .

Arm Shape parameters were also selected by the CMA via the GUI. These parameters modify the positions of the *Goal* keys; therefore they are updated before the timing changes.

## 5.3 Flourishes

As the last step in the implementation of the Effort parameters, we utilize flourishes, which are described as the miscellaneous parameters that contribute to the expressiveness of motions. The original EMOTE model describes flourishes as wrist and elbow rotations. In addition to these we have included head and torso rotation in order to express the character's attention, modeled as:

$$\theta_i^H = h_R \cdot \sin(h_F \pi \tilde{t}_i) \quad (5)$$

$$\theta_i^T = t_R \cdot \sin(t_F \pi \tilde{t}_i) \quad (6)$$

$$\langle \theta_i^H, \theta_i^T \rangle = \langle h_R \cdot \sin(h_F \pi \tilde{t}_i), t_R \cdot \sin(t_F \pi \tilde{t}_i) \rangle \quad (7)$$

where $\theta_i^H$ and $\theta_i^T$ are head and torso angles around the y axis at time $\tilde{t}_i$; $h_R$ and $t_R$ are head and torso rotation coefficients, $h_F$ and $t_F$ are head and torso rotation frequencies. Torso rotation is updated after all the computations, whereas head rotation is fed into the inverse kinematics solver.

# 6. USER STUDY TO MAP LMA PARAMETERS AND OCEAN TRAITS

## 6.1 Experimental Design

We have created an online setting where participants were asked to compare, in terms of personality traits, two side-by-side virtual models performing the same action with different Drives. We made sure that the scenario did not yield any contextual information. For each comparison, we kept two Effort dimensions of a Drive fixed and compared the two poles of the remaining dimension. For example, the questions for testing Space in Action Drive kept Weight and Time identical and showed one character with Indirect and the other with Direct. Thus, there were 12 questions per Effort and a total of 48 Drive comparisons.

We tested one personality dimension for each pair of clips, using a validated survey instrument. There are several tools for assessing personality, including the widely used Revised NEO Personality Inventory [McCrae et al. 2005]. However, even a shorter version of this inventory has 60 items. Because the experiment time is limited we used a brief measure of personality, the Ten-Item Personality Inventory (TIPI) [Gosling et al. 2003]. TIPI qualifies as a validated tool for measuring the Big-Five in subjects and it reaches acceptable levels of convergence with more widely used measures of personality. A sample question format was as follows: "Which character looks MORE *open to new experiences & complex* and LESS *conventional & uncreative*". We used a three-point Likert scale and presented "Left", "Equal" and "Right" as the possible answers; thus the questions were not forced-choice. Both characters were viewed from the same angle and all the other rendering properties were the same. The corresponding Drives were randomly assigned to the left or the right figure. The motions for each question could be played as many times as desired. We displayed the "Submit" button for each question only after both animations ran to the end. In order to test consistency, we showed two different actions: pointing and picking up a pillow from the ground. These two actions were selected by the CMA from a list of several actions due to their expressivity. Supplementary video and Figure 7 (b) show the user interface of the perception experiment.

## 6.2 Participants

We recruited our participants from Amazon Mechanical Turk. We required participation qualifications as having an acceptance rate of $> 95\%$, with an experience on more than 100 human intelligence tasks (HITs). Because we wanted to assess 48 Drive combinations for 2 actions and 5 personality dimensions, our study consisted of a total of 480 questions. In order to ensure participants' attention we kept each HIT as short as possible. Thus, we divided the study into 60 tasks, each one consisting of 8 personality questions and 2

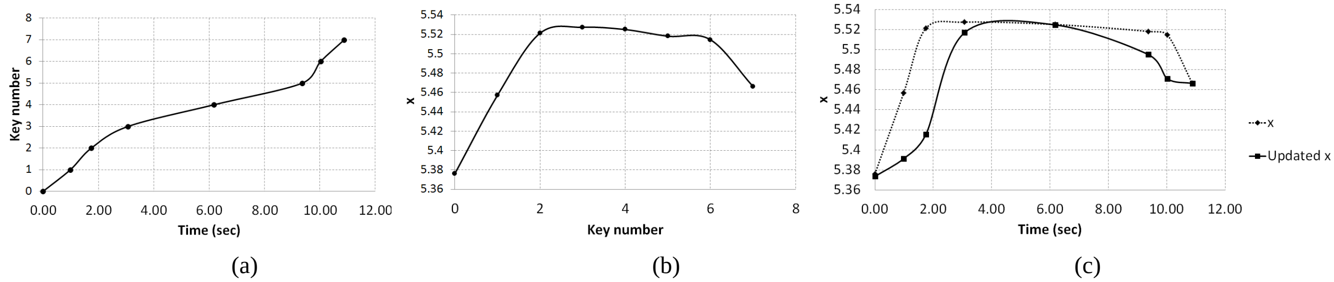



Fig. 5. (a) Key number to time function on which the timing changes are applied. (b) Key number to end-effector position x curve. Keys 0 and 7 are *Goal* keys and all the others are *Via* keys. (c) Time to updated end-effector position curve.

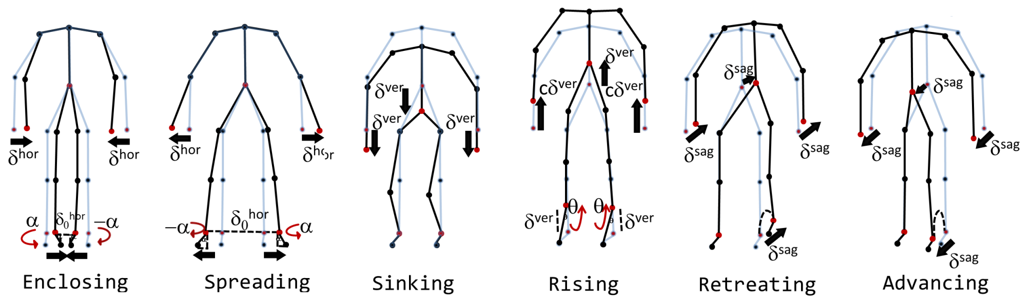



Fig. 6. Shape Qualities and their application on effectors of the inverse kinematics solver. Red dots are the effectors that are explicitly updated by the Shape changes. Black arrows and red curves show translational and rotational changes respectively.

objective quality check questions. The quality check questions displayed the two characters each performing a different action and asked which character was performing a specific action. Answers of the participants who failed to provide correct answers to both of the quality check questions were discarded. In the end, we achieved 30 answers per question, with 244 unique participants with mean age $30.36 \pm 10.57$, 91F/153M, and 233 native/11 non-native English speakers. The HITs were presented in random order and the workers were free to participate in all the 60 HITs.

## 6.3 Analysis

For each personality factor and each motion type, we grouped responses based on which Effort dimension was tested and counted the number of non-neutral answers for each pole of that Effort. We performed two-tailed, paired Student's t-test on the number of responses for the two opposite Effort dimensions and noted the statistically significant effects at the 95% level ($p < 0.05$). (Table I shows the proportion of subjects that selected indulging Efforts out of the total number that made a non-neutral selection for each Effort combination (rows). Statistically significant ratios are highlighted in gray.) Although not all the Drive constellations suggest a statistically significant link between Effort and personality dimensions, combined results provide compelling associations.

Our null hypothesis was that the two groups were not different from each other. Figure 8 shows the box plot diagrams for the correlations between each personality-animation combination and each Effort factor. Because we performed a large number of t-tests we calculated the False Discovery Rate with Benjamini-Hochberg procedure and found the expected false positive rate to be less than 0.069. Considering the significant differences between the answers for both animations, we have derived the correlations in Table II.

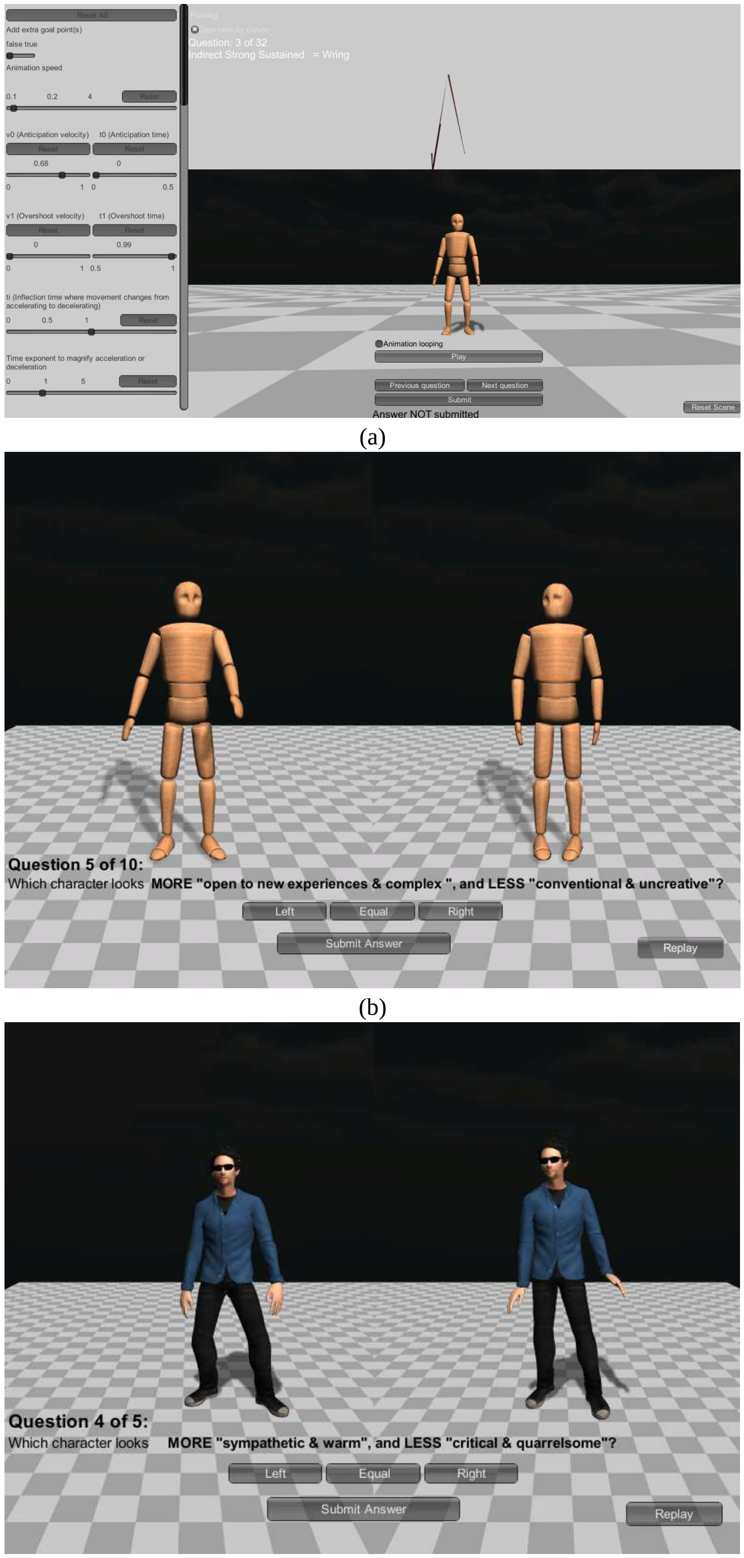
Table II. Effort and OCEAN correlations achieved from the user study

| Personality | Space | Weight | Time | Flow |
|---|---|---|---|---|
| **Openness** | | | | |
| High | Indirect | - | - | Free |
| Low | Direct | - | - | Bound |
| **Conscientiousness** | | | | |
| High | Direct | - | Sustained | Bound |
| Low | Indirect | - | Sudden | Free |
| **Extroversion** | | | | |
| High | Indirect | - | Sudden | Free |
| Low | Direct | - | Sustained | Bound |
| **Agreeableness** | | | | |
| High | - | Light | Sustained | - |
| Low | - | Strong | Sudden | - |
| **Neuroticism** | | | | |
| High | Indirect | - | Sudden | Free |
| Low | Direct | - | Sustained | Bound |

The experimental setting is prepared so that the results are interpreted as collinear. If a pole of an Effort dimension is correlated with a pole of a personality dimension, the other poles of Effort and personality are also correlated with each other. In the light of this design choice, the interpretation of the relationship between each personality and the Effort dimensions are as follows:

**Openness**: Descriptive traits for openness include curiosity and creativity. Correlation of openness with Indirect Space and Free Flow conforms to our expectations as an open person tends to be aware of the surroundings, explore the world, and move without restraint.

**Conscientiousness**: Conscientiousness is described as being careful and organized. This is compatible with the factors Direct, Sustained and Bound as they involve being focused, careful, not in a hurry and controlled.




(c)

Fig. 7. User interfaces for (a) Drive parameter selection by the CMA, (b) personality-perception study for Drives, (c) personality-perception study for motion synchronization.

Table I. Proportions of subjects who selected indulging Efforts out of the total who made a non-neutral selection, for each personality factor and animation of motion comparison

| Effort | Character 1 | | | | Character 2 | | | | Openness | | Conscientious. | | Extroversion | | Agreeableness | | Neuroticism | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | S | W | T | F | S | W | T | F | Point | Pick | Point | Pick | Point | Pick | Point | Pick | Point | Pick |
| Space | Ind | Lgt | Sus | | Dir | Lgt | Sus | | 0.846 | 0.778 | 0.154 | 0.130 | 0.889 | 0.583 | 0.520 | 0.417 | 0.786 | 0.783 |
| Space | Ind | Lgt | Sud | | Dir | Lgt | Sud | | 0.909 | 0.750 | 0.059 | 0.167 | 0.706 | 0.706 | 0.417 | 0.250 | 1.000 | 0.733 |
| Space | Ind | Str | Sus | | Dir | Str | Sus | | 0.679 | 0.727 | 0.333 | 0.318 | 0.826 | 0.783 | 0.522 | 0.708 | 0.885 | 0.826 |
| Space | Ind | Str | Sud | | Dir | Str | Sud | | 0.842 | 0.688 | 0.200 | 0.067 | 0.682 | 0.600 | 0.333 | 0.235 | 0.789 | 0.846 |
| Space | Ind | Lgt | | Fre | Dir | Lgt | | Fre | 0.708 | 0.773 | 0.125 | 0.429 | 0.778 | 0.800 | 0.368 | 0.286 | 0.857 | 0.762 |
| Space | Ind | Lgt | | Bnd | Dir | Lgt | | Bnd | 0.867 | 0.889 | 0.067 | 0.190 | 0.833 | 0.706 | 0.579 | 0.353 | 1.000 | 0.824 |
| Space | Ind | Str | | Fre | Dir | Str | | Fre | 0.636 | 0.800 | 0.263 | 0.389 | 0.467 | 0.765 | 0.353 | 0.591 | 0.714 | 0.706 |
| Space | Ind | Str | | Bnd | Dir | Str | | Bnd | 0.800 | 0.850 | 0.105 | 0.300 | 0.778 | 1.000 | 0.579 | 0.500 | 0.905 | 0.889 |
| Space | Ind | | Sus | Fre | Dir | | Sus | Fre | 0.458 | 0.423 | 0.353 | 0.696 | 0.500 | 0.316 | 0.421 | 0.545 | 0.714 | 0.455 |
| Space | Ind | | Sus | Bnd | Dir | | Sus | Bnd | 0.950 | 0.867 | 0.125 | 0.071 | 0.667 | 0.818 | 0.529 | 0.444 | 0.955 | 0.846 |
| Space | Ind | | Sud | Fre | Dir | | Sud | Fre | 0.556 | 0.444 | 0.421 | 0.643 | 0.786 | 0.385 | 0.643 | 0.467 | 0.600 | 0.538 |
| Space | Ind | | Sud | Bnd | Dir | | Sud | Bnd | 1.000 | 0.857 | 0.000 | 0.429 | 0.933 | 0.833 | 0.313 | 0.182 | 0.875 | 1.000 |
| Weight | Ind | Lgt | Sus | | Ind | Str | Sus | | 0.320 | 0.238 | 0.364 | 0.478 | 0.524 | 0.238 | 0.708 | 0.545 | 0.318 | 0.476 |
| Weight | Ind | Lgt | Sud | | Ind | Str | Sud | | 0.294 | 0.292 | 0.750 | 0.913 | 0.333 | 0.167 | 0.800 | 0.885 | 0.211 | 0.130 |
| Weight | Dir | Lgt | Sus | | Dir | Str | Sus | | 0.842 | 0.400 | 0.450 | 0.556 | 0.833 | 0.500 | 0.700 | 0.810 | 0.353 | 0.444 |
| Weight | Dir | Lgt | Sud | | Dir | Str | Sud | | 0.867 | 0.190 | 0.357 | 0.870 | 0.765 | 0.150 | 0.583 | 0.750 | 0.625 | 0.143 |
| Weight | Ind | Lgt | | Fre | Ind | Str | | Fre | 0.762 | 0.680 | 0.174 | 0.500 | 0.909 | 0.750 | 0.455 | 0.560 | 0.600 | 0.800 |
| Weight | Ind | Lgt | | Bnd | Ind | Str | | Bnd | 0.526 | 0.391 | 0.429 | 0.478 | 0.667 | 0.227 | 0.381 | 0.625 | 0.667 | 0.731 |
| Weight | Dir | Lgt | | Fre | Dir | Str | | Fre | 0.762 | 0.842 | 0.368 | 0.684 | 0.909 | 0.813 | 0.833 | 0.571 | 0.421 | 0.450 |
| Weight | Dir | Lgt | | Bnd | Dir | Str | | Bnd | 0.476 | 0.320 | 0.526 | 0.364 | 0.533 | 0.053 | 0.826 | 0.800 | 0.458 | 0.522 |
| Weight | | Lgt | Sus | Fre | | Str | Sus | Fre | 0.650 | 0.571 | 0.450 | 0.800 | 0.643 | 0.429 | 0.550 | 0.533 | 0.500 | 0.217 |
| Weight | | Lgt | Sus | Bnd | | Str | Sus | Bnd | 0.542 | 0.292 | 0.526 | 0.591 | 0.526 | 0.118 | 0.565 | 0.800 | 0.565 | 0.696 |
| Weight | | Lgt | Sud | Fre | | Str | Sud | Fre | 0.526 | 0.800 | 0.235 | 0.381 | 0.733 | 0.900 | 0.526 | 0.294 | 0.737 | 0.700 |
| Weight | | Lgt | Sud | Bnd | | Str | Sud | Bnd | 0.688 | 0.579 | 0.471 | 0.529 | 0.529 | 0.462 | 0.500 | 0.294 | 0.550 | 0.684 |
| Time | Ind | Lgt | Sus | | Ind | Lgt | Sud | | 0.808 | 0.571 | 0.750 | 0.607 | 0.179 | 0.067 | 0.964 | 0.893 | 0.100 | 0.138 |
| Time | Ind | Str | Sus | | Ind | Str | Sud | | 0.692 | 0.464 | 0.897 | 0.786 | 0.067 | 0.033 | 0.862 | 0.933 | 0.034 | 0.103 |
| Time | Dir | Lgt | Sus | | Dir | Lgt | Sud | | 0.556 | 0.346 | 0.667 | 0.667 | 0.103 | 0.033 | 0.931 | 0.867 | 0.067 | 0.233 |
| Time | Dir | Str | Sus | | Dir | Str | Sud | | 0.481 | 0.300 | 0.750 | 0.724 | 0.034 | 0.067 | 0.931 | 0.857 | 0.103 | 0.241 |
| Time | Ind | | Sus | Fre | Ind | | Sud | Fre | 0.700 | 0.483 | 0.964 | 0.793 | 0.107 | 0.100 | 0.862 | 0.933 | 0.000 | 0.069 |
| Time | Ind | | Sus | Bnd | Ind | | Sud | Bnd | 0.667 | 0.462 | 0.889 | 0.769 | 0.143 | 0.103 | 1.000 | 0.929 | 0.069 | 0.241 |
| Time | Dir | | Sus | Fre | Dir | | Sud | Fre | 0.633 | 0.464 | 0.933 | 0.862 | 0.200 | 0.133 | 0.933 | 0.966 | 0.033 | 0.103 |
| Time | Dir | | Sus | Bnd | Dir | | Sud | Bnd | 0.556 | 0.429 | 0.800 | 0.741 | 0.107 | 0.071 | 0.966 | 0.929 | 0.000 | 0.107 |
| Time | | Lgt | Sus | Fre | | Lgt | Sud | Fre | 0.600 | 0.500 | 0.889 | 0.852 | 0.069 | 0.069 | 0.931 | 0.867 | 0.000 | 0.000 |
| Time | | Lgt | Sus | Bnd | | Lgt | Sud | Bnd | 0.536 | 0.600 | 0.840 | 0.750 | 0.143 | 0.067 | 0.893 | 0.933 | 0.033 | 0.172 |
| Time | | Str | Sus | Fre | | Str | Sud | Fre | 0.533 | 0.433 | 0.833 | 0.714 | 0.065 | 0.033 | 0.933 | 0.966 | 0.067 | 0.200 |
| Time | | Str | Sus | Bnd | | Str | Sud | Bnd | 0.483 | 0.400 | 0.769 | 0.667 | 0.097 | 0.033 | 0.967 | 0.821 | 0.100 | 0.276 |
| Flow | Ind | Lgt | | Fre | Ind | Lgt | | Bnd | 0.880 | 0.833 | 0.154 | 0.346 | 0.926 | 0.893 | 0.500 | 0.250 | 0.808 | 0.680 |
| Flow | Ind | Str | | Fre | Ind | Str | | Bnd | 0.917 | 0.760 | 0.190 | 0.154 | 0.913 | 0.500 | 0.600 | 0.407 | 0.720 | 0.636 |
| Flow | Dir | Lgt | | Fre | Dir | Lgt | | Bnd | 0.931 | 0.897 | 0.267 | 0.231 | 0.931 | 0.966 | 0.593 | 0.393 | 0.615 | 0.586 |
| Flow | Dir | Str | | Fre | Dir | Str | | Bnd | 0.929 | 0.857 | 0.214 | 0.111 | 0.857 | 0.778 | 0.724 | 0.429 | 0.741 | 0.583 |
| Flow | Ind | | Sus | Fre | Ind | | Sus | Bnd | 0.926 | 0.759 | 0.231 | 0.207 | 1.000 | 0.870 | 0.615 | 0.308 | 0.571 | 0.407 |
| Flow | Ind | | Sud | Fre | Ind | | Sud | Bnd | 0.682 | 0.909 | 0.000 | 0.111 | 1.000 | 0.958 | 0.174 | 0.231 | 0.870 | 0.870 |
| Flow | Dir | | Sus | Fre | Dir | | Sus | Bnd | 0.933 | 0.800 | 0.071 | 0.231 | 0.963 | 1.000 | 0.769 | 0.357 | 0.552 | 0.385 |
| Flow | Dir | | Sud | Fre | Dir | | Sud | Bnd | 0.889 | 0.852 | 0.042 | 0.000 | 0.963 | 1.000 | 0.143 | 0.154 | 0.893 | 0.792 |
| Flow | | Lgt | Sus | Fre | | Lgt | Sus | Bnd | 0.929 | 0.893 | 0.227 | 0.241 | 0.917 | 0.957 | 0.714 | 0.357 | 0.731 | 0.393 |
| Flow | | Lgt | Sud | Fre | | Lgt | Sud | Bnd | 0.750 | 0.720 | 0.000 | 0.000 | 0.897 | 0.963 | 0.167 | 0.217 | 1.000 | 0.786 |
| Flow | | Str | Sus | Fre | | Str | Sus | Bnd | 0.815 | 0.800 | 0.148 | 0.074 | 0.958 | 0.840 | 0.741 | 0.370 | 0.571 | 0.654 |
| Flow | | Str | Sud | Fre | | Str | Sud | Bnd | 0.929 | 0.793 | 0.040 | 0.069 | 0.897 | 0.964 | 0.348 | 0.308 | 0.962 | 0.931 |

Dark gray cells highlight statistically significant ratios ($p < 0.05$) that favor indulging Efforts and light gray cells highlight the statistically significant ratios ($p < 0.05$) that favor condensing Efforts.

**Extroversion**: Extroversion is found to be associated with Indirect Space, Sudden Time and Free Flow. Extroverts are interested in their environments; they are not reserved. Thus, they are expected to be perceived as Indirect. On the other hand, reserved introverts refrain from interacting with their surroundings, which explains their Directness. Extroverts are described as energetic whereas introverts are lethargic, which explains Sudden Time for extroversion and Sustained Time for introversion. In fact, Time has the highest correlation with Extroversion among all personality factors. The unrestrained vs. restrained characteristics of Free vs. Bound Flow clarify the difference between the enthusiastic vs. shy traits of extroverts vs. introverts.

**Agreeableness**: Agreeableness is described as being sympathetic and warm, which explains why it is associated with Light Weight since Lightness implies delicacy and buoyancy. Strength, on the other hand, shows standing one's ground, being powerful. Disagreeableness denotes being critical, stubborn, quarrelsome and rude, which may require Strength to some extent. Participants' perception of Sudden motion as rude can be attributed to the sense of urgency and being in a hurry.

**Neuroticism**: Neuroticism suggests being anxious and unstable. It is correlated with Indirect, Sudden and Free motion. Indirect Space is about being multi-focus. The characters with Indirect motion tend to look around when performing a motion, which may have been associated with being anxious and unstable. Sudden movements have fast changes in timing, which tend to seem anxious. Sustained movement implies a sense of relaxation, implying stability which is characterized as being calm. The link between neuroticism and Free motion where the movement is uncontrolled can be explained due to being unable to control oneself when anxious.

## 7. PERSONALITY-DRIVEN MOTION SYNTHESIS

Our system takes as input an animation sequence and the five personality factors as numerical values between -1 and 1. It then makes modifications to the animation in order to reflect the given personalities through movement styles.

### 7.1 Mapping Personality to Motion Parameters

In order to convey a particular personality with motion, we first determine the Effort factors that correspond to the personality traits and then we map these Effort factors to low-level motion features.

**Step 1: OCEAN-to-Effort Mapping.** We utilize the results of the user study to determine the impact of each Effort factor on a specific personality dimension. Figure 9 depicts the number of participants who selected indulging Efforts

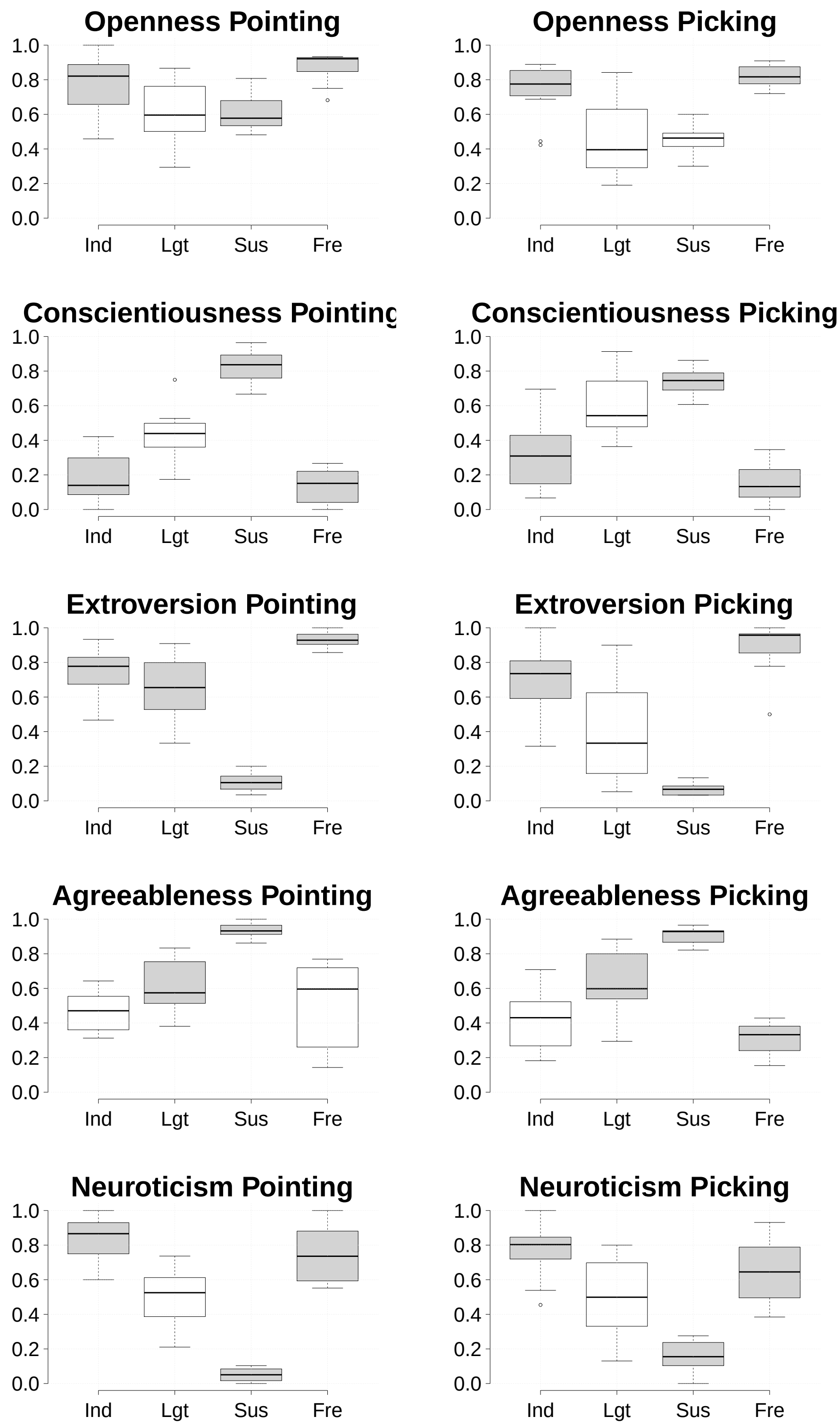



Fig. 8. Box plot diagrams for indulging Effort selection ratios and OCEAN factors with pointing and picking animations. Gray boxes show statistically significant differences ($p < 0.05$), white ones are not significant.

Erratum: The data in the N row of Figure 9 corresponds to high emotional stability, not neuroticism (low emotional stability).



($answersE^{-P}$) and the number of subjects who selected condensing Efforts($answersE^{+P}$) for each OCEAN trait. The table is computed by pooling the answers for both motions (2 animations * 12 questions per animation) considering the significant bias in the nonneutral responses. The proportions of answers for each personality $P \in (O, C, E, A, N)$ and Effort $E \in (Space, Weight, Time, Flow)$ are computed as:

$$r_E^P = \frac{\sum_{i=1}^{24} \sum_{\forall j} answersE^{-P}(i,j)}{\sum_{i=1}^{24} \sum_{\forall j} answersE^{-P}(i,j) + answersE^{+P}(i,j)} \quad (8)$$

The ratios are summarized in Table III.

Table III. Proportions of subjects who selected indulging and condensing Efforts out of the total who made a non-neutral selection calculated for each OCEAN factor.

| Effort | O | C | E | A | N |
|---|---|---|---|---|---|
| **Space** | 0.739 | 0.256 | 0.717 | 0.452 | 0.803 |
| **Weight** | 0.523 | 0.511 | 0.516 | 0.631 | 0.503 |
| **Time** | 0.528 | 0.788 | 0.088 | 0.920 | 0.104 |
| **Flow** | 0.851 | 0.143 | 0.914 | 0.419 | 0.696 |

Dark gray cells highlight statistically significant ratios ($p < 0.05$) for indulging Efforts and light gray cells highlight the statistically significant ratios ($p < 0.05$) for condensing Efforts.

Using these ratios, we derive a normalized Personality-Effort matrix $NPE$ that represents the correlations between indulging Efforts and personality dimensions. First, statistically insignificant correlations are assigned 0, significant values bigger than 0.5 are negated, and significant values less than 0.5 are subtracted from 1. Then, each row is normalized to the range $[-1, 1]$ in order to determine the effect of an Effort on each personality.

$$NPE = \begin{bmatrix} -0.921 & 0.928 & -0.894 & 0 & -1 \\ 0 & 0 & 0 & -1 & 0 \\ 0 & -0.857 & 0.99 & -1 & 0.97 \\ -0.931 & 0.938 & -1 & 0 & -0.762 \end{bmatrix} \quad (9)$$

Given a personality $\mathbf{P}$, the corresponding Effort values $\mathbf{E}$ are then computed as follows:

$$E_i^+ = \max(NPE(i,j) \cdot \mathbf{P}(j)) | NPE(i,j) \cdot \mathbf{P}(j) > 0 \quad (10)$$
$$E_i^- = \min(NPE(i,j) \cdot \mathbf{P}(j)) | NPE(i,j) \cdot \mathbf{P}(j) < 0 \quad (11)$$
$$E_i = E_i^+ + E_i^-, \; \forall \, i \in (1,4) \; \forall \, j \in (1,5) \quad (12)$$

The impact of each Effort on personality and their combination are thus based on the user study results. For instance, consider an equally extrovert and agreeable person with all the other personality factors being neutral. Space will be Indirect with an impact of -0.894, Weight will be Strong with an impact of -1 and Flow will be Free with an impact of -1. The effect of Time is 0.99 on extroversion and -1 on agreeableness. The resulting Time will then be -0.01, which is practically neutral.

**Step 2: Effort-to-Motion Parameter Mapping.** Through the expert study, we already have the motion parameter sets for each Drive as combinations of three extreme Effort values. In order to compute the equations to derive the motion parameters given any combination of Effort values between -1 and 1, we perform multivariate linear regression using this data. (Table IV displays the coefficients of the regression equations. )


Fig. 9. Total number of responders who selected indulging and condensing Effort elements for each OCEAN dimension. There were 24 comparison questions (12 questions x 2 animations). At least 30 participants answered each question. Statistically significant results ($p < 0.05$) are marked with $*$.

At this step, we can define certain constraints such as fixing the head direction, ensuring that an end-effector reaches a target position or keeps its rotation or adjusting the animation speed according to the scenario. Such constraints can be specified during the mapping process and easily integrated via the inverse kinematics solver.

## 7.2 User Study to Validate Personality-Driven Expressive Motion Synthesis

**Experimental Design.** In order to establish that synthesis of motions with personality can be generalized across different actions and human models we performed another perceptual study. We synthesized different motions using our personality-LMA-motion parameter mapping. The question format and visual setting of this study was exactly the same as the previous study (Figure 7 (c)). We asked the participants to compare the personalities of two characters performing the same action using TIPI traits and a three-point Likert scale and presented “Left”, “Equal” and “Right” as the possible answers.

One task consisted of five questions each asking one OCEAN factor. For each task, we synthesized one character as neurotic, disagreeable, introverted, unconscientious and not open to experience and a second character as emotionally stable, agreeable, extroverted, conscientious and open to experience. We performed the synthesis for three models and three actions, so there were nine different tasks. One action (pointing) and one character (wooden mannequin) were kept the same for consistency checking. Two new actions (throwing and walking), and two new characters (realistic-looking male and female human models) were introduced.

**Participants.** We performed the validation of personality mappings using Amazon Mechanical Turk. Qualification requirements were the same as the previous study. We recruited 55 unique participants with mean age $31.33 \pm 10.94$, 17F/38M, and 46 native/9 non-native English speakers. We ensured that each question was answered by 30 different people.

**Analysis.** Assuming the null hypothesis to be that the number of responses for both poles of personality factors are equal, we counted the number of responses in each group for exact personality, oppo-

Table IV. Coefficients of motion parameters related to Effort derived by multivariate linear regression

| Parameter | Description | Intercept | Space | Weight | Time | Flow |
|---|---|---|---|---|---|---|
| $s$ | Animation speed | 0.558 | -0.000 | 0.001 | 0.470 | 0.001 |
| $v_A$ | Anticipation velocity | 0.223 | -0.011 | 0.297 | 0.000 | -0.029 |
| $v_O$ | Overshoot velocity | 0.344 | -0.042 | -0.042 | 0.000 | -0.458 |
| $t_A$ | Anticipation time | 0.031 | -0.002 | 0.041 | 0.008 | -0.002 |
| $t_O$ | Overshoot time | 0.930 | 0.015 | 0.018 | -0.015 | 0.092 |
| $t_{Inf}$ | Inflection time | 0.525 | -0.007 | -0.001 | 0.007 | -0.013 |
| $t_{Exp}$ | Time exponent that magnifies acceleration or deceleration | 1.043 | 0.015 | 0.008 | 0.072 | 0.060 |
| $T$ | Tension | -0.024 | 0.009 | -0.020 | -0.032 | 0.012 |
| $C$ | Continuity | 0.024 | 0.012 | 0.016 | 0.017 | -0.030 |
| $w_B$ | Wrist bend | 0.191 | -0.008 | -0.238 | 0.000 | -0.025 |
| $w_X$ | Initial wrist extension | 0.128 | -0.003 | -0.243 | 0.032 | -0.054 |
| $W_t$ | Wrist twist | 0.160 | -0.010 | -0.053 | 0.010 | -0.196 |
| $w_F$ | Wrist frequency | 0.848 | -0.040 | -0.760 | -0.150 | -0.381 |
| $E_t$ | Elbow twist | 0.281 | -0.009 | 0.039 | -0.005 | -0.313 |
| $e_D$ | Elbow displacement | 0.164 | -0.016 | -0.017 | 0.035 | -0.161 |
| $e_F$ | Elbow frequency | 0.735 | 0.015 | 0.041 | 0.020 | -0.809 |
| $t_R$ | Torso rotation magnitude | 0.290 | -0.043 | 0.040 | 0.010 | -0.331 |
| $t_F$ | Torso rotation frequency | 1.283 | -0.179 | 0.223 | 0.067 | -1.410 |
| $h_R$ | Head rotation magnitude | 1.210 | -0.804 | 0.008 | 0.004 | -0.178 |
| $h_F$ | Head rotation frequency | 1.078 | -1.225 | 0.104 | -0.017 | 0.184 |
| $breath_R$ | Torso squash magnitude for breathing | 0.641 | 0.015 | -0.123 | -0.010 | -0.063 |
| $breath_F$ | Torso squash frequency for breathing | 0.687 | -0.031 | 0.263 | -0.156 | -0.188 |
| $t_{Shape_{inf}}$ | Shape inflection time | 0.404 | 0.051 | -0.229 | -0.010 | 0.057 |
| $encSpr_0$ | Enclosing/Spreading coefficient at $t_0$ | 0.088 | -0.004 | 0.151 | 0.007 | -0.208 |
| $sinRis_0$ | Sinking/Rising coefficient at $t_0$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| $retAdv_0$ | Retreating/Advancing coefficient at $t_0$ | 0.041 | 0.020 | -0.032 | 0.008 | 0.006 |
| $encSpr_1$ | Enclosing/Spreading coefficient at $t_{shapeT}$ | 0.195 | -0.003 | 0.164 | 0.001 | -0.365 |
| $sinRis_1$ | Sinking/Rising coefficient at $t_{shapeT}$ | -0.027 | -0.035 | -0.965 | -0.035 | 0.000 |
| $retAdv_1$ | Retreating/Advancing coefficient at $t_{shapeT}$ | 0.015 | 0.059 | -0.016 | -0.031 | -0.015 |
| $encSpr_2$ | Enclosing/Spreading coefficient at $t_1$ | 0.195 | -0.003 | 0.164 | 0.001 | -0.365 |
| $sinRis_2$ | Sinking/Rising coefficient at $t_2$ | 0.136 | -0.056 | -0.819 | 0.014 | -0.125 |
| $retAdv_2$ | Retreating/Advancing coefficient at $t_1$ | 0.015 | 0.059 | -0.016 | -0.031 | -0.015 |
| $arm_{LX}$ | Left arm Shape in horizontal dimension | 0.167 | 0.060 | 0.027 | -0.030 | -0.172 |
| $arm_{LY}$ | Left arm Shape in vertical dimension | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| $arm_{LZ}$ | Left arm Shape in sagittal dimension | -0.135 | -0.040 | -0.008 | 0.025 | 0.180 |
| $arm_{RX}$ | Right arm Shape in horizontal dimension | 0.153 | 0.047 | 0.017 | 0.015 | -0.149 |
| $arm_{RY}$ | Right arm Shape in vertical dimension | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| $arm_{RZ}$ | Right arm Shape in sagittal dimension | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| *extraGoal* | Whether to define extra goal points | 0.781 | 0.042 | 0.000 | -0.292 | -0.042 |

site personality and neutral answers. Figure 10 shows the diagrams depicting the ratios of desired answers (exact personality) to all the answers in each category. We both performed a t-test assuming the answers were normally distributed, and a binomial test ignoring the neutral answers. The two-tailed p values of both of these tests for all the categories were less than 0.001. The results were highly consistent with our mappings. Ratios of expected answers for each personality can be sorted from highest to lowest as: extroversion with $93.4\%$, neuroticism with $90.8\%$, conscientiousness with $89.4\%$, openness with $74.5\%$ and agreeableness with $74.2\%$. When the responses are sorted according to the actions, ratios were $88.9\%$ for walking, $83.5\%$ for pointing and $81.1\%$ for throwing. For the characters, the female model has the highest ratio with $84.9\%$, followed by the wooden mannequin with $84.6\%$ and the male model with $83.9\%$. Note that under the null hypothesis these values would be $33.3\%$ assuming all the three answers were randomly selected. We also calculated the Pearson correlation ($r$) between our expected answers and participant's answers for each question and found it to be 0.98 with $p < 0.001$.

Instead of a rating-based study displaying a single character, we designed a comparison study due to the subjectivity of the problem. Personality is not an absolute concept and some kind of reference point should be defined first in order to assess the perception of personality in a motion. Overall, the results indicate that personality of a virtual character is highly distinguishable with our technique given a reference point to compare it against. However, some personality factors such as extroversion and neuroticism have higher recognition rates whereas openness and agreeableness have lower values. These results suggest that characteristics of certain personality traits are more difficult to recognize than others by solely looking at an action without context information. Also, the results of action types show us that people's walking styles give more information about their personalities than more physically-challenging actions such as throwing.

## 8. DISCUSSION AND CONCLUSIONS

This work formulates a link between motion parameters and the personality of a virtual character by employing Laban Movement Analysis as a systematic representation of movement qualities. We have quantified the Laban parameters with the help of movement experts and developed a computational system to represent expressive motion. We have formulated a mathematical mapping between personality, Effort and low-level motion parameters using the results of a perception study performed through Amazon Mechanical Turk, and validated these mappings by another perception study through crowdsourcing.

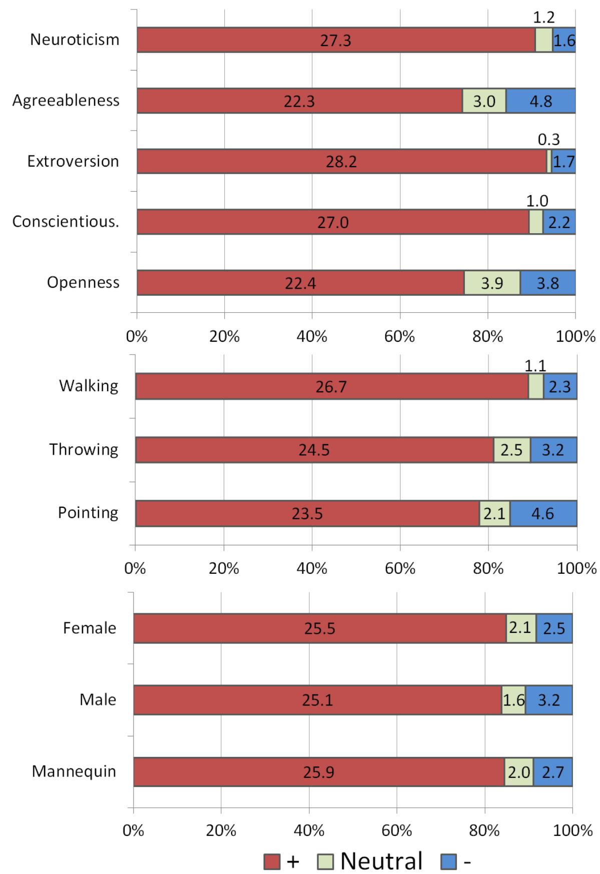



Fig. 10. Accuracy of participants' perception of the virtual characters' personalities ($p < 0.001$). About 30 responders compared each animation pair. Diagrams show the average number of participants that selected the desired response (+ personality), opposite response (- personality) and remained neutral. Responses are grouped by personality type (top), animation (middle) and virtual characters (bottom).

A key contribution of this work is that we have developed a mapping between a standard personality model and LMA qualities, which provide a high level description of movement. This mapping is independent of any particular low-level motion representation. While we provide a comprehensive set of motion parameters which are agreed upon by both of the movement experts, our results are not tied to this representation. An extended or completely different motion model should provide the same personality results, as long as the model is able to replicate the same LMA qualities. Our goal was to generate a clear manifestation of LMA qualities and then to show their relationship with personality. As long as the motion conveys the desired LMA qualities, employing different animation techniques, parameters, or experts should not matter. The final product is the representation of Effort and Shape qualities, which are precise concepts. For example, horizontal head and torso rotations are used to express LMA's Indirect Space factor. Indirectness, however, is not limited to such actions. In general, it implies paying attention to one's global surroundings, and so in specific scenarios, it can be represented solely by gaze control, the choice of which is up to the developer.

In addition to defining a novel relationship between personality and Laban components, we examine the impact of this relationship on its application in computer graphics by presenting a high-level authoring tool for animators. Procedurally expressing personality through motion has the potential to facilitate the authoring of believable and diverse autonomous virtual characters by providing easy controllability. Our system can produce stylized variation of motion by adjusting the Effort qualities and this can be controlled by simply supplying numerical values for personality traits. This is especially useful in crowd simulation scenarios where we desire diversity across motion styles of the agents in a crowd without having to deal with each agent separately or making random choices. Heterogeneity can be achieved even within groups of similar personality types just by varying the distribution of personality parameters. Thus, a particular cluster of agents will look locally diverse movement-wise, yet be consistent throughout the animation.

A difficulty we faced during the preparation of sample scenarios arose from the existing emotional content of available animations. Emotions are short-term and they override the expression of long-term, characteristic traits that make up personality. In order to avoid being overshadowed by emotions, personality can be injected in varying amounts to the motion, enabling more powerful expression. However, this causes cartoonish motion. We specifically refrained from exaggerated movement qualities both during the parametrization of LMA factors and the preparation of animations. Even then, the results of the perception experiments are compelling as they show that people with diverse backgrounds agree on similar aspects of personality-driven movement and the mappings can be generalized across different motion sequences and different human models.

Movement can reflect both personality traits and a person's emotional state. Whereas personality is stable over the long term, emotions are short term. An interesting area for future work is defining relationships between emotions and LMA qualities, and superimposing this relationship on top of personality-edited motion. Similar techniques can be applied to learning the mapping between emotions and motion. Certain emotions are correlated with particular personality traits, such as anger and anxiety being more likely for people high in neuroticism, so movement adjustments applied for these traits may provide a useful starting point for mapping related emotions.

Some limitations we encountered during our research were due to the large parameter space. For example, it would be interesting to ask the two poles of each personality dimension separately. Thus, a non-linear relationship between personality and Effort could be defined. In our study, this would mean doubling the number of questions, which was already very large. We would like to examine such a relationship in the future.

Another limitation of our system is that the motion representation relies solely on kinematic parameters. Some Effort elements such as Free Flow and Strong Weight can be more accurately embodied by using physically-based models. We are interested in exploring the dynamics of motion such as incorporating a muscle tension model as future work. In addition, we plan to capture the motion of several professional actors expressing different personalities and extract the common motion parameters salient to each personality factor computationally. We will then compare them with our current findings.

Furthermore, automatically adapting behavior based on context is another interesting research direction. LMA will still provide a suitable language for this adaptation E.g. more Bound at a job interview and more Free at a party.

Personality plays a crucial role in social interactions. As social interactions become more complicated, different issues such as maintaining the synchronization of motion through spatial and timing edits are raised. Currently, our system focuses on varying how a behavior is executed rather than coordinating high-level behaviors. As a future work, we plan to extend our system with higher-level control structures that implement the temporal and spatial coordination of motions in multi-character scenarios. These can all be solved within the animation framework, for instance by introducing time and space constraints.

## REFERENCES


Barbara Adrian. 2002. *An introduction to LMA for actors: a historical, theoretical, and practical perspective*. Allworth Press; NY. 73 –84 pages.

Jan Allbeck and Norman Badler. 2002. Toward Representing Agent Behaviors Modified by Personality and Emotion. In *Workshop on Embodied Conversational Agents*.

Kenji Amaya, Armin Bruderlin, and Tom Calvert. 1996. Emotion from Motion. In *Conference on Graphics Interface '96*. 222–229.

Laban Effort Bank. 2015. http://www.lmaeffortbank.com/effort.html. (2015). Accessed: 2015-01-19.

Irmgard Bartenieff and Dori Lewis. 1980. *Body Movement: Coping with the environment.* Gordon and Breach, New York.

Durell Bouchard and Norman I. Badler. 2007. Semantic Segmentation of Motion Capture Using Laban Movement Analysis. In *Intelligent Virtual Agents (IVA'07)*.

Matthew Brand and Aaron Hertzmann. 2000. Style Machines, In ACM SIGGRAPH'00. *ACM SIGGRAPH'00* (2000), 183–192.

Shih Pin Chao, Shi Nine Yang, and Tsang Gang Lin. 2006. An LMA-Effort simulator with dynamics parameters for motion capture animation. *Computer Animations and Virtual Worlds* 17, 3-4 (2006), 167–177.

Diane Chi, Monica Costa, Liwei Zhao, and Norman I. Badler. 2000. The emote model for effort and shape. *ACM Computer Graphics (Proceedings of SIGGRAPH'00)* (2000), 173–182.

Luca Chittaro and Milena Serra. 2004. Behavioral programming of autonomous characters based on probabilistic automata and personality. *Journal of Visualization and Computer Animation* 15, 3-4 (2004), 319–326.

Mark Coulson. 2004. Attributing Emotion to Static Body Postures: Recognition Accuracy, Confusions, and Viewpoint Dependence. *Journal of Nonverbal Behavior* 26, 2 (2004), 117–139.

Elizabeth Crane and Melissa Gross. 2007. Motion Capture and Emotion: Affect Detection in Whole Body Movement, Affective Computing and Intelligent Interaction. *Lecture Notes in Computer Science* 4738 (2007), 95–101.

Funda Durupinar, Jan Allbeck, Nuria Pelechano, Ugur Gudukbay, and Norman Badler. 2011. How the Ocean Personality Model Affects the Perception of Crowds. *IEEE Computer Graphics and Applications* 31, 3 (2011), 22–31.

Arjan Egges, Sumedha Kshirsagar, and Nadia Magnenat-Thalmann. 2003. A Model for Personality and Emotion Simulation. *Lecture Notes in Artificial Intelligence* 2773 (2003), 453–461.

Paul Ekman, Wallace V. Friesen, Maureen O'Sullivan, and Klaus Scherer. 1980. Relative importance of face, body, and speech in judgments of personality and affect. *Journal of Personality and Social Psychology* 38, 2 (1980), 270–277.

LMA Glossary. 2015. http://movementhasmeaning.com/glossary/. (2015). Accessed: 2015-01-19.

Lewis R. Goldberg. 1990. An Alternative "Description of Personality": The Big-Five Factor Structure. *Journal of Personality and Social Psychology* 59 (1990), 1216–1229.

Samuel D. Gosling, Sei Jin Ko, Thomas Mannarelli, and Margaret E. Morris. 2002. A Room with a cue: Judgments of personality based on offices and bedrooms. *Journal of Personality and Social Psychology* 82 (2002), 379–39.

Samuel D. Gosling, Peter J. Rentfrow, and William B. Swann. 2003. A very brief measure of the big-five personality domains. *Journal of Research in Personality* 37, 6 (2003), 504–528.

Qin Gu and Zhigang Deng. 2011. Context-aware motion diversification for crowd simulation. *IEEE Computer Graphics and Applications* 5 (2011), 54–65.

Stephen J. Guy, Sujeong Kim, Ming C. Lin, and Dinesh Manocha. 2011. Simulating heterogeneous crowd behaviors using personality trait theory. In *ACM SIGGRAPH/Eurographics Symposium on Computer Animation (SCA'11)*.

B. Hartmann, M. Mancini, and C. Pelachaud. 2006. Implementing Expressive Gesture Synthesis for Embodied Conversational Agents. *Lecture Notes in Artificial Intelligence* 3881 (2006), 188–199.

Eugene Hsu, Kari Pulli, and Jovan Popović. 2005. Style Translation for Human Motion. *ACM Transactions on Graphics (TOG)* 24 (2005), 1082–1089.

Mubbasir Kapadia, I kao Chiang, Tiju Thomas, Norman I. Badler, and Joseph Kider. 2013a. Efficient motion retrieval in large motion databases. In *ACM SIGGRAPH Symposium on Interactive 3D Graphics and Games*.

Mubbasir Kapadia, Alexander Shoulson, Funda Durupinar, and Norman I. Badler. 2013b. Authoring Multi-actor Behaviors in Crowds with Diverse Personalities. In *Modeling, Simulation and Visual Analysis of Crowds*, Saad Ali, Ko Nishino, Dinesh Manocha, and Mubarak Shah (Eds.). The International Series in Video Computing, Vol. 11. Springer New York, 147–180. DOI:http://dx.doi.org/10.1007/978-1-4614-8483-7_7

Michael Kipp, Michael Neff, Kerstin H. Kipp, and Irene Albrecht. 2007. Towards Natural Gesture Synthesis: Evaluating Gesture Units in a Data-Driven Approach to Gesture Synthesis. In *Intelligent Virtual Agents (IVA'07) (IVA '07)*. Springer-Verlag, Berlin, Heidelberg, 15–28.

Mark L. Knapp and Judith A. Hall. 1978. *Nonverbal communication in human interaction*. Holt, Rinehart and Winston, New York.

Yuichi Kobayashi and Jun Ohya. 2006. EM-in-M: Analyze and Synthesize Emotion in Motion. In *Advances in Machine Vision, Image Processing, and Pattern Analysis (LNCS)*, Nanning Zheng, Xiaoyi Jiang, and Xuguang Lan (Eds.), Vol. 4153. 135–143.

Doris H. U. Kochanek and Richard H. Bartels. 1984. Interpolating splines with local tension, continuity, and bias control, In ACM SIGGRAPH'84. *ACM SIGGRAPH'84* 18, 3 (1984), 33–41.

Sergey Levine, Philipp Krähenbühl, Sebastian Thrun, and Vladlen Koltun. 2010. Gesture controllers. *ACM Transactions on Graphics (TOG)* 29, 4 (2010), 124.

Jacqlyn A. Levy and Marshall P. Duke. 2003. The use of laban movement analysis in the study of personality, emotional state and movement style: An exploratory investigation of the veridicality of "body language". *Individual Differences Research* 1, 1 (2003), 39 – 63.

C. Karen Liu, Aaron Hertzmann, and Zoran Popović. 2005. Learning physics-based motion style with nonlinear inverse optimization, In ACM SIGGRAPH'05. *ACM SIGGRAPH'04* 24, 3 (2005), 1071–1081.

Kris Liu, Jackson Tolins, Jean E Fox Tree, Michael Neff, and Marilyn A Walker. 2016. Two techniques for assessing virtual agent personality. *IEEE Transactions on Affective Computing* 7, 1 (2016), 94–105.

Maurizio Mancini and Ginevra Castellano. 2007. Real-Time Analysis and Synthesis of Emotional Gesture Expressivity. In *Affective Computing and Intelligent Interaction*.

Robert R. McCrae, Paul T. Costa, and Thomas A. Martin. 2005. The NEO-PI-3: A more readable revised NEO personality inventory. *Journal of Personality Assessment* 84, 3 (2005), 261–270.

Rachel McDonnell, Sophie Jörg, Joanna McHugh, Fiona Newell, and Carol O'Sullivan. 2008a. Evaluating the Emotional Content of Human Motions on Real and Virtual Characters. In *Applied Perception in Graphics and Visualization (APGV)*. 67–74.

Rachel McDonnell, Michéal Larkin, Simon Dobbyn, Steven Collins, and Carol O'Sullivan. 2008b. Clone attack! Perception of crowd variety. *ACM Transactions on Graphics (Proceedings of SIGGRAPH'08)* 27, 3 (2008), Article no. 26, 8 pages. DOI:http://dx.doi.org/10.1145/1399504.1360625

Matthias R. Mehl, Samuel D. Gosling, and James W. Pennebaker. 2006. Personality in its natural habitat: Manifestations and implicit folk theories of personality in daily life. *Journal of Personality and Social Psychology* 90 (2006), 862–877.

Michael Neff and Eugene Fiume. 2005. AER: Aesthetic Exploration and Refinement for Expressive Character Animation. In *Eurographics/ACM SIGGRAPH Symposium on Computer Animation (SCA'05)*.

Michael Neff, Nicholas Toothman, Robeson Bowmani, Jean E. Fox Tree, and Marilyn Walker. 2011. Don't Scratch! Self-adaptors Reflect Emotional Stability. In *Intelligent Virtual Agents (IVA'11)*. Springer LNAI.

Michael Neff, Yingying Wang, Rob Abbott, and Marilyn Walker. 2010. Evaluating the Effect of Gesture and Language on Personality Perception in Conversational Agents. In *Intelligent Virtual Agents (IVA'10)*. LNCS.

Aline Normoyle, Fannie Liu, Mubbasir Kapadia, Norman I. Badler, and Sophie Joerg. 2013. The Effect of Posture and Dynamics on the Perception of Emotion. In *ACM Symposium on Applied Perception (SAP'13)*.

Marion North. 1972. *Personality Assessment Through Movement*. Macdonald and Evans.

RootMotion. 2015. Final IK, "http://www.root-motion.com". (2015). http://www.root-motion.com/ Accessed: 2015-01-19.

Ali-Akbar Samadani, Sarah J. Burton, Rob Gorbet, and Dana Kulić. 2013. Laban effort and shape analysis of affective hand and arm movements. In *Affective Computing and Intelligent Interaction (ACII)*. 343–348.

Ari Shapiro, Yong Cao, and Petros Faloutsos. 2006. Style Components. In *Graphics Interface'06*. 33–39.

Scott Steketee and Norman I. Badler. 1985. Parametric keyframe interpolation incorporating kinetic adjustment and phasing control, In ACM SIGGRAPH'85. *ACM SIGGRAPH* 19 (1985), 225–262.

Lorenzo Torresani, Peggy Hackney, and Chris Bregler. 2007. Learning Motion Style Synthesis from Perceptual Observations. In *Neural Information Processing Systems (NIPS)*.

Munetoshi Unuma, Ken Anjyo, and Ryozo Takeuchi. 1995. Fourier Principles for Emotion-based Human Figure Animation. In *ACM SIGGRAPH'95*. 91–96.

Vinoba Vinayagamoorthy, Marco Gillies, Anthony Steed, E. Tanguy, Xueni Pan, C. Loscos, and Mel Slater. 2006. Building expression into virtual characters. In *Eurographics Conference State of the Art Reports*.

Liwei Zhao, Monica Costa, and Norman I Badler. 2000. Interpreting Movement Manner. In *Computer Animation Conference, IEEE Computer Society*.

## Appendix: Laban Movement Analysis

Laban Movement Analysis is a technique created by Rudolf Laban to formally describe human movement. It is used in a broad range of fields such as dance, physical therapy, drama, psychology and anthropology. LMA comprises four categories: Body, Effort, Shape and Space. Body defines the structural aspects of the human body during motion. Effort is the dynamic component, which is used to describe the characteristics of movement based on humans' inner attitudes. Shape determines the way these attitudes are expressed through body, and it is manifested in postures. Finally, Space describes how a person connects to their environment; locale directions and paths of a movement, and it is partly related to steering. In our work, we keep Body and Space fixed and we focus on Shape and Effort components.

### Effort

Effort is described through four motion factors, where each factor is a continuum between bipolar Effort elements: indulging and condensing. The Effort elements are Space (Indirect vs. Direct), Weight (Light vs. Strong), Time (Sustained vs. Sudden) and Flow (Free vs. Bound). Each Effort element is characterized by certain trait-descriptive adjectives as [Allbeck and Badler 2002]:

—Indirect: Flexible, meandering, multi-focus
—Direct: Single-focus, channeled, undeviating
—Light: Buoyant, delicate
—Strong: Powerful, having an impact
—Sustained: Lingering, leisurely, indulging in time
—Sudden: Hurried, urgent
—Free: Uncontrolled, abandoned, unlimited
—Bound: Careful, controlled, restrained

Human beings exhibit a variety of Effort combinations. Single Effort elements and combinations of all four Efforts are highly unlikely and they appear only in extreme cases. In our daily lives, we tend to use Effort in combinations of 2 (States) or 3 (Drives). States are more ordinary and common in everyday usage whereas Drives are reserved for extraordinary moments in life. We have more intense feelings in these distinctive moments, therefore, they convey more information about our personality.

### Drives

Drives are combinations of equal parts of three Effort factors. There are four types of Drives:

—Action Drive: Weight + Space + Time. Action Drive is task oriented. Because there is no Flow, it is not concerned with emotions [Bank 2015]. Actors are mostly exposed to Action Drives because these promote the physical manifestation of their actions and objectives [Adrian 2002]. Each combination of Action Drives is provided with a unique name:
  —Punch Action Drive: Strong + Direct + Sudden
  —Dab Action Drive: Light + Direct + Sudden
  —Slash Action Drive: Strong + Indirect + Sudden
  —Flick Action Drive: Light + Indirect + Sudden
  —Press Action Drive: Strong + Direct + Sustained
  —Glide Action Drive: Light + Direct + Sustained
  —Wring Action Drive: Strong + Indirect + Sustained
  —Float Action Drive: Light + Indirect + Sustained
—Passion Drive: Weight + Time + Flow. Passion Drive is about being present in the emotional moment. It deals with awareness of senses, feelings and timing. It is not concerned about external factors and the environment. E.g. A passionate kiss, screaming, being in pain, deep emotional distress/ joy.
—Vision Drive: Time + Space + Flow. Vision Drive is about planning, organizing and attention. Because it has no Weight, it is very external-oriented. E.g. Giving a presentation, parenting.
—Spell Drive: Weight + Space + Flow. Spell drive deals with the self in relationship to the environment. Because it is not concerned with Time, is does not have a planning or pacing aspect. E.g. A long and epic journey, flying, being stuck in traffic and feeling like it will never end.

### Shape

Shape is the link between Effort and Space. It is both about form and the progression of form. Shape Qualities are described in three directions: horizontal (Enclosing vs. Spreading), vertical (Rising vs. Sinking) and sagittal (Retreating vs. Advancing). The definitions of Shape qualities are given as [Glossary 2015]:

—Enclosing: The Shape quality that describes a change toward sideways direction that involves narrowing of the body.
—Spreading: The Shape quality that describes a change toward sideways direction that involves widening of the body.
—Rising: The Shape quality that describes a change toward upwards direction.
—Sinking: The Shape quality that describes a change toward downwards direction.
—Retreating: The Shape quality that describes a change toward backwards direction.
—Advancing: The Shape quality that describes a change toward forwards direction.