Modeling Data-Driven Dominance Traits for Virtual Characters using Gait Analysis

Tanmay Randhavane, Aniket Bera, Emily Kubin, Kurt Gray, Dinesh Manocha

Abstract

We present a data-driven algorithm for generating gaits of virtual characters with varying dominance traits. Our formulation utilizes a user study to establish a data-driven dominance mapping between gaits and dominance labels. We use our dominance mapping to generate walking gaits for virtual characters that exhibit a variety of dominance traits while interacting with the user. Furthermore, we extract gait features based on known criteria in visual perception and psychology literature that can be used to identify the dominance levels of any walking gait. We validate our mapping and the perceived dominance traits by a second user study in an immersive virtual environment. Our gait dominance classification algorithm can classify the dominance traits of gaits with ~73% accuracy. We also present an application of our approach that simulates interpersonal relationships between virtual characters. To the best of our knowledge, ours is the first practical approach to classifying gait dominance and generate dominance traits in virtual characters.

Index Terms

Computer Graphics, Synthesis of Affective Behavior.

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1 INTRODUCTION

There is considerable interest in simulating human-like virtual characters. The set of applications for these simulations includes training, social VR, gaming, virtual crowds, VR therapy, urban modeling, etc. There are many challenges involved in generating the appearance, movements, and plausible behaviors of such virtual human-like characters. The behaviors to be generated include verbal and non-verbal behaviors. Furthermore, many applications need to simulate virtual characters with varied personalities and traits.

Prior studies and evaluations in psychology and virtual environments have shown that some of the components of pedestrian movement, including joint positions and orientations, are important for realistic human perception [1], [2]. As a result, there is considerable recent work on generating plausible trajectories or movements of virtual characters. In the physical world, humans are known to be adept at using many visual cues, including subtle cues, to make impressions of or social judgments about others. As a result, there has been some work on simulating and evaluating the benefits of non-verbal behaviors like gaze, gestures, and gaits [3], [4].

In this paper, we focus on analyzing gait features in real-world scenes and using them to generate gaits of virtual characters that can display a spectrum of dominance traits. A person's gait or style of walking is a unique feature of their overall movement. Gaits have been shown to be an effective biometric cue for visual identification [5] or recognition of biological motion [6]. Previous studies have shown that humans can convey and perceive much information including sex differences [7], emotions [8], moods, and personality traits from gaits. Moreover, walking style also affects what people tend to remember [9]. Overall, non-verbal cues like gaits and the style of walking can guide the perception of emotions [10], [11], moods, and personality traits of characters [12], including dominance and openness.

In terms of modeling any human-like behavior of a virtual character, it is important to define the behavior and understand the factors that influence that behavior. Previous research has formulated *dominance behavior* as the behavior directed towards the control of another through implied or actual threat [13]. Dominance can be defined as a personality trait involving the motive to control others or as some perception of oneself as controlling others. The dominance behavior is manifested through various verbal and non-verbal cues. We focus on non-verbal cues associated with walking gaits to generate virtual characters with dominance traits. This includes the study of behaviors like postural erectness, postural openness, slumped shoulders, etc., which affect the perception of dominance. We also use variations in walking speed where characters with fast-moving gaits are perceived as more dominant than characters with slow-moving gaits. Our work is also inspired by prior work on the visual perception of human gaits. In particular, Johansson [14] showed that a few bright spots, which are used to describe the motions of the main joints of humans, are sufficient to evoke a compelling impression of human activity. Humans can perceive a considerable amount of information from watching other humans' gaits. Therefore, dominance traits of virtual
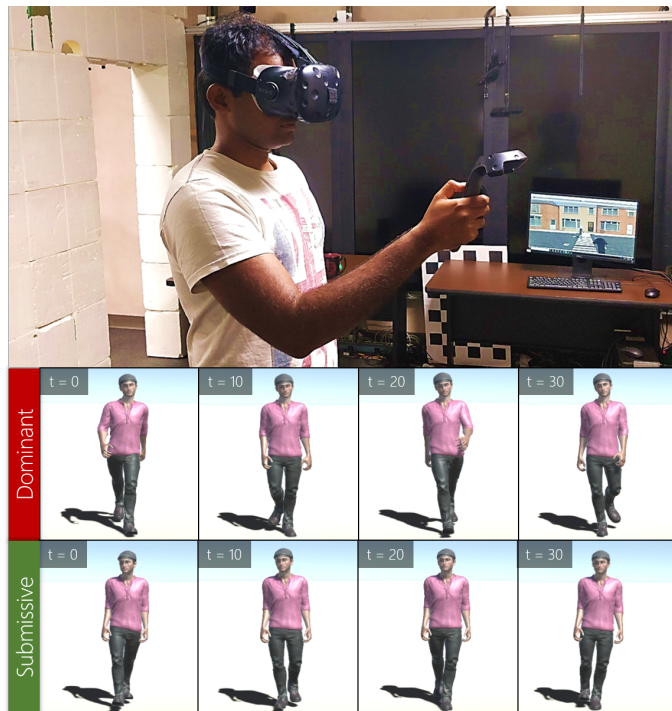

Fig. 1. **Modeling Dominance Traits for Virtual Characters:** Our approach learns dominance traits from motion-captured gaits and computes a data-driven dominance mapping. We use this mapping to interactively generate virtual characters with different dominance traits (below) for an immersed user (top). According to the psychology literature, more leg and hand movement and erect posture indicates a dominant gait, whereas slumped posture and less leg and hand movement indicates a submissive gait.

characters can also be modeled using their walking gaits.

Main Results: We present a data-driven model of dominance traits of virtual characters based on gait analysis (Figure 1). Our formulation is based on using the results of a user study on gait datasets [15], [16], [17] to generate dominance labels for the walking gaits. We use these annotated walking gaits to generate virtual characters with different dominance traits. Based on prior work in visual perception on non-verbal cues related to perceived dominance [18], [19], [20], [21], [22], we extract appropriate features from human gaits. Next, we classify these features into dominance labels using Support Vector Machines trained on the annotated dataset. Overall, our method can be used to identify the dominance of any gait. We also present an application of our approach to simulate interpersonal social relationships relating to dominance between virtual characters.

An overview of our approach is given in Figure 2, where we highlight offline dominance mapping generation and its application to runtime virtual character generation and gait dominance classification algorithms. Our cross-validation results show that our method can be used to classify the dominance traits of any new gait with ~73% accuracy.
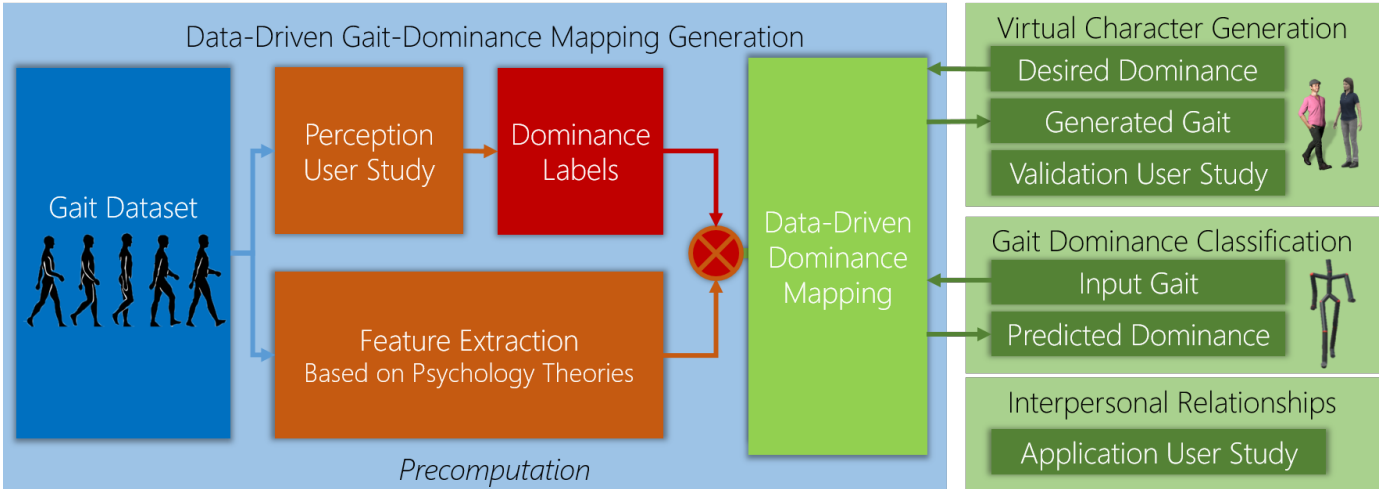
Fig. 2. **Overview:** We highlight the various components of our approach. We start with a gait dataset and perform a perception user study to generate different dominance labels. We also compute different gait-based features representing dominance according to prior work in psychology. Finally, we compute a data-driven mapping between the dominance labels and the features. To generate a character with a specific dominance trait, we use the corresponding gait at real-time using our dominance mapping. Given new gaits, we compute their features and predict the dominance labels. Our approach can be used to simulate interpersonal relationships relating to dominance between virtual characters.

Our contributions include three user studies to model and validate dominance traits:

- Perception User Study: In this web-based study, we obtain dominance labels for gaits that are used to establish a gait dominance mapping (Section 3).
- Validation User Study: In this immersive study, we validate our approach to generating virtual characters with different dominance traits in a virtual environment. We observe statistically significant differences between the dominance traits of virtual characters created using our approach. Results of this extensive study indicate that our data-driven approach can be used to generate virtual characters with the desired levels of dominant and submissive behaviors (Section 5).
- Application User Study: In this immersive study, we present an application for simulating interpersonal social relationships between virtual characters (Section 7). The results of this study indicate that our approach can be used to simulate the interpersonal social relationships relating to dominance between virtual characters.

Overall, our approach to model dominance has the following benefits:

1. Interactive Performance: Our approach can be used to interactively generate virtual characters that exhibit a range of dominance traits.

2. Compatibility: Our approach is orthogonal to different methods used for local navigation or the generation of other personality traits, gaze, emotions, moods, etc.

3. Generalizability: Our approach can be used to identify the dominance levels of any new gait.

4. Interpersonal social Relationships: Our approach can be used to simulate interpersonal social relationships relating to dominance among virtual characters.

The rest of the paper is organized as follows. In Section 2, we review the related work in the fields of behavior modeling and gait analysis. In Section 3, we describe our perception user study. In Section 4, we describe our gait dominance classification algorithm.

We present the details of our validation user study in Section 5 and our classification results in Section 6. In Section 7, we present an application of our approach that simulates interpersonal social relationships between virtual characters and the application user study. We conclude with the limitations and future opportunities of our work in Section 8.

2 RELATED WORK

In this section, we give a brief overview of prior work on behavior modeling of virtual characters and gait analysis.

2.1 Gait Analysis

There is considerable work on automatic recognition of emotions and personalities from body expressions such as gaits. Most works use a feature-based approach where the features are either extracted using purely statistical techniques or are inspired from psychological studies. Some approaches focus on specific activities such as dancing [23], knocking [24], walking [25], games [26], etc., whereas other approaches use a more generalized approach [27], [28]. Some techniques combine both facial and body expressions [29], [30], [31], [32], [33], [34], [35], [36]. Janssen et al. [37] use neural networks to identify emotions from gaits. They observe that the differences between the gaits of individuals were much larger than the differences between emotions. Other approaches find emotions expressed in gaits with the help of neutral expressions [10], [38]. Studies have shown that both posture and movement cues are important for the perception of emotion and personality [10], [39]. Gaits have also been used for activity recognition [40], [41]. Although there is a lot of work on modeling emotion and other personality characteristics [42], [43], there is only a small amount of work available on modeling dominance. Karg et al. [25] treat dominance as a dimension in the emotion space and identify emotions from gaits. Our approach to model dominance in virtual characters and to classify dominance from gaits combines data-driven techniques with a feature-based method inspired by these approaches.

2.2 Behavior Modeling of Virtual Characters

There is considerable literature in psychology, VR, and pedestrian simulation on modeling the behavior of pedestrians and virtual characters. Many rule-based methods have been proposed to model complex behaviors based on motor, perceptual, behavioral, and cognitive components [44]. There is extensive literature on modeling emergent behaviors, starting with Reynold's work [45]. Yeh et al. [46] describe velocity-based methods for modeling different behaviors, including aggression, social priority, authority, protection, and guidance. Other techniques use personality traits to model heterogeneous crowd behaviors [47], [48]. Perceptual or user studies are used to improve the behavior and rendering of virtual characters [49]. McDonnell et al. [50] use perceptual saliency to identify essential features that need to be varied to add visual variety to the appearance of avatars. Virtual character generation approaches have been developed based on the PAD model of emotion by Mehrabian et al. [51]. Vinayagamoorthy et al. [52] summarize approaches that consider body posture and movement features in simulating emotions in virtual characters. McHugh et al. [53] study the relationship between an agent's body posture and his or her perceived emotional state. Clavel et al. [34] combine facial and postural expressions to investigate the overall perception of basic emotions in virtual characters. Pelechaud et al. [54] use gestures to express different emotions in behaviors of virtual characters. Virtual agents with emotional capabilities have been used as museum guides [55]. Su et al. [56] propose a rule-based method to model specific personality types. In this paper, we propose a data-driven method for generating virtual characters with a variety of dominance characteristics. Our approach is complementary to these methods and can be combined with them. We also provide a dominance classification algorithm that can be used to classify the dominance levels of the gaits generated using any method (e.g., Holden et al. [57]).

3 PERCEPTION USER STUDY

To be able to generate gaits that exhibit a range of dominance traits, we use a data-driven approach to compute a mapping between gaits and their dominance labels (Figure 2). During precomputation, we use motion-captured gait datasets as input and obtain dominance labels for each gait using a perception user study. Using the results of this study, we establish a mapping between gaits and dominance. We use this mapping at runtime to generate gaits for virtual characters that have the desired dominance traits. In the rest of this section, we describe the details of this dominance perception study.

3.1 Study Goals

The goal of this perception study was to obtain the dominance labels for gaits using three motion-capture datasets.

3.2 Gait Datasets

We used three publicly available motion captured gait datasets: 36 gaits from the CMU dataset [15], 24 gaits from the ICT dataset [16], and 119 gaits from the BML dataset [17]. Each gait was visualized using a skeleton mesh and rendered from the viewpoint of a camera looking at the mesh from the front (Figure 3). The visualizations were generated with the same frame rate with which they were captured. The 179 resulting videos were displayed to the participants in a web-based user study.
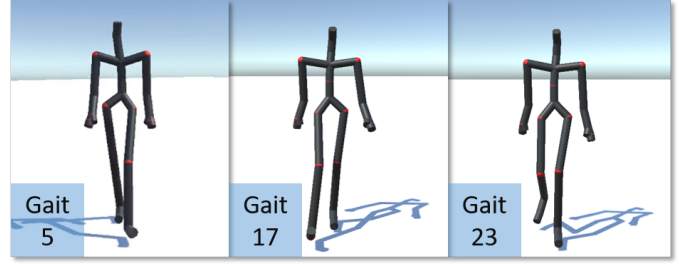

Fig. 3. **Sample Visualization of the Gait Dataset:** We show sample visualizations of the gaits of 3 individuals. Gait videos from 179 motion-captured gaits were displayed to the participants in a web-based user study.

3.3 Participants

Since the data obtained from Amazon Mechanical Turk has been shown to be at least as reliable as those obtained via traditional methods [58], we used it to recruit the participants. A total of 703 participant responses (362 female, 332 male, 9 preferred not to provide gender, $\overline{age} = 36.3$) were used to generate dominance labels. For the smaller CMU and ICT gait datasets, each participant watched and rated a random subset of six videos while other participants watched and rated a random subset of 12 videos from the BML dataset. We assume that our gait dataset of 179 videos is a representative sample of variations of dominance traits.

3.4 Questionnaire

We designed our questions using previous studies from psychology literature [13], [59], [60], [61]. We considered the adjectives submissive, non-confident, sluggish, withdrawn, non-aggressive, fearful, tense, dominant, confident, energetic, outgoing, aggressive, intimidating, and relaxed. These adjectives have been used in previous studies to assess the dominance traits of humans [13], [59], [60], [61]. Based on the results of a pilot user study, we decided to use a subset of these adjectives for the final study. For each video, participants were asked if they found the character to be *submissive, withdrawn, dominant*, and *confident*. The participants answered each question on a five-point Likert scale ranging from "strongly disagree" to "strongly agree."

3.5 Results

For each gait $\mathbf{G}_i$ in the dataset, we obtained a response $r_{i,j}^{adj}$ by a participant j to an adjective $adj \in \{$submissive, withdrawn, dominant, confident$\}$. We analyzed the consistency in the participant responses using a method similar to that in Kleinsmith et al. [8] to estimate how well the participants agreed. We randomly divided the participant responses in two equal sets $\mathbb{P}_1$ and $\mathbb{P}_2$. For each adjective, we computed the average of the participant responses for each set $r_i^{adj,1}$ and $r_i^{adj,2}$:

$$r_i^{adj,1} = \frac{\sum_{j \in \mathbb{P}_1} r_{i,j}^{adj}}{n_{p,1}}, \tag{1}$$

$$r_i^{adj,2} = \frac{\sum_{j \in \mathbb{P}_2} r_{i,j}^{adj}}{n_{p,2}}, \tag{2}$$

TABLE 1
Correlation Between Dominance Adjectives: We provide the correlation coefficients for the dominance adjectives. These adjectives are known to be closely related to an individual's dominance and are therefore highly correlated.

	Submissive	Withdrawn	Dominant	Confident
Submissive	1.00	0.91	-0.90	-0.87
Withdrawn	0.91	1.00	-0.91	-0.94
Dominant	-0.90	-0.91	1.00	0.94
Confident	-0.87	-0.94	0.94	1.00

where $n_{p,1}$ and $n_{p,2}$ are the cardinalities of $\mathbb{P}_1$ and $\mathbb{P}_2$, respectively. We computed the average error e^{adj} between the two means $r_i^{adj,1}$ and $r_i^{adj,2}$:

$$e^{adj} = \frac{|r_i^{adj,1} - r_i^{adj,2}|}{N}, \qquad (3)$$

where $N = 179$ is the number of gaits in the dataset. We observe an average error of 7.09% between the two mean values for the four adjectives, indicating that the participant responses are reliable.

In further analysis, for each gait $\mathbf{G}_i$ in the dataset, we calculated the mean of all participant responses ($r_{i,j}^{adj}$) to each adjective:

$$r_i^{adj} = \frac{\sum_{j=1}^{n_p} r_{i,j}^{adj}}{n_p}, \qquad (4)$$

where n_p is the number of participant responses collected and adj is one of the four adjectives: *submissive, withdrawn, dominant, confident*.

We also analyzed the participant responses to the adjectives. Since all the adjectives capture general impressions of an individual's dominance, we expect a strong correlation between them [13], [59], [60], [61]. This is shown by the correlation coefficients in Table 1.

3.6 Data-Driven Dominance Mapping

The high correlations between the adjectives suggest that the underlying dominance factor in the participant responses can be obtained using factor analysis methods. Therefore, we performed Principal Component Analysis (PCA) on the average participant responses for each video revealing that a single factor can account for 93.78% variance. We use this factor to combine the responses r_i^{sub}, r_i^{with}, r_i^{dom}, r_i^{conf} for a gait $\mathbf{G}_i$ into a scalar value $r_i \in \mathbb{R}$:

$$r_i = 0.43 * r_i^{dom} + 0.54 * r_i^{conf} - 0.44 * r_i^{sub} - 0.57 * r_i^{with}. \qquad (5)$$

The negative coefficients of responses to the submissive and withdrawn adjectives correspond to the fact that their meanings are opposite from those of the dominant and confident adjectives. We also normalize the values such that $r_i \in [-1,1]$ with -1 denoting the minimum observed value and 1 denoting the maximum observed value.

Since there can be a disagreement between observers about perceived dominance [8], instead of using a scalar value for the dominance of a gait, we use five classes as dominance labels: *(Highly Submissive (HS), Submissive (S), Neutral (N), Dominant (D), Highly Dominant (HD))*.

According to McCrae et al. [62], most people lie somewhere in the middle of the personality scale. Using the scalar values of dominance r_i, we obtain the dominance label d_i for a gait $\mathbf{G}_i$ by

TABLE 2
Average Frame Update Time: We present the average frame update time for generating gaits of virtual characters with different dominance traits. We compare the performance to an algorithm that does not consider any dominance traits.

Number of Characters	Without Dominance (in ms)	With Dominance (in ms)
1	11.52	11.53
2	11.53	11.52
5	11.80	11.53
10	11.50	11.85
20	11.88	11.79
50	11.55	11.81
100	12.38	12.59

Algorithm 1: Interactive Virtual Character Generation

Input: desired dominance level d_{des}, gaits
$\mathbf{G}_i, i \in \{1,...,179\}$ and their dominance labels
$d_i, i \in \{1,...,179\}$, time t
Output: character's joint positions for joints
$J_k, k \in \{1,...,16\}$
1 $\mathbf{G}_{des} = \mathbf{G}_i$ where $d_i = d_{des}$
2 $P_{des} = P_t$ where $P_t \in \mathbf{G}_{des}$
3 **for** *joint J_k in skeleton S* **do**
$\quad$ Position J_k = Position J_k^{des} where $J_k^{des} \in P_{des}$
4 Root position $J_1 = navigation(\mathbf{E}, t-1)$

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dividing the gaits into five dominance levels with Neutral level (N) containing most gaits:

$$d_i = \begin{cases} \text{HS} & \text{if } -1 \leq r_i < -0.8 \\ \text{S} & \text{if } -0.8 \leq r_i < -0.5 \\ \text{N} & \text{if } -0.5 \leq r_i \leq 0.5 \\ \text{D} & \text{if } 0.5 < r_i \leq 0.8 \\ \text{HD} & \text{if } 0.8 < r_i \leq 1 \end{cases} \qquad (6)$$

Figure 4 shows sample gaits and their computed labels. Figure 5 shows the variation in gait dominance in accordance with our assumption that the gaits from the three datasets capture the variation in dominance traits.

3.7 Interactive Virtual Character Gait Generation

At runtime, our character generation algorithm (Algorithm 1) takes the desired dominance level d_{des} as input. We can also specify any other movement control requirements. For example, some navigation algorithms constrain a character's walking speed to a maximum value [63]. We represent these requirements as a boolean function $f(G_i)$ that takes a gait G_i as input and returns true if G_i satisfies the requirement and false otherwise. We find the set of gaits $\mathbb{G}$ from the labeled dataset associated with the desired dominance level:

$$\mathbb{G} = G_i \mid d_{des} = d_i \text{ and } f(G_i) = true. \qquad (7)$$

We choose a gait $G_{des} \in \mathbb{G}$ using random selection and update the joint positions of the character in the virtual world using the joint positions from G_{des}. After updating the joint positions of the character, its root position can be calculated using any navigation algorithm [64] to generate the character's movement in the virtual world.

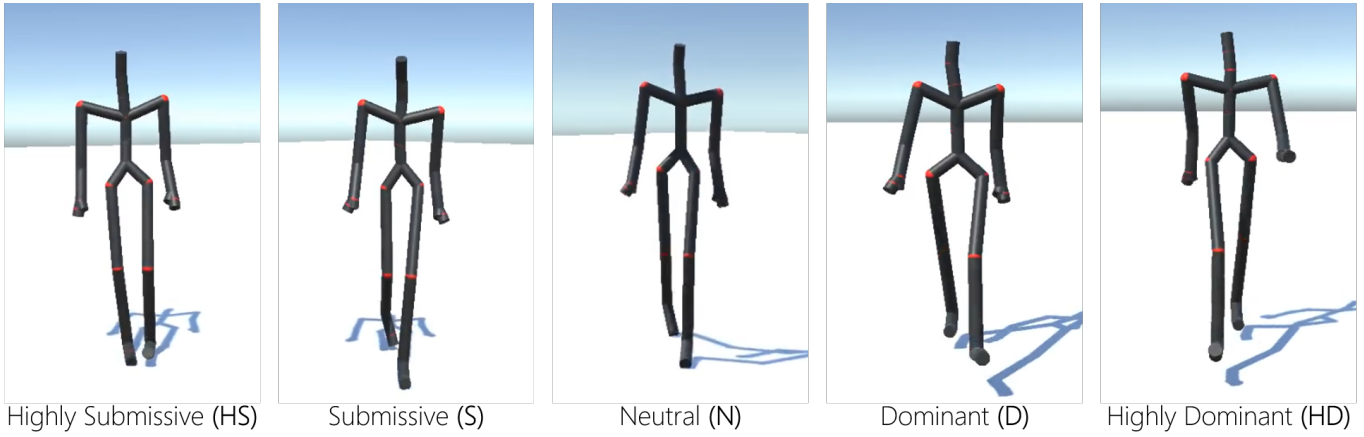| Highly Submissive (HS) | Submissive (S) | Neutral (N) | Dominant (D) | Highly Dominant (HD) |

Fig. 4. **Dominance spectrum:** Based on a perception user study, we obtain dominance labels for motion-captured gaits. As an example, participants rated the character on the left as Highly Submissive (HS), whereas the character on the right as Highly Dominant (HD). According to the psychology literature, more leg and hand movement and erect posture is observed in a dominant gait as compared to a submissive gait.
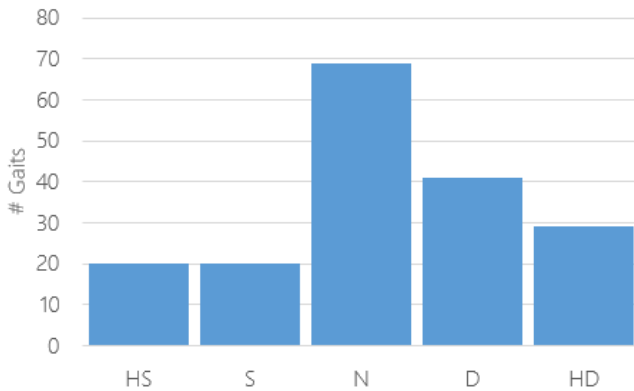

Fig. 5. **Dataset Variation:** We divide 179 gaits into 5 dominance levels using a perception user study: *(Highly Submissive (**HS**), Submissive (**S**), Neutral (**N**), Dominant (**D**), Highly Dominant (**HD**)).*

3.7.1 Interactivity Results

Using our Virtual Character Gait Generation method, we can generate gaits for virtual characters at interactive rates. We present the average frame update time in Table 2. The results show that our algorithm can generate gaits for tens of virtual characters at interactive rates.

4 GAIT DOMINANCE CLASSIFICATION

During runtime simulation, new gaits can be generated using motion blending techniques [65]. To predict the dominance traits of new gaits, we use a feature-based approach. After the perception user study, we get a dominance label (Equation 6) for each gait in the motion-captured gait dataset. If we also extract the feature values from each gait in the motion-captured dataset, then we can train a classifier using the annotated data. This classifier can then classify the dominance traits of any new input gait. For this purpose, it is necessary to understand the features that cause a gait to be perceived as dominant or submissive. We describe these features below.

4.1 Feature Extraction

Previous studies in psychology literature [18], [19], [20], [21], [22] have shown that factors like postural erectness, postural openness, slumped shoulders, walking speed, etc. affect the perception of dominance. Previous work on recognition of emotions and affective states from gaits has also determined features in the form of joint

TABLE 3
Gait Features: Based on visual perception and psychology literature, we extract these features from an input gait. Since both posture and movement features are essential for an accurate prediction of an individual's affective state [8], we define features that include both the posture and the movement features.

| Type	Description	Category
Volume	Bounding box	Posture
Angle	At neck by shoulders	
	At right shoulder by neck and left shoulder	
	At left shoulder by neck and right shoulder	
	At neck by vertical and back	
	At neck by head and back	
Distance	Between right hand and the root joint	
	Between left hand and the root joint	
	Between right foot and the root joint	
	Between left foot and the root joint	
	Between consecutive foot strikes (stride length)	
Area	Triangle between hands and neck	
	Triangle between feet and the root joint	
Speed	Right hand	Movement
	Left hand	
	Head	
	Right foot	
	Left foot	
Acceleration Magnitude	Right hand	
	Left hand	
	Head	
	Right foot	
	Left foot	
Movement Jerk	Right hand	
	Left hand	
	Head	
	Right foot	
	Left foot	
Time	One gait cycle	
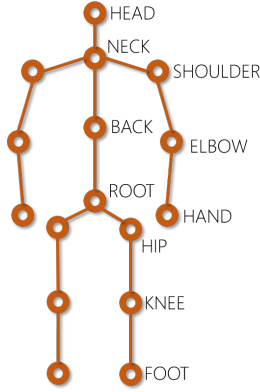
Fig. 6. **Character Representation**: We represent a character as a skeleton with 16 body joints to compute different gait features. The overall configuration of a skeleton, which is used to extract the features, is defined using these joint features.

angles, distances, and velocities of the joints, and space occupied by the body [8], [27]. Since both posture and movement features are essential for an accurate prediction of an individual's affective state [8], we define features that include both the posture and the movement features. We list these gait features in Table 3 and describe them in detail below.

We represent the extracted features of a gait $\mathbf{G}_i$ as a vector $F_i \in \mathbb{R}^{29}$. Given the gait features F_i, we represent the predicted dominance label as d_i^{pred}.

4.1.1 Posture Features

Openness of the limbs has been shown to affect dominance traits. Exhibiting slightly spread hands and legs is perceived as dominant, whereas minimizing the occupied space by pulling hands and legs in towards the torso is perceived as submissive [18], [19], [22], [66]. We model this as the volume of the bounding box, the area of the triangle defined by both hands and neck, the area of the triangle defined by both feet and root, the three angles induced by the triangle formed by both shoulders and neck, and the distances between hands and feet and the root joint. We also use stride length as a feature to measure openness.

Dominant gaits have been observed to involve an erect posture [18], [19], [22], [66]. In contrast, a submissive gait involves a slouched posture with the head and chin pointing down. We represent the head orientation as the angle formed by the head and back joint at the neck. A slouched or erect posture is represented by the angle between the vertical and back formed at the neck.

4.1.2 Movement Features

Movement of body parts such as hand and leg joints are perceived as dominant, whereas less joint movement is perceived as submissive [18], [19], [22], [66]. We model this based on the magnitude of velocity, acceleration, and movement jerk (derivative of acceleration) of the hands, feet, and head.

Fast-moving people are perceived as more dominant than slow-moving people. Low walking speeds are also regarded as less confident, and high walking speeds are perceived as more confident [67]. We model this feature by the time taken to complete one gait cycle and the stride length.

4.1.3 Feature Representation

Given an input gait $\mathbf{G}_i$, we compute features $F_{i,j}$ for each pose P_j corresponding to a frame in the gait. We define the gait feature F_i as the average of $F_{i,j}, j = \{1, 2, .., \tau\}$:

$$F_i = \frac{\sum_i F_{i,j}}{\tau}, \tag{8}$$

We also append gait time and stride length features to F_i.

4.2 Dominance Classification

Given the feature values extracted using the above method and the dominance labels obtained from the perception user study, we train a dominance classifier. For each gait $\mathbf{G}_i$ in the gait dataset, we have a vector of feature values F_i and a dominance label d_i. Before training the classifier, we normalize the feature values to $[-1, 1]$ with -1 denoting the minimum value of the feature and 1 denoting the maximum value of the feature. We use Support Vector Machines (SVMs) to classify the features similar to previous approaches for emotion identification from gait features [27]. We use an RBF kernel with a one-versus-rest decision function of shape [27], [68].

5 VALIDATION USER STUDY

We performed a user study to validate our approach (Algorithm 1) for generating virtual characters with desired dominance levels using our mapping. In this section, we give the details of this user study.

5.1 Study Goals and Expectation

This study aimed to show that virtual characters generated using our approach (Algorithm 1) could exhibit a variety of submissive and dominant personality traits. In particular, we propose the following hypothesis:

Hypothesis: Our data-driven approach can be used to generate virtual characters with varying levels of dominance.

5.2 Experimental Design

The study was conducted based on a within-subjects design. Participants were shown five scenes with a virtual character walking in different environments. Participants performed 10 trials per scene, corresponding to 10 virtual characters with varying levels of predicted dominance. The order of the scenes and the dominance levels of the virtual characters were counterbalanced. Participants performed the study using HTC Vive HMD. Participants could look around in the virtual environment by rotating their heads and could also walk in the tracking space, but there was no interaction with the virtual characters (Figure 1 (top)).

5.2.1 Procedure

After welcoming the participants, they were instructed on the overall process and purpose of the study. They were informed that the study involved using immersive hardware (HMD) and that it may cause nausea and slight discomfort. The experiment was approved by Institutional Review Boards and the Office of Human Research Ethics. Before beginning the experiment, the participants were invited to read and agree to the approved consent form. The participants were asked to provide optional demographic information about their gender and age. The study required approximately 30 minutes, and participants were compensated with a gift card worth $5.

5.2.2 Participants

We recruited 51 participants (38 male, 13 female, $\bar{x}_{age} = 23.2$) from the staff and students of a university.
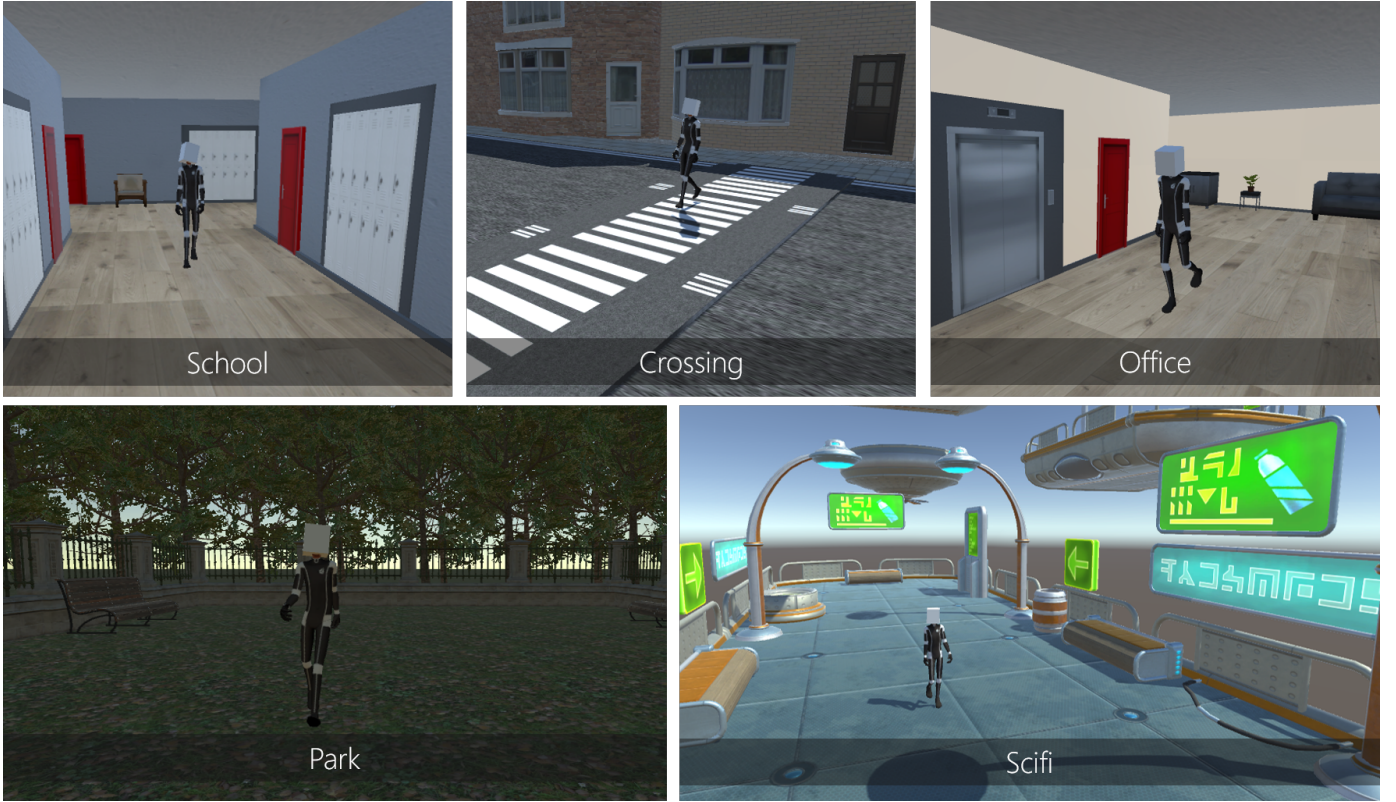
Fig. 7. **Scenarios:** Our validation user study included 5 scenarios, including indoor, outdoor, residential, and fantastical scenes.

5.2.3 Scenarios

We evaluated the dominance characteristics of the virtual characters in five different scenarios (Figure 7):

- **Crossing**: This outdoor scenario had a virtual character crossing a street in a residential environment.
- **Office**: This indoor scenario had a virtual character walking in an office environment.
- **Park**: This outdoor scenario consisted of a virtual character walking in a park.
- **School**: This indoor scenario consisted of a virtual character walking in a school corridor.
- **Scifi**: This fantastical scenario involved a virtual character walking on a floating platform.

In each of the scenarios, we used a template character. The character's clothing and appearance were chosen to minimize the dominance cues from appearance and were kept constant throughout the experiment. The character's face was also hidden behind a solid cube to avoid facial cues. We generated the character's gait with two gaits from each dominance level, resulting in a total of 10 trials. From now on, we represent these gaits as: $HS1, HS2, S1, S2, N1, N2, D1, D2, HD1, HD2$.

5.2.4 Questions

As in the perception user study (Section 3), we asked the participants whether they found the character to be *submissive, withdrawn, dominant*, and *confident* on a five-point Likert scale ranging from "strongly disagree" to "strongly agree."

5.3 Discussion

Here we present and analyze the participant responses. For each scene, we obtained the participant responses $r_{i,j}^{sub}, r_{i,j}^{with}, r_{i,j}^{dom}, r_{i,j}^{conf}$

corresponding to a character simulated with a gait G_i, participant j, and the four adjectives, *submissive, withdrawn, dominant*, and *confident*. For each participant, we converted the responses to the four adjectives into a scalar value $r_{i,j}$ using the principal component in Equation 5:

$$r_{i,j} = 0.43 * r_{i,j}^{dom} + 0.54 * r_{i,j}^{conf} - 0.44 * r_{i,j}^{sub} - 0.57 * r_{i,j}^{with}. \quad (9)$$

For each scene, we computed the mean of the participant responses for each of the 10 gaits:

$$r_i = \frac{\sum_{j=1}^{n_p} r_{i,j}}{n_p}, \quad (10)$$

where n_p is the number of participant responses collected for the character simulated with the gait G_i. We present these mean participant responses in Table 4. We normalized the means $\in [-1,1]$, where a higher value indicates higher dominance. We observed that gaits from higher dominance levels have higher mean values, as predicted by our algorithm.

We also compare the means of participant responses for pairs of gaits with different levels of dominance using paired samples t-tests. We present the p-values from gaits with consecutive levels of predicted dominance in Table 5. In the realistic outdoor *Park* scenario, we observed significant differences ($p < 0.05$) in all the comparisons. For the other outdoor scenario, *Crossing*, the indoor scenarios, *Office* and *School*, and the fantastical scenario, *Scifi*, most comparisons show statistically significant differences. These results support our hypothesis that our data-driven approach (Algorithm 1) can be used to generate virtual characters with varying levels of dominance.

We conducted the user study for five different scenarios. We performed paired sample t-tests for pairs of scenarios to assess whether the dominance levels of the generated characters varied significantly across different scenarios. For most of the characters,

TABLE 4
Reported Dominance: We present the mean values of the normalized participant responses $\in [-1,1]$. We generated 10 characters for each scenario using two gaits from each dominance level: HS, S, N, D, HD. Participants reported higher dominance for more dominant gaits, as predicted by our algorithm, across all the scenarios.

	Crossing	Office	Park	School	Scifi
HS1	-0.88	-0.90	-0.94	-0.93	-0.97
HS2	-0.82	**-0.41**	-0.82	-0.80	-0.80
S1	**-0.45**	-0.53	-0.66	-0.62	-0.55
S2	-0.59	**-0.45**	-0.58	**-0.48**	-0.55
N1	0.17	0.05	-0.10	-0.09	-0.06
N2	-0.10	0.07	-0.27	-0.06	-0.42
D1	0.59	0.62	**0.48**	**0.45**	0.52
D2	0.79	0.72	0.76	0.78	0.70
HD1	1.00	0.84	0.97	0.80	0.90
HD2	0.95	0.99	0.97	0.98	0.91

TABLE 5
Comparison of Means: We compare the means of participant responses for pairs of gaits with different levels of dominance using paired samples t-tests. This table presents the p-values for these comparisons (highlighted values indicate $p \geq 0.05$). We observe statistically significant differences ($p < 0.05$) in the means of reported dominance for pairs of gaits with different predicted dominance levels. These results support our hypothesis that our data-driven approach can be used to generate virtual characters with varying levels of dominance.

Comparison	Crossing	Office	Park	School	Scifi
HS1, S1	0.00	0.00	0.00	0.00	0.00
HS1, S2	0.00	0.00	0.00	0.00	0.00
HS2, S1	0.00	**0.21**	0.04	0.04	0.01
HS2, S2	0.03	**0.64**	0.00	0.00	0.03
S1, N1	0.00	0.00	0.00	0.00	0.00
S1, N2	0.00	0.00	0.00	0.00	**0.29**
S2, N1	0.00	0.00	0.00	0.00	0.00
S2, N2	0.00	0.00	0.01	0.00	**0.27**
N1, D1	0.00	0.00	0.00	0.00	0.00
N1, D2	0.00	0.00	0.00	0.00	0.00
N2, D1	0.00	0.00	0.00	0.00	0.00
N2, D2	0.00	0.00	0.00	0.00	0.00
D1, HD1	0.00	0.02	0.00	0.00	0.00
D1, HD2	0.00	0.00	0.00	0.00	0.00
D2, HD1	0.02	**0.16**	0.02	**0.84**	0.03
D2, HD2	**0.05**	0.00	0.01	0.01	0.01

the dominance levels did not exhibit significant differences across scenarios, as indicated in Table 8.

6 DOMINANCE CLASSIFICATION ACCURACY

In this section, we present the results of the gait dominance classification algorithm. We divide the datasets into training and testing datasets. For each gait $\mathbf{G}_i$ in the dataset, we have a dominance label d_i computed from the perception user study. We train our gait dominance classification algorithm using the training dataset and predict the dominance d_i^{pred} for each gait $\mathbf{G}_i$ in the testing dataset. We define the accuracy of our algorithm as the percentage of correctly predicted gait dominance levels from the testing dataset. Here, we treat dominance labels d_i as the ground truth.

Table 6 presents the results of our experiments. We considered two sets of dominance levels:

- Five dominance levels: HS, S, N, D, HD (Equation 6) and
- Three dominance levels: S, N, D where $S = HS \cup S$ and $D = D \cup HD$

Fig. 8. **Consistency Across Scenarios**: We perform paired samples t-tests between scenarios to assess whether the participant responses for a gait remain consistent across a variety of scenarios. We present a visualization of the p-values obtained for these comparisons. We color the cells where we observed a significant difference ($p < 0.05$) between mean participant responses red and we color the cells where we did not observe a significant difference ($p > 0.05$) green. For most of the gaits, there was not a significant difference ($p > 0.05$) between mean participant responses across scenarios, indicating consistent dominance levels irrespective of the scenario.

TABLE 6
Accuracy of Gait Dominance Classification: We present the percentage accuracy of our gait dominance classification algorithm. We trained our algorithm on the training datasets and tested it on the testing datasets. For the datasets where the training and testing datasets were the same, we performed a 10-fold cross-validation with 2000 iterations.

Training Dataset	Testing Dataset	3 Levels	5 Levels
All	All	72.94	61.33
BML + CMU	BML + CMU	74.02	63.24
BML + ICT	BML + ICT	68.56	48.31
BML	BML	71.05	50.41
BML	CMU	77.78	83.33
BML	ICT	62.50	45.83
BML	CMU + ICT	73.33	71.67

We also considered different training and testing datasets. We trained our algorithm using all the three datasets, using BML and CMU/ICT, and using BML only. We did not train on only CMU and ICT because these datasets contain very few samples. For the datasets where training and testing datasets were the same, we performed a 10-fold cross-validation with 2000 iterations. We observed consistent accuracy for most of the datasets. The performance deteriorated for the ICT dataset. A possible reason for this deterioration is that the dataset is noisier than the BML and CMU datasets. We observe an average accuracy of ~73% and ~61% when using three dominance levels and five dominance levels for classification, respectively.

7 APPLICATION

In this section, we present an application of our approach that models interpersonal social relations between virtual characters. Among the many dimensions of interpersonal social relations, we consider the "vertical" dimension, which relates to power, dominance, status, and social hierarchy [66]. Vertical dimension constructs are defined to be included in situations where there is

- a situationally defined power, expertise, or status (for example, a teacher-student relationship),
- a self-reported dominant or assertive personality, or
- a perceived and/or rated impression of dominance.

TABLE 7
Trials for the Application User Study: Each user performed four trials each for two scenarios in a randomized order. The two characters in the scene were either submissive or dominant, as above.

	Trial 1	Trial 2	Trial 3	Trial 4
Left Character	HS	HS	HD	HD
Right Character	HS	HD	HS	HD

Our approach to generating virtual characters with different perceived dominance traits can be used to simulate situations where there is a relationship belonging to the vertical dimension between virtual characters. To support this argument, we created simplified scenarios where the vertical dimension of interpersonal social relationships between virtual characters was realized and validated with a user study (Figure 9). We discuss the user study in this section.

7.1 Study Goals

We propose the following simplified hypothesis:
Hypothesis: Pairs of characters with different submissive and dominant characteristics can be used to realize the vertical dimension of interpersonal social relations.

7.2 Experimental Design

As in the validation user study (Section 5), we used a within-subjects design in which the participants were asked to participate in two scenarios.

7.2.1 Procedure

The procedure was like that in the validation user study. Participants performed four trials of each of the two scenarios and were compensated with a gift card worth $5.

7.2.2 Participants

We recruited 20 participants (15 male, 5 female, $\bar{x}_{age}$ = 26.2) from the staff and students of a university.

7.2.3 Scenarios

We wanted to evaluate whether the *vertical dimension*, as observed in real-world situations, can be realized in VR by generating virtual characters with varying dominance traits using our approach. We used two scenarios from the validation user study in this experiment: *Office* and *School*. In each of the scenarios, two characters were generated with varying levels of dominance. Each participant performed four trials of each scenario in a randomized order with the two characters having dominance levels as described in Table 7. A single *HS* gait and a single *HD* gait was used for the trials.

We assumed that, if our virtual character generation approach can generate dominant and submissive characters, then the vertical dimension of the relationship between a teacher and a student will cause participants to choose the dominant character as the teacher and the submissive character as the student. Similarly, our assumption in the *Office* case was that because of the dominance relationship between a boss and an employee, participants will choose the dominant character as the boss and the submissive character as the employee.

The appearances of the two characters were similar except for the gaits used, and their faces were hidden behind solid cube as in the validation user study.

7.2.4 Questions

In the *Office* scenario, for each trial, the participants were asked to indicate whether each character was an employee or a boss. They could also choose a third option of *Unsure* if they could not clearly decide. Participants assigned these labels to each character independently. In the *School* scenario, they were asked to indicate whether each character was a student or a teacher, again with the third option of *Unsure*.

7.3 Discussion

Table 8 presents the percentages of participants that chose student, teacher, and unsure for the *School* scene and the percentages that chose employee, boss, and unsure for the *Office* scene.

7.3.1 School Scenario

The results of this scenario suggest that our approach to generating virtual characters with different dominance traits is not enough to create characters that are distinguishable as teacher or student. One possible reason for this result is that the dominance relationship in the vertical dimension between a student and a teacher is not clearly defined and the affective or socio-emotional (horizontal) dimension may be stronger in some cases. The verbal feedback from the participants brought this point to our attention. Another factor that the participants reported as having affected their judgment is that the slow walking gait of the submissive character could be associated with an older teacher.

7.3.2 Office Scenario

Like in the *School* scene, in the *Office* scene, participants were asked to report whether they can decide if the virtual character is an employee or a boss. The results of this scenario suggest that our approach to generating virtual characters with different dominance traits can create characters that are distinguishable as an employee or boss when one character is submissive and the other is dominant, supporting our hypothesis. Although the relationship between submissive traits and the character being an employee was observed, a similar association was not clear when both the characters were dominant. One possible reason for this is that the possibility of two dominant bosses in a single scene was not considered by the participants, leading to the reports of *Unsure*. Overall, the results of our application user study indicate that our approach can be used to simulate the vertical dimension of interpersonal social relationships between virtual characters.

8 CONCLUSION, LIMITATIONS, AND FUTURE WORK

We present a novel approach to computing a data-driven mapping between dominance traits and gait features. This mapping is used at runtime to generate virtual characters with different dominance traits. We validate our approach with a user study in a virtual environment. We present a gait dominance classification method to classify the dominance traits of new input gaits. Our algorithm can classify the dominance of gaits with an accuracy of ~73%. We also present an application of our approach that simulates the vertical dimension of interpersonal social relationships between virtual characters. In our application user study, participants associated roles such as employee or boss to virtual characters based on their dominance traits. To the best of our knowledge, ours is the first approach that models dominance traits for virtual agents

TABLE 8
Application User Study Results: We present the percentages of participants that answered teacher, student, or unsure for the *School* scene (in light gray) and the percentages of participants that answered employee, boss, or unsure for the *Office* scene (in dark gray). For the *Office* scene, our approach to generating virtual characters with different dominance traits is able to create characters that are distinguishable as employees and bosses. Overall, the results of our application user study indicate that our approach can be used to simulate the vertical dimension of interpersonal social relationships between virtual characters.

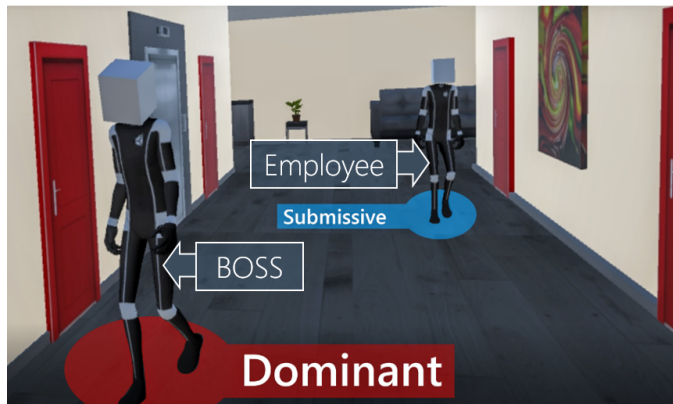|	Trial 1		Trial 2		Trial 3		Trial 4	
	HS	HS	HS	HD	HD	HS	HD	HD
Student	35	40	45	35	30	40	15	20
Teacher	25	20	45	55	60	40	45	40
Unsure	40	40	10	10	10	20	40	40
Employee	60	55	65	5	0	85	25	15
Boss	5	10	10	75	90	0	35	40
Unsure	35	35	25	20	10	15	40	45

Fig. 9. **Interpersonal Social Relationship Between Virtual Characters**: Our approach can be used to realize the vertical dimension of interpersonal social relationships. Members of a pair of dominant and submissive characters generated using our method were perceived by participants as being a boss or an employee depending on their dominance level in our application user study.

at interactive rates. Additions of realistic human behaviors and interactions have been shown to improve the sense of presence experienced by users when immersed in virtual environments [69], [70], [71]. Our approach to simulating virtual characters with a variety of dominance characteristics can be used to simulate the vertical dimension of the interpersonal relationship between virtual agents. Therefore, our approach is applicable to VR applications like social VR, rehabilitation and PTSD treatments, treatment of crowd phobias, evacuation and urban planning, etc. In addition to these VR applications, our approach can also be used for gaming and simulation applications. Simulating virtual characters with variety of dominance traits can improve the fidelity of character simulations for gaming and training applications.

Our approach has some limitations. The dominance feature computation is based on the classification of features from visual perception literature. This classification may not be sufficient to capture all observed dominance behaviors. Furthermore, we assume that the motion gait datasets are noise-free, but in practice noise in the joint positions can affect perception. Gaits extracted from RGB videos using state-of-the-art machine learning techniques [72] contain noise in the joint positions. Our algorithm does not account for these noisy gaits. There are many avenues for future work. In addition to addressing these limitations, we would like to

evaluate the performance of our methods for more than two virtual characters. We would also like to identify the importance of trajectories in addition to gait features on the perception of dominance. Furthermore, we would like to combine these dominance traits with other personality traits and evaluate the performance in virtual environments for different applications.

REFERENCES

[1] C. Ennis, C. Peters, and C. O'Sullivan, "Perceptual effects of scene context and viewpoint for virtual pedestrian crowds," *ACM Trans. Appl. Percept.*, vol. 8, no. 2, pp. 10:1–10:22, Feb. 2011.

[2] N. Pelechano, C. Stocker, J. Allbeck, and N. Badler, "Being a part of the crowd: Towards validating vr crowds using presence," in *Proc. of the 7th International Joint Conference on Autonomous Agents and Multiagent Systems - Volume 1*, 2008, pp. 136–142. [Online]. Available: http://dl.acm.org/citation.cfm?id=1402383.1402407

[3] J. N. Bailenson, A. C. Beall, J. Loomis, J. Blascovich, and M. Turk, "Transformed social interaction, augmented gaze, and social influence in immersive virtual environments," *Human communication research*, vol. 31, no. 4, pp. 511–537, 2005.

[4] S. Narang, A. Best, T. Randhavane, A. Shapiro, and D. Manocha, "PedVR: Simulating gaze-based interactions between a real user and virtual crowds," *Proc. of ACM VRST*, 2016.

[5] L. Wang, T. Tan, H. Ning, and W. Hu, "Silhouette analysis-based gait recognition for human identification," *IEEE transactions on pattern analysis and machine intelligence*, vol. 25, no. 12, pp. 1505–1518, 2003.

[6] T. Beardsworth and T. Buckner, "The ability to recognize oneself from a video recording of ones movements without seeing ones body," *Bulletin of the Psychonomic Society*, vol. 18, no. 1, pp. 19–22, 1981.

[7] D. A. Bruening, R. E. Frimenko, C. D. Goodyear, D. R. Bowden, and A. M. Fullenkamp, "Sex differences in whole body gait kinematics at preferred speeds," *Gait & posture*, vol. 41, no. 2, pp. 540–545, 2015.

[8] A. Kleinsmith and N. Bianchi-Berthouze, "Affective body expression perception and recognition: A survey," *IEEE Transactions on Affective Computing*, vol. 4, no. 1, pp. 15–33, 2013.

[9] J. Michalak, K. Rohde, and N. F. Troje, "How we walk affects what we remember: Gait modifications through biofeedback change negative affective memory bias," *Journal of behavior therapy and experimental psychiatry*, vol. 46, pp. 121–125, 2015.

[10] C. L. Roether, L. Omlor, A. Christensen, and M. A. Giese, "Critical features for the perception of emotion from gait," *Journal of vision*, vol. 9, no. 6, pp. 15–15, 2009.

[11] A. P. Atkinson, W. H. Dittrich, A. J. Gemmell, and A. W. Young, "Emotion perception from dynamic and static body expressions in point-light and full-light displays," *Perception*, vol. 33, no. 6, pp. 717–746, 2004.

[12] A. S. Heberlein, R. Adolphs, D. Tranel, and H. Damasio, "Cortical regions for judgments of emotions and personality traits from point-light walkers," *Journal of Cognitive Neuroscience*, vol. 16, no. 7, pp. 1143–1158, 2004.

[13] C. L. Ridgeway, "Nonverbal behavior, dominance, and the basis of status in task groups," *American Sociological Review*, pp. 683–694, 1987.

[14] G. Johansson, "Visual perception of biological motion and a model for its analysis," *Perception & psychophysics*, vol. 14, no. 2, pp. 201–211, 1973.

[15] "Cmu graphics lab motion capture database," http://mocap.cs.cmu.edu/, 2018, online; accessed 5 August 2018.

[16] S. Narang, A. Best, A. Feng, S.-h. Kang, D. Manocha, and A. Shapiro, "Motion recognition of self and others on realistic 3d avatars," *Computer Animation and Virtual Worlds*, vol. 28, no. 3-4, 2017.

[17] Y. Ma, H. M. Paterson, and F. E. Pollick, "A motion capture library for the study of identity, gender, and emotion perception from biological motion," *Behavior research methods*, vol. 38, no. 1, pp. 134–141, 2006.

[18] P. Furley, M. Dicks, and D. Memmert, "Nonverbal behavior in soccer: The influence of dominant and submissive body language on the impression formation and expectancy of success of soccer players," *Journal of Sport and Exercise Psychology*, vol. 34, no. 1, pp. 61–82, 2012.

[19] G. E. Weisfeld and J. M. Beresford, "Erectness of posture as an indicator of dominance or success in humans," *Motivation and Emotion*, vol. 6, no. 2, pp. 113–131, 1982.

[20] P. G. Curran, "Methods for the detection of carelessly invalid responses in survey data," *Journal of Experimental Social Psychology*, vol. 66, pp. 4–19, 2016.

[21] L. Richards, B. Rollerson, and J. Phillips, "Perceptions of submissiveness: Implications for victimization," *The Journal of psychology*, vol. 125, no. 4, pp. 407–411, 1991.

[22] P. Eisenburg, "Expressive movements related to feelings of dominance," *Arch. Psychol., NY*, no. 211, 1937.

[23] M. Raptis, D. Kirovski, and H. Hoppe, "Real-time classification of dance gestures from skeleton animation," in *Proceedings of the 2011 ACM SIGGRAPH/Eurographics symposium on computer animation*. ACM, 2011, pp. 147–156.

[24] M. M. Gross, E. A. Crane, and B. L. Fredrickson, "Methodology for assessing bodily expression of emotion," *Journal of Nonverbal Behavior*, vol. 34, no. 4, pp. 223–248, 2010.

[25] M. Karg, K. Kuhnlenz, and M. Buss, "Recognition of affect based on gait patterns," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 40, no. 4, pp. 1050–1061, 2010.

[26] A. Kleinsmith, N. Bianchi-Berthouze, and A. Steed, "Automatic recognition of non-acted affective postures," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 41, no. 4, pp. 1027–1038, 2011.

[27] A. Crenn, R. A. Khan, A. Meyer, and S. Bouakaz, "Body expression recognition from animated 3d skeleton," in *International Conference on 3D Imaging (IC3D 2016)*, 2016.

[28] W. Wang, V. Enescu, and H. Sahli, "Adaptive real-time emotion recognition from body movements," *ACM Transactions on Interactive Intelligent Systems (TiiS)*, vol. 5, no. 4, p. 18, 2016.

[29] F. E. Pollick, H. Paterson, and P. Mamassian, "Combining faces and movements to recognize affect," *Journal of Vision*, vol. 4, no. 8, pp. 232–232, 2004.

[30] J. Van den Stock, R. Righart, and B. De Gelder, "Body expressions influence recognition of emotions in the face and voice." *Emotion*, vol. 7, no. 3, p. 487, 2007.

[31] H. K. Meeren, C. C. van Heijnsbergen, and B. de Gelder, "Rapid perceptual integration of facial expression and emotional body language," *Proceedings of the National Academy of Sciences*, vol. 102, no. 45, pp. 16 518–16 523, 2005.

[32] E. R. Tuminello and D. Davidson, "What the face and body reveal: In-group emotion effects and stereotyping of emotion in african american and european american children," *Journal of experimental child psychology*, vol. 110, no. 2, pp. 258–274, 2011.

[33] M. L. Willis, R. Palermo, and D. Burke, "Judging approachability on the face of it: The influence of face and body expressions on the perception of approachability." *Emotion*, vol. 11, no. 3, p. 514, 2011.

[34] C. Clavel, J. Plessier, J.-C. Martin, L. Ach, and B. Morel, "Combining facial and postural expressions of emotions in a virtual character," in *International Workshop on Intelligent Virtual Agents*. Springer, 2009, pp. 287–300.

[35] H. Gunes and M. Piccardi, "Observer annotation of affective display and evaluation of expressivity: Face vs. face-and-body," in *the HCSNet Workshop on the use of vision in human-computer interaction*. Australian Computer Society, 2006.

[36] A. Kapoor, W. Burleson, and R. W. Picard, "Automatic prediction of frustration," *International journal of human-computer studies*, vol. 65, no. 8, pp. 724–736, 2007.

[37] D. Janssen, W. I. Schöllhorn, J. Lubienetzki, K. Fölling, H. Kokenge, and K. Davids, "Recognition of emotions in gait patterns by means of artificial neural nets," *Journal of Nonverbal Behavior*, vol. 32, no. 2, pp. 79–92, 2008.

[38] A. Crenn, A. Meyer, R. A. Khan, H. Konik, and S. Bouakaz, "Toward an efficient body expression recognition based on the synthesis of a neutral movement," in *Proceedings of the 19th ACM International Conference on Multimodal Interaction*. ACM, 2017, pp. 15–22.

[39] A. P. Atkinson, M. L. Tunstall, and W. H. Dittrich, "Evidence for distinct contributions of form and motion information to the recognition of emotions from body gestures," *Cognition*, vol. 104, no. 1, pp. 59–72, 2007.

[40] L. L. Presti and M. La Cascia, "3d skeleton-based human action classification: A survey," *Pattern Recognition*, vol. 53, pp. 130–147, 2016.

[41] J. K. Aggarwal and L. Xia, "Human activity recognition from 3d data: A review," *Pattern Recognition Letters*, vol. 48, pp. 70–80, 2014.

[42] A. Bera, T. Randhavane, and D. Manocha, "Aggressive, tense, or shy? identifying personality traits from crowd videos," in *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI*, vol. 17, 2017, pp. 112–118.

[43] A. Bera, S. Kim, T. Randhavane, S. Pratapa, and D. Manocha, "Glmp-realtime pedestrian path prediction using global and local movement patterns," in *Robotics and Automation (ICRA), 2016 IEEE International Conference on*. IEEE, 2016, pp. 5528–5535.

[44] W. Shao and D. Terzopoulos, "Autonomous pedestrians," in *Symposium on Computer animation*, 2005, pp. 19–28.

[45] C. Reynolds, "Steering Behaviors for Autonomous Characters," in *Game Developers Conference 1999*, 1999.

[46] H. Yeh, S. Curtis, S. Patil, J. van den Berg, D. Manocha, and M. Lin, "Composite agents," in *Symposium on Computer Animation*, 2008, pp. 39–47.

[47] S. J. Guy, S. Kim, M. C. Lin, and D. Manocha, "Simulating heterogeneous crowd behaviors using personality trait theory," in *Symposium on Computer Animation*. ACM, 2011, pp. 43–52.

[48] F. Durupinar, N. Pelechano, J. Allbeck, U. Gü anddü andkbay, and N. Badler, "How the ocean personality model affects the perception of crowds," *Computer Graphics and Applications, IEEE*, vol. 31, no. 3, pp. 22 –31, may-june 2011.

[49] T. Randhavane, A. Bera, and D. Manocha, "F2fcrowds: Planning agent movements to enable face-to-face interactions," *Presence: Teleoperators and Virtual Environments*, vol. 26, no. 2, pp. 228–246, 2017.

[50] R. McDonnell, M. Larkin, B. Hernández, I. Rudomin, and C. O'Sullivan, "Eye-catching crowds: saliency based selective variation," *ACM Transactions on Graphics (TOG)*, 2009.

[51] A. Mehrabian, "Pleasure-arousal-dominance: A general framework for describing and measuring individual differences in temperament," *Current Psychology*, vol. 14, no. 4, pp. 261–292, 1996.

[52] V. Vinayagamoorthy, M. Gillies, A. Steed, E. Tanguy, X. Pan, C. Loscos, and M. Slater, "Building expression into virtual characters," in *Eurographics*, 2006.

[53] J. McHugh, R. McDonnell, C. O'Sullivan, and F. Newell, "Perceiving emotion in crowds: the role of dynamic body postures on the perception of emotion in crowded scenes," *Experimental brain research*, 2010.

[54] C. Pelachaud, "Studies on gesture expressivity for a virtual agent," *Speech Communication*, vol. 51, no. 7, pp. 630–639, 2009.

[55] S. Kopp, L. Gesellensetter, N. C. Krämer, and I. Wachsmuth, "A conversational agent as museum guide–design and evaluation of a real-world application," in *Intelligent virtual agents*. Springer, 2005, pp. 329–343.

[56] W.-P. Su, B. L. Pham, and A. W. Wardhani, "Personality and emotion-based high-level control of affective story characters," *IEEE Transactions on Visualization and Computer Graphics*, vol. 13, no. 2, pp. 281–293, 2007.

[57] D. Holden, T. Komura, and J. Saito, "Phase-functioned neural networks for character control," *ACM Transactions on Graphics (TOG)*, vol. 36, no. 4, p. 42, 2017.

[58] M. Buhrmester, T. Kwang, and S. D. Gosling, "Amazon's mechanical turk: A new source of inexpensive, yet high-quality, data?" *Perspectives on psychological science*, vol. 6, no. 1, pp. 3–5, 2011.

[59] N. O. Rule, R. B. Adams Jr, N. Ambady, and J. B. Freeman, "Perceptions of dominance following glimpses of faces and bodies," *Perception*, vol. 41, no. 6, pp. 687–706, 2012.

[60] N. E. Dunbar and J. K. Burgoon, "Perceptions of power and interactional dominance in interpersonal relationships," *Journal of Social and Personal Relationships*, vol. 22, no. 2, pp. 207–233, 2005.

[61] N. Neave, S. Laing, B. Fink, and J. T. Manning, "Second to fourth digit ratio, testosterone and perceived male dominance," *Proceedings of the Royal Society of London B: Biological Sciences*, vol. 270, no. 1529, pp. 2167–2172, 2003.

[62] R. R. McCrae and O. P. John, "An introduction to the five-factor model and its applications," *Journal of personality*, vol. 60, no. 2, pp. 175–215, 1992.

[63] J. Van Den Berg, S. J. Guy, M. Lin, and D. Manocha, "Reciprocal n-body collision avoidance," in *International Symp. on Robotics Research*, 2011.

[64] J. Van den Berg, M. Lin, and D. Manocha, "Reciprocal velocity obstacles for real-time multi-agent navigation," in *Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on*, may 2008, pp. 1928 –1935.

[65] A. Feng, Y. Huang, M. Kallmann, and A. Shapiro, "An analysis of motion blending techniques," in *International Conference on Motion in Games*. Springer, 2012, pp. 232–243.

[66] J. A. Hall, E. J. Coats, and L. S. LeBeau, "Nonverbal behavior and the vertical dimension of social relations: a meta-analysis." 2005.

[67] D. Clark-Carter, A. Heyes, and C. Howarth, "The efficiency and walking speed of visually impaired people," *Ergonomics*, vol. 29, no. 6, pp. 779–789, 1986.

[68] J. Weston, C. Watkins *et al.*, "Support vector machines for multi-class pattern recognition." in *Esann*, vol. 99, 1999, pp. 219–224.

[69] J. Blascovich, J. Loomis, A. C. Beall, K. R. Swinth, C. L. Hoyt, and J. N. Bailenson, "Immersive virtual environment technology as a methodological tool for social psychology," *Psychological Inquiry*, vol. 13, no. 2, pp. 103–124, 2002.

[70] M. Kyriakou, X. Pan, and Y. Chrysanthou, "Interaction with virtual agentscomparison of the participants' experience between an ivr and a

semi-ivr system," in *2015 IEEE Virtual Reality (VR)*.   IEEE, 2015, pp. 217–218.

[71] R. E. Guadagno, J. Blascovich, J. N. Bailenson, and C. Mccall, "Virtual humans and persuasion: The effects of agency and behavioral realism," *Media Psychology*, vol. 10, no. 1, pp. 1–22, 2007.

[72] R. Dabral, A. Mundhada, U. Kusupati, S. Afaque, and A. Jain, "Structure-aware and temporally coherent 3d human pose estimation," *arXiv preprint arXiv:1711.09250*, 2017.

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