

Identifying Emotions from Walking Using Affective and Deep Features

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Abstract—We present a new data-driven model and algorithm to identify the perceived emotions of individuals based on their walking styles. Given an RGB video of an individual walking, we extract his/her walking gait in the form of a series of 3D poses. Our goal is to exploit the gait features to classify the emotional state of the human into one of four emotions: happy, sad, angry, or neutral. Our perceived emotion identification approach uses deep features learned via LSTM on labeled emotion datasets. Furthermore, we combine these features with affective features computed from gaits using posture and movement cues. These features are classified using a Random Forest Classifier. We show that our mapping between the combined feature space and the perceived emotional state provides 80.07% accuracy in identifying the perceived emotions. In addition to identifying discrete categories of emotions, our algorithm also predicts the values of perceived valence and arousal from gaits. We also present an “*EWalk* (Emotion Walk)” dataset that consists of videos of walking individuals with gaits and labeled emotions. To the best of our knowledge, this is the first gait-based model to identify perceived emotions from videos of walking individuals.

1 INTRODUCTION

MOTIONS play a large role in our lives, defining our experiences and shaping how we view the world and interact with other humans. Perceiving the emotions of social partners helps us understand their behaviors and decide our actions towards them. For example, people communicate very differently with someone they perceive to be angry and hostile than they do with someone they perceive to be calm and content. Furthermore, the emotions of unknown individuals can also govern our behavior, (e.g., emotions of pedestrians at a road-crossing or emotions of passengers in a train station). Because of the importance of perceived emotion in everyday life, automatic emotion recognition is a critical problem in many fields such as games and entertainment, security and law enforcement, shopping, human-computer interaction, human-robot interaction, etc.

Humans perceive the emotions of other individuals using verbal and non-verbal cues. Robots and AI devices that possess speech understanding and natural language processing capabilities are better at interacting with humans. Deep learning techniques can be used for speech emotion recognition and can facilitate better interactions with humans [1].

Understanding the perceived emotions of individuals using non-verbal cues is a challenging problem. Humans use the non-verbal cues of facial expressions and body movements to perceive emotions. With a more extensive availability of data, considerable research has focused on using facial expressions to understand emotion [2]. However, recent studies in psychology question the communicative purpose of facial expressions and doubt the quick, automatic process of perceiving emotions from these ex-

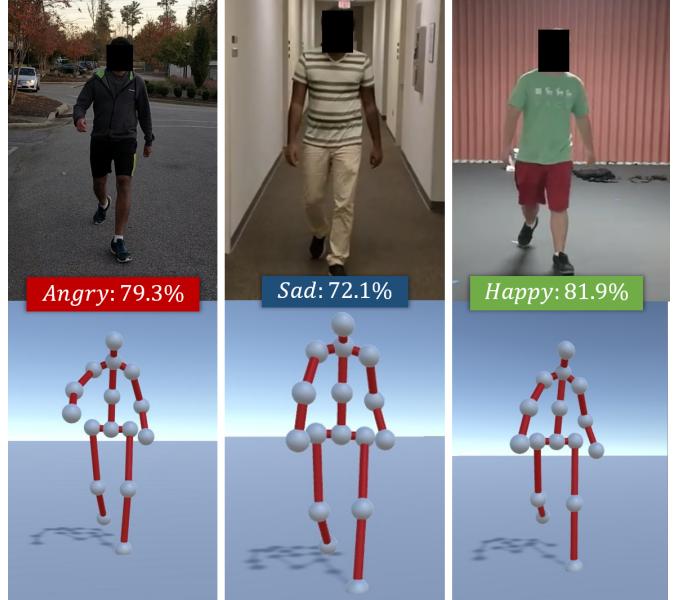


Fig. 1: Identifying Perceived Emotions: We present a novel algorithm to identify the perceived emotions of individuals based on their walking styles. Given an RGB video of an individual walking (top), we extract his/her walking gait as a series of 3D poses (bottom). We use a combination of deep features learned via an LSTM and affective features computed using posture and movement cues to then classify into basic emotions (e.g., happy, sad, etc.) using a Random Forest Classifier.

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pressions [3]. There are situations when facial expressions can be unreliable, such as with “mock” or “referential expressions” [4]. Facial expressions can also be unreliable depending on whether an audience is present [5].

Research has shown that body expressions are also crucial in emotion expression and perception [6]. For example,

when presented with bodies and faces that expressed either anger or fear (matched correctly with each other or as mismatched compound images), observers are biased towards body expression [7]. Aviezer et al.’s study [8] on positive/negative valence in tennis players showed that faces alone were not a diagnostic predictor of valence, but the body alone or the face and body together can be predictive.

Specifically, body expression in walking, or an individual’s gait, has been proven to aid in the perception of emotions. In an early study by Montepare et al. [9], participants were able to identify sadness, anger, happiness, and pride at a significant rate by observing affective features such as increased arm swinging, long strides, a greater foot landing force, and erect posture. Specific movements have also been correlated with specific emotions. For example, sad movements are characterized by a collapsed upper body and low movement activity [10]. Happy movements have a faster pace with more arm swaying [11].

Main Results: We present an automatic emotion identification approach for videos of walking individuals (Figure 1). We classify walking individuals from videos into happy, sad, angry, and neutral emotion categories. These emotions represent emotional states that last for an extended period and are more abundant during walking [12]. We extract gaits from walking videos as 3D poses. We use an LSTM-based approach to obtain deep features by modeling the long-term temporal dependencies in these sequential 3D human poses. We also present spatiotemporal *affective features* representing the posture and movement of walking humans. We combine these affective features with LSTM-based deep features and use a Random Forest Classifier to classify them into four categories of emotion. We observe an improvement of 13.85% in the classification accuracy over other gait-based perceived emotion classification algorithms (Table 5). We refer to our LSTM-based model between affective and deep features and the perceived emotion labels as our novel data-driven mapping.

We also present a new dataset, “*Emotion Walk (EWalk)*,” which contains videos of individuals walking in both indoor and outdoor locations. Our dataset consists of 1384 gaits and the perceived emotions labeled using Mechanical Turk.

Some of the novel components of our work include:

1. A novel data-driven mapping between the affective features extracted from a walking video and the perceived emotions.
2. A novel emotion identification algorithm that combines affective features and deep features, obtaining 80.07% accuracy.
3. A new public domain dataset, *EWalk*, with walking videos, gaits, and labeled emotions.

The rest of the paper is organized as follows. In Section 2, we review the related work in the fields of emotion modeling, bodily expression of emotion, and automatic recognition of emotion using body expressions. In Section 3, we give an overview of our approach and present the affective features. We provide the details of our LSTM-based approach to identifying perceived emotions from walking videos in Section 4. We compare the performance of our method with state-of-the-art methods in Section 5. We present the *EWalk* dataset in Section 6.

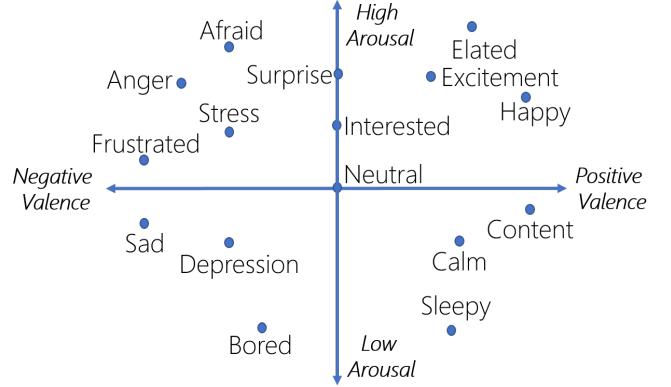


Fig. 2: All discrete emotions can be represented by points on a 2D affect space of Valence and Arousal [13], [14].

2 RELATED WORK

In this section, we give a brief overview of previous works on emotion representation, emotion expression using body posture and movement, and automatic emotion recognition.

2.1 Emotion Representation

Emotions have been represented using both discrete and continuous representations [6], [14], [15]. In this paper, we focus on discrete representations of the emotions and identify four discrete emotions (happy, angry, sad, and neutral). However, a combination of these emotions can be used to obtain the continuous representation (Section 6.4.1). A mapping between continuous representation and the discrete categories developed by Mikels and Morris [16], [17] can be used to predict other emotions.

It is important to distinguish between perceived emotions and actual emotions as we discuss the perception of emotions. One of the most obvious cues to another person’s emotional state is his or her self-report [18]. However, self-reports are not always available; for example, when people observe others remotely (e.g., via cameras), they do not have the ability to ask about their emotional state. Additionally, self-reports can be imperfect because people can experience an emotion without being aware of it or be unable to translate the emotion into words [19]. Therefore, in this paper, we focus on emotions perceived by observers instead of using self-reported measures.

Affect expression combines verbal and nonverbal communication, including eye gaze and body expressions, in addition to facial expressions, intonation, and other cues [20]. Facial expressions—like any element of emotional communication—do not exist in isolation. There is no denying that in certain cases, such as with actors and caricatures, it is appropriate to assume affect based on the visual cues from the face, however, in day-to-day life, this does not account for body expressions. More specifically, the way a person walks, or their gait, has been proven to aid in the perception of that person’s emotion [9].

With the increasing availability of technologies that capture body expression, there is considerable work on the automatic recognition of emotions from body expressions. Most works use a feature-based approach to identify emotion from body expressions automatically. These features are

either extracted using purely statistical techniques or using techniques that are inspired by psychological studies. Karg et al. [21] surveyed body movement-based methods for automatic recognition and generation of affective expression. Many techniques in this area have focused on activities such as knocking [22], dancing [23], games [24], etc. A recent survey discussed various gesture-based emotion recognition techniques [25]. These approaches model gesture features (either handcrafted or learned) and then classify these gestures into emotion classes. For example, Piana et al. [26], [27], [28] presented methods for emotion recognition from motion-captured data or RGB-D videos obtained from Kinect cameras. Their method is focused on characters that are stationary and are performing various gestures using hands and head joints. They recognize emotions using an SVM classifier that classifies features (both handcrafted and learned) from 3D coordinate and silhouette data. Other approaches have used PCA to model non-verbal movement features for emotion recognition [29], [30].

Laban movement analysis (LMA) [31] is a framework for representing the human movement that has widely used for emotion recognition. Many approaches have formulated gesture features based on LMA and used them to recognize emotions [23], [32]. The Body Action and Posture Coding System (BAP) is another framework for coding body movement [33], [34], [35]. Researchers have used BAP to formulate gesture features and used these features for emotion recognition [36].

Deep learning models have also been used to recognize emotions from non-verbal gesture cues. Sapinski et al. [37] used an LSTM-based network to identify emotions from body movement. Savva et al. [24] proposed an RNN-based emotion identification method for players of fully-body computer games. Butepage et al. [38] presented a generative model for human motion prediction and activity classification. Wang et al. [39] proposed an LSTM-based network to recognize pain-related behavior from body expressions. Multimodal approaches that combine cues such as facial expressions, speech, and voice with body expressions have also been proposed [7], [40], [41], [42].

In this work, we focus on pedestrians and present an algorithm to recognize emotions from walking using gaits. Our approach uses both handcrafted features (referred to as the affective features), and deep features learned using an LSTM-based network for emotion recognition.

2.2 Automatic Emotion Recognition from Walking

As shown by Montepare et al. [9], gaits have the potential to convey emotions. Previous research has shown that gaits can be used to recognize emotions. These approaches have formulated features using gaits obtained as 3D positions of joints from Microsoft Kinect or motion-captured data. For example, Li et al. [43], [44] used gaits extracted from Microsoft Kinect and recognized the emotions using Fourier Transform and PCA-based features. Roether et al. [45], [46] identified posture and movement features from gaits by conducting a perception experiment. However, their goal was to formulate a set of expressive features and not emotion recognition. Crenn et al. [47] used handcrafted features from gaits and classified them using SVMs. In the following

work, they generated neutral movements from expressive movements for emotion recognition. They introduced a cost function that is optimized using the Particle Swarm Optimization method to generate a neutral movement. They used the difference between the expressive and neutral movement for emotion recognition. Karg et al. [48], [49], [50] examined gait information for person-dependent affect recognition using motion capture data of a single walking stride. They formulated handcrafted gait features converted to a lower-dimensional space using PCA and then classified using them SVM, Naive Bayes, fully-connected neural networks. Venture et al. [51] used an auto-correlation matrix of the joint angles at each frame of the gait and used similarity indices for classification. Janssen et al. [52] used a neural network for emotion identification from gaits and achieved an accuracy of more than 80%. However, their method requires special devices to compute 3D ground reaction forces during gait, which may not be available in many situations. Daoudi et al. [53] used a manifold of symmetric positive definite matrices to represent body movement and classified them using the Nearest Neighbors method. Kleinsmith et al. [54] used handcrafted features of postures and classified them to recognize affect using a multilayer perceptron automatically. Omlor and Giese [55] identified spatiotemporal features that are specific to different emotions in gaits using a novel blind source separation method. Gross et al. [56] performed an Effort-Shape analysis to identify the characteristics associated with positive and negative emotions. They observed features such as walking speed, increased amplitude of joints, thoracic flexion, etc. were correlated with emotions. However, they did not present any method to use these features for automatic identification of emotions.

Researchers have also attempted to synthesize gaits with different styles. Ribet et al. [57] surveyed the literature on style generation and recognition using body movements. Tilmanne et al. [58] presented methods for generating stylistic gaits using a PCA-based data-driven approach. In the principal component space, they modeled the variability of gaits using Gaussian distributions. In a subsequent work [59], they synthesized stylistic gaits using a method based on Hidden Markov Models (HMMs). This method is based on using neutral walks and modifying them to generate different styles. Troje [60] proposed a framework to classify gender and also used it to synthesize new motion patterns. However, the model is not used for emotion identification. Felis et al. [61] used objective functions to add an emotional aspect to gaits. However, their results only showed sad and angry emotions.

Similar to these approaches of emotion recognition from gaits, we use handcrafted features (referred to as affective features). In contrast to previous methods that either use handcrafted features or deep learning methods, we combine the affective features with deep features extracted using an LSTM-based network. We use the resulting joint features for emotion recognition.

3 APPROACH

In this section, we describe our algorithm (Figure 3) for identifying perceived emotions from RGB videos.

3.1 Notation

For our formulation, we represent a human with a set of 16 joints, as shown in [62] (Figure 4). A pose $P \in \mathbb{R}^{48}$ of a human is a set of 3D positions of each joint $j_i, i \in \{1, 2, \dots, 16\}$. For any RGB video V , we represent the gait extracted using 3D pose estimation as G . The gait G is a set of 3D poses P_1, P_2, \dots, P_τ where τ is the number of frames in the input video V . We represent the extracted affective features of a gait G as F . Given the gait features F , we represent the predicted emotion by $e \in \{\text{happy}, \text{angry}, \text{sad}, \text{neutral}\}$. While neutral is not an emotion, it is still a valid state to be used for classification. In the rest of the paper, we refer to these four categories, including neutral as four emotions for convenience. The four basic emotions represent emotional states that last for an extended period and are more abundant during walking [12]. A combination of these four emotions can be used to predict affective dimensions of valence and arousal and also other emotions [17].

3.2 Overview

Our real-time perceived emotion prediction algorithm is based on a data-driven approach. We present an overview of our approach in Figure 3. During the offline training phase, we use multiple gait datasets (described in Section 4.1) and extract affective features. These affective features are based on psychological characterization [47], [48] and consist of both posture and movement features. We also extract deep features by training an LSTM network. We combine these deep and affective features and train a Random Forest classifier. At runtime, given an RGB video of an individual walking, we extract his/her gait in the form of a set of 3D poses using a state-of-the-art 3D human pose estimation technique [62]. We extract affective and deep features from this gait and identify the perceived emotion using the trained Random Forest classifier. We now describe each component of our algorithm in detail.

3.3 Affective Feature Computation

For an accurate prediction of an individual’s affective state, both posture and movement features are essential [6]. Features in the form of joint angles, distances, and velocities, and space occupied by the body have been used for recognition of emotions and affective states from gaits [47]. Based on these psychological findings, we compute affective features that include both the posture and the movement features.

We represent the extracted affective features of a gait G as a vector $F \in \mathbb{R}^{29}$. For feature extraction, we use a single stride from each gait corresponding to consecutive foot strikes of the same foot. We used a single cycle in our experiments because in some of the datasets (CMU, ICT, EWalk) only a single walk cycle was available. When multiple walk cycles are available, they can be used to increase accuracy.

3.3.1 Posture Features

We compute the features $F_{p,t} \in \mathbb{R}^{12}$ related to the posture P_t of the human at each frame t using the skeletal representation (computed using TimePoseNet Section 4.6). We list

TABLE 1: **Posture Features:** We extract posture features from an input gait using emotion characterization in visual perception and psychology literature [47], [48].

Type	Description
Volume	Bounding box
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

the posture features in Table 1. These posture features are based on prior work by Crenn et al. [47]. They used upper body features such as the area of the triangle between hands and neck, distances between hand, shoulder, and hip joints, and angles at neck and back. However, their formulation does not consider features related to foot joints, which can convey emotions in walking [46]. Therefore, we also include areas, distances, and angles of the feet joints in our posture feature formulation.

We define posture features of the following types:

- Volume: According to Crenn et al. [47], body expansion conveys positive emotions while a person has a more compact posture during negative expressions. We model this by the volume $F_{volume,t} \in \mathbb{R}$ occupied by the bounding box around the human.
- Area: We also model body expansion by areas of triangles between the hands and the neck and between the feet and the root joint $F_{area,t} \in \mathbb{R}^2$.
- Distance: Distances between the feet and the hands can also be used to model body expansion $F_{distance,t} \in \mathbb{R}^4$.
- Angle: Head tilt is used to distinguish between happy and sad emotions [47], [48]. We model this by the angles extended by different joints at the neck $F_{angle,t} \in \mathbb{R}^5$.

We also include stride length as a posture feature. Longer stride lengths convey anger and happiness and shorter stride lengths convey sadness and neutrality [48]. Suppose we represent the positions of the left foot joint j_{lFoot} and the right foot joint j_{rFoot} in frame t as $\vec{p}(j_{lFoot}, t)$ and $\vec{p}(j_{rFoot}, t)$ respectively. Then the stride length $s \in \mathbb{R}$ is computed as:

$$s = \max_{t \in 1..T} \|\vec{p}(j_{lFoot}, t) - \vec{p}(j_{rFoot}, t)\| \quad (1)$$

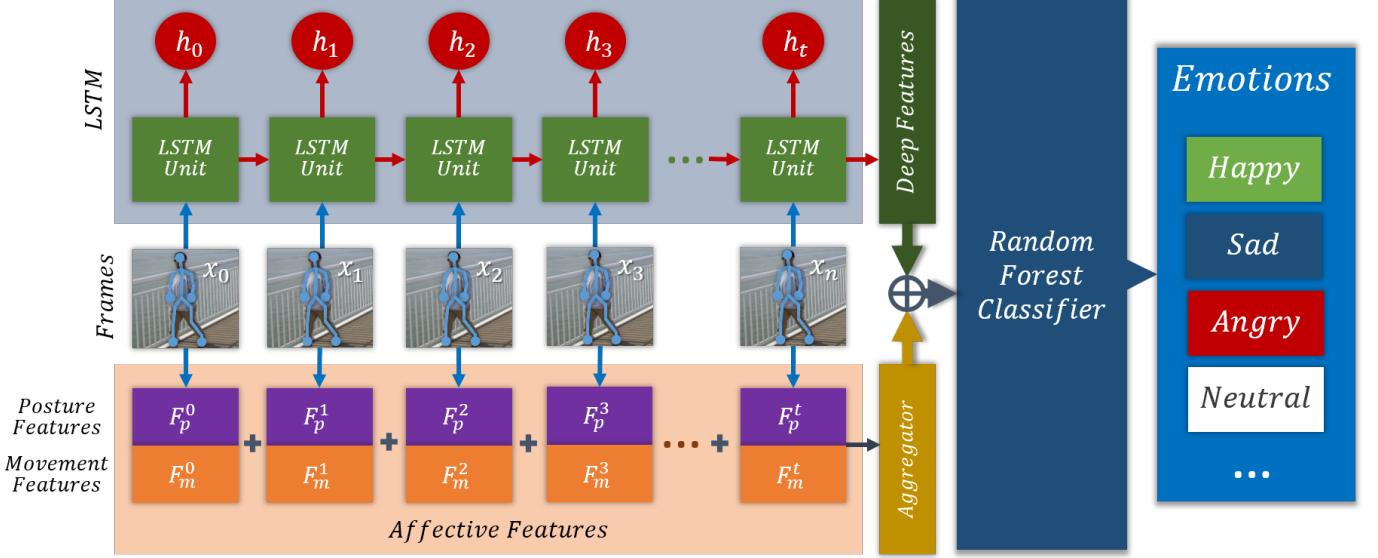


Fig. 3: **Overview:** Given an RGB video of an individual walking, we use a state-of-the-art 3D human pose estimation technique [62] to extract a set of 3D poses. These 3D poses are passed to an LSTM network to extract deep features. We train this LSTM network using multiple gait datasets. We also compute affective features consisting of both posture and movement features using psychological characterization. We concatenate these affective features with deep features and classify the combined features into 4 basic emotions using a Random Forest classifier.

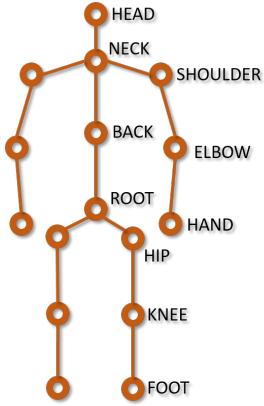


Fig. 4: **Human Representation:** We represent a human by a set of 16 joints. The overall configuration of the human is defined using these joint positions and is used to extract the features.

We define the posture features $F_p \in \mathbb{R}^{13}$ as the average of $F_{p,t}, t = \{1, 2, \dots, \tau\}$ combined with the stride length:

$$F_p = \frac{\sum_t F_{p,t}}{\tau} \cup s, \quad (2)$$

3.3.2 Movement Features

Psychologists have shown that motion is an important characteristic for the perception of different emotions [56]. High arousal emotions are more associated with rapid and increased movements than low arousal emotions. We compute the movement features $F_{m,t} \in \mathbb{R}^{15}$ at frame t by considering the magnitude of the velocity, acceleration, and movement jerk of the hand, foot, and head joints using the skeletal representation. For each of these five joints $j_i, i = 1, \dots, 5$,

TABLE 2: **Movement Features:** We extract movement features from an input gait using emotion characterization in visual perception and psychology literature [47], [48].

Type	Description
Speed	Right hand
	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

we compute the magnitude of the first, second, and third finite derivatives of the position vector $\vec{p}(j_i, t)$ at frame t . We list the movement features in Table 2. These movement features are based on prior work by Crenn et al. [47]. Similar to the posture features, we combine the upper body features from Crenn et al. [47] with lower body features related to feet joints.

Since faster gaits are perceived as happy or angry whereas slower gaits are considered sad [48], we also include the time taken for one walk cycle ($gt \in \mathbb{R}$) as a movement feature. We define the movement features $F_m \in \mathbb{R}^{16}$ as the average of $F_{m,t}, t = \{1, 2, \dots, \tau\}$:

$$F_m = \frac{\sum_t F_{m,t}}{\tau} \cup gt, \quad (3)$$

We combine posture and movement features and define

affective features F as: $F = F_m \cup F_p$.

4 PERCEIVED EMOTION IDENTIFICATION

We use a *vanilla* LSTM network [63] with a cross-entropy loss that models the temporal dependencies in the gait data. We chose an LSTM network to model deep features of walking because it captures the geometric consistency and temporal dependency among video frames for gait modeling [64]. We describe the details of the training of the LSTM in this section.

4.1 Datasets

We used the following publicly available datasets for training our perceived emotion classifier:

- **Human3.6M** [65]: This dataset consists of 3.6 million 3D human images and corresponding poses. It also contains video recordings of 5 female and 6 male professional actors performing actions in 17 scenarios including taking photos, talking on the phone, participating in discussions, etc. The videos were captured at 50 Hz with four calibrated cameras working simultaneously. We used motion-captured gaits from 14 videos of the subjects walking from this dataset.
- **CMU** [66]: The CMU Graphics Lab Motion Capture Database contains motion-captured videos of humans interacting among themselves (*e.g.*, talking, playing together), interacting with the environment (*e.g.*, playgrounds, uneven terrains), performing physical activities (*e.g.*, playing sports, dancing), enacting scenarios (*e.g.*, specific behaviors), and locomoting (*e.g.*, running, walking). In total, there are motion captured gaits from 49 videos of subjects walking with different styles.
- **ICT** [67]: This dataset contains motion-captured gaits from walking videos of 24 subjects. The videos were annotated by the subjects themselves, who were asked to label their own motions as well as motions of other subjects familiar to them.
- **BML** [12]: This dataset contains motion-captured gaits from 30 subjects (15 male and 15 female). The subjects were nonprofessional actors, ranging between 17 and 29 years of age with a mean age of 22 years. For the walking videos, the actors walked in a triangle for 30 sec, turning clockwise and then counterclockwise in two individual conditions. Each subject provided 4 different walking styles in two directions, resulting in 240 different gaits.
- **SIG** [68]: This is a dataset of 41 synthetic gaits generated using local mixtures of autoregressive (MAR) models to capture the complex relationships between the different styles of motion. The local MAR models were developed in real-time by obtaining the nearest examples of given pose inputs in the database. The trained model were able to adapt to the input poses with simple linear transformations. Moreover, the local MAR models were able to predict the timings of synthesized poses in the output style.

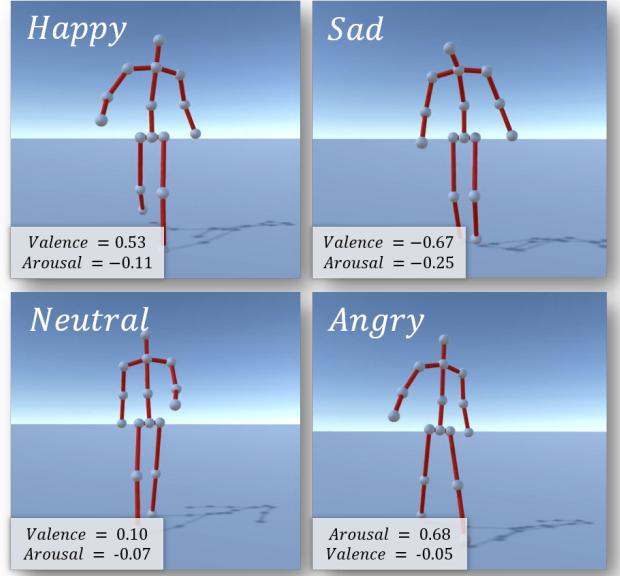


Fig. 5: Gait Visualizations: We show the visualization of the motion-captured gaits of four individuals with their classified emotion labels. Gait videos from 248 motion-captured gaits were displayed to the participants in a web based user study to generate labels. We use that data for training and validation.

- **EWalk (Our novel dataset):** We also collected videos and extracted 1136 gaits using 3D pose estimation. We present details about this dataset in Section 6.

The wide variety of these datasets includes acted as well as non-acting and natural-walking datasets (CMU, ICT) where the subjects were not told to assume an emotion. These datasets provide a good sample of real-world scenarios. For the acted video datasets, we did not use the acted emotion labels for the gaits, but instead obtained the perceived emotion labels with a user study (Section 4.2).

4.2 Perceived Emotion Labeling

We obtained the perceived emotion labels for each gait using a web-based user study.

4.2.1 Procedure

We generated visualizations of each motion-captured gait using a skeleton mesh (Figure 5). For the *EWalk* dataset, we presented the original videos to the participants when they were available. We hid the faces of the actors in these videos to ensure that the emotions were perceived from the movements of the body and gaits, not from the facial expressions.

4.2.2 Participants

We recruited 688 participants (279 female, 406 male, $\bar{age} = 34.8$) from Amazon Mechanical Turk and the participant responses were used to generate perceived emotion labels. Each participant watched and rated 10 videos from one of the datasets. The videos were presented randomly and

TABLE 3: Correlation Between Emotion Responses: We present the correlation between participants’ responses to questions relating to the four emotions.

	Happy	Angry	Sad	Neutral
Happy	1.000	-0.268	-0.775	-0.175
Angry	-0.268	1.000	-0.086	-0.058
Sad	-0.775	-0.086	1.000	-0.036
Neutral	-0.175	-0.058	-0.036	1.000

for each video we obtained a minimum of 10 participant responses. Participants who provided a constant rating to all gaits or responded in a very short time were ignored for further analysis (3 participants total).

4.2.3 Analysis

We asked each participant whether he/she perceived the gait video as happy, angry, sad, or neutral on 5-point Likert items ranging from Strongly Disagree to Strongly Agree. For each gait \mathbf{G}_i in the datasets, we calculated the mean of all participant responses ($r_{i,j}^e$) to each emotion:

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

where n_p is the number of participant responses collected and e is one of the four emotions: angry, sad, happy, neutral.

We analyzed the correlation between participants’ responses to the questions relating to the four emotions (Table 3). A correlation value closer to 1 indicates that the two variables are positively correlated and a correlation value closer to -1 indicates that the two variables are negatively correlated. A correlation value closer to 0 indicates that two variables are uncorrelated. As expected, *happy* and *sad* are negatively correlated and *neutral* is uncorrelated with the other emotions.

Previous research in the psychology literature suggests that social perception is affected by the gender of the observer [69], [70], [71]. To verify that our results do not significantly depend on the gender of the participants, we performed a t-test for differences between the responses by male and female participants. We observed that the gender of the participant did not affect the responses significantly ($t = -0.952, p = 0.353$).

We obtained the emotion label e_i for \mathbf{G}_i as follows:

$$e_i = e \mid r_i^e > \theta, \quad (5)$$

where $\theta = 3.5$ is an experimentally determined threshold for emotion perception.

If there are multiple emotions with average participant responses greater than $r_i^e > \theta$, the gait is not used for training.

4.3 Long Short-Term Memory (LSTM) Networks

LSTM networks [63] are neural networks with special units known as “memory cells” that can store data values from particular time steps in a data sequence for arbitrarily long time steps. Thus, LSTMs are useful for capturing temporal patterns in data sequences and subsequently using those patterns in prediction and classification tasks. To perform supervised classification, LSTMs, like other

neural networks, are trained with a set of training data and corresponding class labels. However, unlike traditional feedforward neural networks that learn structural patterns in the training data, LSTMs learn feature vectors that encode temporal patterns in the training data.

LSTMs achieve this by training one or more “hidden” cells, where the output at every time step at every cell depends on the current input and the outputs at previous time steps. These inputs and outputs to the LSTM cells are controlled by a set of gates. LSTMs commonly have three kinds of gates: the input gate, the output gate, and the forget gate, represented by the following equations:

$$\text{Input Gate } (i): \quad i_t = \sigma(W_i + U_i h_{t-1} + b_i) \quad (6)$$

$$\text{Output Gate } (o): \quad o_t = \sigma(W_o + U_o h_{t-1} + b_o) \quad (7)$$

$$\text{Forget Gate } (f): \quad f_t = \sigma(W_f + U_f h_{t-1} + b_f) \quad (8)$$

where $\sigma(\cdot)$ denotes the activation function and W_g, U_g and b_g denote the weight matrix for the input at the current time step, the weight matrix for the hidden cell at the previous time step, and the bias, on gate $g \in \{i, o, f\}$, respectively. Based on these gates, the hidden cells in the LSTMs are then updated using the following equations:

$$c_t = f_t \circ c_{t-1} + i_t \circ \sigma(W_c x_t + U_c h_t + b_c) \quad (9)$$

$$h_t = \sigma(o_t \circ c_t) \quad (10)$$

where \circ denotes the Hadamard or elementwise product, c is referred to as the cell state, and W_c, U_c and b_c are the weight matrix for the input at the current time step, the weight matrix for the hidden cell at the previous time step, and the bias, on c , respectively.

4.4 Deep Feature Computation

We used the LSTM network shown in Figure 3. We obtained deep features from the final layer of the trained LSTM network. We used the 1384 gaits from the various public datasets (Section 4.1). We also analyzed the extracted deep features using an LSTM encoder-decoder architecture with reconstruction loss. We generated synthetic gaits and observed that our LSTM-based deep features correctly model the 3D positions of joints relative to each other at each frame. The deep features also capture the periodic motion of the hands and legs.

4.4.1 Implementation Details

The training procedure of the LSTM network that we followed is laid out in Algorithm 1. For training, we used a mini-batch size of 8 (*i.e.*, $b = 8$ in Algorithm 1) and 500 training epochs. We used the Adam optimizer [72] with an initial learning rate of 0.1, decreasing it to $\frac{1}{10}$ -th of its current value after 250, 375, and 438 epochs. We also used a momentum of 0.9 and a weight-decay of 5×10^{-4} . The training was carried out on an NVIDIA GeForce GTX 1080 Ti GPU.

Algorithm 1 LSTM Network for Emotion Perception

Input: N training gaits $\{\mathbf{G}_i\}_{i=1\dots N}$ and corresponding emotion labels $\{L_i\}_{i=1\dots N}$.
Output: Network parameters θ such that the loss $\sum_{i=1}^N \|L_i - f_\theta(\mathbf{G}_i)\|^2$ is minimized, where $f_\theta(\cdot)$ denotes the network.

```

1: procedure TRAIN
2:   for number of training epochs do
3:     for number of iterations per epoch do
4:       Sample mini-batch of  $b$  training gaits and cor-
          responding labels
5:       Update the network parameters  $\theta$  w.r.t. the  $b$ 
         samples using backpropagation.

```

4.5 Classification

We concatenate the deep features with affective features and use a Random Forest classifier to classify these concatenated features. Before combining the affective features with the deep features, we normalize them to a range of $[-1, 1]$. We use Random Forest Classifier with 10 estimators and a maximum depth of 5. We use this trained classifier to classify perceived emotions. We refer to this trained classifier as our novel data-driven mapping between affective features and perceived emotion.

4.6 Realtime Perceived Emotion Recognition

At runtime, we take an RGB video as input and use the trained classifier to identify the perceived emotions. We exploit a real-time 3D human pose estimation algorithm, *TimePoseNet* [62] to extract 3D joint positions from RGB videos. *TimePoseNet* uses a semi-supervised learning method that utilizes the more widely available 2D human pose data [73] to learn the 3D information.

TimePoseNet is a single person model and expects a sequence of images cropped closely around the person as input. Therefore, we first run a real-time person detector [74] on each frame of the RGB video and extract a sequence of images cropped closely around the person in the video V . The frames of the input video V are sequentially passed to *TimePoseNet*, which computes a 3D pose output for each input frame. The resultant poses P_1, P_2, \dots, P_τ represent the extracted output gait G . We normalize the output poses so that the root position always coincides with the origin of the 3D space. We extract features of the gait G using the trained LSTM model. We also compute the affective features and classify the combined features using the trained Random Forest classifier.

5 RESULTS

We provide the classification results of our algorithm in this section.

5.1 Analysis of Different Classification Methods

We compare different classifiers to classify our combined deep and affective features and compare the resulting accuracy values in Table 4. These results are computed using 10-fold cross-validation on 1384 gaits in the gait datasets

TABLE 4: **Performance of Different Classification Methods:** We analyze different classification algorithms to classify the concatenated deep and affective features. We observe an accuracy of 80.07% with the Random Forest classifier.

Algorithm (Deep + Affective Features)	Accuracy
LSTM + Support Vector Machines (SVM RBF)	70.04%
LSTM + Support Vector Machines (SVM Linear)	71.01%
<i>LSTM + Random Forest</i>	80.07%

described in Section 4.1. We compared Support Vector Machines (SVMs) with both linear and RBF kernel and Random Forest methods. The SVMs were implemented using the one-vs-one approach for multi-class classification. The Random Forest Classifier was implemented with 10 estimators and a maximum depth of 5. We use the Random Forest classifier in the subsequent results because it provides the highest accuracy (80.07%) of all the classification methods. Additionally, our algorithm achieves 79.72% accuracy on the non-acted datasets (CMU and ICT), indicating that it performs equally well on acted and non-acted data.

5.2 Comparison with Other Methods

In this section, we present the results of our algorithm and compare it with other state-of-the-art methods:

- Karg et al. [48]: This method is based on using gait features related to shoulder, neck, and thorax angles, stride length, and velocity. These features are classified using PCA-based methods. This method only models the posture features for the joints and doesn't model the movement features.
- Venture et al. [51]: This method uses the auto-correlation matrix of the joint angles at each frame and uses similarity indices for classification. The method provides good intra-subject accuracy but performs poorly for the inter-subject databases.
- Crenn et al. [47]: This method uses affective features from both posture and movement and classifies these features using SVMs. This method is trained for more general activities like knocking and does not use information about feet joints.
- Daoudi et al. [53]: This method uses a manifold of symmetric positive definite matrices to represent body movement and classifies them using the Nearest Neighbors method.
- Crenn et al. [75]: This method synthesizes a neutral motion from an input motion and uses the difference between the input and the neutral emotion as the feature for classifying emotions. This method does not use the psychological features associated with walking styles.
- Li et al. [43]: This method uses a Kinect to capture the gaits and identifies whether an individual is angry, happy, or neutral using four walk cycles using a feature-based approach. These features are obtained using Fourier Transform and Principal Component Analysis.

We also compare our results to a baseline where we use the LSTM to classify the gait features into the four emotion classes. Table 5 provides the accuracy results of

TABLE 5: **Accuracy:** Our method with combined deep and affective features classified with a Random Forest classifier achieves an accuracy of 80.07%. We observe an improvement of 13.85% over state-of-the-art emotion identification methods and an improvement of 24.60% over a baseline LSTM-based classifier. All methods were compared on 1384 gaits obtained from the datasets described in Section 4.1

Method	Accuracy
Baseline (Vanilla LSTM)	55.47%
Affective Features Only	68.11%
Karg et al. [48]	39.58%
Venture et al. [51]	30.83%
Crenn et al. [47]	66.22%
Crenn et al. [75]	40.63%
Daoudi et al. [53]	42.52%
Li et al. [43]	53.73%
<i>Our Method (Deep + Affective Features)</i>	80.07%

our algorithm and shows comparisons with other methods. These methods require input in the form of 3D human poses and then they identify the emotions perceived from those gaits. For this experiment, we extracted gaits from the RGB videos of the *EWalk* dataset and then provided them as input to the state-of-the-art methods along with the motion-captured gait datasets. Accuracy results are obtained using 10-fold cross-validation on 1384 gaits from the various datasets (Section 4.1). For this evaluation, the gaits were randomly distributed into training and testing sets, and the accuracy values were obtained by averaging over 1000 random partitions.

We also show the percentage of gaits that the LSTM+Random Forrest classifier correctly classified for each emotion class in Figure 6. As we can see, for every class, around 80% of the gaits are correctly classified, implying that the classifier learns to recognize each class equally well. Further, when the classifier does make mistakes, it tends to confuse neutral and sad gaits more than between any other class pairs.

5.3 Analysis of the Learned Deep Features

For instance, in section 5.3, “the top 3 principal component directions” is stated, however, this is the first mention of PCA without any details about how, when or where PCA was applied.

We visualize the scatter of the deep feature vectors learned by the LSTM network. To visualize the 32 dimensional deep features, we convert them to a 3D space. We use Principal Component Analysis (PCA) and project the features in the top three principal component directions. This is shown in Figure 11. We observe that the data points are well-separated even in the projected dimension. By extension, this implies that the deep features are at least as well separated in their original dimension. Therefore, we can conclude that the LSTM network has learned meaningful representations of the input data that help it distinguish accurately between the different emotion classes.

Additionally, we show the saliency maps given by the network in Figure 12. We selected one sample per emotion (angry, happy, and sad) and presented the postures in each row. For each gait (each row), we use eight sample frames corresponding to eight timesteps. In each row, going from

True Class	Angry	80.47%	7.81%	2.34%	9.38%
	Happy	4.12%	87.05%	6.36%	2.47%
Neutral	1.29%	2.59%	80.53%	15.59%	
Sad	6.61%	4.13%	10.74%	78.52%	
Predicted Class		Angry	Happy	Neutral	Sad

Fig. 6: **Confusion Matrix:** For each emotion class, we show the percentage of gaits belonging to that class that were correctly classified by the LSTM+Random Forest classifier (green background) and the percentage of gaits that were misclassified into other classes (red background).

left to right, we show the evolution of the gait with time. Each posture in the row shows the activation on the joints at the corresponding time step, as assigned by our network. Here, activation refers to the magnitude of the gradient of the loss w.r.t. an input joint (the joint’s “saliency”) upon backpropagation through the learned network. Since all input data for our network are normalized to lie in the range $[0, 1]$, and the gradient of the loss function is smooth w.r.t. the inputs, the activation values for the saliency maps are within the $[0, 1]$ range. The joints are colored according to a gradient with $activation = 1$ denoting red and $activation = 0$ denoting black. The network uses these activation values of activated nodes in all the frames to determine the class label for the gait.

We can observe from Figure 12 that the network focuses mostly on the hand joints (observing arm swinging), the feet joints (observing stride), and the head and neck joints (observing head jerk). Based on the speed and frequency of the movements of these joints, the network decides the class labels. For example, the activation values on the joints for anger (Figure 12 top row) are much higher than the ones for sadness (Figure 12 bottom row), which matches with the psychological studies of how angry and sad gaits typically look. This shows that the features learned by the network are representative of the psychological features humans tend to use when perceiving emotions from gaits [11], [48]. Additionally, as time advances, we can observe the pattern in which our network shifts attention to the different joints, i.e., the pattern in which it considers different joints to be more salient. For example, if the right leg is moved ahead, the network assigns high activation on the joints in the right leg and left arm (and vice versa).

6 EMOTIONAL WALK (*EWalk*) DATASET

In this section, we describe our new dataset of videos of individuals walking. We also provide details about the perceived emotion annotations of the gaits obtained from this dataset.

6.1 Data

The *EWalk* dataset contains 1384 gaits with emotion labels from four basic emotions: happy, angry, sad, and neutral

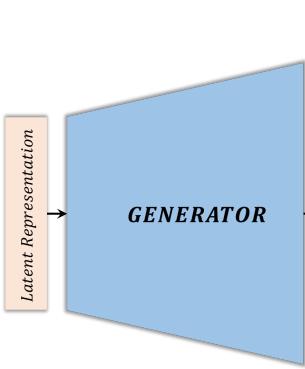


Fig. 7: Generative Adversarial Networks (GANs): The network consists of a generator that generates synthetic data from random samples drawn from a latent distribution space. This is followed by a discriminator that attempts to discriminate between the generated data and the real input data. The objective of the generator is to learn the latent distribution space of the real data whereas the objective of the discriminator is to learn to discriminate between the real data and the synthetic data generated by the generator. The network is said to be learned when the discriminator fails to distinguish between the real and the synthetic data.

(Figure 9). These gaits are either motion-captured or extracted from RGB videos. We also include synthetically generated gaits using state-of-the-art algorithms [68]. In addition to the emotion label for each gait, we also provide values of affective dimensions: valence and arousal.

6.2 Video Collection

We recruited 24 subjects from a university campus. The subjects were from a variety of ethnic backgrounds and included 16 male and 8 female subjects. We recorded the videos in both indoor and outdoor environments. We requested that they walk multiple times with different walking styles. Previous studies show that non-actors and actors are both equally good at walking with different emotions [45]. Therefore, to obtain different walking styles, we suggested that the subjects could assume that they are experiencing a certain emotion and walk accordingly. The subjects started 7m from a stationary camera and walked towards it. The videos were later cropped to include a single walk cycle.

6.3 Data Generation

Once we collect walking videos and annotate them with emotion labels, we can also use them to train generator networks to generate annotated synthetic videos. Generator networks have been applied for generating videos and joint-graph sequences of human actions such as walking, sitting, running, jumping, etc. Such networks are commonly based on either Generative Adversarial Networks (GANs) [76] or Variational Autoencoders (VAEs) [77].

GANs (Figure 7) are comprised of a generator that generates data from random noise samples and a discriminator that discriminates between real data and the data generated by the generator. The generator is considered to be trained

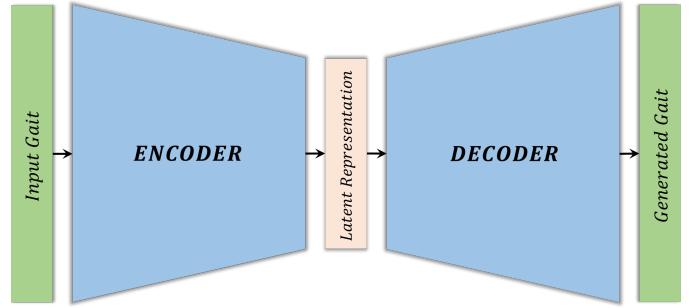


Fig. 8: Variational Autoencoders (VAEs): The encoder consists of an encoder that transforms the input data to a latent distribution space. This is followed by a discriminator that draws random samples from the latent distribution space to generate synthetic data. The objective of the overall network is then to learn the latent distribution space of the real data, so that the synthetic data generated by the decoder belongs to the same distribution space as the real data.

when the discriminator fails to discriminate between the real and the generated data.

VAEs (Figure 8), on the other hand, are comprised of an encoder followed by a decoder. The encoder learns a latent embedding space that best represents the distribution of the real data. The decoder then draws random samples from the latent embedding space to generate synthetic data.

For temporal data such human action videos or joint-graph sequences, two different approaches are commonly taken. One approach is to individually generate each point in the temporal sequence (frames in a video or graphs in a graph sequence) respectively and then fuse them together in a separate network to generate the complete sequence. The methods in [78], [79], for example, use this approach. The network generating the individual points only considers the spatial constraints of the data, whereas the network fusing the points into the sequence only considers the temporal constraints of the data. The alternate approach is to train a single network by providing it both the spatial and temporal constraints of the data. For example, the approach used by Sijie et al. [80]. The first approach is relatively more lightweight, but it does not explicitly consider spatial-temporal inter-dependencies in the data, such as the differences in the arm swinging speeds between angry and sad gaits. While the latter approach does take these inter-dependencies into account, it is also harder to train because of these additional constraints.

6.4 Analysis

We presented the recorded videos to MTurk participants and obtained perceived emotion labels for each video using the method described in Section 4.2. Our data is widely distributed across the four categories with the *Happy* category containing the largest number of gaits (32.07%) and the *Neutral* category containing the smallest number of gaits with 16.35% (Figure 10).

6.4.1 Affective Dimensions

We performed an analysis of the affective dimensions (i.e. valence and arousal). For this purpose, we used the partici-

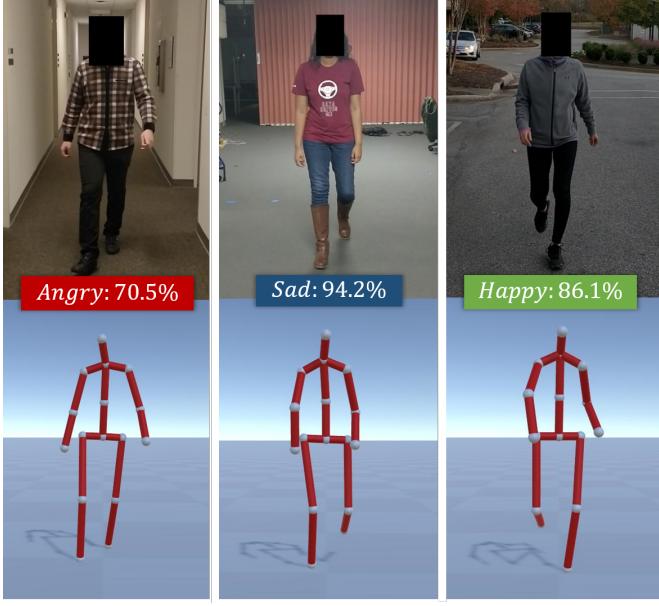


Fig. 9: **EWalk Dataset:** We present the EWalk dataset containing RGB videos of pedestrians walking and the perceived emotion label for each pedestrian.

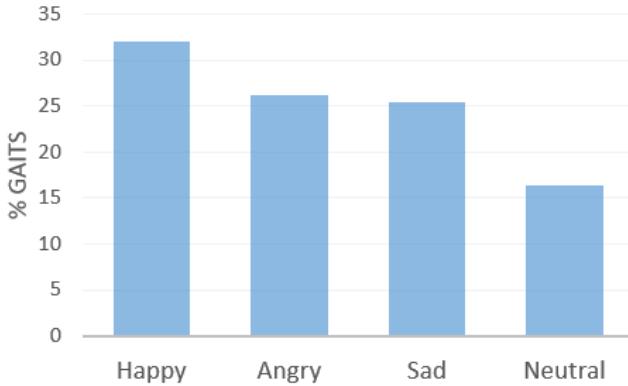


Fig. 10: **Distribution of Emotion in the Datasets:** We present the percentage of gaits that are perceived as belonging to each of the emotion categories (happy, angry, sad, or neutral). We observe that our data is widely distributed.

pant responses to the questions about the happy, angry, and sad emotions. We did not use the responses to the question about the neutral emotion because it corresponds to the origin of the affective space and does not contribute to the valence and arousal dimensions. We performed a Principal Component Analysis (PCA) on the participant responses $[r_i^{happy}, r_i^{angry}, r_i^{sad}]$ and observed that the following two principal components describe 94.66% variance in the data:

$$\begin{bmatrix} PC1 \\ PC2 \end{bmatrix} = \begin{bmatrix} 0.67 & -0.04 & -0.74 \\ -0.35 & 0.86 & -0.37 \end{bmatrix} \quad (11)$$

We observe that the first component with high values of the *Happy* and *Sad* coefficients represents the *valence* dimension of the affective space. The second principal component with high values of the *Anger* coefficient represents the *arousal* dimension of the affective space. Surprisingly, this principal component also has a negative coefficient for the

Happy emotion. This is because a calm walk was often rated as happy by the participants, resulting in low arousal.

6.4.2 Prediction of Affect

We use the principal components from Equation 11 to predict the values of the *arousal* and *valence* dimensions. Suppose, the probabilities predicted by the Random Forest classifier are $p(h)$, $p(a)$, and $p(s)$ corresponding to the emotion classes *happy*, *angry*, and *sad*, respectively. Then we can obtain the values of *valence* and *arousal* as:

$$valence = [0.67 \quad -0.04 \quad -0.74] [p(h) \quad p(a) \quad p(s)]^T \quad (12)$$

$$arousal = [-0.35 \quad 0.86 \quad -0.37] [p(h) \quad p(a) \quad p(s)]^T \quad (13)$$

7 CONCLUSION, LIMITATIONS, AND FUTURE WORK

We presented a novel method for classifying perceived emotions of individuals based on their walking videos. Our method is based on learning deep features computed using LSTM and exploits psychological characterization to compute affective features. The mathematical characterization of computing gait features also has methodological implications for psychology research. This approach explores the basic psychological processes used by humans to perceive emotions of other individuals using multiple dynamic and naturalistic channels of stimuli. We concatenate the deep and affective features and classify the combined features using a Random Forest Classification algorithm. Our algorithm achieves an absolute accuracy of 80.07%, which is an improvement of 24.60% over vanilla LSTM (i.e., using only deep features) and offers an improvement of 13.85% over state-of-the-art emotion identification algorithms. Our approach is the first approach to provide a real-time pipeline for emotion identification from walking videos by leveraging state-of-the-art 3D human pose estimation. We also

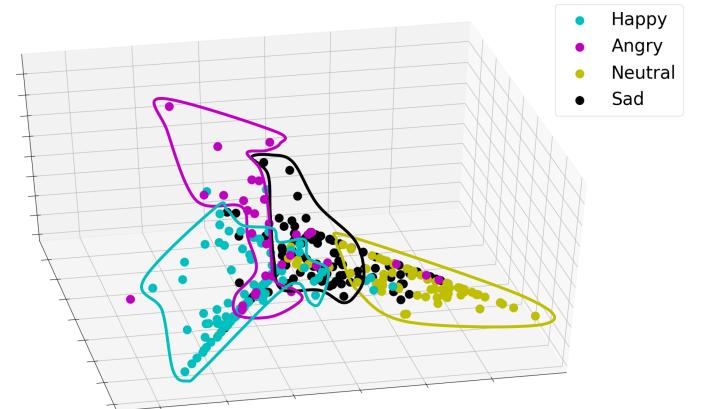


Fig. 11: **Scatter Plot of the Learned Deep Features:** These are the deep features learned by the LSTM network from the input data points, projected in the 3 principal component directions. The different colors correspond to the different input class labels. We can see that the features for the different classes are well-separated in the 3 dimensions. This implies that the LSTM network learns meaningful representations of the input data for accurate classification.

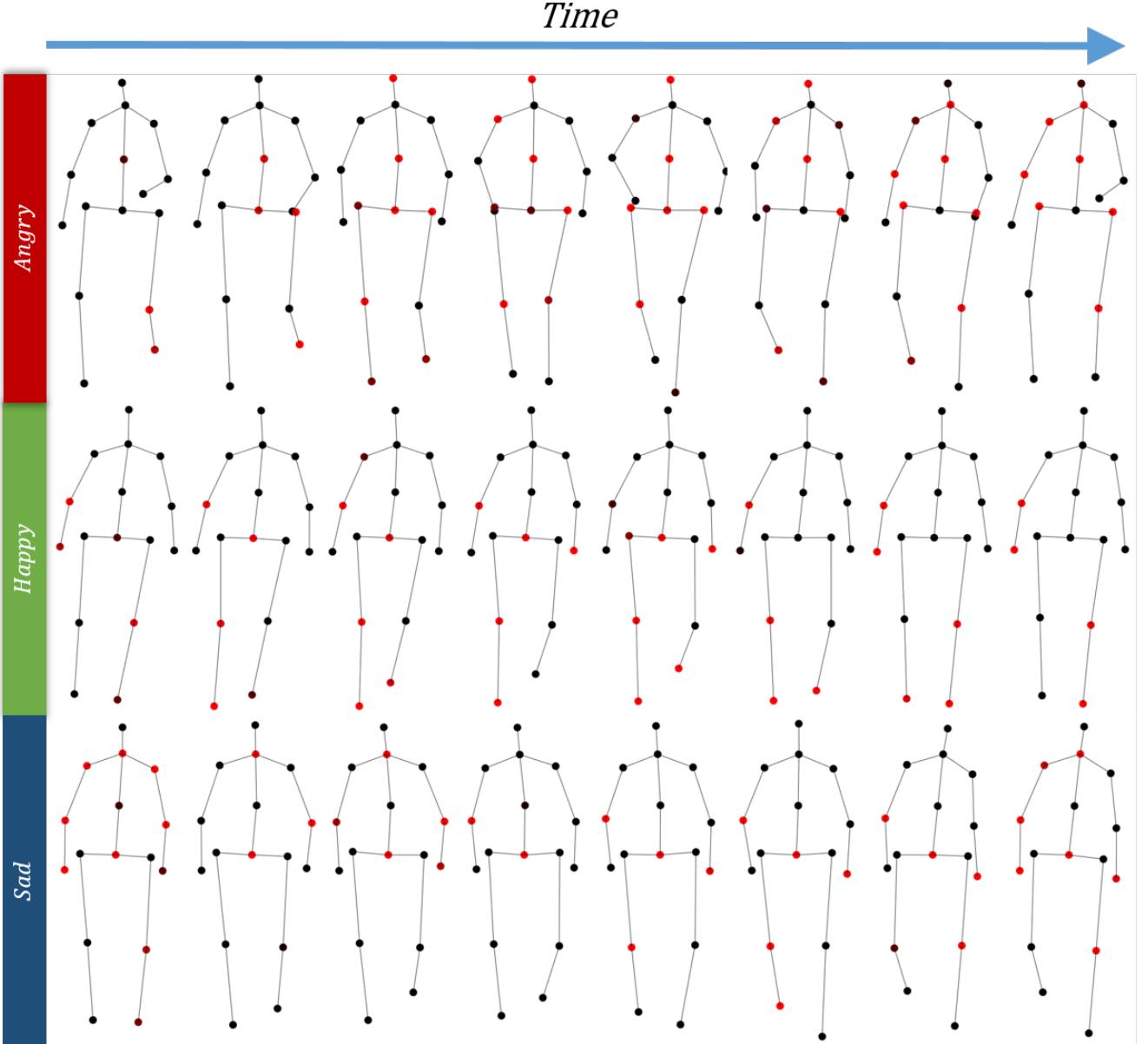


Fig. 12: Saliency Maps: We present the saliency maps for one sample per emotion (angry, happy, and sad) as learned by the network for a single walk cycle. The maps show activations on the joints during the walk cycle. Black represents no activation and red represents high activation. For all the emotion classes, the hand, feet and head joints have high activations, implying that the network deems these joints to be more important for determining the class. Moreover, the activation values on these joints for a high arousal emotion (e.g., angry) are higher than those for a low arousal emotion (e.g., sad), implying the network learns that higher arousal emotions lead to more vigorous joint movements.

present a dataset of videos (EWalk) of individuals walking with their perceived emotion labels. The dataset is collected with subjects from a variety of ethnic backgrounds in both indoor and outdoor environments.

There are some limitations to our approach. The accuracy of our algorithm depends on the accuracy of the 3D human pose estimation and gait extraction algorithms. Therefore, emotion prediction may not be accurate if the estimated 3D human poses or gaits are noisy. Our affective computation requires joint positions from the whole body, but the whole body pose data may not be available if there are occlusions in the video. We assume that the walking motion is natural

and does not involve any accessories (e.g., suitcase, mobile phone, etc.). As part of future work, we would like to collect more datasets and address these issues. We will also attempt to extend our methodology to consider more activities such as running, gesturing, etc. Finally, we would like to combine our method with other emotion identification algorithms that use human speech and facial expressions. We want to explore the effect of individual differences in the perception of emotions. We would also like to explore applications of our approach for simulating virtual agents with desired emotions using gaits.

REFERENCES

- [1] L. Devillers, M. Tahon *et al.*, "Inference of human beings emotional states from speech in human–robot interactions," *IJSR*, 2015.
- [2] F. C. Benitez-Quiroz, R. Srinivasan *et al.*, "Emotionet: An accurate, real-time algorithm for the automatic annotation of a million facial expressions in the wild," in *CVPR*, 2016.
- [3] J. Russell, J. Bachorowski *et al.*, "Facial & vocal expressions of emotion," *Rev. of Psychology*, 2003.
- [4] P. Ekman, "Facial expression and emotion," *American Psychologist*, vol. 48, no. 4, pp. 384–392, 1993.
- [5] J. M. Fernandez-Dols, M. A. Ruiz-Belda *et al.*, "Expression of emotion versus expressions of emotions: Everyday conceptions of spontaneous facial behavior." *Everyday Conceptions of Emotion*, 1995.
- [6] A. Kleinsmith, N. Bianchi-Berthouze *et al.*, "Affective body expression perception and recognition: A survey," *IEEE TAC*, 2013.
- [7] H. Meeren, C. van Heijnsbergen *et al.*, "Rapid perceptual integration of facial expression and emotional body language," *PNAS*, 2005.
- [8] H. Aviezer, Y. Trope *et al.*, "Body cues, not facial expressions, discriminate between intense positive and negative emotions," 2012.
- [9] J. Montepare, S. Goldstein *et al.*, "The identification of emotions from gait information," *Journal of Nonverbal Behavior*, 1987.
- [10] H. Wallbott, "Bodily expression of emotion," *European Journal of Social Psychology*, 1998.
- [11] J. Michalak, N. Troje *et al.*, "Embodiment of sadness and depression-gait patterns associated with dysphoric mood," *Psychosomatic Medicine*, 2009.
- [12] Y. Ma, H. M. Paterson *et al.*, "A motion capture library for the study of identity, gender, and emotion perception from biological motion," *Behavior research methods*, 2006.
- [13] A. Loutfi, J. Widmark *et al.*, "Social agent: Expressions driven by an electronic nose," in *VECMIS*. IEEE, 2003.
- [14] P. Ekman and W. V. Friesen, "Head and body cues in the judgment of emotion: A reformulation," *Perceptual and motor skills*, 1967.
- [15] A. Mehrabian, "Basic dimensions for a general psychological theory implications for personality, social, environmental, and developmental studies," 1980.
- [16] J. Morris, "Observations: Sam: the self-assessment manikin; an efficient cross-cultural measurement of emotional response," *JAR*, 1995.
- [17] J. Mikels, B. Fredrickson *et al.*, "Emotional category data on images from the international affective picture system," *Behavior research methods*, 2005.
- [18] M. D. Robinson and G. L. Clore, "Belief and feeling: Evidence for an accessibility model of emotional self-report," *Psychological Bulletin*, vol. 128, no. 6, pp. 934–960, 2002.
- [19] L. F. Barrett, R. Adolphs, S. Marsella, A. M. Martinez, and S. D. Pollak, "Emotional expressions reconsidered: challenges to inferring emotion from human facial movements," *Psychological Science in the Public Interest*, vol. 20, no. 1, pp. 1–68, 2019.
- [20] R. Picard, "Toward agents that recognize emotion," *Proc. of IMAGINA*, pp. 153–165, 1998.
- [21] M. Karg, A.-A. Samadani, R. Gorbet, K. Kühnlenz, J. Hoey, and D. Kulić, "Body movements for affective expression: A survey of automatic recognition and generation," *IEEE Transactions on Affective Computing*, vol. 4, no. 4, pp. 341–359, 2013.
- [22] M. Gross, E. Crane *et al.*, "Methodology for assessing bodily expression of emotion," *Journal of Nonverbal Behavior*, 2010.
- [23] A. Camurri, I. Lagerlöf, and G. Volpe, "Recognizing emotion from dance movement: comparison of spectator recognition and automated techniques," *International journal of human-computer studies*, vol. 59, no. 1-2, pp. 213–225, 2003.
- [24] N. Savva, A. Scarinzi, and N. Bianchi-Berthouze, "Continuous recognition of player's affective body expression as dynamic quality of aesthetic experience," *IEEE Transactions on Computational Intelligence and AI in games*, vol. 4, no. 3, pp. 199–212, 2012.
- [25] F. Noroozi, D. Kaminska, C. Corneanu, T. Sapinski, S. Escalera, and G. Anbarjafari, "Survey on emotional body gesture recognition," *IEEE transactions on affective computing*, 2018.
- [26] S. Piana, A. Stagliano, F. Odone, and A. Camurri, "Adaptive body gesture representation for automatic emotion recognition," *ACM Transactions on Interactive Intelligent Systems (TiiS)*, vol. 6, no. 1, p. 6, 2016.
- [27] S. Piana, A. Stagliano, F. Odone, A. Verri, and A. Camurri, "Real-time automatic emotion recognition from body gestures," *arXiv preprint arXiv:1402.5047*, 2014.
- [28] S. Piana, A. Stagliano, A. Camurri, and F. Odone, "A set of full-body movement features for emotion recognition to help children affected by autism spectrum condition," in *IDGEI International Workshop*, 2013.
- [29] P. R. De Silva and N. Bianchi-Berthouze, "Modeling human affective postures: an information theoretic characterization of posture features," *Computer Animation and Virtual Worlds*, vol. 15, no. 3-4, pp. 269–276, 2004.
- [30] D. Glowinski, N. Dael, A. Camurri, G. Volpe, M. Mortillaro, and K. Scherer, "Toward a minimal representation of affective gestures," *IEEE Transactions on Affective Computing*, vol. 2, no. 2, pp. 106–118, 2011.
- [31] R. von Laban, *Principles of dance and movement notation*. Brooklyn, NY: Dance Horizons, 1970.
- [32] H. Zacharatos, C. Gatzoulis, Y. Chrysanthou, and A. Aristidou, "Emotion recognition for exergames using laban movement analysis," in *Proceedings of Motion on Games*. ACM, 2013, pp. 61–66.
- [33] N. Dael, M. Mortillaro, and K. R. Scherer, "The body action and posture coding system (bap): Development and reliability," *Journal of Nonverbal Behavior*, vol. 36, no. 2, pp. 97–121, 2012.
- [34] E. M. Huis in t Veld, G. J. Van Boxtel, and B. de Gelder, "The body action coding system i: Muscle activations during the perception and expression of emotion," *Social neuroscience*, vol. 9, no. 3, pp. 249–264, 2014.
- [35] G. J. van Boxtel, B. de Gelder *et al.*, "The body action coding system ii: muscle activations during the perception and expression of emotion," *Frontiers in behavioral neuroscience*, vol. 8, p. 330, 2014.
- [36] N. Dael, M. Mortillaro, and K. R. Scherer, "Emotion expression in body action and posture," *Emotion*, vol. 12, no. 5, p. 1085, 2012.
- [37] T. Sapiński, D. Kamińska, A. Pelikant, and G. Anbarjafari, "Emotion recognition from skeletal movements," *Entropy*, vol. 21, no. 7, p. 646, 2019.
- [38] J. Butepage, M. J. Black, D. Kragic, and H. Kjellstrom, "Deep representation learning for human motion prediction and classification," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017, pp. 6158–6166.
- [39] C. Wang, M. Peng, T. A. Olugbade, N. D. Lane, A. C. d. C. Williams, and N. Bianchi-Berthouze, "Learning temporal and bodily attention in protective movement behavior detection," in *2019 8th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW)*. IEEE, 2019, pp. 324–330.
- [40] J. Wagner, E. Andre, F. Lingenfelser, and J. Kim, "Exploring fusion methods for multimodal emotion recognition with missing data," *IEEE Transactions on Affective Computing*, vol. 2, no. 4, pp. 206–218, 2011.
- [41] T. Balomenos, A. Raouzaiou, S. Ioannou, A. Drosopoulos, K. Kar pouzis, and S. Kollias, "Emotion analysis in man-machine interaction systems," in *International Workshop on Machine Learning for Multimodal Interaction*. Springer, 2004, pp. 318–328.
- [42] G. Caridakis, G. Castellano, L. Kessous, A. Raouzaiou, L. Malatesta, S. Asteriadis, and K. Karpouzis, "Multimodal emotion recognition from expressive faces, body gestures and speech," in *IFIP International Conference on Artificial Intelligence Applications and Innovations*. Springer, 2007, pp. 375–388.
- [43] B. Li, C. Zhu, S. Li, and T. Zhu, "Identifying emotions from non-contact gaits information based on microsoft kinects," *IEEE Transactions on Affective Computing*, vol. 9, no. 4, pp. 585–591, 2016.
- [44] S. Li, L. Cui, C. Zhu, B. Li, N. Zhao, and T. Zhu, "Emotion recognition using kinect motion capture data of human gaits," *PeerJ*, vol. 4, p. e2364, 2016.
- [45] C. Roether, L. Omloj *et al.*, "Critical features for the perception of emotion from gait," *Vision*, 2009.
- [46] C. L. Roether, L. Omloj, and M. A. Giese, "Features in the recognition of emotions from dynamic bodily expression," in *Dynamics of Visual Motion Processing*. Springer, 2009, pp. 313–340.
- [47] A. Crenn, A. Khan *et al.*, "Body expression recognition from anim. 3d skeleton," in *IC3D*, 2016.
- [48] M. Karg, K. Kühnlenz *et al.*, "Recognition of affect based on gait patterns," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 2010.
- [49] M. Karg, R. Jenke, K. Kühnlenz, and M. Buss, "A two-fold pca-approach for inter-individual recognition of emotions in natural walking," in *MLDM posters*, 2009, pp. 51–61.

- [50] M. Karg, R. Jenke, W. Seiberl, K. Kühnlenz, A. Schwirtz, and M. Buss, "A comparison of pca, kPCA and lda for feature extraction to recognize affect in gait kinematics," in *2009 3rd International Conference on Affective Computing and Intelligent Interaction and Workshops*. IEEE, 2009, pp. 1–6.
- [51] G. Venture, H. Kadone *et al.*, "Recognizing emotions conveyed by human gait," *International Journal of Social Robotics*, 2014.
- [52] 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.
- [53] M. Daoudi, "Emotion recognition by body movement representation on the manifold of symmetric positive definite matrices," in *ICIAP*, 2017.
- [54] 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.
- [55] L. Omlor, M. Giese *et al.*, "Extraction of spatio-temporal primitives of emotional body expressions," *Neurocomputing*, 2007.
- [56] M. M. Gross, E. A. Crane, and B. L. Fredrickson, "Effort-shape and kinematic assessment of bodily expression of emotion during gait," *Human Movement Science*, vol. 31, no. 1, pp. 202–221, 2012.
- [57] S. Ribet, H. Wannous, and J.-P. Vandeborre, "Survey on style in 3d human body motion: Taxonomy, data, recognition and its applications," *IEEE Transactions on Affective Computing*, 2019.
- [58] J. Tilmanne and T. Dutoit, "Expressive gait synthesis using pca and gaussian modeling," in *International Conference on Motion in Games*. Springer, 2010, pp. 363–374.
- [59] J. Tilmanne, A. Moinet, and T. Dutoit, "Stylistic gait synthesis based on hidden markov models," *EURASIP Journal on advances in signal processing*, vol. 2012, no. 1, p. 72, 2012.
- [60] N. F. Troje, "Decomposing biological motion: A framework for analysis and synthesis of human gait patterns," *Journal of vision*, vol. 2, no. 5, pp. 2–2, 2002.
- [61] M. L. Felis, K. Mombaur, H. Kadone, and A. Berthoz, "Modeling and identification of emotional aspects of locomotion," *Journal of Computational Science*, vol. 4, no. 4, pp. 255–261, 2013.
- [62] R. Dabral, A. Mundhada *et al.*, "Learning 3d human pose from structure and motion," in *ECCV*, 2018.
- [63] K. Greff, R. K. Srivastava *et al.*, "Lstm: A search space odyssey," *IEEE transactions on neural networks and learning systems*, 2017.
- [64] Y. Luo, J. Ren *et al.*, "Lstm pose machines," in *CVPR*, 2018.
- [65] C. Ionescu, D. Papava *et al.*, "Human3.6m: Large scale datasets and predictive methods for 3d human sensing in natural environments," *TPAMI*, 2014.
- [66] "Cmu graphics lab motion capture database," <http://mocap.cs.cmu.edu/>, 2018.
- [67] S. Narang, A. Best *et al.*, "Motion recognition of self and others on realistic 3d avatars," *Computer Animation & Virtual Worlds*, 2017.
- [68] S. Xia, C. Wang *et al.*, "Realtime style transfer unlabeled heterogeneous human motion," *TOG*, 2015.
- [69] L. L. Carli, S. J. LaFleur, and C. C. Loeber, "Nonverbal behavior, gender, and influence," *Journal of personality and social psychology*, vol. 68, no. 6, p. 1030, 1995.
- [70] J. Forlizzi, J. Zimmerman, V. Mancuso, and S. Kwak, "How interface agents affect interaction between humans and computers," in *Proceedings of the 2007 conference on Designing pleasurable products and interfaces*. ACM, 2007, pp. 209–221.
- [71] N. C. Krämer, B. Karacora, G. Lucas, M. Dehghani, G. Rüther, and J. Gratch, "Closing the gender gap in stem with friendly male instructors? on the effects of rapport behavior and gender of a virtual agent in an instructional interaction," *Computers & Education*, vol. 99, pp. 1–13, 2016.
- [72] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *arXiv preprint arXiv:1412.6980*, 2014.
- [73] T. Lin, M. Maire *et al.*, "Microsoft coco: Common objects in context," in *ECCV*, 2014.
- [74] Z. Cao, T. Simon *et al.*, "Realtime 2d pose estimation using part affinity fields," in *CVPR*, 2017.
- [75] A. Crenn, A. Meyer *et al.*, "Toward an efficient body expression recognition based on the synthesis of a neutral movement," in *ICMI*, 2017.
- [76] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial nets," in *Advances in neural information processing systems*, 2014, pp. 2672–2680.
- [77] D. P. Kingma and M. Welling, "Auto-encoding variational bayes," *arXiv preprint arXiv:1312.6114*, 2013.
- [78] C. Yang, Z. Wang, X. Zhu, C. Huang, J. Shi, and D. Lin, "Pose guided human video generation," in *Proceedings of the European Conference on Computer Vision (ECCV)*, 2018, pp. 201–216.
- [79] H. Cai, C. Bai, Y.-W. Tai, and C.-K. Tang, "Deep video generation, prediction and completion of human action sequences," in *Proceedings of the European Conference on Computer Vision (ECCV)*, 2018, pp. 366–382.
- [80] S. Yan, Y. Xiong, and D. Lin, "Spatial temporal graph convolutional networks for skeleton-based action recognition," in *Thirty-Second AAAI Conference on Artificial Intelligence*, 2018.



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