Recognition of Affect Based on Gait Patterns

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***Abstract*—To provide a means for recognition of affect from a distance, this paper analyzes the capability of gait to reveal a person's affective state. We address interindividual versus person-dependent recognition, recognition based on discrete affective states versus recognition based on affective dimensions, and efficient feature extraction with respect to affect. Principal component analysis (PCA), kernel PCA, linear discriminant analysis, and general discriminant analysis are compared to either reduce temporal information in gait or extract relevant features for classification. Although expression of affect in gait is covered by the primary task of locomotion, person-dependent recognition of motion capture data reaches 95% accuracy based on the observation of a single stride. In particular, different levels of arousal and dominance are suitable for being recognized in gait. It is concluded that gait can be used as an additional modality for the recognition of affect. Application scenarios include monitoring in high-security areas, human–robot interaction, and cognitive home environments.**

***Index Terms*—Affective computing, feature extraction, gait recognition, human motion analysis, pattern classification.**

I. Introduction

NONVERBAL communication plays a major role in future robotics. To simplify human-machine interaction and to increase intuitive communication, nonverbal signals of humans are observed delivering additional cues for a person's mental and physiological state and intentions. Within this research area, affective computing faces the challenges of automatically recognizing a human's affective state, modeling affect, and responding in an appropriate manner to affective interactions [1]. It is expected that integration of affective computing as an aspect of nonverbal communication enhances human-computer and human-robot interaction. Detection of affect is, in general, based on observing facial expressions, linguistic and acoustic features in speech, physiological parameters, gestures, and body motions [1]–[3]. Each modality has its limitations; therefore, recognition based on combining different modalities seems to be more reliable for real-world applications [3], [4]. To provide an additional modality and to enhance recognition of affect from a distance, the human gait is investigated in terms of its ability to reveal a person's affective state.

In recent years, much research has been done to define a normal gait pattern. This task is challenging, because people's individual gait is as unique as their fingerprint [5]. Furthermore, gait is influenced by many factors such as age, weight, and possible gait disorders. How such factors or combinations of them affect gait is still an open question. Usually predefined factors such as knee flexion angles are investigated in clinical and biomechanical studies. In recent years, techniques from machine learning have been applied in therapeutic support for patients with gait disorders, gait-based human identification, and discrimination between human motion types [5]–[15]. Aside from further improvement in human motion reconstruction from recorded data, fundamental advances in behavior representation of motions are required for a wider range of applications of gait analysis [16]. Possible applications for predicting behavior, in particular affective states, are human-robot-interaction, cognitive households, and high-security locations (e.g., airports).

Gait is a natural day-to-day motion, and psychological studies indicate that affective states are expressed in the way people walk; therefore, our paper focuses on the automatic recognition of affect based on gait patterns. Interindividual recognition is compared with human performance. In contrast to person-dependent recognition, interindividual recognition is affected by individual expressions of affect and individual walking styles. Hence, person-dependent recognition is favored for real-world scenarios. Extraction of relevant features from gait patterns is crucial, because recordings of gait patterns are characterized by high dimensionality, time dependence, high variability, and nonlinearities. The unsupervised techniques principal component analysis (PCA) and kernel PCA (KPCA) are compared with the supervised techniques linear discriminant analysis (LDA) and general discriminant analysis (GDA). Furthermore, catching the temporal information of gait trajectories with PCA is compared with extracting statistical parameters. Although expression of affect during walking is covered by the primary task of locomotion, recognition of affective states has been accomplished based on the observation of a single stride. In particular, affective states that differ in arousal are suitable for being detected in gait patterns.

The remainder of this paper is organized as follows. Section II introduces common models for classifying affect, presents recent results in human perception of affect from whole-body motions, and summarizes related work for marker-based gait analysis. The database is described in Section III. Performance of human observers for recognition of affect based on discrete affective states and affective dimensions is presented in Section IV. Section V describes applications

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of PCA, KPCA, LDA, and GDA to time-series data of kinematic parameters. Results for interindividual versus person-dependent recognition and recognition based on affective dimensions are discussed in Section VI. A general discussion is given in Section VII. This paper ends with a conclusion in Section VIII.

II. State of the Art

A. Nature of Emotions

Due to the diverse, versatile, and elusive appearance of emotions in daily life, a universal definition of the term *emotion* does not exist. Rather, emotion is interpreted in a context-specific way. Despite its diverse occurrence, an emotion influences other cognitive processes such as attention, decision making, memory, and perception [1], [17].

Three main directions can be distinguished when defining emotion for scientific analysis: 1) the categorical approach; 2) the dimensional approach; and 3) the appraisal-based approach. Emotions are classified as discrete affective states in the categorical approach. Analysis of facial expressions is often based on the six basic emotions: 1) anger; 2) disgust; 3) fear; 4) joy; 5) sadness; and 6) surprise [3], [18]. Discrete categories are not limited to the basic emotions, but they or a subgroup of them are most frequently studied in affective computing. In the dimensional approach, the emotional state is described as a point in a continuous space. The independent and bipolar axes of the continuous space for the PAD model are pleasure, arousal, and dominance [19]. Mapping between discrete emotional states and the PAD model is investigated in [20] and [21]. For example, discrete categories such as happiness, amusement, and contentment are related to high pleasure, whereas anger, fear, and sadness are related to low pleasure. Both approaches are shown as alternatives. The PAD model allows graduation of the emotional state, whereas discrete states are more related to general linguistic usage. Due to its complexity, the appraisal-based approach is less used for recognition of emotional states. It finds more application as a psychological concept for explaining how emotions develop, influence, and are influenced by interaction with the environment [17], [22].

Recent studies have concentrated on the embodiment of emotions [23]. As the Latin origin of the word *emotion*[1] implies, emotion is not only limited to personal feelings but is also expressed in facial expressions, speech, gestures, and body motions. The body has more degrees of freedom than what is actually required for basic movements. Using this advantage for the expression of emotions is brought to perfection by actors and dancers.

Lazarus defines emotion as the combination of physiological disturbance, action tendencies, which are not necessarily acted out, and affect, which is the subjective experience during an emotion [24]. In accordance with this definition, this paper analyzes recognition of affect in gait patterns. Both a set of discrete affective states and the PAD model are taken as the basis.

[1] *Emovere* = to move out.

B. Affect in Whole-Body Motions

Various psychological studies indicate that humans can recognize not only the intended action but also gender [25], identity [26], and even emotions [27]–[29] from body movements. In general, recognition is based on discrete affective states. The categories happy, sad, and angry are more distinctive in motion than categories such as pride and disgust. Analysis of the arm movements drinking and knocking shows that the discrete affective states used in this paper are aligned with the arousal–pleasure space if human judgments are taken as the basis [30]. Furthermore, arousal is highly correlated with velocity, acceleration, and jerk of the movement. Bernhardt and Robinson's comparable study uses a support vector machine (SVM) for classification [31]. The affective states angry and sad are more recognizable than neutral or happy. Kleinsmith *et al.* examine the role of affective dimensions in static postures for automatic recognition [32]. The error rate is lower than 21% for each affective dimension arousal, valence, potency, and avoidance based on a neural network. In conclusion, the dimensional approach is shown as a comparable alternative to discrete affective categories for analyzing affect in whole-body motions.

In psychology, evidence exists that affect can be expressed in walking and recognized by human observers. In 1987, Montepare *et al.*'s psychological study indicated that observers can identify affect from variations in walking styles [33]. Furthermore, the affective states sadness and anger are easier to recognize than pride for human observers. In addition, Michalak *et al.*'s study supports that sadness and depression are embodied in the way people walk [34]. Crane and Gross showed that bodily expressions of felt and recognized affect are associated with affect-specific changes in gait kinematics and do not solely depend on gesticulatory behavior [35]. They identified velocity, cadence, head orientation, and shoulder and elbow range of motion as significant parameters that are affected by emotions. In particular, the perception of fear is facilitated if the walker who displays fear is female due to similar kinematics for fearful gait and female specific gait [36]. Roether *et al.* indicate that kinematic parameters that are critical for the perception of affect closely match features that correspond to changes in motor behavior [37]. Although movement speed influences the perception of affect, their study provides evidence of additional affect-specific features in gait that cannot be explained by variations in gait speed alone. In addition to these findings, Heberlein *et al.* suggest that the perception of affect and personality traits is accomplished by partially dissociable neural systems that process gait patterns in the brain [38].

To the authors' knowledge, only one work studies the recognition of affect in walking with techniques from machine learning [39]. Janssen *et al.* investigated the recognition of four affective states through artificial neural nets. The person-dependent recognition rate reaches 83.7%, on the average, based on kinetic data that are measured with a force plate in the ground. However, the interindividual recognition rate remains around chance level. Walking while listening to calming, excitatory, or no music is up to 79% classifiable by using kinematic parameters.

Motivated by evidence from psychology and cybernetics that affect is expressed in walking, our paper has investigated the applicability of gait as an additional channel in affective computing. In particular, this paper focuses on the aspects interindividual versus person-dependent recognition and classification of affect based on either discrete categories or dimensions, because both aspects have been less studied with respect to gait in the literature but are central for automatic recognition.

C. Marker-Based Gait Analysis

Although recognition by using vision-based features that are extracted from the shape of a walker is more applicable for real-world scenarios, model-based features give more insight into the underlying kinematics. For this reason, the latter method is preferred in clinical, biomechanical, and methodological studies. Advantages of high resolution and more reliable calculation of kinematic parameters contrast with an artificial setup that is required for marker-based optical motion tracking.

Although marker-based gait analysis has commonly been used in medical and biomechanical studies for more than a decade, data analysis is traditionally based on statistics. To improve the extraction of useful information from highly correlated time-dependent gait parameters, several approaches have been undertaken, including methods from machine learning [6], [7], [37], [39]–[41]. An overview is given in [6] and [7]. Clustering, multivariate techniques, neural networks, and time-frequency analysis have been applied to short-term recordings. Fractal analysis is only applicable to long-term recordings, because it estimates long-range correlations. However, Chau points out that there is a lack of objective comparisons between multiple methods. Wu and Liu investigate the capability of KPCA to capture nonlinear relationships in gait patterns [40]. KPCA slightly increases the recognition of age compared to PCA. Troje presents a two-stage PCA for gender recognition [41]. Roether *et al.* introduce a phase-adapted blind source separation algorithm to minimize redundancy in the parameterization of gait patterns [37]. Still, comparison with regard to the number of kinematic parameters that are considered for analysis, different methods for capturing the temporal characteristics of gait, and different classifiers is an open issue.

III. Database

A gait database has been recorded at Technische Universität München (TU München), with the purpose of gaining larger understanding of the influence of affect on gait patterns and its application to the recognition of affect [42]. The design of the database focused on interindividual versus person-dependent analysis and the use of affective dimensions versus discrete affective states. The gait of 13 male nonprofessional actors (mean age: 25.8) was recorded with a Vicon optical tracking system (240 Hz). A number of 35 passive markers were affixed to the participant's skin, where anatomic points define the marker positions. Based on the Plug-in Gait model, the Vicon software provides marker positions, joint centers, and joint angles over time for further data analysis.

Due to a highly artificial environment and frequent repetition of each affective state, successful elicitation of affect is challenging, and it has been decided to pose affect. Although actors tend to produce stereotypes or to exaggerate expressive behavior, some evidence exists in the literature that posed affective expressions represent an approximation to really felt affective expressions [43]. Participants were asked to feel angry, happy, neutral, or sad and to imagine a situation in which they feel a particular affect. Each recording contains at least two strides, and each trial was repeated ten times. Participants walked straight on in the laboratory hall. In addition, extremes of the dimensions of the PAD model were recorded so that the gait database also contains ten walks of each participant, expressing the affective states displeased, content, bored, excited, obedient, and dominant.

For further data analysis, a single stride is extracted from each gait. Overall, the database contains 520 strides for analyzing discrete affective states and 780 strides for analyzing affective dimensions.

IV. Human Performance

Due to the questionable ground truth of a human's affective state and person-dependent estimation of affect, affect-expressive databases are commonly evaluated by human observers. The evaluation can be used either for annotation or for performance comparison. In our case, the gait patterns are labeled by the instruction that the walkers got, and human evaluation is used as a basis for accuracy comparison.

With the intention that human observers rate the affective state of a walker based only on kinematic parameters, a graphical animation of an abstract puppet has been designed. Further advantages of the graphical animation are that there is no influence of the physique and facial expression of the walkers on the evaluation. One gait of each affective state for each walker has been mapped to the animated puppet. Fourier transform is applied to retrieve a parametric description of the captured joint angles $\varphi_i(t)$ over time, i.e.,

$$\varphi_i(t) = \sum_{j=1}^{10} A_j \sin(2\pi f_j + \Phi_j) \tag{1}$$

where the ten frequencies f_j with the highest absolute amplitude A_j and associated phase shifts Φ_j achieve a good approximation of the recorded angle $\varphi_i(t)$. The duration of a single stride is very short for human judgment; therefore, the individual gait patterns are extrapolated using the parametric equation (1), with each rendered video lasting 7 s. Fig. 1 shows snapshots of the rendered movies for the affective states neutral, happy, angry, and sad.

Thirty participants (mean age: 25.8 $\pm$ 3.5) took part in the experiment. To avoid boredom during the experiment, the upper limit for the duration of the experiment was set to 30 min. Hence, animations were presented to two different groups: A and B. Group A watched all animations of walkers 1–6, and Group B watched all animations of walkers 7–13.

First, participants rated the animated puppets that express discrete affective states. The average recognition rate for four

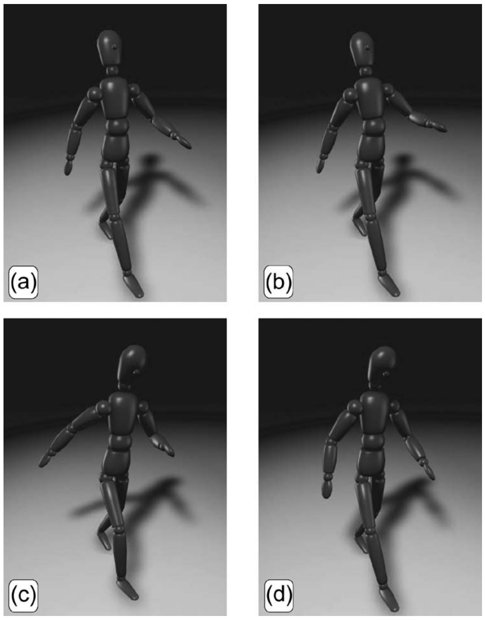

Fig. 1. Captured joint angles are mapped to an abstract puppet. The rendered animations have been evaluated by human observers. In the snapshots, one walker expresses the affective states (a) neutral, (b) happy, (c) angry, and (d) sad.

TABLE I
ACCURACY OF HUMAN OBSERVERS (IN PERCENT)

	Neutral	Happy	Sad	Angry	All
Accuracy	69	53	73	57	63

affective states is 63%, whereas human observers tend to recognize, in particular, the state sad best (see Table I). Furthermore, participants were asked to rate, on a five-item Likert scale, how difficult it had been to estimate each of the discrete affective states. A one-way repeated-measures analysis of variance (ANOVA) was used to test for significant differences in the degree of difficulty across the four affective states. The degree of difficulty in estimating affective states significantly differs: $F_{3,87} = 2.91$, $p = 0.04$, and $\eta_p^2 = 0.09$. Pairwise comparison indicates that the affective state sad $(\text{mean} = 2.47)$ was perceived to be significantly easier to recognize than the affective state neutral $(\text{mean} = 3.23)$.

In the subsequent experiment, participants rated the animated walkers who expressed either a low, medium, or high level of pleasure, arousal, or dominance. Participants rated the level of expressed affective dimension on a five-item Likert scale, i.e., corresponding row of the self-assessment manikin (SAM) questionnaire [44]. Accuracy for all three levels on each dimension is above chance. The mean accuracy for the dimensions pleasure, arousal, and dominance is 55%, 61%, and 53%, respectively. A two-way repeated-measures ANOVA with the within-subject factors level of expressed affective dimension and identity of walker indicates that the participants' ratings significantly differ due to different affective expressions of the walkers. Statistical analysis has separately been conducted for Groups A and B. In both groups, ratings significantly differ for the dimensions pleasure ($F_{2,28,A} = 48.76$, $F_{2,28,B} = 166.73$, $p_{A,B} =$

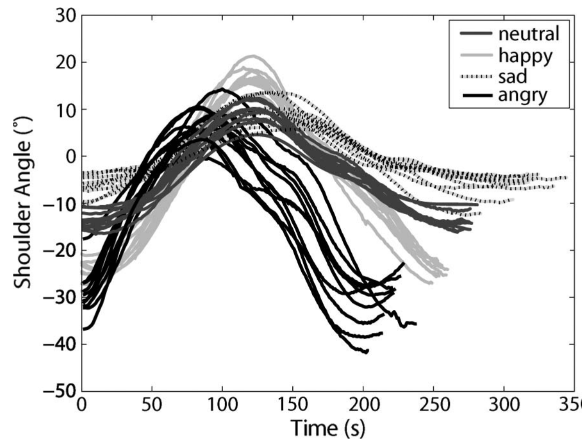

Fig. 2. Trajectories of the right-shoulder angle differ with respect to the expressed affect. Ten recordings of one walker are plotted for each affective state.

$.00$, $\eta^2_{P,A} = 0.78$, $\eta^2_{P,B} = 0.92$), arousal ($F_{2,28,A} = 283.94$, $F_{2,28,B} = 428.56, p_{A,B} = .00, \eta^2_{P,A} = 0.95, \eta^2_{P,B} = 0.97$) and dominance ($F_{1.26,17.57,A} = 65.51$, $F_{2,28,B} = 512.85$, $p_{A,B} = .00$, $\eta^2_{P,A} = 0.82$, $\eta^2_{P,B} = 0.97$). Although the identity of walker and interaction effects between walker and level of expression significantly influence the ratings, the effect size indicates that the level of expression explains most of the variance in the subjects' ratings. Thus, human observers can significantly distinguish levels of affective expression in the gait patterns of the database. Subsequent pairwise comparisons for each dimension pleasure, arousal, and dominance support this conclusion.

Finally, participants were asked to rate the degree of difficulty in estimating different levels of pleasure, arousal, or dominance on a five-item Likert scale. In this case, one-way repeated-measures ANOVA indicates that there are significant differences in estimating different levels of either pleasure, arousal, or dominance: $F(2, 58) = 7.09$, $p = .00$, $\eta_p^2 = 0.20$. The following pairwise comparison shows that pleasure is significantly harder to estimate than different levels of arousal. Underlying reasons are that different levels of pleasure are harder to retrieve from gait patterns, are harder to express in walking, or a combination of both.

Based on these results, we conclude that humans can recognize different affective states in the gait patterns of both databases, with one database considering discrete affective states and the other one based on the PAD model. Hence, both databases are suitable for investigating the performance of automatic recognition. Applied techniques are presented in the next section.

V. METHODS

Classification of gait patterns is challenging for techniques from machine learning, because data of gait recordings are high dimensional, time dependent, and highly variable, and gait variables interact in a nonlinear relationship [6]. Furthermore, retrieving the affective state of the walker from gait patterns faces the challenge of extracting patterns that are not directly observable but are rather covered by the primary task

TABLE II
KINEMATIC FEATURES OF SIGNIFICANT SUBSECTION

Factor	Parameter
Stride Length	Length of One Stride
Cadence	Time for One Stride
Velocity	Cadence/(Stride Length)
Neck Angle (Forward Tilt)	Min, Mean, Max
Shoulder Angle (Flexion)	Min, Mean, Max
Shoulder Angle (Abduction)	Min, Mean, Max
Thorax Angle (Forward Tilt)	Min, Mean, Max

of locomotion. Fig. 2 illustrates the influence of affect on the right-shoulder angle. The trajectories that describe forward and backward movements of the right arm are from the same walker as in Fig. 1. The influence of affect on walking differs between individuals and between joint angles and is usually less distinguishable by graphical investigation, as shown in Fig. 2. Because walking is a symmetric movement, the following analysis focuses on the right side of the body. Furthermore, we use joint angles as a basis for feature extraction and classification; therefore, comparing the performance of automatic classification with human observers is based on the same information from the recordings.

Improvement in accuracy can be achieved by either optimizing the classifier or feature extraction. This paper focuses on comparing three standard classifiers and improving feature extraction so that the accuracy of automatic classification matches or even outperforms human evaluation.

A. Statistical Parameters of Joint Angle Trajectories

The velocity of movement is related to affective states [30], [35], [37]; therefore, the parameters velocity, stride length, and cadence (VSC) are separately analyzed. Minimum, mean, and maximum are calculated for each joint angle. Considered joint angles are head, neck, shoulder, elbow, thorax, spine, ankle, and foot progress angle for each rotation axis. Part of the joint angles (see Table II) are noted in the literature as being significantly influenced by affect [35] and form a subgroup that is separately analyzed. Summing up, the kinematic parameters are split in three groups. Classification and optional dimension reduction are based on $\mathbf{x}_{kin} \in R^M$ with dimension M, which contains one of the following sets of kinematic parameters:

- solely VSC ($M = 3$);
- minimum, mean, and maximum of significant joint angles, including VSC ($M = 15$);
- minimum, mean, and maximum of all joint angles, including VSC ($M = 69$).

Transforming the feature space can improve classification. With this purpose, PCA, KPCA, LDA, and GDA are applied to the significant subsection and to all joint angles [45]–[47]. The mean and standard deviation of the feature vector $\mathbf{x}_{kin,norm}$ are normalized for PCA and KPCA.

1) PCA: PCA, also known as the Karhunen–Lòeve transformation, transforms the original data space to an orthogonal set of principal components (PCs). PCs $\mathbf{u}_i$ with the highest eigenvalues λ_i represent the vectors with maximum variance in the data set. The eigenvalue problem to be solved is defined as

$$\left(\frac{1}{N}\sum_{n=1}^{N}\mathbf{x}_{kin,norm}\mathbf{x}_{kin,norm}^T\right)\mathbf{u}_i = \lambda_i\mathbf{u}_i \qquad \text{with } i = 1,\ldots,M \tag{2}$$

with N observations of $\mathbf{x}_{kin,norm}$. The term within the brackets in (2) is the covariance matrix. Original data are mapped on up to a maximum of M PCs. Dimension reduction is achieved if the coefficients of the first m PCs are used for classification, with $m < M$. PCA is an unsupervised technique; therefore, it is not guaranteed that the projection that maximizes the variance in the data also maximizes the representation of affect in the transformed feature space. Furthermore, PCA is a linear technique and does not take underlying nonlinearities into account.

2) KPCA: One nonlinear extension of PCA is KPCA [48]. Its advantages are nonlinearity of eigenvectors and a higher number of eigenvectors. KPCA maps the original data vector $\mathbf{x}_{kin,norm}$ into a feature space F by using a nonlinear map Φ as follows:

$$\Phi : R^M \rightarrow F, \quad \mathbf{x}_{kin,norm} \mapsto \mathbf{X}_{kin,norm}. \tag{3}$$

Then, it performs linear PCA in the high-dimensional space F, which corresponds to a nonlinear PCA in the original data space. The covariance matrix $\mathbf{C}$ is given by

$$\mathbf{C} = \frac{1}{N}\sum_{j=1}^{N}\Phi(\mathbf{x}_{kin,norm,j})\Phi^T(\mathbf{x}_{kin,norm,j}). \tag{4}$$

Applying the kernel trick, the eigenvalue problem becomes

$$\begin{aligned} &N\lambda\mathbf{a} = \mathbf{K}\mathbf{a} \\ &\text{with } K_{ij} := \Phi(\mathbf{x}_{kin,norm,i})^T\Phi(\mathbf{x}_{kin,norm,j}) \end{aligned} \tag{5}$$

where the scalar product of Φ can be substituted by a kernel function $K(\mathbf{x},\mathbf{y})$. In this paper, a polynomial kernel $K = (\mathbf{x}^T\mathbf{y})^d$ and a Gaussian kernel $K = \exp((-\|\mathbf{x} - \mathbf{y}\|^2)(2\sigma^2)^{-1})$ are used. In contrast to PCA, KPCA can find up to N, in general number of instances, eigenvectors.

3) LDA: In contrast to algorithms based on PCA, LDA considers class membership for dimension reduction. The main idea of LDA is to separate class means of the projected directions well while achieving a small variance around these means. Like PCA, the derived features of LDA are linear combinations of the original data. For a c-class problem, the maximum number of eigenvectors $\mathbf{w}_k$ is $(c-1)$; in our case, the number of eigenvectors is 3. Based on the total mean $\mathbf{m} = (1/N)\sum_{i=1}^{N}\mathbf{x}_{kin,i}$, the mean $\mathbf{m}_j$ for samples $\mathbf{x}_{kin,i}^j$ of each class j, and the number of samples n_j for each class, the between-class scatter matrix S_B

$$S_B := \sum_{j=1}^{c} n_j(\mathbf{m}_j - \mathbf{m})(\mathbf{m}_j - \mathbf{m})^T \tag{6}$$

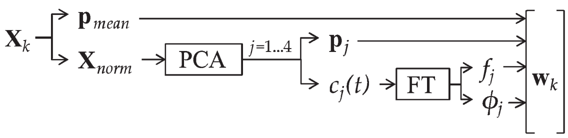

Fig. 3. Mathematical description $\mathbf{w}_k$ of one walk k contains the mean posture $\mathbf{p}_{mean}$, four eigenpostures $\mathbf{p}_j$, four frequencies f_j, and three phase shifts ϕ_j.

and the within-class scatter matrix S_W

$$S_W := \sum_{j=1}^{c}\sum_{i=1}^{l_j}\left(\mathbf{x}^j_{kin,i} - \mathbf{m}_j\right)\left(\mathbf{x}^j_{kin,i} - \mathbf{m}_j\right)^T \tag{7}$$

are defined. Maximizing the between-class measure while minimizing the within-class measure leads to the following eigenvalue problem:

$$(S_B - \lambda_k S_W)\mathbf{w}_k = 0 \quad \text{with } k = 1, 2, 3. \tag{8}$$

Although LDA takes class affiliation into account, it does not necessarily outperform PCA if training sets are small compared to feature dimension [49].

Similar to KPCA, GDA uses the kernel trick to compute LDA in a high-dimensional feature space without ever having to explicitly map into it [50]. Polynomial and Gaussian kernels have been applied to calculate interindividual and person-dependent recognition rates. Accuracy does not exceed chance level; therefore, results will not be further reported in this paper.

B. Modeling Joint Angle Trajectories by Eigenpostures

In contrast to computing the minimum, mean, and maximum of a time series that corresponds to a joint angle, the approach based on eigenpostures directly applies PCA to the complete data set of one gait. The procedure (see Fig. 3) is leant on eigenpostures and eigenwalkers, as proposed by Troje [41].

First, spatial information in the data set of one gait is reduced. The vector $\mathbf{x}(t) \in R^{23}$ contains the x-, y-, and z-rotation of each joint angle at time step t. The complete data set of one walk is described by the matrix

$$\mathbf{X} = [\mathbf{x}(1), \mathbf{x}(2), \ldots, \mathbf{x}(T)] \tag{9}$$

which contains T frames. PCA requires the matrix $\mathbf{X}$ to be normalized. Therefore, the mean posture $\mathbf{p}_{mean} = (1/T)\sum_{t=1}^{T}\mathbf{x}(t)$ is subtracted, and the data set is divided by its standard deviation $\mathbf{p}_{std}$ for unit variance. PCA is applied to $\mathbf{X}_{norm}$. Dimension reduction is achieved by using only the four eigenvectors, called eigenpostures $\mathbf{p}_j$, with the highest eigenvalues for further data analysis. Hence, the gait of one walker $\mathbf{p}(t)$ at time step t is described by

$$\mathbf{p}(t) = \mathbf{p}_{mean} + \mathrm{diag}(\mathbf{p}_{std})\sum_{j=1}^{4} c_j(t)\mathbf{p}_j \tag{10}$$

where $c_j(t)$, $1 \le j \le 4$, are the coefficients of $\mathbf{x}_{norm}(t)$ after transformation.

Temporal information is covered by the coefficients $c_j(t)$. Human walking is periodic, and each recording covers at least one stride; therefore, Fourier transformation is applied to model the temporal behavior of the coefficients $c_j(t)$. The leakage effect is reduced using a Hamming window. The main frequency f_j and phase ϕ_j are extracted. The phase of the first eigenposture ϕ_0 is set to zero, and ϕ_j for $j = 2, 3, 4$ are shifted by their difference to ϕ_0. The individual gait of one person $\mathbf{p}(t)$ is modeled as follows:

$$\mathbf{p}(t) = \mathbf{p}_{mean} + \mathrm{diag}(\mathbf{p}_{std})\mathbf{p}_1 \sin(2\pi f_1 t) + \mathrm{diag}(\mathbf{p}_{std})\sum_{j=2}^{4}\mathbf{p}_j \sin(2\pi f_j t + \phi_j). \tag{11}$$

Third, a second PCA extracts most relevant information among different walks of one walker and among different walkers. The description of a single walk $\mathbf{w}_k$ contains the mean posture $\mathbf{p}_{mean}$, four eigenpostures $\mathbf{p}_{j,k}$, four frequencies $f_{j,k}$, and three phase shifts $\phi_{j,k}$, i.e.,

$$\mathbf{w}_k = \left[\mathbf{p}^T_{mean}, \mathbf{p}^T_{1,k}, \ldots, \mathbf{p}^T_{4,k}, f_{1,k}, \ldots, f_{4,k}, \phi_{2,k}, \ldots, \phi_{4,k}\right]^T. \tag{12}$$

The matrix $\mathbf{W}$ contains, for example, all walks $\mathbf{w}_k$ of one walker who expresses different affective states for person-dependent recognition. Eigenvectors of the second PCA, which is applied to $\mathbf{W}$, are called eigenwalkers. Their coefficients are used for final classification. Results of this approach, later referred to as PCA-FT-PCA, are given for classification based on the coefficients of all eigenwalkers.

Note that replacing the first PCA, the second PCA, or both PCAs by KPCA does not significantly improve accuracy. Furthermore, the second PCA can be replaced by LDA or GDA. In this case, the number of instances in the training set is approximately four times smaller than the dimension of a single instance $\mathbf{w}_k$; therefore, the performance of LDA and GDA is low.

C. Classification

For recognition, several standard classifiers are compared. Naive Bayes is a classifier, which estimates probabilities of the membership in each class. It is robust to irrelevant features. However, features that are not conditionally independent or are not Gaussian distributed decrease accuracy. Nearest neighbor (NN) using Euclidean distance is a nonparametric technique. It can produce arbitrarily shaped decision boundaries and is susceptible to noise. In addition to NN and naive Bayes, SVMs afford good results in emotion recognition. A L1 soft-margin SVM with a radial basis function as a kernel ($c = 1.0$, $\gamma = 0.01$) is also used for classification [51]. The SVM learning problem is a convex optimization problem; therefore, the optimal solution is calculated in contrast to neural networks, which can get stuck in local minima. Standard SVM is limited to two-class problems. Common extension to multiclass problems is the one-against-one method.

The number of samples in the data sets is small; therefore, the recognition rate is calculated using leave-one-out cross validation.

TABLE III
ACCURACY FOR INTERINDIVIDUAL AFFECT RECOGNITION (IN PERCENT)

Feature	NN	Naive Bayes	SVM
PCA-FT-PCA	43	41	57
Velocity, Cadence, Stride Length	52	45	45
Significant Subsection	**63**	49	47
Sig. Subsection + PCA (15PC)	58	52	**62**
Sig. Subsection + KPCA (15PC)	36	**60**	**60**
Sig. Subsection + LDA	**63**	55	**62**
All Joint Angles	56	45	25
All Joint Angles + PCA (30PC)	51	50	**69**
All Joint Angles + KPCA (23PC)	28	58	25
All Joint Angles + LDA	52	53	53

TABLE IV
AVERAGE ACCURACY FOR PERSON-DEPENDENT AFFECT RECOGNITION (IN PERCENT)

Feature	NN	Naive Bayes	SVM
PCA-FT-PCA	70	70	78
Velocity, Cadence, Stride Length	84	83	76
Significant Subsection	87	**93**	**89**
Sig. Subsection + PCA (15PC)	**91**	85	**89**
Sig. Subsection + KPCA (15PC)	87	75	88
Sig. Subsection + LDA	**93**	**93**	**93**
All Joint Angles	**91**	**93**	79
All Joint Angles + PCA (15PC)	**92**	**92**	**95**
All Joint Angles + KPCA (15PC)	88	47	25
All Joint Angles + LDA	47	45	47

VI. RESULTS

A. Interindividual Versus Person-Dependent Recognition

In this section, we present and discuss each of the aforementioned feature extraction techniques for marker-based gait analysis in the context of affect recognition. In particular, we focus on the interference of identity on retrieving discrete affective states from gait patterns. It is expected that individual walking styles and individual expressions of affect influence recognition performance.

1) Interindividual Recognition: The concept of interindividual recognition is that the sample set contains all recordings of the walker, who is left out in the training set. This concept is comparable to recognizing the affective state of an unknown walker. Iteratively, the accuracy is calculated for each walker who is left out. Table III compares accuracy for different feature extraction methods. If the extra success, compared to a random predictor, is above 45%, results are marked bold. The highest accuracy of 69% is achieved when PCA is applied to all joint angles and the first 30 PCs are used. Although accuracy, with 69%, is above chance level and comparable to human performance (see Section IV), this result still means that 1/3 of the samples are misclassified. We conclude that, without further knowledge of the walker such as identity, both individual differences in walking style and expression of affect complicate reliable estimation of affect that is purely based on the kinematics of walking.

2) Person-Dependent Recognition: The previous section shows that interindividual recognition of discrete affective states is accomplishable above chance level but can be improved if individuality is considered. For this reason, the classifiers are individually trained for person-dependent recognition, i.e., the training set of each walker contains nine exemplars of neutral, happy, sad, and angry walking. One exemplar of each affective state is iteratively left out so that the training sets are balanced. Accuracy is separately calculated for each walker, and the mean accuracy among all walkers is reported in Table IV. Extra success above 85% is marked bold. Interpretation of Table IV allows conclusions about the performance of different feature extraction methods and comparison of interindividual versus person-dependent recognition. In the latter case, it is obvious that accuracy strongly increases for person-dependent recognition and reaches a maximum of 95% accuracy, which means a 93% extra success compared to a random predictor.

Comparing the accuracy achieved with different feature extractions reveals the following interesting points.

1) Extracting eigenpostures and eigenwalkers from the data sets, which include all joint angles, leads to 78% accuracy. For observations that include only a single stride, the performance of PCA to extract relevant temporal information from time series is less efficient than applying basic statistical parameters such as minimum, mean, and maximum to the joint angles over time.
2) A recognition rate that is above 80% is already achieved if classification uses only the features VSC. In accordance with [30], [35], and [37], the velocity of movement contains fundamental information about the affective state of a walker. The discrete affective states neutral and angry are best distinguishable. Although velocity already gives a good estimate of the affective state, estimation based only on this factor can easily be distorted in real-world scenarios.
3) Naive Bayes and NN perform well by using the statistical parameters of all joint angles with 93% and 91%, respectively, although the number of instances in the training sets is approximately half the number of features. Reducing the number of features to 15, with PCA, leads to the same performance of 92%–95% and thus does not discard relevant information with regard to affect. A comparable accuracy of 87%–93% among all three classifiers is achieved when statistical parameters are calculated for only the joint angles that are referred to in the literature as significant [35], [37]. Therefore, one can conclude that reducing the number of statistical parameters by unsupervised PCA without any expert knowledge is as efficient for classification as involving expert knowledge, which has been obtained by statistical hypothesis testing beforehand.
4) As stated in the literature, dimension reduction by using LDA does not necessarily outperform PCA, although it considers class affiliations [49]. Fig. 4 illustrates the accuracy of PCA and LDA when the number of kinematic

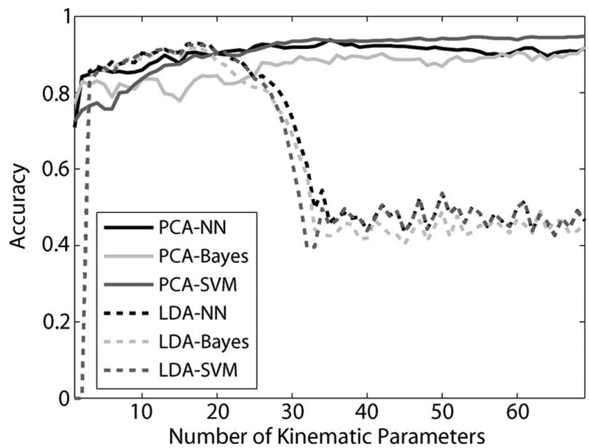

Fig. 4. Although LDA considers class affiliation, it outperforms PCA only for small numbers of kinematic parameters in relation to the number of instances in the training set.

parameters is increased. The number of instances in the training set $n_{train} = 36$ is held constant. PCA reduces the number of parameters to 15 PCs. For a small number of kinematic parameters, LDA reduces the feature space more efficiently than PCA. As soon as the within-class scatter matrix S_w becomes singular, which is the case if the number of kinematic parameters exceeds 32, the accuracy of LDA stays around 40%–50%. PCA is more robust to the high dimensionality of the original space. The accuracy of PCA even slightly increases by adding more kinematic parameters.

5) As noted in [47], nonlinear techniques do not necessarily outperform linear techniques for dimensionality reduction in real-world tasks. In our case, KPCA extracts relevant features from the original parameter space, but its overall performance is less than feature extraction with PCA. This result is in contrast to [40], which reports an increase of 5% by using KPCA instead of PCA for a two-class separation task. We can conclude that the advantage of KPCA over PCA depends on the application. Results for GDA have not been added to Tables III and IV, because recognition rates have not exceeded chance level.

6) Although naive Bayes, SVM, and NN have different assumptions about the data, accuracy generally differs little among the classifiers, particularly when feature space transformation such as PCA or LDA has previously been applied. The low performance of SVM in some cases is traced back to the fact that the parameter γ of the kernel function and cost c have not been optimized for each particular case. The good performance of NN reveals that the expression of different affective states forms separable clusters in the feature space. Assuming normally distributed features, naive Bayes performs well in the person-dependent case, whereas a mixture of Gaussians for each feature caused by the individuality of the walkers complicates interindividual recognition with naive Bayes.

Person-dependent recognition reveals the optimal accuracy, which is achievable by excluding interindividual differences in expressing affect and walking styles. Accuracy is only affected by a person's fluctuations in walking and acting a specific affective state. Comparing person-dependent with interindividual recognition suggests integrating identity in the estimation of affective states. The next section investigates what performance is achievable if the identity is previously estimated and the following recognition of affective states is based on the estimated identity.

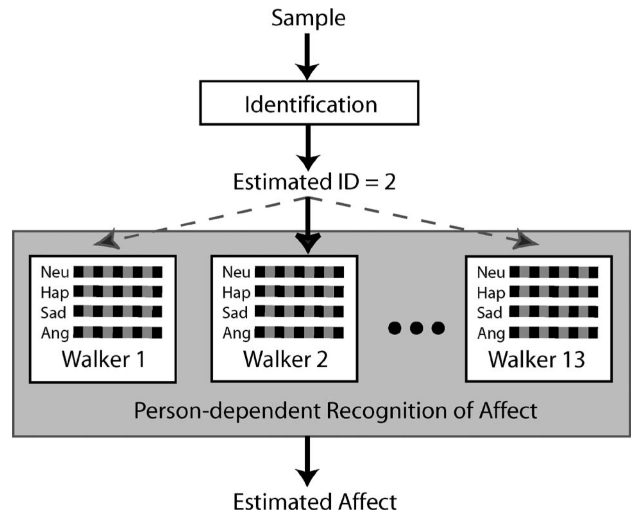

Fig. 5. In a two-stage classification, first, the identity of a walker is estimated, and then, person-dependent recognition of affect is performed based on the estimated identity.

TABLE V
ACCURACY FOR IDENTIFICATION (IN PERCENT)

Feature	NN	Naive Bayes	SVM
Velocity, Cadence, Stride Length	34	23	17
Significant Subsection	94	85	95
Significant Subsection + PCA	98	86	87
Significant Subsection + LDA	92	90	93
All Joint Angles	99	98	71
All Joint Angles + PCA	99	97	99
All Joint Angles + LDA	**99.6**	**99**	**99**

3) Person-Dependent Recognition Based on Estimated Identity: The good performance of person-dependent recognition faces the problem that identity is not necessarily given. This section combines identification based on kinematic parameters with the following recognition of affect. The concept is illustrated in Fig. 5. As in the previous sections, the mean accuracy among all walkers is calculated for the evaluation of this concept. Iteratively, four affective gait patterns of each walker are left out from the training sets. As shown in the previous section, extracting temporal information with PCA is less suitable than calculation of statistical parameters. For this reason, the approach based on eigenpostures and eigenwalkers is excluded from further analysis. The same case holds for KPCA with regard to dimension reduction.

Table V shows the results for identification based on kinematic parameters. In contrast to the recognition of affect, identification performs poorly based only on the parameters VSC. The best result is achieved if LDA is applied to the statistical parameters of all joint angles. Note that the training set contains

TABLE VI
ACCURACY OF AFFECT RECOGNITION BASED ON THE ESTIMATED IDENTITY (IN PERCENT)

Feature	NN	Naive Bayes	SVM
Significant Subsection	84	**89**	86
Significant Subsection + PCA	**90**	81	87
Significant Subsection + LDA	87	88	88
All Joint Angles	**91**	**93**	79
All Joint Angles + PCA	**92**	**89**	**91**
All Joint Angles + LDA	45	45	45

TABLE VII
IDENTIFICATION UNDER DIFFERENT AFFECTIVE STATES (IN PERCENT)

	Test Set			
Training Set	**Neutral**	**Happy**	**Sad**	**Angry**
Neutral	100	95	87	87
Happy	99	100	85	93
Sad	92	77	100	54
Angry	91	86	86	100

$n_{train} = 13 \cdot 9 \cdot 4$ instances for identification; therefore, n_{train} is much larger than the dimension of kinematic parameters in this case, and the within-class scatter matrix does not become singular. Thus, the good performance of LDA for identification does not contradict the good performance of PCA for the recognition of affect, considering that the statistical parameters of all joint angles form the basis. LDA that is applied to the statistical parameters of all joint angles in combination with NN is used to estimate identity for the following recognition of affect.

The resulting recognition of affect based on estimated identity performs almost as well as the recognition of affect based on real identity, i.e., a 93% recognition rate is achieved (see Table VI). This result is traced back to the fact that identification is performed with 99.6% accuracy. Hence, the dynamics of kinematic parameters contain information of identity and affect. Recognition of the affective states of a walker benefits from taking the information in the kinematics about identity into account. Knowledge about the walker significantly increases accuracy compared to recognizing the affective state of an unknown walker (see Table III).

4) Relevance of Affect for Identification: The strong influence of identity on the recognition of affect raises the question whether identification can also be influenced by different affective states of a walker. For this purpose, identification of walkers who express one affective state, e.g., happy, is performed based on a training set that contains only trials of another affective state, e.g., neutral. Results are shown in Table VII. Identification has been performed by applying LDA to the statistical parameters of all joint angles and by using NN as classifier (see Section VI-A3) on feature extraction for identification. If the same affective state underlies both training and testing set, the identity is estimated with 100% accuracy for our database. However, if training and testing sets differ in the affective state, which the walker expresses during walking, the accuracy significantly decreases. Therefore, we can conclude that identification also suffers from interference caused by affect.

TABLE VIII
ACCURACY FOR AFFECTIVE DIMENSIONS (IN PERCENT)

Feature	Pleasure	Arousal	Dominance
Velocity, Cadence, Stride Length	72	91	79
Significant Subsection	87	95	96
Sig. Subsection + PCA (7PC)	83	91	94
Sig. Subsection + LDA	80	91	92
All Joint Angles	88	**97**	**96**
All Joint Angles + PCA (7PC)	83	95	96
All Joint Angles + LDA	48	50	55

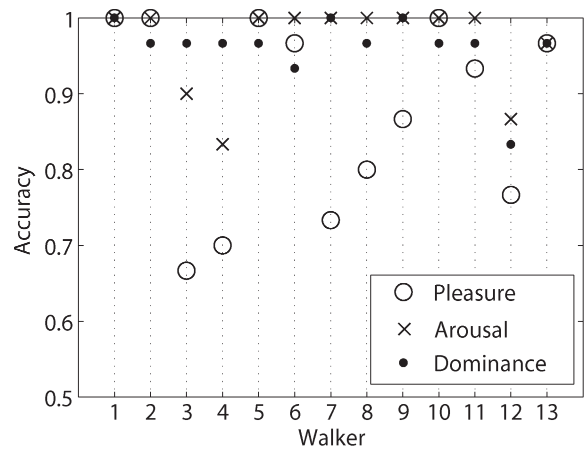

Fig. 6. For all walkers, three different levels of arousal are equal or even more recognizable than different levels of pleasure.

B. Recognition Based on the PAD Model

By analyzing the confusion matrix for the recognition of discrete affective states in walking, the states sad and angry are generally more recognizable than the state happy. The states sad and angry highly differ in arousal, whereas arousal is similar for happy and angry, which mainly differ in pleasure. This result leads to the assumption that the dimension arousal is more easily recognizable in walking than pleasure. The dimensions pleasure, arousal, and dominance of the PAD model are highly uncorrelated; therefore, recognition for each dimension is separately investigated. Person-dependent recognition distinguishes between low, medium, and high pleasure, arousal, or dominance. Accuracy is separately calculated for each walker by using NN, and the mean accuracy for each dimension is listed in Table VIII.

Regardless of feature extraction, the mean accuracy for pleasure is lower than the mean accuracy for dominance and arousal. In addition to the expected high accuracy for arousal, different levels of dominance are also well distinguishable in gait patterns. Accuracy reaches 97% for arousal and 96% for dominance when classification is applied to the statistical parameters of all joint angles. The accuracy for individual walkers is shown in Fig. 6 for this case. Different levels of pleasure are less recognizable than different levels of arousal and dominance for most walkers. Depending on the walker, either dominance or arousal is best distinguishable.

The hypothesis that different levels of pleasure are less recognizable in gait patterns for automatic recognition is confirmed. It is concluded that gait can better reveal different levels of arousal and dominance compared to pleasure. This result is also in accordance with human performance (see Section IV).

VII. General Discussion

We have focused on three central aspects with regard to the recognition of affective states in gait patterns: 1) interindividual versus person-dependent recognition; 2) recognition based on discrete affective states versus extremes of the affective dimensions pleasure, arousal, and dominance; and 3) comparison of different feature extraction methods for marker-based gait analysis.

Although interindividual recognition of affective states is accomplishable above chance and in the range of human performance, person-dependent recognition outperforms this method. Extra success, compared to a random predictor, is twice as much. It is concluded that recognition is highly affected by individual walking styles and individual expressions of affect. Identity and affect interact vice versa; therefore, accuracy for identification decreases when classification is performed for affective samples that are not included in the training set.

In accordance with related literature, which studies arm movements, automatic recognition based on gait patterns also tends to recognize affective states that differ in arousal better than states that differ in pleasure [30], [31]. Based on this result, it is concluded that gait is suited for delivering cues about the activation of a walker.

A comparison between PCA and LDA shows that performance depends on the number of features relative to the number of instances in the training set. Improvement in recognition by replacing PCA with KPCA is application dependent.

Last, automatic recognition uses a single stride in contrast to human performance, which is based on videos that last 7 s. The captured gait kinematics have been visualized by an animated puppet; therefore, this case is a potential hint that human perception from 2-D motions is based on techniques that require observations of at least three strides.

Due to its limitations and the fact that people do not always walk, the main application for recognition of affect based on gait is as an additional modality for multimodal recognition of affect. It fills gaps in automatic recognition when neither speech nor facial expression is available or for long-distance observations. Scenarios include high-security systems, human-robot-interaction (e.g., when a human approaches an unknown robot), and affective households.

This paper is based on acted affect; therefore, further studies are required for spontaneous affect. This case automatically requires video-based analysis, because a highly artificial setup for marker-based recording complicates repetitive elicitation of affect during walking. Further potential side aspects of affect recognition from gait patterns include interference by gender, age, weight, and disorders of the walker.

The following challenges have to be accomplished to transfer the recognition of affect in walking from the laboratory to the real world. Still, markerless video-based human motion reconstruction is not as accurate as marker-based systems [16]. Recognition of affect would definitely benefit from further refinement in retrieving detailed motion and, thus, kinematic parameters from video. This paper has shown that good recognition is already achieved using significant kinematic parameters of the upper body in combination with speed and speed-related parameters such as stride length and cadence. Hence, high accuracy in the reconstruction of motion is particularly required for the upper body. Furthermore, recognition is based on the kinematics of one side of the body. Due to the periodic and symmetric nature of gait, kinematics of the other side of the body, if available, can be used to increase accuracy or verification of the measurements, outlier detection, or reconstruction of partially occluded areas. For integration in multimodal emotion recognition systems, the combination with previous action recognition, e.g., [12], is a prerequisite for delivering reliable recognition rates.

VIII. Conclusion

Acted affective states have been distinguishable with techniques from machine learning by observing a single stride. Recognition of affect from walking is influenced by individual walking styles and expression of affect. Person-dependent recognition reaches accuracy above 90% for four affective states. In particular, affective states that differ in arousal are more distinguishable than affective states that differ in pleasure. Comparison between PCA, LDA, and KPCA has shown that although PCA is an unsupervised technique, it outperforms LDA if the number of features is large compared to the number of instances in the training set. Based on these findings, it is concluded that gait can reveal affect for automatic recognition.

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References

[1] R. Picard, *Affective Computing*. Cambridge, MA: MIT Press, 1997.

[2] C. Peter and R. Beale, *Affect and Emotion in Human—Computer Interaction*. New York: Springer-Verlag, 2008.

[3] Z. Zeng, M. Pantic, G. Roisman, and T. Huang, “A survey of affect recognition methods: Audio, visual, and spontaneous expressions,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 31, no. 1, pp. 39–58, Jan. 2009.

[4] H. Gunes and M. Piccardi, “Automatic temporal segment detection and affect recognition from face and body display,” *IEEE Trans. Syst., Man, Cybern. B: Cybern.*, vol. 39, no. 1, pp. 64–84, Feb. 2009.

[5] A. Kale, A. Sundaresan, A. Rajagopalan, N. Cuntoor, A. Roy-Chowdhury, V. Krüger, and R. Chellappa, “Identification of humans using gait,” *IEEE Trans. Image Process.*, vol. 13, no. 9, pp. 1163–1173, Sep. 2004.

[6] T. Chau, "A review of analytical techniques for gait data—Part 1: Fuzzy, statistical and fractal methods," *Gait Posture*, vol. 13, no. 1, pp. 49–66, Feb. 2001.

[7] T. Chau, "A review of analytical techniques for gait data—Part 2: Neural network and wavelet methods," *Gait Posture*, vol. 13, no. 2, pp. 102–120, Apr. 2001.

[8] M. Nixon, T. Tan, and R. Chellappa, *Human Identification Based on Gait*. New York: Springer-Verlag, 2006.

[9] S. Sarkar, P. Phillips, Z. Liu, I. Vega, P. Grother, and K. Bowyer, "The humanID gait challenge problem: Data sets, performance, and analysis," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 27, no. 2, pp. 162–177, Feb. 2005.

[10] L. Wang, T. Tan, H. Ning, and W. Hu, "Silhouette-analysis-based gait recognition for human identification," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 12, pp. 1505–1518, Dec. 2003.

[11] L. Wang and D. Suter, "Learning and matching of dynamic shape manifolds for human action recognition," *IEEE Trans. Image Process.*, vol. 16, no. 6, pp. 1646–1661, Jun. 2007.

[12] D. Kulic, W. Takano, and Y. Nakamura, "Incremental learning, clustering and hierarchy formation of whole-body motion patterns using adaptive hidden Markov chains," *Int. J. Robot. Res.*, vol. 27, no. 7, pp. 761–784, Jul. 2008.

[13] L. Lee and W. Grimson, "Gait analysis for recognition and classification," in *Proc. IEEE Int. Conf. Autom. Face Gesture Recog.*, 2002, pp. 148–155.

[14] N. Boulgouris, D. Hatzinakos, and K. Plataniotis, "Gait recognition: A challenging signal processing technology for biometric identification," *IEEE Signal Process. Mag.*, vol. 22, no. 6, pp. 78–90, Nov. 2005.

[15] J. Han and B. Bhanu, "Individual recognition using gait energy image," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 2, pp. 316–322, Feb. 2006.

[16] T. Moeslund, A. Hilton, and V. Krüger, "A survey of advances in vision-based human motion capture and analysis," *Comput. Vis. Image Underst.*, vol. 104, no. 2/3, pp. 90–126, Nov./Dec. 2006.

[17] E. Rolls, *Emotion Explained*. London, U.K.: Oxford Univ. Press, 2007.

[18] P. Ekman and W. Friesen, "A new pan-cultural facial expression of emotion," *Motivation Emotion*, vol. 10, no. 2, pp. 159–168, Jun. 1986.

[19] J. Russell and A. Mehrabian, "Evidence for a three-factor theory of emotions," *J. Res. Personality*, vol. 11, no. 3, pp. 273–294, Sep. 1977.

[20] J. Mikels, B. Fredrickson, G. Larkin, C. Lindberg, S. Magold, and P. Reuter-Lorenz, "Emotional category data on images from the international affective picture system," *Behavior Res. Methods*, vol. 37, no. 4, pp. 626–630, 2005.

[21] J. Morris, "Observations: SAM: The self-assessment manikin—An efficient cross-cultural measurement of emotional response," *J. Advertising Res.*, vol. 35, pp. 63–68, Nov. 1995.

[22] K. Scherer, *Handbook of Cognition and Emotion*. New York: Wiley, 1999, ch. Appraisal Theory, pp. 637–663.

[23] P. Niedenthal, "Embodying emotion," *Science*, vol. 316, no. 5827, pp. 1002–1005, May 2007.

[24] R. Lazarus, *Emotion and Adaptation*. London, U.K.: Oxford Univ. Press, 1991.

[25] L. Kozlowski and J. Cutting, "Recognizing the sex of a walker from a dynamic point-light display," *Perception Psychophysics*, vol. 21, no. 6, pp. 575–580, 1977.

[26] J. Cutting and L. Kozlowski, "Recognizing friends by their walk: Gait perception without familiarity cues," *Bull. Psychonomic Soc.*, vol. 9, no. 5, pp. 353–356, 1977.

[27] S. Brownlow, A. Dixon, C. Egbert, and R. Radcliffe, "Perception of movement and dancer characteristics from point-light displays of dance," *Psych. Rec.*, vol. 47, pp. 411–421, 1997.

[28] M. Coulson, "Attributing emotion to static body postures: Recognition accuracy, confusions, and viewpoint dependence," *Nonverbal Behavior*, vol. 28, no. 2, pp. 117–139, Jun. 2004.

[29] W. Dittrich, T. Troscianko, S. L. Ans, and D. Morgan, "Perception of emotion from dynamic point-light displays represented in dance," *Perception*, vol. 25, no. 6, pp. 727–738, 1996.

[30] F. Pollick, H. Paterson, A. Bruderlin, and A. Sanford, "Perceiving affect from arm movement," *Cognition*, vol. 82, no. 2, pp. B51–B61, Dec. 2001.

[31] D. Bernhardt and P. Robinson, "Detecting affect from nonstylized body motions," in *Proc. Int. Conf. Affective Comput. Intell. Interaction*, vol. 4738, *LNCS*, 2007, pp. 59–70.

[32] A. Kleinsmith and N. Bianchi-Berthouze, "Recognizing affective dimensions from body posture," in *Proc. Int. Conf. Affective Computing Intell. Interaction*, vol. 4738, *LNCS*, 2007, pp. 48–58.

[33] J. Montepare, S. Goldstein, and A. Clausen, "The identification of emotions from gait information," *Nonverbal Behavior*, vol. 11, no. 1, pp. 33–42, Mar. 1987.

[34] J. Michalak, N. Troje, J. Fischer, P. Vollmar, T. Heidenreich, and D. Schulte, "Embodiment of sadness and depression: Gait patterns associated with dysphoric mood," *Psychosomatic Med.*, vol. 71, no. 5, pp. 580–587, Jun. 2009.

[35] E. Crane and M. Gross, "Motion capture and emotion: Affect detection in whole-body movement," in *Proc. Int. Conf. Affective Comput. Intell. Interaction*, vol. 4738, *LNCS*, 2007, pp. 95–101.

[36] S. Halovic and C. Kroos, "Facilitating the perception of anger and fear in male and female walkers," in *Proc. AISB: Symp. Mental States, Emotions Embodiment*, 2009.

[37] C. Roether, L. Omlor, A. Christensen, and M. Giese, "Critical features for the perception of emotion from gait," *J. Vis.*, vol. 9, no. 6, pp. 1–32, Jun. 2009.

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

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

[40] J. Wu, J. Wang, and L. Liu, "Feature extraction via KPCA for classification of gait patterns," *Hum. Mov. Sci.*, vol. 26, no. 3, pp. 393–411, Jun. 2007.

[41] N. Troje, "Decomposing biological motion: A framework for analysis and synthesis of human gait patterns," *J. Vis.*, vol. 2, no. 5, pp. 371–387, 2002.

[42] 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 patterns," in *Proc. Int. Conf. Affective Comput. Intell. Interaction*, 2009, pp. 195–200.

[43] M. Zuckermann, D. Larrance, J. Hall, R. DeFrank, and R. Rosenthal, "Posed and spontaneous communication of emotion via facial and vocal cues," *Personality*, vol. 47, no. 4, pp. 712–733, Dec. 1978.

[44] P. Lang, "Behavioral treatment and biobehavioral assessment: Computer applications," in *Technology in Mental Health Care Delivery Systems*. Norwood, NJ: Ablex, 1980, pp. 119–l37.

[45] C. Bishop, *Pattern Recognition and Machine Learning*. New York: Springer-Verlag, 2006.

[46] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern Classification*. Hoboken, NJ: Wiley, 2001.

[47] L. van der Maaten, E. Postma, and H. van den Herik, *Dimensionality Reduction: A Comparative Review*, Tilburg, The Netherlands, 2009. Tech. Rep. [Online]. Available: http://www.tilburguniversity.nl/faculties/humanities/ticc/research/technicalreports/TR2009005.pdf

[48] B. Schölkopf, A. Smola, and K.-R. Müller, "Kernel principal component analysis," in *Proc. Int. Conf. Artif. Neural Netw.*, vol. 1327, *LNCS*, 1997, pp. 583–588.

[49] A. Martinez and A. Kak, "PCA versus LDA," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 23, no. 2, pp. 228–233, Feb. 2001.

[50] G. Baudat and F. Anouar, "Generalized discriminant analysis using a kernel approach," *Neural Comput.*, vol. 12, no. 10, pp. 2385–2404, Oct. 2000.

[51] C.-C. Chang and C.-J. Lin, *LIBSVM: A Library for Support Vector Machines*, 2001. [Online]. Available: http://www.csie.ntu.edu.tw/cjlin/libsvm

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