EXPRESSION AND AUTOMATIC RECOGNITION OF EXHAUSTION IN NATURAL WALKING

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ABSTRACT

Besides their function, human body movements express ones personality, intention and emotions, and give cues about a person's condition.
This work focuses on the expression of exhaustion during natural walking. The gait of 14 participants was recorded using 3d optical tracking. Physical exhaustion was induced by performing full-body exercises at a rowing ergometer. A student's t-test analysis of predefined parameters like ankle stroke, range of motion (ROM) of human joints and center of gravity (COG), revealed that, first, there exist significant changes between normal and exhausted gait patterns and, secondly, the expression of exhaustion differs strongly among subjects.
The same data sets were analyzed with techniques from machine learning to investigate if automatic recognition of an exhausted gait is possible. Principle Component Analysis (PCA) and Fourier Transformation were applied to the data set for feature extraction. Linear Discriminant Analysis (LDA), Naive Bayes, K-Nearest Neighbor Clustering (KNN) and Support Vector Machine (SVM) were compared for classification. Classification of exhaustion was achieved with various classifiers, but recognition of an unknown gait is challenging. Without features standardized to normal gait, recognition above chance was accomplished only with K-Nearest Neighbor Clustering.

KEYWORDS

Recognition of Exhaustion, Gait Analysis, PCA, Fourier Transformation, Student's T-Test, Walking

1. INTRODUCTION

Nonverbal communication will play a major role in future robotics. To simplify human machine interaction and to increase intuitive communication, nonverbal signals of humans will be observed and deliver additional cues of a person's mental and physiological state as well as intentions.

Humans use body movement besides speech, mimic and gesture for nonverbal communication. In this work the human gait is investigated in terms of its ability to express exhaustion.

In the recent years, a lot of research has been done to define a normal gait pattern. This is a challenging task as a person's individual gait is as unique as its fingerprint. Furthermore, the gait is influenced by many factors, like age, weight and complaints. How a lot of these factors or combinations of them affect the normal gait is still an open question. Usually, predefined factors, like knee flexion angle, are investigated. In the last years, many machine learning techniques have been applied to various problems in the area of therapeutic support for patients with gait complaints. Also, interest in psychological factors came up and the expression of emotions in human movements has been studied.

In our study, physical exhaustion was induced by full body exercises. Normal and exhausted gaits of participants were recorded and student's t-test revealed that the range of motion (ROM) of the shoulder and the amplitude of the center of gravity (COG) increased significantly during exhaustion. But other predefined parameters, like step length, vary strongly among participants. This leads to the conclusion that exhaustion has a highly individual effect on gait patterns.

In a next step, it was analyzed if machine learning is able to identify common features of exhaustion and if automatic recognition of exhaustion is possible. A feature extraction method, which does not standardize the gait to a person's normal gait, was applied to the data set. It consists of a PCA within the data of one recording, a Fourier Transformation, and a second PCA over all recordings. Finally, different classifiers were applied to the feature vectors. Classification between normal and exhausted gait was achieved with most classifiers, but recognition was a challenging task, because most classifiers did not converge in this case. A recognition rate above chance was reached with 1-Nearest Neighbor Clustering.

This work can contribute to various fields in human machine interaction. Possible application scenarios are monitoring of the physical status of elderly people, detection of exhaustion during laborious work in a cognitive factory or establishing a general gait model which includes the impact of different factors on normal motion.

The remainder of this paper is structured as follows: section 2 gives an overview about psychological research in human body movements. Section 3 describes the experimental setup as well as the methodological procedure. The next section summarizes our results followed by a discussion. In the end, a conclusion is given.

2. STATE OF THE ART

In 1973, Johansson showed that human movement can be displayed by illuminating only the joints of the body. Further studies demonstrated that human observers could recognize actions (Brownlos, 1997), gender (Kozlowski,1977) or even a familiar person (Cuttin, 1977) on the basis of joint movements presented with the "Johansson display".

Barlow (1972) suggested that their might exist a grandfather cell in the human brain which is sensitive to human motion and that an aggregation of these cells would work as feature detector for human motion.

In reference to Kozlowski et al. (1977), human observers can recognize the gender of point-light walkers in the "Johansson display" with a performance of 63% correct classification. Whereas, manipulations like occlusion, increased arm swing or unnatural arm swings reduced the recognition rate. Further experiments of Barclay et al. (1978) showed that at least two complete gait cycles are required to determine gender. Also, alternating the play-back speed of the videos showing point-light walkers reduced recognition rates almost at chance level. Furthermore, representing the point-light walkers upside-down leads to detection of the opposite gender. They followed that this effect is due to different body proportions of men and women. Men tend to have wider shoulders than hips and women tend to have the opposite ratio.

Troje (2002) used two consecutive PCA transformations to extract relevant features from gait data for automatic gender classification. His results showed that dynamic information in the gait patterns contain more reliable diagnostic cues than the structure.

Recent studies deal with motion patterns which express affect. An affect is the subjective experience of a person during an emotion. The emotion self contains 1) physiological turbulence, 2) action tendencies that are not necessary acted out and 3) affect (Lazarus, 1991 p36). Emotions influence ones mimic, speech, gestures, posture and physiological parameters like heart rate. Mimic, speech and gesture are primary indicators and a lot of research is ongoing in these areas.

In 1996, Dittrich et al. investigated the expression of emotions in dance. Point-light videos were recorded from trained dancers, who conveyed the emotions fear, anger, grief, joy, surprise and disgust. Human observers classified the videos to 88% correct. Also, Pollick et al. (2000) showed that the affective states afraid, angry, happy, neutral and sad can be recognized during knocking. The error rate was lower than 29% for presenting full videos.

In the field of affective computing, automatic recognition of emotions is investigated in motions. Kleinsmith et al. (2007) showed that recognition rates of acted postures reached better classification results in dimensional space than for discrete emotional states.

Pollick et al. (2006) recorded data and provided a motion captured data base for analyzing affective states in human motion. The motions are knocking, throwing, lifting and walking. In contrast to many other studies the affective states neutral, happy, angry and sad are non-stylized, i.e. not played by actors. The affective states angry and sad are better recognizable than neutral or happy during non-stylized knocking (Bernhard, 2007).

Barry et al. (2005) followed a quite different approach. They recorded motion data of dancers, captured the emotion expressed by the dancer using a recognition machine, and mapped it to scripted visual effects. Also, Riley et al. (2003) transferred expressions gathered from human motion. They map the recorded movements to motions of a humanoid using a fast full-body inverse kinematics method.

Concerning human gait in terms of exhaustion there is not too much that can be found in literature. Especially there is, to the authors' knowledge, just one paper concerning non-pathologic states of exhaustion during walking in everyday locomotion. In 1934 Spielberg (1934) investigated workers carrying stones and analyzed their gaits before and after work. Reduced step length and a difference in the vertical foot kinematic could be found. Brisswalter et al. (1998), focused on more sports like locomotion, analyzed competition proofed walkers and found step length and foot kinematics strongly affected by exhaustion. Comparable results like decreased step frequency and increased intra-individual variance in knee-kinematics (Candau et al. 1998) or decreased maximum knee flexion angle (Seyfarth et al. 2001) can be found in literature (Verkerke et al. 1998; Le Bris et al. 2006). Nevertheless there is a lack of data dealing with everyday human locomotion during exhaustion although it is known that arising fatigue influences muscular contractile efficiency and proprioceptive properties and therefore the overall outcome of motion (Morris et al. 2002).

Table 1.Automatic recognition of affective states in human body movements.

	Motion	**Affective States**	**Feature Extraction**	**Classification**	**Recog. Rate**
A.Kleinsmith et al. (2007)	Static Posture	Valence, Arousal, Potency, Avoidance, 3 Discrete States for Each Dimension	Non-linear Mixture Discriminant Analysis	Neural Network	90 %
A.Kleinsmith et al. (2007)	Static Posture	Angry, Confused, Fear, Happy, Interest, Relaxed, Sad, Startled and Surprised	Non-linear Mixture Discriminant Analysis	Neural Network	70 %
Bernhardt et al. (2007)	Non-stylized knocking (Pollick, 2001)	Neutral, Happy, Angry, Sad	Energy Function	SVM	83 %
Kapur et al. (2005)	Stylized Body Movements	Sad, Joy, Anger, Fear	Mean of Velocity and Acceleration, Standard Deviation of Position, Velocity and Acceleration	SVM	84 %
Castellano et al. (2007)	Arm Movement Expressivity	Anger, Pleasure, Sadness, Joy	Predefined Features	Nearest Neighbor Clustering	68 %

3. METHOD

3.1 Experimental Setup

The gait of 14 male subjects (mean age 25.3 ± 2.7 years; BMI 23.5 ± 1.9 kg/m^2) before and during exhaustion was recorded with a VICON optical tracking system. 35 passive markers were affixed to the skin of the subjects, where anatomic points define the position, and 6 VICON infrared cameras were used for 3-D recording with a frame rate of 240 Hz. The VICON software provides marker positions and calculated joint angles for further data analysis.

Each participant completed the following procedure. First, the individual gait was recorded three times. Then, each subject performed a standardized warm-up program followed by a maximum power test on a rowing ergometer. After 5 minutes rest, a second maximum test was performed and had to be continued until power decreased below 40% of individual maximum. Exercise length was about 3-4 minutes and subjects reached a mean heart-rate maximum of 178.5 (±9.8) bpm. Then, three consecutive steps of the exhausted subjects were recorded three times.

3.2 Statistic Analysis

As mentioned data was tracked from 3 gait trials in normal and exhausted states respectively. Thereafter, to define specific values of the parameters, means of three gait circles were calculated. All parameters were checked on normal distribution (David-test). For statistical student's t-test analysis, left and right side segments respectively were analyzed each for 7 of the subjects dedicated by accident. Therefore 14 sets (7 left sides and 7 right sides) of kinematic parameters were used. Software programs Microsoft Office Excel 2007 and SPSS for windows (Version 15.0) were used for data processing.

3.3 Feature Extraction and Classification

35 markers in a 3-dimensional space afford a 105 dimensional vector for each time step. As this original data set is redundant, high dimensional and variable, effective feature extraction is crucial for further classification.

For automatic recognition of an unknown gait, we chose a feature selection method which does not require information about an individual's normal gait. Instead of investigating a set of predefined features, we extracted structural and dynamical cues by PCA and Fourier Transformation (FT). The procedure is leant on eigenpostures (EP) and eigenwalkers as proposed by Troje (2002), which is similar to Rosales' and Scarloff's (2000).

First, the variance within the gait of a particular recording defines the eigenpostures. PCA is applied to a person's individual gait pattern. This results in a mean posture vector $\underline{p}_{mean}$ and Principle Components (PCs), each of them is 105 dimensional. The first four PCs, named eigenpostures $\underline{p}_i$, are used for further data analysis according to Troje (2002). The gait of one person at a specific time step can be described by *(1)*

$$\underline{p} = \underline{p}_{mean} + \sum_{i=1}^{4} c_i \underline{p}_i \qquad \text{with} \qquad \underline{p}, \underline{p}_{mean,} \underline{p}_i \in R^{105\times 1} \qquad (1)$$

Dimension reduction is achieved, if only the coefficients c_i of the first four eigenpostures are regarded for each time step. The dynamic information of one individual gait is represented by the changes over time of these coefficients c_i, whose main frequency and phase shift is extracted with FT. The leakage effect was reduced using a Hamming filter. The phase shift of the first eigenposture was always set to zero and the others were adapted. As we used no treadmill for recording, the frequency of the third and fourth eigenposture was not twice the frequency of the first (Troje, 2002). So, we added separate frequencies for the second, third and forth eigenposture to the complete representation for an individual walk. The individual normal or exhausted gait of one person is modeled as follows *(2)*:

$$\underline{p}(t) = \underline{p}_{mean} + \underline{p}_1 \sin(2\pi f_1 t) + \sum_{i=2}^{4} \underline{p}_i \sin(2\pi f_i t + \varphi_i) \qquad (2)$$

In total, the vector w_i of an individual walk contains one main posture vector, four eigenpostures, four frequencies and three phase shifts. Its dimension is 5*105+4+3=531. Thereafter, a second PCA transformation is applied to this representation over all participants. Instead of evaluating a 531 dimensional vector, only the coefficients of the second PCA built the feature vector for classification. The dimension of the feature vector depends on the rank of the input matrix, used for the second PCA, containing the vectors w_i of all participants. The dimension is usually lower than the number of recordings.

Linear Discriminant Analysis, Naive Bayes, 1-Nearest Neighbor Clustering using Euclidean distance and L1 soft-margin Support Vector Machine using a linear kernel with cost value equal 1 (Chang, 2001) were used for classification and recognition of exhausted gait patterns.

4. RESULTS

4.1 Statistic Survey

Following results of kinematic data are described as mean inter-individual differences of the parameters of normal and exhausted states in percent (Fig. 1).

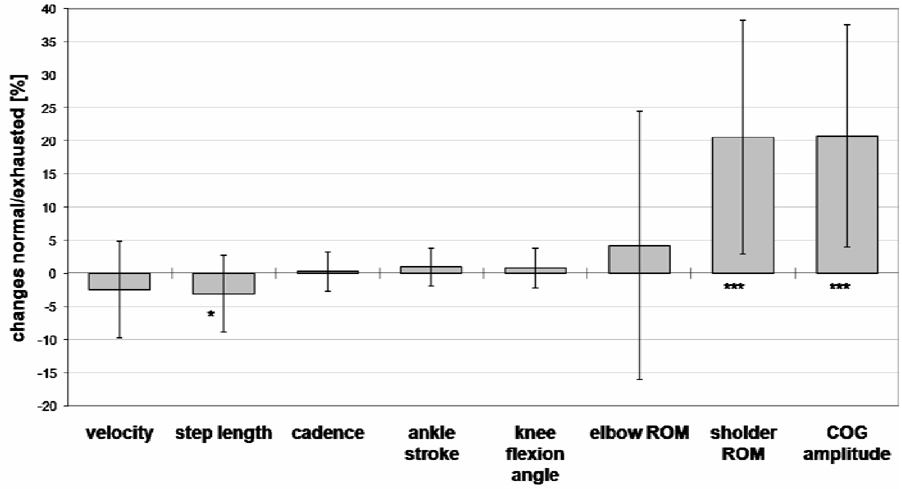


Fig. 1: Mean changes (n=14) of specific gait parameters before and during exhaustion in percent. Significant changes (*) in step length. Highly significant (***) changes in lateral COG (center of gravity) amplitude and shoulder ROM (range of motion) in ante and retroversion.

In exhausted state, gait velocity was reduced about 2.5% with standard deviation of 7.3%. Step length shortened significantly by about 3.1% (± 5.8%). Cadence, ankle stroke and maximum knee flexion angle didn't show any significant differences. ROM of elbow joint increased by 4.2% but with a standard deviation of 20% high individual variances could be found. Increase with high significance could be found in shoulder joint ROM (20.6%; ±17.7) and lateral amplitude of COG (20.7%; ±16.7).

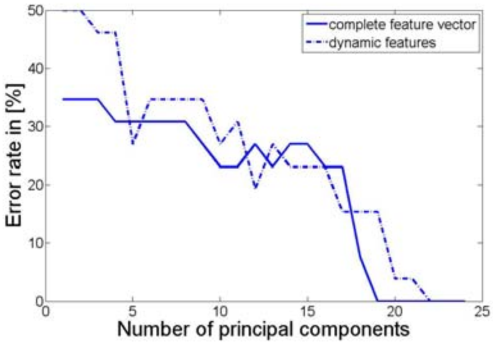
Velocity, step length and cadence are parameters that highly depend on each other. Individual velocity varied dramatically between -17.7% and +8.7% but most subjects (9/14) slowed down in exhausted states. Step length tended to shorten and according to velocity the same 9 subjects reacted the same way to exhaustion. In exhausted state ROM of the shoulder joint increased for all subjects (except one, -13.6%). But the level varied highly from 1.2% to 44.6%. Concerning the ROM of the elbow joint it could be found almost equally both decreased and increased affected by exhaustion ranging from -29.3% to +37.4%. Lateral amplitude of the COG showed similar characteristics as the shoulder joint. Just three subjects had less or no change in lateral amplitude (<3%), whereas the other subjects reacted with an increase of up to 49.6% during exhaustion. Ankle stroke changes between normal and exhausted gait ranged from +5.4% to -4%. Maximum knee flexion angle increased slightly in 10 out of 14 subjects between 1.1% and 3.6%. Decrease was found between 0.4% and 6.3%.

4.2 Automatic Classification and Recognition

As it can be concluded from the previous subsection, exhaustion highly affects an individual's gait. However, the modality of expression for several predefined parameters differs among subjects. This complicates automatic recognition of exhaustion. To overcome this difficulty, several classifiers were tried. Besides Linear Discrimant Analysis (LDA), other classifiers, as 1-Nearest Neighbor Clustering (1NN), Naive Bayes and Support Vector Machine (SVM) were applied to the feature vectors.

First, classification of normal and exhausted gait patterns was analyzed. 100% correct classification was achieved for all classifiers except Naive Bayes. Converging of the classifiers differed. LDA converged to 100% if at least the coefficients of 19 PCs of the second PCA were used as features and if the PCs are ordered according their weights for LDA. SVM converges faster if joint angles are used as input data for feature extraction instead of marker positions. 1-NN Clustering is independent of the number of PCs, because the correct class was assigned to each training set.

Also, the classification performance based on different elements in the feature vector was investigated. Figure 3 and 4 show that 100% correct classification can be achieved, if the complete vector w_i is used for the second PCA. Classification based only on the first, second, third or fourth eigenposture used for the vector w_i led to similar results. The dynamic feature vector contains the complete vector w_i without the mean posture.



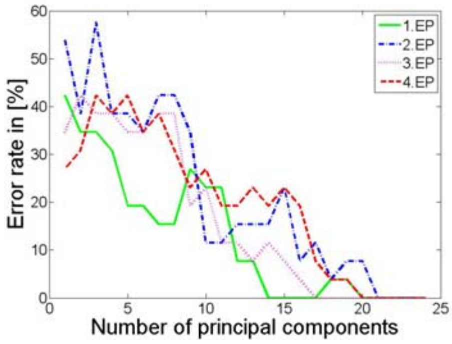


Fig. 3 & 4: Classification of exhausted and normal gait patterns was achieved, if the number of principle components of the second PCA is increased. In this case, LDA was used for classification and the input data was marker positions. The feature vector can contain all elements of w_i, or only separate eigenpostures. The vector w_i contains all elements except the mean posture for calculating the dynamic feature vector.

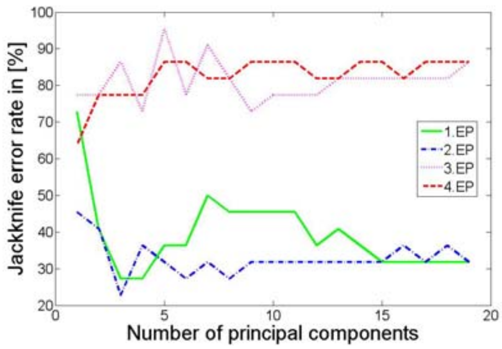


Fig. 5: For KNN Clustering, the recognition rate converges if the number of PCs increases. Also, the first and the second PC seem to contain most information for recognition of exhaustion. In this case, joint angles were used as input for feature extraction.

The more interesting case was recognition of an unknown gait pattern. The jackknife procedure, which takes one data set as sample and the others as training data and iterates the sample set through the complete data set, was used to calculate the recognition error. In this case, most classifiers except KNN did not converge. If marker positions are used for feature extraction, most variance in the data set is along the locomotion from one side of the hall to the other. Though the joint angle representation is approximated to fit the Plug-in Gait Model, recognition results are similar. Further Eigenpostures are orthogonal to the first and differ, if marker positions or joint angles are used for feature extraction.

Complete data sets were required for automatic classification. As 2 exhausted data sets were incomplete, the classification rate based only on prior probabilities was shifted to 54% (accordingly 55% for joint angle representation due to 4 incomplete normal and 2 incomplete exhausted data sets).

Table 2 gives an overview about the achieved classification and recognition rates.

Table 2. Recognition and Classification Rates for different classifiers. The symbol ⦸ indicates that the classifier did not converge and the symbol * is used for those classifiers, for which classification rate is independent of the number of PCs.

	Input Data	Classification	Recognition	Features
LDA	Marker Position	100 % (19PC)	⦸	All
Naïve Bayes	Marker Position	96 %	⦸	All
1NN	Marker Position	100 % *	65 %	2. Eigenposture
1NN	Joint Angles	100 % *	68 %	1. Eigenposture
SVM	Marker Position	100 % (14PC)	⦸	All
SVM	Joint Angles	100 % (14PC)	⦸	All

5. DISCUSSION

The results of the statistical study demonstrate both significant inter-individual as well as intra-individual changes in specific parameters between normal and exhausted human gait. Especially lateral alteration of COG and ROM of the shoulder joint appears to be good signs to detect exhaustion in human gait. The fact that there was a great variance in how subjects reacted to exhausted states shows that walking has an extremely individual occurrence. We conclude from our results that for the bigger part of parameters exhaustion is not defined as a change in a specific direction but as total change in an individual dimension. Exhaustion therefore extremely influences human gait but the outcome of disturbance of the individual coordination control is hard to classify.

PCA in combination with FT was used to classify normal and exhausted gait. As most classifiers failed to recognize an unknown gait pattern, it is suggested that the feature extraction method must be improved. Possible candidates are Independent Component Analysis (ICA) instead of PCA. Also, feature extraction based on knowing the normal gait of a person instead of a blind classifier can improve the results. Then, the features represent the difference of a person's normal gait to its exhausted gait. However, as most parameters differ among persons, this is also not trivial. Also, the normal gait of a person must be known in advance.

Another point to discuss is the way to induce exhaustion. As mentioned by Chabran et al. (2002) the term "fatigue" (as a synonym for exhaustion in Chabran's study) covers multiple events so that the effects and the nature of fatigue are highly dependent on the task used to induce the phenomenon (Enoka & Stuart 1992). According to this there might be different results analyzing human gait in exhausted state when induced by running on a treadmill or cycling but nevertheless we think there will be significant changes in specific parameters of human gait as well. Hence, in order to find analogies concerning the influence of different states of exhaustion on human gait parameters additional investigations in future research should be done.

6. CONCLUSION

Though it is difficult for a human observer to distinguish between a normal and an exhausted gait shown in a point light display without further information like respiration frequency, significant changes in the gait patterns occurred. Statistical student's t-test analysis revealed that among participants these changes were cancelled out, because most participants reacted individually to exhaustion. It concludes that exhaustion is usually an aberration of the normal, highly coordinated gait and differs within individuals.

This complicates automatic recognition, as identical gait patterns for exhaustion are hardly obvious. A feature extraction method based on PCA and Fourier Transformation was used to classify the gait of normal and exhausted walkers. Different classifiers were tried. All, except Naive Bayes achieved 100 % correct classification. As the expression of exhaustion is particular for each person, recognition of exhaustion in an unknown gait pattern was more challenging. With 1-Nearest Neighbor Clustering a recognition rate of 68 % was achieved.

Further improvement can be gained, if instead of PCA Independent Component Analysis (ICA) is used for feature extraction, so that elements in which the data sets differ most built the feature vector. Also, classification, based on person-individual features can improve recognition, but therefore the normal gait of a person is to be known first. Furthermore, statistical analysis of velocity, speed and acceleration might reveal further features.

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