# IDENTIFICATION OF FATIGUE-RELATED KINEMATIC CHANGES IN ELITE RUNNERS USING A SUPPORT VECTOR MACHINE APPROACH

**Bernd J. Stetter[1], Felix Möhler[1], Frieder C. Krafft[1], Stefan Sell[1,2], Thorsten Stein[1]**

**Institute of Sports and Sports Science, Karlsruhe Institute of Technology, Karlsruhe, Germany[1]**
**Joint Center Black Forest, Hospital Neuenbuerg, Neuenbuerg, Germany[2]**

Understanding the kinematic changes underlying fatigue is essential in running biomechanics. The aim of this study was to identify fatigue-related kinematic changes in elite runners using a support vector machine approach. Full-body kinematics of thirteen trained runners were recorded in a non-fatigued and a fatigued state during treadmill running at their individual fatigue-speed. A support vector machine was trained and used to identify kinematic differences between the non-fatigued and fatigued state based on principal component scores. Strides during non-fatigued and fatigued running could be separated with 99.4% classification accuracy. Four upper limb (two shoulder and two elbow), four lower limb (one ankle, two knee and one hip) and two trunk (one thoracic and one lumbar spine) principal component scores were identified as most discriminative kinematic features between non-fatigued and fatigued running. The findings of the study suggest the feasibility of a support vector machine approach to identify subtle fatigue-related kinematic changes in elite runners.

**KEYWORDS:** Running biomechanics, fatigue, motion analysis, machine learning.

**INTRODUCTION:** Long-distance running is performed by people of all ages and from recreational to elite level. Running kinematics are of interest for coaches and sport scientists, as they have a great potential for evaluating technical adaptations or risk factors for injuries. Although fatigue-related kinematic changes in elite runners are considered to be small (Maas et al., 2018), they may contain significant information with respect to related injuries (Phinyomark et al., 2015). So far, only a limited number of studies in elite runners on fatigue-related kinematic changes exist and findings are inconsistent (Möhler et al., 2019; Maas et al., 2018). Most studies have focused on recreational runners and have primary shown fatigue-induced alterations in knee and hip flexion, ankle plantar flexion as well as trunk flexion (Maas et al., 2018). These changes were typically analyzed on discrete 3-dimensional (3D) kinematic variables using univariate and multivariate statistical methods.
In recent years, several analysis approaches based on machine learning, such as support vector machines (SVM), have been applied to comprehensively investigate age, gender, performance and injury-related effects in running kinematics (Nigg et al., 2012; Clermont et al., 2019). The use of such vector-based methods allows to compare the data of the entire stride as well as for systematic differences to be characterized. Janssen et al. (2011) used a SVM to diagnose fatigue in gait patterns with high probability (98.1%). Additionally, Clermont et al. (2019) presented the usability of a SVM approach, in combination with a principal component analysis (PCA) to classify higher- and lower-mileage runners (classification accuracy 92.6%). To the authors' knowledge, these methods have never been applied to examine fatigue-induced differences in running kinematics in elite runners. Thus, the purpose of this study was to investigate fatigue-related kinematic changes in elite runners by a SVM approach.

**METHODS:**
Thirteen healthy experienced runners (age 23.5 ± 3.6 years; height 1.80 ± 0.06 m; body mass 66.8 ± 5.4 kg; weekly training 6.5 ± 1.7 hours; 10 km record 32:59 ± 01:19 min) participated in this study. The individual fatigue speed (FS), the speed which a participant should be able to run for a maximum of 10 min, was determined one-week prior the biomechanical testing, using a lactate threshold test and the critical power concept (Monod & Scherrer, 1965). Biomechanical testing was performed on a treadmill. Initially, the participants walked 6 minutes followed by a 6 minutes run to get familiarized and warmed up. Subsequently, participants ran

at their individual FS (19.27 ± 0.72 km/h on average) until exhaustion. A motion capture system (200 Hz, Vicon Motion Systems; Oxford Metrics Group, Oxford, UK) was used to record full body kinematics of 19 consecutive strides at two time points: First, 15 s after the treadmill reached FS (non-fatigued state) and second, about 20 s prior to exhaustion (fatigued state). Data were processed using Vicon Nexus software and a 10Hz low-pass filter (fourth order Butterworth filter). Joint angles were calculated using the ALASKA-full-body Dynamicus model (insys GmbH, Chemnitz, Germany) and each stride (from right foot strike to right foot strike) was time normalized to 100 time steps. Foot strikes were identified as the point in time when the vertical speed of the heel or foot marker changed its sign (Leitch et al., 2011).
The subsequent analysis combined a PCA for feature selection with a SVM for classification (Nigg et al., 2012; Clermont et al., 2019). The main intention of the PCA was to obtain a lower-dimensional representation of the joint angle waveforms, due to the fact that there exists a high risk of overfitting when using a SVM on a data set, which contains a high number of features relative to the number of observations (Mohr et al., 2019). The data from all participants (13 runners x 19 strides x 2 states = 494 observations) were concatenated and a PCA was separately applied to each of the 47 joint angle waveforms (4 x 2-dimensional joints + 13 x 3D joints). Thereby, the original data were transformed into a set of uncorrelated variables, i.e. the principal components (PCs). PC scores were calculated for the PCs that retained 80% (Meyer et al., 2015) of the individual joint angle waveform by projecting the data on these PCs. This led in total to 62 features (the number of features was waveform-specific and ranged from one to three for the individual joint angle waveform) for the further SVM analysis.
A matrix was created based on the PC scores with 494 rows that represented the observations and 62 columns that represented the features. This matrix was standardized by subtracting the individual means and dividing it by standard deviations. The standardized matrix served as input for the SVM analysis. A linear-kernel SVM was used to classify strides by determining the optimal separating hyperplane, which maximized separation between the data of the two states (non-fatigued and fatigued). A leave-one-out cross-validation method was used to assess the statistical significance and generalization of the SVM (Mohr et al., 2019). The cross-validation involved training the SVM with all strides from 12 runners and then testing with the strides from the remaining runner. The classification rate (CR) was determined for each cross-validation iteration, as the number of correctly predicted test observations divided by the number of strides. A single CR was computed by averaging the CR from the 13 cross-validation iterations. A binomial test was used to assess whether the CR is statistically higher than chance. Since our study was motivated by a biomechanical interest in fatigue-related kinematic changes in running, we interpreted the ten PCs with the highest loading for the classification by going back to the joint angle waveforms. Therefore, absolute loadings of the returned discriminant vector, pointing in the direction of the largest difference between the data for the two running states, were calculated and PCA transformations reversed.

**RESULTS:** Runners reported their perceived fatigue as 19.6 ± 0.7 on a Borg Scale (maximum exertion = 20). The 47 joint angle waveforms that were used for PCA led to a total of 62 retained PCs. According to the leave-one-out cross-validation, 99.4% of strides were classified correctly with respect to the running state (non-fatigued or fatigued) ($p<0.05$). Table 1 illustrates the top ten PCs according to their loading on the discriminant vector. This set comprises 4 upper limb PCs, 4 lower limb PCs, and 2 trunk PCs. Figure 1 represents the raw waveform, the loading vector and the single PC reconstruction for a representative upper limb, lower limb, and trunk joint angle.

**DISCUSSION:** This study aimed to reveal fatigue-related kinematic changes in elite runners using a SVM approach on joint angle waveforms. The analysis of the SVM discriminant loadings in combination with the back transformation to the joint angle waveforms, allows a biomechanical interpretation of fatigue-related kinematic changes. The results of the study demonstrated that distinct lower limb, upper limb and trunk kinematic differences exist between running in a non-fatigued and fatigued state. Differences occurred across the sagittal, frontal

**Table 1: Top ten PCs (out of 62) ranked in descending order following the absolute discriminant vector loading of the SVM. Means are calculated based on the PC reconstructions.**

| Principal component (PC) | Discriminant vector loading [a.u.] | Mean non-fatigued state (SD) [°] | Mean fatigued state (SD) [°] | Explained variance [%] |
|---|---|---|---|---|
| 1. Shoulder, sagittal, right, PC1 | 0.414 | -14.99 (2.51) | -13.20 (2.26) | 92.8 |
| 2. Elbow, horizontal, left, PC2 | 0.278 | 1.10 (0.53) | 1.15 (0.50) | 22.5 |
| 3. Ankle, frontal, left, PC1 | 0.250 | -5.25 (1.80) | -4.79 (1.73) | 80.1 |
| 4. Shoulder, horizontal, right, PC1 | 0.243 | 24.80 (14.83) | 24.78 (15.02) | 96.1 |
| 5. Knee, horizontal, right, PC2 | 0.225 | 0.13 (0.66) | 0.10 (0.67) | 11.8 |
| 6. Elbow, horizontal, left, PC1 | 0.225 | 0.28 (19.98) | 2.52 (20.53) | 73.5 |
| 7. Thoracic spine, horizontal, PC1 | 0.188 | 0.64 (0.12) | 0.73 (0.15) | 93.0 |
| 8. Lumbar spine, horizontal, PC1 | 0.174 | 0.04 (0.01) | 0.04 (0.01) | 92.5 |
| 9. Knee, frontal, left, PC1 | 0.170 | -0.15 (4.25) | -0.21 (4.57) | 75.8 |
| 10. Hip, sagittal, left, PC1 | 0.166 | 8.93 (0.68) | 9.30 (0.70) | 95.7 |

and horizontal plane. These results support previous studies that reported differences on discrete 3D kinematic variables (Koblbauer et al., 2014, Chan-Roper et al. 2012). Koblbauer et al. (2014) described an increase in trunk inclination experienced during running-induced fatigue in novice runners. The observed changes in trunk motion (thoracic and lumbar spine)

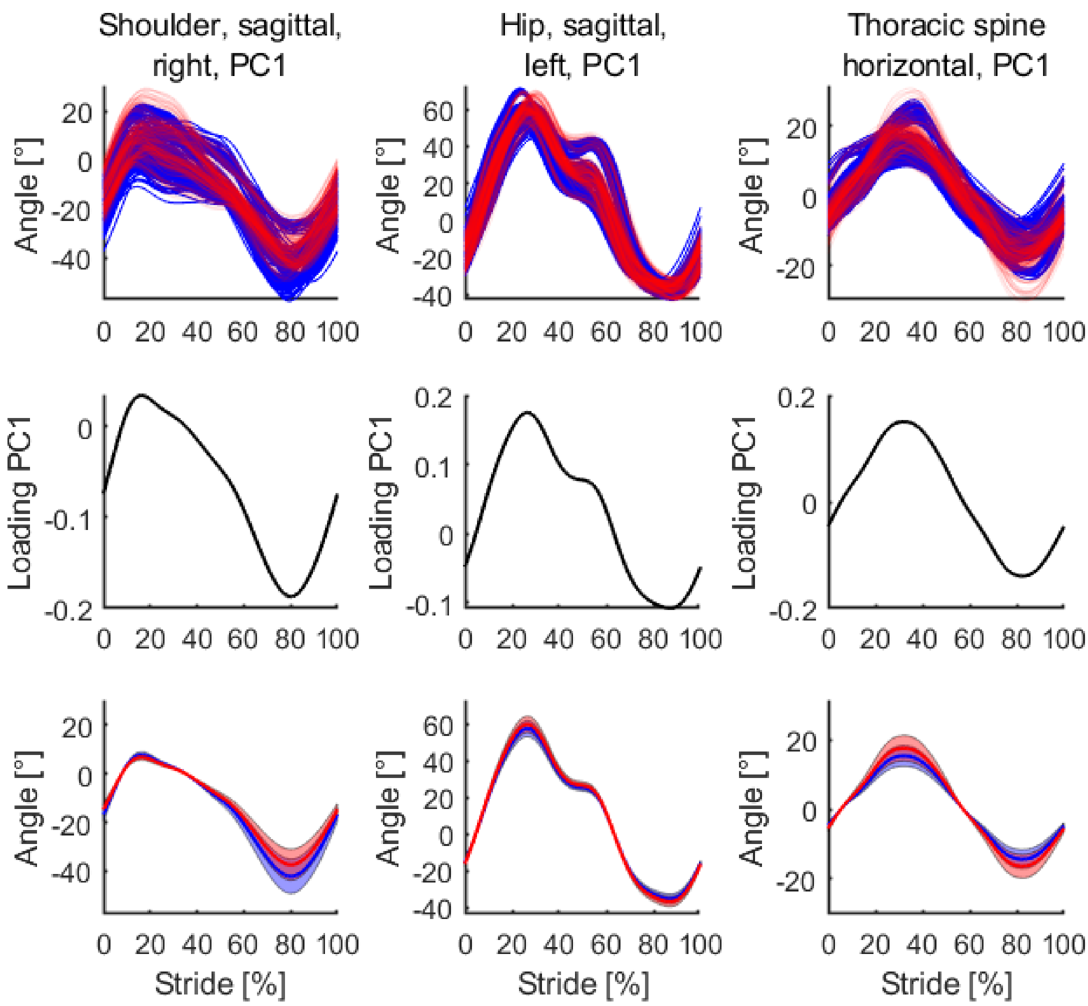


**Figure 1: Joint angle waveforms (top), PC loading vectors (middle) and the single PC reconstructions (bottom) for three exemplary PCs. The blue and red color reflect the non-fatigued and fatigued state, respectively. The PC reconstructions are presented as mean and standard deviation.**

in this study reflect similar fatigue-related adaptations. The mean increase of hip flexion in the fatigued state (fatigued state 9.30 ± 0.70 vs non-fatigued state 8.93 ± 0.68) is supported by Chan-Roper et al. (2012). Previously identified changes in sagittal knee kinematics (Chan-Roper et al., 2012) were not observed among the top ten PCs to discriminate the non-fatigued and fatigued state. Although observed absolute kinematic changes were small (e.g., increase of mean hip flexion angle = 4.1%), the SVM classified strides correctly (CR = 99.4%), with respect to the non-fatigued or fatigued running state. Comparable or slightly lower classification rates were shown in previous applications, e.g., classifying fatigue in gait (CR = 98.1%) (Janssen et al., 2011) or separating higher- and lower-milage runners (CR = 92.6%) (Clermont et al., 2019). By focusing on observed results, although elite runners show less pronounced changes in running kinematics with fatigue compared to novice runners (Maas et al, 2018), fatigue-related kinematic changes were found to be of systematic nature. Consequently, fatigue-related kinematic changes might contain valuable information with respect to running performance or running-related injuries.

**CONCLUSION:** The application of a SVM on full body kinematics proved to be capable to discriminate running between a fatigued and non-fatigued state. The high classification rate indicated the significance of biomechanical differences due to fatigue in elite runners. Discriminative kinematic features were identified on the upper and lower body. Fatigue-related kinematic changes might be associated with the loading of body structures and may help to understand potential biomechanical changes due to overuse. Future research is requested on the combination of the presented approach with wearable measurement technology. Consequently, fatigue-related kinematic changes could be identified under field conditions and could be taken into account by athletes and coaches when analyzing training adaptations and/or a runner's injury risk.

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