Systematic Comparison of the Influence of Different Data Preprocessing Methods on the Classification of Gait Using Machine Learning

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ABSTRACT

Human movements are characterized by highly non-linear and multi-dimensional interactions within the motor system. Therefore, the future of human movement analysis requires procedures that enhance the classification of movement patterns into relevant groups and support practitioners in their decisions. In this regard, the use of data-driven techniques seems to be particularly suitable to generate classification models. Recently, an increasing emphasis on machine-learning applications has led to a significant contribution e.g. in increasing the classification accuracy. In order to ensure the generalizability of the machine-learning models, different data preprocessing steps are usually carried out to process the measured raw data before the classifications. In the past, various methods have been used for each of these preprocessing steps. However, there are hardly any standard procedures or rather systematic comparisons of these different methods and their impact on the classification accuracy. Therefore, the aim of this analysis is to compare different combinations of commonly applied data preprocessing steps and test their effects on the classification accuracy of gait patterns.

A publicly available dataset on intra-individual changes of gait patterns was used for this analysis. Forty-two healthy subjects performed 6 sessions of 15 gait trials for one day. For each trial, two force plates recorded the three-dimensional ground reaction forces (GRF). The data was preprocessed with the following steps: GRF filtering, time derivative, time normalization, data reduction, weight normalization and data scaling. Subsequently, combinations of all methods from each individual preprocessing step were analyzed and compared with respect to their prediction accuracy in a six-session classification using Support Vector Machines, Random Forest Classifiers and Multi-Layer Perceptrons.
The results indicate that filtering GRF data and a supervised data reduction (e.g., using Principal Components Analysis) lead to increased prediction accuracies of the machine-learning classifiers. Interestingly, the weight normalization and the number of data points (above a certain minimum) in the time normalization does not have a substantial effect. In conclusion, the present results provide first domain-specific recommendations for commonly applied data preprocessing methods and might help to build more comparable and more robust classification models based on machine learning that are suitable for a practical application.

Keywords: gait classification, data selection, data processing, ground reaction force, jerk, artificial neural network, support vector machine, random forest

1 INTRODUCTION

Human movements are characterized by highly non-linear and multi-dimensional interactions within the motor system (Wolf et al., 2006; Chau, 2001a). In this regard, the use of data-driven techniques seems to be particularly suitable to generate predictive and classification models. In recent years, different approaches based on machine-learning techniques such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs) or Random Forest Classifiers (RFCs) have been suggested in order to support the decision making of practitioners in the field of human movement analysis, e.g. in classifying movement patterns into relevant groups (Figueiredo et al., 2018; Schöllhorn, 2004). Most machine-learning applications in human movements are found in human gait using biomechanical data (Phinyomark et al., 2018; Figueiredo et al., 2018; Schöllhorn, 2004; Halilaj et al., 2018; Ferber et al., 2016). Although it is generally striking that there are more and more promising applications of machine learning in the field of human movement analysis, the applications are very diverse and differ in their objectives, samples and classification. In order to fulfill the application requirements and to ensure the generalizability of the results, a number of stages are usually carried out to process the raw data in classifications using machine learning. Typically, machine-learning classifications of gait patterns consist of a preprocessing and a classification stage (Figueiredo et al., 2018).

The preprocessing stage can be distinguished in feature extraction, feature normalization, and feature selection. The classification stage includes cross validation, model building and validation, as well as evaluation. Different methods have been used for each stage and there is no clear consensus on how to proceed in each of these stages. This is particularly the case for the preprocessing stages of the measured raw data before the classification stage, where there are hardly any recommendations, standard procedures or systematic comparisons of these different preprocessing stages and their impact on the classification accuracy (Slijepcevic et al., 2019). The following six steps, for example, can be derived from the preprocessing stage: (1) Ground reaction force (GRF) filtering, (2) time derivative, (3) time normalization, (4) data reduction, (5) weight normalization, and (6) data scaling.

(1) There are a number of possible noise sources in the recording of biomechanical data. Noise can be reduced by careful experimental procedures, however, cannot be completely removed (Challis, 1999). So far there is less known about optimal filter-cut-off frequencies in biomechanical gait analysis (Schreven et al., 2015), an optimal range in which a general optimal cut-off frequency could lie and the effect of GRF filtering on the accuracy of machine-learning classification.

(2) In the majority of cases, time-continuous waveforms or time-discrete gait variables are measured and used for the classification (Schöllhorn, 2004; Figueiredo et al., 2018). Although, some authors also used time derivatives or data in the frequency or frequency-time domain from time-continuous waveforms (Schöllhorn, 2004; Figueiredo et al., 2018). A transformation, which has barely been applied so far, is the first-time
derivative of the acceleration, the jerk. However, the jerk might describe human gait more precisely than velocity and acceleration, especially when the GRFs are measured. The jerk can be determined directly by calculating the first-time derivative of the GRF measured by force plates.

(3) Feature normalization has been applied in order to achieve more robust classification models (Figueiredo et al., 2018). A normalization in time is commonly applied to normalize the biomechanical waveforms as percentage of the step, stride or stance phase (Alaqtash et al., 2011a,b; Zhang et al., 2014; Eskofier et al., 2013; Kaczmareczyk et al., 2009). It is differentiated among other things between 101 points in time (Eskofier et al., 2013), 1000 points in time (Slijepcevic et al., 2017) or the percentage occurrence per step cycle (Su and Wu, 2000).

(4) The purpose of data reduction is to reduce the amount of data to the most relevant features. A dimensionally reduction is often performed in order to determine which data is to be retained and which can be discarded. The use of dimension reduction can speed up computing time or reduce storage costs for data analysis. However, it should be noted that these feature selection approaches can not only reduce computation costs, but could also improve the classification accuracy (Phinyomark et al., 2018). Beside the unsupervised selection of single time-discrete gait variables (Schöllhorn, 2004; Begg and Kamruzzaman, 2005), typical methods for reducing the dimensionality of the data is, for example, the Principal Component Analysis (Eskofier et al., 2013; Badesa et al., 2014; Lee et al., 2009; Deluzio and Astephen, 2007).

(5) Another way of feature normalization is weight or height normalization. Weight and height normalizations in amplitude are a frequently used method to control for inter-individual differences in kinetic and kinematic variables (Wannop et al., 2012). To what extent the multiplication by a constant factor influences the classification has not yet been investigated to the best of our knowledge.

(6) A third way of feature normalization is data scaling. Data scaling is often performed to normalize the amplitude of one or different variable time courses (Laroche et al., 2014; Mao et al., 2008). The z-score method is mainly used (Begg et al., 2005; Begg and Kamruzzaman, 2005). In machine learning, scaling to a variable or variable waveform the interval 0 to 1 or -1 to 1 is common in order to minimize amplitude-related weightings when training the classifiers (Hsu et al., 2016). To the best of our knowledge, it has not yet been investigated whether it makes a difference to scale over a single gait trial or over all trials of one subject in one session.

In summary, there has been a lack of domain-specific standard procedures and recommendations, especially for the various data preprocessing steps commonly applied before machine-learning classifications. Therefore, the aim of this analysis is to compare different commonly applied data preprocessing steps and examine their effect on the classification accuracy using different machine-learning classifiers (ANN, SVM, RFC). A systematic comparison is of particular interest for deriving domain-specific recommendations, finding best practice models and the optimization of machine-learning classifications of human gait data. The analysis is based on the classification problem described by Horst et al. (2017), who investigated intra-individual gait patterns across different time-scales over one day.

2 MATERIALS AND METHODS

2.1 Sample and experimental protocol

The publicly available dataset on intra-individual changes of gait patterns by Horst et al. (2019, 2017) and two unpublished studies (Daffner, 2018; Hassan, 2019) following the same experimental protocol were used for this analysis. In total, the joint dataset consisted of 42 physically active participants (22 females,
20 males; 25.6 ± 6.1 years; 1.72 ± 0.09 m; 66.9 ± 10.7 kg) without gait pathology and free of lower extremity injuries.

**Figure 1.** Experimental procedure with the chronological order of the six sessions (S1-S6) and the duration of the rest periods between subsequent sessions.

As presented in Figure 1, the participants performed 6 sessions (S1-S6) of 15 gait trials in each session, while there was no intervention between the sessions. After the first, third and fifth session, the participants had a break of 10 mins until the beginning of the subsequent session. Between S2 and S3 was a break of 30 mins and between S4 and S5 the break was 90 mins. The participants were instructed to walk a 10-meter-long path at a self-selected speed barefooted. For each trial, three-dimensional GRFs were recorded by means of two Kistler force plates of type 9287CA (Kistler, Switzerland) at a frequency of 1000 Hz. The Qualisys Track Manager 2.7 software (Qualisys AB, Sweden) managed the recording. During the investigation, the laboratory environment was kept constant and each subject was analyzed by the same assessor only. The full description of the experimental procedure can be found in the original study (Horst et al., 2017).

### 2.2 Data processing

The stance phase of the right and left foot was determined using a vertical GRF threshold of 20 Newton. Different combinations of commonly used data preprocessing steps, which typically precede machine-learning classifications of biomechanical gait patterns have been compared (Figure 2). Within the introduced stage of preprocessing, the following six data preprocessing steps were investigated: (1. GRF filtering) comparing filtered and unfiltered GRF data. The method described by Challis (1999) was used to determine the optimal cut-off frequencies ($f_c$) for the respective gait trials. The optimal filter frequencies were calculated for each foot and each of the three dimensions in each gait trial separatively. (2. Time derivative) comparing the recorded GRF and the first-time derivative of the GRF, the jerk. The jerk was calculated by temporally derivating the GRF for each time interval. (3. Time normalization) comparing the number of time points for the time normalization to the stance phase. Each variable was time normalized to 11, 101 and 1001 data points, respectively. (4. Data reduction) comparing non-reduced, time-continuous waveforms (TC), time-discrete gait variables (TD) and principle components by a reduction using Principal Component Analysis (PCA) applied to the time-continuous waveforms. The resulting features, i.e. the main components explaining 98% of the total deviation, were retained in the input data. The time-discrete gait variables of the fore-aft and medio-lateral shear force were the minimum and the the maximum values as well as their occurrence during the stance phase, and of the vertical force the minimum and the two local maxima values as well as their occurrence during the stance phase. This resulted in 28 time-discrete gait variables for GRF data and 24 time-discrete gait variables for jerk data. (5. Weight normalization)
comparing whether weight normalization to the body weight of every session was performed or not. The normalization to the body weight before every season would exclude the impact of any changes in the body mass during the investigation. (6. Data scaling) comparing different data scaling techniques. Scaling is a common procedure for data processing prior to classifications of gait data (Chau, 2001a,b). It was carried out to ensure an equal contribution of all variabilities to the prediction accuracies and to avoid dominance of variables with greater numeric range (Hsu et al., 2016). On the one hand, this involved a z-transformation over all trails and one over each single trail combined with a scaling to the range of -1 to 1 (Hsu et al., 2016), determined over all trails or over each single trail. The combination of these amplitude normalizations results in four different scaling methods.

**Figure 2.** Combinations of commonly used data preprocessing steps before machine-learning classifications. (1) Data points per foot and dimension. (2) Time-continuous waveforms without reduction (TC), time-discrete gait variables by an unsupervised reduction (TD) and principle components by a supervised reduction using Principal Component Analysis (PCA). (3) Z-transformation combined with scaling from -1 to 1 over single trails (ST) or all trials (AT). $f_c$: individual optimal filter cut-off frequency. (4) Jerk: first-time derivative of GRF.

The data preprocessing was managed within Matlab R2017b (MathWorks, USA) and all combinations of each methods of each data preprocessing and classification step were performed in the current analysis in the order described in Figure 2. In total, the analysis included 432 different combinations of data preprocessing and classification step methods (432 = 2 GRF filtering $\times$ 2 Time derivative $\times$ 3 Time normalization $\times$ 3 Data reduction $\times$ 2 Weight normalization $\times$ 4 Data scaling $\times$ 3 Classifier). In the two methods TD and PCA for data reduction, the data scaling could not be applied for all methods. In many cases, all values of a time-discrete gait variable or a principle component were identical (Figure 2: Data scaling: z: ST or [-1, 1]: ST) and thus no variance occurred, which is necessary for the calculation of the data scaling. Only, the data scaling over all trials from one subject (Figure 2: Data scaling: z: AT, [-1, 1]: AT) could be performed for all three methods of data reduction. In order to keep the number of considered combinations the same for all methods of a data preprocessing step, only the data scaling of all attempts of one subject (Figure 2: Data scaling: z: AT, [-1, 1]: AT) was considered for the descriptive and statistical analysis in the results section. This scaling also led to by far the best prediction accuracies. Consequently, 216 different combinations of data preprocessing and classification step methods (216 = 2 GRF filtering $\times$ 2 Time derivative $\times$ 3 Time normalization $\times$ 3 Data reduction $\times$ 2 Weight normalization $\times$ 1 Data scaling $\times$ 3 Classifier) were compared quantitatively with each other on basis of the prediction accuracy.

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2.3 Data classification

The intra-individual classification of gait patterns was based on the 90 trails (90 = 6 sessions x 15 trials) of each participant. For each trial, a concatenated vector of the three-dimensional variables of both force plates was used for the classification. Due to the different time normalization and data reduction methods, the resulting length of the input feature vectors differed (Table 1).

Table 1. Length of the resulting input feature vectors depending on different combinations of preprocessing methods.

| Data reduction | Time normalization | Time derivative | GRF filtering | Length of input feature vector |
|----------------|--------------------|----------------|--------------|-------------------------------|
| TC             | 11                 | GRF; Jerk      | No; Yes      | 66 = 11 * 3 * 2               |
|                | 101                | GRF; Jerk      | No; Yes      | 606 = 101 * 3 * 2             |
|                | 1001               | GRF; Jerk      | No; Yes      | 6006 = 1001 * 3 * 2           |
| TD             | 11; 101; 1001      | GRF            | No; Yes      | 28 = 7 * 2 * 2                |
|                |                    | Jerk           | No; Yes      | 24 = 6 * 2 * 2                |
| PCA            | 11                 | GRF            | No           | 46 (44,47)                    |
|                |                    | Jerk           | Yes          | 47 (44,48)                    |
|                | 101                | GRF            | No           | 78 (73, 83)                   |
|                |                    | Jerk           | Yes          | 72.5 (69, 79)                 |
|                | 1001               | GRF            | No           | 79 (73, 84)                   |
|                |                    | Jerk           | Yes          | 72 (68, 79)                   |
|                | 1001               | GRF            | No           | 369 (341, 386)                |
|                |                    | Jerk           | Yes          | 108 (97, 120)                 |

Note: TC: time-continuous waveforms for three dimensions (*3) and two steps (*2); TD: time-discrete gait variables of minima and maxima of the three dimensions (GRF: 7; Jerk: 6) for two steps (*2) and their relative occurrences (*2); PCA: Median and interquartile distance of the number of principle components.

The classification based on the following three supervised machine-learning classifiers with an exhaustive hyper-parameter search: (1) Support Vector Machines (SVMs) (Boser et al., 1992; Cortes and Vapnik, 1995; Müller et al., 2001; Schölkopf and Smola, 2002) using a linear kernel and a grid search to determine the best cost parameter \( C = 2^{-5}, 2^{-4.75},..., 2^{15} \). (2) Random Forest Classifiers (RFCs) (Breiman, 2001) with the Gini coefficient as decision criterion. Different numbers of trees \( (n_{estimators} = 200, 225,..., 350) \) and maximal tree depth \((n_{depth} = 4, 5,..., 8)\) were determined empirically via grid search. (3) Multi-Layer Perceptrons (MLPs) (Bishop, 1995) with one hidden layer of size \( 2^6 \) (= 64 neurons) and 2000 iterations with the solver Adam for weight optimization. The regularization parameter \( \alpha = 10^{-1}, 10^{-2},..., 10^{-7} \) was determined via grid search in the cross-validation.

The ability to distinguish gait patterns of one test session from gait patterns of other test sessions was investigated in a multi-class classification (six-session classification) setting. The prediction accuracies were calculated over a stratified 15-fold cross validation configuration. 78 of 90 parts of the data were used for training, 6 of 90 parts were used as a validation set and the remaining 6 of 90 parts was reserved for
testing. The 6 samples per test split were evenly distributed across all session partitions and are excluded from the complete training and validation process. Only 6 samples were selected for the test split because we wanted to guarantee as much training data as possible. In order to get meaningful results, the Training Validation Test splitting was stratified repeated 15 times so that each attempt was exactly once in the test set. The classification was performed within Python 3.6.3 (Python Software Foundation, USA) using the scikit-learn toolbox (0.19.2) [Pedregosa et al., 2011]. In order to cope with the amount of possible combinations of preprocessing methods, the analysis was run on 6 machines, utilizing 30 parallel processes each.

2.4 Statistical analysis

For the comparison of the different combinations of the described preprocessing steps, the mean prediction accuracies were compared statistically. Each mean value combined all combinations of preprocessing steps where the preprocessing method was part of. The Shapiro-Wilk test showed that none of the examined variables violated the normal distribution assumption ($p \geq .125$). For the comparison of all combinations of the preprocessing methods, paired-samples $t$-test and repeated-measures ANOVAs were calculated for the variables of time derivative, GRF filtering and weight normalization. For the ANOVAs post hoc Bonferroni corrected paired-samples $t$-tests were calculated for the variables of time normalization, data reduction and classifier. Furthermore, the effect sizes $d$ and $\eta^2_p$ were calculated; $d$ and $\eta^2_p$ are considered a small effect for $|d| = .20$ and $\eta^2_p = .06$, a medium effect for $|d| = .50$ and $.06 < \eta^2_p < .14$ and a large effect for $|d| = .80$ and $\eta^2_p > .14$ (Cohen, 1988). The $p$-value at which research is considered worth to be continued (Fisher, 1922) has been set to $p = .05$. To determine a best practice model, all combinations of data preprocessing methods were ranked according to their mean prediction accuracy over 15-fold cross validation and the rank sum was calculated.

3 RESULTS

3.1 Average performance of different data preprocessing methods

This analysis compares 216 different combinations of data preprocessing methods based on the resulting prediction accuracy. Table 2 displays the mean prediction accuracy for each individual participant over the 15-fold cross validation. Figure 3 shows the mean prediction accuracies over all participants. It is noticeable that the highest mean prediction accuracies were achieved using PCA, while the normalization to 1001 and 101 data points or the weighting has only a minor effect on the prediction accuracy. The time normalization to only 11 data points and the reduction to time-discrete gait variables gave particularly poor results. Concerning the machine-learning classifiers, the RFC achieved the highest mean prediction accuracies followed by the SVM and the MLP.

3.1.1 GRF filtering

A paired-samples $t$-test was performed to determine if there were differences in prediction accuracy in unfiltered GRF data compared to $f_c$ - filtered GRF data across all subjects. The mean prediction accuracy of the filtered GRF data ($M = 49.6\%, SD = 8.0\%$) was significantly higher than that of the unfiltered GRF data ($M = 46.0\%, SD = 7.5\%$) and also showed a high effect size ($t(41) = 7.662, p < .001, |d| = 2.393$).

3.1.2 Time derivative

A paired-samples $t$-test was conducted to compare the prediction accuracy of GRF and jerk across all subjects. The mean prediction accuracy of GRF ($M = 50.0\%, SD = 8.0\%$) was significantly higher than
that of the jerk ($M = 45.6\%, SD = 7.5\%$) and also showed a large effect size ($t(41) = 9.403, p < .001, |d| = 2.937$).

### 3.1.3 Time normalization

A repeated-measures ANOVA determined that there is a significant global effect with large effect size of prediction accuracy between time normalization to 1001, 101 and 11 data points ($F(2,000, 82,000) = 331.405, p < .001, \eta^2_p = .890$). Post hoc paired-samples $t$-test with Bonferroni correction revealed that there is no significant difference ($t(41) = 1.716, p = .094, |d| = .536$) between a time normalization to 1001 ($M = 50.6\%, SD = 7.9\%$) data points and 101 data points ($M = 50.1\%, SD = 7.9\%$). However, the time normalization to 1001 data points performed significantly better ($t(41) = 20.183, p < .001, |d| = 6.304$) than time normalized to 11 data points ($M = 42.7\%, SD = 7.2\%$). Also the time normalization to 101 data points performed significantly better than to 11 data points ($t(41) = 22.129, p < .001, |d| = 6.912$). Both effect sizes are considered as large.

### 3.1.4 Data reduction

A one-way repeated-measures ANOVA was conducted to compare the prediction accuracy of PCA ($M = 54.9\%, SD = 8.5\%$), TC ($M = 50.9\%, SD = 8.8\%$) and TD ($M = 37.5\%, SD = 6.5\%$). The Huynh-Feldt corrected results showed a highly significant main effect with a large effect size ($F(1,763, 66,985) = 344.393, p < .001, \eta^2_p = .894$). Bonferroni corrected post hoc paired-samples $t$-tests showed that PCA performed highly significantly better than TC ($t(41) = 7.541, p < .001, |d| = 2.355$) and TD ($t(41) = 22.351, p < .001, |d| = 6.981$). The effect size for both comparisons is considered as large. Furthermore TC performed also highly significant better than TD with a large effect size ($t(41) = 17.903, p < .001, |d| = 5.592$).
3.1.5 Weight normalization

A paired-samples t-test was conducted to compare the prediction accuracy of weight-normalized and non-weight-normalized data across all subjects. There was no significant difference ($t(41) = -0.097$, $p = 0.923$, $|d| = 0.030$) in the prediction accuracies for non-weight-normalized data ($M = 47.8\%, SD = 7.5\%$) and weight-normalized data ($M = 47.8\%, SD = 7.7\%$).

3.1.6 Machine-learning classifier

A repeated-measures ANOVA with Huynh-Feldt correction showed a highly significantly global effect with large effect size ($F(1.634, 66.985) = 56.701, p < 0.001, \eta^2_p = 0.580$) between the predicted accuracies by SVM ($M = 48.5\%, SD = 7.9\%$), MLP ($M = 45.3\%, SD = 6.8\%$) and RFC ($M = 49.6\%, SD = 8.4\%$). Post hoc Bonferroni corrected paired-samples t-test revealed that RFC performed significantly better, with a large effect size, than SVM ($t(41) = 3.816, p < .001, |d| = 1.192$) and MLP ($t(41) = 8.720, p < .001, |d| = 2.724$). Also the SVM performed significantly better than MLP with a large effect ($t(41) = 7.207, p < .001, |d| = 2.251$).

3.2 Best practice combinations of different data preprocessing methods

In addition to the mean prediction accuracies for each method of all preprocessing and classification steps, Table 3 shows the 30 combinations with the highest overall prediction accuracies (the complete list can be found in Supplementary Table 1). It is particularly noticeable that the first 30 ranks were all achieved using PCA for feature reduction. Furthermore, the first eight ranked combinations used GRF data. The first twelve ranked combinations were classified with SVM, while the highest prediction accuracy was 13th with MLP and 27th with RFC.

Table 4 shows the rank scores of all classifications performed for the 216 combinations of the different preprocessing steps. The PCA achieved a particularly high rank score with 93.2% of the maximum achievable rank score. In addition, the GRF with 77.2% and the GRF filtering with 73.8% finished with high rank scores. Again, there are no or only minor differences within the weight normalization and the time normalization to 1001 and 101 data points. Among the classifiers, the SVM achieved the highest rank score, just ahead of the MLP and RFC.

4 DISCUSSION

A growing number of promising machine-learning applications could be found in the field of human movement analysis. However, these approaches differ in terms of objectives, samples and classifications. Furthermore, there is a lack of standard procedures and recommendations within the different methodological approaches, especially with respect to data preprocessing steps usually performed prior to machine-learning classification. In this regard, the current analysis comprised a systematic comparison of different preprocessing steps and their effects on the prediction accuracy of different machine-learning classifiers. The results revealed first domain-specific recommendations for the preprocessing of GRF data prior to machine-learning classifications. This includes, for example, benefits of filtering GRF data and supervised feature reduction techniques (e.g., PCA) compared to non-reduced (time-continuous waveforms) or unsupervised feature reduction techniques (time-discrete gait variables). On the other hand, the results indicate that the normalization to a constant factor (weight normalization) and the number of data points (above a certain minimum) used during time normalization seem to have little influence on the prediction accuracy. Furthermore, the first-time derivative (jerk) could not achieve advantages over the GRF in terms of prediction accuracy. In general, the present results can help to find domain-specific standard
procedures for the preprocessing of data that may enable to improve machine-learning classifications in human movement analysis make different approaches better comparable in the future. It should be noted, however, that the results presented are based solely on predictive accuracy and do not provide information about the effects on the trained models.

4.1 GRF filtering

The present results indicate that the filtered GRF data led to significantly higher mean prediction accuracies and rank scores than the unfiltered GRF data. The results were especially striking for the classifications of jerk data. While no clear trend could be derived for the best ranked combinations of GRF data, most of the best ranked combinations of jerk data were filtered. To our knowledge, this analysis was the first that investigated whether a filter (using an optimal filter cut-off frequency) affects the prediction accuracy of GRF data in human gait (Schreven et al., 2015). The present findings suggest that machine-learning classification should use filtered GRF data. However, it should be noted that the estimation of the optimal filter cut-off frequency using the method described by Challis (1999) is only one out of several possibilities to set a cut-off frequency. Because the individual filter cut-off frequencies were separately calculated for trail and each variable, so it is not yet possible to recommend a generally valid unique cut-off frequency.

4.2 Time derivative

With respect to the feature extraction using the first-time derivative, our analysis revealed that the GRF achieved significantly higher prediction accuracies compared to the jerk. In addition, the highest prediction accuracies were also achieved with the GRF. However, it needs to be noted that the highest prediction accuracies using jerk data were only 1% lower than the highest prediction accuracies using GRF data. Because the time derivative alone did not increase the prediction accuracy, it might be helpful to aggregate different feature extraction methods to improve classification models (Slijepcevic et al., 2019).

4.3 Time normalization

The time normalization to 101 and 1001 data points was significantly better than that to only 11 data points. These results are in line with current research, where 101 and 1001 values are commonly used (Eskofier et al., 2013; Slijepcevic et al., 2017). The best ranks were achieved using the time normalization to 1001 data points, but these were only slightly higher than those time normalized to 101 data points. In both methods, the highest prediction accuracies where achieved in combination with PCA. In terms of computational costs, it is advisable to weigh up to what extent relatively small improvements in the prediction accuracy justify the additional time required for classification. Furthermore, if computational cost is an important factor, a time normalization to fewer data points (above a certain minimum) could also be useful, since the results showed only little influence on the prediction accuracy.

4.4 Data reduction

This analysis showed that PCA, which is frequently used in research (Figueiredo et al., 2018; Phinyomark et al., 2018; Halilaj et al., 2018), also achieves the highest prediction accuracies and ranks, compared with time-continuous waveforms and time-discrete gait variables. The highest prediction accuracy of a machine-learning model based on time-continuous waveforms was 6.5% lower than that of PCA. Machine-learning models solely according to time-discrete characteristics is not recommended based on these analysis results. In line with Phinyomark et al. (2018), reducing the amount of data to the relevant characteristics is not only a cost-reducing method, but can also improve machine-learning classifications.
4.5 Weight normalization

While weight normalization is necessary in inter-individual comparisons (Laroche et al., 2014; Mao et al., 2008), there have been no recommendations regarding intra-personal comparisons so far. The results of this analysis suggest that performing or not performing weight normalization leads to almost the same results and therefore shows no difference in prediction accuracy. Consequently, multiplication by a constant factor seems to play no role in the machine-learning classifications. This could be particularly interesting if different datasets are combined.

4.6 Machine-learning classifier

Three commonly used machine-learning classifiers were compared in this analysis: ANN in form of MLP, SVM and RFC. The RFC achieved significantly higher mean prediction accuracies than MLP and SVM across all data preprocessing methods. One possible explanation could be that the RFC is more robust to a time normalization to a lower number of data points or time-discrete gait variables than the SVM or MLP. However, the best ranks were achieved with SVM followed by MLP, while the RFC reached the lowest prediction accuracies. For gait data the SVM seems to be a powerful machine-learning classifier as often described in the literature (Figueiredo et al., 2018). MLP provided only mediocre results for prediction accuracy and ranks, which could be due to the fact that the total amount of data is simply too small for a neural network (Begg and Kamruzzaman, 2005; Begg et al., 2005; Lai et al., 2008; Chau, 2001b). In addition, the MLPs required the most of the calculation time for classification; SVM and RFC took about the same time. Based on the presented results, using linear SVMs for the classification of gait data can be recommended. Furthermore, in line with recent research (Slijepcevic et al., 2019), a majority vote could possibly provide an even better classification. However, it should be noted that only a small selection of possible classifiers and corresponding architectures as well as a grid search procedures were examined in this analysis.

5 CONCLUSION

Based on a systematic comparison, the results provide first domain-specific recommendations for commonly used preprocessing methods prior to classifications using machine learning. However, caution is advised here, as the present findings may be limited to the classification task examined (six-session classification of intra-individual gait patterns) or even to the dataset. Furthermore, the derived recommendations are based exclusively on the prediction accuracy of the models. Therefore, no information can be obtained about the actual impact of the preprocessing methods and their combinations on training or class representation in the models. Overall, it can be concluded that domain-specific standard procedures for machine-learning classifications are essential to create comparable and robust classification models that meet the requirements for practical applications in human movement analysis and enable to support practitioners in their decisions.

6 CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

This work is a preprint and has not yet been peer-reviewed
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8 DATA AVAILABILITY STATEMENT

The dataset generated and analyzed during the current study will be public upon publication.

9 AUTHOR CONTRIBUTIONS

FH, SD, IH recorded the data. JB, FH, WIS conceived the presented idea. JB, FH, SG performed the data analysis. JB, FH wrote the manuscript. JB, FH, SG designed the figures. JB, FH, SG, SD, IH, WIS reviewed and approved the final manuscript.

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Table 2. Mean prediction accuracy for each individual participant depending on each preprocessing method and machine-learning classifier. Each mean value combines all combinations of preprocessing steps where the preprocessing method was part of (n=42).

|                | GRF filtering | Time derivative | Time normalization | Data reduction | Weight normalization | Classifier |
|----------------|---------------|-----------------|--------------------|---------------|---------------------|------------|
| No            | Yes            | No              | Yes               | No            | Yes                 | No         |
| S01           | 48.3          | 52.3            | 51.6              | 48.9          | 44.5                | 53.3       |
| S02           | 32.4          | 37.7            | 36.2              | 33.9          | 31.3                | 36.3       |
| S03           | 47.0          | 53.8            | 50.8              | 50.0          | 46.6                | 54.3       |
| S04           | 54.1          | 60.3            | 59.4              | 55.3          | 51.8                | 60.0       |
| S05           | 60.2          | 59.8            | 62.4              | 57.6          | 59.7                | 61.1       |
| S06           | 48.9          | 49.2            | 49.3              | 48.9          | 42.2                | 52.5       |
| S07           | 41.3          | 50.7            | 45.8              | 46.2          | 40.8                | 49.8       |
| S08           | 53.6          | 59.8            | 57.9              | 55.7          | 52.6                | 59.5       |
| S09           | 52.5          | 57.1            | 55.9              | 53.7          | 49.2                | 59.0       |
| S10           | 51.2          | 50.4            | 51.0              | 50.5          | 44.1                | 53.6       |
| S11           | 48.9          | 50.9            | 53.1              | 46.8          | 52.5                | 50.7       |
| S12           | 44.0          | 41.2            | 46.4              | 38.8          | 37.1                | 44.9       |
| S13           | 40.9          | 44.4            | 45.0              | 40.3          | 38.0                | 46.6       |
| S14           | 43.8          | 43.1            | 48.0              | 39.0          | 37.8                | 46.6       |
| S15           | 50.3          | 54.9            | 56.9              | 48.3          | 46.9                | 56.9       |
| S16           | 41.8          | 43.0            | 43.3              | 41.5          | 36.8                | 44.7       |
| S17           | 38.1          | 38.4            | 40.6              | 35.7          | 31.1                | 42.0       |
| S18           | 32.7          | 37.6            | 34.7              | 33.9          | 31.2                | 35.5       |
| S19           | 35.7          | 36.6            | 40.1              | 32.2          | 33.7                | 37.5       |
| S20           | 38.3          | 44.0            | 41.9              | 40.5          | 36.0                | 42.9       |
| S21           | 35.6          | 38.2            | 39.3              | 34.4          | 33.6                | 38.7       |
| S22           | 42.9          | 42.3            | 46.0              | 38.2          | 37.0                | 43.6       |
| S23           | 41.2          | 44.9            | 45.0              | 41.0          | 37.8                | 44.7       |
| S24           | 46.0          | 54.8            | 51.7              | 49.1          | 44.4                | 52.2       |
| S25           | 44.5          | 51.9            | 49.7              | 46.7          | 44.6                | 46.6       |
| S26           | 59.1          | 61.2            | 65.0              | 55.4          | 53.4                | 62.6       |
| S27           | 40.8          | 41.0            | 39.7              | 42.0          | 35.5                | 43.3       |
| S28           | 46.0          | 55.7            | 53.0              | 48.7          | 44.4                | 53.4       |
| S29           | 41.2          | 45.9            | 42.6              | 44.4          | 39.9                | 45.3       |
| S30           | 40.9          | 42.9            | 45.9              | 38.2          | 37.3                | 43.1       |
| S31           | 62.2          | 63.6            | 64.8              | 61.0          | 55.0                | 66.0       |
| S32           | 53.0          | 56.6            | 58.1              | 51.5          | 49.7                | 55.6       |
| S33           | 45.5          | 51.7            | 50.0              | 47.2          | 40.9                | 50.9       |
| S34           | 60.9          | 62.7            | 64.8              | 58.7          | 56.3                | 63.5       |
| S35           | 49.3          | 56.4            | 56.9              | 49.2          | 45.4                | 57.0       |
| S36           | 46.9          | 49.0            | 51.1              | 44.8          | 43.5                | 49.8       |
| S37           | 40.5          | 43.6            | 45.6              | 38.5          | 37.8                | 42.9       |
| S38           | 45.1          | 48.5            | 49.6              | 44.0          | 41.6                | 48.1       |
| S39           | 52.5          | 53.7            | 56.9              | 49.3          | 50.2                | 53.3       |
| S40           | 52.2          | 60.3            | 60.6              | 51.9          | 48.6                | 58.1       |
| S41           | 48.9          | 53.9            | 55.0              | 47.8          | 45.3                | 53.0       |
| S42           | 35.4          | 38.2            | 40.3              | 33.6          | 32.8                | 37.6       |

| GRF filtering | Time derivative | Time normalization | Data reduction | Weight normalization | Classifier |
|---------------|-----------------|--------------------|---------------|---------------------|------------|
| No            | Yes             | No                 | Yes           | No                  | Yes        |
| M             | 46.0            | 49.6              | 50.0          | 45.6                | 42.7       |
| SD            | 7.5             | 8.0               | 8.0           | 7.5                 | 7.2        |
Table 3. Top 30 combinations of preprocessing methods, ranked by the mean prediction accuracy over the 15-fold cross validation.

| Rank | GRF filtering | Time derivate | Time normalization | Data reduction | Weight normalization | Classifier | M    | SD  |
|------|---------------|---------------|--------------------|----------------|---------------------|------------|------|-----|
| 1    | No            | GRF           | 1001               | PCA            | No                  | SVM        | 61.6 | 9.2 |
| 2    | No            | GRF           | 1001               | PCA            | Yes                 | SVM        | 61.3 | 10.7|
| 3    | No            | GRF           | 101                | PCA            | Yes                 | SVM        | 61.1 | 9.8 |
| 4    | Yes           | GRF           | 1001               | PCA            | No                  | SVM        | 61.1 | 9.3 |
| 5    | No            | GRF           | 101                | PCA            | Yes                 | SVM        | 61.0 | 9.9 |
| 6    | Yes           | GRF           | 101                | PCA            | Yes                 | SVM        | 60.9 | 11.2|
| 7    | Yes           | GRF           | 1001               | PCA            | Yes                 | SVM        | 60.8 | 10.9|
| 8    | Yes           | GRF           | 101                | PCA            | Yes                 | SVM        | 60.7 | 10.8|
| 9    | Yes           | Jerk          | 1001               | PCA            | No                  | SVM        | 60.6 | 10.3|
| 10   | Yes           | Jerk          | 1001               | PCA            | Yes                 | SVM        | 60.4 | 10.4|
| 11   | Yes           | Jerk          | 101                | PCA            | No                  | SVM        | 60.3 | 10.2|
| 12   | Yes           | Jerk          | 101                | PCA            | Yes                 | SVM        | 60.2 | 10.6|
| 13   | No            | GRF           | 1001               | PCA            | No                  | MLP        | 60.1 | 9.2 |
| 14   | Yes           | GRF           | 101                | PCA            | No                  | MLP        | 60.1 | 9.9 |
| 15   | Yes           | GRF           | 1001               | PCA            | Yes                 | MLP        | 59.9 | 9.8 |
| 16   | No            | GRF           | 101                | PCA            | Yes                 | MLP        | 59.7 | 9.8 |
| 17   | Yes           | GRF           | 1001               | PCA            | No                  | MLP        | 59.5 | 8.9 |
| 18   | No            | GRF           | 101                | PCA            | Yes                 | MLP        | 59.4 | 10.0|
| 19   | Yes           | GRF           | 101                | PCA            | Yes                 | MLP        | 59.4 | 9.1 |
| 20   | No            | GRF           | 1001               | PCA            | Yes                 | MLP        | 58.8 | 9.2 |
| 21   | Yes           | Jerk          | 1001               | PCA            | No                  | MLP        | 58.6 | 10.3|
| 22   | Yes           | Jerk          | 1001               | PCA            | No                  | MLP        | 58.6 | 9.0 |
| 23   | Yes           | Jerk          | 101                | PCA            | Yes                 | MLP        | 58.5 | 10.1|
| 24   | Yes           | Jerk          | 101                | PCA            | Yes                 | SVM        | 57.4 | 10.1|
| 25   | Yes           | Jerk          | 1001               | PCA            | Yes                 | SVM        | 57.3 | 10.3|
| 26   | No            | Jerk          | 1001               | PCA            | Yes                 | RFC        | 57.1 | 8.7 |
| 27   | Yes           | Jerk          | 1001               | PCA            | Yes                 | RFC        | 57.0 | 9.8 |
| 28   | Yes           | GRF           | 1001               | PCA            | Yes                 | RFC        | 56.8 | 9.7 |
| 29   | Yes           | GRF           | 101                | PCA            | No                  | RFC        | 56.7 | 9.5 |
| 30   | Yes           | GRF           | 101                | PCA            | No                  | RFC        | 56.7 | 9.5 |

*Note:* The mean accuracies and standard deviations are rounded; therefore, identical values may occur in the table. However, there are no pairwise identical values, so the ranking is unique.
Table 4. Rank scores of all combinations of preprocessing methods depending on their mean prediction accuracy over the 15-fold cross validation.

| GRF filtering | Time derivative | Time normalization | Data reduction | Weight normalization | Classifier |
|---------------|-----------------|--------------------|----------------|----------------------|------------|
| No | Yes | GRF | Jerk | 11 | 101 | 1001 | TC | TD | PCA | No | Yes | SVM | RFC | MLP |
| Score | 10351 | 12869 | 13469 | 9751 | 5530 | 8772 | 8918 | 7794 | 3517 | 11909 | 11622 | 11598 | 8155 | 7167 | 7898 |
| %max | 39.2 | 60.8 | 65.9 | 34.1 | 19.1 | 40.0 | 40.9 | 33.7 | 6.2 | 60.1 | 50.1 | 49.9 | 36.0 | 29.6 | 34.3 |

Note: The total rank score is for each preprocessing step is 23220. For GRF filtering, time derivative, and weight normalization the minimum rank score is 5778 (0.0%) and the maximum rank score is 17442 (100.0%). For data reduction, time normalization and classifiers the minimum rank score is 2556 (0.0%) and the maximum is 12780 (65.7%). %max: relative rank score of ranks scaled to the interval between the minimum rank score and the maximum total rank score.