# Feature-Based Gait Pattern Classification for a Robotic Walking Frame

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**Abstract.** This paper presents a system for fast detection of gait patterns of walking frame users, where the challenge is to recognize a change in activity before the signal behaves stationary. The system is used as a basis for inferring the user's intention in order to develop an improved shared-control strategy for an electric-driven walking frame. The data required for gait pattern identification is recorded by a set of low budget infrared distance sensors. We compare different sliding window based feature extraction methods in combination with classical machine learning algorithms in order to realize a fast real-time online gait classification. Moreover, a simple hierarchical feature extraction method is proposed and evaluated on our data-set.

**Keywords:** Multivariate Time-series · Feature Extraction · DWT · FFT · Shared Control · Elderly Care.

## 1 Introduction

Machine Learning with applications in care of the elderly has recently found great interest in science as well as in commercial products and services. There are applications ranging from social companion robots to smart-home-systems, adapted to the needs of elderly people. We describe the development of a machine learning driven solution for control of an electric-driven walking frame. The existing system, on which we build in the following, is supporting the user by a fifth wheel as driving element. This wheel is controlled via the momentum inserted by the user, following a simple control strategy (perpetuating the momentum). This way of control is intuitive, as the user does not need to give any input by means of handles or buttons. However, in some situations the walking frame does not behave as it is supposed to. In one example, the walking frame will continue driving until it is explicitly stopped by a counter-force (the user actively impeding or an obstacle stopping the walking frame). This behavior is not desirable, because elderly people may not give such distinct inputs. Beyond that, the forces acting on the frame are ambiguous, i. e. they can be either a consequence of the user's motions or of the environment (e. g. up-/downhill route). To counter this problem we need to infer the user's intention to walk or

to stop from it's actual activity. An obvious solution is to develop a fast gait classifier for the given system based on multivariate sensor data capturing the user's movements. In the following, several ways to implement such a multivariate time-series classifier are described and evaluated.

There are, however, numerous methods to approach time-series classification. We do not claim to provide a full survey-like comparison of all state-of-the-art algorithms. In order to facilitate potential marketability, we try to avoid high computational complexity and to develop a narrow system (few low-cost sensors). We demonstrate the performance and feasibility of several important methods for our application. Specifically, we focus on feature-based interval methods in combination with standard classifiers.

## 2 Related Work

There are many machine learning projects aiming for an enhanced functionality of walking frames. Often the applications focus on navigation and/or inferring user intention (user-modeling). To name just a few: [1] describes a system that provides navigational aid to the elderly using probabilistic models; [2] presents a robotic walker that learns a user-model from navigational activity in assisted living environment. [3] describes the use of handles with sensors capturing linear forces in order to grasp the user's intention; additionally, the walking aid uses a path planner for obstacle avoidance. In [4] an ADL-assistance system (Activities of Daily Living) is described; one of the topics addressed is gait monitoring and analysis. The gait monitoring system is used to detect pathological gait patterns in order to handle such. The user data is recorded via a laser range finder (LRF) mounted to the walking frame and analyzed using Hidden Markov Models to classify the different gait stages. [5] describes a method to control "Mobility Assistive Devices" based on gait analysis. They extract features such as velocities, positions and distances from the LRF data, and use it for a conceptual gait analysis. In [6] a LSTM-based method for on-line gait stability analysis based on RGB-D and LRF sensors is described. In [7] a robotic walker for gait rehabilitation of stroke patients is implemented as a shared-control system using wearable motion sensors and force/torque sensing. [8] use hierarchical Hidden Markov Models and point out the advantages of such compared to Support Vector Machines (especially for inferring user activities). A "complex distributed home automation and robotics system providing health monitoring and (socially interactive) assistance in daily living tasks to the elderly (and their caregivers) at home" is presented in [9], furthermore the technological challenges in development of such a system are pointed out. [10] recently presented the evaluation of a gait-analysis system for shared-control based on pressure sensor data at the handle of a walking aid and draw positive conclusions concerning the applicability of such a system.

Regarding time-series classification there are numerous algorithms (cf. [11]) that perform either feature, distance or model based classification [12]. In the following we focus on the first category.

Feature based methods have been successfully applied for many time-series classification tasks (see [13–17]). We focus on simple statistical feature extraction methods inspired by PAA and SAX ([18, 19]), Wavelet features (theory in [20–22], for applications see e. g. [23, 24]) and Fourier features.

## 3 System description

Our system is comprised of multiple functions (similar to the ones listed above), among which we focus on gait analysis as input to a shared-control system. For this purpose we use six infrared distance sensors positioned to capture objects in the region of interest. We use force sensors in the handles (force sensitive resistor pads) to gain more information about the user's behavior. Additionally, the walking frame is equipped with an inertia measurement unit and an odometer at the rigid wheels, such that forces acting on the walking frame and the resulting velocities as well as the covered distance are monitored. For localization and navigation we use several other hardware components. Yet, in the following we consider only the data obtained by the infrared sensors pointing to the user's legs. In Figure 2 sample data is given.


**Fig. 1.** The walking frame used for data acquisition. The sensors are all directed to the expected position of the user's legs ($s_4$ and $s_5$ are attached to the rods holding the rigid wheels, pointing to the user's feet).

### 3.1 Sensory System Details

Figure 1 shows the prototype used for all the experiments. We use infrared sensors with ranges of 20 cm-150 cm ($s_0, s_1$), 10 cm-80 cm ($s_2, s_3$) and 4 cm-30 cm ($s_4, s_5$) to monitor the user's leg movements. The infrared sensors output analog distance values, coded as voltage, which is converted to a 10 bit digital signal. The sampling interval is $T_s = 0.0165\,\mathrm{s}$. Although the prototype offers several other sensors, in the following we restrict to infrared sensor data. This is mainly

because we are striving for an economic solution. An obvious cheap alternative would be ultrasonic sensors, yet such turned out to be unsatisfying. The main reasons for this are low spacial resolution, high sensitivity to fading and losses due to absorption in material (especially cloth).

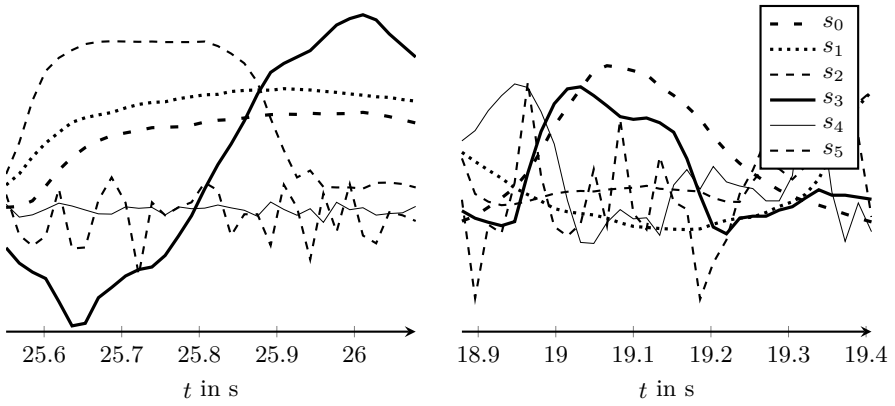


**Fig. 2.** Scaled sample data recorded by the infrared sensors (left: a person sitting down on the walking frame, right: a person walking, scaling only for visualization).

## 4 Gait Classification

For gait analysis we use classical machine learning methods to detect whether the user is walking or not, i.e. carrying out another activity (e. g. sitting down on the walking frame, cf. Figure 2). The data set includes activities such as sitting down, getting up or sitting on the walking frame's seating, standing in front of the walking frame (resting or moving), technical failures (covered sensors, sporadic sensor failure) and different kind of walking data (slow, fast, crooked, small and tall persons, ...). We compare several algorithms applied to this binary classification problem, namely Support Vector Machines (SVM), XGBoost (XGB), Random Forests (RF), Gaussian Naive Bayes (NB) and as a baseline for comparison 1-Nearest-Neighbor (based on Dynamic Time Warping, 1NN-DTW and using euclidean distance, 1NN-ED).

### 4.1 Feature Extraction

The data consists of a $d$-dimensional time series (restricted to at maximum 6 infrared sensors, i. e. $d \leq 6$), which is processed using a sliding window (we use a Tukey-window with $\alpha = 0.1$ which proved to be a good choice). Thus a data window of width $w$ is a multivariate time series (batch) $s \in \mathbb{R}^{d \times w}$. In order to enable a fast classification of incoming events, the sliding window must be as

narrow as possible. On the other hand a narrow window makes classification more difficult, i. e. there is a trade-off between reactivity and accuracy. In order to capture the shape of the current signal, we compare several methods:

- computing the Discrete Wavelet Transform (DWT, using Daubechies-Wavelets) for each variable/dimension and pick the $k$ largest coefficients (value and position/translation)
- extraction of Fourier coefficients as features (considering $k$ largest Fourier coefficients and their position/frequency)
- statistical features (mean and extrema on "dyadic" intervals for each variable)

Capturing $k$ largest values is advantageous compared to using a threshold, because it results in a lower dimension of the input space, yet the most relevant information is kept (assuming the transformed data to be sparse). That this assumption holds up can be seen from Figure 3, where some sample data and the sparse Wavelet and Fourier representation are depicted.

In the following we use a window of width $w = 32$ (corresponding to 0.528 s, cf. Figure 2), which is the smallest possible size that is still leading to an acceptable accuracy. We use overlapping windows (50% overlap) in order to speed up the system further. A dyadic window size is convenient to avoid the necessity of (zero) padding.

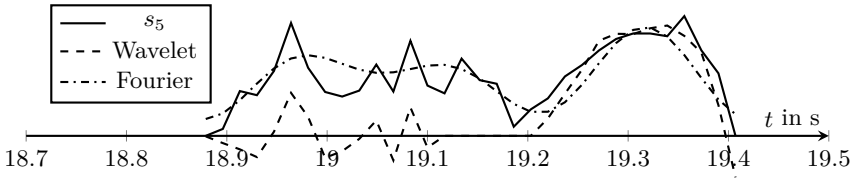


**Fig. 3.** Visualization of feature extraction via Fourier and Wavelet transform. The graphs show windowed sample data (Tukey-window, $\alpha = 0.1$) and the information given in the feature vectors, when using Fourier or Wavelet features (inverse transforms of sparse coefficient vectors). Here $k = 2$, hence for Fourier features the two largest coefficients and their frequencies are kept (4 features). The Wavelet representation results from a two level Wavelet transform ($k = 2$ and $n = 2$ resulting in 8 features)

**Wavelet Features** We use the $n$-th level discrete Wavelet transform and extract the largest coefficients on each decomposition level as features. This means we transform the multivariate time series—for each variable separately—and from the coefficients on each decomposition level we extract the position and amplitude of the $k$ largest detail and approximation coefficients (for example, when $k = 3$ and $n = 3$ we get 54 features for each multivariate batch $s$, with $s \in \mathbb{R}^{6\times w}$). We use the "db3"-wavelet (Daubechies-Wavelet with three vanishing

moments), which—in an empirical analysis—turned out to be a good choice. Wavelets of wider support are not useful, because those are leading to strong border effects. Beyond that, higher order wavelets are weak in peak detection, which is important for our purpose.

**Fourier Features** Another way to capture the shape of gait pattern is the Fourier transform. To extract the relevant data the Fast Fourier transform (FFT) is computed and again $k$ largest coefficients are extracted (position/frequency and amplitude). The resulting features are easy to interpret, as the DC-part (which is usually the largest coefficient) is the mean distance of the leg to the respective sensor and the higher frequencies render the speed and amplitude of the leg movement.

**Hierarchical Statistical Features** Besides the feature extraction methods listed above we propose the extraction of basic statistical features in a hierarchical manner (closely related to a discrete Haar-Wavelet transform), especially the interval-wise extraction of local mean (similar to PAA) and local extrema. The basic idea is, to compute the mean of $2^i$ sub-sequences and from that recursively the mean of $2^{i-1}$ up to the whole series mean (see Figure 4). Additionally, the minima and maxima of the respective sub-sequences are captured. This is computationally efficient (the computation of the mean yields a sparse matrix factorization, cf. Wavelet-Analysis) and leads to effective features. We refer to this as *Dyadic Statistical Features* (DSF).

**Feature Scaling** To scale data we either use standard scaling or min-max normalization based on the training data $\mathcal{X}_T$, i. e. either $x' = (x - \overline{x}_T)/\, s_T$ (where sample mean $\overline{x}_T$ and sample variance $s_T$ are determined from the training set) or $x' = (x - \min_i x)/(\max_i x_i - \min_i x_i)$, where $x_i \in \mathcal{X}_T$.

### 4.2 Classification Results

As mentioned above we compare common classifiers in combination with the previously introduced feature extraction methods for our problem. Although XGBoost, Random Forests and Support Vector Machines usually outperform Naive Bayes, we consider it for better comparability and in order to "rank" the classification problem. For all classifiers we find—if necessary—optimized parameters by cross validated ($k = 5$) grid search and use 50% of the data as training set. The classes are balanced. For each classifier we use the one feature scaling method out of the above mentioned with best performance. Beyond that we optimized the number of used coefficients (the parameter $k$ used along with FFT and DWT feature extraction) for each experiment separately. We use the accuracy on the test set as a score to compare our classifiers. To characterize the data set we computed the accuracy using 1NN-DTW, which is 0.898, and 1NN-ED, which is 0.876. Although especially 1NN-DTW is too slow for application in

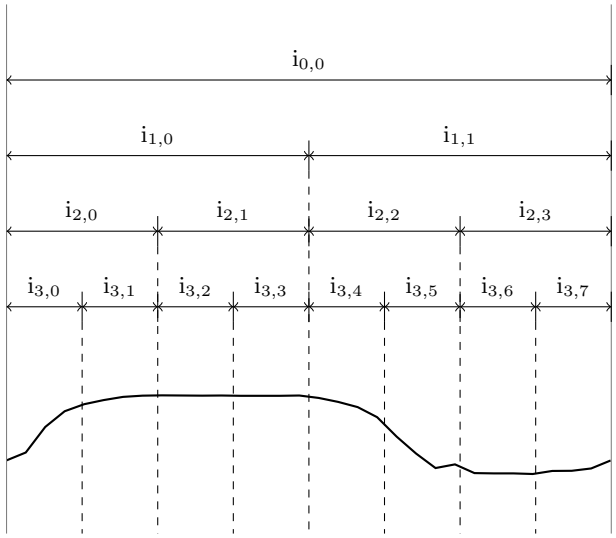


**Fig. 4.** Dyadic statistical feature extraction: for each of the intervals $i_{m,n}$ the mean along with the extrema are extracted ($\{\text{mean}(i_{m,n}), \max(i_{m,n}), \min(i_{m,n})\}\forall m, n$). Applying a recursive scheme, the complexity reduces to $\mathcal{O}(n \log n)$.

our system, it is a good baseline for comparison. The results of our experiments are given in Table 1 and Figure 5.

**Table 1.** Comparison of Support Vector Machines (SVM), XGBoost (XGB), Random Forests (RF)—all with best performing parameters—and Gaussian Naive Bayes (NB) using the feature extraction methods listed above. The accuracy using 1NN-DTW is 0.898, the accuracy with 1NN-ED is 0.876.

| *Accuracy* | SVM | XGB | RF | NB |
|---|---|---|---|---|
| Wavelets | 0.955 | **0.981** | **0.978** | **0.882** |
| Fourier | 0.944 | 0.962 | 0.945 | 0.892 |
| Statistical | **0.964** | 0.944 | 0.941 | 0.703 |

## 5 Conclusion and Future Work

The presented methods were tested on the running system under realistic conditions, leading to satisfactory results, yet there is need for further improvements.

| | | | |
|---|---|---|---|
| TP 0.982 | FP 0.021 | TP 0.967 | FP 0.044 |
| FN 0.018 | TN 0.979 | FN 0.033 | TN 0.956 |
| DWT (XGB) | | FFT (SVM) | |

| | | | |
|---|---|---|---|
| TP 0.972 | FP 0.044 | TP 0.946 | FP 0.149 |
| FN 0.028 | TN 0.956 | FN 0.054 | TN 0.851 |
| DSF (SVM) | | 1NN-DTW | |

**Fig. 5.** Confusion matrices for different feature extraction methods (with best performing classifier) and 1NN-DTW.

The system's response is fast (i.e. an accurate classification is achieved with a narrow window), but for best usability of the walking frame the user's desired speed should be estimated. Beyond that the user's specific state should be inferred from the gait data, where especially a fall detection is of interest.

The results of statistical feature extraction on dyadic intervals are promising. The method should be evaluated on benchmark data-sets.

Finally, the presented data-set is eligible for testing variable selection, whereat the application motivates this attempt. It has to be investigated whether the number of sensors can be reduced, i. e. only a subset of sensors (e. g. $s_0, s_1, s_3$) can used for classification without substantial decrease in accuracy in order to increase the efficiency of the system.

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