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A Novel Approach for Gait Phase Estimation for different Locomotion Modes using Kinematic Shank Information ⋆

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Abstract: This paper presents a novel approach for continuous gait phase estimation for human level walking, stair ascent and stair descent relying only on the kinematic variables of the shank, which are measurable by a single Inertial Measurement Unit (IMU) placed at the shank. We use data from an experiment with an instrumented stair to train Artificial Neural Networks (ANNs) and to obtain the data necessary for a k-Nearest-Neighbour (kNN) method. Both methods are used for a continuous gait phase estimation separately for each of the three locomotion modes level walking, stair ascent and stair descent. The so called pseudo-velocities are introduced, a substitution for translational velocities as input values. The presented gait phase estimation with ANNs achieves a good performance (mean absolute error $< 6\,\%$) for all three locomotion modes for one test subject and is much faster in comparison to a kNN approach. The use of ANNs seams promising regarding performance and speed for a future implementation on an active prosthesis.

Keywords: Gait Phase, Gait Analysis, Machine Learning, Artificial Neural Network, Locomotion, Stair Climbing, Assisted Walking, Prosthesis, Inertial Measurement Unit.

1. INTRODUCTION

Active lower limb prostheses have the potential to improve the mobility of people with lower limb amputation. Aside from the mechanical design, the development of an appropriate control for different locomotion modes is still challenging [Herr and Grabowski (2011), Rezazadeh et al. (2018), Sup et al. (2009), Windrich et al. (2016)].

The support given by a lower limb prosthesis to a person with amputation depends on the knowledge of the current or intended locomotion mode and the so called gait phase. This paper focuses on the gait phase. It represents the relative progression between start and end of one specific stride. The gait phase has a value between $0\,\%$ to $100\,\%$ and starts at $0\,\%$ with the contact of the foot with the ground (in general the heel, therefore called heel-strike) and ends with the same foot touching the ground again at $100\,\%$.

During one stride two distinct phases are essential for human walking. The stance phase and the swing phase are distinguished by the foot having contact with the ground (stance) or being in the air (swing). The stance phase is the part of a stride, that allows to interact with the environment and the swing phase is used to move the foot to a new position for the next ground contact. For an active support with a prosthesis the stance phase is the most important part. A good estimation of the gait phase is especially important for a person wearing the active prosthesis at tasks with a higher risk of injuries, due to the danger of falling or stumbling, such as stair ambulation [Jacobs (2016)].

As a consequence, besides the knowledge of the current locomotion mode, a appropriate gait phase estimation is very important for the control of an active prosthesis and its save use. A controller setup for an active ankle prothesis can consist of a high-level gait phase estimation and locomotion mode classification followed by a mid-level control using the gait phase and locomotion mode to select a specific position or torque [Holgate et al. (2009), Grimmer et al. (2017) . Finally a low-level control realizes the desired position or torque of the active ankle prothesis.

For level ground walking a continuous gait phase estimation can be realized e.g. by phase plane approaches introduced by Holgate et al. (2009) and used for example by Rezazadeh et al. (2018) or Quintero et al. (2017). Recently, model based approaches have been used for level ground walking too, e.g. by Seo et al. (2019) or Kang et al. (2020).

For walking on stairs, using kinematic data from the thigh was demonstrated to be a viable option [Quintero et al.

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(2017), Bartlett and Goldfarb (2018)]. However, prostheses for users with transtibial amputation do not have kinematic information from the thigh available without additional instrumentation. Ledoux and Goldfarb (2017) use four discrete states during one stride cycle of stair ascent to eliminate the need of a continuous gait phase value, but need the input of the user to transition between the states.

To the best of the authors' knowledge no approach for continuous gait phase estimation for stair ambulation, with only kinematic data from the shank, can be found in literature up to now.

Therefore, this paper presents a novel approach for estimating the gait phase continuously during level walking, stair ascent and stair descent that only uses the kinematic data acquirable with an Inertial Measurement Unit (IMU) mounted at the shank.

As mentioned earlier, active prostheses need the knowledge of the current locomotion mode for a proper support of the user. The classification of the locomotion mode and the estimation of a transition is part of a lot of different research [Young and Hargrove (2016), Stolyarov et al. (2018), Xu et al. (2018), Simon et al. (2018)]. Hence, we presume knowledge of the current locomotion mode is given. Therefore, we develop three individual gait phase estimators for level walking, stair ascent and stair descent.

We hypothesize that by using more than two input features a gait phase estimation with only kinematic shank information is feasible not only for ground level walking but also for stair ascent and descent.

The approach is not to manually search for additional candidates to further develop the phase plane method (like in Villarreal and Gregg (2014)), but to use a set of kinematic data of the shank as input values to generate an estimator for the gait phase for each of the three locomotion modes using machine learning regression methods. A k-Nearest-Neighbour (kNN) approach and Artificial Neural Networks (ANNs) are compared in this work. These selection was made to consider a simple model free approach (kNN) and a more complex model based approach (ANN).

The limitation to kinematic data from the shank is more challenging but favourable because the acquired values are generally available when using an active transtibial prosthesis with an integrated IMU. Therefore, kinematic shank data offers suitable candidates for an easy implementation in existing and future systems without the need of additional sensors.

The remainder of the paper is structured as follows. Sec. 2 gives an overview of the used dataset, the input and output variables including a novel surrogate for translational velocity and it presents the approach for the gait phase estimation with kNN and ANNs. Sec. 3 evaluates and discusses the results of the tests for one subject of the experimental dataset with a final conclusion given in Sec. 4.

2. METHOD

The estimation of gait phase can be treated as a regression problem and is therefore approached with a regression method capable of utilizing an existing dataset of level and stair walking.

2.1 Experimental Dataset

The dataset used in this work was measured during a stair walking experiment at the Locomotion Laboratory of the Technical University of Darmstadt and will be presented in detail in a further publication. The necessary information for this work is given by a short overview.

Twelve subjects without mobility impairments (age: 25.4 ± 4.5 years, height: 180.1 ± 4.6 cm and mass: 74.6 ± 7.9 kg) walked at an instrumented track including a staircase and a level area before and after the staircase. The study protocol was approved by the institutional review board of TU Darmstadt. The track was equipped with a motion capture system (Qualisys, Sweden) to track the subjects kinematics in the 3D-space and force plates (Kistler, Switzerland) to capture the ground reaction forces (GRF). Each subject was equipped with several IMUs from which only the shank IMUs are of interest for this work. Each subject walked on the track ten times upstairs and downstairs at three different stair slopes (19°, 30° and 40°).

After the experiment the data was further processed to extract each stride and label it with the corresponding locomotion mode and continuous gait phase values. The start of a stride was determined by the heel strike event and the end of a stride was determined by the next heel strike of that foot. Both events were determined by the GRF. The gait phase was determined by two continuous heel strike events. Based on both heel strike timings, the progress can be determined (in percent of stride time).

Overall 2128 strides of level walking, 1067 strides of stair ascent and 1415 strides of stair descent could be measured, extracted and labelled from the twelve subjects.

Despite the limitation to kinematic values available by measurement through a shank mounted IMU, the shank angle φ and the shank angular velocity $\dot{\varphi}$ in this work are obtained from the motion capture data from the dataset with OpenSim [Seth et al. (2018)]. The use of motion capture data is not a violation of the limitation of available values, because all used values can be measured by the IMU respectively calculated from measured values. The motion capture data had to be used, because the angular velocity data from the IMU of the dataset was not available at the time of this work.

2.2 Input Features

The choice of input features has a huge influence on the quality of the gait phase estimation, but is in this work limited to values that can be measured or computed only from data available from a shank mounted IMU. That choice was made to develop a method that can be implemented on an active ankle prosthesis without the need for additional wearable sensors or other measurement devices.

The shank IMU can measure translational accelerations and angular velocities in three dimensions. First trials showed, that only using translational accelerations and angular velocities do not result in an acceptable estimation of the gait phase. Therefore, additional input features had to be chosen.

The phase plane approach shows, that shank angle information is useful to estimate the gait phase [Holgate et al. (2009)]. By using only one IMU, the shank angle can be calculated from angular velocities and translational accelerations through a Kalman-filter approach [Rehbinder and Hu (2001)] or a complementary filter [Gui et al. (2015)]. Hence, the shank angle meets the constraints and is used as an input feature.

Another candidate for an input feature is the translational velocity. A new approach to substitute it is presented in this work. We assume that the additional benefit of adding the translational velocity as an input feature comes primarily from the information of prior sample points, that is always present when integrating a value from acceleration to velocity. For a suitable input feature of the gait phase estimation it is not important to get a correct velocity, but a value that contains the needed additional information for a better regression.

Such a value is generated in this paper by integration of the translational acceleration and following high-pass filtering to eliminate the offset and drift of an integrated acceleration. The result is an input feature we refer to as pseudo-velocity for which no knowledge of the offset or complex post-processing of the IMU data is required.

The combination of an integration followed by a first order high-pass filter can be condensed to a first order low-pass filter:

$$\frac{1}{s}\frac{s}{Ts+1} = \frac{1}{Ts+1}.$$

The time constant of the low-pass filter is set to $T = \frac{1}{3}$ s. With this low-pass filter the pseudo-velocities in y- and z-direction are generated.

In the end, six input features are used, which are presented in Table 1. The orientation of the shank coordinate system is defined as shown in Fig. 1 and the gait is simplified to a two dimensional motion in the sagittal plane.

Table 1. Input features for the gait phase estimation using only kinematic data of the shank.

Shank angle	φ
Shank angular velocity	$\dot{\varphi}$
Translational acceleration	$\ddot{y}$ and $\ddot{z}$
Pseudo-velocities	$\tilde{\dot{y}}$ and $\tilde{\dot{z}}$

2.3 Outputs

The gait phase $g_{\%}$ can accept values between $0\,\%$ and $100\,\%$ and $g_{\%} = 100\,\%$ is the same as $g_{\%} = 0\,\%$ of the following stride because of the periodic nature of walking. This generates a problem because the regression has to fit very similar input data belonging to the output $g_{\%} = 0\,\%$ or $g_{\%} = 100\,\%$, which leads to a discontinuity and reduces the output quality of the regression significantly.

This work presents a solution for this problem by transforming the gait phase into polar coordinates, which are represented by a radius r and an angle ϑ, but can also be represented by two coordinates x and y in the Cartesian coordinate system (see Fig. 2). A similar approach was development and presented independently by Seo et al. (2019).

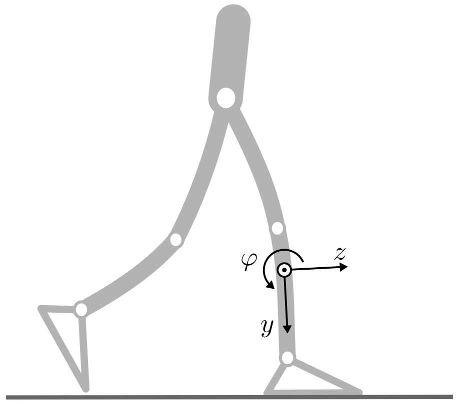

Fig. 1. Shank coordinate system in sagittal plane used for kinematic values.

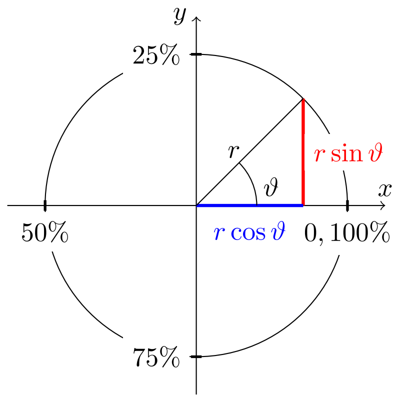

Fig. 2. Representation of the transformation from polar to Cartesian coordinates of the gait phase to generate continuous values.

To transform the gait phase $g_{\%}$ to x and y coordinates the gait phase $g_{\%}$ first is converted to radian and afterwards to x- and y-coordinates with

$$x = r\cos\left(\frac{g_{\%}2\pi}{100}\right),$$
$$y = r\sin\left(\frac{g_{\%}2\pi}{100}\right)$$

and a constant radius $r = 1$. The additional dimension of information available with the radius r is not used for the moment.

With this transformation a continuous calculation of the gait phase is possible and no jump at $0\,\%/100\,\%$ occurs. As a result of the transformation the regression problem has the two output values x and y. The estimated output values have to be transformed back to obtain the estimated gait phase $\hat{g}_{\%}$.

2.4 k-Nearest-Neighbour

The first method investigated is k-Nearest-Neighbour (kNN), which is a model free approach. It is implemented with the euclidean norm as distance measure. The number

Table 2. Hyperparameter settings of the three Artificial Neural Networks for gait phase estimation after hyperparameter optimization.

Mode	Layers	Nodes	Dropout	Regularization
Level Walking	2	50, 50	0.2	0.001
Stair Ascent	2	20, 50	0.2	0.015
Stair Descent	2	50, 50	0.2	0.001

of neighbours used for the regression is set to $k = 5$ during a validation phase as a trade-off between accuracy and computation time. With regard to implementation purposes the kNN is challenging because of the storage space required for the data set.

2.5 Artificial Neural Network

A model based method is used as a second method besides the kNN, because the potential of using the trained method on unknown test subjects or users of prostheses should be high. This is necessary because the process of training a method for a specific user can be cumbersome. The Artificial Neural Network (ANN) was chosen because of its well known capability of generalization and the property of being able to be a general approximator [Cybenko (1989)].

The hyperparameters of the ANN were chosen by a systematic trial and error optimization. Upper limits for the depth (max. 3 layers) and the height (max. 50 neurons per layer) have been defined to take into account a possible implementation of the trained networks on an active prosthesis in the future.

The chosen hyperparameters of the selected ANNs are presented in Table 2. The ANNs are implemented using `Python 3.7` [Van Rossum and Drake (2009)] and `Keras 2.2.4` [Chollet et al. (2015)]. For training the `Adam`-Algorithm [Kingma and Ba (2014)] is used and a dropout rate is implemented. Start values of the weights are randomly initialized with the default uniform distribution. The activation function in the hidden layers is a ReLu function and because of the regression-type problem, the output layer has a linear activation function.

2.6 Dataset Processing

The dataset from the experiment is separated for training (nine subjects), validation (two subjects) and testing (one subject) purposes with the ANN.

The training data is used to train the ANN in combination with the validation data to tune the hyperparameters and validate the training quality. To prevent the ANN from over-fitting to the training data, the validation data is also used during training in order to stop the training based on the regression quality of the validation data. Therefore, the training is stopped after 5 consecutive epochs of the whole training data without an improvement of the validation loss. The trained model of the last epoch is then selected.

After finalizing the hyperparameters and training the ANN, the test data is used to evaluate the presented method with data that was not used for training the ANN or for selecting the hyperparameters. This is important because every human has specific individual characteristics in its gait and by training the ANN partially learns these patterns of the training subjects too. Therefore, the use of a new subject as test data is a greater challenge for testing and evaluating the quality of the gait phase estimation with ANN after final training and hyperparameter choice.

Table 3. Error comparison of gait phase estimation for three locomotion modes for the test data with k-Nearest-Neighbour and Artifical Neural Networks.

		MAE in %	
Mode	Strides	kNN	ANN
Level Walking	180	3.2	2.9
Stair Ascent	90	4.1	5.6
Stair Descent	119	5.4	3.3

The kNN uses the same training data as dataset, the same validation data to set the hyperparameter k, and the same testing data as used for ANN.

2.7 Evaluation Method

To evaluate the quality of the gait phase estimation a comparison between kNN and ANN is performed. Due to the nature of being a new approach for stair ascent and descent no results from the literature can be used to compare the results.

The quality of the estimation is evaluated with the testing data. Complete strides are used to simulate continuous walking. With this approach the change of the estimated gait phase from sample point to sample point can be evaluated. This is important because too large jumps or changes in the estimated gait phase could lead to unwanted behaviour of an active prosthesis using the estimation for its controls. Additionally, the quantitative quality of the estimation through the mean absolute regression error (MAE) is evaluated.

For later implementation purposes the computation time is important too. Therefore, the execution times for KNN and ANN were conducted. For each method an execution of the entire test data with both methods is conducted at a workstation ten times. To take variability during computation into account, the mean computation time per sample of all ten trials is calculated.

3. RESULTS & DISCUSSION

The presentation of results of the gait phase estimation for the test data of one subject and their discussion has to be separated into the different locomotion modes and is evaluated over multiple strides of each locomotion mode. The mean absolute regression error (MAE) is used as general measurement for the quality of the two regression methods. Additionally, the gait phase estimation during a single stride is evaluated, because a smooth course of the gait phase is desired. As last evaluation criteria the computation time is examined.

3.1 Estimation Performance

The MAE of the kNN and ANN over the tested strides are listed in Table 3 and shows lower error values for level

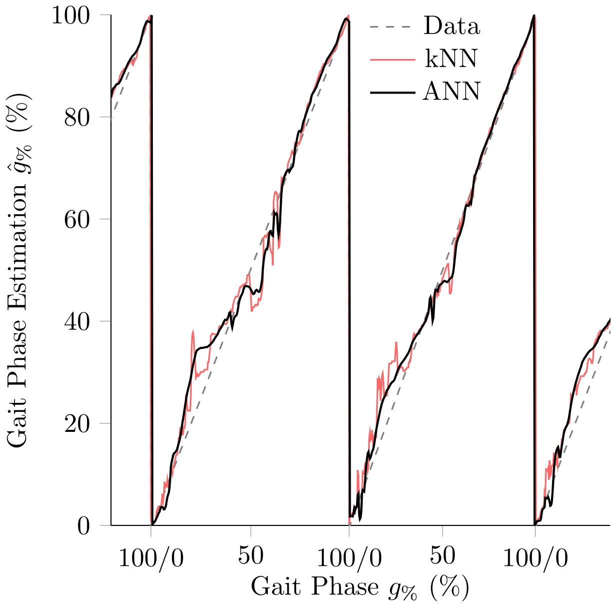

Fig. 3. Gait phase estimation of k-Nearest-Neighbour and Artificial Neural Network for two exemplary strides of level walking from the test data of one subject.

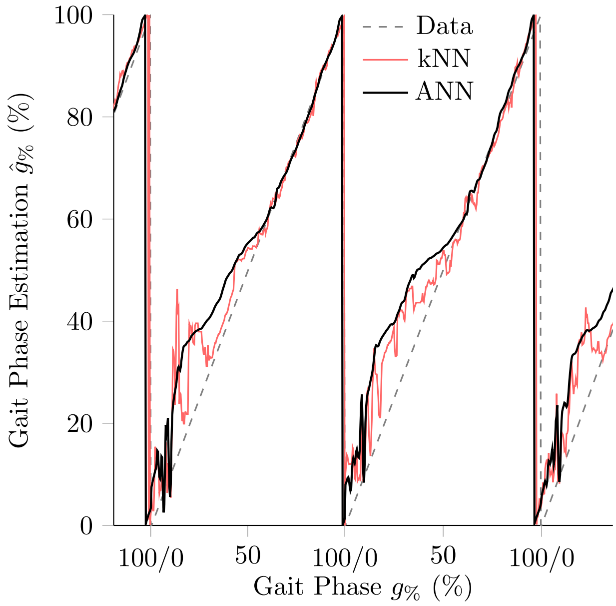

Fig. 4. Gait phase estimation of k-Nearest-Neighbour and Artificial Neural Network for two exemplary strides of stair ascent from the test data of one subject.

walking and stair descent for the ANN, but higher error values for stair ascent compared to the kNN.

To further evaluate the regression performance of both methods a complete stride has to be evaluated especially with regard to smoothness. For the evaluation two exemplary strides are chosen from the test data. The following Figs. 3 to 5 show on the x-axis the real gait phase from the test data and on the y-axis the gait phase estimation. For level walking the performance of the gait phase estimation of the kNN and the ANN is very similar as can be seen in Fig. 3. During the two presented strides both methods can estimate the gait phase quite well but the ANN shows a smoother overall behaviour. The results (courses of plots) are comparable to the quality of the shown gait phase estimation results with the phase plane approach in Holgate et al. (2009).

Compared to level walking, stair ascent and stair descent are more difficult tasks for the gait phase estimation as can be seen in higher MAEs, but both the kNN and the ANN show promising results. With the chosen input features setup the gait phase estimation during stair ascent seems to be more challenging than during stair descent, which results in the higher MAEs.

For stair ascent Fig. 4 shows an offset in the estimation during the first half of a stride for the kNN and the ANN with overall better performance of the ANN because of the smoother behaviour, despite the higher MAE mentioned before. The high frequency disturbances at the beginning of a stride of the ANN in Fig. 4 may be linked to disturbances that occur in the acceleration data due to the impact of the foot during heel-strike. Why this effect is only visible in the gait phase estimation for stair ascent and not for the other two locomotion modes, despite having similar disturbances in the acceleration data, has to be further investigated. Stair descent shows the best performance for the ANN of all three locomotion modes

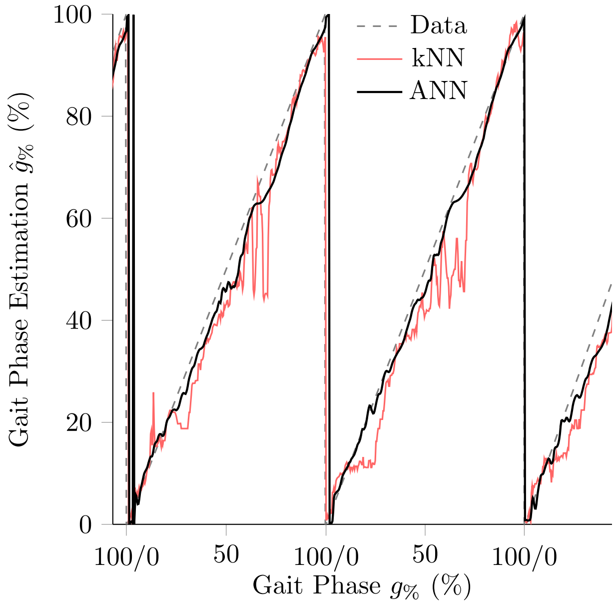

Fig. 5. Gait phase estimation of k-Nearest-Neighbour and Artificial Neural Network for two exemplary strides of stair descent from the test data of one subject.

with regard to smoothness. The kNN method has high frequency disturbances during the transition from stance to swing phase, which do not occur for ANN (Fig. 5).

For level walking and stair ascend the gait phase estimation is more accurate for gait phase values between 60% and 100% than it is for gait phase values between 0% and 60%. This timing fits to the transition from stance phase to swing phase occurring at $g_{\%} \approx 60\%$ [Grimmer et al. (2020)].

Based on this result, we assume that it is easier to detect the gait phase during swing, compared to stance.

Table 4. Computation time per sample point of the gait phase estimation of k-Nearest-Neighbour and Artificial Neural Network for the test data on a common workstation.

	Time in s	
Mode	kNN	ANN
Level Walking	2.918×10^{-4}	6.8×10^{-6}
Stair Ascent	1.511×10^{-4}	6.9×10^{-6}
Stair Descent	1.780×10^{-4}	6.7×10^{-6}

3.2 Computation Time

The mean computation time per sample of all ten trials is shown in Table 4 for each of the three locomotion modes. For all locomotion modes the computation time of one sample point of the ANN is over one order of magnitude smaller compared to the kNN. In addition, with a larger dataset the kNN is going to become even slower, because the access of the dataset and the identification of the nearest neighbours need more time and result in a higher computation time per sample point. This limits the possibility of adding more data from other experiments in the future or adding additional input features. The ANN is not affected by this after training.

The results suggest that the kNN needs too much computation time to be implemented for an online gait phase estimation on a prosthesis because of the in general more limited computation power of a micro controller. For the sampling frequency of the dataset of $f = 200\,\mathrm{Hz}$ respectively $t_{\mathrm{sample}} = 5 \times 10^{-3}\,\mathrm{s}$ the computation time of the kNN is too close to the sample time. Regarding the computation on a workstation, the feasibility of an implementation of the kNN on the micro controller of a prosthesis in real-time is questionable. With regard to computation time the ANN approach is much more preferable.

3.3 Cross-Validation

In Weigand et al. (2020) we conducted a Leave-P-Groups-Out Cross-Validation (LPGOCV) and tested all combinations of one training subject and two validation subjects for the dataset and ANNs presented in this paper. The results suggest the use of all subjects of the dataset to be viable. The subject selected for the test data in the dataset split mentioned in section 2.6 (subject twelve) is the worst case selection with regard to the MAE of the regression.

The LPGOCV results support the feasibility of the presented ANN based gait phase estimation.

4. CONCLUSION

This work presents a new approach for gait phase estimation using solely kinematic data from the shank in combination with two regression methods, k-Nearest-Neighbour and Artificial Neural Network, and a higher dimensional input space.

The presented transformation of the gait phase to cartesian coordinates enables the use of regression methods for the gait phase estimation because of the continuity of the surrogate variables. In addition, the transformation offers a new degree of freedom for the regression because the radius r can be used to encode additional information like walking speed or stair slope.

The introduction of the pseudo-velocity yields a good substitute for the real velocity, which is more difficult to measure or calculate. The results imply that the information incorporated in the pseudo-velocity is of interest, not the absolute value of the velocity. Further research will be done to look into the possibility of substituting the shank angle with a pseudo-angle too.

The gait phase can be estimated for the three locomotion modes level waking, stair ascend and stair descent for the test data of one subject with a mean absolute error $< 6\,\%$. The results of Weigand et al. (2020) show that this is the worst case MAE for the given dataset.

Future work should also focus on post-processing of the estimated gait phase, to improve the overall performance and in particular increase the smoothness. For the ANN additional topologies like Recurrent Neural Networks can be investigated.

We believe that ANNs are a promising method to determine the gait phase of level walking and stair ambulation as part of the control of an active transtibial prosthesis.

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