Continuous locomotion mode recognition and gait phase estimation based on a shank-mounted IMU with artificial neural networks

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Abstract—To improve the control of wearable robotics for gait assistance, we present an approach for continuous locomotion mode recognition as well as gait phase and stair slope estimation based on artificial neural networks that include time history information. The input features consist exclusively of processed variables that can be measured with a single shank-mounted inertial measurement unit. We introduce a wearable device to acquire real-world environment test data to demonstrate the performance and the robustness of the approach. Mean absolute error (gait phase, stair slope) and mean absolute error was in between

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users’ locomotion mode and gait phase can be appropriate for optimal assistive support [1].

To obtain locomotion mode and gait phase, direct and indirect sensory information can be used. Direct sensory information requires some form of direct connection to the user, e.g. measuring muscle activity on the skin with surface electromyography (sEMG) [2], or with implants, such as either an agonist-antagonist myoneural interface [3] or load sensors to measure the interaction force between the device and the user [4]. These approaches have limited user applicability [5], ease of use, and robustness [6], though they are still being actively researched.

Indirect sensory information utilizes kinematic and kinetic measurements to estimate the locomotion mode and the gait phase. Inertial measurement units (IMUs) can be used to measure kinematic signals such as translational accelerations and angular velocities. Compared to sEMG, IMUs are robust and can be used in a wide range of everyday devices and can be easily attached to the user. Acquiring human kinetics such as joint torques requires measuring ground reaction forces (GRFs) in a laboratory setup. For everyday applications, measurements of GRFs are largely only available for wearable robotics and not for prostheses.

Recently, research has focused on machine learning-based approaches for locomotion mode recognition [6]. In [7], a dynamic Bayesian network is proposed that uses distinct classifiers for locomotion mode recognition at certain predefined stride events. For each event a 300 ms window of data from 13 mechanical prosthesis-based sensors is used to calculate a likelihood for the current locomotion mode. To incorporate past predictions a prior probability for each gait mode is calculated based on the prediction of the last event. In [8] a 300 ms window at the beginning of each stride is used for the locomotion mode recognition based on sEMG data with dynamic Bayesian networks. A time window approach with a shank-based IMU was used in [9] where a decision tree based on neural networks as judgment nodes achieved high accuracy on classifying locomotion modes. However, transitions between the modes were not considered and the test data was not obtained in a different setup compared to the training data. Other approaches such as that in [10] use multiple sensor systems, which are more challenging to incorporate in real-world applications.

Gait phase estimation can be realized by phase plane approaches [11], [12] and machine learning regression [13], [14], [15]. Seo et al. [13] used recurrent neural networks (RNNs) with long short-term memory nodes (LSTMs) in combination with a shank-mounted IMU to estimate the

I. INTRODUCTION

Human locomotion is a complex process consisting of different locomotion modes, such as level walking or stair climbing, to navigate different environments. Each mode has specific support characteristics throughout the stride where the progress within a stride is called the gait phase. A specific event, e.g. the heel strike, is chosen as the beginning and the end of a stride. The beginning of the stride corresponds to a gait phase of 0 % and the end to 100 % where the recurrence of the same event (heel strike) also defines the beginning of the following stride. Both locomotion mode and gait phase contain useful information that can be used in the control of locomotion tasks. For wearable robotics, like powered prostheses or exoskeletons, knowledge of the
gait phase for level walking. Results show that subject-
specific training data improved the overall performance of the
estimation. In [14] artificial neural networks (ANNs) were
used to estimate different walking speeds and the gait phase
of level walking with a robotic hip exoskeleton that included
two IMUs (thigh, trunk) and a hip encoder.

In [15], [16] we presented a proof of concept for a
continuous gait phase estimation for level walking (LW),
stair ascent (SA) and stair descent (SD) using ANNs with
fully connected layers relying only on kinematic data from
the shank as features. These features can be obtained with a
single IMU mounted to the shank. However, we discovered
that the performance of this approach was partially limited
due to similar measurement data in the mid stance and the
early swing phase. One way to overcome this limitation is
to utilize past measurements or time history information.
In [17], the use of time history information improved the
estimation performance of both the gait phase and stair slope
by over 30% using a single ANN. The test data had mean
absolute errors (MAE) of <3% for gait phase estimation and
<4° for stair slope estimation, though stair slope estimation
was found to be quite noisy.

The present work extends our previous use of an ANN
for gait phase and stair slope estimation based on a shank-
mounted IMU [15], [16], [17]. Specifically, we develop an
additional ANN for continuous locomotion mode recognition
without predefined stride events for level walking, stair
ascent and stair descent to realize a complete high level
control for a powered transfibial prosthesis.

We hypothesize that it is possible to distinguish the locomo-
tion modes LW, SA and SD with an ANN continuously
throughout a stride. Our approach differs from the work
of others that classify stride segments [7] or whole strides
[18] and therefore these approaches do not result in a
classification for each sample. Further, as already observed
for the gait phase estimation [17], we hypothesize that using
time history information will improve the performance of the
locomotion mode recognition.

A laboratory-based dataset from a prior work [15], [19]
that includes subjects without mobility impairment perform-
ing level walking and stair ambulation was used to train
the ANNs. As the dataset was acquired in a laboratory
setup it may not appropriately represent real-world scenarios.
Therefore, the trained ANNs could have higher prediction
errors if robotic hardware uses different sensors and sensor
fixations from the ones used to acquire the training data. To
allow for transferability to real-world scenarios and for use of
different hardware, a mobile hardware setup was developed
and used to collect test data in a real-world environment. As
the data is additionally obtained from different subjects than
in [19], it can be considered as a true test scenario that is used
to evaluate the robustness of the prediction of gait phase,
stair slope and locomotion mode. We hypothesize that the
performance for the test data from the laboratory experiment
is slightly higher than that for the real-world environment due
to the sum of differences in the real-world experiment.

The training data for the ANNs only contains steady
gait conditions. However, transitions between level walking
and stair ambulation are important for wearable lower limb
robotic control to avoid falls and injury, for which humans
with impaired gait are at increased risk [20]. Therefore, we
qualitatively analyzed the behavior of the trained ANNs with
respect to the unknown transitions as well. We hypothesize
that the gait phase during transitions will be detected with
similar performance as that during steady gait. In addition
we think that the estimated stair slope and the classified
locomotion modes will gradually change with respect to the
transition between two steady locomotion modes.

II. METHODS

In the following sections the machine learning approach
for the gait phase and stair slope estimation ANN is presented
first. Then, the differences of the ANN regarding the locomo-
tion mode recognition are stated and the data preprocessing
for the ANNs is introduced.

A. Gait Phase and Stair Slope Estimation

For the gait phase and stair slope estimation we use an
adapted ANN layout based on prior works [15], [17] with
fully connected layers and a moving time window for the
input features. In comparison to RNNs this results in the
utilisation of time history information without the need for
more complex ANN architectures.

As in [15] only IMU measurements from the sagittal plane
are used, resulting in two accelerations and one angular
velocity. In combination with the pseudo-integration [II-C.2]
for each of these measured quantities and the time window
a total of 6 · nwindow features are used as inputs for the ANN.

All data used with the ANNs has a sampling frequency of
200 Hz, resulting in a sampling interval Tsample of 5 ms. The
time window length is Twindow = nwindow · Tsample. The ANN
is evaluated at each sample point resulting in updated output
every Tsample.

In contrast to our prior work [17], a cascaded structure for
the hidden layer was not used, thus resulting in uniformly
large layers. Hyperparameters were selected after a hyperpa-
rameter optimization (HPO) over a search space (Table I)
on an eight-core desktop computer with GPU utilization
(Nvidia RTX 2080) in Neural Network Intelligence (NNI)
[21] with a Gaussian process (GP) based Bayesian optimiza-
tion. Selected parameters are presented bold in Table I. The
optimal time window length of 300 ms from HPO matches
that independently selected time window length of other
approaches [14], [22].

Start values of the network weights were randomly ini-
tialized with a default uniform distribution. The activation
function of the hidden layers was a ReLu function. Due to the
regression-type nature of estimating a continuous value like
gait phase and slope the output layer has a linear activation
function. The loss function for the training was a mean
squared error and early stopping based on the validation loss
with a patience of four was used.

The ANN were implemented using Python 3.8 [23]
and Tensorflow 2.2. For training the Adam-Algorithm
[24] is used.
TABLE I: Parameter space for HPO for the ANN for gait phase and stair slope estimation. Selected parameters appear in bold. Time Window Length $T_{\text{window}} = n_{\text{window}} \cdot T_{\text{sample}}$.

| Hyperparameter         | Range                                |
|------------------------|--------------------------------------|
| Dropout Rate           | [0, 0.5]                             |
| Batch Size             | 128, 256, 512, 1024, 2048, 4096       |
| Layer Size             | 32, 64, 128, 256, 512, 1024           |
| Hidden Layer Number    | 1, 2, 3, 4, 5, 6, 7, 8, 9             |
| Time Window Length     | $n_{\text{window}}$                  |
|                        | $T_{\text{window}}$                  |
|                        | 5 ms - 375 ms (300 ms)                |

TABLE II: Parameter space for HPO for the ANN for locomotion mode recognition. Selected parameters appear in bold.

| Hyperparameter         | Range                                |
|------------------------|--------------------------------------|
| Dropout Rate           | 0-0.5 (0.15)                         |
| Batch Size             | 128, 256, 512, 1024, 2048, 4096       |
| Layer Size             | 32, 64, 128, 256, 512, 1024           |
| Hidden Layer Number    | 1, 2, 3, 4, 5, 6, 7, 8, 9             |
| Time Window Length     | $n_{\text{window}}$                  |
|                        | $T_{\text{window}}$                  |
|                        | 60 samples                            |

B. Locomotion Mode Recognition

The classification ANN used for locomotion mode recognition uses the same input space as in the ANN for the gait phase and stair slope estimation in Section II-A. The output classes are LW, SA and SD as locomotion modes of interest. Note that we use a single classifier that is independent of the gait phase and thereby provide a prediction for each sample utilizing a sliding window of the most recent measurements (time history information). This is in contrast to [25] where it is stated that continuous classification requires multiple classifiers for different segments of a stride, as our approach eliminates the need for multiple classifiers. The hyperparameters for the classifier ANN in Table II were selected by a grid search optimization based on the same parameter space as given in Table I. Only the time window length was selected based on the HPO of the gait phase and slope ANN to achieve consistency with the input feature dimension. A hyperbolic tangent activation function was used for the hidden layers. Due to the classification-type nature of the locomotion mode recognition the output layer used a softmax activation function. The loss function for training was the categorical cross entropy and early stopping was used based on the validation loss with a patience of ten. The ANN for recognition was implemented in the same way as mentioned above for ANN for estimation.

To determine the performance increase due to using the time history information, an additional ANN with no time window ($n_{\text{window}} = 1$) was trained.

C. Data Preprocessing

The following steps were used to preprocess the data. Note that these procedures are independent of the source of the dataset whether it be laboratory-based or real-world data.

1) Low-pass Filter: A second order low-pass Butterworth filter with a $f_{\text{cutoff}} = 12$Hz was used to remove high frequency noise in IMU accelerations and angular velocities, which appear due to touchdown-related impacts as well as general measurement noise. To determine the cutoff frequency, the amplitude spectrum of the laboratory dataset was analyzed with a fast Fourier transformation (FFT).

2) Pseudo-Integration: The IMUs measure translational accelerations and angular velocities in three dimensions. Previously, it was shown that angle data can be beneficial for gait phase estimation [11]. Angle data can be calculated from IMU measurements through a Kalman-filter [26] or a complementary filter [27]. To realize the potential benefits of using angle information without the need to implement complex filters we introduced pseudo values of the angle, which are calculated by a pseudo-integration that consists of an integration followed by a first order high-pass [15]. This combination results in a drift-free qualitative representation of the integration. A similar approach is used in [11]. The combination of an integration followed by a first order high-pass filter can be condensed to a first order low-pass filter

$$G_{\text{pseudoInt}}(s) = \frac{1}{s} \left(\frac{s}{Ts + 1}\right) = \frac{1}{T_s + 1}$$

leaving the time constant $T$ of the filter to be set. The value of $T$ is set individually for angular velocities and translational accelerations by comparing the angle and translational velocities measured in the laboratory dataset to their pseudo counterparts. A compromise between a very strong (large $T$, less signal information) and a very weak (small $T$, very similar to the original signal, i.e. the angular velocity and the translational acceleration) low-pass filter must be identified. The time constants for the pseudo angle and the pseudo velocity were set to $T_{\text{angle}} = 1$ s and $T_{\text{velo}} = \frac{1}{3}$ s, respectively.

As an example, Fig. II shows the pseudo angle derived by pseudo-integration and the real angle measured in the lab. The major differences are the time lag of the pseudo value and the offset. The latter will be removed later in the process by the normalization of the input features. Therefore, the performance of the ANN should not be affected by the quantitative error of the pseudo values relative to real integrated values.

3) Gait Phase Separation: To improve the robustness and the usability for later use in a prosthetic high level control, the gait phase estimation is time-normalized within
two sections of the stride. Touchdown and liftoff events are used to separate the stride into stance and swing phases. We set a fixed gait phase of \( g_{\text{lim}} = 63 \% \) for the liftoff event as this is the middle of the liftoff gait phase range observed in [19]. The gait phase is then defined to linearly increase from 0 % to 63 % during the stance phase and from 63 % to 100 % during the swing phase. As a result the gait phase values depend on three events (touchdown, liftoff, next touchdown), which results in two linear sections with different slopes. This reduces differences occurring from variability between strides, individual timing or varying terrain. It is also beneficial for the ankle prosthesis application as stance and swing phase are often treated differently from a control perspective.

4) Gait Phase Transformation: In cyclic gait patterns, the gait phase percentage shows a discontinuity between the end of one stride (\( g_{\text{lim}} = 100 \% \)) and the beginning of the following stride (\( g_{\text{lim}} = 0 \% \)). To replicate the discontinuity within the gait phase estimator an infinite gradient would be necessary at the junction of two strides. It is plausible that the discontinuity in the gait phase results in an insufficient estimation performance around the beginning and the end of a stride. To overcome this problem, we introduced a two-dimensional cartesian coordinate transformation [15]. This transformation was independently introduced in [13] and [14], too.

The gait phase value \( g_{\%} \) can be considered an angle of a circle with a specific radius \( r \), which is then transformed into cartesian coordinates

\[
x = r \cos \left( \frac{g_{\%} \times 2\pi}{100} \right),
\]

\[
y = r \sin \left( \frac{g_{\%} \times 2\pi}{100} \right),
\]

to obtain a continuous representation of the gait phase with the cost of adding one extra dimension to the output values of the ANN for the gait phase. The estimated output values must be transformed back with a post-processing step to obtain the gait phase estimation as percentage of the stride.

The two values \( x \) and \( y \) representing the gait phase and the stair slope are the three outputs of the estimation ANN.

5) Normalization: A normalization of input features and output labels improves the optimization stability during ANN training [28]. A naive normalization approach would be based on the mean and standard deviation (STD) of the entire training data. During preliminary tests with data measured from sensor hardware other than that from which the training data were acquired, the ANNs were found to have poor estimation and recognition quality. We explain this by deviations in the sensor orientations and mounting height on the shank from variable mounting of the IMUs during the real-world environment experiments. These deviations result in IMU measurements of differing amplitudes. In this case, we decided to normalize the input features of each real-world experiment dataset based on the mean and the STD of that specific experiment, which resulted in much better performance of the ANNs. The normalization values can easily be obtained for a new sensor system with a few measured strides. Different locomotion modes exhibit different values for the mean and the STD. Therefore, using the mean and the STD of the complete dataset makes the normalization dependent on the distribution of the different locomotion modes. For this reason we only use steady LW data for normalization.

III. EXPERIMENTS

The study protocols for the laboratory and the real-world experiment were approved by the institutional review board of Technical University of Darmstadt, Germany. All subjects provided written informed consent in accordance with the Declaration of Helsinki.

A. Laboratory Dataset

The laboratory dataset used in this work was previously recorded during a stair walking experiment at the Locomotion Laboratory of the Technical University of Darmstadt [19].

During the experiment twelve subjects (age: 25.4 (45) years, height: 180.1 (46) cm and mass: 74.6 (79) kg, all male) were recorded while walking on an instrumented track that included a staircase and a level area before and after the staircase. Force plates (Kistler, Switzerland) were mounted within the track and staircase to capture GRFs. Each subject was equipped with combined sEMG and IMU sensors (Delsys Trigno, US), from which only the shank IMU data is of interest for this work.

1) Experimental Protocol: Prior to recording, subjects could familiarize themselves with the instrumented track, and force plates were arranged individually to match the preferred step length. Each subject walked along the track, ascending and descending the staircase ten times for each of three different stair slopes (19°, 30° and 40°).

Following the experiment the vertical GRF and IMU data (translational accelerations and angular velocity) were extracted and the locomotion mode and the stair slope values were set according to the experimental protocol. The gait phase values had to be calculated based on the GRFs. The beginning and the end of a stride were timed by the touchdown event and the following touchdown of the same foot, respectively. Both touchdown events were determined by the rise of the vertical GRF in the corresponding force plate. The gait phase was set as a percentage of stride duration based on the beginning (0 %) and end (100 %) of the stride as well as the stance-swing phase division previously described.

In total 2128 strides of LW, 1067 strides of SA and 1415 strides of SD were evaluated from the twelve subjects. All signals were equalized to a sample frequency of 200 Hz.

Due to the data being measured from individual subjects the data is split into training, validation and test data from nine, two and one of the twelve subjects, respectively. This process was based on the results of a cross-validation in [16]. This split by subjects is also intended to provide a test of transferability to different individuals.
the sum of all three FSRs per foot gait phase, the FSR data need to be further processed. First, locomotion mode). To specify the outputs of the ANNs (gait phase, stair slope, collection session, we have all of the necessary information SD). With manually-measured stair slopes used during a data locomotion mode by pressing the respective button (LW, SA, SD). With manually-measured stair slopes used during a data collection session, we have all of the necessary information to specify the outputs of the ANNs (gait phase, stair slope, locomotion mode).

1) Ground Contact Determination: To obtain the correct gait phase, the FSR data need to be further processed. First, the sum of all three FSRs per foot

\[ F_{\text{sum}} = F_{\text{heel}} + F_{\text{toe}} + F_{\text{ball}} \]

is calculated, which qualitatively resembles the curve of the vertical GRF during ground contact but with a different scaling. As only the touchdown and liftoff are of interest to determine the gait phase, a qualitative representation of the vertical GRF is sufficient.

Secondly, similar to the laboratory dataset containing vertical GRF, the FSR data allows us to determine the touchdown and liftoff by the rise and fall of \( F_{\text{sum}} \). A threshold value is set by manually inspecting \( F_{\text{sum}} \) for each foot and selecting the threshold based on the noise level during the swing phase. One threshold for each leg is specified for each individual experiment to account for subject-specific differences (e.g. tightness of the shoe or changes in FSR placement and subject weight).

2) Data Processing: The FRIMU2 contains an IMU at each shank that records translational accelerations and angular velocity. The IMU values are processed in the same manner as in the laboratory-based dataset.

A cleaning procedure is used to remove artifacts such as irregular long or short strides and instances of turning on the spot or standing. A stride is removed if one of the following three criteria is met. First, the maximum sagittal angular velocity is below \( |1| \times 1 \text{s}^{-1} \). Second, the maximum vertical translational acceleration is below \( |0.1| \text{m s}^{-1} \). Third, the total stride length is smaller than 0.8 s or larger than 1.4 s.

3) Experimental Protocol: Test data of three subjects (age: 28.3(38) years, height: 187(5) cm and mass: 77.3(110) kg, all male) was collected with FRIMU2.

Each subject walked in a stairwell of a five-story building that included ten flights of stairs with a 26° stair slope. Subjects had the FRIMU2 device mounted as shown in Fig. 2. The locomotion mode was input by the subject during walking via the hand-held control unit by pressing the up, down or left button for SA, SD or LW, respectively. The subjects were told to press the button while the leading limb was in the swing phase when entering or exiting each staircase.

Each experimental trial had a variable duration due to the subjects’ preferred walking speed; trials lasted 220 s, 230 s, 220 s for subject 1, 2, and 3, respectively. Each subject was given time to become acquainted with the hand-held control unit and the staircase. The LW strides in the real-world experiment provide an additional challenge to the trained ANNs; while the ANNs were trained with data from a straight instrumented track in the laboratory experiment, the real-world staircase layout included a 180° turn with a radius of approximately 3 m each half-flight of stairs. This difference from straight locomotion creates a gait disturbance and therefore offers insights on the robustness of the ANNs.

In addition, FRIMU2 data of one subject was measured while walking up and down a long, level hallway. This experiment allows us to investigate LW in more detail without the subject turning around as in the five-story building staircase.

IV. RESULTS & DISCUSSION

The mean absolute error (MAE) of the gait phase and the stair slope estimation from the ANN were calculated as quantitative performance measure. The gait phase value is obtained by transformation from the cartesian output values of the ANN as described in Section II. The performance of
TABLE III: Error measures for gait phase estimation, slope estimation and locomotion mode recognition with and without time history.

| $T_{\text{window}}$ | Measures | Laboratory dataset | Real-world dataset |
|-----------------------|-----------|--------------------|--------------------|
|                       |           | Train | Val | Test | Sub1 | Sub2 | Sub3 | Hallway | Sub3 |
| Gait Phase | 300 ms | MAE in % | 1.2 | 1.6 | 2.0 | 2.5 | 2.6 | 2.2 | 3.5 |
| Stair Slope | 300 ms | MAE in ° | 2.2 | 3.0 | 3.3 | 2.6 | 3.4 | 3.8 | 1.0 |
| Locomotion Mode | 300 ms | Accuracy in % | 99.98 | 99.74 | 99.67 | 99.57 | 98.80 | 98.60 | 98.51 |
| Locomotion Mode | - | Accuracy in % | 99.39 | 94.41 | 97.91 | 96.39 | 95.14 | 94.90 | 97.82 |

locomotion mode recognition is quantified by accuracy of the predicted value relative to the true value.

To analyze steady gait conditions and to compare real-world data with the laboratory-measured data, transition data were excluded from the real-world test dataset. Since humans need approximately one stride duration for the longest transition (SA to LW) [19], we decided to exclude 1.29 s (258 samples) before and after the manually-entered locomotion mode change entered by the subjects. This period is twice as long as the longest stride duration observed in [19]. This post-processing step should leave only steady locomotion data if the locomotion mode change was input anytime during the transition phase. Due to the nature of the human-based input errors (remaining transitions within the steady gait data) can not be ruled out completely by this approach. For the laboratory dataset, from which only steady LW, SA and SD strides were included, no transition exclusion is necessary.

For the laboratory dataset, gait phase and stair slope show a slight increase in MAE for the validation and test data relative to the training data Table III. Locomotion mode accuracy declines slightly in the validation and test data relative to the training data. Such results could be expected as both datasets contain subject-specific gait unknown to the ANNs from training.

Comparing the real-world test data to the laboratory test data shows slight increases for the MAE of the gait phase and slight decreases for the accuracy of the locomotion mode for all three subjects. Comparing the same data for stair slope only subject 1 has a decrease in MAE, while subjects 2 and 3 have slight increases. Such a result is in line with our hypotheses and demonstrates the robustness of the approach considering the differences in the laboratory and real-world experimental setup. These differences include sensor hardware, sensor placement and a real-world staircase with a difference in slope and turns between flights of stairs.

Despite the differences between the real-world and laboratory setups, the MAEs for the gait phase estimation are still better than our previous results for the laboratory dataset in [15] where no time history information was utilized for the input features. This highlights the benefits of using the time history approach for gait phase estimation.

Locomotion mode recognition performance is close to perfect for the laboratory dataset with little differences between the training, validation and test data. The performance decrease with real-world test data is lower than the decrease in test data performance for the LSTM-based ANNs in [29]. This result is promising as [29] collected training and test data using the same hardware setup.

The accuracy of the locomotion mode recognition for hall-}

way data with subject 3 is similar to that accuracy achieved with combinations of stair ambulation and level walking. Therefore, we assume that stair ambulation has similar recognition quality as level walking and that level walking while turning on the landings between half-staircases has no negative impact on the results. The MAE of the gait phase in the real-world hallway data was slightly higher than in the real-world stair ambulation data and in the laboratory data. We do not have an explanation on the reason for this finding but it is possible this could be attributed to differences in locomotion speed, which was not controlled in this trial.

As hypothesized, the use of time history information for the input features improves locomotion mode recognition for both datasets. Here, the additional information of the input features allows for a better distinction between conditions. As such information can be easily integrated without additional sensors, without more complex machine learning algorithms and without a major increase in computation cost, we highly recommend including time history information.

Since the transition timings in the real-world experiment with FRIMU2 are input by the user (dashed vertical lines in Fig. 3a and Fig. 3b), the accuracy of the timings is uncertain. A qualitative inspection of the results was therefore performed to evaluate the ANN performance with time history information for transitions that were not used in training. Fig. 3a and Fig. 3b are used to represent these qualitative results.

Fig. 3a and Fig. 3b show 20 s from a 220 s and 230 s real-world trial for the right leg of test subject 1 during stair ascent and the left leg from subject 2 for stair descent, respectively. Fig. 3a and Fig. 3b contain multiple transitions between locomotion modes and include the LW portions during the 180° turn in the half-step staircase.

The gait phase estimation matches our hypothesis with an almost similar quality for the steady strides and the transition strides. The estimated gait phase starts at 0% and reaches 100% without having unexpected behavior like sudden jumps in between. These results reflect the robustness of the trained ANN when facing test data with different sensor hardware, a different stair height, different sensor placement, transitions, and turns between stair segments.

Small consistent overestimations of the gait phase occurred during the transition from SA to LW at $t = 166$ s (Fig. 3a) and for LW to SD between $t = 76$ s and $t = 78$ s (Fig. 3b). For the LW to SA and the SD to LW transitions no visible deviations occurred.
V. CONCLUSIONS

In this work we were able to estimate both gait phase and stair slope as well as predict continuously the locomotion mode for steady level walking and stair ambulation. We used artificial neural networks with fully connected layers with input features utilizing time history information. The performance decrease in the real-world test data is lower than that in [29] where an RNN with LSTMs was used.
To obtain test data in real-world environments the FRIMU2 mobile device was developed. With FRIMU2 we could show that the trained ANNs achieved high robustness to different subjects, sensor hardware, sensor fixation, shank height and shank arrangement.

In addition, we investigated the ability of the network to predict transitions between level walking and stair ambulation for which the network was not trained. It was found that gait phase estimation, stair slope estimation and locomotion mode recognition performed as expected with real-world usable quality for transitions between level walking and stair descent. However, for transitions that include stair ascent additional methods are required to achieve a similar performance as that with stair descent.

One way to improve the performance of our approaches could be individualization of the ANNs to the user to take the user-specific gait into account. With the FRIMU2 setup the necessary data can be collected easily. For subjects with an amputation this could even be done using their prosthesis used in everyday life before using a powered prosthesis with an amputation this could even be done using their prosthesis the necessary data can be collected easily. For subjects with the user-specific gait into account. With the FRIMU2 setup could be individualization of the ANNs to the user to take

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