Cross-Validation results for a gait phase estimation with Artificial Neural Networks

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Abstract: The knowledge of the gait phase can improve the support of an active prosthesis to increase the mobility of people with transtibial amputations. A Cross-Validation is used in this work to evaluate a novel approach for continuous gait phase estimation with Artificial Neural Networks. The estimation of the gait phase only uses kinematic variables of the shank, which are measurable by a single Inertial Measurement Unit placed at the shank. The dataset is separated in training data, validation data and test data with a Leave-P-Groups-Out-Approach. With the results, a statement can be made whether the dataset is big enough, or needs additional subjects. With the exemption for one test subject the choice of test subject does not change the quality of the regression significantly.

I. Introduction

For people with transtibial amputations active ankle prostheses have the potential to improve their mobility, but need knowledge of the progression during a stride, the so called gait phase.

We present a novel approach for gait phase estimation using only kinematic data of the shank. The shank data can be measured with an Inertial Measurement Unit (IMU) mounted at the shank of an active ankle prosthesis. Unlike methods that use thigh data, e.g., in [1], the limitation to kinematic data of the shank avoids the need for additional sensors if implemented on an active ankle prosthesis.

Artificial Neural Networks (ANN) are used for the gait phase estimation. We assume the knowledge of the current locomotion mode of the user for the gait phase estimation, because the classification of locomotion modes is the topic of different research, e.g. in [2]. Hence, we develop three individual estimators for the three investigated locomotion modes level walking, stair ascent and stair descent.

To improve estimation quality a Cross-Validation is conducted and evaluated.

II. Methods

The estimation of the 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 and a good generalization ability.

II.I. Experimental dataset

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 on an instrumented track including a staircase and a level area before and after the staircase.

II.II. Artificial neural network

Six input features are chosen for the ANNs. The outputs are x-y-coordinates of the unity circle (-1 to 1) resulting in a polar angle representing a transformed gait phase (0% to 100%). Hence, a continuous value at the end of one step and the beginning of the next step exists.

II.III. Inputs

The six input features used for the ANNs are extracted from the experimental dataset with the shank angle φ and the shank angular velocity $\dot{\varphi}$ calculated from motion capture data and the translational acceleration $\ddot{y}$ and $\ddot{z}$ from a shank mounted IMU. As a substitute for translational velocities, a so-called pseudo-velocity is introduced, due to the more complicated calculation of translational velocities from acceleration information from IMUs. The pseudo-velocity is acquired by an integration followed by a first-order high-pass filter. Taken together these two steps can be summarized into a first-order low-pass filter. A cut-off frequency of 3 Hz is chosen.

Table 1: Input features for 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 $\tilde{\dot{z}}$

II.IV. Cross-validation

The Cross-Validation performed in this work consists of two sets of Leave-P-groups-Out splits. The groups in this context are the individual subjects from the dataset. The first set of splits is a Leave-1-group-Out and generates twelve test datasets consisting of one subject each. The second split is then a Leave-2-groups-Out for splitting the remaining subjects of the dataset into all combinations of two validation subjects and nine training subjects resulting in

55 combinations for each of the training splits. In total 660 combinations are investigated.

For the test splits the ANN with the lowest Mean-Absolute-Error on the validation data is selected for further comparison between the test subjects.

III. Results and discussion

The Mean-Absolute-Error (MAE) of the gait phase estimation for each split is used to quantify the double Leave-P-Groups-Out-Cross-Validation results.

The results for level walking are shown in Figure 1. The twelfth test subjects has a much higher MAE then the other test subjects, indicating a different walking pattern then the rest of the subjects. Therefore, the gait phase estimation results in higher errors. For the rest of the test subjects the MAE of the test data is close to the MAE of the validation data. Except for the eighth and tenth subject the chosen ANNs (best model) result in lower test data MAEs then the mean validation MAEs.

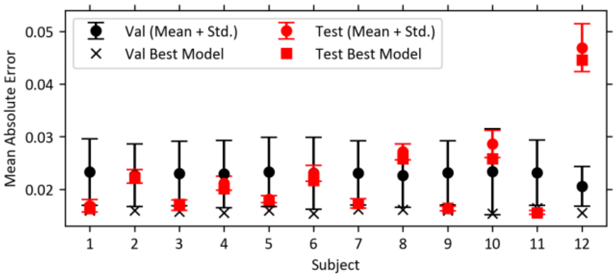

Figure 1: Cross-Validation results for all test subjects and train-validation splits with standard derivation for level walking.

The results for stair ascent in Figure 2 show a more diverse pattern than the level walking results. Compared to the mean MAEs of the validation data, three test subjects (3, 8, and 12) show a significantly worse result in the MAEs for the test data for the selected best model ANNs. The MAEs of the validation data show a uniform pattern. Compared to level walking it can be argued that additional subjects could improve the quality of the regression because of the higher count of test subjects with a larger MAE.

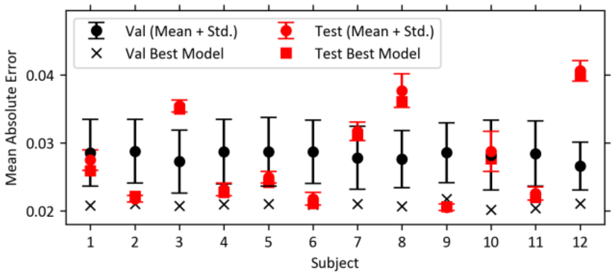

Figure 2: Cross-Validation results for all test subjects and train-validation splits with standard derivation for stair ascent.

In Figure 3 stair ascent results show the most uniform MAEs for test and validation data. The mean MAEs have a total of around 1 % (test) and less than 0.5 % (validation). However, for seven test subjects the chosen ANN results in worse MAEs than the mean MAE of the validation data.

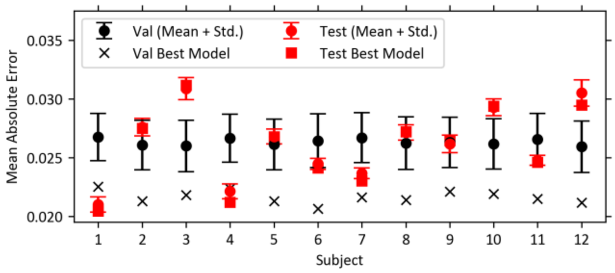

Figure 3: Cross-Validation results for all test subjects and train-validation splits with standard derivation for stair descent.

Overall, all the Leave-P-Groups-Out-Cross-Validations offer the possibility to improve the estimation results without the need of additional subjects or additional input features. In comparison to conducted tests with a fixed randomly chosen distribution, the Cross-Validation offers the possibility to choose an ANN with a lower MAE for the same test subject. This is because of the systematic selection of training and validation subjects.

The results for all three locomotion modes indicate that choosing the best model for a specific test subject based on the lowest MAE for the validation data seems reasonable.

IV. Conclusions

This work investigates an optimized use of an experimental dataset for a new approach of gait phase estimation relying only on kinematic data from the shank by cross validating it with a double Leave-P-groups-Out split.

The use of a Cross-validation has the potential to improve the MAE in comparison to a randomly chosen training-validation-test split up to 2% at cost of a higher time to train all splits.

The double split shows some variance in the results for different test subject for all three investigated locomotion modes. However, the Cross-Validation still implies that the use of the whole dataset as training and validation data with testing afterwards on an active lower prosthesis to be feasible because of the low variance between the chosen training-validation subjects combinations.

In addition, the a systematic selection of training and validation data to incorporate better individual gait patterns of specific subjects can improve the overall generalization performance in comparison to a randomly chosen split.

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Author's statement

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