Gait Feedback and Correction Generation Using Multivariate Signal Learning

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Abstract

Gait analysis is the systematic study of human locomotion using external visual and sensory observations. Data extraction from such observations enables the quantitative assessment of human motion skills that can lead to feedback discovery and physical ability evaluation. Current research methods in human gait analysis cover a substantial portion on gait-phase identification, locomotion recognition and gait trajectory prediction. Although recognizing and predicting human phase-gait cycles is important for understanding and analyzing physical motor ability, it is insufficient to provide objective gait rate feedback and motor function recovery. In this work we introduce and implement the Feedback Recovery Network (FDRNet). FDRNet is a novel deep neural network architecture able to provide objective personalized quantitative gait feedback discovery and correction on multivariate time-series data. We train FDRNet using an online available dataset containing 1020 multivariate gait signals from 230 subjects undergoing a fixed protocol: standing still, walking 10 m, turning around, walking back and stopping. The measured population is composed of healthy subjects as well as patients with neurological or orthopedic disorders. The FDRNet holds promise for automation in personalized rehabilitation and considers the potential of creating new technology in the area of physical ability performance assessments.

1. Introduction

Gait analysis is the systematic study of human locomotion using external observations. These observations are mainly derived from either visual information such as video recordings collected using cameras or other signal data information extracted using wearable sensor devices like XSens [1]. Video recordings require intensive data pre-processing and cleaning techniques before they can be used. The quality of the data coming from video sources is limited on the camera and configuration environment equipment, the ability to eliminate occlusions and the reliability of feature key-point extractors. On the other hand, raw data extraction using wearable sensor devices is a more reliable option since the data quality depends only on high precision sensors provided by the manufacturer. Wearable sensor devices achieve high quality 3D motion capture by tracking the coordinates of specific joint points like right and left knee, heel, feet, arm and the head of the human body.

In this work we utilize an online freely available dataset [19] consisting of 1020 multivariate gait signals from 230 subjects. The measured population of this dataset was composed of healthy subjects, neurological and orthopedic individuals. Gait data are collected during a fixed physical task: standing still, walking 10 m, turning around, walking back to the start point and stopping.

The first step of this work is to explore the dataset [19] which shows different gait signals among individuals with different physical conditions (healthy, neurological, pathological) and different physical characteristics (i.e age, weight, height, healthy state). After we are able to extract signal data form each population we group neurological and pathological samples into a single impaired group and keep healthy samples separate. Our goal is to feed the healthy and impaired data to train a multivariate neural network to learn the characteristics of normal and abnormal gait behavior aiming at quantitative feedback discovery and correction.

The deep learning architecture is designed to output quantitative multivariate feedback for gait correction based on N=16 control signal variables describing the left and right foot activity. Given the big size of the data and the limited hardware resources we train the network only for the left foot activity signals but the same algorithm can be applied to train the full dataset by just changing the input size.

Vertical Acceleration Left	LAV
X-axis Acceleration Left	LAX
Y-axis Acceleration Left	LAY
Z-axis Acceleration Left	LAZ
Vertical Rotation Left	LRV
X-axis Rotation Left	LRX
Y-axis Rotation Left	LRY
Z-axis Rotation Left	LRZ

Table 1. Left foot gait signal variables

Specifically, for each foot there are 8 different signal variables that are summarized in the table 1. The variables are defined based on 3 upper case characters where the first one denotes the orientation right [R] or left [L] foot (here left), the second one the type of motion with [A]: acceleration in m/s^2 and [R]: rotation in deg/s and the last one denotes the motion orientation as [V] Vertical, [X] X-axis, [Y] Y-axis and [Z] Z-axis based on the coordinate system of the Xsens device [19]. Obviously, all the accelerations for the right foot are given by replacing the first character from L to R. Similarly, the rotations are given by replacing the second character from A to R and so forth.

Once we perform the training over the population of the dataset [19] our network provides fast inference on quantitative gait feedback. The feedback signal is an $M\times$ N tensor that describes the amount of gait signal correction with respect to the ideal gate rates. The dimension M of the feedback tensor describes the number of time steps of the signal and it varies depending on the velocity of each individual during the protocol task (walking 10-meter and return). N represents the 16 different accelerations and rotations of both feet per signal gait.

The proposed methodology of this work is a first effort towards the development of a new neural network architecture aiming at automation in personalized rehabilitation such as precision monitoring and fast recovery in sports and/or in rehabilitation as well as in the development of objective assessments in physical ability evaluation. The later one can be extended to provide feedback on other physical ability assessments in different configurations including but not limited to climbing, running, jumping and psychometrics in physical demanding jobs.

2. Related Work

There is a substantial portion of recent research that investigates kinematics problems related to gait analysis in human motion. David Kreuzer and Michael Munz [8] used deep convolutional networks combined with LSTM networks to recognize gait phases using inertial measurement units. They were able to predict the gait cycles using 7 signal channels on a small data set of 11 healthy subjects. Angel Peinado-Contreras and Mario Munoz-Organero [14] followed a similar approach to identify gait patterns from 15 people using data captured from smartphone accelerometers and gyroscope sensors. For their work they used an online available dataset created by Timo Sztyler and Heiner-While Stuckenschmidt [18]. Although they were able to achieve a good accuracy on the classification task of gait-phase recognition they did not provide any information related to gait measure comparisons between different subjects which is very important for biometric assessments. Furthermore, the data they used to train their networks captured from a very small population of only healthy subjects. This data scales are insufficient to provide accurate and robust results to characterize gait-cycles in a real case scenario of different individuals. Walking patterns can vary significantly in subjects of different physical characteristics and conditions. A tall person shows a larger step cycle than a shorter one. Also, a healthy person shows a more symmetrical behavior of gait rates compared to a patient or an injured one. These variances in walking patterns can introduce significant biases that may cause inaccurate outcomes, especially in real cases scenarios of larger and diverse populations.

Another group of researchers [21] extended the LSTM time-series network architecture to predict gait phase trajectory. In their work, Jaroug et al. utilized time-series data using Visual 3D (C-motion, Inc, Version 6) to compute linear and vertical acceleration for the thigh, shank, and foot segments of the right limb

[5]. Similar to [8] and [14] their analysis was limited on a small scale population of 15 only healthy individuals. Their results showed that the walking speed was found to be slightly decreasing each year among male and female candidates [15]. However, their work did not include any cases of predicting slower speeds to accommodate predictions related to older or impaired individuals who may walk at slower rates. Moreover, the restriction of using data that represent only healthy populations limited their ability to understand the difference of gait patterns between healthy and patient subjects that would lead to potential feedback discovery in human gait like falls prevention [2] [9] [10] [11].

Based on the current state-of-the-art research in gait analysis, outcomes seem limited on tasks related to predicting gait phase cycles based on small-scale data captured from healthy individuals. Such investigations, although are important to understand the mechanisms of gait cycles in human walking rates they are insufficient to provide meaningful assessments in rehabilitation and motor ability recovery. In this work we introduce a novel deep neural network architecture aiming at objective quantitative gait feedback discovery and correction. The novelty of our approach is based on 1) understanding the fundamental differences in gaits between healthy individuals and patients, 2) identify ideal objective gait patterns using multivariate gait signals from healthy subjects of diverse physical characteristics (age, weight, height) and 3) train a deep neural network to provide quantitative gait feedback and correction in the motor skills of pathological and neurological populations.

3. Method

We introduce the FDRNet, a new deep neural network architecture for multivariate signal feedback generation and correction. FDRNet is trained on an online gait dataset [19] with N=16 signal variables per time step.

3.1. Dataset

The dataset consists of 1020 multivariate gait signals from 230 subjects using inertial measurement units. The 230 subjects include 3 different populations including healthy subjects as well as patients with neurological or orthopedic disabilities. In total there are 1020 multivariate gait signals collected with two inertial measurement units, one for capturing the accelerations around the x,y,z axes and the vertical acceleration and one for capturing the angular velocities in the same directions correspondingly. This way each signal is described by 16 different numerical values, 8 for the right and 8 for the left foot activities. The 3D motion capture technology used to collect the data is the Xsens [1] wearable sensor device. The signals were recorded based on a fix activity protocol: standing still for 6 seconds, walking 10 meters straight at preferred walking speed on a level surface to a previously shown turn point, turning around (without previous specification of a turning side), walking back to the starting point and stopping while standing for 2 seconds as shown in Fig. 1. The amount of time-steps in the dataset represent a total of 8.5 hours of gait time with more than 40,000 footsteps. In this work we train the FDRNet on a total of 484 samples with half of them coming from patients and the other half from healthy population.

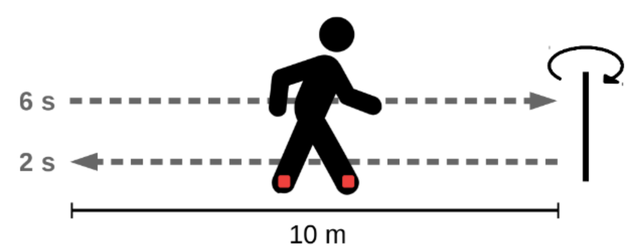

Figure 1. Schematic view of the protocol. Red squares indicate the locations of the IMUs. Image taken from [19]
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The dataset also includes metadata describing the physical characteristics and conditions of each individual such as gender, age, weight, height, health status. Some of those metadata are the body mass index in kg/m^2, the foot laterality as left or right foot, the walked distance in m/sec, the walking speed in km/h based on the average walking speed during the trial as well as the right and left foot activity with the exact indices of start and end time-stamps of the successive activity periods for the right and left foot correspondingly. In this work, given the big data size and the limited hardware resources we train the FDRNet only on left foot activity signals. The exact size of the input samples are described in the section 3.2.

3.2. Network Architecture

Most deep neural network architectures are based on the concept of encoding [3] that converts the training samples into feature representations depending on the learning task. Some architectures are designed to perform feature recognition tasks like object classification [17] or segmentation [16] using supervised or unsupervised learning. Other architectures aim at context generation based on prior information like a text in natural language processing [4] or images in computer vision [6]. In each case, the key factor of the architecture design is based on the objective of the learning task and the type of the input data.

Here, we introduce the gait Feedback Discovery and Recovery network (FDRNet). The FDRNet receives input from multivariate signals describing the gaits of healthy and patient samples and it learns to generate feedback recovery signals.

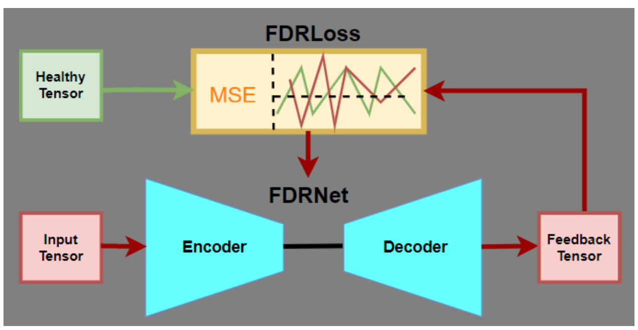

Figure 2. Schematic Representation of the FDRNet.

The data flow in the FDRNet is described here:

- The FDRNet receives the training data. Each training sample has a tensor size 1042×16.
- The encoder layer converts the input data into training features.
- A hidden linear layer of 250 neurons receives and compresses the features down to 100 neurons.
- The decoder is an output linear layer that receives the 100 updated weights and generates a feedback tensor of size equal to the size of the input tensor.
- For the activation functions we use the Rectified Linear Unit (RELU) which returns max(0, x).

3.3. Loss Function

The Loss function of the FDRNet receives both the generated feedback tensor and the healthy tensor and computes a feedback score which serves as the actual loss. The feedback is a function that computes the numerical gap between the generated and the healthy tensors of equal sizes 1042×16. Since FDRNet generates gait feedback on multivariate 16-channel signals, this gap describes the deviation of each one of these 16 signals from the healthy ones with one-to-one correspondence. To this end, for the first signal of the generated sample, which accounts for the left foot vertical accelerations [LAV], the feedback is a new 1042-size tensor with the computed absolute difference values from the [LAV] signal values in the healthy sample. In the same way the feedback is computed for all the 16 different signals resulting in the output of 1042×16 size feedback tensor. Finally, the loss function returns the mean squared error between the feedback and the healthy tensors that is required for the back-propagation phase during the training of the model. The MSE loss is computed using Equation 1, where Feedback and Target are tensors of total size N. In this work N = 1042.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Feedback - Target)^2 \qquad (1)$$

3.4. Model Training

We FDRNet has 5.88M trainable parameters and we train for 2.5 hours (0.5 hour / epoch) on a single 12MB RAM Titan X GPU using a total 242 healthy and 242 impaired (pathological and neurological) samples. We use the pytorch Stochastic Gradient Descent (SGD) optimizer with a small learning-rate value of 2E-5 to initiate training. In each training loop the network updates its weights by the back-propagation of the loss gradients to enhance learning. Our goal is to keep training the network until a reasonably small loss score is achieved. However, The big size and the multivariate character of the input tensor makes it hard for the FDRNet to gain deep learning rates. The reasons why a multivariate signal feedback generation network is hard to train can vary depending on the network architecture and the training parameters but here are briefly discuss some basic ones.

FDRNet is a type of tensor generation network that it's output size, here 1042×16 = 16672 can make the training hard because of vanishing gradient problems [12]. Vanishing gradients is one of the biggest challenges towards gaining deeper learning rates in neural networks and can be described as the inability of the network to avoid reaching zero or almost zero gradients. Very small gradients occur when the length of the training sequence components becomes larger and therefore the weights take smaller and smaller values leading to negligible or even zero learning rates.

The problem of vanishing gradients is also present to other long-sequence generation based neural network architectures as well. In computer vision, the Generative Adversarial Networks (GAN) [6] are known to be hard to achieve high learning rates. GANs are trained to generate images. If we consider the large tensor size of a typical generated image to be about $128 \times 128 = 16384$ pixel intensity values, we can see that the same vanishing gradient problem mainly causes poor training or it takes a lot of time and computing power to achieve good quality results. Of course in each architecture there are more and different reasons responsible for the training rates but for the purpose of this project we just highlight the training difficulty of long-sequence components.

Another training difficulty is that the FDRNet trained using data collected from times-series signals of varying time-step lengths. Some individuals performed the walking 10-meter and return task in around 18 seconds and others in more or less time. This means that the signals extracted from the motion capture machine were not uniform and therefore we modeled them at a maximum of 1042 time-step length per sample. We will discuss more details on this in sections 4 and 5.

We stop the FDRNet training at loss = 0.02 and we save the model to be used for new sample inferences. We test our results by using new gait signals as inputs to the trained network. The new inputs are samples from only pathological or neurological populations on our dataset [19]. The FDRNet generates feedback correction gait signals that quantitatively describe how the impaired individual should need to walk in order to reach a healthy state gait. We validate our results by computing the mean squared error of the generated feedback signal with the actual healthy signal sample.

For all the FDRNet training we used the jupiter-2.cs.umn.edu server, property that belongs to the Center of Distributed Robotics at the Minnesota Robotics Institute. In order to achieve higher learning rates more FDRNet training is required. Given that a single training loop takes about 30 minutes in a single GPU we recommend migrating the FDRNet on a distributed multi-GPU cloud environment to speedup training.

4. Results

We trained the FDRNet in a few epochs and we provide feedback on some basic outcomes. We can observe a decrease in the loss curve with a minimum value of 0.02 that indicates that the FDRNet starts the learning process. The training loss curve is illustrated in the figure 3.

We use the mean square error as our main metric to compare both the normal, impaired and feedback generated tensors. The following table 2 summarizes the values of MSE error between normal and impaired (left) and normal and feedback (right) gait signals.

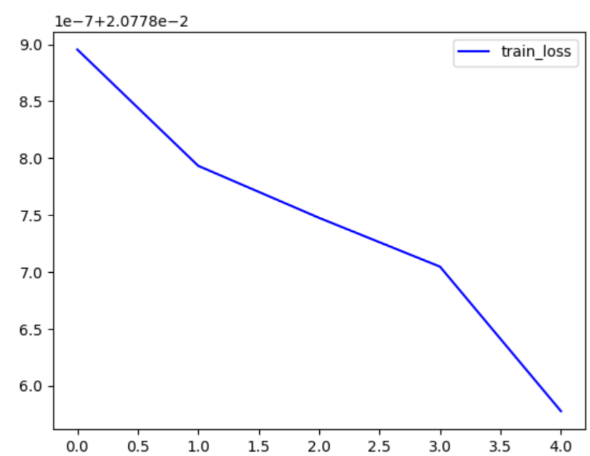

Figure 3. FDRNet training loss curve

Looking at the MSE errors we can see that for the linear accelerations in all directions the network performed well returning smaller errors between the healthy and feedback tensors as expected. On the other side, if we pay attention at the errors on rotations we see that the smaller MSE errors are between the healthy and impaired samples and not between the healthy and feedback ones. This contradicts our expectations to gain smaller error between the healthy

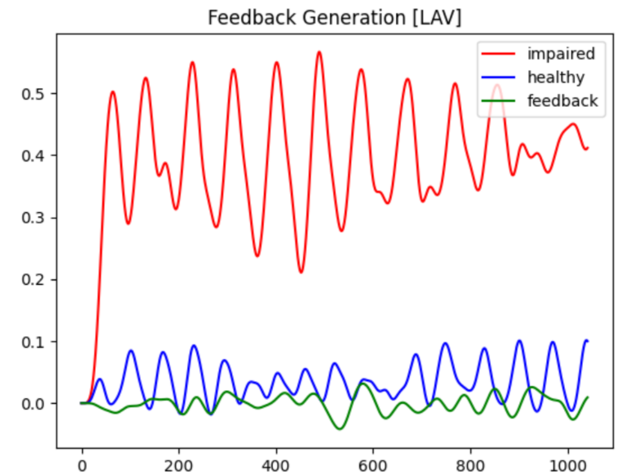

Figure 4. Left foot vertical accelerations

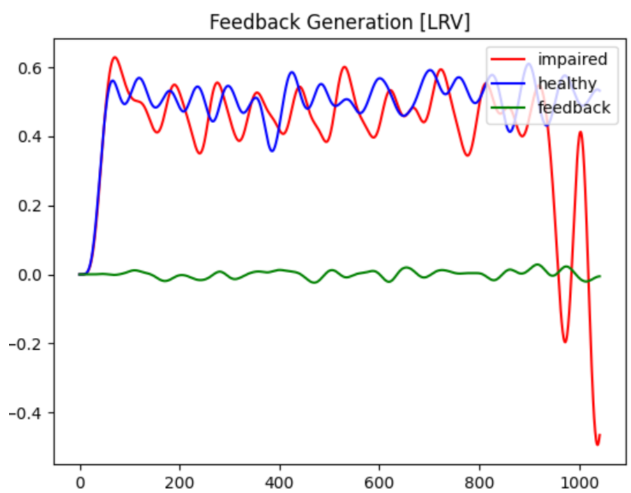

Figure 5. Left foot vertical rotations

and the feedback tensors since feedback is generated to minimize the gap between healthy and impaired samples. This can be explained by the fact that the rotation gait signals seem to be quite not different between a healthy and an impaired individual whereas the gait signals of linear accelerations are much different correspondingly. This means that the network's ability to learn and generate feedback becomes weaker when the healthy and impaired signals tend to have small MSE error. This makes sense since a neural network cannot easily discriminate data having very similar values into separate categories and it is true in every deep learning task. We can also visually interpret this by the next

Signal	H/I	H/F
LAV	0.138	0.002
LAX	0.323	0.055
LAY	0.062	0.004
LAZ	0.205	0.010
LRV	0.040	0.233
LRX	0.052	0.105
LRY	0.372	0.220
LRZ	0.138	0.154
TOT	0.289	0.122

Table 2. MSE errors of the FDRNet inference on left foot activity samples. H/I is the mse error between healthy and impaired samples and H/F the mse error between healthy and the generated feedback.

2 figures that illustrate the generated feedback curves for the left foot activity signals on linear accelerations, figure 4 and rotations, figure 5.

5. Discussion

We trained the FDRNet using fixed size 16-variate time-series signals using an online available gait data dataset [19] consisting of healthy and pathological samples. Due to computational time and power limitations the training we performed is not yet sufficient enough to achieve high fidelity predictions on the generated gait feedback signals. However, our results indicate that a reasonable training has been achieved that makes FDRNet capable of estimating the generation of a feedback tensor with 16 different signals. Given that the main purpose of this project is focused on the conceptual intuition and implementation of a new neural network architecture rather than optimizing the networks performance, we are satisfied by this result and we provide clear explanations and directions for the FDRNet's performance. Namely:

- Limitations on both hardware resource and time restricted us to train the FDRNet for a few epochs on a single GPU considering that each training loop takes about 30 minutes to complete. To this extend, we did not perform any hyper-parameter tuning or other calibrations to the network. We are excited to perform further training and fine-tuning using multi-GPU environments that may lead to greater learning rates.

- Our dataset consists of non-uniform multivariate time-series data that is hard to fully normalize in an absolute uniform format. We decided to model our data by creating fixed size time-steps per sample that may introduced data redundancies because of signal overlaps. Future experimentation with different or learnable time-step lengths may provide further performance insights.

- Given the gait signals have high amplitude frequencies we smoothed our results using a band type low pass filter [7] using a cutt-off frequency of 0.5 rad/s a sampling frequency of 30 rad/sec and a 6-order polynomial filter for visualization purposes.

- For the computation of the loss gradients required for the pack-propagation and the weight updates we used the default pytorh auto-grad features [13] that provides an implicit mean reduction of the loss gradients that may also affected the learning performance. Future work can investigate the implementation of the full loss gradients and the back-propagation steps from scratch. This will might provide useful information on the learning capacity that the FDRNet model can handle.

- We implemented the FDRNet by making use of very simple linear neural network units without adding more sophisticated stacks to our architecture. A future integration of more advanced neural network stages like transformer self-attention mechanisms [20] and dropouts may further enhance learning and increase the overall network's performance.

- Based on computing power limitations we were able to train signal data account for only the left foot activity of the initial dataset. However, FDRNet is designed in a way to work with different samples and sizes. To this end, training the FDRNet on right foot activity signals or both left and right can be easily achieved with zero changes to the source code. The only thing that needs to be modified is the input and output tensor sizes.

- Plots from all the 16 feedback generation signals are available at Appendix A.

6. Conclusion

Gait analysis can provide useful information of human motor skills based on multivariate signals extracted using a motion capturing device. Tracked signals can be processed to quantitative analyze motor abilities like gait, running, jumping and others. The outcomes of such analysis can lead to feedback discovery and objective physical ability evaluation in personalized rehabilitation which can offer significant assessment improvements and lead to more personalized treatment plans. Current research methods in human gait analysis has provide insights on gait-phase identification and gait-cycles prediction. Moreover, most works have investigated gait patterns using data extracted by either healthy or only impaired populations and therefore an analysis on understanding the deeper quantitative differences between normal and abnormal gaits is still unexplored. To be more precise, although recognizing phase-gait cycles is important for understanding and analyzing physical motor ability, it is insufficient to provide objective gait rate feedback and motor function recovery.

In this work we make a first attempt towards the implementation of a new network architecture design to provide meaningful feedback discovery on multivariate time-series from gait data. We implement FDRNet, a deep neural network that is capable of signal feedback and correction generation using an online dataset of 1042 multivariate gait signals. We train FDRNet using an online available dataset containing 1020 multivariate gait signals from 230 subjects undergoing a fixed protocol: standing still, walking 10 m, turning around, walking back and stopping. The measured population was composed of healthy subjects as well as patients with neurological or orthopedic disorders. We found that the FDRNet, yet not fully optimized, is able to successfully generate feedback and correction on multivariate time-series signals. While at the current stage FDRNet is not ready to provide high fidelity predictions on the generated feedback, a potential optimized future version of it holds promise for automation in personalized rehabilitation and considers the potential of creating new technology in the area of physical ability performance assessments.

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Appendix A

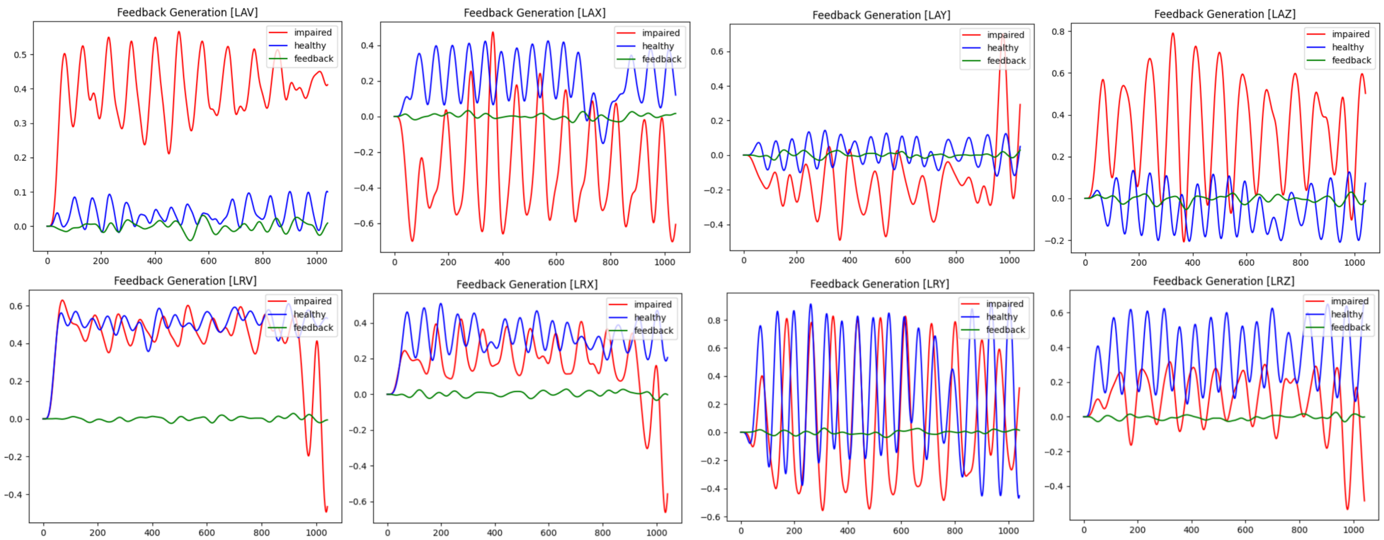

Figure 6. Feedback Generation - left foot activity signals

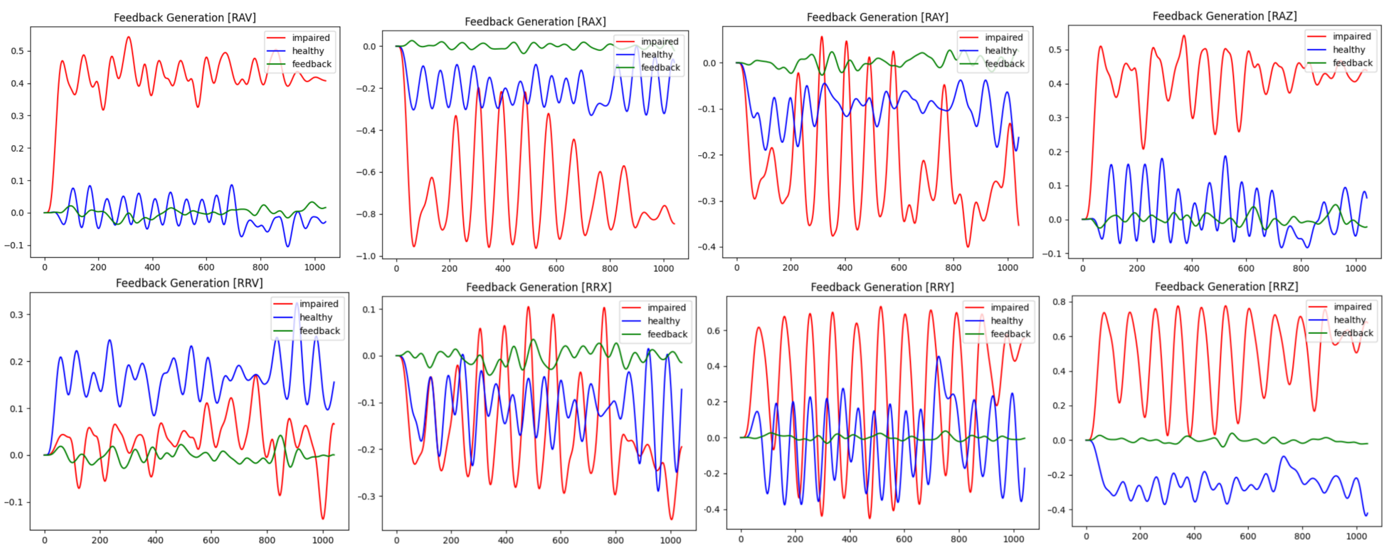

Figure 7. Feedback Generation - right foot activity signals