Recurrent Neural Network for Gait Pathology Detection

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Abstract: This work presents a pathology detection system on the lower train. For this, a database of healthy subjects has been captured. Due to the nonexistence of pathological gait databases, pathology walks have been simulated. The users used sole padding in order to simulate clubfoot walk. The database consists of acceleration, angular acceleration, magnetic field signals and the angles between the joints. The algorithm extracts fragments of the signals which are used to train a recurrent neural network (RNN). To optimize the results, hand-tuning method was used to modify the hyperparameters. Using the best configuration, we have a 97% accuracy training with 90% of the database. Although, if we train with only 50% of the data the accuracy reaches at 91%. The results obtained show the solution feasibility, although further research should be done using real lower train pathologies.

1 INTRODUCTION

Nowadays, in the world of medicine, there are new techniques that help in the diagnosis. An example of this is breast cancer detection (Fear et al., 2002; Henriksen et al., 2018). However, for the case of the lower train pathology detection, this is not so extended. In this field, there are some machines that perform gait analysis. The analysis of the walk gives information like the pressure of the tread, joint angle, the cadence of the walk, etc. The information obtained is commonly used in rehabilitation progress. Some examples are the rehabilitation in patients with motor-impaired (Banala SK, Agrawal SK, 2007; Raveh et al., 2019), strokes (Dickstein, 2008; M.H. et al., 1997; Go et al., 2019) to cerebral palsy (Kainz et al., 2017; Moreau et al., 2016; Rutović et al., 2019). Nevertheless, all this data can be used in order to diagnosis lower train problems like sprains or fractures.

The problems of these machines are that work in a closed environment since most are optical and need fixed cameras: this compels the patient to move to the clinic. This is a disadvantage due to the way of walking can be affected by the environment (Del Din et al., 2016).

One solution is to use inertial sensors. Usually, these sensors have a small size and can be attached to the body to record its movements. These systems only need a HUB to connect all the devices and to save the data.

The aim of this study is to build a system capable of separating healthy walks from pathology walks and the laterality of them. For this purpose, a database has been collected with healthy users and three kinds of walks: normal, right injury and left injury walks. These injuries have been simulated. On this database, a neural network has been applied to classifying the walks. A study of the hyperparameters has been done to find the best configuration.

This paper is divided into 6 sections: Section 2 explains gait variability and the factors that can affect it, in section 3 the protocol of the database collection and the capture system is described. Data processing is defined in section 4. And the results and conclusions are in sections 5 and 6.

2 WALK VARIABILITY

Each person walks different from the others, even more, the walks of the same person differ. However, there are some characteristics intrinsic to the way of walking. These characteristics show a pattern in the gait of each user. This pattern can be used to recognize users (Fernandez-Lopez et al., 2017), or in the way of walking with some disease or injury.

The variability can occur due to some disease (Schaafsma et al., 2003), surgery (Khouri and Desailly, 2013), physiological differences (walking speed increases with the stature (Winter, 2010)) or

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different surfaces (a beach, a flat surface, a park, etc.). Some disorders like Parkinson's, Huntington's or Alzheimer's disease can increase gait variability (Yu et al., 2009). For example, patients with Parkinson's disease tend to walk with reduced gait speed and shorter stride (Schaafsma et al., 2003). So, the change in gait parameters can point some disease. It can also be used as an indicator to predict the risk of falling down in elderly people (Hausdorff et al., 2001).

Gait variability is helpful in the case of gait recognition. However, in some cases, like physiological variances or different surfaces, it is a problem at the time to identify pathologies. For example, the walking pattern with a sprain can be quite different between people.

3 DATABASE DESCRIPTION

There are some public databases with gait signals. But there is no database available with healthy and pathological walks. Because of the unavailability of proper databases, we created our own database. In this section, the proceedings of the database, the equipment used in the acquisition and the dataset are explained.

3.1 Capture System

Tech-MCS V3, a portable kinematics movement acquire system was used to collect the database. This system consists of a hub to store the data and 7 inertial measurement units (IMU). Each IMU has one accelerometer, one gyroscope and one magnetometer, all of them work in 3D. The signals of each sensor are merged to obtain the orientation of the IMUs. The process is used in a sensorial fusion process in order to obtain orientation using inertial information. This process is performed by an Extended Kalman Filter (EKF) that runs in each IMU. Diagram of the process is presented in Figure 1. The orientation data can be used to obtain the angle data of the joints.

To acquire the data, the seven IMUs were attached the following way: two at the foot, two at the middle of the shin, two at the middle of the sank and one at the lumbar. In each walk, 81 signals were recorded.

The angle data correspond to different leg movements. In Figure 3 the movements of each joint are presented. The first one belongs to the sagittal plane (x-axis), in which the flexion and extension take place. The coronal plane (y-axis) is the next one; this consists of the movement of the leg from right to left and vice versa. The last one is the rotation of the joints over themselves.

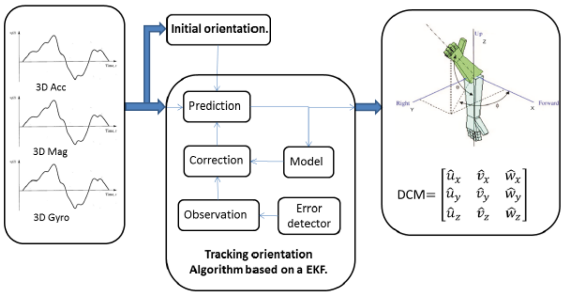

Figure 1: Process of the IMU to obtain the 3D orientation.

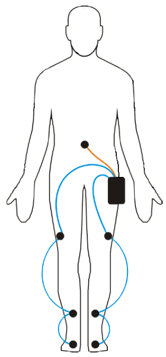

Figure 2: Positions of the IMUs in the body.

3.2 Protocol

A database of healthy and fake-pathological gait was collected. In order to isolate the pathology studied in this experiment, the people that collaborated did not have any gait impediment, that means that no person in the database suffers from sprains, surgeries, flat foot, etc.

When simulating a pathology some points must be taken into account.

1. Easiness and comfortability for the user.
2. Replicability for all users.
3. Similarity with real pathology.

Sprains can be simulated using a bandage. But is not easy and, in some cases can cause some pain. Finally, clubfoot walk is simulated using sole padding.

In order to perform as real as a possible experiment we consider the following rules:

- Comfortability: the users wear his/her own clothes and shoes. The only restriction is not to use high heels or flip-flops, due to it is not possible to use them with sole padding.
- Freedom: The users can perform the visit when and wherever they want. The only restriction is the walking path must be flat.

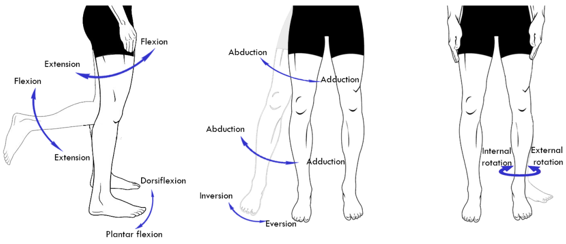

Figure 3: Different movements per plane.

Each user made three sessions, 15 days passed from session one and two, and two months between two and three. By doing this we eliminate variables such as exhaustion or temporal pain in the users. Each visit is made up of:

- 8 free walks.
- 4 walks with the sole padding in the right feet
- 4 walks with the sole padding in the left feet

3.3 Dataset

For this study, 31 healthy people were recruited. Of these users, only 21 did the second visit, and of these 21 only 7 did the third one.

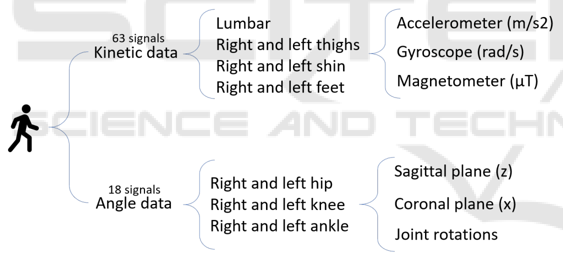

Figure 4: Schema of the recorded data.

As an addition, two people with an ankle sprain (one on the right and the other one in the left) were recruited for the experiment. Each user did 10 walks walking freely. These people will be used at the end to test if the system is capable of identifying real pathology having been trained with fake pathology.

Table 1: Number of users, walks, and samples per visit.

Visit	Users	Walks	Samples
1st	31	496	1984
2nd	21	336	1344
3rd	7	112	448
Total	59	994	3776

As we can see in 1 there are 3776 samples, 1888 are from healthy walks, and 944 from each left and right limp walk. The ranged age of de database is from 18 to 77 years old, and the gender distribution is 47 % female and 53%, male.

4 SYSTEM

The aim of the system is to distinguish between right-limp walks, left-limp walks and no limp walks. The system is divided into three steps. The first step is the pre-processing, where the signals are filtered, once the signal is filtered the signal is divided into fragments. Lastly these fragments are classified using a neural network. In Figure 5 the workflow of the whole system is presented.

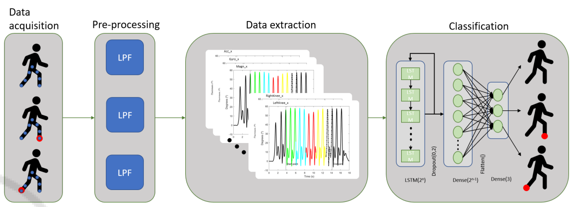

Figure 5: System workflow.

4.1 Pre-processing

Due to the nature of the gait signals, the bigger part of the information is low frequency. So, to remove unnecessary noise the signals were filtered by a Butterworth low pass filter. The Butterworth filter is used due to its simplicity and the -3 dB gain at the cut-off frequency. We set the cut-off frequency, approximately, in the frequency where the power spectrum falls down under -40 dB. To find this frequency all the signals were studied. Heuristically a group of different cut-off frequencies were obtained.

Table 2: Cut-off frequencies of the different signals.

Position	Signal	Frequency (Hz)
All	Angle	20
Lumbar and thigh	Accelerometer	20
	Gyroscope	10
	Magnetometer	10
Shin and feet	Accelerometer	40
	Gyroscope	20
	Magnetometer	20

Once the signals are filtered the next step is to extract the data.

4.2 Data Extraction

Walking is a pseudo-periodic movement, this means that it is almost the same movement every time: right step, left step and repeat. These pseudo-periodic movements are called gait cycles. In some studies, these gait cycles are used as a basic unit for biometric recognition (Fernandez-Lopez et al., 2018).

In this study, instead of gait cycles, a bigger part of the data is used as a basic unit. By using fragments larger than the gait cycles the evolution from the right to the left and then from the left to the right step can be observed, having much more information to locate the pathologies.

- To avoid non-stable signal there must be at least three seconds left before the start point. There also must be three seconds left between the endpoint and the end of the signal;
- All the 81 signals of a walk must be trimmed using the same points;
- The start and endpoint must be the same moment in the cycle.

Once the constraints are fixed, the next step is to perform the frame extraction. Since all the signals in a walk are synchronized, the timestamps of all signals are the same. This is why once we find the beginning and end of a fragment in one signal the same timestamps are used to fragment the remaining 80 signals.

To choose the model signal, all the signals were studied. The signals with the clearest cycles are from the hip and the knee. There are not noteworthy differences between the signals from the right and the left, so the right signals were selected. Once the laterality of the signals was selected, the signals of the hip and the knee were inspected. The one with clearer results is the knee signal, this signal corresponds with the flexion/extension movement. Thus, the right knee signal is used as a model signal for the data extraction process.

The first step of the extraction process is to segment the gait cycles. In this study, the maximum point is used as the beginning of the cycle. This point corresponds to the position where the right leg is fully stretched forward, that is, the knee has the greatest extension angle. To find the proper maximum values, and avoid the local maximum data, the peaks must accomplish that:

- The distance between peaks must be greater than 900 ms (Fernandez-Lopez et al., 2017).
- The peak must be placed in the upper third.

Once the edges of the fragment are found, all the signals in a walk are trimmed off in segments. After

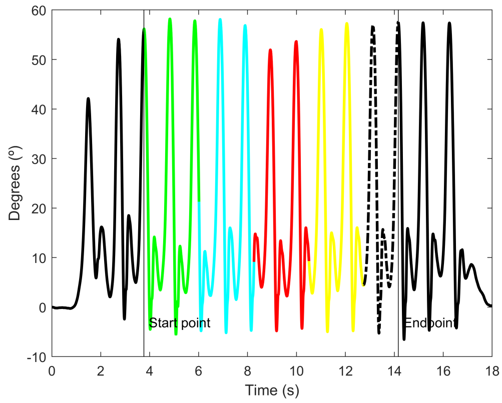

Figure 6: Right knee signals. Different colours represent different final fragments. Black and doted signal are discarded.

the fragments have been obtained, the problem arises from the fragments of each user and walk have a different duration. To solve this problem, all the signals are trimmed to the length of the shorter one. Since the signals still long enough, all of them are divided into four segments.

In order to prepare the data to feed the neural network, it has to be organised in samples. Each sample is a matrix of N x 81 where N represents the number of samples of the fragment. Each column represents the different axis (x, y and z) and sensors (accelerometer, gyroscope, magnetometer and body angles). Following is presented the organization of the data inside the matrix.

$$\begin{bmatrix} Acc_x(1) & Acc_y(1) & Acc_z(1) & \cdots & LAnkle_x(1) & LAnkle_y(1) & LAnkle_z(1) \\ Acc_x(2) & Acc_y(2) & Acc_z(2) & \cdots & LAnkle_x(2) & LAnkle_y(2) & LAnkle_z(2) \\ Acc_x(3) & Acc_y(3) & Acc_z(3) & \cdots & LAnkle_x(3) & LAnkle_y(3) & LAnkle_z(3) \\ . & . & . & \ldots & . & . & . \\ . & . & . & \ldots & . & . & . \\ . & . & . & \ldots & . & . & . \\ Acc_x(N) & Acc_y(N) & Acc_z(N) & \cdots & LAnkle_x(N) & LAnkle_y(N) & LAnkle_z(N) \end{bmatrix}$$

4.3 Neural Network

With the aim of develop a neural network (NN), the python deep learning library Keras (Chollet et al., 2015) is utilised.

To feed the neural network (NN) the data is organized in a matrix. The output data corresponds to one of the three cases of walk: no limp, left limp or right limp.

A NN is a group of algorithms that attempt to recognize the relationship of a group of data through a process that mimics the way the human brain operates. Depending on the data there are some NN that fit better. In these algorithms, there are multiple options for configuration. In order to obtain the better results, the number of layers, the neurons of each layer, number of filters, the activation algorithm, ratio of training/testing, etc. can be set up. These adjustable parameters are called hyperparameters.

There is not a fixed rule about how many layers should be used. Three layers are the minimum number of layers we can have. More layers can give better results, but it will be harder to train. This study compares the results and the training time of two neural networks: the first one with three layers and the second one with four layers. The number of neurons per layer is also studied. To do this the relationship between the layers is fixed. The input layer has 2^n neurons. The hidden layers have 2^{n-1} neurons. The output layer never has 3 neurons, since it is the number of classes to predict. The value of n starts in 2. The value is increased by 1 until the results stop improving. Thus, the results of how changes the accuracy with the complexity of the NN can be observed.

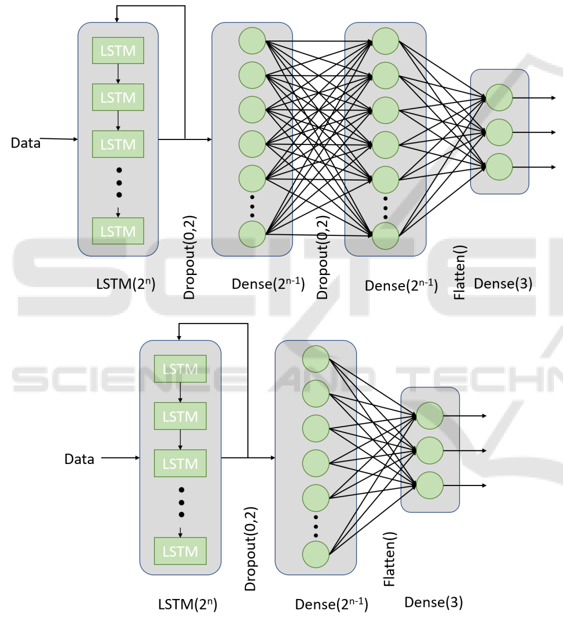

Figure 7: Structure of the neural networks.

Due to gait signals being temporal, a recurrent neural network (RNN) (Hochreiter and Schmidhuber, 1997) is used. The structure of the three-layer NN is shown in Figure 7. The input layer is an RNN with 2^n Long Short-Term Memory (LSTM). The hidden layer is a Dense layer and the output layer is a three neurons layer. To avoid overfitting and improve the accuracy of the system a dropout of 0.2 is performed after the RNN layer. The structure of the four-layer NN is the same, but it includes another dense layer between the hidden layer and the output layer.

After each layer we use an activation function. After the RNN and the hidden layers, we use relu, as it maintains linearity. However, for the output layer, we use a sigmoid function to get a probabilistic output.

In this study, to obtain the best results of the NN the ratio of training/testing data and the number of neurons in each layer have been analysed. The ratio of train/test data goes from 10/90 % to 90/10 %.

5 RESULTS

The results of the different configuration of the system are presented below. First case under study is the effects of changing the ratin of raining/testing data and the numbers of neurons per layer. Following this the outcomes of adding an extra layer to the RNN are presented. Two experiments have been performed: to classify two real pathologies with the RNN and to check if the system classifies equally right and left walks. The results of these experiments are presented at the end of the section.

The first parameter to study is the training-testing ratio. In the state of the art, there is not a fixed ratio of training-testing for the data, even though it is recommended 20-40% for testing and 80-60% for training. To solve this problem and to give a clearer solution, we trained the network with different percentage of data between 10 and 90%. For each ratio of data, the algorithm has been trained and tested 10 times and the final accuracy is the mean value of all of them.

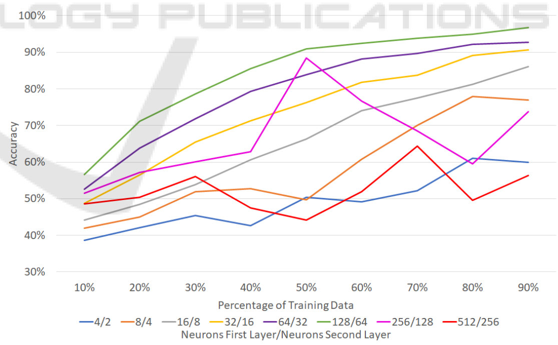

Figure 8: Results of 3 layers network. Different colors represent different neurons per layer.

In Figure 8 and 9, we can see the accuracy of the algorithm against the percentage of training data. In general, a bigger training dataset provides better results. However, we can notice that there is a point from which the increase of the training data does not provide significant improvement. This point is lower when the ratio of training data is bigger. For example, in the network with $n = 7$ (128/64/64 neurons) training with only 50% of the data, the 91% of the frames are correctly classified,. However, if the training data is increased until 90% the accuracy only improves 6%.

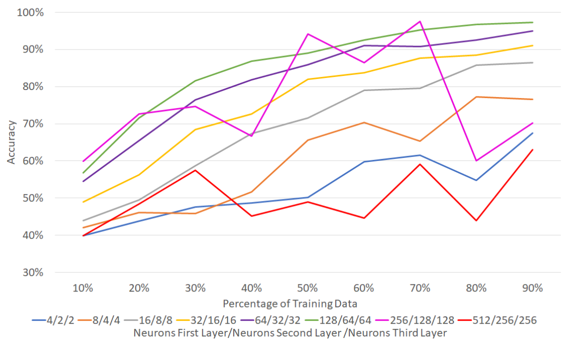

Figure 9: Results of 4 layers network. Different colors represent different neurons per layer.

A different number of neurons per layers has been used in order to find the best configuration. The number of neurons per layer has been increased until the improvement stops. As we can see in Figure 8 and 9 the accuracy grows with the number of neurons. The more neurons the layers have, better the results. This can be appreciated especially in the networks with 16/8, 32/16, 64/32 and 128/64. The optimal configuration occurs when $n = 8$ and it produces a network with 256 neurons in the first layer and 128 in the second and the third. The accuracy of this network does not fit into any pattern. In Figure 8, the accuracy of the network with a ratio of 50/50 of the data is 88%, but it suddenly drops to 60% with a bigger training dataset. This behaviour is due to the complexity of the network as it is too high. On the other hand, the networks with $n = 2$ and $n = 3$ have similar conduct, but in this case, is due to not enough complexity.

Up to now, the best configuration is the one with $n = 7$ and 90% of training data. The last hyperparameter under study is the number of layers of the NN. Two different NN have been created to determine the influence of adding a layer: the first one with 3 layers and the other one with 4. Figure 8 shows the results of the 3-layer NN. The outcomes of the 4-layer NN are presented in Figure 9. We can verify that the results for both are similar.

Figure 10 presents the comparison of the best configuration of NN with 3 and 4 layers and the training time of each. As we can see the improvement in the best case is lower than 3%. So, there is no significant improvement adding an extra layer to the NN.

For all the possible configuration of the RNN the one that offers the best results is the one with 128/64/64 neurons per layer and with 4 layers. In order to test the RNN two experiments have been performed: classifying walks of two users with sprain,

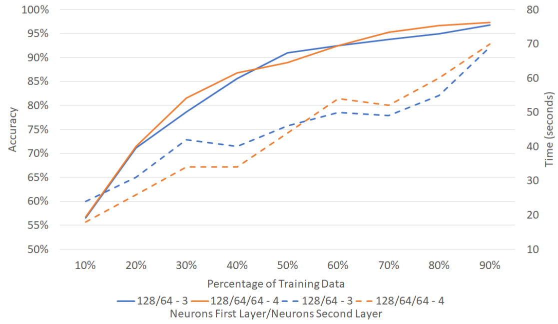

Figure 10: Comparison of the results with 3 and 4 layers. The dotted line shows time. The solid line shows the accuracy.

and to check if the system classifies equally all the cases.

For the first experiment two users with real ankle sprain have been recruited. Each of these users has done 10 walks, so 80 frames have been classified. The results of classifying the frames are presented in table 3.

Table 3: Accuracy of classify sprain fragments.

Percentage of training data	Accuracy (%)
50 %	45
60 %	50
70 %	66
80 %	71
90 %	83

The classification of the frames have been done using the NN with 4 layers and 128/64/64 neurons per layer. The network have been trained using the fake pathology data, this network shows a result of 83% of accuracy classifying the samples. The drop in the accuracy may be due to there are not sprains in the training dataset. Even though it is not a negligible result, it cannot be considered since the data used is not enough.

The last experiment lies in to check if there is any difference in the accuracy when classifying the different walks separately. The network has been trained with all data and tested only with the corresponding cases. Seven cases have been studied: healthy walk and left limp, healthy walk and right limp, either right or left limp, only left, only right, only healthy and all the walks. The accuracy against the ratio of training/testing data is presented in figure 11. The results show that there is no significant difference when classifying the different cases.

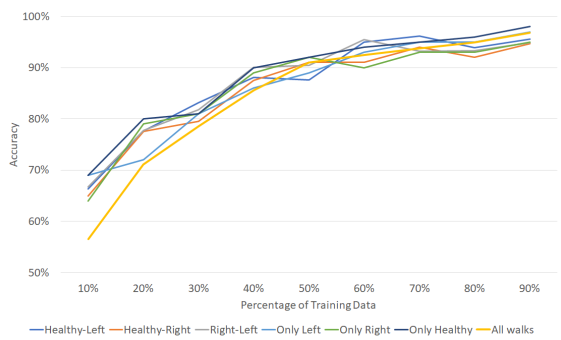

Figure 11: Comparison of classification the walks separately.

6 CONCLUSIONS AND FUTURE WORK

The aim of this paper is to present a system capable of classifying pathology walks using RNN. The signals of the lower train are recorded using a commercial device, that records signals from accelerometer, gyroscope, magnetometer and orientation data. The signals are filtered and processed in order to extract the information required to feed the neural network. With the aim to obtain the optimal configuration of the NN hand-tunning of the hyperparameters has been done, among them the ratio of training/testing data, number of neurons per layer and number of layers have been studied.

To the light of the outcomes, we can see that, in general cases, the accuracy of the system rises with the training ratio. There are two cases where it is not precise. This happens when the complexity of the NN is too elevate, and the results do not converge at any point. Adding an extra layer to the NN improves less than 3% the accuracy of the system, however, it does not increase significatively the effort.

The experiment of classifying the real cases of pathology walks give proper results. However, the experiment does not have a significant impact due to the testing does not hold abundant data. Additionally, it is able to classify equally the walks from the right and left and the health walks.

Even though this system works and classifies properly the walks, there are some improvements that would be interesting to perform. The first one is to study the influence of the origin (e.g. the beginning or the middle of the walk) and the amount of data of the fragments. In this way, if the amount of data can be reduced without remarkable changes in the accuracy the algorithm can be optimized.

Once a system capable of distinguishing walk limp and the laterality of them, the next step is to try the system with real pathologies. So, the next step is the acquisition of a new database of users with different problems in the lower train. In this case, the algorithm should be refined to get as a result, not only the laterality of the limp but also the joint where it occurs.

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