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(artigo/relatório de projecto)

Classification of the underlying surface of a walking humanoid robot using a LSTM-RNN

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Resumo In the study of biped humanoid robots it is crucial to achieve high precision and robustness in locomotion. Humanoid robots that operate in real world environments need to be able to physically recognize different grounds to best adapt their gait without losing their dynamic stability. This work describes the collection and preparation of a dataset of contact forces, obtained with eight force tactile sensors, mixed with the robot internal inertial sensor information for determining the underlying surface of a walking humanoid robot. For this classification, the data is acquired for four different slippery floors at a rate of 100Hz and it is used as input for a long short-term memory (LSTM) recurrent neural network (RNN). After testing different learning models architectures and tuning the models parameters a good mapping between inputs and targets is achieved with classification accuracies greater than 90%.

Palavras-Chave Humanoid robot locomotion · LSTM-RNN · Floor classification

1 Introduction

The study of humanoids increasingly contributes to several scientific areas of which it is possible to extrapolate improvements to our lives, such as in walking rehabilitation, dangerous works, or elderly assistance. To achieve a robot capable of servicing and assisting people, first it has to be able to perform fundamental locomotion tasks such as balancing and walking [1]. Despite the efforts made in the past years, humanoid locomotion is still a challenging problem without definitive solution. Developing a good system that allows a biped robot to walk on unknown and diversified floors, i.e slippery floors, requires the system to be intelligent and autonomous to adapt in real time so that the robot can successfully overcome the barriers found during locomotion tasks [2]. In most of the bipedal locomotion approaches, hard contacts with the ground are assumed, whereas, in real life scenarios this is normally not accurate. Despite the several developments over the years, there are no explicit implementations which deal with the changing floor properties [3]. This oversight may lead to disastrous consequences, i.e the biped robot falls while walking on a non-modeled ground, most of the times preventing the robot to continue its locomotion tasks.

Having an intelligent algorithm that allows the robot to identify the terrain with good certainty, using force sensors installed on its feet or assembled under it, will give the possibility to eliminate most of the falls while walking on different surfaces [4]. The increasing progresses made in the areas of artificial intelligence and machine learning, lead to a significant impact in the reported field. With the rise of techniques such as neural networks, recurrent neural networks, deep learning and reinforcement learning, humanoids can now perform tasks that previously seemed far-fetched. Learning a mapping between states and actions is an ill-posed problem due to the dimensionality of the search space the robot is faced with. Machine Learning (ML) algorithms use an efficient form to recovery important information from large databases [5].

In this work the capabilities of a long short-term memory (LSTM) recurrent neural network (first presented in [6]) were analysed to classify the underlying surface of a walking robot. To feed the network (1) a wearable instrumented system assembled to a robot foot was used to measure the ground reaction forces (GRFs) and (2) the internal robot inertial sensor was used to

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measure the body accelerations and inclinations on different slippery floors. The choice of this type of network was due to its feedback loop which serves as a kind of memory. This means that the past inputs leave a footprint on the model that is expected to be an asset, for example, when the humanoid robot moves from one floor to another. Since a new floor, with different properties, will affect the robot step it is expected that the network will easily detect this change by evaluating the past steps. Several published works in the field of humanoid robots show the applicabilities and capabilities of the LSTM-RNN. For example, in [7] a LSTM-RNN model is used to classify 6 different robot behaviours based on 10 robot joint time sequences. In [8] it is used to generate a robotic motion from the observations of the human movements for achieving fast and responsive human robot collaborative tasks, avoiding the trouble of solving an inverse kinematics or motion planning problem. In another example [9] the authors use a LSTM network to classify motor fault in mobile robots achieving accuracies of 87%.

The reminder of this work is divided as follows. Section II presents the materials and methods for the data collection and manipulation. The LSTM network implementation and experimental results are presented in Section III. Lastly, section IV presents the conclusions and future challenges.

2 Materials and methods

On past research an instrumented system, introduced in [10], was developed to be seamlessly assembled on a walking humanoid robot to measure real-time vertical and horizontal ground reaction forces (GRFs). The ITshoe (Fig. 1) has two main parts, outer shoe and inner shoe, and was designed to be used with the humanoid robot NAO. The outer shoe is the instrumented part of the system, whereas the inner shoe is used to link the outer shoe with the robot's foot. The ITshoe is designed to measure and transmit raw data at a frequency of 100 Hz and it is composed by a sensing unit (eight A301 flexiforce sensors), acquisition unit (electrical conditioning and power supply), and a streaming unit (WiFi module). The GRFs are divided into total normal force (vGRFs) and total horizontal force (hGRFs). The hGRFs can be represented in the sagittal and transverse plane as depicted in Fig. 1, and calculated as follows:

$$Fh_{st} = \frac{\sqrt{2}}{2} \cdot [(S1_{45} + S2_{45}) - (S3_{45} + S4_{45})] \tag{1}$$

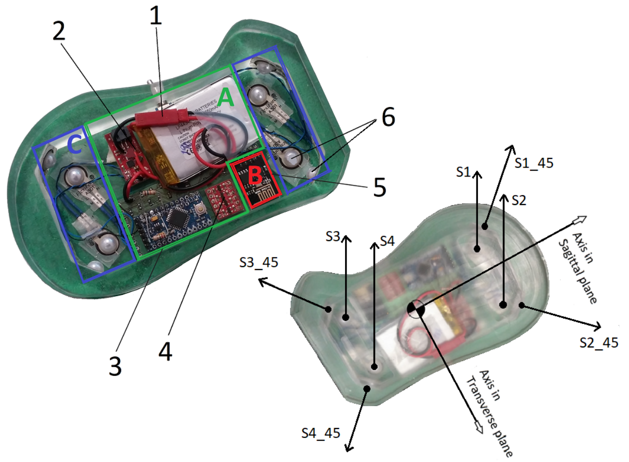

Figura 1. ITshoe schematic structure. The green block (A) is the acquisition unit, the red block (B) is the streaming unit, and the blue block (C) is the sensing unit. The main elements of these units are subtitled with numbers: 1- Battery; 2- Step-up voltage regulator; 3- Micro-controller; 4- Bi-directional level converter; 5- WiFi module; 6- Force sensor. On the right side it is visible the position of the eight force sensors and the reference axis used to decompose the tangential forces.

$$Fh_{tt} = \frac{\sqrt{2}}{2} \cdot [(S2_{45} + S4_{45}) - (S1_{45} + S3_{45})] \tag{2}$$

where Fh_{st} is the total horizontal force in the sagittal plane, Fh_{tt} is the total horizontal force in the transverse plane and $S1_{45}$ to $S4_{45}$ are the sensors used to measure these tangential forces.

The datasets presented on this work were recorded using the ITshoes and the robot NAO.

2.1 Floor classification problem

In this work, was made an attempt to identify which one of the four different slippery floors the humanoid robot NAO walked on, having as hypothesis that each floor has a particular signature when identified by the force sensors that measure the contact forces between the biped feet and the ground, together with the robot 3-axis gyroscope, acceleration and body inclination data. Fig 2 shows the layout used to collect data for the addressed classification problem. The system *NAO+ITshoes* is used to collect data while the humanoid NAO walks on the 4 different floors presented here. Table 1 presents the measured coefficient of friction (CoF) for the different materials used as floors.

Figura 2. Layout for data collection.

Tabela 1. Floors coefficient of friction.

Material	Coefficient of Friction
Acrylic-PTFE	0.11
Acrylic-Aluminium	0.20
Acrylic-Melamine	0.26
Acrylic-PE-HD	0.33

2.2 Data manipulation

The output signals from each one of the available ITshoes and Robot sensors were sampled and stored during real-time experiences for subsequent offline analysis. Before classifying the floors using the LSTM-RNN, it is necessary to pre-process the raw data. The following procedure describes the developed algorithm methodology to extract the data that corresponds to the humanoid robot steps and to ease its representation to be used as inputs for the learning approach. The algorithm reads the recorded raw data from the database and outputs only the data that corresponds to moments when the robot's foot is in contact with the floor, as follows:

(i) Use the calibration curves to convert each sensor ($S(i)$) raw data into forces, as described by the following equation:

$$F(i) = \frac{b(i)}{R(i)(\frac{1024}{S(i)})-1} \times \frac{1}{m(i)}, \quad , \quad i \in \{1,2,...,8\} \tag{3}$$

where R is the voltage divider resistor, m and b are the calibration curve slope and y-intercept respectively, and 1024 (2^{10}) refers to a 10-bit analog to digital converter (ADC);

(ii) Obtain the start and end of each step: $Fn(i) \approx 0$ (normal force = 0, robot foot is in the air);

(iii) Use the indexes i ($Fn(i) \neq 0$) to filter the data points for all the recorded variables;

(iv) Normalize each recorded variable to be inside the range [-1,1] ;

(v) Reshape the data according to the LSTM needs.

2.3 Data for LSTM training, validation and testing

The resulting dataset for this work includes 5235 robot steps sequences. Each input sequence consists of 11 features, each composed by 100 data points. The 11 selected features are as follows:

1. Fh_{st} = Horizontal force in the sagittal plane (N)
2. Fh_{tt} = Horizontal force in the transverse plane (N)
3. Gx = Gyroscope X axis ($\frac{rad}{s}$)
4. Gy = Gyroscope Y axis ($\frac{rad}{s}$)
5. Gz = Gyroscope Z axis ($\frac{rad}{s}$)
6. AccX = Accelerometer X axis ($\frac{m}{s^2}$)
7. AccY = Accelerometer Y axis ($\frac{m}{s^2}$)
8. AccZ = Accelerometer Z axis ($\frac{m}{s^2}$)
9. BIx = Body inclination X axis (rad)
10. BIy = Body inclination Y axis (rad)
11. BIz = Body inclination Z axis (rad)

Since it is expected to classify four different floors (classes), our target matrix has 4 lines by N number of steps, being that only one of the lines is filled with the value 1 and the others with the value 0 (e.g [1,0,0,0]'. means that the target is the 1st floor). The data is prepared and randomly divided into three subsets: the training set (60%), which is used for computing the gradient and updating the network weights and biases; the validation set (20%) to measure network generalization and to halt training when generalization stops improving; and the test set (20%) that is used to compare the different LSTM networks, as well as evaluate the ability of the network to correctly classify the floors. To make the classification process more accurate and less biased, a 10-fold cross validation was applied to the data so that the LSTM model was trained 10 times, each

Tabela 2. Dimensions of the input and target matrices

	Input	Target
Training	(3141,100,11)	(3141,4,1)
Validation	(1047,100,11)	(1047,4,1)
Testing	(1047,100,11)	(1047,4,1)

time with a different train/validation/test split. Table 2 shows the final dimensions of the input and target matrices.

3 LSTM-RNN experimental results

RNN is the feed-backward version of the conventional feed-forward neural network. It allows the output of one neuron at time step ti to be the input of the same neuron at time step $ti + 1$. Standard RNN methods suffer from the vanishing gradient problem [9]. To overcome this problem, [6] developed the LSTM unit. LSTM units are fit to store and access information over long periods of time. LSTMs achieve this through their 3-gate architecture, which consists of an input, an output, and a forget gate.

The LSTM models developed in this work, were build using the open source neural network library Keras, running on top of the machine learning platform TensorFlow. The API Keras is written in Python. Several LSTM networks configurations were implemented to classify the different floors from the input layer of 11 features and 3 time steps. For the first developed model (Fig. 3), a LSTM 50 layer with activation functions "sigmoid"and a dense 4 layer with activation function "softmax"to output the classification was used as a base model to start training.

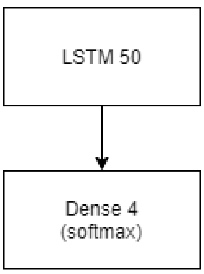

Figura 3. LSTM base model.

The optimizer used in all the training trials was the Adam optimizer because of its ability to converge quickly while traditionally performing better than most other optimizers. After training the model several times, Fig. 4 and 5 present the loss *vs* epochs and accuracy *vs* epochs, correspondingly, for this base model.

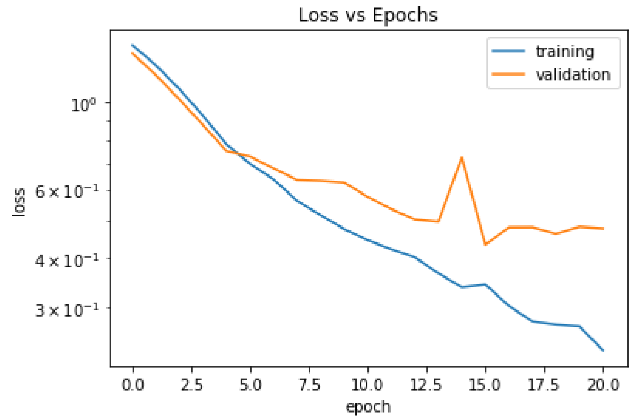

Figura 4. Base model, Loss vs Epochs.

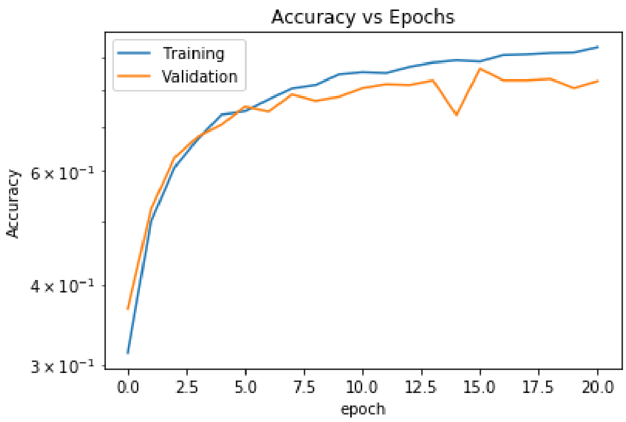

Figura 5. Base model, Accuracy vs Epochs

The loss of the model was evaluated using a categorical cross-entropy. Evaluating this network using the test set allowed to conclude that this network could only correctly classify approximately 65.8% of steps.

From here, more layers were added to the base model and their influence in the network performance was evaluated. It was noticed that adding a new dense layer with a activation function "tanh"to the network with the same number of hidden neurons reduced the loss error of the network, whereas adding more did not improved the results. A dropout layer was also added to the model since it is commonly used to combat overfitting and to improve the model performance. This layer is used as a regularization method where input and recurrent connections to LSTM units are probabilistically excluded from activation and weights updates while training a network. Multiple LSTM models architectures were implemented and trained with a varying number of hidden neurons, different activation functions, batch sizes, learning rates and dropout probabilities. Table 3 shows the evaluated range for some of these

Tabela 3. Network parameters evaluated range.

	Range	Best
Hidden neurons	50 to 500	300
Learning rate	0.1 to 0.00001	0.0001
Batch size	16 to 512	256
Dropout probability	0.1 to 0.5	0.2

parameters as well as the chosen value that produced the best results.

Fig. 6 shows the optimized model obtained for this multi-classification problem using the chosen best parameters. This model has 4 layers: a LSTM layer with 300 hidden neurons and a "sigmoid"activation functions, a dense 300 layer, a dropout 0.2 layer and a dense 4 layer with "softmax"activation functions. Fig. 7 and 8 present the optimized model loss vs epochs and accuracy vs epochs.

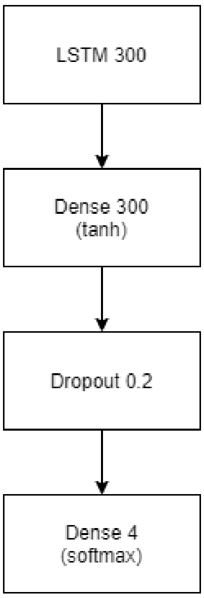

Figura 6. Optimized LSTM model.

It is seen that this new model reduced the loss error and increased the accuracy when compared with the base model. Additionally, after applying cross validation the model presented an average training accuracy of 98.1%, validation accuracy of 91.1% and test accuracy of 91.7%, which means that the model correctly classified 960 out of 1047 steps.

4 Conclusions

This work addressed a floor classification problem using a LSTM recurrent neural network model based on the ITshoes force data together with the robot internal inertial sensor data. A dataset of 5235 labelled steps of a walking biped robot over four different floors were collected and used to train, validate and test the multiple learning models. After several attempts to optimize the LSTM base model and after tuning its parameters the initial 65.8% accuracy was greatly increased to 91.7%. Although the results look promising, for future work it is expected to implement this network in real-time and verify its ability to correctly classify different floors, as well as, compare its results with other computational intelligent techniques.

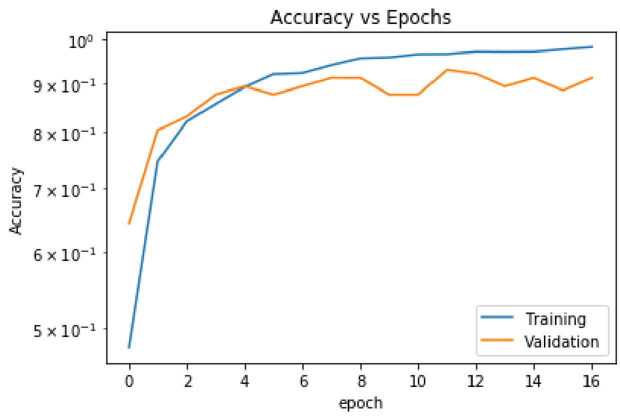

Figura 7. Optimized model, Accuracy vs Epochs.

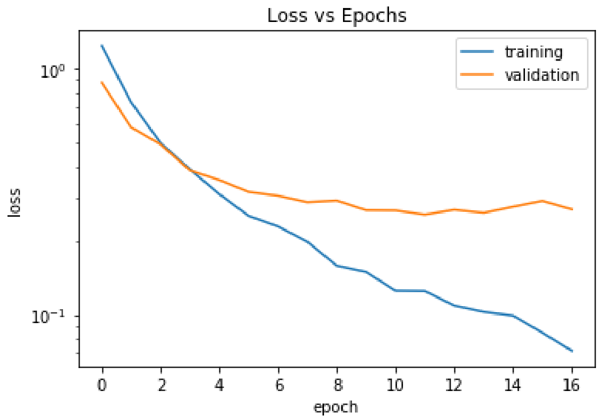

Figura 8. Optimized model, Loss vs Epochs.

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