

Lower-Limb Falling Detection System Using Gated Recurrent Neural Networks

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Abstract—Accidental falls are one of the most common causes of premature disability and mortality related to unnatural causes. This affects mainly the elderly population. With the current aging of the population, the rate of accidental falls increases. Computer systems for gait analysis and fast assistance in ubiquitous environments can be effective tools to prevent these accidents. In this article we present the advances in the creation of an intelligent device for detecting falls and risk situations based on accelerometer signals registered on the user’s ankle. The proposed method makes use of Deep Learning techniques, specifically Gated Recurrent Neural Networks. The results show that the proposed model is a viable alternative to detect falls and fall risk, which can be implemented in low performance devices for greater autonomy, lower cost and comfortable portability. These results open the possibility of combining fall detection with a biomechanical analysis system to identify gait deficiencies and their relation with falls.

Keywords—fall detection; fall prevention; accelerometer; Gated Recurrent Neural Networks.

I. INTRODUCTION

Elderly people commonly suffer falls, which can drastically reduce their quality of life, their capabilities for independent living and, in many cases, their sense of self efficiency. This is a very significant public health problem in a worldwide scale. World Health Organization (WHO) reports indicate that around 30% of seniors over 65 years old suffer at least one fall per year and the fall rate increases significantly with age [1]. There are many age related factors associated with this increased fall rate including cognitive, affective, sensory, musculoskeletal, neurological, and metabolic changes [2]. It is also well known that gender is also a key factor as women fall more often than men and sustain more injuries when they fall [3]. Many factors related to falls have also an important influence on the person gait. Thus, we can study a person gait in order to predict their future probability of falling [4] and, also, it would be interesting to study the capability of wearable devices to perform both gait analysis [5] and fall detection tasks [6][7].

An important factor with a significant impact in falls is that many elderly people lose confidence and adopt a more sedentary life, losing mobility and increasing the probability of falling because of their poor shape [8][9]. Direct consequences of falls include injuries to muscles, bone fractures and head trauma among others. Major injuries pose significant risk for post-fall morbidity and mortality and have strong economic impacts on family and public health providers [10].

Devices that monitor user activity and ideally alert when a fall has occurred are known as Fall Detection Systems (FDS). Their main objective is to distinguish between Activity of Daily Living (ADL) and fall events (alerting when this one happens) [11]. On one hand, context-aware systems use sensors installed in the environment: users don’t need to wear any special device and they do not have significant computational or energy limitations. However, these solutions are limited to specific areas and are prone to privacy related ethical issues. On the other hand, wearable devices allow

user monitoring without any dependence with environment-based sensors. These systems are usually based on simple sensors such as accelerometers or gyroscopes, that can be integrated in low-power devices to increase their battery life [12]. Wearable FDS require a periodic sensor monitoring process (several times per second) that may demand a significant power consumption; but, if fall detection is performed in the embedded device, the algorithm may reduce the detection accuracy and increase the response time.

Regarding fall detection algorithms two main families are widely used: threshold based and machine learning based algorithms. Delving into Machine Learning systems, Gated Recurrent Neural Networks (RNN), such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) are Deep Learning networks specifically designed for sequence processing. Recent studies have shown the potential of RNNs for dynamic signal classifications [13] and specifically for accelerometer data [14][15].

Considering the other function that we want to embed into our wearable device, Gait Analysis Systems (GAS) have been available for a long time and are widely used in rehabilitation scenarios [16]. A good survey of the different technologies available for gait analysis can be found at [17]. As in the case of fall detector and GAS can either be environment based or wearable. Wearable GAS are popular in the fitness related communities. Moreover, our group developed and tested an embedded GAS placed in a wearable device [18].

Thus, analyzing the publications related to these devices it is clear that gait analysis can be performed using a sensor in the foot or the ankle. However, it is not clear that wearable FDS can perform adequately when they are attached to these locations.

The main goal would be to create a combined FDS and GAS device (Fall Detection and Gait Analysis System: FDGAS) so that we can use gait data to forecast possible falls. In this work, we will study the feasibility of a lower-limb FDS. As the feasibility of a lower-limb GAS has already been established, if we are able to prove that our intermediate goal is reachable then, we would be able to achieve the final goal of design and evaluating the FDGAS.

The article is organized as follows: Section II describes Gated Recurrent Neural Networks used for the Deep Learning classification algorithm; Section III describes the wearable device and the database used for the training process; Section IV presents the results obtained after the training and testing phases; and, finally, Section V includes the discussion regarding the effectiveness of the trained Deep Learning models and the final conclusions of the work.

II. GATED RECURRENT NEURAL NETWORKS

Recurrent Neural Networks are Deep Learning architectures specifically designed to extract features from sequential data, such as time varying signals. Gated Neural Networks are a newer version of RNN that solve traditional problems that affect the learning process of these networks. They add a vector as an information storage component called cell, which stores information acquired during the sequence analysis, relevant to process the rest of the sequence. Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) are the most popular architectures of this type, which has demonstrated

good performance in problems such as signal classification [13][14]. The main differences between them are the way they update and use the stored information in the cells during the sequence analysis (See Figure 1). An LSTM cell management system consists of three activation functions called gates to add new information to the cell (input gate), remove current information stored (forget gate) and pass information to the neural network that considers relevant to process the sequence in an specific stage (output gate). In case of a GRU cell, there are only two gates, which adds (update gate) and removes (reset gate) information from the cell respectively, allowing all stored information to be used by the neural network throughout the sequence analysis. Both kind of Recurrent Neural Networks have similar performance, although GRU is theoretically more efficient due to having two gates.

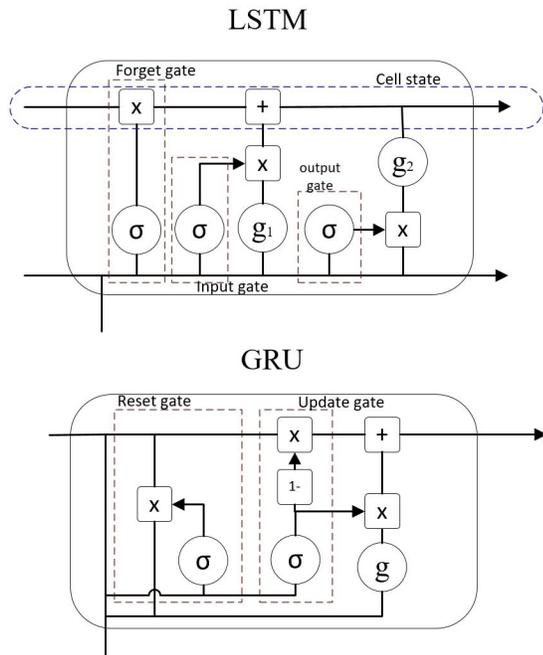


Figure. 1. LSTM and GRU cells.

III. MATERIALS AND METHODS

A. Data register device

To collect data, we developed a data acquisition prototype using a ST-nucleo L432KC low-power microcontroller, that obtains tri-axial acceleration data from an ADXL345 accelerometer and transmits it via Bluetooth to check the correct sensing of the data in real time during the activity recording. The microcontroller frequency sampling and transmission was configured at 25Hz. The accelerometer was configured to work with a precision of $\pm 16g$. The x axis of the accelerometer was aligned with the horizontal line, y axis with the vertical, and z axis was in the march direction.

B. Dataset acquisition

A set of activities were selected for this work, including Activities of Daily Living, fall risk situation and falls. We proposed 7 ADL, two of which include a fall risk phase, and 4 different falls (Table I). The subjects who performed the activities were 7 volunteers, 6 males and 1 female. The volunteers had heights between 1.60 and 1.95 meters, weights between 70 and 110 kilograms and ages between 24 and 30. All the activities were registered with the device placed on the right ankle.

The ADL that the volunteers performed are described in Table I:

TABLE I. TYPE OF ACTIVITIES RECORDED.

Parameter	Set of values for grid search
ADL	
Activity 1	The subject sits down on a chair.
Activity 2	The subject gets up from a chair.
Activity 3	The subject walks calmly.
Activity 4	The subject goes down the stairs.
Activity 5	The subject goes up the stairs.
Activity 6	The user trips over with the right foot.
Activity 7	The user trips over with the left foot.
Falls	
Activity 8	The user falls backwards.
Activity 9	The subject falls to the left.
Activity 10	The subject falls to the right.
Activity 11	The subject falls forward.

C. Data labelling and block segmentation analysis

Each sample in the activity records was labelled according to what part of the activity it belongs to. Four classes were considered:

- **Fall**: if the sample is part of the moment of fall in an activity.
- **Risk**: if the sample is part of the moment of risk of falling, before a fall or recovering the balance in a stumble.
- **ADL**: if the sample is part of walking or another ADL contemplated in the activity set.
- **Background (BKG)**: if the sample does not belong to any of the previous classes. This class includes moments of stillness at the beginning or end of the record of each activity. It also contemplates the period of inactivity after a fall.

Two of the authors labeled the samples and verified the result. All the activities were also recorded in a video as support material for labeling.

The Gated Recurrent Neural Networks input should have a short fixed length for better performance. For this reason, each activity record should be split in segments having the same number of temporal samples. Henceforth, each segment will be referred to as a block, and the number of samples as width. Since fall and risk events last a short time, this fact is an advantage since it allows a detection in real time. Additionally, each block needs to be associated to a unique label. The criteria established to select a label was according to the percentage of samples of the most relevant class (fall, risk, ADL, BKG). BKG was the default class, that is, the label chosen when the block does not contain the minimum percentage of samples of each other class. In this study, different width and minimum percentage of fall, risk and ADL classes were used. Data augmentation was also used by establishing a window stride during the record split. Different stride values were also analyzed.

D. Model training and evaluation

Two basic models based on Recurrent Neural Networks were assessed. They are consisting of a batch normalization layer, a recurrent layer, LSTM and GRU respectively, and a dense layer with four nodes and softmax for class inference (See Figure 2). The results in [12] show that this architecture has a high performance with data acquired at the waist to infer three classes (fall, risk and ADL-BKG combined) and low computational complexity allowing a classification in real time. A weighted loss function was applied to offset the imbalance of the data.

Hold-out validation and grid-search were used for hyperparameter optimization. The hyperparameters consisted of the number of nodes of the recurrent layer (N), dropout rate (Dr), learning rate (lr) and batch size (bs). The set of values used for each hyperparameter is shown in Table II.

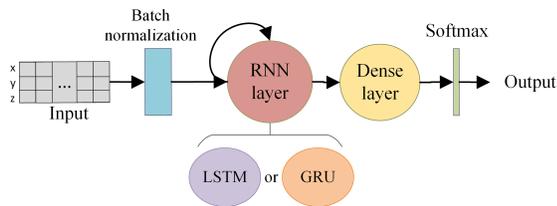


Figure. 2. Diagram of the Gated RNN architectures assessed.

TABLE II. GRID SEARCH VALUES FOR EXHAUSTIVE PARAMETERS OPTIMIZATION.

Parameter	Set of values for grid search
Learning rate	0.0001, 0.0005, 0.001
Batch size	32, 64
Number of nodes	16, 32, 48
Dropout	0.15, 0.25

To assess the effectiveness of the models, we use a set of metrics, that is, macro recall or sensitivity, precision and macro f1-score, and specificity. They are expressed as follows:

$$Precision_m = \sum_c \frac{TP_c}{TP_c + FP_c}, c \in classes \quad (1)$$

$$Recall_m(sensitivity) = \sum_c \frac{TP_c}{TP_c + FN_c}, c \in classes \quad (2)$$

$$Specificity = \sum_c \frac{TN_c}{TN_c + FP_c}, c \in classes \quad (3)$$

$$F1 - score_m = 2 * \frac{precision_m * recall_m}{precision_m + recall_m} \quad (4)$$

where m index refers to macro metric and $classes = \{BKG, ADL, risk, fall\}$. TP_c , FP_c and FN_c denote the number of true positives, false positives and false negatives of each class $c \in classes$, respectively. Finally, TN_c denotes the number of true negatives of each class $c \in classes$.

IV. RESULTS

The results obtained after optimization for the two models are presented in Table IV. The models were trained using the resulting dataset from 6 users and tested with the data from 1 user. The dataset distribution before data segmentation and augmentation is shown in Table III.

TABLE III. DATASET DISTRIBUTION FOR EACH SUBSET.

Subset	Total	Blocks			
		ADL	BKG	Alert	Fall
Training	5,621	1,179	3,553	348	541
Test	1,259	422	698	57	82

The confusion matrix can be observed in Figure 3. The metrics values obtained before grid search optimization are shown in table IV. The GRU model reached a better performance, but it does not get a significant difference, that matches with results in [19]. These similarity on result by comparing the two types of RNN layers are somewhat similar to [12]. Since the GRU layers present quite lower computational costs, it can be a better option for a low power energy device.

The performance obtained with these models and data is somewhat low compared to the current state-of-the-art. However, there are several limitations that influence the results. First, a classification problem with four classes has been carried out. A binary problem would probably have reached higher success rates but, with this problem we wanted to analyze the ability of the model to distinguish several classes. Second, the dataset created is quite small to train Deep Learning models, because it has many features to optimize. We have not contemplated the analysis of more complex models for this reason, since the number of features would be considerably higher. Finally, no preprocessing of the data values has been performed. Considering these factors, the results obtained show that these models have great potential to identify falls and risk situations with accelerometer data positioned on the ankle and without filtering.

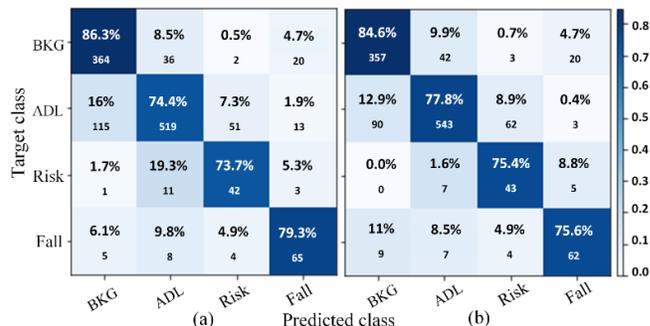


Figure. 3. Confusion matrices for the LSTM model in (a) and GRU model in (b).

TABLE IV. RESULTS OBTAINED AFTER GRID SEARCH OPTIMIZATION.

RNN type	Precision _m	Recall _m	Specificity	F1score _m
LSTM	0.681	0.784	0.920	0.729
GRU	0.691	0.790	0.925	0.737

The results obtained after these preliminary tests demonstrate the feasibility of using a fall detection system located in the lower limb. This fact is the main novelty of this work, since in the literature can only be found works that place the device on the waist or upper extremities. However, this study has limitations that must be detailed:

- The final number of volunteers used to obtain the database is limited: in future studies it is necessary to expand the number of people.
- Due to lack of time, a single data collection was carried out for each activity and person. It is important to expand the samples in the future to have, at least, 3 data collection of each activity from each person.
- The previous deficiencies mean that the results obtained in this preliminary study are not as good as those obtained in other fall detection systems (not located in the lower limbs). However, the improvement of the previous points in subsequent studies will improve those results.

V. CONCLUSION

The performance reached with simple LSTM and GRU models indicates the feasibility to extract features to identify ADL, falls and risk events (in falling detection systems). This work demonstrates that FDS can be placed in the lower limbs in order to combine the information obtained from it with Gait Analysis Systems (GAS). This is the main novelty of this work.

However, in order to improve the results obtained in this work, it is necessary to deepen into these systems with more complex

architectures and larger datasets, as well as in the application of appropriate data preprocessing techniques.

In future works, this lower-limb FDS will be combined with the GAS to create a high-level system able to detect any abnormality during the daily activities of the patient.

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