

# Task-Specific Gait Analysis: Faller versus Non-Faller Comparative Study

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## Abstract

In this paper, a comparative analysis of walking patterns during different cognitive states is conducted, followed by the classification of our database into Fallers and Non-fallers; by Fallers we describe subjects with repeated falling history. Vertical Ground Reaction Forces (VGRF) acquired from underneath the heel and toes of both feet are processed and analyzed for that endeavor. The subjects underwent three levels of tasks: 1) Single task: Walking at self-selected-speed (MS), 2) Dual task: Walking while performing a verbal fluency task (MF) and 3) Complex Dual task: Walking while counting backwards (MD). The ultimate objective of our research is fall prediction among the elderly by characterizing the variation of time-domain feature of Gait signals. For that, walking VGRF is analyzed and tested for the existence of indicators of the effect of dual task on subject falling susceptibility, whether parametric or pattern-wise analysis. As a result to our work, dual task in Fallers VGRF signals were recognized at 74% while at those non-fallers were recognized at 85%. Most importantly, subjects with history of fall have shown more potential to change the way they walk while performing mathematical cognitive task.

## Keywords

Task-Specific Gait Analysis, Vertical Ground Reaction Force, Fallers/Non-Fallers

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## 1. Introduction

As a person ages, all physiological functions tend to decline in several aspects leading to serious physical and mental failures. Accidental falls at old age is one of the main concerns that have received remarkable attention, nowadays. Elderly

fall has been studied thoroughly in an attempt to predict its occurrence and eventually prevent it or fix its causes [1] [2] [3].

Recent research stated several risk factors for elderly accidental fall such as: environmental hazards, sensorimotor deficits and impaired balance. In fact, recent studies evaluate the effect of cognition on walking patterns or Gait [4] [5] [6], showing that when the cognitive capacity of old aged people is reduced, they are less likely to acquire stability while performing other tasks. Loss of central neurons and associated synaptic connections accumulation lead to reduced processing speed and insufficiency in handling several processes simultaneously. Moreover, persons may give a spontaneous reaction in prioritizing their attention, therefore the magnitude and direction of the dual task interference will be influenced differently [7]. For instance, a previous study was objected to observe the effect of following two simultaneous instructions, walking and talking, on elderly subjects, concluding the prioritization of walking over talking [8]. As stated by Plummer et al in [9], when old people walk, the dual task interference can highly limit their mobility and increase the risk of falling. In addition, a research study highlighted the difference in gait velocity and stride-to-stride variability between older, middle-aged and younger adults during dual tasks [10], concluding that gait velocity decreases with age while stride variability increases. It is also believed that elderly falling can be predicted by studying the efficiency of visual coordination in dual-task walking [11].

Going back to the principle of dual task paradigm, which is based on a neuropsychology procedure, we remark that it is currently being used to study the interference between motor tasks (e.g. walking) and cognitive processing (e.g. verbal fluency tasks). In other words, the walking mechanism that seems automatic and cognition-free at a young age becomes a complex motor task as a person ages [12]. Therefore, executing motor and verbal fluency tasks while walking leads to gait disturbances because of the challenging effort made to concentrate on remaining in balance [13].

Different research papers focus on features such as stride-to-stride variability and gait stability in order to make such fall prediction. However, more focus should be oriented towards the effect of performing dual tasks on gait variability.

That being clarified, our study focuses on walking VGRF signal analysis to distinguish the effect of dual task behavior on both faller and non-faller gait characteristics, which will help orthotists, prosthetists, clinicians and experts in gait mechanics in developing their rehabilitation programs for patients who suffer from gait performance deficiency.

## **2. Methodology**

### **2.1. Database**

In collaboration between the Laboratory of Signal Analysis and Industrial Processes (LASPI) in Roanne and the University Hospital Center (CHU) of Saint-Étienne, experiments were carried out between years 2009 and 2011 with

more than 600 elderly participants who aged between 85 and 93. VGRF signals were acquired at a sampling frequency of 128 Hz using two independent sensors placed underneath the heel and metatarsus/toes of each foot, through an artificial innersole (SMTECH FOOT-SWITCH) placed in the shoe (**Figure 1**). The sensors bear a pressure of 40 g/cm<sup>2</sup> corresponding to the state of foot/ground contact. Each participant was asked to perform three single and compound tasks: 1) Single task: Walking at self-selected-speed (MS), 2) Dual task: Walking by performing a verbal fluency task (MF) and 3) walking while counting backwards (MD). Sixty subjects were randomly chosen, thirty of which are non-fallers while the thirty others are fallers to serve the goal of analysis before building the final adequate classifier. For classification purposes, nine of each group was randomly selected for our analysis while the remaining subjects' data was left out for Neural Network training.

## 2.2. Procedure

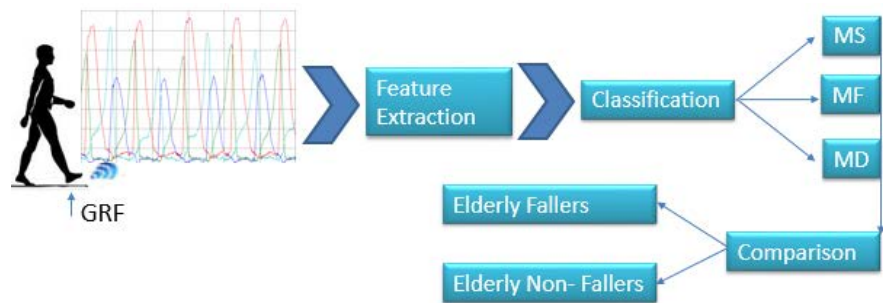
The recorded signals are 4 signals from both the right and left foot. The impact and active peaks of each signal are being separated by first differencing. Then a set of features from both time and frequency domain are extracted to form input to a classifier. A comparison in the results is then conducted between elderly fallers and non-fallers. **Figure 2** summarizes the flowchart of the algorithmic work followed in this paper.

## 2.3. Perspective

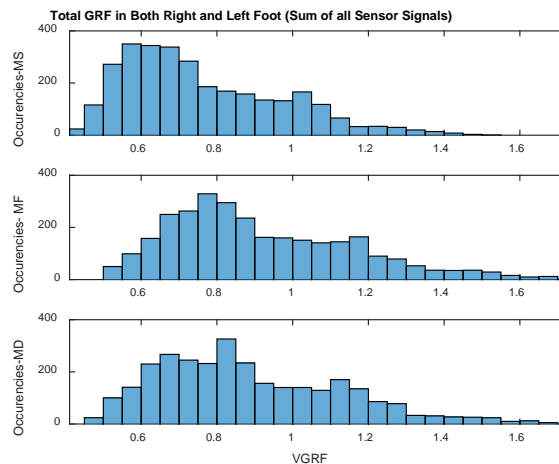
In order to classify VGRF in different modes of walking conditions, it seems beneficial to focus on how such walking conditions will impact the VGRF time series. That's why there is a need for certain features that well describe and characterize the signal and those mainly based on statistical tools. For instance, by having the histogram as shown **Figure 3**, the alteration in three categories will



**Figure 1.** SMTECH foot-switch.



**Figure 2.** A summary of the algorithm for classification and comparison.



**Figure 3.** Histogram of total GRF for bothe right and left foot.

not appear easily by only capturing the first moments (like mean and variance) of the signal. The total of all sensors' signal is considered here for the purpose of capturing VGRF at all instants where the body is in contact with the ground.

As the three walking patterns shares most of low order statistical information, one would also realize the same conclusion that would also appear when it comes for dealing with higher order moments. The signals look almost the same. Consequently, looking again on the time series signal itself would be an asset if related to the physical situations that a person could encounter while walking. For illustration, usual walking mainly record a little bit faster in speed than the two other types of walking condition. Moreover, while performing a certain cognitive task, people intend to have more concentrated power during feet switching as in the case from left foot toe-off to the right foot heel strike. This is to avoid slipping. Then it becomes more difficult to differentiate walking (MF) from (MD). As those two tasks can be classified to under the act of remembering, one could realise that this is highly related to level of knowledge a person have and also to the level of his/her intelligence. It is typically easier to remember numbers than to remember the names like name of animals that start with letter "w". therefore the rate of oscillation is expected to be higher on MD walking condition than on MF. In the contrary more effort is needed in MD and therefore more power cost is required while walking to overcome falling.

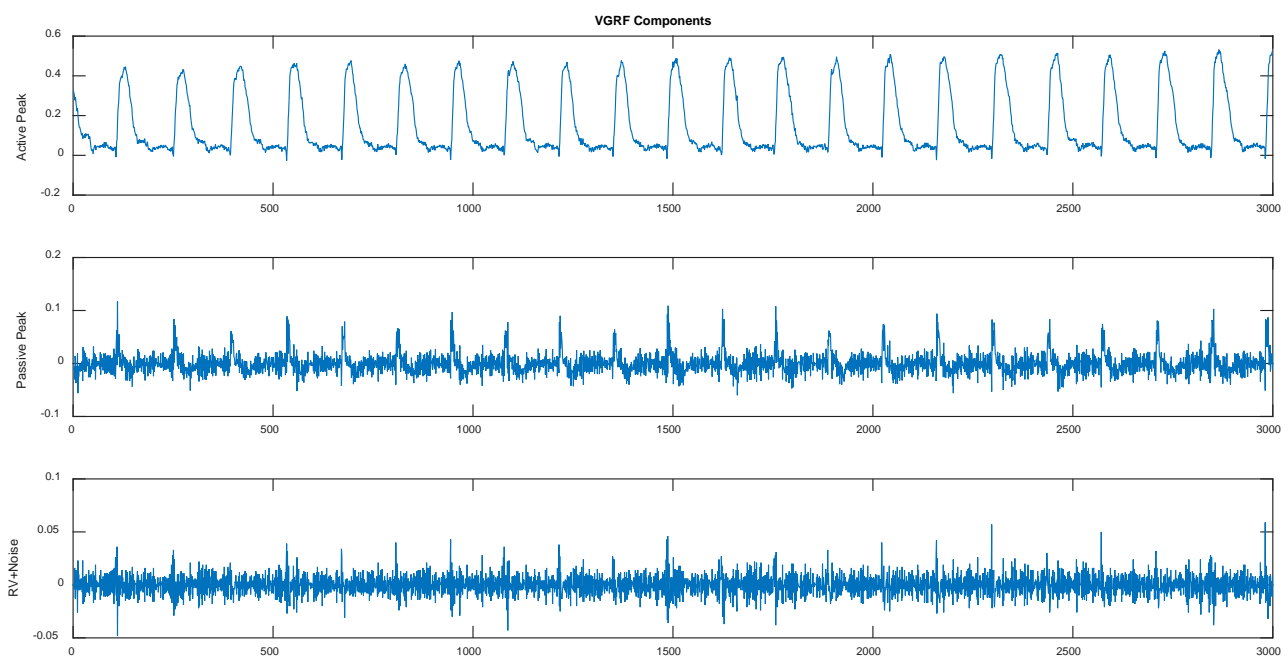
### 3. Featuring Walking with Cognitive Tasks

#### 3.1. MS & MF

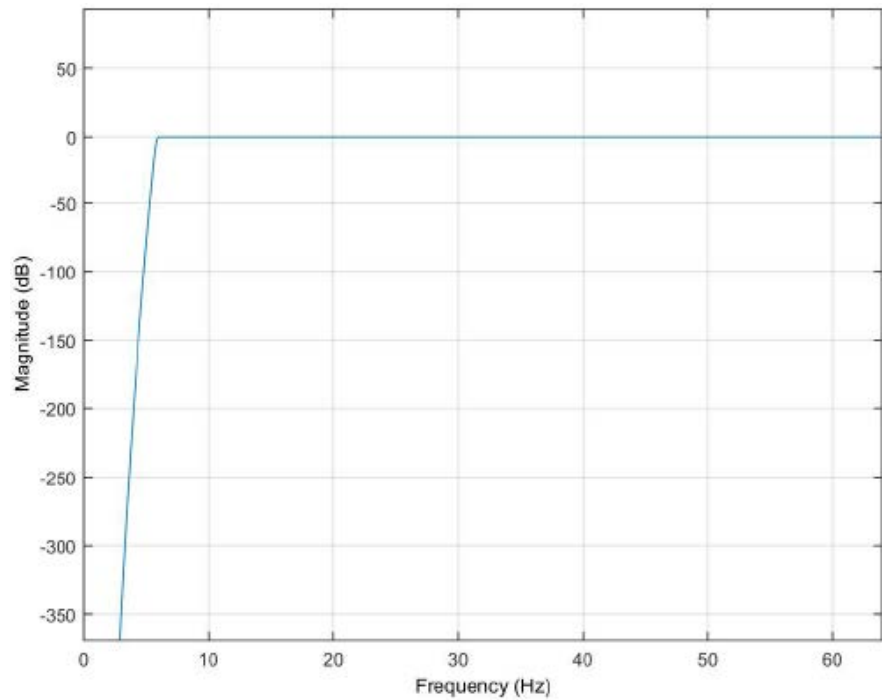
VGRF captured by each sensor is made up of three main important parts. The first part is mainly the active peak and is related directly to weight of subject. The second part represents the passive peak and this is representing the moments of push off and propulsion of the gait signal. The first two parts forms the periodic part of the signal that forces it be non-stationary. The third part is related to higher oscillations and corresponds to random variable part of the signal in addition to noise. That's why modeling requires the investigation of the third part which will be investigated on a further study. The three parts can be separated by first differencing and second differencing respectively as shown in **Figure 4**. Those are intended to the moments of stance phase discarding the noise during swing phase.

#### 3.2. Filter Design

Butterworth High pass filter is designed based on a 128 Hz Sampling frequency with the stop band frequency and pass band frequency of 5.2 Hz and 5.9 Hz respectively. The stop band attenuation is tuned to 60 dB and pass band ripple is set to 1 db. Knowing that, the band is set to pass band to match it exactly. The Butterworth is chosen to give a wider transition band and more stable time domain as shown in **Figure 5**. Our range of interest is above 5 Hz since we are interested with the variations that occur at high frequencies during walking. Low frequency components correspond to rhythm and speed of subject. In a previous work, we have shown that the active part is below the 5 Hz [14]. That is why



**Figure 4.** The three main components of VGRF captured from the sensor underneath the heel of the right foot.



**Figure 5.** Highpass digital filter.

considering frequencies above 5 Hz give more intuition on fluctuations and fast dynamic changes in the signal.

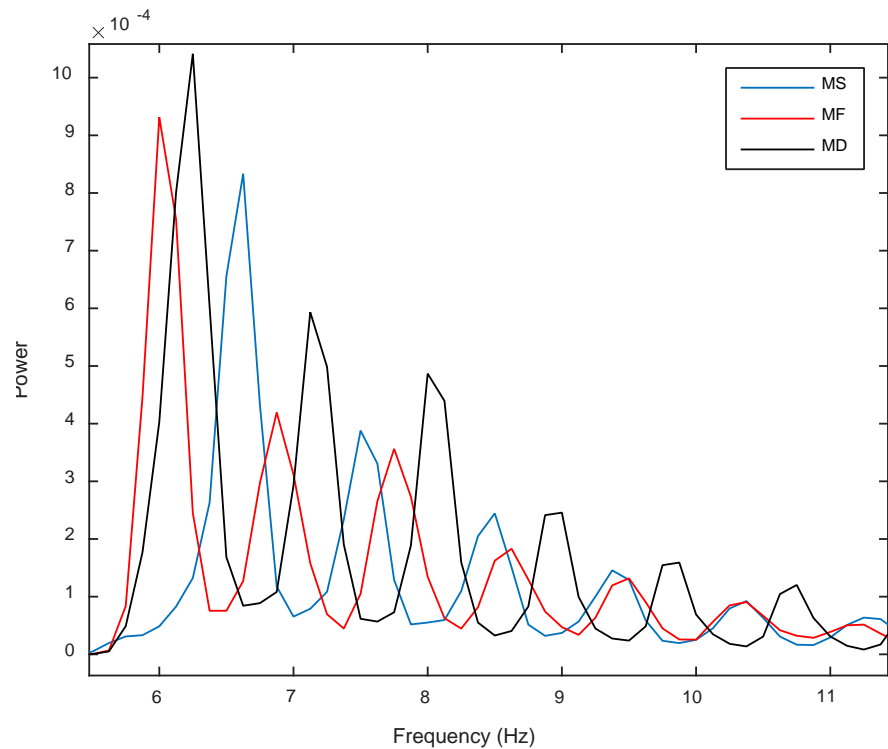
To isolate the different components of the signal variations then the high pass digital filtering is used. The filter is then applied over the raw signals. Thus two main components will be the outcomes of such filtering. The first one is due to body weight and usually tends to affect the first harmonics and second part is the fluctuations within the signal due to different walking tasks conditions. For instance a comparison between the power spectral densities using Welch's method is shown in **Figure 6**. It is clearly indicate a shift between peaks during different tasks and this is a good source to compute subject's speed. More interestingly, the rate of decay from peak-to-peak distance forms a decent pointer to similarities and differences between different tasks at different ranges of frequencies.

### 3.3. Feature Extraction

Derived features from original signals must be not redundant and instructive that will eventually end in reducing the dimension of data for interpretation. As the number of variables involved in gait signal features are huge and expected to be correlated at a higher level of complexity, this study will focuses only on a small set of features stemmed from the above analysis. The featured used are summarized below:

- Mean: adding all values and dividing by how many:

$$\bar{x} = \frac{1}{m} \sum_{i=1}^m x_i \quad (1)$$



**Figure 6.** Welch power spectral density estimate.

- Root mean square: is the quadratic mean denoted as square root for the square of the mean:

$$X_{RMS} = \sqrt{\frac{1}{N} \sum_{n=1}^N |X_n|^2} \quad (2)$$

- Autocorrelation: defined as correlation of the signal with a delayed version of a copy of the same signal indicating the level of similarity.

$$\Sigma = \frac{1}{m} \sum_{i=1}^m (\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})^T \quad (3)$$

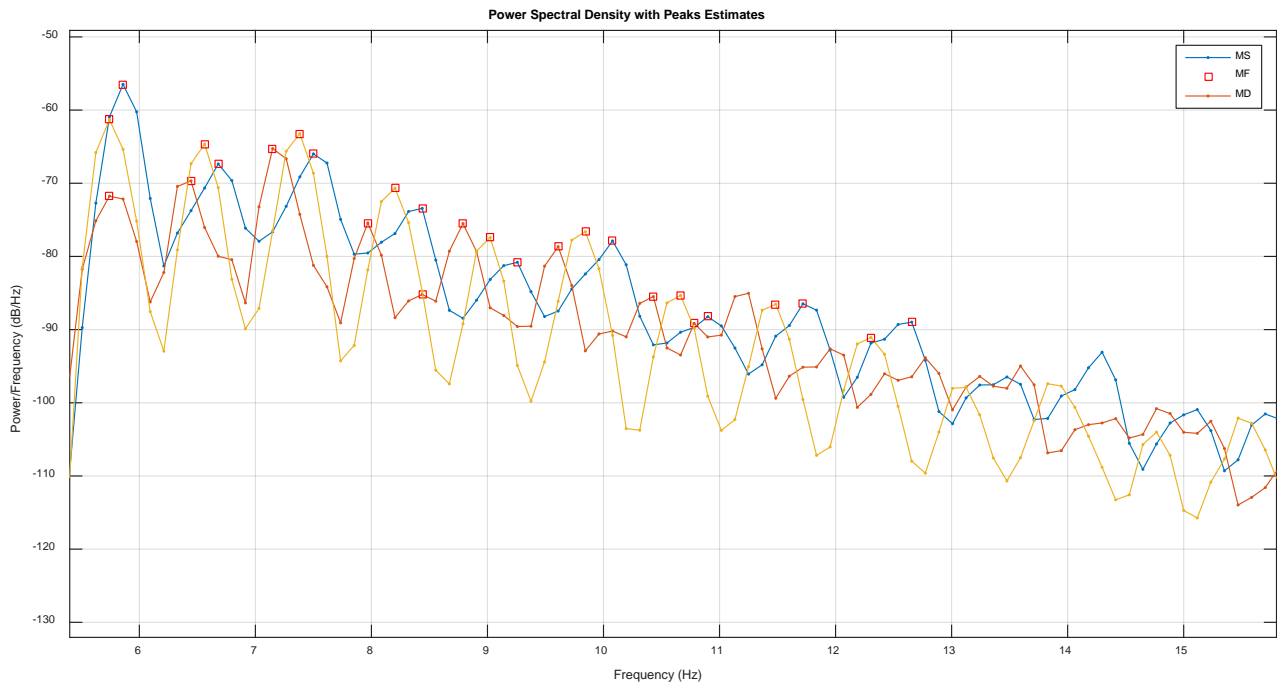
The autocorrelation of signals extracted from the four sensors is computed then the height of main peak in addition to the height and position of second peak are derived then

$$R_{xx} = \frac{\Sigma}{\sigma^2}$$

where  $\sigma$  is the sample variance of time series

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2} \quad (4)$$

- The first 6 peaks in the Pwelch Spectral are spotted to extract their height and position as shown in **Figure 7**. In general the power spectral density is mathematically linked to the autocorrelation structure by the discrete-time Fourier transform as a function of physical frequency (f):



**Figure 7.** The first 6 peaks are localized in the power spectral density.

$$P_{xx}(f) = \frac{1}{f} \sum_{m=-\infty}^{\infty} R_{xx}(m) e^{-2j\pi mf / f_s} \quad (5)$$

#### 4. Results and Conclusions

The purpose of this study is not to test the power of which classification technique to use rather than to see how the algorithm behaves between fallers and non-faller at different walking conditions. This is supported by neural network in particular multi-layer perceptron (MLP) for signal classification and below is how our data used:

- 70% training
- 15% validation
- 15% testing

Neural Network (**Figure 8**) with 18 nodes in hidden layer is chosen. This choice is based after increasing the number of nodes in ascending order with one node at a time until we are satisfied with the results.

**Figure 9** demonstrates the confusion matrix that represents the prediction of the network performance between actual target and output class for both non-fallers and fallers. For non-fallers, out of the 13 actual MS walking task, the neural network predicted only one with MD cognitive task. In fact, none is being predicted to have MF task. In coherence, none out of the 7 MF tasks were predicted to have MS task. Therefore a good classification between MS and MF is achieved but the MD tasks still have some common feature between MS and MF. This indicates that MD task shares some properties from both MS and MD and therefore more features must be developed. The opposite is true for fallers were

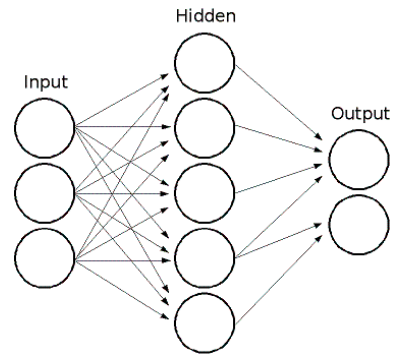
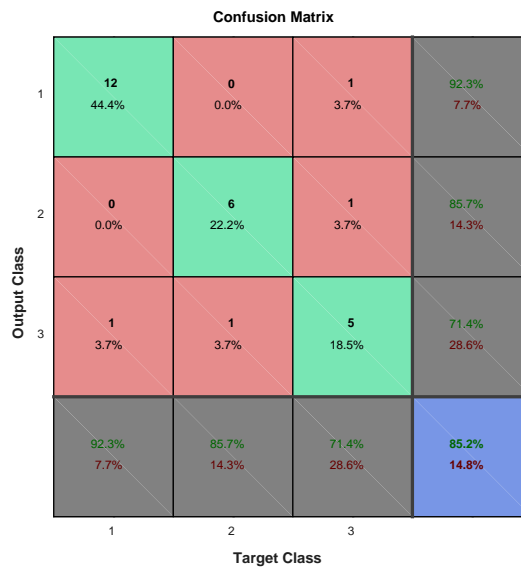
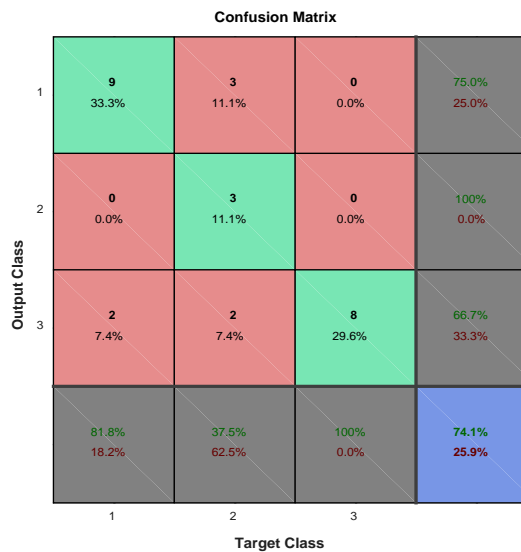


Figure 8. Sample of neural network architecture.



(a)



(b)

Figure 9. Confusion matrix plot for the target and output data in targets and outputs for both non-fallers (a) and fallers (b).

the system examined some trouble in classifying the MS and MF and pretty work in classifying all MD tasks as MD tasks. Most importantly the prediction is decreased to 37.5% in case of MF task. Apparently, different cognitive tasks have different effects on the way we walk which is highly correlated to whether having a previous experience of falling or not. In addition, verbal performance affects human gait tremendously when examining a history of fall. In addition, the classification of mathematical cognitive task is relatively better in fallers than non-fallers.

In summary, this analysis provides a comparative study between fallers and non-fallers based on built algorithm associated with GRF sensory measurements. We were able to spot differences between different tasks based on the signal's content. A classification algorithm is then generated to predict to which of three tasks such signal belongs. The results show that counting downwards while walking is better employed in classification purposes between different tasks in both subjects with a history of falling which is more than those non-fallers subjects. However such an important result is deteriorated when subjects are asked to perform verbal fluency dual task. Thus, such feature extracted must be adapted to different subject's situations whether walking with or without a dual task. However, with such a limited and elementary feature we were able to achieve good results with a reduced computational time complexity. In a further study, more features will be examined and which are constrained at the same range of computational time typically for real time operational and standalone systems. The results then will be generalized over different datasets to classify subjects with or without falling history that enhances the prediction of falling in elderly.

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