Intelligent Systems

Project

Developing of a neural system, a Mamdani-type fuzzy inference system and a Sugeno-type fuzzy inference system for the identification of a volunteer position/activity

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SUMMARY

1 – PROJECT SPECIFICATIONS

The project requires the analysis of a set of medical data. The application context is dermatology and, in particular, the compression therapy by means of bandages in the treatment of venous ulcers of the leg.

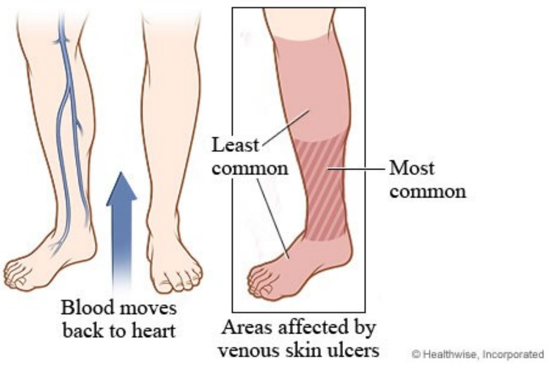


FIGURE 1 *COMPRESSION THERAPY*

In dermatology, venous ulcers are very frequent lesion of the skin of the legs, due to a compromised functioning of the blood circulation. To repair these ulcers, the blood circulation must be enhanced by exploiting the calf muscle pump which allows the blood to be moved back to the heart. The basic way to re-establish the blood circulation is the compression therapy.

In the compression therapy, the doctor applies a compression bandage on the leg of the patient providing a given pressure of the ulcer area. The pressure applied by the bandage allows to repair the ulcer, typically, in a few months.

The pressure applied by the bandage, and thus the efficiency of the therapy, depends on several factors:

- The type of bandage (depending, e.g., on the elasticity);
- The correct application of the bandage: an appropriate pressure should be applied in several parts of the leg according to the position of the ulcer, and the pressure should remain constant as much as possible between bandage applications;
- The activities performed by the patient during the therapy (e.g., walking, standing, etc.).

1.1 – DATA DESCRIPTION

The data refer to 10 volunteers. A compression bandage was applied to their calf. Three sensors were applied in three different position to measure sub-bandage pressure. Each volunteer wears the bandage for 12 minutes. During this time, the volunteer perform different activities or maintains their positions. Each activity/position is performed/maintained for about 3 minutes. The sensors measure the pressure with the sampling time of about 82 ms. The positions/activities taken into account are the following:

A. Supine position
B. Dorsiflexion standing
C. Walking
D. Stair climbing

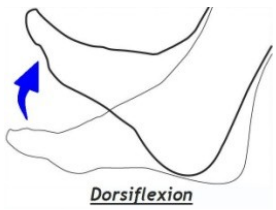


FIGURE 2 *DORSIFLEXION ACTIVITY*

The data are organized as follows. One folder for each volunteer is provided. In each folder there are 4 files, one for each position/activity performed. Each file contains the measurements of the three sensors (in the first three columns), and the corresponding sampling time (in the last column). Please, note that the sensor measurements are electrical resistance and are measured in Ohms.

1.2 – OBJECTIVE

The objective of the project is twofold: on the one hand, we want to identify the position/activity of the volunteer by analyzing the pressure of the bandage, i.e., to distinguish among supine position, dorsiflexion standing, walking and stair climbing; on the other hand, we want to find out the least temporal interval that is necessary and sufficient to recognize the position/activity.

2 – DATA ANALYSIS

Given the data organization described in the previous chapter, each signal coming from a sensor is a set of approximately 2000 samples. Rather than give all these data as input of our system, we prefer to appropriately represent the signal in terms of a reduced number of features that can summarize the information of the original signals.

For this reason in the following paragraphs we are going to evaluate the signal after a preliminar feature extraction phase.

2.1 – DATA INITIALIZATION

At the starting point we have to deal with raw signals that are quite difficult to analyze. This force the use of a pre-processing phase with the purpose to "clean up" the data in order to ease the management and the computations (*Appendix A.1*). From the calf pressure measurements of different activities we observe that the three different sensors may show different shapes and shifts due to their position under the calf sub-bandage. For this reason we also introduced a fourth "virtual" sensor, obtained as the sum of the former three, to summarize the overall measurement.

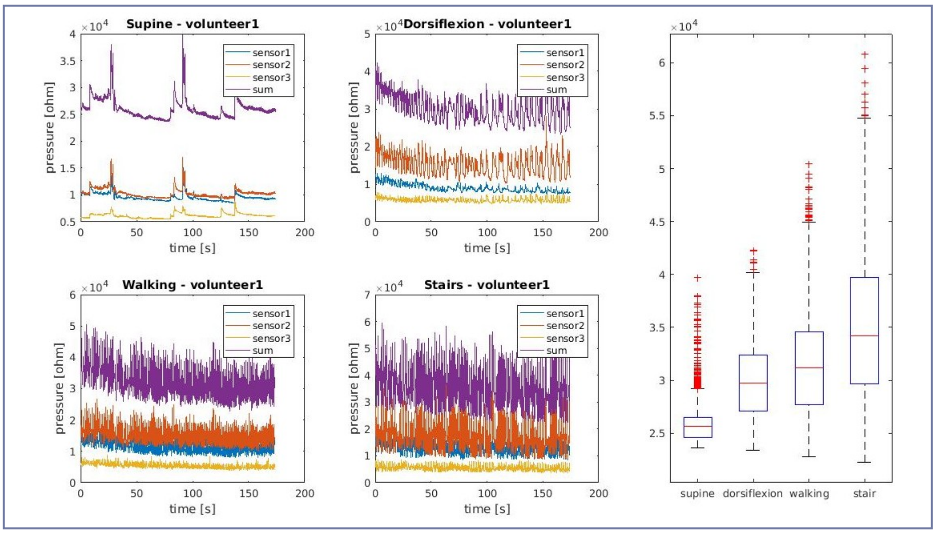


FIGURE 1 *SIGNALS AND BOXPLOTS OF POSITION/ACTIVITIES MEASURED ON VOLUNTEER 1*

Moreover our data should be sliced to obtain several pieces of the 3 minutes long signals for each activity. This has a twofold profit: firstly, we split every signal to find out the least temporal interval that is necessary and sufficient to recognize the position/activity. Sexondly, we have much more signals that we can be used to train/test/validate our neural systems (*Appendix A.2*).

Notice that the origial signals have been sampled with a sampling period of ~82ms (or with a 12.2Hz sampling rate). Therefore we can compute the number N of samples needed to form a M-seconds long slice of the signal using the following formula:

$$N = 12.2Hz \times M\ sec$$

A vector with several of these values has been defined to switch quickly among different temporal intervals in our project. The values are computed for the following intervals: 3sec, 5sec, 10sec, 12sec, 15sec, 20sec, 30sec, 1min, 2min.

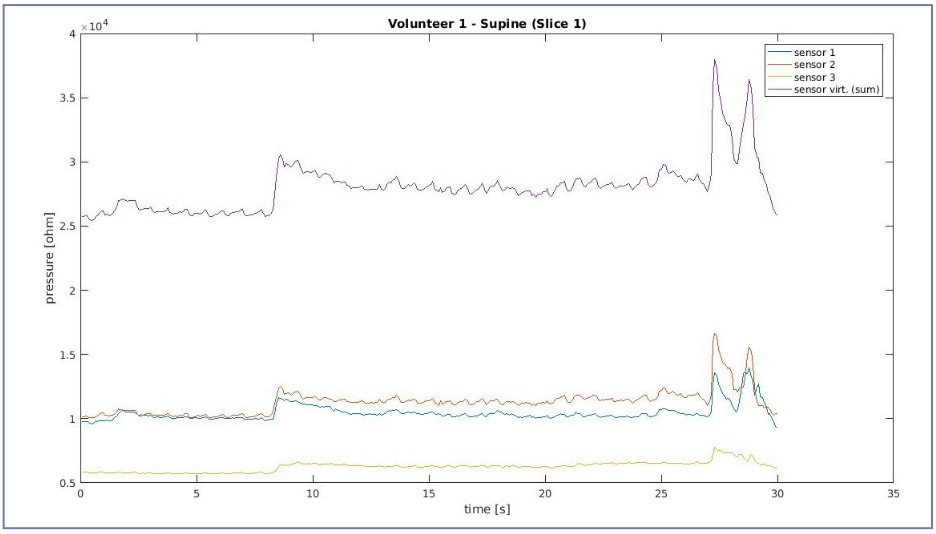


FIGURE 2 *FIRST 30-SECONDS-LONG SLICE OF THE SUPINE SIGNALS FROM VOLUNTEER*

2.2 – DATA CLEANING

The signals we are going to process are obtained from pressure sensors. As like as every real world signal they are affected from noise that deteriorates the signal.

For this reason it is the norm to apply some cleaning techniques before any feature extraction.

2.2.1 – SIGNAL SMOOTHING

One of the most common smoothing technique is the use of Savitzky-Golay filter: this is a digital filter that can be applied to a set of digital data points for the purpose of smoothing the data, with a consequent increase of the signal-to-noise ratio, without excessive distortions of the signal. This is achieved, in a process known as convolution, by fitting successive sub-sets of adjacent data points with a low-degree polynomial by the method of linear least squares.

For our project we used a third-order polynomial and a frame length of 7 (*Appendix A.3*).

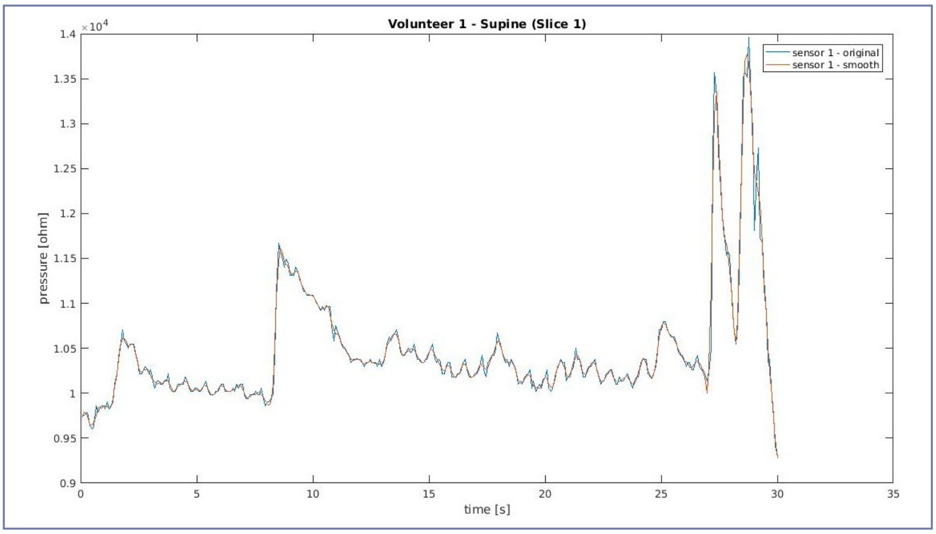


FIGURE 3 *SAVITZKY-GOLAY FILTER APPLIED TO A SIGNAL SLICE*

2.2.2 – NORMALIZATION

Another important point to deal with is the following: signals may have different scale and shift (see ***Figure 2***). This is a huge problem since we would like to compare them. To solve this problem we rely on the normalization process.

Since our dataset may contain some outliers we use Z-score normalization of the signal X, rather than the simpler Min/Max normalization, since Z-score is not affected from outliers. Z-score can be described with the formula below:

$$Z = \frac{X - \mu}{\sigma}$$

where, with μ and σ we respectively define mean and standard deviation of the signal.

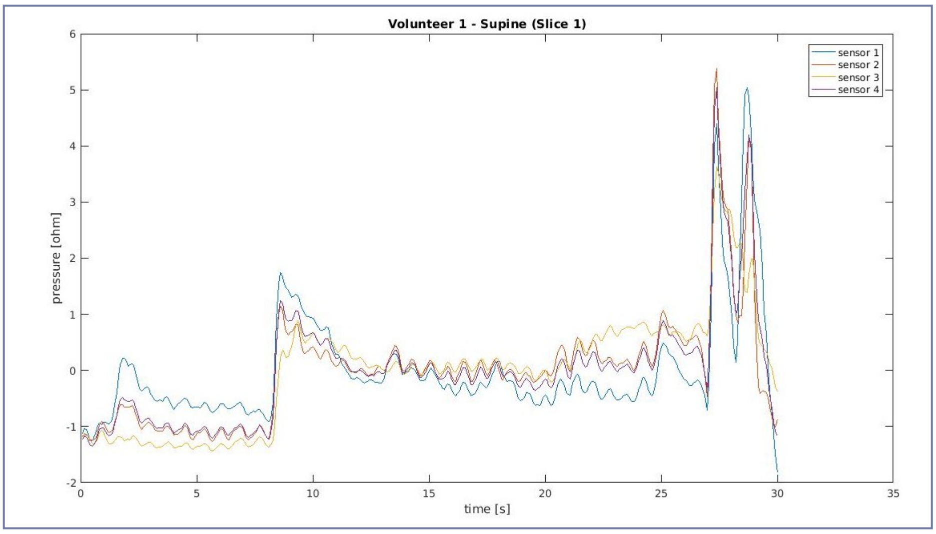


FIGURE 4 *NORMALIZED SIGNALS*

2.3 – FEATURE EXTRACTION

The signals, as whole, are quite difficult to analyze, than our goal is to represent them in terms of a reduced set of features. In order to do that we start analyzing signals' shape.

From ***Figure 1***, representing the 4 activities of the volunteer 1, it become immediately evident that signals belonging on different activities can be discriminated by the following temporal characteristics:

- **Max/Min**: the maximum and minimum values of each signals may be significatively important;
- **First/Third Quartile**: as like as max/min, with the benefict to elide outliers;
- **Standardized moments**:
  - **1st std. moment (mean)**: after the normalization phase the mean value has been nullified;
  - **2nd std. moment (variance)**: the same as for mean value.
  - **3rd std. moment (skewness)**: is a measure of the asymmetry, computed as
    $$\widetilde{\mu_3} = \frac{E[(X-\mu)^3]}{\sqrt{(E[(X-\mu)^2])^3}};$$
  - **4th std. moment (kurtosis)**: is a measure of the "tailedness", measured as:

$$\widetilde{\mu_4} = \frac{E[(X-\mu)^4]}{\sqrt{(E[(X-\mu)^2])^4}};$$

- **Autocorrelation**: is the correlation of a signal with a delayed copy of itself as a function of delay, and can be obtained with
$$R_{xx}(\Delta) = \frac{E[(X_t-\mu)(X_{t+\Delta}-\mu)]}{\sigma^2}$$
For this project we take in consideration the first 20 lags (Δ=1,2,…,20).

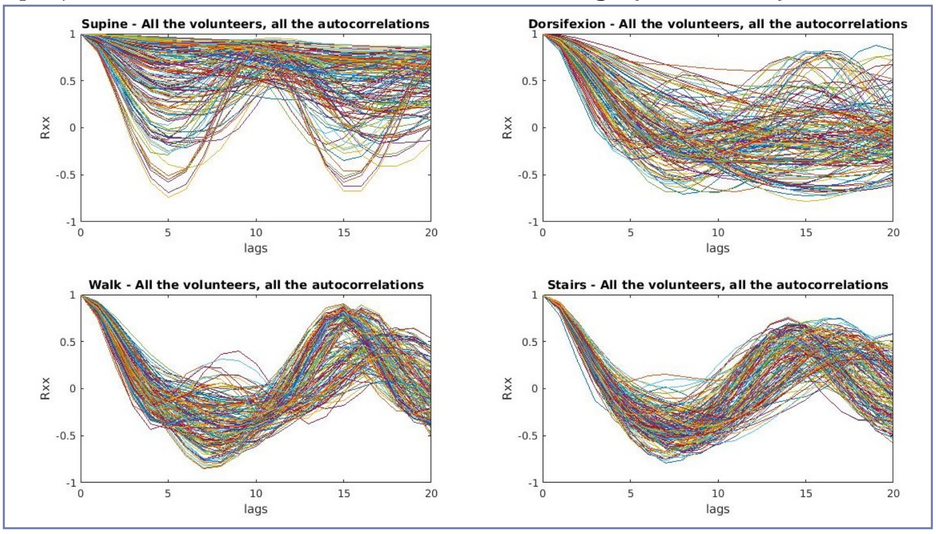


FIGURE 5 *AUTOCORRELATIONS FOR ALL THE ACTIVITIES OF EVERY VOLUNTEER*

In addition, performing some spectral analysis, we can infeer common frequential features for spectra for the same positions/actvities (see ***Figure 6***). We can introduce some frequency features that look appropiated:

- **Fundamental frequency** (f_0): achieved by detecting the maximum peak abscissa of the signals' spectrum, obtained by Fast Fourier Transform (FFT) formula,
$$X_n = \sum_{k=0}^{N-1} x_k e^{-i\frac{2\pi}{N}kq} \ \ (\mathrm{q} = 0,1,\dots,\mathrm{N}-1)$$
To faster compute f_0 we can approximate it with the maximum value of the FFT;
- **Amplitude of the f_0 peak** (amp);
- **Power Spectral Density** (PSD): obtained from the spectrum through the formula,
$$P_X = \sum_{n=-\infty}^{+\infty} |X_n|^2.$$

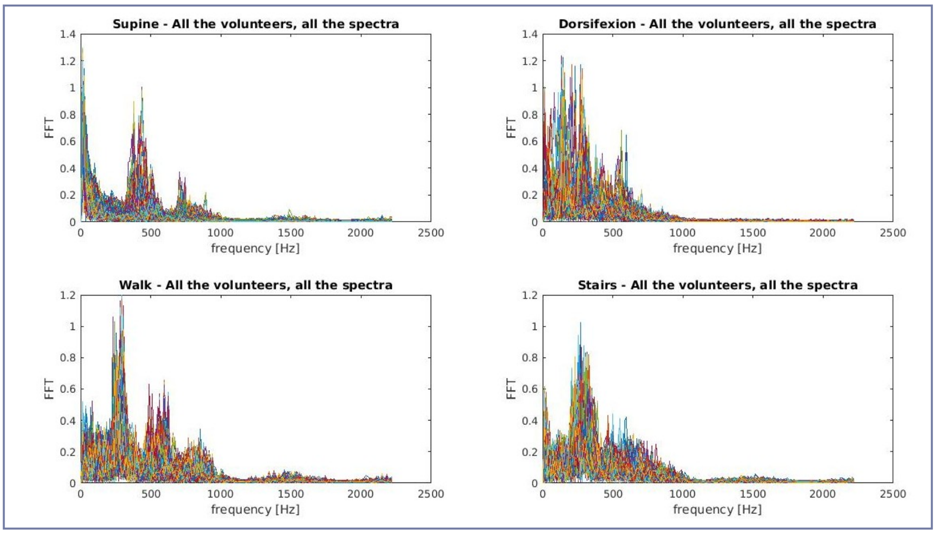


FIGURE 6 *FAST FOURIER TRANSFORMS FOR EVERY VOLUNTEER SEPARATED ON ACTIVITY/POSITION*

The feature extraction phase is showed in the *Appendix A.4*.

2.4 – FEATURE SELECTION

So far we have obtained 29 features: max, min, first and third quartile, skewness, kurtosis, autocorrelations (20), f0, amp and PSD. But we have to compute these for each of the 4 sensors (3 real + 1 virtual). Therefore we are in presence of a total of 116 features.

They are still a lot of inputs for the system, thus we have to select only the more significant for the activity classification.

2.4.1 – SEQUENTIAL FEATURE SELECTION

To understand whose and how many are the most important features needed to discriminate among positions/activities, we can take advantage of the tools MATLAB makes available to us.

One of this is "`sequentialfs`", that selects a subset of features from the input data matrix basing on the the result of the criterion function (*Appendix A.8*). Every detail can be found in the MATLAB documentation.

We have run the sequentialfs several times, so that to establish that, on average, the number of features beyond which the criterion value is negligible for the activity classification is of 6 features (see the table belove).

```
Start forward sequential feature selection:
Initial columns included:  none
Columns that can not be included:  none
Step 1, added column 27, criterion value 0.331288
Step 2, added column 36, criterion value 0.208589
Step 3, added column 41, criterion value 0.153374
Step 4, added column 73, criterion value 0.122699
Step 5, added column 46, criterion value 0.0797546
Step 6, added column 1, criterion value 0.0736196
Final columns included:  1 27 36 41 46 73
```

TABLE 1 *FEATURE SELECTION*

3 – NEURAL NETWORK

Neural networks are good at recognizing patterns. MATLAB provides two ways to solve this kind of problems:

- Use the `nprtool` GUI;
- Use a command-line solution.

It is generally best to start with the GUI, and then to use the GUI to automatically generate command-line scripts. All the reasoning in the sections below take form in the script showed in Appendix B.1.

Before using either one of the two methods listed above, the first step is to define the problem by selecting a data set.

3.1 – DEFINING THE PROBLEM

To define a pattern recognition problem, we arrange a set of input features vectors (the ones selected in paragraph 2.4 – Feature selection) as columns in a matrix. Then we arrange another set of vectors so that they indicate the classes to which the input vectors are assigned. Target vector have 4 elements (we have 4 activities to classify), where for each target vector, one element is 1 and the others are 0.

3.2 – TRAIN THE NEURAL NETWORK

To train the neural network we have to ask a preliminary question:

"What's the best number of hidden neurons?"

In order to answer, we write down some script code to perform the following computations:

- For more values for the number n, number of hidden neurons:
    - Train the network 10 times;
    - Compute the average performance (Mean Square Error);
- Choice as final number of hidden neurons the one that produces the best performance value (least MSE).

Then we automatically generate the command-line script from the graphical tool "`nprtool`" for the Neural Network with chosen number of hidden neurons. The settings used for the division of data is the following: 70% training, 15% validation and 15% testing.

3.3 – NETWORK OUTPUTS EVALUATION

Once we have got our network trained, we can use it to compute some network outputs. These can be used to evaluate its "goodness". These information can be showed in diagrams such as **Confusion Matrix** and **ROC plots**.

Some of the information we can deduce from these diagrams are:

- **Accuracy (ACC)**: Overall, how often is the classifier correct?

- $\frac{TP+TN}{P+N}$
- **Precision (PPV)**: How many times the classifier is correct in predicting a class over its overall predictions of that class?
  - $\frac{TP}{TP+FP}$
- **Sensitivity** or Recall **(TPR)**: How many times the classifier predicts the correct class among all the overall actual occurrences of that class?
  - $\frac{TP}{TP+FN}$
- **Miss rate (FNR)**: How many times the classifier does not predict a class?
  - $\frac{FN}{TP+FN} = 1 - TPR$
- **Specificity (TNR)**: When the classifier is correct at not classify an input as a class over the whole not-members of that class?
  - $\frac{TN}{TN+FP}$
- **Fall-out** (false alarm): When the classifier predicts a class, wrongly?
  - $\frac{FP}{TN+FP}$.

3.2.1 – SMALLER NECESSARY TIME INTERVAL

Now that we have described the procedure to produce the neural network, we can apply it for different time intervals, in order to find the least necessary time interval. There is not a "*best*" time interval because, obviously, it is relative to the performance we are asking to the neural network.

We run a script (*Appendix B.1*) that is able to choice the best number of hidden neurons for the neural network, by running 10 times the training with a number "*n*" of hidden neurons, and computing the mean error as measure of performance. Repeating the training phase 10 times we attenuate the neural network bias for a single class, that's an usual error due to an unbalanced distribution of the classes in training, test and validation sets. Then, the algorithm chooses the network with lower mean error, and use it to run 10 times the training. Among the latter 10 networks, the one with best performance is chosen.

The following ***Table 2*** shows, with percentage, the results obtained for every class and for each interval.

Intervals	Performances	Classes			
		Supine	Dorsiflexion	Walking	Stair climbing
3sec	Accuracy (ACC)	96,25	90,51	87,76	85,00
	Precision (PPV)	93,42	79,73	73,75	72,41
	Sensitivity (TPR)	91,19	83,72	79,71	64,56
	Specificity (TNR)	97,90	92,81	90,46	91,81
	Miss rate (FNR)	8,81	16,28	20,29	35,44
	Fall-out (FPR)	2,10	7,19	9,54	8,19
	Model Accuracy	79,77			
5sec	Accuracy (ACC)	97,27	93,79	89,17	86,29
	Precision (PPV)	94,50	88,34	77,17	73,21
	Sensitivity (TPR)	94,50	86,75	80,66	71,21
	Specificity (TNR)	98,19	96,15	92,01	91,31
	Miss rate (FNR)	5,50	13,25	19,34	28,79
	Fall-out (FPR)	1,81	3,85	7,99	8,69
	Model Accuracy	83,26			
10sec	Accuracy (ACC)	99,53	95,75	91,34	89,13
	Precision (PPV)	98,73	92,36	83,02	77,78
	Sensitivity (TPR)	99,36	90,62	82,50	79,25
	Specificity (TNR)	99,58	97,47	94,32	92,44
	Miss rate (FNR)	0,64	9,38	17,50	20,75
	Fall-out (FPR)	0,42	2,53	5,68	7,56
	Model Accuracy	87,87			
12sec	Accuracy (ACC)	98,46	95,97	93,09	91,36
	Precision (PPV)	96,15	92,31	88,00	81,62
	Sensitivity (TPR)	97,66	91,60	83,97	84,73
	Specificity (TNR)	98,73	97,44	96,15	93,59
	Miss rate (FNR)	2,34	8,40	16,03	15,27
	Fall-out (FPR)	1,27	2,56	3,85	6,41
	Model Accuracy	89,44			
15sec	Accuracy (ACC)	99,25	98,26	96,27	95,77
	Precision (PPV)	98,98	97,00	93,00	90,38
	Sensitivity (TPR)	97,98	96,04	92,08	93,07
	Specificity (TNR)	99,67	99,00	97,67	96,68
	Miss rate (FNR)	2,02	3,96	7,92	6,93
	Fall-out (FPR)	0,33	1,00	2,33	3,32
	Model Accuracy	94,78			
20sec	Accuracy (ACC)	99,65	98,94	96,47	96,47
	Precision (PPV)	100,00	97,22	94,20	91,78
	Sensitivity (TPR)	98,57	98,59	91,55	94,37
	Specificity (TNR)	100,00	99,06	98,11	97,17
	Miss rate (FNR)	1,43	1,41	8,45	5,63
	Fall-out (FPR)	0,00	0,94	1,89	2,83
	Model Accuracy	95,76			

30sec	Accuracy (ACC)	100,00	100,00	99,39	99,39
	Precision (PPV)	100,00	100,00	100,00	97,62
	Sensitivity (TPR)	100,00	100,00	97,56	100,00
	Specificity (TNR)	100,00	100,00	100,00	99,18
	Miss rate (FNR)	0,00	0,00	2,44	0,00
	Fall-out (FPR)	0,00	0,00	0,00	0,82
	Model Accuracy	99,39			
1min	Accuracy (ACC)	100,00	97,73	95,45	97,73
	Precision (PPV)	100,00	91,67	100,00	91,67
	Sensitivity (TPR)	100,00	100,00	81,82	100,00
	Specificity (TNR)	100,00	96,97	100,00	96,97
	Miss rate (FNR)	0,00	0,00	18,18	0,00
	Fall-out (FPR)	0,00	3,03	0,00	3,03
	Model Accuracy	95,45			

TABLE 2 *PERFORMANCE OF NEURAL NETWORKS VERSUS VARING TIME INTERVALS*

It is noteworthy that with an interval long 20 seconds it is possible to reach an accuracy of about 95%. With a 30 seconds interval the accuracy rise to 99%, and the first 2 classes are classified without errors.

It is also important to notice how with the 1 minute long intervals the accuracy decrease. This can be attributed to the lower number of signal pieces available to train the network.

4 – FUZZY INFERENCE SYSTEM

In this chapter we develop a Mamdani-type Fuzzy Inference System (FIS) with the help of the MATLAB *Fuzzy Logic Toolbox Graphical User Interface Tools*.

For this system we fix the time interval to the best we have found with neural network, i.e. 30 seconds long time intervals.

4.1 – FUZZY INFERENCE SYSTEM

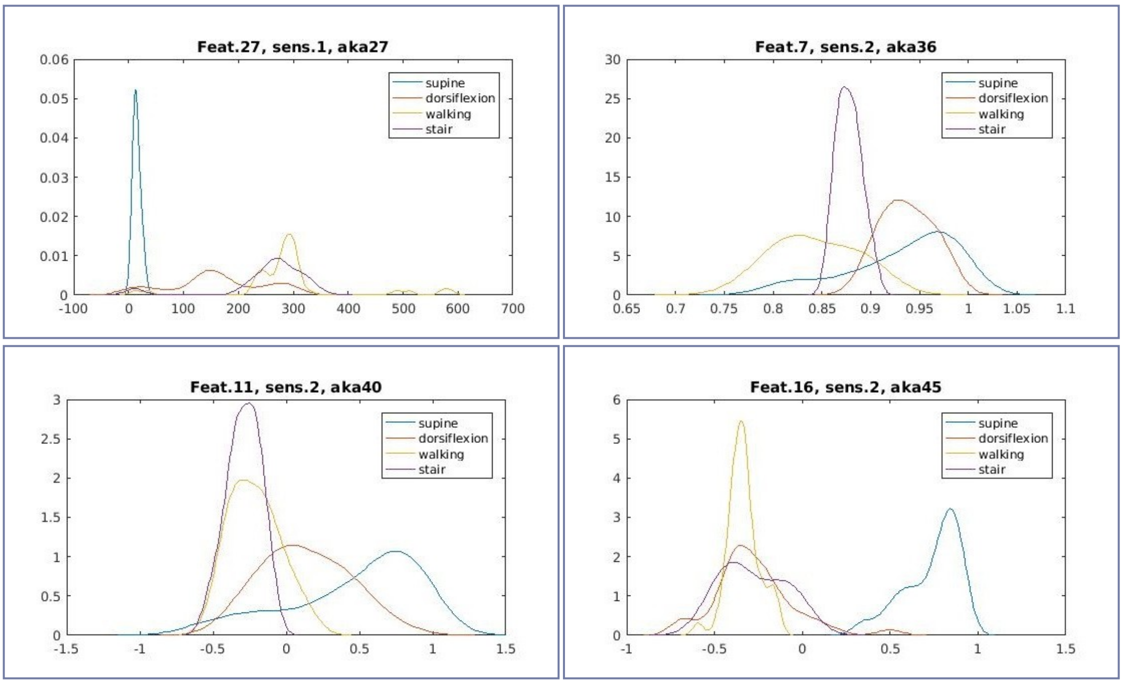
For the definition of the problem, we first run the command “`fuzzy`“ on MATLAB, in order to start the *FIS editor*.

From the showing GUI we introduce inputs and outputs of the FIS.

4.1.1 – FEATURE SELECTION

Since, this time, the choice of the features lies on our ability to write down the membership functions, we prefer to plot the Probability Mass Function (PMF) of each feature, so that it’s easier for us to take the features in which activities differ the most (Appendix C.1).

From the plots we have chosen the following features:



The resulting system is a 4inputs-1output.

Its structure is showed in the figure below.

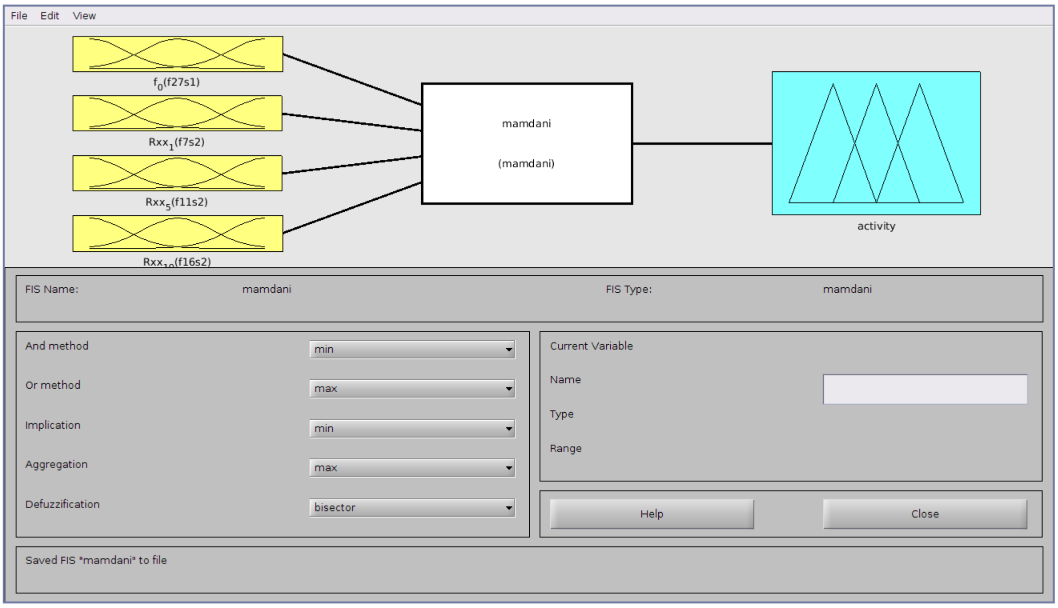


FIGURE 7 *FIS STRUCTURE*

4.2 – MEMBERSHIP FUNCTIONS

From the PMFs chosen in the previous paragraph, we use the *Membership Function Editor* to write the following membership functions.

4.2.1 – FEATURE #27 (FOUNDAMENTAL FREQUENCY, FEATURE 27, SENSOR 1)

This input variable has been named f_0(f27s1). The range of the values for this feature is [-100 700].

LINGUISTIC VARIABLES

Linguistic variable	Type of membership function	Parameters
low	trampmf	[-100 -100 27.08 61.99]
medium	gbellmf	[79.4 1.87 120.1]
high	trampmf	[40.5 235.9 700 700]

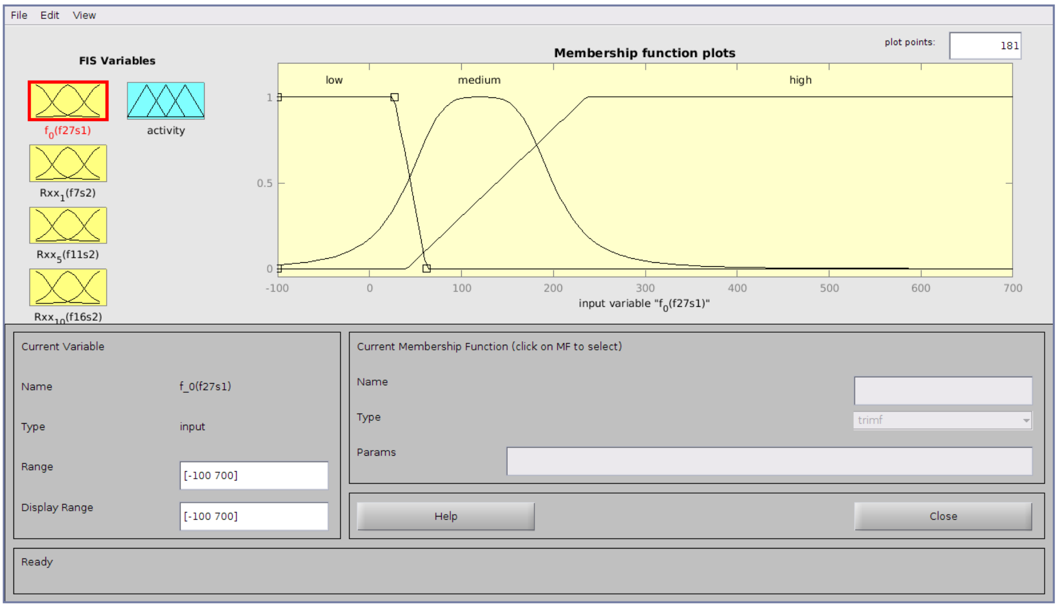


FIGURE 8 *MF FOR THE FEATURE #27*

4.2.2 – FEATURE #36 (AUTOCORRELATION, DELTA=1, FEATURE 7, SENSOR 2)

This input variable has been named $Rxx_1(f7s2)$ and the range of the values for this feature is [0.65 1.1].

LINGUISTIC VARIABLES

Linguistic variable	Type of membership function	Parameters
Low	trampmf	[0.6187 0.6187 0.8207 0.8997]
medium	gaussmf	[0.02266 0.88]
high	gbellmf	[0.167 4.3 1.063]

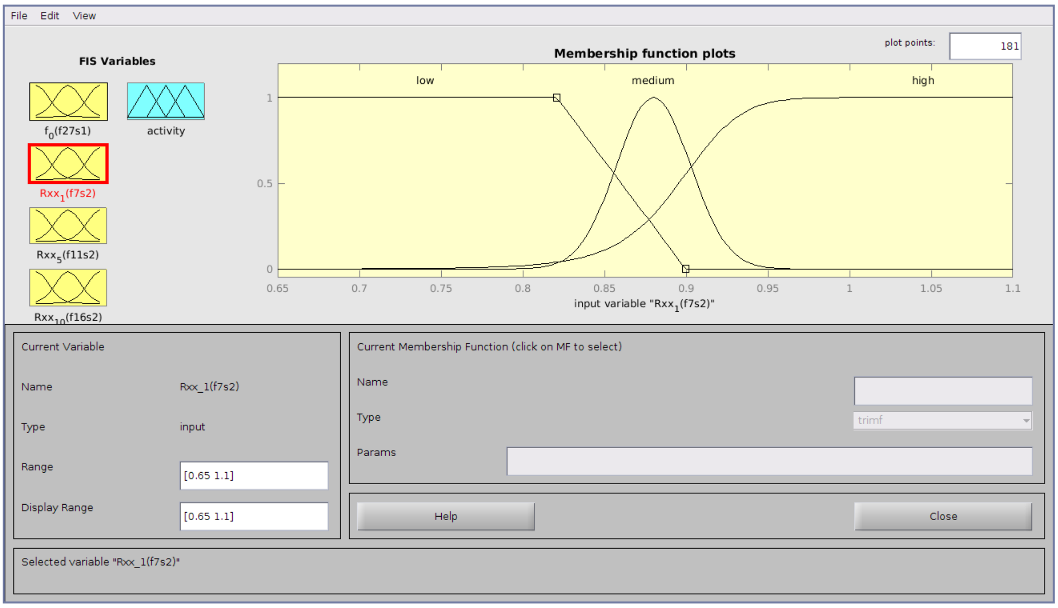


***FIGURE 9** MF FOR THE FEATURE #36*

4.2.3 – FEATURE #40 (AUTOCORRELATION, DELTA=5, FEATURE 11, SENSOR 2)

This input variable name is *$Rxx_5(f11s2)$* and the range of the values for this feature is [-1.5 1.5].

LINGUISTIC VARIABLES

Linguistic variable	Type of membership function	Parameters
Low	gaussmf	[0.299 -0.2449]
medium	gbellmf	[0.3259 1.55 0.1]
high	trampmf	[-0.9986 0.7353 1.5 1.5]

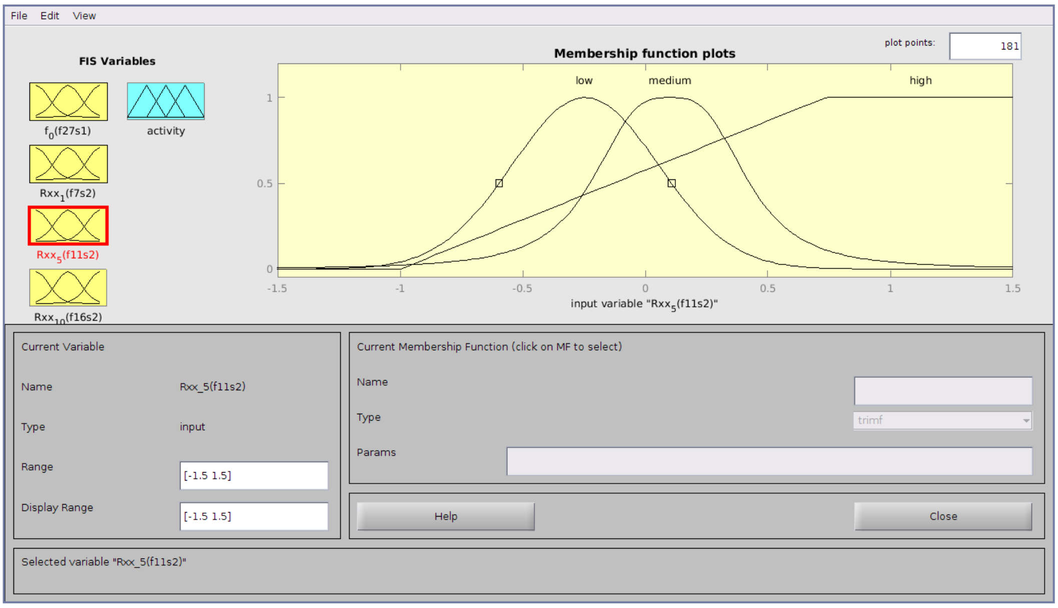


***FIGURE 10** MF FOR THE FEATURE #40*

4.2.4 – FEATURE #45 (AUTOCORRELATION, DELTA=11, FEATURE 16, SENSOR 2)

The last input variable name is $Rxx_{10}(f16s2)$. The range of values for this feature is [-1.5 1.5].

LINGUISTIC VARIABLES

Linguistic variable	Type of membership function	Parameters
low	trampmf	[-1 -1 -0.1709 0.722]
high	trampmf	[0.0635 0.4515 1.5 1.5]

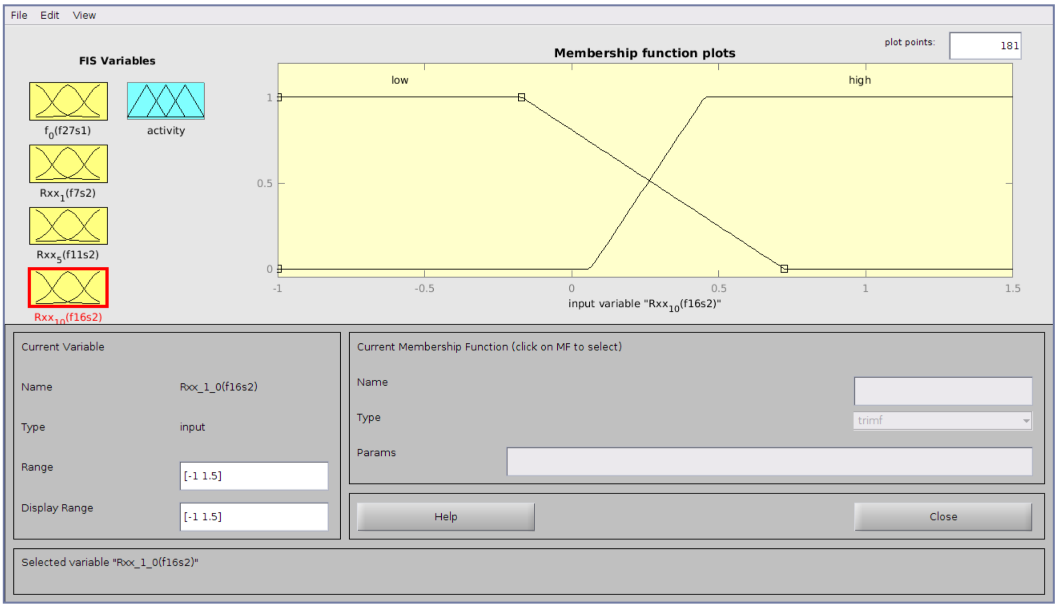


***FIGURE 11** MF FOR THE FEATURE #45*

4.2.5 – ACTIVITY

The only output variable name is *activity* and the range of the values for this feature is [0 1].

LINGUISTIC VARIABLES

Linguistic variable	Type of membership function	Parameters
supine	Trimf	[0 0.2 0.4]
dorsiflexion	Trimf	[0.2 0.4 0.6]
walking	Trimf	[0.4 0.6 0.8]
stair	Trimf	[0.6 0.8 1]

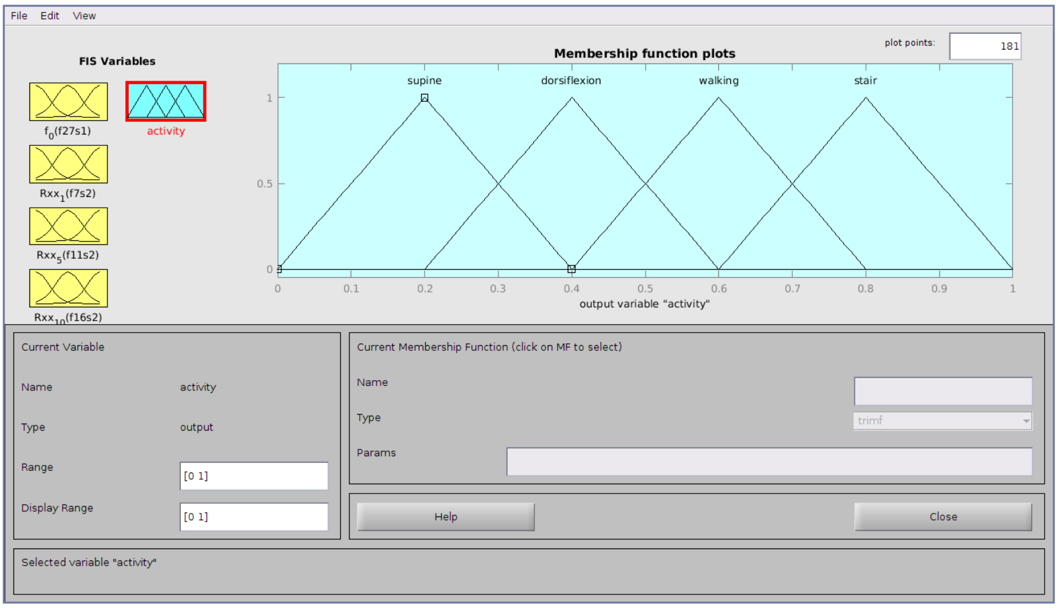


FIGURE 12 *MF FOR THE OUTPUT*

4.3 – RULES

Now we can write the rules that our FIS have to use in order to infer the output. In this regard the *Rule Editor* helps us.

The rules we are going to use are the following:

1. *If (f_0(f27s1) is low) and (Rxx_1(f7s2) is high) and (Rxx_5(f11s2) is high) and (Rxx_{10}(f16s2) is high) then (activity is supine) (1)*
2. *If (f_0(f27s1) is medium) and (Rxx_1(f7s2) is high) and (Rxx_5(f11s2) is medium) and (Rxx_{10}(f16s2) is low) then (activity is dorsiflexion) (1)*
3. *If (f_0(f27s1) is high) and (Rxx_1(f7s2) is low) and (Rxx_5(f11s2) is low) and (Rxx_{10}(f16s2) is low) then (activity is walking) (1)*
4. *If (f_0(f27s1) is high) and (Rxx_1(f7s2) is medium) and (Rxx_5(f11s2) is low) and (Rxx_{10}(f16s2) is low) then (activity is stair) (1)*

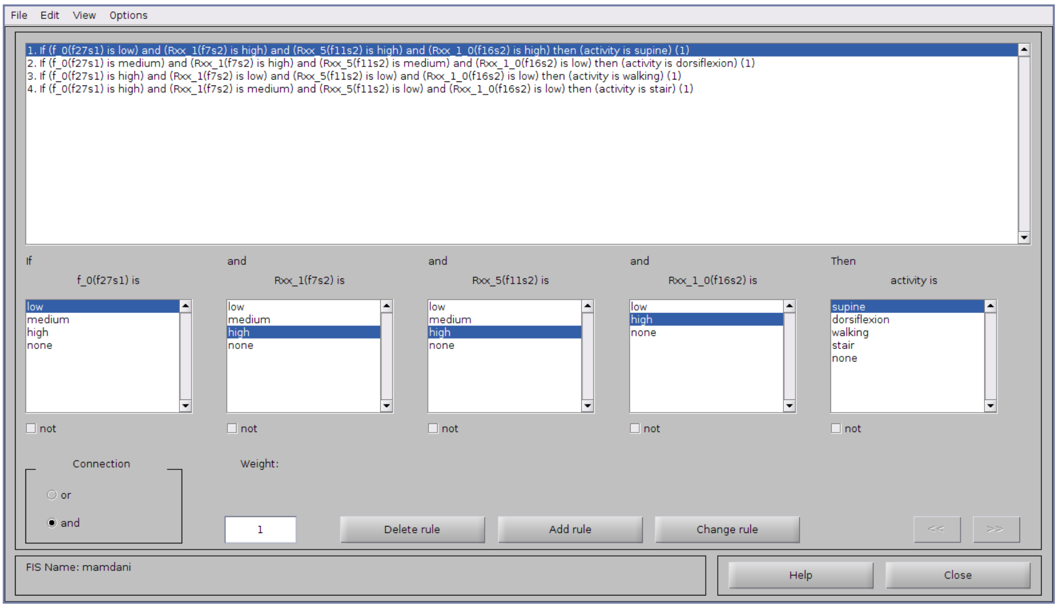


***FIGURE 13** RULES FOR MAMDANI FIS*

4.4 – PERFORMANCE EVALUATION

We plot the results of our FIS in ***Figure 14***.

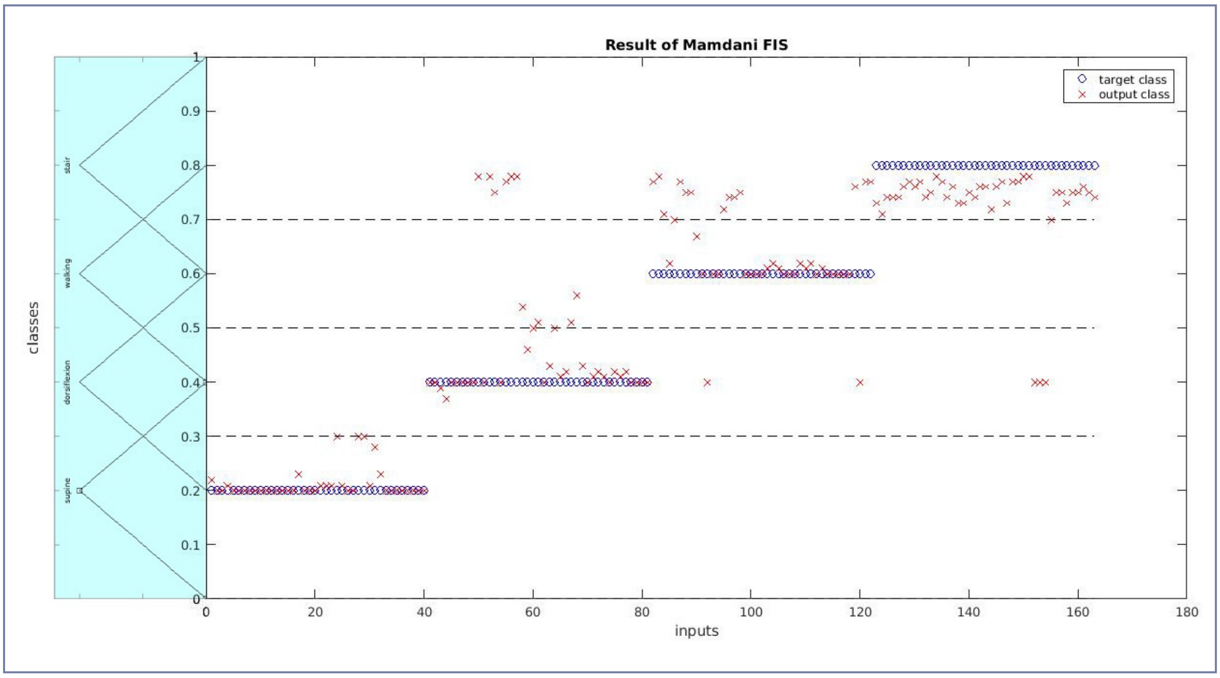


FIGURE 14 *RESULTS OF MAMDANI FIS*

For the evaluation of FIS performance we can still use the same script used for neural networks (Appendix B.2).

The results are displayed in the following tables.

		Target class			
		Supine	Dorsiflexion	Walking	Stair climbing
Output class	Supine	37	0	0	0
	Dorsiflexion	3	29	2	3
	Walking	0	6	25	0
	Stair climbing	0	6	14	38

TABLE 3 *CONFUSION MATRIX OF MAMDANI FIS*

Intervals	**Performances**	**Classes**			
		Supine	**Dorsiflexion**	**Walking**	**Stair climbing**
30 sec	Accuracy (ACC)	98,16	87,73	86,50	85,89
	Precision (PPV)	100,00	78,38	80,65	65,52
	Sensitivity (TPR)	92,50	70,73	60,98	92,68
	Specificity (TNR)	100,00	93,44	95,08	83,61
	Miss rate (FNR)	7,50	29,27	39,02	7,32
	Fall-out (FPR)	0,00	6,56	4,92	16,39
	Model Accuracy	**79,14**			

TABLE 4 *PERFORMANCE OF MAMDANI FIS*

From tables above (***Table 3*** and ***Table 4***) we can deduce that the main problem is the misclassification of walking activities that are evaluated as stair climbing.

5 – ADAPTIVE NETWORK-BASED FIS

For the FIS system we preferred a Mamdani-type, taking advantage of the higher interpretability at expense of the detriment of accuracy. Whereas for the ANFIS system we prefer to start with a Sugeno-type FIS, to obtain a greater accuracy.

It is not always easy to build linear (sometime second order) membership functions, but MATLAB provides the command "`mam2sug`" that Transforms Mamdani fuzzy inference system into Sugeno fuzzy inference system. We wrote a script (Appendix D.1) that, in addition to this conversion, randomly separate, in a balanced way, the input data set in three parts for training, testing and validating with a proportion of 70%, 15% and 15% respectively.

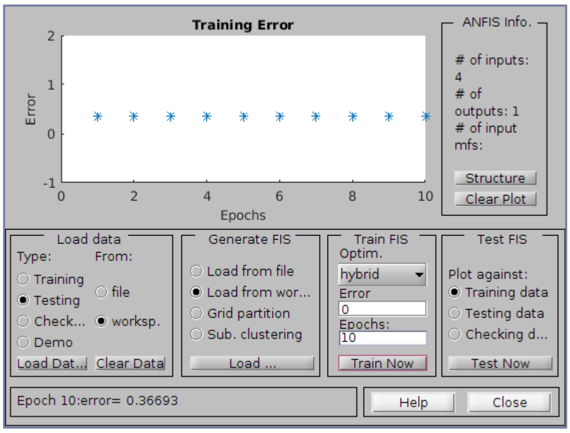


FIGURE 15 TRAINIG PHASE OF ANFIS

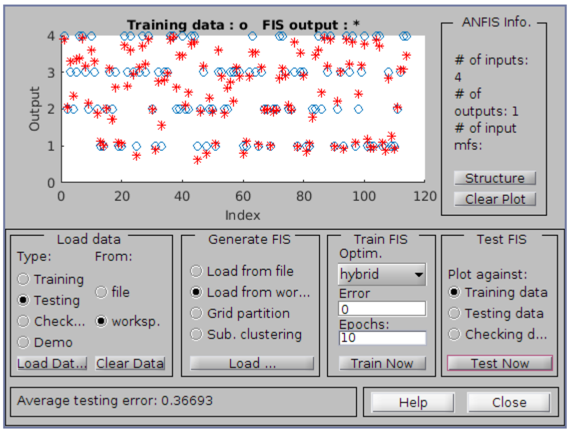


FIGURE 16 TEST OF ANFIS

With the help of MATLAB ANFIS Editor, started typing the command "`andfisedit`", we loaded each dataset, the Sugeno-type FIS and started the training it with an hybrid optimization method (**Last Square Estimate** (LSE) combined with **gradient method**), a zero step error and 30 epochs. The hybrid optimization method is a combination of least-squares and back-propagation gradient descent method.

The performance obtained are showed in the following tables.

		Target class			
		Supine	Dorsiflexion	Walking	Stair climbing
Output class	Supine	7	0	0	0
	Dorsiflexion	0	3	0	0
	Walking	0	4	6	0
	Stair climbing	0	0	1	7

TABLE 5 CONFUSION MATRIX OF SUGENO ANFIS

Intervals	Performances	Classes			
		Supine	Dorsiflexion	Walking	Stair climbing
30 sec	Accuracy (ACC)	100,00	85,71	82,14	96,43
	Precision (PPV)	100,00	100,00	60,00	87,50
	Sensitivity (TPR)	100,00	42,86	85,71	100,00
	Specificity (TNR)	100,00	100,00	80,95	95,24
	Miss rate (FNR)	0,00	57,14	14,29	0,00
	Fall-out (FPR)	0,00	0,00	19,05	4,76
	Model Accuracy	**82,14**			

TABLE 6 *PERFORMANCE OF SUGENO ANFIS*

From the tables above we can deduce that the main problem is the misclassification of dorsiflexion activities that are evaluated as walking.

6 – CONCLUSIONS

Starting from the sensor signals we have computed some features both from temporal and frequency domains, able to represent the main characteristics of each activity/position.

We have developed a neural network, a Mamdani-type fuzzy inference system and a Sugeno-type adaptive neuro-fuzzy inference system.

The results for the neural network showed that the accuracy of our system can reach 99% for signals long enough (30 seconds time interval), but even with littler interval the accuracy is still acceptable.

The Mamdani-type FIS, as expected, was not so accurate (less than 80%), mainly due to the easier form of its membership rules.

With the Sugeno-type ANFIS, generate starting from the Mamdani-type FIS, we increased the performance surpass the 82% of accuracy.

APPENDIX A – DATA PRE-PROCESSING

A.1 INIT.M

```
%% 01 Data initialization - init.m
% - Data are grouped by activity/position and collected in a structure.
addpath('gitProjects/intelligent-system/');
load('ProjectWS.mat');

% This variable disable plots, so to fast computations.
showPlots = false;

% Neglect first row, it's just a row of zeros for every activity.
supine = {V01A(2:end,:), V02A(2:end,:), V03A(2:end,:), V04A(2:end,:),...
    V05A(2:end,:), V06A(2:end,:), V07A(2:end,:), V08A(2:end,:), ...
    V09A(2:end,:), V10A(2:end,:)};

dorsiflexion = {V01B(2:end,:), V02B(2:end,:), V03B(2:end,:), ...
    V04B(2:end,:), V05B(2:end,:), V06B(2:end,:), V07B(2:end,:), ...
    V08B(2:end,:), V09B(2:end,:), V10B(2:end,:)};

walking = {V01C(2:end,:), V02C(2:end,:), V03C(2:end,:), V04C(2:end,:),...
    V05C(2:end,:), V06C(2:end,:), V07C(2:end,:), V08C(2:end,:), ...
    V09C(2:end,:), V10C(2:end,:)};

stair = {V01D(2:end,:), V02D(2:end,:), V03D(2:end,:), V04D(2:end,:),...
    V05D(2:end,:), V06D(2:end,:), V07D(2:end,:), V08D(2:end,:), ...
    V09D(2:end,:), V10D(2:end,:)};

% Build the structure.
Struct = struct('supine',supine,'dorsiflexion',dorsiflexion,'walking',...
    walking,'stair',stair);

for i=1:10
    % - Create a new signal as the sum of the three existing components
    %   and append at the other components.
    Struct(i).supine = ...
        [Struct(i).supine(:,4), Struct(i).supine(:,1:3), ...
        sum(Struct(i).supine(:,1:3),2)];
    Struct(i).dorsiflexion = ...
        [Struct(i).dorsiflexion(:,4), Struct(i).dorsiflexion(:,1:3), ...
        sum(Struct(i).dorsiflexion(:,1:3),2)];
    Struct(i).walking = ...
        [Struct(i).walking(:,4), Struct(i).walking(:,1:3), ...
        sum(Struct(i).walking(:,1:3),2)];
    Struct(i).stair = ...
        [Struct(i).stair(:,4), Struct(i).stair(:,1:3), ...
        sum(Struct(i).stair(:,1:3),2)];

    % - Plot of each volunteer's activity/position signal and boxplot
    %   to better show patterns, time features, probability distribution.
    if showPlots
        % full screen figure
        figure('units','normalized','outerposition',[0 0 1 1]);

        subplot(2,3,1);
        plot(Struct(i).supine(:,1),Struct(i).supine(:,2:5));
        title(strcat('Supine - volunteer ',num2str(i)));
        legend('sensor1','sensor2','sensor3','sum');
        xlabel('time [s]');
        ylabel('pressure [ohm]');

        subplot(2,3,2);
        plot(Struct(i).dorsiflexion(:,1),Struct(i).dorsiflexion(:,2:5));
        title(strcat('Dorsiflexion - volunteer ',num2str(i)));
        legend('sensor1','sensor2','sensor3','sum');
        xlabel('time [s]');
        ylabel('pressure [ohm]');

        subplot(2,3,4);
        plot(Struct(i).walking(:,1),Struct(i).walking(:,2:5));
        title(strcat('Walking - volunteer ',num2str(i)));
```

```
        legend('sensor1','sensor2','sensor3','sum');
        xlabel('time [s]');
        ylabel('pressure [ohm]');

        subplot(2,3,5);
        plot(Struct(i).stair(:,1),Struct(i).stair(:,2:5));
        title(strcat('Stairs - volunteer ',num2str(i)));
        legend('sensor1','sensor2','sensor3','sum');
        xlabel('time [s]');
        ylabel('pressure [ohm]');

        subplot(2,3,[3 6]);
        var = [Struct(i).supine(:,5)' Struct(i).dorsiflexion(:,5)'...
            Struct(i).walking(:,5)' Struct(i).stair(:,5)'];
        var = var./3;
        grp = [zeros(1,length(Struct(i).supine)), ...
            ones(1,length(Struct(i).dorsiflexion)), ...
            2.*ones(1,length(Struct(i).walking)), ...
            3.*ones(1,length(Struct(i).stair))];
        boxplot(var,grp,'Labels',{'supine','dorsiflexion','walking',...
            'stair'});
    end
end

clear supine dorsiflexion walking stair i;

% clean origen structures
clear V01A V01B V01C V01D ...
    V02A V02B V02C V02D ...
    V03A V03B V03C V03D ...
    V04A V04B V04C V04D ...
    V05A V05B V05C V05D ...
    V06A V06B V06C V06D ...
    V07A V07B V07C V07D ...
    V08A V08B V08C V08D ...
    V09A V09B V09C V09D ...
    V10A V10B V10C V10D;
```

A.2 SPLIT.M

```
%% 02 Data splitting - split.m
% - We need to split every signal to find out the least temporal interval
%   that is necessary and sufficient to recognize the position/activity.

% N.B. We are using a sampling period of ~82ms (12.2Hz).
% Number of samples based on the interval size:
% N1 = 12.2Hz * 3sec = 36.6;  %3sec
% N2 = 61;                    %5sec
% N3 = 122;                   %10sec
% N4 = 144.4;                 %12sec
% N5 = 183;                   %15sec
% N6 = 244;                   %20sec
% N7 = 366;                   %30sec
% N8 = 732;                   %1min
% N9 = 1464;                  %2min - not enough signals to train NN
% N = 2196;                   %3min - NO SIGNAL HAS A 3min LONG TRACE
N = [37 61 122 145 183 244 366 732];

% The index only need to use one choice among the upper showed.
index = 7;
clear A B C D;
A = Struct(1).supine(1:N(index), 2:5);
B = Struct(1).dorsiflexion(1:N(index), 2:5);
C = Struct(1).walking(1:N(index), 2:5);
D = Struct(1).stair(1:N(index), 2:5);

% If the piece of signal cannot fill entirely the number of samples
% needed, it wont be used:
% "length(Struct(i).<activity>)/N(j)" is used just for its integer part so
% to truncate incomplete pieces of signal.
for i=1:10
    for k=2:length(Struct(i).supine)/N(index)
        A = [A Struct(i).supine(1+N(index)*(k-1):k*N(index), 2:5)];
    end
    for k=2:length(Struct(i).dorsiflexion)/N(index)
        B = [B Struct(i).dorsiflexion(1+N(index)*(k-1):k*N(index), 2:5)];
    end
    for k=2:length(Struct(i).walking)/N(index)
        C = [C Struct(i).walking(1+N(index)*(k-1):k*N(index), 2:5)];
    end
    for k=2:length(Struct(i).stair)/N(index)
        D = [D Struct(i).stair(1+N(index)*(k-1):k*N(index), 2:5)];
    end
end

clear i k;
clear Struct;

if showPlots
    figure, plot(0.082*(1:size(A,1)),A(:,1:4))
    title('Volunteer 1 - Supine (Slice 1)')
    xlabel('time [s]')
    ylabel('pressure [ohm]')
    legend('sensor 1', 'sensor 2', 'sensor 3', 'sensor virt. (sum)')
end

```

A.3 CLEANING.M

```
%% 03 Data cleaning - cleaning.m
% Clean the signal from noise by mean of a smoothing filter
% (Savitzky-Golay Filter), sgolayfilt(X,K,F):
%  - K=3, third-order polynomial;
%  - F=7, just an odd value greater than the piece of signal;

clear smoothA;
smoothA = sgolayfilt(A,3,7);
if showPlots
    figure, plot(0.082*(1:size(smoothA,1)),[A(:,1) smoothA(:,1)])
    title('Volunteer 1 - Supine (Slice 1)');
    xlabel('time [s]');
    ylabel('pressure [ohm]');
    legend('sensor 1 - original', 'sensor 1 - smooth');
end

clear smoothB;
smoothB = sgolayfilt(B,3,7);

clear smoothC;
smoothC = sgolayfilt(C,3,7);

clear smoothD;
smoothD = sgolayfilt(D,3,7);

clear A B C D;

% Use Z-score normalization for each signal, in order to be able to compare
% signals.
smoothA = zscore(smoothA);
smoothB = zscore(smoothB);
smoothC = zscore(smoothC);
smoothD = zscore(smoothD);

if showPlots
    figure, plot(0.082*(1:size(smoothA)),smoothA(:,1:4))
    title('Volunteer 1 - Supine (Slice 1)');
    xlabel('time [s]');
    ylabel('pressure [ohm]');
    legend('sensor 1', 'sensor 2', 'sensor 3', 'sensor 4');
end

```

A.4 FEATUREEX.M

```
%% 04 Feature extraction - featureEx.m
% Obtain a set of temporal feature starting from the N(j) samples of the
% signal.
featuresA = [max(smoothA); min(smoothA); quantile(smoothA,[.25 .5]); ...
    skewness(smoothA); kurtosis(smoothA)];
featuresB = [max(smoothB); min(smoothB); quantile(smoothB,[.25 .5]); ...
    skewness(smoothB); kurtosis(smoothB)];
featuresC = [max(smoothC); min(smoothC); quantile(smoothC,[.25 .5]); ...
    skewness(smoothC); kurtosis(smoothC)];
featuresD = [max(smoothD); min(smoothD); quantile(smoothD,[.25 .5]); ...
    skewness(smoothD); kurtosis(smoothD)];

% Autocorrelation: computed at lags 0,1,2, ... T= min[20,length(y)-1]
RxxA = my_autocorr(smoothA); % See my_autocorr.m
RxxB = my_autocorr(smoothB);
RxxC = my_autocorr(smoothC);
RxxD = my_autocorr(smoothD);

if showPlots
    figure('units','normalized','outerposition',[0 0 1 1]);

    subplot(2,2,1);
    plot(0:20,RxxA);
    title('Supine - All the volunteers, all the autocorrelations');
    xlabel('lags');
    ylabel('Rxx');

    subplot(2,2,2);
    plot(0:20,RxxB);
    title('Dorsifexion - All the volunteers, all the autocorrelations');
    xlabel('lags');
    ylabel('Rxx');

    subplot(2,2,3);
    plot(0:20,RxxC);
    title('Walk - All the volunteers, all the autocorrelations');
    xlabel('lags');
    ylabel('Rxx');

    subplot(2,2,4);
    plot(0:20,RxxD);
    title('Stairs - All the volunteers, all the autocorrelations');
    xlabel('lags');
    ylabel('Rxx');
end

% first value, autocorr with lags=0 is always equal to 1
% (it's irrelevant)
featuresA = [featuresA; RxxA(2:end,:)];
featuresB = [featuresB; RxxB(2:end,:)];
featuresC = [featuresC; RxxC(2:end,:)];
featuresD = [featuresD; RxxD(2:end,:)];

clear RxxA RxxB RxxC RxxD;

% Frequential features:
% - Fundamental frequency f0
% - Power Spectral Density PSD

% Define the frequency domain
f = 12.2*(0:N(index)/2-1);

% Compute the single-sided spectrum
fftA = my_fft(smoothA,N(index)); % See my_fft.m
fftB = my_fft(smoothB,N(index));
fftC = my_fft(smoothC,N(index));
fftD = my_fft(smoothD,N(index));

if(showPlots)
    figure('units','normalized','outerposition',[0 0 1 1]);

    subplot(2,2,1);
    plot(f,fftA);
    title('Supine - All the volunteers, all the spectra');
```

```
    xlabel('frequency [Hz]');
    ylabel('FFT');

    subplot(2,2,2);
    plot(f,fftB);
    title('Dorsifexion - All the volunteers, all the spectra');
    xlabel('frequency [Hz]');
    ylabel('FFT');

    subplot(2,2,3);
    plot(f,fftC);
    title('Walk - All the volunteers, all the spectra');
    xlabel('frequency [Hz]');
    ylabel('FFT');

    subplot(2,2,4);
    plot(f,fftD);
    title('Stairs - All the volunteers, all the spectra');
    xlabel('frequency [Hz]');
    ylabel('FFT');
end

% The max amplitude should be a good approximation for the fundamental
% frequency
[amp, x] = max(fftA);
% [~, x2] = findpeaks(fftA, 'MinPeakProminence', 0.7*max(fftA));

% PSD
PSD = sum(fftA.^2);
% figure
% plot(f,fftA(:,[1 11 111]));
% hold on;
% plot(f(x([1 11 111])),y([1 11 111]),'rv');
featuresA = [featuresA; f(x); amp; PSD];

[amp, x] = max(fftB);
featuresB = [featuresB; f(x); amp; sum(fftB.^2)];
[amp, x] = max(fftC);
featuresC = [featuresC; f(x); amp; sum(fftC.^2)];
[amp, x] = max(fftD);
featuresD = [featuresD; f(x); amp; sum(fftD.^2)];

clear smoothA smoothB smoothC smoothD f i fftA fftB fftC fftD amp x PSD;

%% Rotate matrix
% Since we use 4 columns to represent 3 sensor signals + 1 "virtual"
% sensor (the sum), we move all the features of the same piece of signal
% on the same column.
newFeaturesA = rotate_features(featuresA);
newFeaturesB = rotate_features(featuresB);
newFeaturesC = rotate_features(featuresC);
newFeaturesD = rotate_features(featuresD);

clear featuresA featuresB featuresC featuresD;

```

A.5 ROTATE_FEATURES.M

```
function f = rotate_features (features)
    f = [features(:,1); features(:,2); features(:,3); ...
                   features(:,4)];
        for k=1:size(features,2)/4-1;
               f = [f [features(:,4*k+1); features(:,4*k+2); features(:,4*k+3); ...
                   features(:,4*k+4)]];
        end
end

```

A.6 MY_AUTOCORR.M

```
% My extension of autocorr(), in order to compute autocorr on a matrix of
% more than 1 signal, where each column is a different signal
function Rxx = my_autocorr (matrix)
        % If "matrix" has only a column, I only need to compute correlation once
        Rxx = autocorr(matrix(:,1));

        for k=2:size(matrix,2)
                Rxx = [Rxx autocorr(matrix(:,k))];
        end
end
```

A.7 MY_FFT.M

```
function f = my_fft (matrix, ind)
    if(mod(ind,2)~=0), ind = ind-1; end
        f = fft(matrix);
        f = abs(f./ind);
        f(ind/2+1:end, :) = [];
        f= f.*2;
end
```

A.8 FEATURESEL.M

```
%% 05 Feature Selection
% Sequential feature selection

% Fix the number of features on which we would like to reduce each signal
num_features = 4;

% Classify each activity with a different class:
% Y = 0 => supine
% Y = 1 => dorsiflexion
% Y = 2 => walking
% Y = 3 => stairs
sizeA = size(newFeaturesA,2);
sizeB = size(newFeaturesB,2);
sizeC = size(newFeaturesC,2);
sizeD = size(newFeaturesD,2);
X = [newFeaturesA     newFeaturesB   newFeaturesC     newFeaturesD]';
Y = [zeros(sizeA,1);  ones(sizeB,1); 2*ones(sizeC,1); 3*ones(sizeD,1)];

f = @(xtrain, ytrain, xtest, ytest) ...
    sum(ytest ~= classify(xtest, xtrain, ytrain));
if showPlots
    opts = statset('display','iter');
    [fs, ~] = sequentialfs(f,X,Y,'nfeatures',num_features,...
        'options',opts);
else
    [fs, ~] = sequentialfs(f,X,Y,'nfeatures',num_features);
end

clear f;

```

APPENDIX B –NEURAL NETWORK

B.1 NEUR_NETW.M

```
%% 06 Neural network

% "What's the best number of hidden neurons?"
inputs = X(:,fs)';
targets = zeros(4,size(X,1));
targets(1,1:sizeA) = 1;
targets(2,sizeA+1:sizeA+sizeB) = 1;
targets(3,sizeA+sizeB+1:sizeA+sizeB+sizeC) = 1;
targets(4,sizeA+sizeB+sizeC+1:end) = 1;

n1 = num_features;  % lowest number of hidden neurons
n2 = 10; % highest number of hidden neurons

% preallocate followings' for speed
performances = zeros(10,1);
meanPerformance = zeros(n2-n1+1,1);

for n = n1:1:n2,
    % Create a Pattern Recognition Network
    hiddenLayerSize = n;

    for k=1:10,
        net = patternnet(hiddenLayerSize);

        % Setup Division of Data for Training, Validation, Testing
        net.divideParam.trainRatio = 70/100;
        net.divideParam.valRatio = 15/100;
        net.divideParam.testRatio = 15/100;

        % hide window: speed up computations
        net.trainParam.showWindow = false;

        % Train the Network
        [net,~] = train(net,inputs,targets);

        % Test the Network
        outputs = net(inputs);
        performances(k) = perform(net,targets,outputs);
    end
    meanPerformance(n-n1+1) = mean(performances);
end

if showPlots
    figure, plot(n1:n2, meanPerformance, 'r-o');
    title('MSE: less is better');
    ylabel('mean square error');
    xlabel('# of hidden neurons');
    legend('mean performance');
end

%% Train the neural network
% Best among the networks with chosen number of hidden neurons
[~,hiddenLayerSize] = min(meanPerformance);
hiddenLayerSize = hiddenLayerSize + n1 - 1;
perf = inf;
for k=1:10,
    net_temp = patternnet(hiddenLayerSize);
    % Setup Division of Data for Training, Validation, Testing
    net_temp.divideParam.trainRatio = 70/100;
    net_temp.divideParam.valRatio = 15/100;
    net_temp.divideParam.testRatio = 15/100;

    % hide window: speed up computations
    net_temp.trainParam.showWindow = showPlots;

    % Train the Network
    [net_temp,~] = train(net_temp,inputs,targets);

```

```
    % Test the Network
    outputs = net_temp(inputs);
    perf_temp = perform(net_temp,targets,outputs);
    if(perf_temp < perf),
        best_net = net_temp;
        perf = perf_temp;
    end
end

clear n1 n2 n performances meanPerformance;
clear k perf perf_temp net net_temp outputs hiddenLayerSize;

%% Print evaluations

outputs = best_net(inputs);
% errors = gsubtract(targets,outputs);
% performance = perform(best_net,targets,outputs);

% % View the Network
% view(best_net)
%
% % Plots
% figure, plotperform(tr)
% figure, plottrainstate(tr)
% figure, plotconfusion(targets,outputs)
% figure, ploterrhist(errors)

clear best_net;

[actual,~,~] = find(targets);
[~,predict] = max(outputs);
cfmatrix2(actual',predict,[1 2 3 4], 1, 1);

clear predict outputs;
```

B.2 CFMATRIX2.M

```
%% https://it.mathworks.com/matlabcentral/fileexchange/21212-confusion-matrix---matching-
matrix-along-with-precision--sensitivity--specificity-and-model-accuracy

function [confmatrix] = cfmatrix2 ...
    (actual, predict, classlist, per, printout)
% CFMATRIX2 calculates the confusion matrix for any prediction
% algorithm ( prediction algorithm generates a list of classes to which
% each test feature vector is assigned );
%
% Outputs: confusion matrix
%
%                 Actual Classes
%                   p       n
%              ___|_____|______|
%    Predicted  p'|     |      |
%      Classes  n'|     |      |
%
%           Also the TP, FP, FN and TN are output for each class based
%           on http://en.wikipedia.org/wiki/Confusion_matrix
%           The Precision, Sensitivity and Specificity for each class
%           have also been added in this update along with the overall
%           accuracy of the model ( ModelAccuracy ).
…
% If classlist not entered: make classlist equal to all
% unique elements of actual
if (nargin < 2)
   error('Not enough input arguments. Need atleast two vectors as input');
elseif (nargin == 2)
    classlist = unique(actual); % default values from actual
    per = 0;
    printout = 1;
elseif (nargin == 3)
    per = 0; % default is numbers and input 1 or higher for percentage
    printout = 1;
elseif (nargin == 4)
    printout = 1; % default is silent output ( 0 ); one or higher printsout
elseif (nargin > 5)
   error('Too many input arguments.');
end


if (length(actual) ~= length(predict))
    error('First two inputs need to be vectors with equal size.');
elseif ((size(actual,1) ~= 1) && (size(actual,2) ~= 1))
    error('First input needs to be a vector and not a matrix');
elseif ((size(predict,1) ~= 1) && (size(predict,2) ~= 1))
    error('Second input needs to be a vector and not a matrix');
end
format short g;
n_class = length(classlist);
confmatrix = zeros(n_class);
line_two =        '----------';
line_three =      '_________|';

for i = 1:n_class
    for j = 1:n_class
        m = (predict == classlist(i) ...
           & actual   == classlist(j));
        confmatrix(i,j) = sum(m);
    end
    line_two = strcat(line_two,'---',num2str(classlist(i)),'-----');
    line_three = strcat(line_three,'__________');
end

TPFPFNTN    = zeros(4, n_class);
Accuracy    = zeros(1, n_class);
Precision   = zeros(1, n_class);
Sensitivity = zeros(1, n_class);
Specificity = zeros(1, n_class);
MissRate    = zeros(1, n_class);
Fall_Out    = zeros(1, n_class);

temps1 = sprintf('    TP   ');
temps2 = sprintf('    FP   ');
```

```
temps3 = sprintf('    FN  ');
temps4 = sprintf('    TN  ');
temps5 = sprintf('Accur.  ');
temps6 = sprintf('Preci.  ');
temps7 = sprintf('Sensi.  ');
temps8 = sprintf('Speci.  ');
temps9 = sprintf('MissR.  ');
temps10= sprintf('FallO.  ');

for i = 1:n_class
    % TP
    TPFPFNTN(1, i) = confmatrix(i,i);
    temps1 = strcat(temps1,sprintf(' |   %3d \t',TPFPFNTN(1, i)));

    % FP
    TPFPFNTN(2, i) = sum(confmatrix(i,:))-confmatrix(i,i);
    temps2 = strcat(temps2,sprintf(' |   %3d \t',TPFPFNTN(2, i) ));

    % FN
    TPFPFNTN(3, i) = sum(confmatrix(:,i))-confmatrix(i,i);
    temps3 = strcat(temps3,sprintf(' |   %3d \t',TPFPFNTN(3, i) ));

    % TN
    TPFPFNTN(4, i) = sum(confmatrix(:)) - sum(confmatrix(i,:)) -...
        sum(confmatrix(:,i)) + confmatrix(i,i);
    temps4 = strcat(temps4,sprintf(' |   %3d \t',TPFPFNTN(4, i) ));

    % Accuracy(class) = (TP(class)+TN(class))/all
    Accuracy(i) = (TPFPFNTN(1, i)+TPFPFNTN(4, i))/sum(confmatrix(:))*100;
    temps5 = strcat(temps5,sprintf(' |   %3.2f \t',Accuracy(i) ));

    % Precision(class) = TP(class) / ( TP(class) + FP(class) )
    Precision(i) = TPFPFNTN(1, i) / sum(confmatrix(i,:))*100;
    temps6 = strcat(temps6,sprintf(' |   %3.2f \t',Precision(i) ));

    % Sensitivity(class) = Recall(class) = TruePositiveRate(class)
    % = TP(class) / ( TP(class) + FN(class) )
    Sensitivity(i) = TPFPFNTN(1, i) / sum(confmatrix(:,i))*100;
    temps7 = strcat(temps7,sprintf(' |   %3.2f \t',Sensitivity(i) ));

    % Specificity ( mostly used in 2 class problems )=
    % TrueNegativeRate(class)
    % = TN(class) / ( TN(class) + FP(class) )
    Specificity(i) = TPFPFNTN(4, i) / ( TPFPFNTN(4, i) + TPFPFNTN(2, i) )*100;
    temps8 = strcat(temps8,sprintf(' |   %3.2f \t',Specificity(i) ));

    % Miss rate = FN(class) / ( TP(class) + FN(class) )
    MissRate(i) = TPFPFNTN(3, i)/sum(confmatrix(:,i))*100;
    temps9 = strcat(temps9,sprintf(' |   %3.2f \t',MissRate(i) ));

    % Fall-out = FP(class) / ( TN(class) + FP(class) )
    Fall_Out(i) = TPFPFNTN(2, i)/( TPFPFNTN(4, i) + TPFPFNTN(2, i) )*100;
    temps10 = strcat(temps10,sprintf(' |   %3.2f \t',Fall_Out(i) ));

end

ModelAccuracy = sum(diag(confmatrix))/sum(confmatrix(:))*100;
temps11 = sprintf('Model Accuracy is %1.2f ',ModelAccuracy);

if (per > 0) % ( if > 0 implies true; < 0 implies false )
    confmatrix = (confmatrix ./ length(actual)).*100;
end

if ( printout > 0 ) % ( if > 0 printout; < 0 no printout )
    disp('------------------------------------------');
    disp('             Actual Classes');
    disp(line_two);
    disp('Predicted|                    ');
    disp('  Classes|                    ');
    disp(line_three);

    for i = 1:n_class
        temps = sprintf('      %d             ',i);
        for j = 1:n_class
            temps = strcat(temps,sprintf(' |    %3.1f    ',confmatrix(i,j)));
        end
```

```
        disp(temps);
        clear temps
    end
    disp('------------------------------------------');

    disp('------------------------------------------');
    disp('             Actual Classes');
    disp(line_two);
    disp(temps1); disp(temps2); disp(temps3); disp(temps4);
    disp(temps5); disp(temps6); disp(temps7); disp(temps8);
    disp(temps9); disp(temps10);
    disp('------------------------------------------');
    disp(temps11);
    disp('------------------------------------------');
end
clear temps1 temps2 temps3 temps4 temps5 temps6 temps7 temps8 temps9 temps10 temps11
```

APPENDIX C –FUZZY INFERENCE SYSTEM

C.1 – FUZZY_SYS.M

```
%% 07 Fuzzy inference system
% How to define good membership functions?
% try to plot the distributions of values for every feature and choice the
% most separated, i.e. choice the features that better help to distinguish
% among classes of position/activities

% Plot boxplots to better distinguish among mean, quartiles, max and min of
% every feature distribution
if(showPlots),
    for k=mod(find(fs),29),

        figure,
        for w=0:3
            subplot(2,2,w+1);
            var = [newFeaturesA(w*29 + k,:)'; ...
                newFeaturesB(w*29 + k,:)'; ...
                newFeaturesC(w*29 + k,:)';  ...
                newFeaturesD(w*29 + k,:)'];
            grp = [zeros(1,size(newFeaturesA,2)), ...
                ones(1,size(newFeaturesB,2)), ...
                2.*ones(1,size(newFeaturesC,2)), ...
                3.*ones(1,size(newFeaturesD,2))];
            boxplot(var,grp,'Labels',{'A','B','C','D'});
            tmp_title = 'Feature ';
            tmp_title = strcat(tmp_title,num2str(k));
            tmp_title = strcat(tmp_title,', sensor ');
            tmp_title = strcat(tmp_title,num2str(w+1));
            tmp_title = strcat(tmp_title,': alias ');
            tmp_title = strcat(tmp_title,num2str(w*29 + k));
            title(tmp_title);
            clear tmp_title;
        end
    end
end

%% Plot PDF of every feature to ease the definition of membership functions

if(showPlots),
    for k=mod(find(fs),29), % features
        figure,
        for w=0:3, % sensors
            subplot(2,2,w+1);
            [f,xi] = ksdensity(newFeaturesA(w*29+k,:));
            plot(xi,f);
            hold on;
            [f,xi] = ksdensity(newFeaturesB(w*29+k,:));
            plot(xi,f);
            [f,xi] = ksdensity(newFeaturesC(w*29+k,:));
            plot(xi,f);
            [f,xi] = ksdensity(newFeaturesD(w*29+k,:));
            plot(xi,f);
            title_str = strcat('Feat.',num2str(k));
            title_str = strcat(title_str,', sens.');
            title_str = strcat(title_str,num2str(w+1));
            title_str = strcat(title_str,', aka ');
            title_str = strcat(title_str,num2str(w*29+k));
            title(title_str);
            clear title_str;
            legend('supine','dorsiflexion','walking','stair');
        end
    end

    clear f xi;
end

%%

fs(:)=0;
```

```
fs([27 36 40 45]) = 1;

% mamdani = readfis('mamdani.fis');
mamdani = readfis('mamdani.fis');

inputs = X(:,fs);

size1 = sizeA;
size2 = size1+sizeB;
size3 = size2+sizeC;
size4 = size3+sizeD;
targets = zeros(size(Y,1),1);
targets(1:size1) = 0.2;
targets(size1+1:size2) = 0.4;
targets(size2+1:size3) = 0.6;
targets(size3+1:end) = 0.8;

outputs = evalfis(inputs,mamdani);
% errors = gsubtract(targets,outputs);
% pre_error = sqrt(mean(errors.^2))

if(showPlots),
    figure,
    plot(1:size(outputs,1),targets,'bo',1:size(outputs,1),outputs,'rx');
    hold on;
    plot(1:size(outputs,1),zeros(1,size(outputs,1)),'k--');
    plot(1:size(outputs,1),0.3*ones(1,size(outputs,1)),'k--');
    plot(1:size(outputs,1),0.5*ones(1,size(outputs,1)),'k--');
    plot(1:size(outputs,1),0.7*ones(1,size(outputs,1)),'k--');
    plot(1:size(outputs,1),ones(1,size(outputs,1)),'k--');
    title('Result of Mamdani FIS');
    xlabel('inputs');
    ylabel('classes');
    legend('target class','output class');
end

% just to better understand plot
for k=1:size(outputs,1)
    if outputs(k)<0.3
        outputs(k) = 0.2;
    elseif outputs(k)<0.5
        outputs(k) = 0.4;
    elseif outputs(k)<0.7
        outputs(k) = 0.6;
    else
        outputs(k) = 0.8;
    end
end

% figure,
% plot(1:size(outputs,1),targets,'bo',1:size(outputs,1),outputs,'rx');
% title('Result of Mamdani FIS');
% xlabel('inputs');
% ylabel('classes');
% legend('target class','output class');

% figure, plot(outputs(1:size1),1:size1,'bo');
% hold on;
% plot(outputs(size1+1:size2),size1+1:size2,'go');
% plot(outputs(size2+1:size3),size2+1:size3,'ro');
% plot(outputs(size3+1:end),size3+1:size4,'ko');

cfmatrix2(actual',(outputs.*5)',[1 2 3 4], 0, 1);

clear k;
```

APPENDIX D –ADAPTIVE NEURO FIS

D.1 – ADAPTIVENEUROFIS.M

```
%% 08 ANFIS
inputs2 = [inputs actual];

index = randperm(size(inputs2,1));

indTrain = floor(size(inputs2,1)*70/100);
indTest = floor(size(inputs2,1)*15/100);
% indVal = floor(size(inputs2,1)*15/100);

inTrain = inputs2(index(1:indTrain),:);
inTest = inputs2(index(indTrain+1:indTrain+indTest),:);
inVal = inputs2(index(end-indTest:end),:);

sugeno = mam2sug(mamdani);

anfisedit;

%%
outputs = evalfis(inputs,sugeno0);

if(showPlots),
    figure,
    plot(1:size(outputs,1),targets.*5,'bo',1:size(outputs,1),outputs,'rx');
    title('Result of Mamdani FIS');
    xlabel('inputs');
    ylabel('classes');
    legend('target class','output class');
end

% just to better understand plot
for k=1:size(outputs,1)
    if outputs(k)<1.5
        outputs(k) = 1;
    elseif outputs(k)<2.5
        outputs(k) = 2;
    elseif outputs(k)<3.5
        outputs(k) = 3;
    else
        outputs(k) = 4;
    end
end

cfmatrix2(actual',outputs',[1 2 3 4], 0, 1);
```