# Chapter 3
# Results

Flowchart of EMG signal processing executed in our experiments is shown in Fig. 3.1. According to flowchart, after data acquisition phase, all recorded signals underwent noise filtering as preprocessing phase. Long-time recording signals are cut off in a windowing procedure as long as 20,000 samples or 10 s records with 2 kHz sampling rate. Each window is split into sub-windows with length of 100–5,000 samples. For all windows, 70 % of samples are set for training procedure and rest of samples for testing purpose. After multiple runs of training and testing procedures for different lengths of windows, windows length of 2,000 samples (corresponding to 1 s signal recording) was chosen. Therefore, each window (with 20,000 samples) is split into 10 sub-windows each one with 2,000 samples. Seventy percent of sub-windows are still considered for training purpose (7 sub-windows) and rests for testing purpose (3 sub-windows).

For evaluating classifier, mean-squared error is used which is most common criterion defined as below:

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y}_i)$$

where $y_i$ and $\bar{y}_i$ are real and desired outputs of network, respectively, and $N$ is total number of samples. MSE of training process shows trainability of system, and MSE of testing samples indicates system's modeling capability.

True classification rate is defined as rate of true assigned samples to their classes to whole number of samples as below:

$$\text{Classification Rate} = \frac{\text{True assigned samples}}{\text{Total number of samples}}$$



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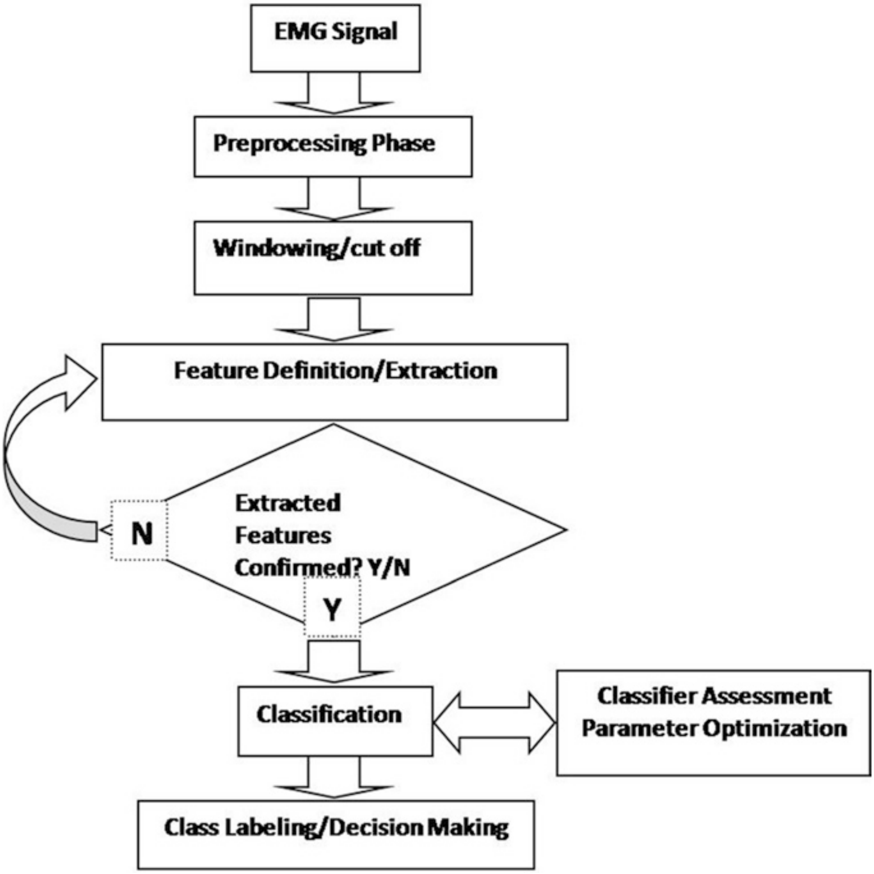


**Fig. 3.1** Flowchart of EMG signal characterization process used in this work

The flowchart of procedure sequence of EMG signal characterization is shown in Fig. 3.1. As it is illustrated in flowchart, there are two main assessment sections on process, one for evaluating extracted features and another one for evaluating and structure optimization of classifier. Therefore, evaluation of potential features is taken into account. The reference classifier for this step is a multilayer perceptron (MLP) as an efficient artificial neural network with least square back propagation learning algorithm.

The MLP used in this part of simulation has 1 hidden layer and 20 neurons in the hidden layer. Transfer function was used as tangent sigmoid mathematics function. Inputs of MLP are extracted features, and network is trained based on training samples described earlier.

According to Table 3.1, combinations of RMS + WL and RMS + MAV + WL yield best result for quadriceps muscle. For biceps muscle, lowest MSE corresponds to combination of MAV and VAR according to Table 3.2.

**Table 3.1** Training and testing errors of MLP network for one or a set of features corresponding to the EMG signals of quadriceps muscle contraction

| Item | Extracted feature(s) | MSE of training | MSE of testing |
|---|---|---|---|
| 1 | RMS | 0.0642 | 0.1183 |
| 2 | MAV | 0.0562 | 0.0894 |
| 3 | ZC | 0.0754 | 0.0644 |
| 4 | SSI | 0.0650 | 0.0927 |
| 5 | WL | 0.0614 | 0.0854 |
| 6 | RMS + MAV | 0.0532 | 0.0721 |
| 7 | RMS + WL | 0.05 | 0.0609 |
| 8 | RMS + VAR | 0.0648 | 0.0847 |
| 9 | RMS + SSI | 0.0625 | 0.0858 |
| 10 | RMS + ZC | 0.0622 | 0.0751 |
| 11 | MAV + VAR | 0.0537 | 0.0741 |
| 12 | RMS + MAV + WL | 0.0498 | 0.0638 |
| 13 | RMS + MAV + ZC | 0.0593 | 0.0654 |
| 14 | RMS + MAV + VAR | 0.0571 | 0.0709 |

**Table 3.2** Training and testing errors of the MLP network for one or a set of features corresponding to the EMG signals of biceps muscle in a dynamic test

| Item | Extracted feature(s) | MSE of training | MSE of testing |
|---|---|---|---|
| 1 | IEMG | 0.4259 | 0.0510 |
| 2 | MAV | 0.4239 | 0.0982 |
| 3 | SSI | 0.5844 | 0.0360 |
| 4 | RMS | 0.6869 | 0.0357 |
| 5 | WL | 0.5487 | 0.0476 |
| 6 | ZC | 0.4884 | 0.0585 |
| 7 | CV | 0.6820 | 0.1095 |
| 8 | VAR | 0.7064 | 0.0138 |
| 9 | RMS + MAV | 0.6415 | 0.0159 |
| 10 | RMS + SSI | 0.6202 | 0.0345 |
| 11 | RMS + VAR | 0.6649 | 0.0104 |
| 12 | RMS + ZC | 0.5940 | 0.0351 |
| 13 | RMS + WL | 0.6609 | 0.0128 |
| 14 | MAV + VAR | 0.6407 | 0.0088 |

From results of Tables 3.3, 3.4, and 3.5, it can be inferred that isometric contraction test, compared to two other contractions, has lower MSE values when it is modeled. It should be noted that these MSE errors correspond to distance to relative class and misclassification of force of a muscle with a higher or lower class of force do not affect course of treatment significantly. In Tables 3.3, 3.4, and 3.5, more appropriate features are colored red according to their MSE values which are selective features for isometric contraction (ISO), maximum voluntary

**Table 3.3** Best results for biceps, deltoid, triceps, quadriceps, and tibialis anterior muscles (ISO)

| Muscle | Gender | Appropriate features | MSE of training | MSE of testing |
|---|---|---|---|---|
| Biceps | Female | RMS | 0.0509 | 0.0566 |
| | Female | MAV + SSI | 0.0565 | 0.0452 |
| | Female | MAV + WL | 0.0585 | 0.0399 |
| | Male | RMS | 0.0394 | 0.0229 |
| | Male | RMS + WL | 0.0396 | 0.0222 |
| Deltoid | Male | RMS + WL | 0.1585 | 0.1060 |
| | Male | RMS + SSI + VAR + WL + IEMG | 0.1921 | 0.0672 |
| Triceps | Female | RMS + WL | 0.0403 | 0.0457 |
| | Female | RMS + WL + MAV | 0.0522 | 0.0442 |
| | Male | RMS + ZC | 0.0161 | 0.0095 |
| | Male | RMS + MAV + WL | 0.013 | 0.0076 |
| | Male | RMS + MAV + ZC | 0.0127 | 0.0062 |
| Quadriceps | Female | RMS + WL | 0.065 | 0.079 |
| | Female | RMS + ZC | 0.0668 | 0.0799 |
| | Female | RMS + MAV + VAR | 0.0906 | 0.0792 |
| Tibialis anterior | Female | RMS + WL | 0.0368 | 0.0453 |
| | Female | RMS + VAR | 0.0387 | 0.0436 |
| | Male | RMS + WL | 0.0893 | 0.0769 |
| | Male | RMS + ZC | 0.0959 | 0.1849 |

**Table 3.4** Best results for biceps, deltoid, triceps, quadriceps, and tibialis anterior muscles (MVC)

| Muscle | Gender | Appropriate features | MSE of training | MSE of testing |
|---|---|---|---|---|
| Biceps | Female | RMS + SSI | 0.0306 | 0.0138 |
| | Female | RMS + ZC | 0.029 | 0.0206 |
| | Male | RMS + ZC + MAV | 0.0208 | 0.0165 |
| Deltoid | Female | ZC | 0.0255 | 0.0217 |
| | Male | RMS | 0.1651 | 0.1619 |
| Triceps | Female | RMS + MAV + ZC | 0.0624 | 0.0596 |
| | Female | RMS + MAV + WL | 0.067 | 0.0583 |
| | Male | MAV | 0.0109 | 0.1132 |
| | Male | WL | 0.0754 | 0.1112 |
| Quadriceps | Female | RMS + MAV | 0.577 | 0.0661 |
| | Female | RMS + WL | 0.0617 | 0.0668 |
| Tibialis anterior | Female | RMS + WL | 0.0424 | 0.0334 |
| | Female | RMS + MAV | 0.0484 | 0.0341 |
| | Male | RMS + WL | 0.0451 | 0.0405 |
| | Male | RMS + WL + MAV | 0.0549 | 0.0605 |

**Table 3.5** Best results for biceps, deltoid, triceps, quadriceps, and tibialis anterior muscles (dynamics)

| Muscle | Gender | Appropriate features | MSE of training | MSE of testing |
|---|---|---|---|---|
| Biceps | Female | IEMG | 0.0510 | 0.0425 |
| | Female | MAV | 0.0982 | 0.0423 |
| | Male | ZC | 0.1556 | 0.1083 |
| Deltoid | Female | RMS + WL | 0.0229 | 0.0194 |
| | Male | RMS + ZC | 0.0881 | 0.1565 |
| Triceps | Female | RMS + MAV | 0.1054 | 0.0981 |
| | Female | RMS + VAR | 0.1042 | 0.0927 |
| | Male | ZC | 0.0425 | 0.0517 |
| | Male | RMS + MAV | 0.0852 | 0.0861 |
| Quadriceps | Female | RMS + WL | 0.05 | 0.609 |
| | Female | RMS + WL + MAV | 0.0498 | 0.639 |
| Tibialis anterior | Female | RMS + WL | 0.0851 | 0.085 |
| | Female | RMS + ZC | 0.0722 | 0.053 |
| | Male | RMS | 0.1017 | 0.1409 |
| | Male | RMS + WL | 0.0983 | 0.103 |

contraction (MVC), and dynamic contraction, respectively. One primary purpose of developing an expert system to perform feature extraction and sample classification is to achieve a standard evaluation procedure and to reduce therapist affectivity on evaluation quality.

After most suitable features are extracted by reference classifier, an evaluation is performed to find a robust and efficient classifier. Neuro-fuzzy network is a potential for this task which is compared to some other well-known classifiers in this part of experiment.

For neuro-fuzzy classifier, a combination of least squares and back propagation method was used as learning algorithm. Trapezoidal and Gaussian membership functions are commonly used as shape of fuzzy sets of inputting nodes. Number of 2–4 membership functions is suggested for each variable in EMG signal modeling problem.

Table 3.6 shows results of implementing five types of classifiers for classification of EMG signals according to extracted features. Due to difference between muscles power of two groups of gender, male and female, we separated males and females in analysis of their EMG signals of mentioned muscles. Classes of muscle forces are separated and samples are assigned to their relative classed. True assignments of samples to their classes define classification rate in percent as criteria for evaluation of classifier in addition to training and testing capability.

**Table 3.6** Classifier evaluation for classification of EMG signals (muscle force) according to extracted features

| Classifier | Features | MSE of train | MSE of test | Run time (s) | Uncertainty (%) | Classification rate (%) |
|---|---|---|---|---|---|---|
| K-NN | RMS + WL | – | – | ~2 | 0 | ~76 |
| FFNN-1 | RMS + WL | 0.024 | 0.021 | ~12 | ~4 | ~79 |
| FFNN-2 | RMS + WL | 0.022 | 0.020 | ~18 | ~7 | ~83 |
| FFNN-3 | RMS + WL | 0.017 | 0.018 | ~22 | ~9 | ~85 |
| ERNN | RMS + WL | ~5e−06 | 0.312 | ~14 | ~12 | ~71 |
| F.C-means | RMS + WL | – | – | ~5 | ~5 | ~80 |
| NFS-1 | RMS + WL | 0.003 | 0.011 | ~7 | ~2 | ~82 |
| NFS-2 | RMS + WL | 0.001 | 0.002 | ~11 | ~2 | ~85 |
| NFS-3 | RMS + WL | 3.1e−04 | 4.7e−04 | ~23 | ~3 | ~87 |
| NFS-4 | RMS + WL | 2.3e−04 | 3.9e−04 | ~31 | ~3 | ~88 |
| NFS-5 | RMS + WL | 2.1e−04 | 3.3e−04 | ~39 | ~3 | ~89 |
| NFS-6 | RMS + WL | 2.1e−04 | 2.9e−04 | ~43 | ~4 | ~91 |

*K-NN* K-nearest neighbor, *FFNN* feed-forward neural network, *ERBNN* Elman recurrent neural network, *F.C-means* fuzzy C-means, *NFS* neuro-fuzzy system

Except deterministic algorithm of K-NN, rests involve an uncertainty which means respective variations of outputs in a sequence of executions

FFNN-1: ([10, 1], 'Logsig','Purelin','Trainlm', 500)
FFNN-2: ([20, 1], 'Logsig','Purelin','Trainlm', 500)
FFNN-3: ([20, 1], 'Logsig','Purelin','Trainlm', 1000)
ERNN: (Spread = 0.01)
NFS-1: (NumMFs = 2, MFtype:'Gaussmf', 300)
NFS-2: (NumMFs = 2, MFtype:'Gaussmf', 500)
NFS-3: (NumMFs = 3, MFtype:'Gaussmf', 300)
NFS-4: (NumMFs = 3, MFtype:'Gaussmf', 500)
NFS-5: (NumMFs = 4, MFtype:'Gaussmf', 300)
NFS-6: (NumMFs = 4, MFtype:'Gaussmf', 500)