Classification and Clustering of Parkinson's and Healthy Control Gait Dynamics Using LDA and K-means

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Abstract: *Problem arises when distinct morphologic changes are not seen in the electromyographic waveform of normal (control) and Parkinson's subjects during data interpretation. This study aimed to ascertain whether neuro-degenerative disease, e.g., Parkinson's disease (PD) affects gait and mobility with comparison to the healthy control. Fifteen subjects (left and right foot) from both the groups are selected where the signal is obtained using force-sensitive resistors (Gait Dynamics in Neuro-Degenerative Disease Data Base). The proposed methodology is divided into five parts: (i) 1 hr recording of gait dynamics data are segmented into three intervals (0-20 min, 20-40 min and 40-60 min); (ii) Normalization of each segmented data (20 min), i.e., preprocessing (noise and baseline drift removal); (iii) Then the frequency domain powers for each segments are calculated which further introduced features in the successive stages for classification and clustering; (iv) The classification of Parkinson's disease and healthy control group is accomplished using Linear Discriminant Analysis (LDA); (v) Clustering of these two classes is performed using K-means clustering algorithm taking same sets of features. Certainly the classification and clustering results signify the classification probability using frequency domain power of gait dynamics/electromyogram signal. The re-substitution error of LDA during classification is found to be 21.11%. Moreover, significant and precise classification and clustering results are achieved between PD and control taking left-right foot frequency domain power as classification features.*

Keywords: *Parkinson's disease, Healthy control, Gait dynamics, Power in frequency domain, Linear discriminant analysis, K-means clustering.*

Introduction

Gait analysis is used for assessing locomotors disabilities and evaluating corrective and therapeutic procedures [34]. As each muscle provides a specific function, the basic information to be gained by dynamic electromyography is phasing within the gait cycle [29]. Kugler [20] had described a technique which automatically classified between Parkinson's disease (PD) patients and healthy controls using surface electromyographic (EMG) signals from standardized gait tests. Gait analysis reveals a characteristic pattern of leg muscle activation in PD, increased tibialis anterior activity during the swing phase and reduced amplitude of the EMG response and poor modulation in the leg extensor muscles during the stance phase [8, 9]. Gait disorders in PD may be either prominent or, even in the advanced stages of the disease, mild. Certain clinical features are more likely to be associated with disturbed gait: rapid course of motor symptoms [3]. Adaptability-of-Gait test has potential to identify a new gait performance between severe PD, moderate PD and age-matched controls [33]. Roland *et al.* [32] proposed a study to use EMG to dissociate frailty phenotypes in females with PD during routine daily activities and provide insight into how PD associated motor declines contributes to frailty and functional decline. Hausdorff *et al.* [15] have studied the detailed insight on

variation and resemblance among the proteins sequences of patients having Alzheimer's, Parkinson's and Huntington's diseases. Paul *et al.* [28] have analyzed the impacts of nsSNPs on structure and function of Paraxonase 1 using different bioinformatics tools which helps in identifying deleterious non-synonymous single nucleotide polymorphisms (nsSNPs) in a disease related gene. Cook *et al.* [6], DeLuca *et al.* [7] and Lofterod *et al.* [23] stated about the fundamental research on gait control and the associated mechanisms. They also discussed how gait analysis evolved as a clinical tool for surgical planning on cerebral palsy cases. Pollo [31] assessed the efficacy of surgical interventions, and evaluated the rate of deterioration in progressive disorders to evaluate the impact of medication and orthopedic aids. Carvalho [5] and Sousa [36] identified gait patterns, speed of walking, mechanical work made by the main muscular groups during the diverse phases, etc..

Bazner *et al.* [4], Frenkel-Toledo *et al.* [11] and Yogev *et al.* [38] described the computerized force-sensitive system which was used to quantify gait cycle timing, specifically the swing time and the stride-to-stride variability of swing time. The system measures the forces underneath the foot as a function of time.

The gait patterns can be influenced by almost any variable such as age, weight, diseases, strength, walking surface, etc. [37]. Usually the gait patterns are obtained from force platforms that measure the ground reaction forces (GRF), equal and opposite to the ones made by the foot on the ground. Fig. 1 is a representation of a typical healthy subject GRF pattern during half a walking cycle (between the pink bars). It is divided in a (antero-posterior) breaking phase and an accelerating phase. For each leg, the point where no antero-posterior force is done (the location of the pink bars) is the point where the foot is under the hip [5].

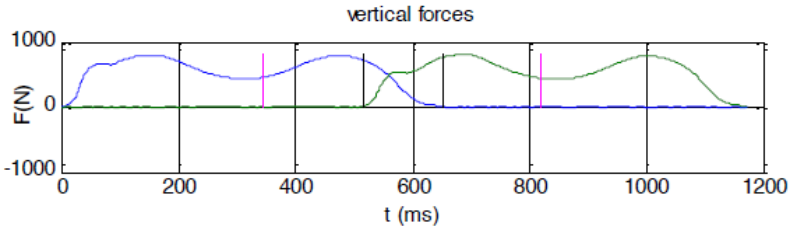


Fig. 1 Typical GRF gait pattern (adapted from Carvalho [5])

One of the typical features of gait in patients with PD is that the overall movement pattern remains more or less normal, except for the markedly reduced angular displacements in hip, knee and ankle joints [18, 25, 26]. Two of the difficulties encountered in performing an analysis of gait involved data manipulation and interpretation. The interpretative difficulty arises from the fact that these channels show dissimilar patterns among patients with the same syndrome [12, 13, 19, 30]. Even among normal individuals there exist dissimilar EMG patterns [1, 27, 35]. Kunju *et al.* [21] proposed a technique which processed and analyzed EMG signal using filtering techniques. The results showed a marked variation in the root mean square amplitude levels and median frequency of EMG as the subject's walking pace changed [21]. Here, frequency domain power of both right and left foot were taken as features for classification between control and Parkinson's gait dynamics.

Methodologies

Fig. 2 illustrates the different methods adopted for this gait dynamics study. The following sections demonstrate the workflow starting from the gait dynamics database generation to the classification of the control and Parkinson's subjects.

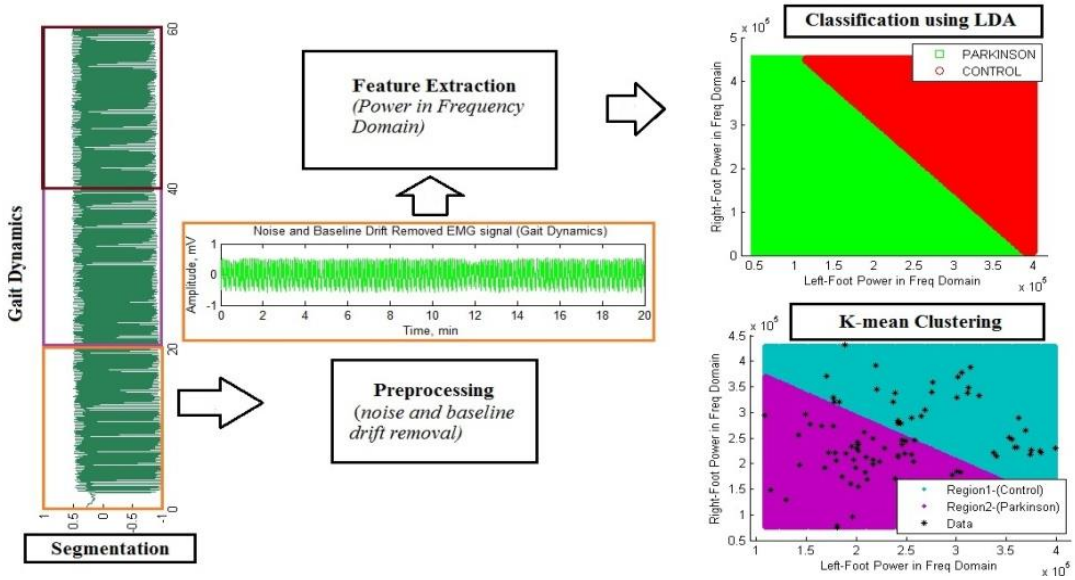


Fig. 2 Block diagram of proposed methodologies

Gait Dynamics in Neuro-Degenerative Disease Data Base

To understand better the pathophysiology of these diseases and to improve our ability to measure responses to therapeutic interventions, it may be helpful to quantify gait dynamics accurately. The records used in the proposed methodology in Gait Dynamics in Neuro-Degenerative Disease Data Base [15] are from patients with PD (n = 15) and records from 15 healthy control subjects (Table 1). The raw data were obtained using force-sensitive resistors, with the output roughly proportional to the force under the foot. Here the selected recordings are having 1 hour length and 2 rows (signals) with 90000 columns (samples/signal) for left-right foots; sampling frequency: 300 Hz and sampling interval: 0.003(3) sec.

Segmentation and pre-processing

The 1 hour gait data having 90000 columns (samples/signal) for left-right foots are segmented into three parts each having 30000 columns (samples/signal), i.e., 20 min, respectively. The EMG signals are passed through pre-processing stages where the baseline drifts and noise (i.e., low frequency and high frequency components) are eliminated. The baseline drift of EMG signal (Fig. 3) is removed by applying moving average filtering [17] and the process is equivalent to low pass filtering with the response of the smoothing given by the difference equation:

$$Y_s(i) = \frac{1}{2N+1}\left(Y(i+N) + Y(i+N-1) + \ldots + Y(i-N)\right), \quad (1)$$

where $Y_s(i)$ is the smoothed value for the i^{th} data point, N is the number of neighboring data points on either side of i, and $2N + 1$ is the span. The moving average smoothing method used by Curve Fitting Toolbox follows these rules [17]:

- The span must be odd.
- The data point to be smoothed must be at the center of the span.
- The span is adjusted for data points that cannot accommodate the specified number of neighbours on either side.
- The end points are not smoothed because a span cannot be defined.

Table 1. Subjects information of Gait Dynamics in Neuro-Degenerative Disease Data Base

Group	Age (years)	Height (meters)	Weight (kg)	Gender	Gait speed (m/sec)	Duration/ Severity
control1	57	1.94	95	f	1.33	0
control2	22	1.94	70	m	1.47	0
control3	23	1.83	66	f	1.44	0
control4	52	1.78	73	f	1.54	0
control5	47	1.94	82	f	1.54	0
control6	30	1.81	59	f	1.26	0
control7	22	1.86	64	f	1.54	0
control8	22	1.78	64	f	1.33	0
control9	32	1.83	68	f	1.47	0
control10	38	1.67	57	f	1.4	0
control11	69	1.72	68	f	0.91	0
control12	74	1.89	77	m	1.26	0
control13	61	1.86	60	f	1.33	0
control14	20	1.9	57	f	1.33	0
control15	20	1.83	50	f	1.19	0
park1	77	2	86	m	0.98	4
park2	44	1.67	54	f	1.26	1.5
park3	80	1.81	77	m	0.98	2
park4	74	1.72	43	f	0.91	3.5
park5	75	1.92	91	m	1.05	2
park6	53	2	86	m	1.33	2
park7	64	1.67	54	f	0.91	4
park8	64	1.83	73	m	0.84	4
park9	68	1.92	84	m	1.05	1.5
park10	60	1.94	74	m	1.19	3
park11	74	2.04	100	m	0.5	3
park12	57	1.72	65	f	0.98	3
park13	79	1.68	59	f	0.84	3
park14	57	2.13	84	m	0.98	3
park15	76	2	96	m	1.19	2.5

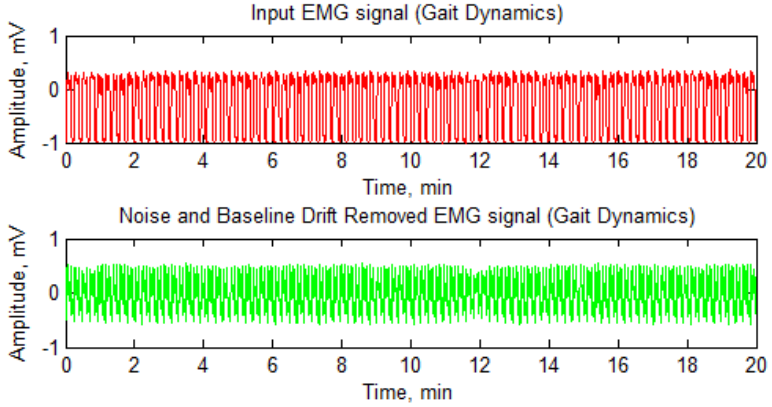


Fig. 3 Segmented and pre-processed EMG signal

The noise cancellation (Fig. 3) is performed with Discrete Wavelet Transform (DWT) [2] for the gait dynamic/EMG signal. The DWT of a signal *x* is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response *g* resulting in a convolution of the two:

$$y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]\, g[n-k]. \tag{2}$$

The signal is also decomposed simultaneously using a high-pass filter *h*. The outputs are giving (Fig. 4) the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass). It is important that the two filters are related to each other and they are known as a quadrature mirror filter.

Fig. 4 Block diagram of filter analysis

However, since half the frequencies of the signal have now been removed, half the samples can be discarded according to Nyquist's rule. The filter outputs are then sub sampled by 2. In the next two formulas, the notation is the opposite: *g* denotes high pass and *h* – low pass as is Mallat's and the common notation:

$$y_{low}[n] = \sum_{k=-\infty}^{\infty} x[k]\, h[2n-k], \tag{3}$$

$$y_{high}[n] = \sum_{k=-\infty}^{\infty} x[k]\, g[2n-k]. \tag{4}$$

Results analysis

Frequency domain power

Power spectral density describes how the power of a signal or time series is distributed over the different frequencies. The average power *P* of a signal *x*(*t*) is the following time average:

$$P = \lim_{T\to\infty} \frac{1}{2T} \int_{-T}^{T} x(t)^2\, dt\ . \tag{5}$$

So the total average power is computed as the sum of the power of all the frequency components of the 20 min gait dynamic signal. Left-right foot gait dynamic frequency domain powers are tabulated in Table 2.

Linear discriminant analysis

In this case, multi-class Linear Discriminant Analysis (LDA) (Fig. 5) is used to classify two unknown group of EMG signals (i.e., PD and control) based on the frequency domain features (e.g., left-right foot frequency domain power) by calculating of mean, global mean, mean subtraction, transpose, covariance, probability, frequencies and at the end defining thresholds for each class on the distributed space area [14].

Table 2. Frequency domain powers of gait dynamics data

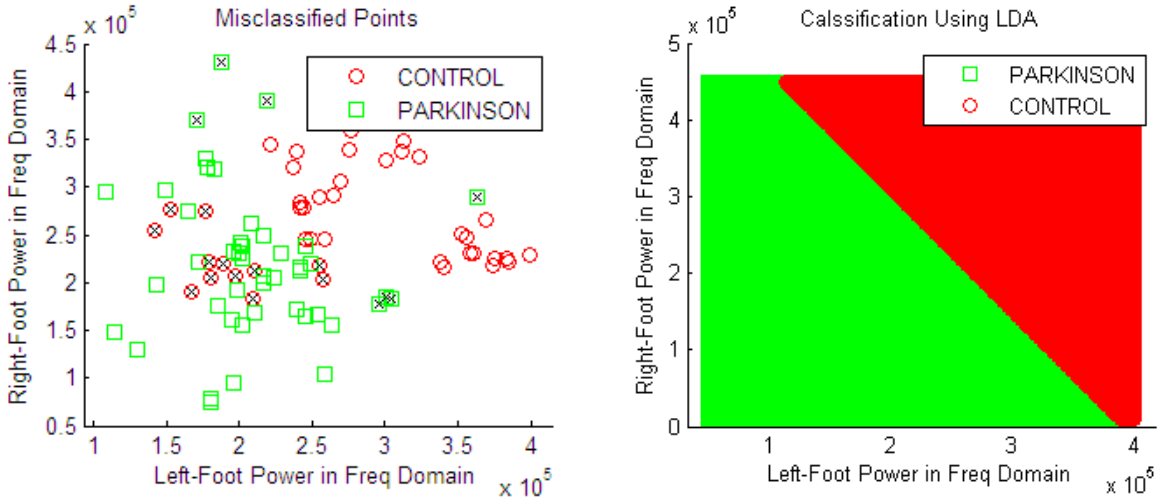
Subject No	Time (min)	CL_PF[a]	CR_PF[b]	PL_PF[c]	PR_PF[d]
1	0-20	3.1271e+05	3.4865e+05	1.7192e+05	2.2076e+05
	20-40	2.7568e+05	3.3898e+05	2.0067e+05	2.4239e+05
	40-60	2.7687e+05	3.5937e+05	2.0211e+05	2.3759e+05
2	0-20	2.2092e+05	3.4539e+05	1.9976e+05	2.3055e+05
	20-40	1.7661e+05	2.7386e+05	2.1665e+05	2.0676e+05
	40-60	1.8913e+05	2.1937e+05	2.4219e+05	2.1641e+05
3	0-20	3.7444e+05	2.1823e+05	2.0253e+05	1.5603e+05
	20-40	3.9933e+05	2.2950e+05	2.1071e+05	1.6909e+05
	40-60	3.8379e+05	2.2437e+05	1.9435e+05	1.6102e+05
4	0-20	2.5809e+05	2.4491e+05	2.2362e+05	2.0417e+05
	20-40	2.4929e+05	2.4455e+05	2.4165e+05	2.1304e+05
	40-60	2.4544e+05	2.4608e+05	2.4894e+05	2.1941e+05
5	0-20	2.5729e+05	2.0405e+05	3.6301e+05	2.8953e+05
	20-40	1.4262e+05	2.5528e+05	1.4938e+05	2.9659e+05
	40-60	1.5329e+05	2.7650e+05	1.0833e+05	2.9480e+05
6	0-20	3.5596e+05	2.4761e+05	2.2817e+05	2.3037e+05
	20-40	3.5255e+05	2.5104e+05	2.1643e+05	2.4923e+05
	40-60	3.6962e+05	2.6476e+05	2.0758e+05	2.6181e+05
7	0-20	2.5492e+05	2.8901e+05	1.9902e+05	1.9167e+05
	20-40	2.6495e+05	2.9207e+05	2.1643e+05	1.9878e+05
	40-60	2.6920e+05	3.0526e+05	1.2948e+05	1.2976e+05
8	0-20	2.1024e+05	2.1176e+05	1.9652e+05	9.5291e+04
	20-40	1.7993e+05	2.0495e+05	1.8061e+05	7.4609e+04
	40-60	1.6784e+05	1.9124e+05	1.8062e+05	7.8080e+04
9	0-20	3.2321e+05	3.3188e+05	1.7693e+05	3.2925e+05
	20-40	3.1115e+05	3.3721e+05	1.7793e+05	3.2114e+05
	40-60	3.0096e+05	3.2844e+05	1.8255e+05	3.1965e+05
10	0-20	3.0582e+05	3.7786e+05	1.8827e+05	4.3117e+05
	20-40	3.1379e+05	3.8864e+05	1.7032e+05	3.7005e+05
	40-60	3.0189e+05	3.6905e+05	2.1930e+05	3.9099e+05
11	0-20	3.7527e+05	2.2605e+05	1.4265e+05	1.9703e+05
	20-40	3.5871e+05	2.3161e+05	1.1440e+05	1.4822e+05
	40-60	3.8496e+05	2.2133e+05	1.8558e+05	1.7516e+05
12	0-20	3.6059e+05	2.3104e+05	2.6311e+05	1.5553e+05
	20-40	3.4068e+05	2.1518e+05	2.5417e+05	1.6636e+05
	40-60	3.3783e+05	2.2133e+05	2.4508e+05	1.6544e+05
13	0-20	2.3918e+05	3.3716e+05	3.0053e+05	1.8468e+05
	20-40	2.5516e+05	2.1745e+05	3.0485e+05	1.8270e+05
	40-60	2.3702e+05	3.2087e+05	2.9633e+05	1.7793e+05
14	0-20	2.4474e+05	2.7825e+05	1.6497e+05	2.7418e+05
	20-40	2.4177e+05	2.7805e+05	2.3931e+05	1.7114e+05
	40-60	2.4173e+05	2.8423e+05	2.5805e+05	1.0363e+05
15	0-20	1.7909e+05	2.2138e+05	2.4601e+05	2.3766e+05
	20-40	1.9765e+05	2.0728e+05	2.0257e+05	2.2520e+05
	40-60	2.0883e+05	1.8233e+05	1.9581e+05	2.3346e+05

[a]CL_PF = Control(Left-foot)_Power in Frequency Domain,
[b]CR_PF = Control(Right-foot)_Power in Frequency Domain,
[c]PL_PF = Parkinson's(Left-foot)_Power in Frequency Domain,
[d]PR_PF = Parkinson's(Right-foot)_Power in Frequency Domain.

Duda *et al.* [10] described the mathematical derivation of the LDA as follows:

$$d_i(x)\ln\left(P(C_i)\right)+x^{\mathrm{T}}C^{-1}m_i+\frac{1}{2}m_i^{\mathrm{T}}C^{-1}m_i\,, \tag{6}$$

where m_i is the N length of mean vector for i^{th} class, C_i is the $N\times N$ covariance matrix for the i^{th} class, $P(C_i)$ is the prior probability of class C_i. The selected class is the one that has the highest value of $d_i(x)$.



a) misclassification result b) classification using LDA

Fig. 5 Classification of Parkinson's and control gait dynamics using LDA

K-means clustering

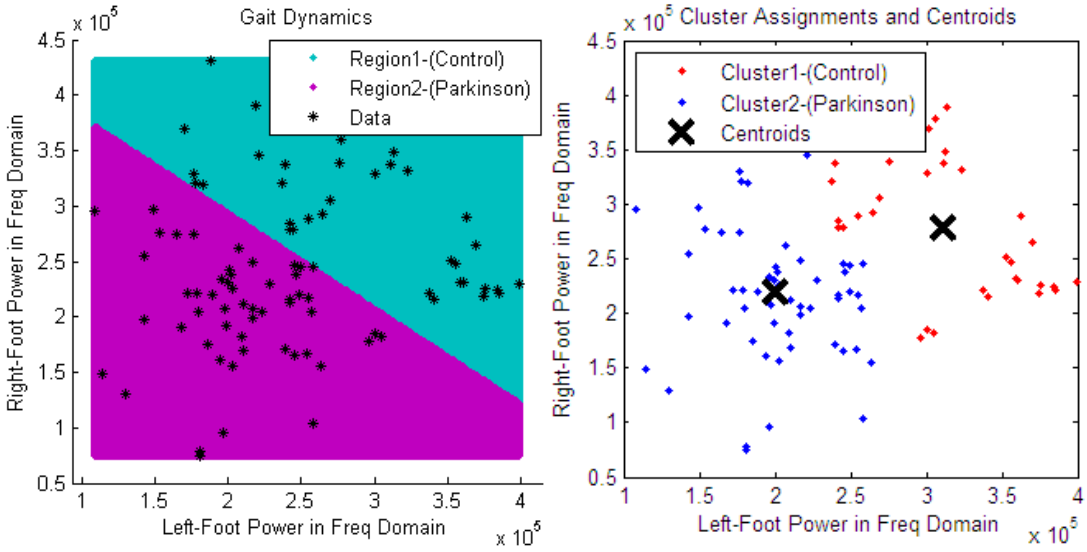
K-means clustering is a method of vector quantization and is implemented in this gait dynamic study to cluster (Fig. 6) the PD and control EMG signals using same sets of features. Given a set of observations $(x_1, x_2, \ldots, x_n)$, where each observation is a d-dimensional real vector, K-means clustering aims to partition the n observations into sets $S=\{S_1, S_2, \ldots, S_k\}$, $(k\leq n)$ so as to minimize the within-cluster sum of squares (WCSS) (sum of distance functions of each point in the cluster to the K center). In other words, its objective is to find:

$$arg\min(s)\sum_{i=1}^{k}\sum_{x\in S_i}\|X-\mu_i\|^2, \tag{7}$$

where μ_i is the mean of points in S_i.

For a given set of K-means $m_1^{(1)},\ldots,m_k^{(1)}$, the algorithm proceeds by alternating between two steps [24]:

Assignment step: Assign each observation to the cluster whose mean yields the least WCSS. Since the sum of squares is the squared Euclidean distance, this is intuitively the "nearest" mean.



a) partition into two clusters b) cluster assignments and centroids

Fig. 6 Clustering of two regions using K-means

$$S_i^{(t)} = \left\{ x_p : \| x_p - m_i^{(t)} \|^2 \le \| x_p - m_j^{(t)} \|^2 \ \forall j, 1 \le j \le k \right\}, \tag{8}$$

where each x_p is assigned to exactly one $S^{(t)}$, even if it could be assigned to two or more of them.

Update step: Calculate the new means to be the centroids of the observations in the new clusters

$$m_i^{(t+1)} = \frac{1}{\left| S_i^{(t)} \right|} \sum_{x_{j \in S_i^{(t)}}} x_j \, . \tag{9}$$

Since the arithmetic mean is a least-squares estimator, this also minimizes the WCSS objective.

Discussions

Li [22] discussed the application of a neural network in medical diagnosis using back propagation and results calculated as "*Among the training samples, the detection accuracy rate for Parkinson's patients is 100%, the detection accuracy rate for non-Parkinson's patients is 95% and misdiagnosis rate is 5%. Among the testing samples, the detection accuracy rate for Parkinson's patients is 96.3%, the detection accuracy rate for non-Parkinson's patients is 93.3% and misdiagnosis rate is 6.7%*". Tabulated frequency domain powers (Table 1) of left-right foot were introduced as the classifier parameters for the LDA and K-means clustering techniques. Fig. 5(a) shows the misclassification result (cross marks) during classification by LDA.

The re-substitution error of LDA is found to be 21.11% and the misclassification error for quadratic discriminant analysis is 18.89%. Moreover, LDA is precisely classifying these two classes (Fig. 5(b)) taking left-right foot frequency domain power as classifier features. Using the same sets of features in K-means clustering, significant results achieved (Fig. 6) in partitioning and cluster assignments of control and Parkinson's regions. The best total sum of distances = 7.66504e+06 where replicate is 4 and total iterations are 7. The EMG signals from Gait Dynamics in Neuro-Degenerative Disease Database were recorded using force-sensitive

resistors, which show no significant morphological changes in the signals patterns of PD and control. The amplitude changes and strides length are also calculated before selecting frequency domain power of signal as a feature. But both the amplitude and average stride length could not contribute sufficiently to be marked as classifier features for this study. The energy-power domain changes for healthy and neuro-degenerative disease may be considered as a noticeable parameter in gait dynamic study.

Conclusion

Dynamic electromyography offers a means of directly tracking muscle activity. The myo-electric signal sufficiently parallels the intensity of muscle action to serve as a useful indicator of its mechanical effect. Previous methods were based on observations and prone to errors related to person's walking alteration pattern. Here signal processing techniques were implemented in sequential order which leads to classification of PD and control subjects. Initially the raw data were subjected to normalization (i.e., noise and baseline drift cancellation) for further processing (i.e., feature extraction, classification and clustering). LDA and K-means significantly performed the classification and clustering operations respectively. The visual interpretations of these results are clearly showing the two different classes, e.g., Parkinson's disease and control subjects. Further research can be accomplished in the field of pattern recognition and classification between amyotrophic lateral sclerosis, Parkinson's disease and control.

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