MICRORECORDING OF WRITER`S SPASM SIGNALS WITH NATURALLY DEVELOPED COMPLEX REAL-TIME AUTOMATIC MULTI-CHANNEL INTELLECTUAL EMG:

WC Data Analysis using Multivariate Signal processing Techniques

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ABSTRACT

Mirror movements (MMs) are seen in the right hand in Writer’s Cramp (WC) chaos conditions when writing with the left hand. These MMs can be similar to the original dystonic movement while writing with the right hand (concordant) or in the opposite direction (discordant). The basic signal data consisted in this study of EMG-data gathered from 5 weights of the right hand, when the subject inscribed first with right hand (RH) and then, with his/her left hand (LH) i.e., right hand writing signal (RHWS) and left hand writing signal (LHWS). Duration of signal recording was 10 seconds, with 3 kHz sampling frequency, giving 30,000 readings for each weight vector, 1,50,000 samples for 5 weights. The neuro-sensors are embedded in the RH and signal acquisition was performed while writing from both LH and RH. The left hand writing is mainly to see the mirror objects (i.e., movements) of RH. Advanced multivariate techniques employed in the present study include singular value decomposition (SVD)/ Eigen analysis, principal component analysis (PCA), Distance function, simple and (hierarchical) clustering, Canonical correlation/multidimensional scaling and EMG Coherence. The principal component (PC) scores of the 12 chaos conditions showed 80% variance in our computation in the scatter plot diagram. The cluster analysis based on dissimilarity among the subjects' signals show a possibility that, in addition to the grouping of patients as C or D, some other groupings may also be meaningful. EMG-EMG coherence was assessed in the Writer’s cramp hand weights (muscles), namely ECR, ECU, FCR, FCU, and fifth. These observations suggest that the nature of EMG-EMG coherence in dystonia writer’s cramp may be constrained by the descending motor systems, both in terms of their anatomical distribution and their frequency characteristics.

Keywords— Electromyography (EMG), Writer’s Cram (WC), Dystonia, Microelectrode-Recording (MER), signal processing, Principal Component signal Analysis (PCA), Clustering analysis.

I. INTRODUCTION

Bio-digital signals are massively curved data streams which convey relevant information pertaining to the functioning of the human body [1]-[12]. The signals may be of varied origins such as electrical, mechanical,
chemical, acoustics, etc. While acquiring these signals, information may not be obvious because of distortion noise introduced into the signals through (user, instrument, etc), external mainline and hum frequencies (50Hz), presence of signals coming from other interacting systems and instruments, in addition to errors introduced by measurements and physical and physiological factors. Therefore, acquiring and processing the physiological events is a major concern. The other kinds of problems are due to aliasing and leakage of spectral data. To overcome such constraints, appropriate sampling and suitable windowing must be done to eliminate aliasing and minimize the spectral contamination. In this study Dystonia Writer’s cramp movement disorder data acquired with our own indigenously developed real-time multi-channel electromyography (EMG) and implemented with the multivariate signal processing techniques.

Writer’s spasm is one of the commonest focal dystonias occurring 1 in every 500 population [4], [13]. Dystonia is currently defined as a neurological syndrome characterized by involuntary, sustained, patterned, and often repetitive muscle contractions of opposing muscles, causing twisting movements or abnormal postures [14]. Dystonia in writer's cramp is assessed while the subject performs the tasks like drawing spiral symbol, writing while dictating, etc and is rated as per the writer's cramp rating scale (WRCS [3])

II. OBJECTIVES

The goal of the investigation was to build EMG indigenously and record the Writer’s data (voluminous signals) and to establish quantifiable EMG difference in subjects with concordant mirror movements from those with discordant MMs, at micro level and to analyze the data using multivariate signal processing techniques.

III. METHODS

A suitable multi-channel EMG was designed and fabricated indigenously to record digitized EMG signals simultaneously with a set of five innocuous micro-neuro-sensors (50µ). The basic signal data consisted of EMG-data gathered from 5 muscles of right hand, when the subject wrote first with right hand and then, wrote with his/her left hand i.e., right hand writing signal (RHWS) and left hand writing signal (LHWS). Duration of signal recording was 10 seconds, with 3 kHz-sampling frequency, giving 30,000 readings for each weight-muscle and 1,50,000 samples for five weights. Though micro-electrodes can reach the target muscles, still there is a co-contraction between the muscles and this is due to the force (at 30 degrees) applied by the subject during task of writing [2]-[7]. From each signal (of 30,000 sample points) 300 blocks of length 100 constructed and their means are computed. Then after ‘centering’ the signal (i.e., subtracting DC components) SDs were calculated. The amplitude values within 1 SD are treated as ‘noise’ and the means of blocks whose mean values are within 1 SD taken as zero i.e., containing only ‘noise’; only those blocks whose means are greater, in absolute value, than these SDs, are considered as having ‘signal components’. For all 12 subjects, the first five signals represent ‘Left hand Writing Signal (LHWS), next five signals represents ‘Right Hand Writing Signal’ (RHWS), and for all 12 subjects first four muscles of Left Hand Writing (LHW) and Right hand Writing (RHW) are unique (i.e., ECR & ECU, FCR & FCU) and each time the 5th muscle gets changed. The plots for 4 discordant (D) groups are shown in Fig 1–2. Plots of the blocks means, without noise and after suppression of noises are presented (below)
The number of ‘signals’ thus isolated from muscles on R and L hand signals, are given in Table 1.

First 5 columns referring to RHW, next 5 columns to LHW signal unit counts.

Table 1: The number of ‘signals’ isolated from the muscles on the right and the left hand signals

<table>
<thead>
<tr>
<th>Subjects</th>
<th>ECR</th>
<th>ECU</th>
<th>FCR</th>
<th>FCU</th>
<th>5th Muscle</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>101</td>
<td>81</td>
<td>84</td>
<td>85</td>
<td>65</td>
</tr>
<tr>
<td>A2</td>
<td>6</td>
<td>78</td>
<td>73</td>
<td>66</td>
<td>6</td>
</tr>
<tr>
<td>A3</td>
<td>122</td>
<td>103</td>
<td>97</td>
<td>82</td>
<td>94</td>
</tr>
<tr>
<td>A4</td>
<td>79</td>
<td>77</td>
<td>59</td>
<td>76</td>
<td>72</td>
</tr>
<tr>
<td>A5</td>
<td>90</td>
<td>71</td>
<td>79</td>
<td>86</td>
<td>4</td>
</tr>
<tr>
<td>A6</td>
<td>87</td>
<td>87</td>
<td>82</td>
<td>68</td>
<td>88</td>
</tr>
<tr>
<td>A7</td>
<td>89</td>
<td>81</td>
<td>95</td>
<td>90</td>
<td>83</td>
</tr>
<tr>
<td>A8</td>
<td>75</td>
<td>90</td>
<td>101</td>
<td>99</td>
<td>92</td>
</tr>
<tr>
<td>A9</td>
<td>74</td>
<td>53</td>
<td>54</td>
<td>21</td>
<td>98</td>
</tr>
<tr>
<td>A10</td>
<td>50</td>
<td>7</td>
<td>77</td>
<td>83</td>
<td>53</td>
</tr>
<tr>
<td>A11</td>
<td>88</td>
<td>93</td>
<td>91</td>
<td>101</td>
<td>102</td>
</tr>
<tr>
<td>A12</td>
<td>105</td>
<td>88</td>
<td>84</td>
<td>78</td>
<td>93</td>
</tr>
</tbody>
</table>

From this table we can observe that, right hand ECR muscle for subject A1 has 101 signal components/ or units, left hand ECR muscle has 150 units. Hence, LHW muscles activity is more than RHW muscles activity. The differences in these counts, between muscles pairs were also computed.
A scatter plot of these scores is shown in the Fig 3.

Their distances are summarized in the Euclidean space, which subject is nearer to and which are the farthest to each other.

![Fig. 3 Scatter plot first two P.C. Scores ( ~ 80% of variation)](image)

From this plot, it is also suggestive that \{a3, a11, a12\}, \{a10, a5\} may form two similar lineal ordered sets, though the distances are much larger than in the case of the first set.

Subjects \{a8, a9\} are isolated and are very farthest to each other and thus explaining 80% variance.

IV. RESULTS AND DISCUSSION

From the plot of the first two principal component (PC) scores of the 12 dystonic conditions (Fig 3, the following results are obtained and conclusions were drawn:

The points are well scattered out, without clear pattern except for the case of patients \{a6, a4, a7\}. These three are near enough to one another as compared to the remaining nine patients. Indeed, these three seem to form a lineal ordered like radial curves set (and thus forming ellipsoidal curves or resembling clouds in the space or conglomerative) with a4 coming between a6 and a7. It is also suggestive that \{a3, a11, a12\}, \{a10, a5\} may form two similar lineal ordered sets, though the distances are much larger than in the case of the first set.

Subjects \{a8, a9\} are isolated and are very farthest to each other and thus explaining 80% variance.

However, these findings are to be cross-validated with clinical findings on the same patients. It is interesting that the D group subjects do not form a cluster in this scenario. This perhaps needs further looking into the clinical picture of patterns, other than the C and D groupings.

One other approach, which is being investigated, is to examine the distribution of _signal—blocks_ like _horse-jumps_ and the effect on the same when block size (which on a-priori grounds are taken as 100 consecutive samples in deciding about the noisiness of the horse-jump (block), is changed.

Also, one can go for a micro-analysis of the structure of the _signals_ by using the principal component analysis (PCA) and other multivariate techniques of the _signal—block_ (horse-jumps) data. However, they do not seem to be of immediate relevance in clinical, differential diagnosis, and hence are beyond the purview of the present study. The future developments for clinical utility needed the study of _normal_ peoples' data as a control. In order to detect which patient is likely to have muscular diseases and/or movement disorders, from their
interference EMG, it is necessary to be able to predict the number of motor units and the percentage content of abnormal signal units (SUs) within it. The number of SUs computed using signal decomposition is given in Table 1. In this connection, the variances of principal component (PC) scores for mean (not shown the Figures here), the scores obtained are (9.5056 0.9306 0.7124 0.0466 0.0148 0.0029 0.0014 0.0005 0.0002 0.0000 out of a total of 11.215). The Eigen-vectors give the weightages to be given for the 10 means/ standard deviations as the case may be, to construct 10 scores as combinations of the 10 means/ standard deviations for each patient. These scores are such that they have variability’s in decreasing order and are uncorrelated.

V. CONCLUSIONS

Microelectrode recording is useful to identify and confirm the tract in which DBS electrodes are placed and is most useful in determining the depth of electrodes placement but has to be taken in consideration with effects seen on macro stimulation. MER signal measurements are potentially useful for quantifying the effects of DBS on the neuromuscular function of PD conditions. These measurements in combination with the PC-based tracking method can be used to quantify the effects of DBS objectively, cost-effectively and non-invasively. In further studies, the presented approach could be tested in helping the adjustment of DBS settings. In addition, the sensitivity of the presented method to different types of PD should be estimated more carefully in further studies. The availability of microelectrode recording results in a vast data regarding the functioning on the neurons situated deep in the brain and may help in further untying mysteries of the brain.

REFERENCES


