EMBEDDING SPACE NORMALISATION IN 
RECURRENT QUANTIFICATION ANALYSIS OF EMG

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Abstract—A nonlinear dynamical signal analysis technique, recurrence quantification analysis (RQA), was applied to surface EMG recorded during a series of isometric contractions. The way in which a threshold parameter was chosen affected the features found through RQA. A procedure is presented that effectively normalises signals with respect to each other in the embedding space representation used by RQA, resulting in a set of features that vary with the force exerted by the muscle. However, interpretation of the results is limited by the current inability of RQA to take the activity of multiple muscles into account.

Keywords—recurrence quantification analysis, nonlinear dynamics, EMG

I. INTRODUCTION

A. Aim

The aim of this study is to investigate the applicability of a nonlinear dynamical analysis technique, ‘recurrence quantification analysis’, to the problem of examining the electrical activity of muscles during isometric contractions. It has been recently observed [1] that features obtained through this technique may vary with the force produced by muscles. Here we have applied the analysis during contractions at specific force levels.

B. Nonlinear dynamics and embedding theorem

The field of nonlinear dynamics is concerned with the way in which variables describing a system vary with respect to each other instead of time. If the system is way in which variables describing a system vary with respect to each other instead of time. If the system is a nonlinear one, then it can be modelled by applying the ‘embedding theorem’ [2].

The embedding theorem is based on the concept that an observed scalar signal is a 1D projection of the dynamics of the system which are represented in d dimensions. The dynamics can then be reconstructed in a different vector space with d_E dimensions, using only the data in the scalar signal. Suppose that the recorded data is a sampled and quantised signal x(n). Then embedding vectors y(n) are constructed from successively delayed samples of the signal:

\[ y(n) = [s(n), s(n + T), ..., s(n + (d_E - 1)T)] \]

where T is an integer multiple of the sampling period and d_E is the chosen dimension. T is commonly chosen as the lag corresponding to the first zero of the autocorrelation function of x(n), although it has also been argued that the first local minimum of the auto mutual information function is more appropriate [3]. For d_E, we use a test for false nearest neighbours [4]. A vector y^{'i}(n) is a false nearest neighbour to vector y(n) if it is the closest vector to y when they are embedded using dimension d, but much further away in dimension d + 1. Ideally, d_E should be chosen so that there are no false nearest neighbours; in practice, < 1% false nearest neighbours is accepted to allow for the effects of random noise.

C. Recurrence plots and RQA

Several tools have been developed to analyse the dynamics described by embedding vectors y(n). One such technique is recurrence quantification analysis (RQA), an extension of a graphical method called recurrence plot analysis. A recurrence plot shows the times when two vectors y(i) and y(j) are close to each other, i.e. when y(j) is within a distance r of y(i) [5]. If y(j) is close to y(i) then point (i, j) is called a recurrent point and a plot of all recurrent points is called a recurrence plot. Recurrent points form a variety of patterns, the most important being upwards diagonal line segments. These indicate that the dynamics represented by a series of vectors are later repeated, hence there is some determinism in the dynamics. An example of a recurrence plot is shown in Fig. 1.

Recurrence plots are most usefully described using a set of features collectively known as recurrence quantification analysis (RQA). These are [5]:

- REC (% recurrence), the percentage of the recurrence plot covered by recurrent points;
- DET (% determinism), the percentage of recurrent points contained in upwards diagonal line segments;
- D/R, the ratio of DET to REC;
- L_{max}, the maximum length of upwards diagonal line segments;
- ER (entropy of recurrence), the entropy of the distribution of lengths of upwards diagonal line segments;
- TLR (trend of local recurrence), a measure of the change in density of recurrent points away from the line i = j. Stationary signals have a TLR value close to zero.

\[ r = \text{distance between } y(i) \text{ and } y(j) \]

\[ d_E = \text{dimension used in embedding} \]
D. Embedding space normalisation

The threshold for generating recurrence plots is often specified in terms of another value, e.g. 10% of the maximum Euclidean distance between embedding vectors. Let us call this specification a relative threshold, \( r_{\text{rel}} \), and call the numerical value of the distance the actual threshold, \( r_{\text{act}} \). Then \( r_{\text{act}} \) is simply the result of evaluating the specification \( r_{\text{rel}} \). Any scaling or DC offset of the signal \( s(n) \) has no effect on the recurrence plot provided that \( r_{\text{rel}} \) is specified in the same way (Table 1). This has the same effect as normalising the embedding vectors, although it is really \( r_{\text{act}} \) that is scaled rather than the vectors themselves. We call this effect embedding space normalisation. In some situations, such as EMG recorded at different levels of muscular force, it may be useful to retain the amplitude relationship that is otherwise lost through embedding space normalisation. In this isometric force study, we propose to do this by calculating \( r_{\text{act}} \) from \( r_{\text{rel}} \) for the EMG at a single force level only, then using \( r_{\text{act}} \) as the threshold for finding recurrence plots at all other force levels.

II. EXPERIMENTAL METHODS

Six healthy male subjects aged 20–36 (mean ± 1sd = 24 ± 6 years) volunteered for this study. Subjects were seated and instructed to flex their right wrist against a cantilever beam with their upper arm vertical, elbow flexed at 90° and forearm supine (palm up). The beam was instrumented with four strain gauges in full bridge arrangement. Surface EMG was recorded from the right biceps brachii muscle using Noro-Trode™ adhesive dual Ag-AgCl electrodes (Myotronics-Noromed, Inc.) and 63 dB, custom-built 10–500 Hz EMG amplifiers. Skin preparation prior to attaching electrodes included wiping with an isopropyl alcohol swab to dissolve skin oils, shaving hair from the recording site and rubbing the skin 20 times with 800-grade silicon carbide paper to thin the keratin layer and thereby decrease the skin’s resistance. Data was recorded digitally at 1000 samples / s using a 12-bit data acquisition card with input limits ± 5 V (National Instruments PC-LPM-16PnP).

Subjects viewed the output from the strain gauge bridge along with a target line on a computer monitor. The maximum force achievable at the wrist was determined by instructing the subjects to follow an increasing target as far as possible. EMG was then recorded while the subjects attempted to maintain 0, 10, 30, 50 and 70% of this maximum force over 7 s. Subjects rested for 5–7 minutes between trials in order to avoid fatigue effects.

RQA was performed on an epoch of 1 s (1000 points) selected from each recording. Embedding parameters \( T \) and \( d_E \) were different for each signal. \( T \) was taken as the lag corresponding to the first minimum of the auto mutual information function, calculated as described in [6]. \( d_E \) was chosen as the lowest dimension for which the percentage of false nearest neighbours was < 1% [4]. Values for \( T \) were 4 ± 1 sample and values for \( d_E \) were 18 ± 5 (mean ± 1sd). Recurrence plots were generated in two ways:

1. Using the same relative threshold \( r_{\text{rel}} \) at each force level, \( r_{\text{rel}} \) was chosen as 30% of the maximum distance between embedding vectors; for each signal, this value was in the range of thresholds where \( \log(\text{REC}) \) varied linearly with \( \log(r) \) [7].

2. Using the same actual threshold \( r_{\text{act}} \) at each force level, \( r_{\text{act}} \) was calculated from \( r_{\text{rel}} = 30\% \) of the maximum distance between embedding vectors only for the signal corresponding to 50% of the maximum force. This was then used as the threshold for all five recurrence plots for that subject. The signal at 50% of the maximum force was chosen because \( r_{\text{act}} \) increased with force for a given \( r_{\text{rel}} \).

Table 1. A: RQA features calculated from the recurrence plot in Fig. 1. B: RQA features calculated from a recurrence plot for the same EMG signal as in Fig. 1 but scaled by –2 and offset by 2V. Again \( T = 5, d_E = 15, r_{\text{rel}} = 30\% \) of the maximum distance between vectors as for Fig. 1. By keeping \( r_{\text{rel}} \) the same (so that \( r_{\text{act}} \) has doubled), the scaling and offset have not affected the RQA features.

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
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<tbody>
<tr>
<td>REC (%)</td>
<td>1.34</td>
<td>1.34</td>
</tr>
<tr>
<td>DET (%)</td>
<td>70.9</td>
<td>70.9</td>
</tr>
<tr>
<td>D/R</td>
<td>52.9</td>
<td>52.9</td>
</tr>
<tr>
<td>( I_{\text{max}} )</td>
<td>929</td>
<td>929</td>
</tr>
<tr>
<td>ER (bits)</td>
<td>0.918</td>
<td>0.918</td>
</tr>
<tr>
<td>TLR</td>
<td>-0.0017</td>
<td>-0.0017</td>
</tr>
<tr>
<td>( r_{\text{act}} )</td>
<td>4.64</td>
<td>9.28</td>
</tr>
</tbody>
</table>
Figure 2. RQA features calculated using different thresholds to generate the recurrence plots at each force level. A: $L_{\text{max}}$, B: REC (%), C: D/R, D: $L_{\text{max}}^{-1}$, E: DET (%), F: ER (bits). Horizontal scale: % maximum force. No trends are evident in the plots.

Figure 3. RQA features calculated using the same threshold to generate the recurrence plots at each force level. A: $L_{\text{max}}$, B: REC (%), C: D/R, D: $L_{\text{max}}^{-1}$, E: DET (%), F: ER (bits). Horizontal scale: % maximum force. There appear to be trends particularly in plots A and C, but not for all subjects.
III. RESULTS

The results for each subject, along with the mean results, are shown in Figs. 2 and 3. Individual subjects are represented by different markers and the mean values are joined with a line. TLR is not shown as this was within ± 0.02, indicating that the analysed sections of the EMG signals were stationary. Both $l_{\text{max}}$ and $l_{\text{max}}^{-1}$ are shown since $l_{\text{max}}^{-1}$ is correlated with other measures of rates of divergence of the trajectories traced by embedding vectors [8].

Where $r_{\text{rel}}$ was the same for each force (Fig. 2), it is difficult to observe any trend in the variation of RQA features with increased force. In contrast, using the same $r_{\text{rel}}$ for each force level (Fig. 3) appears to result in quite different values at different force levels with the exception of ER. There is still considerable inter-subject variability however, and the trends indicated by the mean values are not followed for every subject.

IV. DISCUSSION AND CONCLUSION

Using the same actual threshold value for generating the five recurrence plots for each subject resulted in a clearer variation of the RQA features with force than if the same relative threshold was used. However, the relationship between force and any given feature is still ambiguous. Even the more promising features, particularly $l_{\text{max}}$ and D/R, have large inter-subject variability. This may be expected from warnings that RQA features should not be interpreted as absolute quantities since they depend on the parameters chosen to generate recurrence plots [8], as was demonstrated here. Even so, the overall trend was not followed for every subject, regardless of specific values.

This may be explained by an assumption made about the EMG-force relationship investigated here. The recorded force is not that produced by the muscle as such, but instead proportional to the moment about the elbow joint. In performing RQA on the EMG from m. biceps brachii at different force levels, we have assumed that this muscle is solely responsible for this moment. This is not a valid assumption since at least two other major elbow flexors, m. brachialis and m. brachioradialis, also contribute. Some of the variability observed in these results may therefore reflect different muscle recruitment strategies in attempting to produce a constant moment. Comparing with other studies [1], changes in DET with force were examined in a similar experiment to this. During a varying-force contraction, DET was found to increase with force (cf. Fig. 3) but results from a series of constant force contractions at different levels indicated no clear relationship.

It may be argued that if the same actual threshold should be used with a set of signals, then the same embedding parameters should be used so that the dimension of the embedding space remains constant.

We performed the analysis again using this approach, and found that the variation of the RQA features with force closely resembled that shown in Fig. 3. This is not surprising, since the standard deviation of $T$ was < 1 sample and the standard deviation of $d_{\text{E}}$ was less than 2 for most subjects.

In conclusion, using the same embedding and (actual) threshold when performing RQA on a set of EMG signals ensures that the signals are normalised with respect to each other rather than to themselves in the embedding space. However, more work is required on ways to include the EMG from multiple muscles in RQA before any real benefits from using this signal processing method in muscle force studies are likely to be seen.

REFERENCES