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Principal Components of Recurrence Quantification Analysis of EMG

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Abstract—**A nonlinear dynamical signal analysis technique, recurrence quantification analysis (RQA), was applied to surface electromyograms (EMG) recorded during a series of isometric contractions. None of the ten RQA features calculated adequately related the EMG to the force level so principal components analysis was applied to combine these features into a lower number of variables. Linear regression of the first principal component gave similar lines for each subject. However, the error was too great for these lines to be used in predicting force from the principal component.**

Keywords—**EMG, nonlinear dynamics, recurrence quantification analysis, principal components analysis.**

I. Introduction

A. Aim

The aim of this study was to investigate the applicability of a nonlinear dynamical analysis technique, 'recurrence quantification analysis' (RQA), to the problem of examining the electrical activity of muscles (electromyogram, EMG) during isometric contractions. Recently [1], it was observed that features obtained through RQA may vary with the force produced by muscles. It has also been reported [2] that more meaningful results may be obtained applying principal components analysis (PCA) to a set of RQA features. To investigate this for EMG, we recorded signals from volunteers during muscular contractions at specific force levels and applied a joint RQA-PCA process.

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 described by d variables $x_1, x_2, \ldots, x_d$, then this relationship is the path traced by the vector $[x_1, \ldots, x_d]$. In many physical and physiological systems however, it is only possible to measure a single variable. For example, the EMG signal might be the only quantity recorded from a neuromuscular system. The dynamics of such systems can be modelled by applying the 'embedding theorem' [3].

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 $s(n)$. Then *embedding vectors* $\mathbf{y}(n)$ are constructed from successively delayed samples of the signal:

$$\mathbf{y}(n) = [s(n), s(n+T), \ldots, s(n+(d_E-1)T)]$$

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 $s(n)$, although it has also been argued that the first local minimum of the auto mutual information function is more appropriate [4]. Little difference was found between these two measures for the signals recorded in this study. A test for false nearest neighbours can be used to find an appropriate value for d_E [5]. A vector $\mathbf{y}^F(n)$ is a false nearest neighbour to vector $\mathbf{y}(n)$ if $\mathbf{y}^F$ is the closest vector to $\mathbf{y}$ when they are embedded in 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 $\mathbf{y}(n)$. One such technique is based on a graphical method called recurrence plot analysis [6]. A recurrence plot shows the times when two vectors $\mathbf{y}(i)$ and $\mathbf{y}(j)$ are close to each other, i.e. when $\mathbf{y}(j)$ is within a distance r of $\mathbf{y}(i)$. If $\mathbf{y}(j)$ is close to $\mathbf{y}(i)$ 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. The plot is symmetrical about $i = j$ because if (i, j) is a recurrent point then from the above definition, (j, i) is also a recurrent point. Although the way in which recurrent points are determined seems straightforward, it is difficult to obtain much useful information from the plot by visual inspection

Recurrence plots are most usefully described using a set of features collectively known as *recurrence quantification analysis* (RQA). These are [6, 7]:

- 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 $i = j$;

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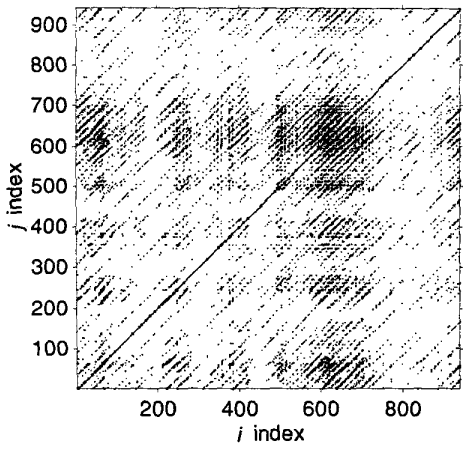

Fig. 1. Recurrence plot of one second of a surface EMG signal recorded from subject 2 at 30% MVC force level.

- T_1 (mean recurrence time of the first type), the average time taken for a point in the embedding space to be 'revisited';
- T_2 (mean recurrence time of the second type), the average time taken for a point in the embedding space to be 'revisited' excluding times of one unit.

In addition to L_{max}, we also calculated the mean and median lengths of upwards diagonal line segments, L_{mean} and L_{med}.

The TLR measure can be useful when applying other signal processing methods that demand stationarity, since stationary signals have a TLR value close to zero.

II. Experimental Methods

A. Data Acquisition

Eight healthy male subjects aged 18–36 years (mean = 24) volunteered for this study. Skinfold thickness as measured over the right biceps brachii muscle was 2.5–6 mm (mean 3.5 mm). 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. Prior to attaching the electrodes, the recording site was prepared by 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 maximal voluntary contraction (MVC), taken as 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 the MVC over 7 s. Subjects rested for 5–7 minutes between trials in order to avoid fatigue effects.

B. Analysis

RQA was performed on an epoch of 1 s (1000 points) selected from each recording. Embedding parameters T, d_E and the distance threshold r were different for each subject, but the same parameters (calculated from the 70% MVC recordings) were used for all recordings from a given subject. T was taken as the lag corresponding to the first minimum of the auto mutual information function, calculated as described in [8]. d_E was chosen as the lowest dimension for which the percentage of false nearest neighbours was < 1% [4]. T was 4 samples for each subject and values for d_E were 15–23 (mean = 17). To calculate threshold r, first values corresponding to 30% of the maximum distance between embedding vectors at each force level were calculated. r was then chosen halfway between the maximum and minimum values.

Since the ten RQA features have different units, each was divided by its standard deviation before applying PCA. This 'standardised' data was then projected onto the principal components for further analysis.

III. Results

A. Individual RQA features

Plots of the changes in RQA features vs force levels were not encouraging. Overall, the three line lengths L_{max}, L_{mean} and L_{med} decreased with increasing force, as did REC. The ratio D/R increased, but there was little overall pattern otherwise. Fig. 2 shows plots of REC, D/R and ER. REC and D/R possibly follow power laws, but it is difficult to tell for certain given the low number of force levels. Certainly there is little to suggest there is a more useful relationship between these features and force than there is between RMS amplitude of the EMG and force.

B. RQA features combined via PCA

It was found that the total variability of the standardised features was completely explained by four principal components, with the first two components explaining 79–96% (mean 86%). Generally, the three largest weights for the first component (PC1) corresponded to REC, L_{mean} and L_{med}; the three largest weights for the second component (PC2) corresponded to D/R, ER and T_2 or TLR.

Fig. 3 shows the RQA features data for all subjects projected onto PC1 and PC2 (i.e. the linear combination of the RQA features indicated by the weights in PC1 and PC2), along with the mean results. PC1 generally decreases with increasing force, although not at all uniformly. PC2 generally has a local minimum at 30% MVC, except for one subject

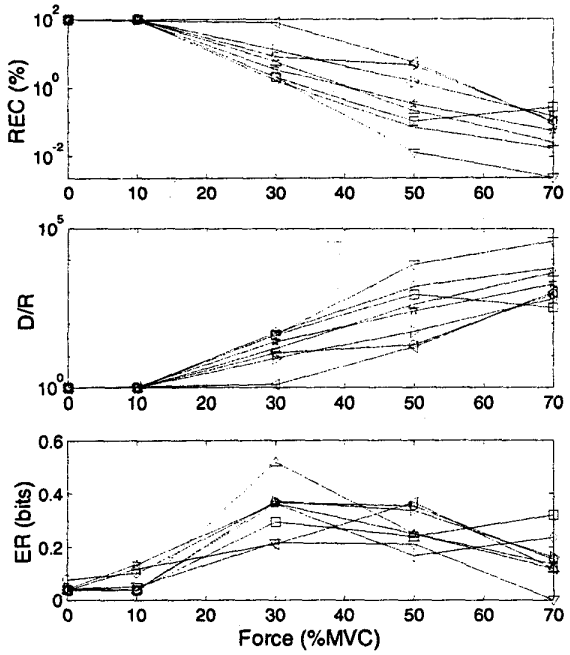

Fig. 2. Variation of some RQA features with force (for all subjects).

with a minimum at 50% MVC. More striking is the projection of the data onto the PC1-PC2 plane (Fig. 4) which shows that as force increases, a U-shaped trajectory is traced out clockwise in the plane.

Another surprising result was obtained by applying a least-squares linear regression to the projection of data on PC1 (Fig. 5), with the slopes of the lines for each subject appearing similar (between –0.061 and –0.088 units/%MVC, *mean* = –0.076 units/%MVC) and the lines intersecting at the 32% MVC force level where PC1 is 0.

IV. Discussion and Conclusion

An unfulfilled goal of EMG signal processing is to find a definitive relationship between the EMG and force produced by the muscle, or at least the torque about a joint since this is easier to measure than muscular force. Such a relationship would make it possible to determine the force or torque from the EMG. While some of these results are interesting, particularly the behaviour in the PC1-PC2 plane and the closeness of the slopes of the regression lines for projections on PC1, it is unlikely that they are particularly useful in terms of this goal. The difference between the projected RQA data values and the values along the lines of best fit (Fig. 5) are too great for the lines to be used in predicting force levels. Also, the projections on PC1 were only monotonically decreasing for 3 out of the 8 subjects (Fig. 3). Due to the low sampling of this curve (only five force values), it is unclear whether or not this is due to errors for the other subjects.

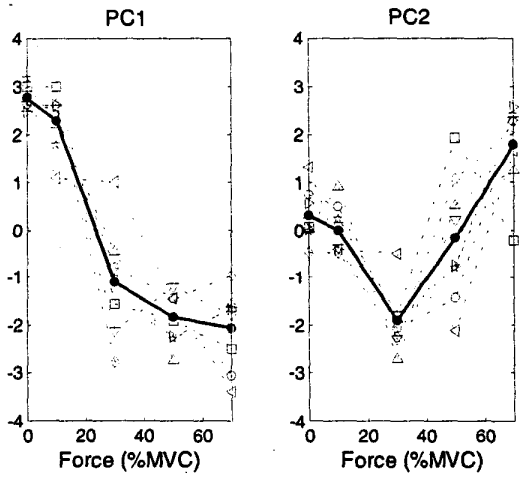

Fig. 3. RQA feature data in terms of the first two principal components (PC1 and PC2). Dashed lines: results for individual subjects. Solid lines: mean result.

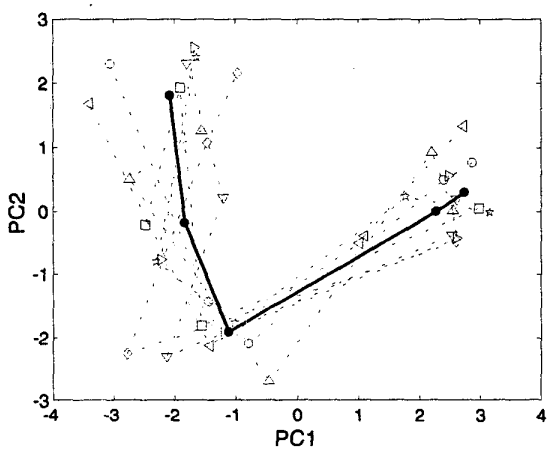

Fig. 4. RQA feature data projected onto the PC1-PC2 plane. Dashed lines: results for individual subjects. Solid lines: mean result.

The low sampling of force values also makes the task of performing PCA an ill-posed problem, since there are more RQA features than force levels. So differences between projections on the components for different subjects may be reduced if more force levels were examined. Of course, this would require subjects to volunteer much more of their time.

Another limitation in attempting to use these results is that this analysis was performed with static forces, over 1 s epochs during which the EMG signal was roughly stationary (as indicated by |TLR| < 0.008 for all signals). If the force changes during the analysed epochs then it becomes even more difficult to relate RQA variables or a linear combination of them to specific force levels. But in another study where RQA was used on EMG signals for studying fatigue [9], the feature DET changed earlier than other parameters after a step load increase. Whether the magnitude of the change in DET was necessarily related to the magnitude of the change in the load was not reported, nor

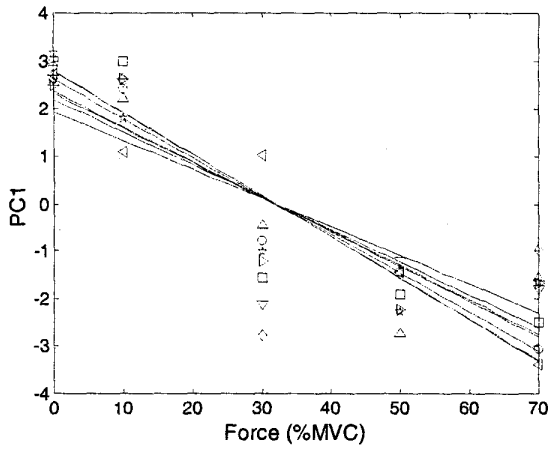

Fig. 5. Linear regression of RQA feature data projected onto PC1. The actual values for each subject are also shown (cf. fig. 3).

were the effects of different loads. Interestingly, and in contrast with the results shown in Fig. 2, there was little change in REC in that study.

One problem that has so far been ignored is that only the EMG of m. biceps brachii has been considered as contributing to the torque about the elbow joint, when in fact there are at least two other main elbow flexor muscles that also contribute. It is unlikely that EMG will be successfully related to the torque about a joint until methods are developed that incorporate the activities of all the muscles contributing to that torque.

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