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Title: Modelling Multivariate Biomechanical Measurements of the Spine During a Rowing Exercise

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Abstract

Objective. To investigate the ability of statistical techniques to detect systematic changes in rowing technique during a rowing session and to discriminate between rowers of different abilities with and without back pain.

Design. Statistical techniques were applied to kinematic datasets of elite level rowers, in order to construct an empirical model of the rowing stroke.

Background. The size and complexity of datasets generated by biomechanical kinematics evaluations has led to opportunities for analysing pathology whilst introducing substantial challenges for statistical analysis.

Methods. Spinal motion and load output of 18 International and national standard competitive rowers were monitored during ergometer rowing sessions. International rower data were used to construct an empirical model of this activity. Linear stroke models were derived using principal components and a generalised cross-validation procedure. Performance characteristics of the identified models were calculated for all rowing groups. The stroke model was applied to distinguishing pattern variations within and between rowers. A multivariate logistic regression analysis was carried out to examine the relationship between stroke model parameters on the incidence of low back pain.

Results. 90% of the variability in the data was explained by the first three principal component variables. Stroke models with three basis functions were selected for each variable. The models performed well on the national rowers, providing validation of the models. A 2-variable model showed a significant difference between the rowing stroke characteristics of rowers with and without low back pain ($P < 0.01$).

Conclusions. A parsimonious collection of empirical models effectively describes motion and load characteristics of ergometer rowing. Patterns in rowing technique are found to be strongly associated with the incidence lower back pain.

Relevance

Empirical statistical models can be used to track changes in rowing technique, and discriminate between different rowing groups. This may impact rowing training, and rehabilitation.

Keywords: cross-validation, kinematics, principal component analysis, growth curve modeling, analysis of variance, low back pain, risk analysis.

Introduction

The aim of this work was (i) to create an empirical model which parametrically described the biomechanics of a repetitive activity and to test the validity of that model on a set of data that was not used in the construction of the form of the model, and (ii) to use the model to test the hypothesis that rowing stroke technique is associated with the incidence of low back pain.

Methods

A data acquisition and measurement system was used to quantify the movement of the lower back during exercise on a rowing ergometer in terms of absolute position (y – vertical in the sagittal plane of the rowing machine and z – horizontal in the sagittal plane of the rowing machine) and absolute orientation (three angles, roll azimuth and elevation) of two sites on the lower spine (the twelfth thoracic spinous process overlying the thoraco-lumbar junction and the sacrum just below the lumbo-sacral junction) and one site on the thigh (Bull and McGregor, 2000). This was extended to include force data at the handle of the ergometer.

A database of information on 18 International and national elite rowers was created. The data were sampled from ergometer sessions lasting between 20 to 60 minutes. In each session rowers maintained a steady stroke rate of between 17 and 19 strokes per minute. The raw data acquisition times were re-formatted according to individual strokes with a fixed number ($T = 100$) of measurement times per stroke (Bull and McGregor, 2000). Thus the data can be represented as an array $\{X_{ts}^{(j)}, t = 1,2,...,T; s = 1,2,...,S_j; j = 1,2,...,N\}$ where $X_{ts}^{(j)}$ is the 16-dimensional multivariate measurement made at time t in the s'th stroke of the j'th rower. The first N_o rowers are the International rowers and the remaining $N_r = N - N_o$ are the national rowers. The components of the multivariate measurement are divided into a 15-dimensional position vector $P_{ts}^{(j)}$ and a 1-dimensional load value $L_{ts}^{(j)}$, thus $X_{ts}^{(j)} = (P_{ts}^{(j)}, L_{ts}^{(j)})$. The s'th stroke is approximated as

$$X_{ts}^{(j)} = m(t \mid \theta_s^j) + \varepsilon_{ts}^{(j)}$$

where $m(t \mid \theta_s^j)$ is an appropriate model form and θ_s^j is a set of stroke parameters - specific to the particular stroke under consideration. The error term, $\varepsilon_{ts}^{(j)}$, represents negligible deviations from the model. If a suitable model can be developed then the analysis of experiments could be reduced to the study of the behaviour of the derived parameters θ_s^j - as in the growth curve analysis of repeated measures (Loslever, 1993; Mardia et al., 1979).

This analysis separately considers the position and load portions of the data and focuses on linear forms for the model. Principal components analysis (PCA) is used. The statistical model is restricted to the data obtained from the International rowers. The other data are used to evaluate the performance of the identified model. First, the model construction for the load variable is described. After this the approach is generalized to derive an analogous model for the position data.

Stroke Model for Load

The load is normalized by dividing by the cumulative exerted force, $L_{.s}^{(j)} = \sum_{t=1}^{T} L_{ts}^{(j)}$, producing $z_{ts}^{(j)}$ where $z_{ts}^{(j)} = \dfrac{L_{ts}^{(j)}}{L_{.s}^{(j)}}$. The model form, $m_z(t \mid \theta)$, for $z_{ts}^{(j)}$ is linear i.e.

$$m_z(t \mid \theta) = \mu(t) + \theta_1 \gamma_1(t) + \theta_2 \gamma_2(t) + \ldots + \theta_K \gamma_K(t) \qquad \text{Equation 1}$$

Given the data $\{z_{ts}^{(j)}, t = 1,2,\ldots,T; s = 1,2,\ldots,S_j; j = 1,2,\ldots,N_o\}$, values for the vectors $(\mu(t), \gamma_1(t), \gamma_2(t),\ldots,\gamma_K(t), t = 1,2,\ldots,T)$ are chosen to minimize the residual sum of squares deviation (RSS) between the available International rowers' data and the model, i.e.

$$RSS(\mu,\gamma_1,\gamma_2,...,\gamma_K)=\sum_{j=1}^{N_0}\sum_{s=1}^{S_j}\left\{\min_{\theta}\sum_{t=1}^{T}\left[z_{ts}^{(j)}-\mu(t)-\theta_1\gamma_1(t)-\theta_2\gamma_2(t)-...-\theta_K\gamma_K(t)\right]^2\right\}$$

The solution is given by the mean, $\hat{\mu}(t)=\frac{1}{S^*}\sum_{s,j}z_{ts}^{(j)}$ with $(S^*=\sum_{j=1}^{N_0}S_j)$ and $(\hat{\gamma}_1,\hat{\gamma}_2,...,\hat{\gamma}_K)$ first $K\leq T$ eigenvectors of the covariance matrix $\sum_{tt'}=\frac{1}{S^*}\sum_{s,j}\left[z_{ts}^{(j)}-\hat{\mu}(t)\right]\left[z_{ts}^{(j)}-\hat{\mu}(t')\right]$ (Mardia et al., 1979). A generalized cross-validation (GCV) criterion (Wahba, 1990) is applied to evaluate how the predictive error of the model varies as a function of the number of terms (K) included. The criterion used is:

$$GCV(K)=\sum_{j=1}^{N_0}\sum_{s=1}^{S_j}\frac{\sum_{t=1}^{T}\left[z_{ts}^{(j)}-\hat{\mu}(t)-\theta_{1s}^{j}\hat{\gamma}_1(t)-\theta_{2s}^{j}\hat{\gamma}_2(t)-...-\theta_{Ks}^{j}\hat{\gamma}_K(t)\right]^2}{\left[1-\frac{K}{\tilde{T}}\right]^2}$$

Here $\{\theta_{ks}^{(j)}k=1,2,...,K\}$ are the minimum least squares set of model coefficients for representation of the *s*'th stroke of the *j*'th subject. A value $\tilde{T}\leq T$ is used in the denominator of the GCV criterion to adjust for the fact that the T measurements on a given stroke cannot be considered as statistically independent. The data have strong positive auto-correlation because the raw data are sampled and then interpolated to produce equi-spaced values at T fixed points throughout the stroke. $\tilde{T}$ is selected so that $K=\tilde{T}$ explains 99% of the variance in the data. Thus the GCV criterion will focus on models that have no more than $\tilde{T}$ terms.

Generalization to Spine Position Modeling

The position data $\{P_{lts}^{(j)},l=1,2,...,15;t=1,2,...,T;s=1,2,...,S_j;j=1,2,...,N\}$ are standardized, separately for each rower. Thus $P_{ts}^{(j)}\rightarrow\tilde{P}_{ts}^{(j)}$ where:

$$\tilde{P}_{lts}^{(j)}=\frac{P_{lts}^{(j)}-\overline{P}_{l..}^{(j)}}{sd_l^{(j)}}$$

Here $\overline{P}_{l..}^{(j)}$ and $sd_l^{(j)}$ are the mean and standard deviation of the l'th component of the j'th rowers position values i.e. $\overline{P}_{l..}^{(j)} = \frac{1}{TS_j}\sum_{s,t} P_{lts}^{(j)}$ and $sd_l^{(j)} = \sqrt{\frac{1}{TS_j}\sum_{s,t}\left[P_{ts}^{(j)} - \overline{P}_{l..}^{(j)}\right]^2}$. This standardized position data could be analyzed to produce separate stroke models for each of its 15 components. Given that the different items of position data are highly correlated it may be reasonable to focus on a reduced set of variables for analysis. By principal component analysis (PCA) how well the system can be represented in terms of $M < 15$ derived variables (degrees of freedom) can be examined. Using data from the 6 International rowers, 90% of the variability in the data is explained by the first 3 principal components and 98% by the first 6 components. There is a dramatic fall in the amount variability explained after the first 2 or perhaps 3 principal components. Therefore, the analysis is restricted to the first 3 principal components of the position data for modeling. The reduced variables are given by $V_{ts}^{(j)}$ with $V_{ts}^{(j)} = \Delta\,\tilde{P}_{ts}^{(j)}$ and $\Delta_{3\times15}$ is a rotation or loading matrix. The derived variables are labelled as Forward Motion, Torsion Contrast and Roll Contrast. These arbitrary labels were used, because they reflect the relative loading of the derived position variables. Separate stroke models were developed for each of these derived position variables. Thus models of the form below are obtained for each of the three derived position variables.

$$m_v(t \mid \theta) = \mu(t) + \theta_1\gamma_1(t) + \theta_2\gamma_2(t) + \ldots + \theta_K\gamma_K(t) \qquad \text{Equation 2}$$

The values of $(\mu, \gamma_1, \gamma_2, \ldots, \gamma_K)$ and the number of terms (K) are selected using the same techniques as described by the load analysis above.

Results

The statistical behaviour of the load and derived principal components are presented in Figure 1. Models with varying numbers of terms (K) were evaluated for each of the four variables under consideration. Two terms $(K = 2)$ are optimal for Load, Forward Motion and

Roll Contrast, while three terms $(K = 3)$ are optimal for description of the Torsion Contrast. The GCV performance characteristics substantially deteriorate with larger values of K.

Models with $K = 3$ terms were selected for each variable. The parameters $(\gamma_1, \gamma_2, \gamma_3)$ of the respective models are presented in Figure 2. The load parameters are focused on the drive phase of the stroke, whereas the position parameters have important structures in both the drive and recovery phases of the stroke. The first parameters (γ_1) in each model provides for a complementary adjustment to two distinct parts of the stroke - a positive adjustment in one area is associated with a negative adjustment in another. This may allow the stroke model to adjust to variations in the phase of mean profile. For example, the γ_1 pattern for load provides the ability to model strokes in which the load peaks before or after the peak in the average load. This scenario is shown in Figure 1a. There is some similarity between the parameters arising in the models of Forward Motion, Torsion and Roll Contrast. In each case the second parameter, γ_2, is relatively flat so that relative position of the stroke can be moved forwards or backwards. The third parameter for position variable models and the second parameter of the load allows the model to capture strokes profiles which are more or less sharp than the mean profile. The third parameter of the load model is the most complex but would allow the model to capture load profiles which are sharper/broader at the beginning and broader/sharper at the end of the drive.

Performance characteristics (R^2 statistics) of the identified models for International and national rowers are reported in Table 1. Although the model development was carried out only using data from the International rowers, the models identified perform very well on the national rowers. This is a strong validation of the models identified.

Factors Associated with a History of Low Back Pain

Nine out of the 18 rowers had suffered low back pain (LBP) previously. The statistical behaviour of the ergometer session stroke model parameters were examined for differences between rowers with and without a history of LBP. The mean and standard deviation of the stroke model parameters over the ergometer session were determined and a 2-sample 2-sided Student's *t*-tests carried out to to compare the values of these variables in these two groups. The most notable differences between the groups are obtained for the mean of the third load parameter ($P = 0.036$) and the standard deviation of the first parameter of forward motion ($P = 0.052$). The group with a history of LBP has higher values for both these variables.

A logistic regression analysis was carried out to obtain a more comprehensive picture of the relationship between the model parameters and the history of LBP. This analysis evaluates the relationship between the odds (ψ) of a history of LBP (the odds of a history of LBP is defined as $\psi = \frac{\pi}{1-\pi}$ where π is the probability or risk of a history of LBP). After dropping variables showing the weakest association with a history of LBP, a two-variable model was developed:

$$\log(\psi) = 0.32(\pm.76) + 1.97(\pm1.04)\overline{L3} + 2.28(\pm1.38)\sigma(F1) \qquad \text{Equation 3}$$

where $\overline{L3}$ is the mean for a given rower over strokes of the third parameter in the stroke model for load and $\sigma(F1)$ is the standard deviation for a given rower over stokes of the first parameter in the stroke model for the forward motion variable. Both variables were standardized to have mean zero and unit variance across the 18 rowers in the dataset. While neither variable has reached formal statistical significance at the 0.05 level (the relevant 2-sided *P*-values are 0.059 and 0.098 respectively), the sample size of 18 involved here is very modest. It should be noted that the estimated effects are substantial and by even doubling the number of rowers there would be ample power to statistically validate the above relation. The separation between the rowers with and without a history of LBP in terms of these variables is shown in Figure 3. The optimal linear separation associated with the logistic model (dotted line) is also shown. The linear combination of variables in equation 3 defines a potential risk factor for a history of LBP. The average value of this variable differs significantly between rowers with and without a history of LBP ($p = 0.0028$).

Using the dotted line in Figure 3 to separate rowers with a history of LBP (above the line) from rowers without a history of LBP (below the line), we see that six of the nine rowers with a history of LBP are correctly classified, as are 8 of the 9 rowers without a history of LBP. This is an overall success rate of 78% which is excellent given that a history of LBP is a largely a self-reported variable. In clinical terms it may be important to identify rowers whose technique indicates a potential to develop LBP, although these statistics do not prove a causative link. Better classification of individuals with a history of LBP at a cost of misclassifying individuals without a history of LBP could be desirable. By moving the line slightly (dashed line in Figure 3) it is possible to classify eight of the nine rowers with a history of LBP correctly at the cost of misclassifying 2 of the rowers without a history of LBP. The overall misclassification rate remains the same but this classifier is better able to pick out the rowers with a history of LBP.

Discussion

Improvements in technology have facilitated detailed kinematics analysis of specific complex tasks such as rowing. The output from such analysis is vast and complex, making clinical interpretation almost impossible. In this example, our goal was to construct a parametric model of the rowing stroke to describe how the displacements and force characteristics behave during this stroke. Ultimately this would mean that the stroke could be characterised by a reduced set of parameters making a clinical interpretation possible and the identification of rowing trends feasible. Statistical analysis in an experimental setting would then be performed in terms of these configurations. For example, it may be possible to relate an injury such as LBP to specific configurations of the biomechanical parameters and provide interactive user feedback on desired refinements.

The model parameters used to discriminate between rowers with and without a history of LBP are not immediately related to clinical variables but are related to technical errors identified by rowing coaches. It is possible to deduce some clinical significance from these. The two parameters used are shown in equation 3. $\overline{L3}$ is related to the skewness of the load profile. This suggests that rowers with a very sharp, or heavy, catch tend to have a higher probability of LBP. A sharp catch is related to the onset of force applied at the handle. It is conceivable that a rower who applies force very quickly may not have the postural control in the trunk to control the transfer of that force from the hands through the kinematic chain to the trunk and then the feet and thus may develop LBP. This is interesting, because there are distinctly different rowing techniques, where coaches focus on either achieving a very rapid force production at the catch, or a slower rate of force production. Further work needs to be conducted to assess the effect of this variable.

$\sigma(F1)$ assesses variability in the forward motion position variable. To the extent that variability here is a measure of the rower's ability to control the motion and achieve the appropriate stroke length, it is reasonable to suggest that rowers with a history of LBP would show less control. The slope of the line in Figure 3 suggests that both variables are almost equally important. Alternative modelling techniques may be applied to discern if these two variables are not more closely related. This could be done by, for example, not separating the load variable from the position variables in the stroke model principal component analysis. However, by doing this the model would be further removed from direct clinical measures, and would thus be less clinically-relevant.

This preliminary statistical analysis has shown that it is possible to reduce a complex set of biomechanical parameters to identify rowing trends. The reduction in the set of variables has introduced the problem of understanding the clinical signficance of these variables which are combinations of direct measures of position and load. It is our intention to use different statistical tools to create an ‘expert’ set of reduced variables which are more clearly related to the direct measures. The relationship to LBP is an important one and we envisage the development of this tool to include activities other than rowing.

Acknowledgement

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Figure Legends

Figure 1 Statistical behaviour of the ergometer strokes of the 6 International (left) and 12 non-international rowers (right). The mean (solid), 25^{th} and 75^{th} percentiles (dashed) of normalised load (a), forward motion (b), torsion contrast (c) and roll contrast (d) are shown.

Figure 2 Estimated components of the Stroke Models identified for (a) load, (b) forward motion, (c) torsion contrast and (d) roll contrast. $(\gamma_1, \gamma_2, \gamma_3)$ are in columns one, two and three – see equations (1) and (2).

Figure 3 Standardised values of the low back pain risk variables according to equation 3. The lines of separation associated with this model are shown. Rowers with a history of low back pain are labelled (P), those without are labelled (N).

Table 1. Performance statistics for stroke models.

Variable	Fit(R^2) International	Fit(R^2) Non-International
Load	.94	.88
Forward Motion	.69	.73
Torsion Contrast	.77	.77
Roll Contrast	.88	.70

Figure 1

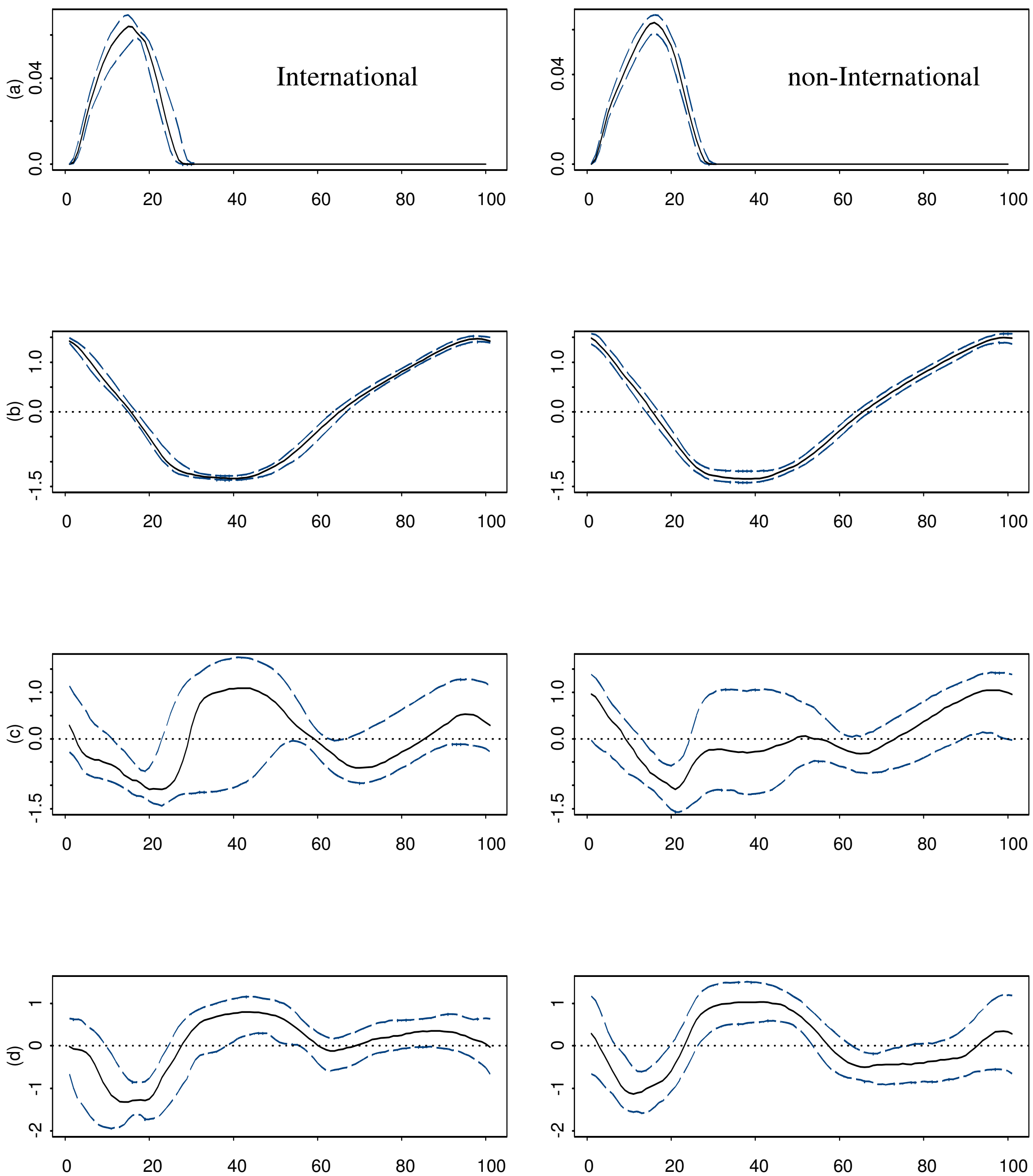

International
non-International
(a)
(b)
(c)
(d)
0
20
40
60
80
100
0.0
0.04
-1.5
1.0
-2
-1
1

Figure 2

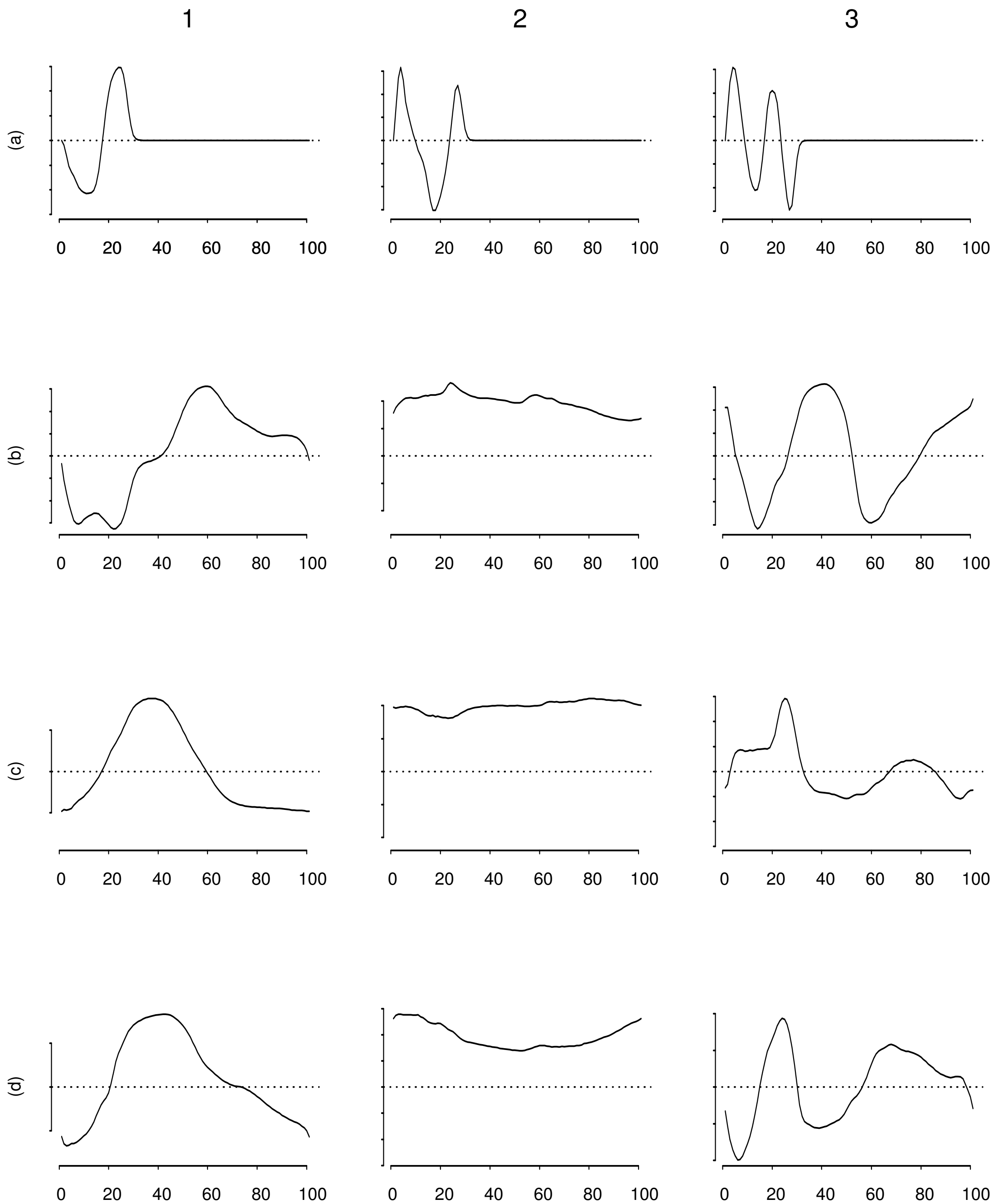
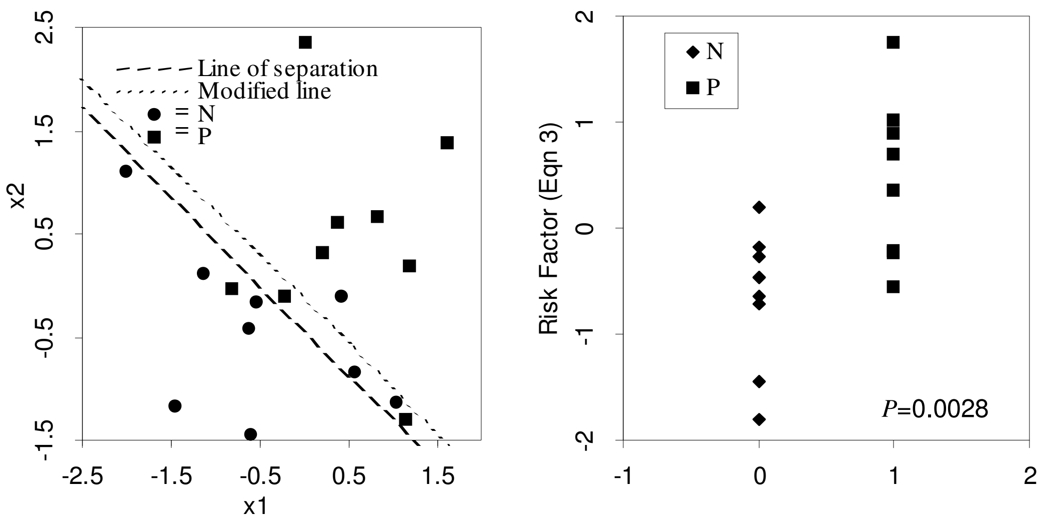


Figure 3


Line of separation
Modified line
= N
= P
x2
x1
2.5
1.5
0.5
-0.5
-1.5
-2.5
-1.5
-0.5
0.5
1.5
N
P
Risk Factor (Eqn 3)
P=0.0028
2
1
0
-1
-2
-1
0
1
2