Statistical analyses of repeated measures in physiological research: a tutorial

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Kristensen, Michael, and Thomas Hansen. Statistical analyses of repeated measures in physiological research: a tutorial. Adv Physiol Educ 28: 2-14, 2004; 10.1152/advan.00042.2003.—Experimental designs involving repeated measurements on experimental units are widely used in physiological research. Often, relatively many consecutive observations on each experimental unit are involved and the data may be quite nonlinear. Yet evidently, one of the most commonly used statistical methods for dealing with such data sets in physiological research is the repeated-measurements ANOVA model. The problem herewith is that it is not well suited for data sets with many consecutive measurements; it does not deal with nonlinear features of the data, and the interpretability of the model may be low. The use of inappropriate statistical models increases the likelihood of drawing wrong conclusions. The aim of this article is to illustrate, for a reasonably typical repeated-measurements data set, how fundamental assumptions of the repeated-measurements ANOVA model are inappropriate and how researchers may benefit from adopting different modeling approaches using a variety of different kinds of models. We emphasize intuitive ideas rather than mathematical rigor. We illustrate how such models represent alternatives that 1) can have much higher interpretability, 2) are more likely to meet underlying assumptions, 3) provide better fitted models, and 4) are readily implemented in widely distributed software products.

Experimental Setup

Male Wistar rats weighing 80 ± 5 g were anesthetized with mebumal delivered intraperitoneally at a dose of 5 mg/100 g body wt and then killed by cervical dislocation. Before the experiment, the animals were kept at 20°C with day/night lengths of, respectively, 10 and 14 h. Animals were fed ad libitum. The handling of animals was in accordance with Danish Animal Welfare Regulations.
Both soleus muscles were excised from each animal immediately and were randomly selected to be placed into a Krebs-Ringer solution (in mM: 122 NaCl, 25 NaHCO₃, 2.8 KCl, 1.2 KH₂PO₄, 1.2 MgSO₄, 1.3 CaCl₂, 5.0 D-glucose) with or without pinacidil. The Krebs-Ringer solution was equilibrated at room temperature, before and throughout the experiment, with a mixture of 5% CO₂-95% O₂ (pH 7.4).

After 1 h of incubation in either placebo or 100 μM pinacidil-Krebs-Ringer solution, the muscles were adjusted to produce the same passive force on a force transducer and then stimulated once. After another 5 min of incubation, the muscles were stimulated to fatigue [1-s-long trains (33-Hz pulse) with 2-s brake between each train continuing for 7 min]. Force data were recorded with an A/D converter (Duo-18, version 1.1). Data were recorded every 30 s, giving rise to 15 different time points. The reduction in force was measured relative to the first time point at t = 0 by transforming the raw force measurements xᵢⱼ according to

\[ yᵢⱼ = 100 \times xᵢⱼ / x₀ᵢ \]  (1)

We index the observations as follows: time is indexed by \( t = 0, 1, \ldots, T \) (here \( T = 14 \)); treatment group is indexed by \( i = 1, 2, \ldots, I \) (here \( I = 2 \)) and finally experimental units (animals) are indexed by \( j = 1, 2, \ldots, n \) (here \( n = 7 \)). The data appear in Table 1 and in Fig. 1.

### Controlling Variability Among Experimental Units

Often, experimental units vary in different but more or less uninteresting ways. Laboratory animals may differ subtly in size and other characteristics. Such differences are likely to be controlled statistically rather than something that one is specifically interested in.

Another aspect of the variability among experimental units is if different units react differently to the treatments. Figure 1 provides an example of this problem. Animal VI “flips” the treatment effect. With this animal, the placebo curve is below the pinacidil curve, whereas the other six animals show the opposite pattern of reaction. We refer to this phenomenon as an “interaction” between experimental units and treatment. Such interactions pose considerably more trouble than simple variability among experimental units because it means that any treatment effect cannot generally be assessed. Even if the average pinacidil curve had been considerably below the average placebo curve, one cannot conclude that pinacidil speeds up fatigue when some animals flip the treatment responses. The reason is that this conclusion can be assessed only for those animals that do not flip the curves. Obviously, the problematic flippers give no weight to the conclusion that pinacidil speeds up fatigue.

The different ways that these two kinds of variability are handled depend on one’s choice of statistical model and will be discussed later.

### Repeated Measurements: Controlling Variability Within Experimental Units

Whereas observations from different experimental units may very well be independent—assuming proper experimental design—different observations from the same animal are probably not independent. In fact, observations from the same experimental unit are likely to resemble one another compared with observations from different experimental units. We say that observations from the same experimental unit are correlated (6, 14, 34). In our example, there are two levels of within-experimental unit correlations.

First, the two different soleus muscles from each animal subjected to the placebo and the pinacidil treatments respectively may be correlated. Because the muscles in each pair originate from the same animal they are likely to resemble each other more than they resemble randomly selected muscles from other animals. Furthermore, as the experiment progresses, correlations between the two muscles within each pair are likely to ease, because treatment effects will start to override biologically (e.g., genetically) based correlations.

Second, more important, however, is the correlation among consecutive measurements of the same muscle: measurements taken 30 s apart are highly correlated, and even measurements further apart are likely to be correlated. To illustrate this, we correlate all observations taken at time point \( t = 1, 2, \ldots, 13 \) to all subsequent observations \( t' = 2, 3, \ldots, 14 \) (we ignore the

### Table 1. Entire data set of relative forces

<table>
<thead>
<tr>
<th>Animal</th>
<th>Time</th>
<th>Placebo First and Pinacidil Second</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>100.0</td>
<td>100.0</td>
</tr>
<tr>
<td>1</td>
<td>79.8</td>
<td>42.7</td>
</tr>
<tr>
<td>2</td>
<td>68.2</td>
<td>29.9</td>
</tr>
<tr>
<td>3</td>
<td>59.6</td>
<td>19.7</td>
</tr>
<tr>
<td>4</td>
<td>53.5</td>
<td>12.8</td>
</tr>
<tr>
<td>5</td>
<td>49.5</td>
<td>10.7</td>
</tr>
<tr>
<td>6</td>
<td>45.5</td>
<td>9.4</td>
</tr>
<tr>
<td>7</td>
<td>41.4</td>
<td>8.5</td>
</tr>
<tr>
<td>8</td>
<td>36.4</td>
<td>8.1</td>
</tr>
<tr>
<td>9</td>
<td>32.3</td>
<td>7.7</td>
</tr>
<tr>
<td>10</td>
<td>29.8</td>
<td>7.3</td>
</tr>
<tr>
<td>11</td>
<td>26.8</td>
<td>7.7</td>
</tr>
<tr>
<td>12</td>
<td>24.2</td>
<td>7.7</td>
</tr>
<tr>
<td>13</td>
<td>22.2</td>
<td>7.7</td>
</tr>
<tr>
<td>14</td>
<td>20.2</td>
<td>7.7</td>
</tr>
</tbody>
</table>
first time point). This corresponds to correlating all rows in Table 1 to all subsequent rows and then proceeding until one correlates time points 13 and 14. The result is \((14 \times 13)/2 = 91\) correlation coefficients. Now, 13 of these correlations are between observations that are one time step apart \((t, t+1)\), 12 are between observations that are two time steps apart \((t, t+2)\), and so on. The 91 correlation coefficients are depicted in Fig. 2, grouped into categories according to the length of the time distance between observations.

Figure 2 shows that 1) the correlation coefficients are generally high \(r \approx 0.75\), and 2) there is an almost monotonous decrease in the correlation as the distance between consecutive measurements increases.

**Treatment Groups**

In most experiments, interest centers on systematic differences among two or more treatment groups. In our pinacidil experiment, we are interested in whether the onset of fatigue is more rapid in the muscles that received the pinacidil treatment compared with muscles receiving the placebo treatment. How to characterize such differences depends on the particular statistical model one chooses. This choice, however, must accommodate the discussed different properties of the data at hand.

**STATISTICAL MODELS**

In this section, we will discuss various types of statistical analyses designed to handle types of data sets like the one considered in our example. Additionally, we will focus on ways of adapting one’s data to be fitted by relatively simple statistical models. If one can accommodate one’s data to such simple models, e.g., by log-transforming the response or by considering only some part(s) of the entire data set, this is clearly worthwhile doing.

We will discuss several types of models, each with its virtues and shortcomings. The models we will consider are

- **M1**: repeated-measurements ANOVA on \(y_{ij}\)
- **M2**: linear mixed-effects model on \(\log(y_{ij})\) and using fewer of the consecutive measurements
- **M3**: nonlinear model for each set of observations from each muscle, coupled with a two-way ANOVA on parameter estimates
- **M4**: nonlinear mixed-effects model

For further discussion see Refs. 6, 14, 25, 34, and 36. All the models considered are relatively straightforward to implement in SAS and S-PLUS/R.

We by no means wish to imply that the four models constitute an exhaustive list of possible applicable models. Rather,
the models are chosen to illustrate various aspects of the data set at hand and different ways of approaching the problem of analyzing the data.

The first two models we consider are ANOVA-like models insofar as they treat time as a qualitative variable without any particular order among the 15 levels (time points). On the other hand, the two latter models regard time as a quantitative (and continuous) variable.

**Notation**

To be able freely to discuss various statistical features of the considered models, some notation must be agreed on.

A statistical model is a functional relationship between the response $y_{tij}$ and certain predictors or explanatory variables. In our case, predictors are time, treatment group, animal ID, and possible combinations thereof.

During the statistical analysis we estimate effects of the predictors. An effect is a scalar with which we want to characterize the effects of, e.g., treatment groups or time on the response. One can think of an effect as, e.g., a regression coefficient in a linear regression, the mean difference between two treatments, or the variance of the response among subjects.

Having estimated the effects, we also say that the model has been estimated. Using the estimated model, we can predict the outcome, which we denote using a $\star$ superscripted to the variable in question, e.g., $y_{tij}\star$. For example, if one fits a linear regression model $q(t) = a + (b \times t)$ to some data pairs $(t,q)$ and estimates $a\star = 2$ and $b\star = -0.5$, the predicted outcome at $t = 7$ is $q\star = 1.5$.

A model's fit to the data can be measured by the residuals, which are here defined as the difference between the observed data and the predicted values $r_{tij} = y_{tij} - y_{tij}\star$. Thus for each observation there is one corresponding residual.

M1: Repeated-Measurements ANOVA Model

The repeated-measurements ANOVA model may be thought of as designed to assess treatment differences while controlling between-subject variability when each of these is measured "a few" consecutive times. The model is, as such, simple to interpret and does—apparently—take into account the various aspects of the repeated-measurements data set (6, 14, 34). Furthermore, it is readily implemented in many software packages, and this is presumably the reason why many researchers adopt the model. The interesting question is, however, whether it performs sufficiently well.

In our discussion here of the repeated-measurements ANOVA model, we focus on four of its shortcomings that are readily checked and that are likely to be encountered in connection with its use in physiological research. Thus we do not discuss all assumptions of the model, insofar as many of these are unlikely to be violated to any detrimental degree. The four aspects of the model are 1) interpretability, 2) model fit, 3)
within-experimental-unit correlations, and 4) variance homogeneity of the residuals among the 15 different time points.

**Analysis and results.** Table 2 shows the results of applying the repeated-measurements ANOVA model to the data in Table 1. The effect of time is obvious, indicating that the relative strength force changes (decreases) over time. Furthermore, there is a significant time × treatment interaction. This corresponds to the conclusions that can be reached by a set of time-by-time t-tests: there are differences between treatment groups at some time points but not at others. The treatment effect is almost significant \((P = 0.0839)\), but, due to the significant time × treatment interaction, we conclude that the pinacidil treatment has some effect, although it varies over time. It is important to stress that, under the repeated-measurements model, there is an effect of the pinacidil treatment notwithstanding that it varies over time.

**Interpretability.** The interpretation of a treatment effect depends on the presence/absence of whether the treatment factor enters into interaction terms (like time × treatment or animal × treatment).

**Absence of interaction terms.** The interpretation of a treatment effect is that, averaged across the 15 time points and the seven animals, the mean pinacidil strength force differs from the mean placebo strength force. It means that we expect a constant difference between the two treatments. Given the mean placebo strength force. It means that we expect a constant difference between the two treatments. Given the mean placebo strength force. It means that we expect a constant difference between the two treatments. Therefore, the interpretation of a treatment effect is completely detached from the biological reality of the experiment.

**Presence of interaction terms.** In this scenario, the interpretation of a treatment effect becomes close to biologically meaningless. For example, if there is an interaction between time and treatment, any inference about the effect of treatments must be qualified or conditioned by particular time points. In our case, it implies that the speed-up effect that pinacidil has on fatigue is present at time points 2–5, say, but not at other time points. Similarly, interactions between animals and treatment imply that discussion of treatment effects must be qualified by stating which animals we are discussing (all but the flipper, animal VI, say).

Naturally, the expected effects of pinacidil are corroborated by the significant time × treatment interaction.

**Model fit.** The second problem with the model is its lack of fit. Any reasonable model must be able to predict the observations to some reasonable degree of accuracy. When the observations to the predicted values are compared (Fig. 1), it is obvious that the fit is very poor. Especially, the four animals, animals I, IV, VI, and VII fit the model very poorly. Put simply, this indicates that the model is incorrect.

**Within-experimental-unit correlations.** A third drawback of the repeated-measurements ANOVA model regards the way it handles the within-experimental unit correlations (Fig. 2). When applying the repeated-measurements ANOVA model, one assumes that the correlations among the residuals from the same muscle remain constant across different time points. One way to check this assumption is described in the discussion of the M2-model. Another way is to consider plots like Fig. 2. Although this figure shows the correlations among observations rather than their corresponding residuals, the conspicuous systematic changes (decrease) in the correlation coefficients—as the time distance between consecutive measurements increases—strongly suggest that assuming a constant correlation across time points is untenable. However, plots like Fig. 2 do not indicate “how wrong” this assumption is.

**Variance homogeneity.** The fourth and last of the problems that we will discuss in connection with the repeated-measurements ANOVA model is the assumption of variance homogeneity. When using the models discussed here, one assumes that the variances of the residuals at each of the 15 different time points are more or less constant. To assess this graphically, one can plot the residuals from each time point as box plots (Fig. 3). The distance between the end points of each “whisker” indicates variability in the residuals at each time point. Clearly, this variability is not constant. There are 15 variances (one for each time point), and the range thereof is 14.6–154.0 (time points 14 and 2, respectively). On the basis of Fig. 3 alone, the assumption of a constant variance through time is clearly unrealistic.

**M2: Linear Mixed-Effects Model on log(ytij)**

The discussion above provides a clear example of some shortcomings of the repeated-measurements ANOVA model. However, several of the encountered problems can easily be remedied by 1) log-transforming the response, 2) considering fewer time points (e.g., every 2nd observation), and 3) allowing a somewhat more elaborate correlation pattern among the consecutive measurements of the same muscle than just one constant correlation.

Briefly, the reasons to expect that these three actions may remedy the problems encountered are as follows. If the onset of fatigue follows an exponential decay—and Fig. 1 might suggest just that—log-transforming the data would linearize the response curves. And linear response curves are much easier to fit. Furthermore, log-transforming the data reduces overall...
variance in the data and may thus help to remedy the problems of variance heterogeneity (Fig. 3). Finally, with the use of untransformed data, the treatment effect corresponds to comparing the difference between two means \( d = y(\text{pinacidil}) - y(\text{placebo}) \) [where the \( y(\text{pinacidil}) \) and \( y(\text{placebo}) \) represents the overall means within each of the two treatments] to zero. If \( d \) differs from zero, the two treatments differ. We argued above that \( d \) has little biological relevance. However, if we analyze log(\( y_t \)) rather than \( y_t \), the treatment effect becomes a difference on a log scale, and back-transformed to the original scale this difference becomes a ratio \( d' = y(\text{pinacidil})/y(\text{placebo}) \). And on the original scale, assuming a constant factor between the two treatments is probably not so far-fetched. The reason for analyzing fewer time points is simply that, in this way, the model becomes simpler insofar as fewer between-time points correlations must be handled. The last action is in line therewith. The more complex the between-time points correlations can be modeled, the more reasonable the model becomes.

**Analysis and results.** Our first objective is to choose how we wish to model the way that correlations among observations at consecutive time points depend on the time distance among the observations. One common way to do this is to fit a model with only the factors of direct interest, including a term for each of the different time points (a so-called saturated model) and obtain the residuals from this analysis (6, 34). In our case, this model is an ordinary two-way ANOVA, with treatment, time, and their interaction included. Having calculated the residuals thus obtained, we correlate all observation pairs that are one, two, and up to 13 time steps apart (we ignore the first \( t = 0 \) time point). Figure 4 shows the results of these calculations.
based on a two-way ANOVA of log($y_{ij}$), using observations taken at both even and uneven time points.

Considering the accuracy with which each correlation coefficient [denoted $\rho(h)$, where $h$ is the time step size] is estimated, it seems reasonable to expect that the correlation decreases according to

$$\rho(h) = k \times r^h$$

where $k$ is a constant, and $r \approx 1$. The reason is that Fig. 4 shows a close-to-linear decrease in $\rho(h)$ with increasing $h$, and if $r \approx 1$, the power function (Eq. 2) is close to linear for moderate $h$. Thus performing a linear regression of $\log(\rho(h)) = \log(k) + h \times \log(r)$ and viewing $\log(r)$ as the unknown regression coefficient yields $r^* = 0.98$ and $k^* = 1.01$. In the statistical jargon used in the analysis of repeated measurements, a correlation structure like Eq. 2 is termed a first-order autoregressive function, and it is readily implemented in software packages like SAS and S-PLUS/R (14, 25, 34).

Table 3 shows the result of the analysis of the pinacidil data with the three modifications discussed [log-transformation, dropping (every even) time points, and using the first-order autoregressive correlation structure]. The Q-tests are so-called likelihood ratio tests and are approximately $\chi^2$-distributed with the degrees of freedom shown in the df column. The pinacidil treatment is, in this analysis, significant ($P = 0.0194$), with a log-average difference between the placebo and the pinacidil treatments of $d^* = 0.33$. This means that muscles in the placebo treatment are on average exp(0.33) = 1.39 times (or 39%) more powerful than muscles in the pinacidil treatment measured as the relative force. Naturally, the interaction between treatment and time still makes interpreting the treatment effect difficult, as previously discussed. Thus the model predicts that, as time progresses from $t = 1$ over $t = 7$ to $t = 13$, the ratio between the placebo and the pinacidil averages changes from 1.15 over 1.62 to 1.23. Hence the need to qualify the treatment effects by stating the time point at which one considers the difference/ratio between the two treatments.

Figure 5 shows the fit of this model to the log-transformed data. The fit is not great. Although the response curves have been considerably linearized, the fit still does not capture nonlinear features of the log-transformed data; we are still left with what seems to be a wrong model.

Apart from the poor fit between model and data, the three actions taken actually perform quite well. 1) The correlation between adjacent time points ($r^*$ from Eq. 2) is 0.94, which corresponds very well to Fig. 4. 2) Using Bartlett’s test (28) to test variance homogeneity among the seven different time points yields that the variances have been indeed homogenized (data not shown). 3) The variability among animals is no longer significant (data not shown), and the troublesome interaction between animals and treatment groups is confounded with the correlation between adjacent time points (6, 14, 34). 4) Finally, the log-transformed data have a more meaningful biological interpretation, albeit still not perfect.

**NONLINEAR MODELS**

One basic premise of the two applied models is that they are linear and that the response can be predicted by linear combinations of treatment and time effects. Many of the articles cited here present repeated-measurements data that are quite nonlinear (e.g., Refs. 7, 16, 17, 19, 20, 26, 30, 31, 35), so it seems natural to try to model the data by using nonlinear models. Above, it was argued that, if the force decay was exponential, log-transforming the response would yield a linear model. However, log($y_{ij}$) is still not linear.

On the basis of knowledge of the mechanics of the experiment, some features of the data might be predicted a priori and help to build a reasonable nonlinear model. Looking at the figures showing the original data, one can argue that, because the experiment is terminated after 8 min, the decay in force is not allowed to reach zero. Rather, one could view the response curves as exponential plus some constant. Moreover, the model should encompass the fact that all observations equal 100% relative force at the first time point (the y-axis intercept). How precisely the onset of fatigue develops through time is probably not easy to predict, but assuming an exponential decay is at least flexible.

One function that accommodates these features is

$$y(t) = \alpha_1 \times \exp(\alpha_2 \times t) + \alpha_3$$

where the three parameters have the following interpretations: $\alpha_2$ characterizes the decay in muscle force as time progresses. Obviously, $\alpha_2 < 0$. The more negative $\alpha_2$ becomes, the faster the decay; $\alpha_3$ is the asymptotic relative strength force as time progresses. Finally, the sum $\alpha_1 + \alpha_3$ is the y-axis intercept, i.e., the relative force at the first time point (should be close to 100). Additionally, from the equation $\alpha_1 \times \exp(\alpha_2 \times t_{ij}) + \alpha_3 = (\alpha_1 + \alpha_3)/2$, we see that the half-time to the observed maximal fatigue is

$$t_{1/2} = \log([(\alpha_1 - \alpha_3)(2\alpha_1)/\alpha_2]$$

There are several possible ways by which one can come from the mechanistic function (Eq. 3) to a statistical analysis. Here and in the following paragraph, we will describe two quite different methods.

When we consider the interpretation of the $\alpha$-parameters and the expected physiological effects of pinacidil (speeding up fatigue), we could suggest the following (one-sided) hypothesis

$$\alpha_3(\text{placebo}) > \alpha_3(\text{pinacidil})$$

Whether the $\alpha_1$ and $\alpha_3$ should differ between treatments is less clear.

Hence, one strategy could be to let one or all three $\alpha$-parameters depend on treatment group

$$y_{ij} = \begin{cases} \alpha_{11} \times \exp(\alpha_{21} \times t) + \alpha_{31} & \text{for placebo} \\ \alpha_{12} \times \exp(\alpha_{22} \times t) + \alpha_{32} & \text{for pinacidil} \end{cases}$$

and then test whether $\alpha_{11} = \alpha_{12}$, $\alpha_{21} = \alpha_{22}$, and $\alpha_{31} = \alpha_{32}$.
Looking at Fig. 1, it is obvious that this model does not hold. The speed of onset of fatigue among animals varies clearly. For example, animal I responds very strongly to pinacidil (the onset of fatigue is rapid), whereas animal VI flips the treatments. Apparently, there is also a substantial variation in the asymptotic relative force among animals. The points raised here suggest that there is an individual animal-level variability in the \( \alpha \)-parameters regardless of any treatment effects thereon.

**M3: Paired t-Test or Two-Way ANOVA of \( \alpha \)-Parameter Estimates**

Because the \( \alpha \)-parameters have reasonably obvious interpretations, one strategy to deal with the problem of animal-level variability in the responses could be to fit Eq. 3 to each individual muscle. For a particular \( \alpha \)-parameter (\( \alpha_2 \), say), this would result in 14 different estimates of \( \alpha_2 \) grouped into two treatments and seven animals. Because of the distinct interpretation, we could then proceed without loss of meaning, analyzing the 14 \( \alpha_2 \) estimates by, e.g., paired \( t \)-tests or a two-way ANOVA (had there been more than two treatment groups) (6, 14).

Table 4 shows the results of performing this analysis. Using the paired \( t \)-test (thus controlling among animal variability), we find that, when the two treatment groups are compared, only the \( \alpha_2 \)-parameter differs marginally significantly, implying that the onset of fatigue is marginally faster in the pinacidil group compared with the placebo group. This conclusion is quite strong insofar as it is in compliance with pinacidil’s expected physiological effects.

Note that this type of analysis makes little sense unless the parameters of the model can be interpreted in some relevant way.

<table>
<thead>
<tr>
<th>Animal</th>
<th>( \alpha_1 ) Placebo</th>
<th>( \alpha_1 ) Pinacidil</th>
<th>( \alpha_2 ) Placebo</th>
<th>( \alpha_2 ) Pinacidil</th>
<th>( \alpha_3 ) Placebo</th>
<th>( \alpha_3 ) Pinacidil</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>79.89</td>
<td>90.18</td>
<td>-0.18</td>
<td>-0.81</td>
<td>15.77</td>
<td>8.33</td>
</tr>
<tr>
<td>II</td>
<td>77.16</td>
<td>75.46</td>
<td>-0.16</td>
<td>-0.34</td>
<td>18.47</td>
<td>25.23</td>
</tr>
<tr>
<td>III</td>
<td>76.89</td>
<td>81.47</td>
<td>-0.26</td>
<td>-0.45</td>
<td>16.41</td>
<td>16.40</td>
</tr>
<tr>
<td>IV</td>
<td>81.71</td>
<td>86.36</td>
<td>-0.39</td>
<td>-0.83</td>
<td>14.33</td>
<td>12.83</td>
</tr>
<tr>
<td>V</td>
<td>80.72</td>
<td>92.87</td>
<td>-0.15</td>
<td>-0.22</td>
<td>14.51</td>
<td>9.51</td>
</tr>
<tr>
<td>VI</td>
<td>84.05</td>
<td>81.42</td>
<td>-0.23</td>
<td>-0.16</td>
<td>13.78</td>
<td>16.49</td>
</tr>
<tr>
<td>VII</td>
<td>92.87</td>
<td>86.32</td>
<td>-0.13</td>
<td>-0.19</td>
<td>11.02</td>
<td>13.06</td>
</tr>
<tr>
<td>Mean</td>
<td>81.90</td>
<td>84.87</td>
<td>-0.22</td>
<td>-0.43</td>
<td>14.90</td>
<td>14.55</td>
</tr>
</tbody>
</table>

\( t \)-Test: -1.14, 2.34, 0.19, 0.19

\( P \) Value: 0.2995, 0.0577, 0.8548

The \( \alpha \)-parameters are estimated for each muscle separately using SAS proc nlin. This method is referred to in the text as the M3 model.
biological way (6, 14). Moreover, the fit is naturally reasonably good insofar as each muscle has been fitted to Eq. 3 (Fig. 6). It is important to stress that the assumptions underlying the analysis above are quite simple. 1) The model (Eq. 3) must be reasonably correct. 2) The pairwise differences between group-specific parameter estimates are assumed to be normally distributed. This latter assumption is probably as good as any assumption, insofar as it is virtually impossible to check given only seven pairwise observations. Moreover, it is easy to overcome problems of nonnormality by using either nonparametric tests (e.g., the Mann-Whitney U-test) or, e.g., bootstrap statistics (5, 28). We have estimated a nonparametric bootstrap confidence interval for the difference between the group-specific $H_{21}$-parameters ($H_{21}^{H21}$) and the resulting 95% confidence interval, based on 1,000 resamples, to be $[0.06; 0.39]$, significantly above zero, corroborating the result from the t-test.

**M4: Nonlinear Mixed-Effects Model**

The last type of analysis considered may be thought of as a combination of the M1 and M3 models. The idea is simply that the nonlinear model (Eq. 3) apparently fits the data well when the $H_i$-parameters are allowed to vary among animals or muscles. So, if Eq. 3 could be modified to incorporate treatment effects (which we are interested in) while allowing subject-specific variability in the $H_i$-parameters, the analysis could be conducted in one overall analysis.

To incorporate such variability, Eq. 3 may be extended to encompass individual muscle-specific variation (6, 14, 25)

$$y_{ij} = \alpha_{1i} \times \exp([\alpha_2 + u_{2ij}] \times t) + [\alpha_3 + u_{3ij}]$$

where subscripts are similar to those used in Eq. 1. The three $H_i$-parameters are thus allowed to vary between treatment groups. The two $u_i$-parameters characterize $u_{2ij}$: individual variation in the decay of relative strength force, and $u_{3ij}$: individual variation in asymptotic fatigue. The reason not to include a random variable associated with the $H_1$-parameter is that the sum $\alpha_{1i} + \alpha_{2i}$ is the y-axis intercept and that two random variables associated therewith would be highly correlated. To avoid this, the $H_1$-parameter does not have an associated random variable.

A rigorous interpretation of this latter model (Eq. 6) is not as straightforward as one might prefer. The reason is that the expected value of this model differs from the right-hand-side expression of the model without random effects (Eq. 3) (6, 14, 25). However, the qualitative interpretation of the three $H_i$-parameters of the model is the same as that of the model without random effects. This is because the random effects are estimated parameters and not tested effects.
rameters remains unchanged. One possible way of interpreting the $\alpha$-parameters is to consider the effects of changing their values. Consider, for example, a lowering of $\alpha_2$ from $-0.20$ to $-0.40$. In the model without any random muscle-specific components (Eq. 3), this lowering in $\alpha_2$ halves $t_{ij}$. However, in the model with random muscle-specific components (Eq. 6), we can state only that $t_{ij}$ decreases. Alternatively, we can state that there is a positive correlation between $\alpha_2$ and $t_{ij}$ in the model with random animal-specific effects.

The parameters $u_{12}$ and $u_{3j}$ are assumed to be normally distributed “errors” associated with the $\alpha_{12}$- and $\alpha_{3j}$-parameters following a two-dimensional normal distribution. As such, they are characterized by the variance of the two $u_{ij}$-parameters (denoted $\sigma^2_{12}$ and $\sigma^2_{3j}$, respectively) and the covariance between them (denoted $\sigma_{12,3j}$, see below for explanation). Qualitatively, the idea of the two $u_{ij}$-parameters is that the different experimental units are not expected to react completely uniformly to the treatments and, hence, cannot be expected to follow one and the same functional relationship. Thus the two $u_{ij}$-parameters allow the model to harbor individual random variation owing to differences among muscles. Although the qualitative idea of the two $u_{ij}$-parameters remains, the interpretation of the two $u_{ij}$-parameters is not as straightforward as indicated above.

The reason is that we, at least as a start, do not assume that the $u_{ij}$-parameters are independent of one another; rather, the covariance—or equally, the correlation—characterizes the dependence between the two $u_{ij}$-parameters. To explain the meaning of this: if, for example, animals that, for whatever reason, lose relative force comparatively “fast” [meaning that $u_{12}$ is “small” (negative) in order for the exponential part of the model to decrease “fast”], if these animals, for whatever unknown reason, maintain a comparatively “high” asymptotic relative force [meaning that $u_{3j}$ is “big” (positive)], the covariance is negative, and vice versa.

Table 5 shows the results of the nonlinear mixed-effects model. The presence of the covariances and covariance of the two $u_{ij}$-parameters is considered as noise and is, as such, just complicating the analysis/interpretation, although they help to fit the model to the data. Therefore, before proceeding to test the three $\alpha$-parameters (treatment effects) we first want, if possible, to test whether the two variances $\sigma^2_{12}$ and $\sigma^2_{3j}$ and the covariance $\sigma_{12,3j}$ contribute significantly to the fit of the model. Table 5, top and middle, shows the results of these tests. Fortunately, the covariance between the two $u_{ij}$-parameters is not significant and is hence removed from the model ($\sigma_{12,3j}^* = 0.245, P = 0.1681$). It comes as little surprise that the two variances associated with the two $u_{ij}$-parameters are very significant indeed ($\sigma^2_{12} = 0.035, P < 0.0001$ and $\sigma^2_{3j} = 10.395, P < 0.0001$).

Last, we test the three $\alpha$-parameters, i.e., whether the y-axis intercept, speed of onset of fatigue, and asymptotic fatigue differ between the two treatments. Only the $\alpha_{2}$-parameters differ between treatments (Table 5, bottom: $P = 0.0429$). The loss in relative force is thus faster in the pinacidil group ($\alpha_{21} = -0.42, SE = 0.176$) compared with the placebo group ($\alpha_{21} = -0.22, SE = 0.073$). This difference between the two groups may be quantified by stating that the $t_{ij}$ in the placebo group is approximately twice that of the pinacidil group.

To complete our analysis, we assess whether the fitted model actually fits the data well (Fig. 1). The complete lines comprise the fitted model predictions, and for all animals the fitted model is very close to the actual data. This even regards the two most abnormal animals (animals I and VI). Finally, the interpretability of the model is high compared with the repeated-measures ANOVA model. Especially, the two fixed parameters $\alpha_2$ and $\alpha_3$ have clear and logical interpretations.

**CONCLUSIONS AND RECOMMENDATIONS**

We have reviewed four different kinds of models analyzing the same repeated-measurements data. Each model has its pros and cons and is suitable in certain situations. Furthermore, we have illustrated and focused on features of the statistical analysis that need to be considered explicitly during the analysis of repeated-measurements data. In this final section, we will focus on 1) checking of model assumptions, 2) checking of model fit, 3) the model’s interpretability, 4) other possible models, and finally 5) software implementation. Throughout, we assume the discussion to center on repeated-measures data. We will additionally assume that different experimental units are independent and that responses either comply with assumptions regarding normality of residuals or have been transformed to comply therewith.

**Model Assumptions**

It is important to bear in mind that any statistical analysis depends on the fulfillment of certain assumptions. Some assumptions are strong, in the sense that “much is needed” for their fulfillment, whereas others are comparatively weak. Assumptions that should routinely be checked include variance homogeneity of the residuals and correlation structure of the consecutive measurements on the same experimental units.

Plots like Figs. 2–4 are well suited in this respect. They can give hints to appropriate correlation structures and pointers to transformations that may help to remedy variance heterogeneity.

**Model Fit**

When performing a parametric statistical analysis, one assumes an underlying model, a functional relationship between response and explanatory variables. If the model does not fit the data (i.e., predicted values are “far” from observed values).
the model is incorrect. Whether the lack of fit is sufficiently large to be detrimental to the analysis or acceptable is to a large degree subjective. However, obvious “wrong models” consistently predict values wrongly. For example, the repeated-measurements ANOVA model almost consistently over- or underpredicts values. The observed values are not randomly scattered around the predicted curves; they deviate consistently.

When one is assessing model fit, the most useful tool is plots of response and predicted values against one or more explanatory variables (time and/or treatments) preferably for each experimental unit (25).

Interpretability

A somewhat overlooked part of the data analysis is the interpretation of the statistical models (25). The repeated-measurements ANOVA model is well suited (its interpretation makes biological sense) when the responses in different treatments are reasonably parallel over time. This means that differences between treatments are reasonably constant. However, if responses are not parallel (and cannot be transformed to parallelism), or if treatment interacts with time, say, the interpretation of the repeated-measurements ANOVA model becomes difficult. For example, when Keller et al. (13, their Fig. 1) find a significant treatment effect (difference of the “low glycogen trail” and “control trail”) on the plasma concentration of interleukin 6 during a 3-h exercise experiment, this probably makes little sense insofar as there probably exists time × treatment effects. This is, however, acknowledged by the authors, who use post hoc t-tests to assess pairwise differences at different time points. Nevertheless, the use of post hoc t-tests (e.g., Refs. 14 and 36) corresponds to reporting time × treatment effects, thus making the reporting of overall treatment effects appear rather confusing.

However this may be, compared with “mechanistic” (nonlinear) models with easy-to-interpret parameters, the interpretation of ANOVA-like models is often less biologically obvious.

Other Possible Models

The four models discussed by no means comprise an exhaustive list of possible models that can be used to analyze our pinacidil experiment. Our opinion is that models M1 and M2 full short because of the inherently nonlinear nature of the data (and of the log-transformed data). It is beyond the scope of this study to consider in detail other types of models, but we will consider one type, random intercept polynomial regressions.

Nonlinearity can be incorporated into statistical models by other means than the M3 and M4 models. One could, for example, consider polynomial regressions of \( y_{ij} \) on time and higher orders thereof and let the corresponding regression coefficients depend on treatment group. One such possible model could be

\[
y_{ij} = (\alpha_0 + b_{0i}) + [(\alpha_1 + b_{1i}) \times \text{time}^1] + [(\alpha_2 + b_{2i}) \times \text{time}^2] + \cdots + [(\alpha_s + b_{si}) \times \text{time}^s]
\]

where the \( \alpha \)-parameters are regression coefficients and the \( b_{pi} \)'s are individual, subject-specific variations therein. This would correspond to fitting an \( s \)-degree polynomial to each subject and then testing whether the regression coefficients (the \( \alpha \)'s) differ between treatments (6, 14, 34). This method is relatively straightforward and easy to implement in different software packages. However, the interpretation of this polynomial fit is not so straightforward. Let us, for the purpose of argument, assume that \( s = 3 \), so we are fitting a third-degree polynomial function to the data. Let us furthermore assume that the regression coefficients for time\(^2\) differ between the two treatments. If \( \alpha_{12} > \alpha_{22} \), we cannot conclude that the onset of fatigue is faster, say, in the \( i \)th treatment compared with the \( i \)th treatment. The reason is that shapes of the predicted curves depend on the “interaction” of the three regression coefficients (\( \alpha_{11} \), \( \alpha_{12} \), and \( \alpha_{13} \)).

Software

All of the discussed models can be implemented in SAS and S-PLUS/R. In the APPENDIX, we list the SAS code used to analyze models M1–M4. Moreover, models M1 and M3 can be implemented in GUI software like SigmaStat.

Recommendations

Given that the repeated-measurements ANOVA model is widely used, the question as to the circumstances under which the model is appropriate arises. Assuming that 1) one is interested in properties of the data that may adequately be coined by, e.g., treatment or time point averages and 2) variances are reasonably homogeneous among different time points and treatments (obtained by, e.g., transforming the data), the repeated-measurements ANOVA model may very well be appropriate if the number of repeated measurements is “small” (<5, say) and the distance between adjacent time points “large” and equidistant (6, 14, 34, 36).

Several factors make the use of nonlinear (mixed-effects) models, like the two presented in this paper, attractive alternatives to simpler ANOVA-like methods. First, occasionally the functional form of the model can be predicted on the basis of knowledge of the mechanisms of study systems. One primary advantage thereof is that model parameters can have stringent interpretations enabling much clearer conclusions. Second, the flexibility of nonlinear models makes them almost tailor-made to fit repeated-measurement data from physiological experiments. Although a model not fitting the data is synonymous with the model being wrong, one cannot conclude otherwise that a model that does fit the data is correct in a mechanistic sense. Yet often the interpretation of model parameters suffices. Third, treating time as a continuous variable rather than as a factor, such as in the repeated-measurements ANOVA model, seems much more appropriate. Fourth and finally, the fact that nonlinear models are relatively easy to implement in several widely distributed software packages makes the nonlinear models an attractive alternative to the ANOVA-like analyses.

APPENDIX: SAS CODE

The Data

The data of the four analyses must be on the following format:

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Time</th>
<th>Animal</th>
<th>Animal_ID</th>
<th>Y</th>
<th>logY</th>
</tr>
</thead>
<tbody>
<tr>
<td>Placebo</td>
<td>0</td>
<td>I</td>
<td>5</td>
<td>100,000</td>
<td>4.60517</td>
</tr>
<tr>
<td>Placebo</td>
<td>1</td>
<td>I</td>
<td>5</td>
<td>79,798</td>
<td>4.37950</td>
</tr>
<tr>
<td>Placebo</td>
<td>2</td>
<td>I</td>
<td>5</td>
<td>68,182</td>
<td>4.22218</td>
</tr>
<tr>
<td>Placebo</td>
<td>3</td>
<td>I</td>
<td>5</td>
<td>59,596</td>
<td>4.08759</td>
</tr>
</tbody>
</table>
Repeated-Measurements ANOVA

1. proc mixed data=Pinacidil method=MIVQUE0;
2. class Animal Treatment Time;
3. model Y = Treatment Time Treatment*Time;
4. random Animal*Treatment;
5. repeated/Type=CS Subject=Animal*Treatment;
6. estimate 'Placebo - Pinacidil' Treatment -1.0 +1.0;
7. run; quit;

Linear Mixed-Effects Model on log(y_{ij})

1: proc nlin data=Pinacidil method=marquardt;
2: by Animal Treatment;
3: parms alpha1=80 alpha2=-0.25 alpha3=15;
4: model Y = alpha1*exp(alpha2*Time) + alpha3;
5: output out=Parameter PARMS=alpha2 alpha3;
6: data Parameter;
7: set Parameter;
8: if Time=0;
9: /*AnimalTreatment alpha1 alpha2 alpha3
10: I: Placebo 79.8898 -0.17978 15.7739
11: I: Pinacidil 90.1777 -0.80868 8.3330
12: II: Placebo 77.1571 -0.16329 18.4717
13: II: Pinacidil 75.4576 -0.34351 25.2337
14: III: Placebo 76.8947 -0.26500 16.4085
15: III: Pinacidil 81.4740 -0.44850 16.3985
16: IV: Placebo 81.7068 -0.39405 14.3307
17: IV: Pinacidil 86.3574 -0.83024 12.8309
18: V: Placebo 80.7214 -0.15237 14.5055
19: V: Pinacidil 92.8730 -0.22106 9.5056
20: VI: Placebo 84.0525 -0.22540 13.7762
21: VI: Pinacidil 81.4218 -0.15598 16.4902
22: VII: Placebo 82.9760 -0.13062 11.0187
23: VII: Pinacidil 86.3162 -0.19384 13.0602*/
24:.
25: proc mixed data=Parameter method=ML;
26: class Animal Treatment;
27: model alpha2 = Treatment;
28: random Animal;
29: estimate 'Placebo - Pinacidil' Treatment -1.0 +1.0;
30: run; quit;

Nonlinear Mixed-Effects Model

In the SAS code below the variable Treat equals 1 when the treatment group is Pinacidil and 0 otherwise (treatment group is Placebo).

1: proc nlmixed data=Pinacidil method=marquardt;
2: by Animal Treatment;
3: parms mu1=82 mu2=-0.28 mu3=17 a1= -4 a2= -0.08 a3=3 s_u2=0.05 s_u3=21 corr2_3=0 s=5;
3: pred = (mu1 + a1*Treat)*exp((mu2 + a2*Treat + u2)*Time)+mu3+e3*Treat+u3;
4: model Y ~ normal(pred,s);
5: random u2 u3 ~ normal([0,0],[s_u2,corr2_3,s_u3])
subject=Animal_ID;
6: PREDICT pred out=pred;
7: run; quit;

1. Invokes the nlmixed procedure on the Pinacidil data set.
2. Defines starting values for the parameters to the iterative method used to estimate the model.
3. Corresponds to Eq. 6. Note that the treatment effects on the three α-parameters has been defined via dummy variables. Thus the three α-parameters for the placebo group equals μ1, μ2, and μ3, respectively, whereas the three α-parameters in the pinacidil group equals μ1+a1, μ2+a2, and μ3+a3, respectively.
4. Defines that Y = yij is normally distributed with mean pred and variance σ (seeParms statement).
5. Defines the distribution of the two random effects u1 and u2 (two-dimensional normal). The subject=Animal_ID defines that the hierarchical level of the two random effects is Animal_ID, which is a variable taking different numerical values for each individual muscle.
6. Defines an output data set (pred) to include (among other things) the predicted values from the model.

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REFERENCES