Arch. Biol. Med. Exp. *23:* 307-314 (1990)
Printed in Chile

ARIMA Modelling of Chronospsychometric Self-Evaluation of Drive and Mood

Modelos ARIMA para la Autoevaluación Cronopsicométrica de Animo e Impulso

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The expanding study of biological rhythms requires the use of refined methods of time series analysis. We propose the use of ARIMA (Autoregressive Integrated Moving Averages) model, a powerful statistical tool of relatively recent development. A group of 5 patients with Affective Disorders (2 bipolars, 3 unipolars) and 1 patient with Adjustment Disorder self-assessed their AS every 8 hours for about a month. The affective state (AS) was estimated for 4 indicators: the two main constructs (Mood and Drive) of the segmented Visual Scale ESTA III and two bipolar items (Anxiety and Drowsiness). Mood and Drive are continuous variables, while Anxiety and Drowsiness are ordinal ones. Strictly speaking, ARIMA modelling is not valid with ordinal data. However, comparison of models of the two kinds of variables reveals no significant differences. This points out to a certain robustness of the method. Most of the series were non-stationary but could be transformed taking no more than two differences. The models made a very good fit of the data. Statistically significant coefficients on different lags may indicate the presence of circadian and infradian periodicities in the series. Further applications of ARIMA models to biological and psychological rhythmometry may be quite useful.

Biological systems, from the subcellular to the behavioral level, undergo rhythmic oscillations in activity during the life cycle. Some of these periodicities are in the range of the solar day (circadian), others have shorter (ultradian) or longer (infradian) periods. Many of these oscillations are not a passive response to environmental fluctuations (or "Zeitgebers"). They are produced by the biological systems themselves and represent a temporal structure thought to be as important to physiology as spatial structure. Chronobiology, the study of biological rhythms, has been considered a sort of "anatomy in time" (Pauly, 1983). The interested reader is referred to several reviews about biological rhythms, their general properties and their mechanisms, published during the last years (Edmunds, 1983; Klevecz *et al.*, 1984; Jacklet, 1984; Johnson and Hastings, 1986; Minors and Waterhouse, 1986).

Longitudinal observation and measurement of biological phenomena generate a specific kind of data. Their properties call for specific statistical methods for their analysis. Longitudinal data of biological variables sampled at regular intervals have been traditionally analyzed by methods such as the Periodogram (Enright, 1965; Fuentes-Pardo and Vargas, 1979), and the Cosinor (Van Cauter and Huyberechts, 1973). Several other techniques have also been described, but have been less frequently used (Mercer, 1960; Sollberger, 1965; Van Cauter, 1974; Dörrschidt and Beck, 1974; Phipps, 1975; Enright, 1981; Kraemer *et al.*, 1984; Monk and Fookson, 1986; Monk, 1987). All of them seek to establish periodicities in the data, and to describe them in terms of phase, amplitude, mean value and wareform, while assessing the reliability of those parameters.

In spite of their usefulness, the above methods are not free of limitations and are far from being ideal. One of their main pitfalls is that most of them assume that the data can be modelled by the addition of sine functions of different amplitudes and phases. In other words, they

assume a certain behavior (sinusoidallity) in the data.

However, there exist more powerful and complex methods to analyze time series data, which do not make these kinds of assumptions: the Autoregressive Integrated Moving Averages (ARIMA) models (Box and Jenkins, 1976) and the Spectral Analyses (Priestley, 1981). To the best or our knowledge, ARIMA models have not been used to analyze chronobiological data. One exception is a chronopsychometric study of time sense of endogenous depressives (Richter and Benzenhöfer, 1985). Nevertheless, that study used an insufficient number of observations and failed to analyze the non-stationary series. The latter is quite possible, as it will be shown in our examples.

The first aim of this paper, therefore, is to report on the use of ARIMA models in the context of chronobiological research. They have already been successfully used in other fields (Economics, Engineering, etc.) with data of dynamic behavior.

Although biological rhythmicity influences behavioral indicators, there is a relative lack of chronobiological studies involving psychological variables compared with the amount of studies with physiological ones (Sciolla and Lolas, 1987). This lack of information concerning subjective or experiential aspects of biological rhythmicity can be partly accounted for by a lack of appropriate indicators, i.e., valid, reliable, and representative. Visual analogic or segmented scales seem specially suitable for chronobiological research (Sciolla and Lolas, 1988).

The lack of chronopsychometric information is all the more regrettable in the field of chronobiological research of affective disorders. Since long, it has been held the idea that certain alterations of biological time-keeping could underlie the etiopathogenesis of these disorders (Wehr and Goodwin, 1983; Risco *et al.*, 1990). The characteristic modifications of affective state (AS) in them have been traditionally regarded as one of their main diagnostic criteria. A systematic chronopsychometry of AS in affective patients could add valuable information to the body of data which sustain the tenable –yet unproven– chronobiological hypothesis of affective disorders.

Using a visual segmented scale, the Eppendorfer Stimmungs Antriebs Skala (ESTA) - III, we have conducted longitudinal studies of AS in both patients and normals, under the assumption that the variable AS could depend on two constituent variables called "Mood" and "Drive". Each one of them is quantified through self-assessment of 20 feelings set up as bipolar items in the scale. Drive is related to a hypothetical system of behavioral energisation akin to the notion of arousal in behavioral personality research, which probably relates to a substrate that includes corticoreticular loops (Strelau, 1987). Mood refers to qualitative modulation of activation or arousal level in the sense of hedonic or positive-negative connotations. These constructs were originally developed by Supprian (1975a) on the basis of data derived from verbal reports of AS made by affective patients; they were factor analyzed and tested for predictive validity in a number of bipolar patients (Supprian 1975c, d, e). We prepared the Spanish version used in this study, which includes some modifications of the original German version (see Methods ii).

The second aim of this paper is to report on the use of ARIMA models on chronopsychometric data gathered with ESTA III in a group of affective patients and controls. Data from this group have already been analyzed with ordinary chronobiological methodology (Sciolla *et al.*, submited for publication). Therefore, these two papers conform a preliminary report of a longitudinal study of AS aimed at finding out whether alterations in physiological rhythms (e.g., hormones, body temperature, sleep-wake cycle, etc.) have their counterpart in psychological ones.

METHODS

i) *Subjects:*

Nineteen subjects gave informed consent to participate in the study and were subjected to a structured interview, including Feighner's (Feighner *et al.*, 1972), RDC (Spitzer *et al.*, 1978),

DSM-III (American Psychiatric Association, 1980), criteria and selected items from the Newcastle Scale (Carney *et al.*, 1965) regarding endogenous/non endogenous dichotomy. Subjects under 18 and over 60 years, as well as those meeting criteria for Schizophrenic Disorders or Organic Mental Disorders, were excluded.

The six subjects who completed the study were diagnosed as: Bipolar Disorder (2) and Major Depression (3) and Adjustment Disorder (1). All patients were symptom free. Four were males. Age ranged from 27 to 45 years (see Table III).

Clinical state was evaluated at the beginning and end of the study by means of the Hamilton Depression Scale (Hamilton, 1960; Hamilton, 1967) and the Bech-Rafaelsen Scale for Mania (Bech *et al.*, 1978). The impact of life events was measured with the Holmes and Rahe Scale (Holmes and Rahe, 1967). Personality traits were assessed with the Eysenck Personality Questionnaire Revised (EPQ-R) (Eynseck *et al.*, 1985).

ii) *Testing and Scales*

ESTA-III can be described as a segmented visual scale (Eastwood *et al.*, 1984), also termed discretized analogic scale (Beach *et al.*, 1986), and was originally developed by Supprian (Supprian, 1975a). Spontaneous verbal expressions made by manic-depressive patients regarding their AS were condensed into 20 items by means of statistical methods. Two main factors of AS, called "Mood" and "Drive" because of their psychophysiological characteristics, were isolated by means of Factor Analysis. Each one of these two factors was quantified scoring 10 items, each item containing two polar statements about a certain feeling. The segmented rectangles for self-assessment were placed between the two lists of opposing feelings. The central segment had a neutral value (0). Increasing degrees of intensity were arranged around that neutral value. Each segment was numbered from one (1) to seven (7), and a verbal expression of intensity (from "almost nothing" to "extreme") was added. Mood or Drive scores were obtained averaging the corresponding 10 items. In our Spanish version, we added two bipolar items as further indicators of AS: "Anxiety-Easiness" and "Drowsiness-Alertness" (from now on "Anxiety" and "Drowsiness", respectively).

The subjects were also asked to include information regarding date and time of assessment, phase of menstrual cycle, the time at which they went to bed and got asleep the previous night (sleep latency), and the time at which they woke up and got up that day (waking up latency).

AS assessments were made three times a day every eight hours. At least 100 observations per patient were needed for statistical purposes, the whole study spanning about a month. Subjects reported here largely complied with this requisite.

iii) *Statistical Procedures:*

In this section we will briefly discuss the statistical modelling and analysis of a time series data set. For a detailed discussion of these topics see for example, Box and Jenkins (1976) or Fuller (1976).

Let x_t, $t = 1, 2, ..., n$, be a time series observed at regular time intervals. The class of Autoregressive Moving Average, ARMA (p, q), models is defined by the following equation:

$$x_t = a_1 x_{t-1} + ... + a_p x_{t-p} + \mu_t + b_1 \mu_{t-1} + ... + b_q \mu_{t-q} \quad (1)$$

$$(1 - a_1 B - a_2 B^2 - ... - a_p B^p)\, x_t = (1 + b_1 B + + b_2 B^2 + ... + b_q B^q)\, \mu_t \quad (2)$$

$$a(B)\, x_t = b(B)\, \mu_t ,$$

where

$$a(B) = (1 - a_1 B - a_2 B^2 - ... - a_p B^p), \quad (3)$$

$$b(B) = (1 + b_1 B + b_2 B^2 + ... + b_q B^q), \quad (4)$$

$$B^s x_t = x_{t-s},\ s = 1, 2, ... \quad (5)$$

and $\{\mu_t\}$ is a white noise, i.e. a sequence of independent, identically distributed random variables.

If the time series is not stationary (i.e., the mean of the series is not constant and changes over time), we proceed by taking as many differences as necessary to make the series stationary. If we have taken d differences, the resulting stationary series, w_t, may be represented by an ARMA (p, q) model:

$$a(B) w_t = b(B)\, \mu_t \quad (60$$

where

$$w_t = \nabla^d x_t , \quad (7)$$

$$\nabla^d{}_s = (1 - B^s)^d \ , \nabla^1 = \nabla = (1 - B). \quad (8)$$

Equations (6), (7) and (8) define the ARIMA (p, d, q) model for the original time series x_t:

$$a(B) \nabla^d x_t = b(B)\ \mu_t . \quad (9)$$

To identify the appropriate model to represent the stationay time series, we estimate several model with different values of p and q. The model

chosen will be the one with all the coefficients statistically significant and whose residuals behave like a random noise.

The parameters will be regarded as statistically significant (different from zero) whenever the T-statistic is around 2, or greater than 2, in absolute value.

To study the behaviour of the residuals, we inspect the following statistic:

$$Q = n'(n'+2)\sum_{j=1}^{m} r_j(\hat{u})/(n'-j), \qquad (10)$$

where $\hat{u}_t$ are the residuals from the fitted model, that is:

$$\hat{u}_t = x_t - \hat{a}_1 x_{t-1} - \ldots - \hat{a}_p x_{t-p} - \hat{b}_1 \mu_{t-1} - \ldots - \hat{b}_q \mu_{t-q}, \qquad (11)$$

$$r_j(\hat{u}) = \sum_{t=1}^{n'-j} \hat{u}_t \hat{u}_{t+j} \Big/ \sum_{t=1}^{n'} \hat{u}_t^2, \qquad (12)$$

which is the autocorrelation function of the residuals,

$n' = n-d$ = number of observations after taking d differences, (13)

$k' =$ number of estimated parameters, 14)

$M =$ 24 (M may be chosen arbitrarily, however, it is recommended that it should be greater than 20); (15)

finally $\hat{a}_j$ and $\hat{b}_j$ are the estimated coefficients. Under the null hypothesis (H_O) that the residuals behave like a random noise, it may be shown that Q has a Chi-square distribution with M−k' degrees of freedom, that is $Q \sim \chi^2(M-k')$. We would accept H_O for small values of Q. However, in the tables below, we report the p-value, that is $P(Q > Q_O)$, where Q_O is the observed value of Q. If the p-value is $\geqslant 0.2$, we may be highly confident that the residuals behave like a white noise and this confidence increases with the p-value.

To confirm the results obtained from the Q statistic, we may use the normalized cumulative periodogram. This can be used to detect the presence of a periodic component in the residuals. The normalized cumulative periodogram is defined by:

$$G_r = \frac{\sum_{j-1}^{r} I(2\Pi j/n')}{\sum_{j=1}^{m} I(2\Pi j/n')} \qquad r = 1, 2, \ldots, m \qquad (16)$$

where

$$I(2\Pi j/n') = \sum_{t=1}^{n'} \mu_t \cos(2\Pi jt|n')^2 + \sum_{t=1}^{n'} \mu_t \operatorname{sen}(2\Pi jt/n')^2 \qquad (17)$$

and

$$m = \begin{cases} (n'-2)/2 & \text{if } n' \text{ is even} \\ (n'-1)/2 & \text{if } n' \text{ is odd} \end{cases} \qquad (18)$$

To test $H_O: \mu_t \sim N(O; \sigma^2)$, we may use the Kolmogorov-Smirnow statistic:

$$K = \operatorname{Sup}_r |G_r - r/m| \qquad (19)$$

We would reject H_O with a significance level α if $K > K_\alpha$ where $P(K > K_\alpha) \Leftrightarrow \alpha$. Note that since μ_t is unknown, the analysis has to be based on the residuals. If we compute G_r from μ_t rather than μ_t, then the test is only approximately valid for large samples.

RESULTS

Eight subjects have completed the study. Two were excluded for the following reasons: one patient's series behaved as random noise in the periodicity analysis reported elsewhere (Sciolla *et al.*, 1990). Subsequent interviews revealed that this patient did not complied appropiately with the instructions of the study. The other subject (control, with no mental disorder) had an insufficient number of observations for ARIMA modelling. The following comments are based on the remaining 6 subjects. Due to space limitations, only two cases are reported in detail. The ARIMA models obtained for the other four cases were similar to the ones reported here (Tables I and II).

1. Most of the series were non-stationary. In other words, they contained trends (the mean value of the series increased or decreased along the time of observation) which need to be removed in order to estimate a model. All the series under

TABLE I

ARIMA models of patient PAI-07 (Unipolar), based on 105 observations

Variable	ARIMA model	$P(Q > Q_o)$ K
Mood	$\nabla X_t = \mu_t + 0.382\mu_{t-1} - 0.203\mu_{t-6} + 0.158\mu_{t-7}$	0.630
	(4.17) (−2.06) (1.57)	0.062*
Drive	$\nabla_6 \nabla X_t = \mu_t + 0.386\mu_{t-1} + 0.552\mu_{t-6} - 0.205\mu_{t-7}$	0.531
	(4.02) (6.12) (−1.99)	0.071*
Anxiety	$\nabla X_t = \mu_t + 0.473\mu_{t-1} + 0.25\mu_{t-2}$	0.531
	(4.93) (2.68)	0.081*
Drowsiness	$\nabla_6 \nabla X_t = \mu_t + 0.940\mu_{t-1} + 0.856\mu_{t-6} - 0.766\mu_{t-7}$	0.610
	(19.88) (12.76) (−9.64)	0.135*

T statistics (ratio of estimated coefficient over standard desviation) given in parentheses below each estimated coefficient. $P(Q > Q_o)$, probability of getting a Q value larger than observed value Q_o. K, Kolmogorov-Smirnov goodness of fit statistic. (*) H_o not rejected at the 5% level.

TABLE II

ARIMA models of patient PAI-02 (rapid bipolar cycler), based on 182 observations

Variable	ARIMA model	$P(Q > Q_o)$ K
Mood	$\nabla X_t = 0.196\nabla X_{t-11} + 0.146\nabla X_{t-17} - 0.204\nabla X_{t-21} - 0.213\nabla X_{t-23} + 0.213\nabla X_{t-28} + 0.708\mu_{t-1}$	0.986
	(−2.39) (1.68) (−2.31) (−2.44) (2.36) (13.12)	0.052*
Drive	$\nabla X_t = -0.178\nabla X_{t-21} + \mu_t + 0.789\mu_{t-1}$	0.551
	(−1.98) (17.08)	0.56*
Anxiety	$\nabla X_t = -0.1799\nabla X_{t-5} + \mu_t + 0.622\mu_{t-1}$	0.982
	(−2.40) (11.69)	0.042*
Drowsiness	$\nabla X_t = -0.167\nabla X_{t-5} + 0.214\nabla X_{t-12} - 0.181\nabla X_{t-19} + 0.243\nabla X_{t-22} + \mu_t + 0.768\mu_{t-1}$	9.910
	(−2.32) (2.99) (−252) (3.29) (15.69)	0.064*

Legend as in Table I.

study could be made stationary taking only one difference. The exceptions were Drive and Drowsiness series of patient PAI-07 (Table I) for which two differences were needed.

2. The estimated ARIMA models produced a very good data fit, with residuals behaving as "white noise" (Tables I and II).

3. Different equations were obtained for different individuals. Nonetheless, the equations of Drive and Drowsiness presented identical structures (the same lags for autoregressive and moving average parts of the equations) for subjects CAI-01 and PAI-07, and to a lesser extent those for subjects PAI-03. Somewhat similar conclusions may be arrived at for Mood and Anxiety, but not necessarily for the same individuals (Table III).

4. Table III also shows the dynamic behavior of all series considered, since any given observation is related to previous ones of the same series. In a number of cases the presence of an autoregressive term at lag 21 gives some indication of the existence of a 7 days periodicity in the data.

TABLE III

Subject (diagnosis) (sex) (age)		Lag for autoregressive term X_t	Lag for moving average term μ_t
CAI-01	Mo	4, 5	2, 7
(Control)	De	1, 3, 4	1
(Female)	Ax	1	1
(31 y)	Ds	1, 3, 4	1
PAI-02	Mo	11, 17, 21, 23, 28	1
(Bipolar)	De	21	1
(Male)	Ax	5	1
(45 y)	Ds	5, 12, 19, 22	1
PAI-03	Mo	1	1
(Bipolar)	De	3, 12, 21	1
(Male)	Ax	1	1
(27 y)	Ds	3, 7, 12, 21	1
PAI-05	Mo	1, 3	2, 3
(Unipolar)	De	1, 3	2, 3
(Female)	Ax	3	1, 7
(32 y)	Ds	1, 2, 3	1, 2, 3
PAI-07	Mo	1	1, 6, 7
(Unipolar)	De	1, 6, 7	1, 6, 7
(Male)	Ax	1	1, 2
(34 y)	Ds	1, 6, 7	1, 6, 7
PAI-09	Mo	3, 7, 9	1, 2
(Unipolar)	De	1, 2, 10	3, 4
(Male)	Ax	1, 2, 3	2, 3
(30 y)	Ds	1, 3, 15, 21	2, 3

Mo = Mood, De = Drive; Ax = Anxiety; Ds = Drowsiness.

5. In a number of cases the models estimated for Mood and Drive resembled those of Anxiety and Drowsiness.

DISCUSSION

Chronopsychometric data of AS from one non-affective and five affective patients were successfully modelled through a computer-assited procedure. This analysis yielded valuable information regarding the statistic-mathematical behavior of the time series. This, in turn, allowed the comparison of the different series within individuals and between them. Thus, the equations of Drive and Drowsiness, and to a lesser extent those of Mood and Anxiety, were similar for each subjet. This could mean that Drive is more readily influenced by circadian variations of cortical arousal than Mood or Anxiety do. ARIMA modelling of the series also gave information concerning the presence of periodicities in the data. The latter does not make the traditional procedures for periodicity analysis useless. On the contrary, ARIMA models can strenghthen, say, Cosinor analysis, since they are free from assumptions concerning the data behavior.

It must be noted that ARIMA analysis is only strictly correct for continuous variables. We may regard Mood and Drive as continuous, since they are produced by averaging scores from a number of items. However, Anxiety and Drowsiness data are clearly not continuous, being only of the ordinal type. In spite of this, we may think of the underlying processes for Anxiety and Drowsiness as being continuous, although we are only able to approximate them by ordinal kind of variables. However, it is interesting to note that the analysis for these variables is consistent with that of Mood and Drive. Therefore, we may regard the representa-

tion of Anxiety and Drowsiness by means of ARIMA models as approximately valid. It is stressed that these *post hoc* considerations point toward an unexpected robustness of the method under discussion. Nevertheless, additional work clearly needs to be done in this sense.

The applicability and usefulness of ARIMA models to analyze chronopsychometric data as discussed above, seem to guarantee further chronobiological applications of them. Studies with temporal isolation have shown that, besides their endogenous character, psychological circadian rhythms behave just as physiological ones. The statistical analysis of both kinds of rhythms has been the same. Therefore, there is no theoretical reason that may preclude the use of ARIMA models in chronopsychometric data, in particular to expand to chronobiological data in general.

ACKNOWLEDGMENT

This study was supporter by Grant Nr. 1287/88 from the National Fund of Science and Technology (FONDECYT), Chile.

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