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The International Federation of Automatic Control
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The Institute of Management Sciences

SUPPORT SYSTEMS FOR DECISION AND NEGOTIATION PROCESSES

Preprints of the IFAC/IFORS/IIASA/TIMS Workshop

Warsaw, Poland

June 24-26, 1992

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VOLUME 2:

Names of first authors: **L-Z**

Natural Discrete-Event Process Forecasting:
A Decision Support System

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Abstract. A decision support system for the analysis and forecasting of natural discrete-event processes is considered. The corresponding method is based on sample path analysis using event-to-event operations. An application of the method in the computer-aided decision support system for long-range weather forecasting is mentioned.

Keywords. Natural Discrete-Event Process, Sample Path Analysis, Event-to-Event Operations, Decision Support System, Forecasting.

1 Introduction

Forecasting of climatic, hydrological, geophysical and the other natural processes has become, due to its importance, one of the most topical problems. The objective of the forecasting is the determination of a future state or behaviour of the considered process based on up to now available information and supported by the possibility of its realization.

The forecasting is a multiparameter problem with a great deal of uncertainty owing to little knowledge of some aspects of the considered process. While for short time or space intervals the natural system may be viewed as a closed one, for long intervals the supposition of constant external conditions is not justified and we are faced to an open system with external effects and relations, Reznikov (1982).

Different points of view may be considered to categorize the data that represent a natural process and/or the corresponding methods of analysis and forecasting. In this way, the numerically and non-numerically valued data can be distinguished. While a number of objective methods deals with the numerical data, the processing of non-numerical or non-numerically interpreted ones is not so elaborated and, moreover, it exhibits often an important role of subjectivity. From another point of view, the many different objective forecasting methods might be grouped into two general categories: dynamical and statistical. The concentration of a vast amount of data and the solving of system dynamic equations characterize the former category, the methods of statistical processing of averaged data with sufficiently long history fall into the latter one. The statistic-dynamical methods of forecasting have been introduced with promising results, however, the requirements of special data archives limit their broad application, Glahn and Lowry (1972), Klein, Lewis and Enger (1959), Reznikov (1982).

A growing need for analysis and modelling of systems and processes, whose terms corre-

spond to logical or symbolic rather than numerical values, initiated a broad research of this field. A number of approaches to the analysis and modelling of such systems and processes, called discrete-event ones, has been proposed to reflect the different aspects of their behaviour and the many areas where they arise, Ho (1989), Varaiya and Kurzhanski (1988), Workshop (1991). The proposed models are usually classified into two classes, logical and temporal, where a key element is a timing of events, Varaiya and Kurzhanski (1988). Another two classes of models, qualitative and quantitative, can be distinguished. In the former class, a set of possible event paths and the qualitative aspects are considered to study the system behaviour, Cassandras and Strickland (1989), Hoare (1985), Milner (1980), Ramadge and Wonham (1987), the latter models utilize numerical characteristics to represent that, Ho (1987), Zeigler (1984).

The forecasting problem as stated above is closely related to a pattern recognition problem, Pík and Bružek (1989). That is concerning with assigning a given pattern (e.g., object, phenomenon) to one of the known classes. There are two fundamental approaches used to solve pattern recognition problems: the decision-theoretic or discriminant approach and the structural or syntactic one. While the decision-theoretic approach is more suitable for numerically expressed patterns, the structural approach, as it is based on an analogy between the structure of patterns and the syntax of a language, suits to patterns represented by formal symbols, e.g., Ferrate G., Pavlidis T., Sanfeliu A., and Bunke H. (1987).

In the paper, a decision support system for the analysis and forecasting of natural discrete event processes is considered. In Section 2 we summarize some basic concepts used in the method of sample path analysis described in Section 3. An application of the decision support system is illustrated in Section 4.

2 Event, Distance, Discrete-Event Process

An alphabet is a finite nonempty set the elements of which we call symbols, events, or states. If Σ is an alphabet, then Σ^* denotes the set of all sequences of symbols of the alphabet Σ including the sequence λ consisting of no symbols. The length of a sequence X , written $|X|$, means the number of symbols in X when each symbol is counted as many times as it occurs, $|\lambda| = 0$. A sequence X is a subsequence of a sequence Y iff there are sequences X_1 and X_2 such that $Y = X_1 X X_2$, where $X_1 X X_2$ denotes the concatenation of the sequences X_1 , X , and X_2 .

The sample path analysis considered in the method is based on the notion of distance between two event sequences. To determine it, a proper use of event-to-event operations is needed to change the one sequence into the other. The following operations are considered to transform a sequence X into a sequence Y , $X, Y \in \Sigma^*$:

1. deleting one event from X ,
2. inserting one event into Y ,
3. substituting one event of X for another single event.

The considered operations can be written as a pair of events $s = (a, b) \neq (\lambda, \lambda)$, $a, b \in \Sigma \cup \{\lambda\}$, where 1. $b = \lambda$, 2. $a = \lambda$, 3. $a, b \neq \lambda$, respectively.

To reflect a difference in the application of the operations, a nonnegative real number is associated with each event operation. Two modifications of the transformation of the event sequences are considered.

The former is based on a stochastic mapping $T : E \cup \{\lambda\} \rightarrow E \cup \{\lambda\}$, E is an alphabet of events, $T(a) = b$, $(a, b) \neq (\lambda, \lambda)$, with a probability $q(b/a)$ associated with each event-to-event operation $t = (a, b)$.

Supposing the independence assumption for the considered operations, and at most one transformation of each event, the probability of the transformation X into Y , $q(Y/X)$, $X = a_1 a_2 \dots a_n$, is defined by

$$q(Y/X) = \max_{Y^k \in \tau} q(Y^k/X) = \max_{Y^k \in \tau} \{\prod_{j=1}^n q(\alpha_j^k/a_j)\},$$

where τ is a set of all partitions of Y into n subsequences, $Y^k = \alpha_1^k \alpha_2^k \dots \alpha_n^k$, $\alpha_j^k \in E^*$, $j = 1, 2, \dots, n$, Lu and Fu (1977).

As follows from the definition of $q(Y/X)$, it corresponds to the most likely way of transforming X into Y .

The latter modification introduces the Levenshtein metric for an optimal representation of the event sequences, Levenshtein (1966). A nonnegative real number $w(s)$ associated with each event operation is called a weight of the operation $s = (a, b)$. The notion of $w(s)$ is extended to a series of operations $S = s_1, s_2, \dots, s_m$ using

$$w(S) = \sum_{i=1}^m w(s_i) \text{ and } w(S) = 0 \text{ for } m = 0.$$

The weighted distance $d_w(X, Y)$ from $X \in E^*$ to $Y \in E^*$ is defined by

$$d_w(X, Y) = \min_S \{w(S) : S \text{ is a transformation of } Y \text{ from } X\}.$$

Procedures following the algorithm of Wagner and Fischer are commonly used for the computation of the weighted distance. In Wagner and Fischer (1974), dynamic programming is applied and the corresponding time complexity is $O(|X| \times |Y|)$.

A transformation of the event sequences is called length-preserving if it transforms X into Y and $|X| = |Y|$.

A discrete-event system (DES) is defined as a 3-tuple

$$DES = (S, E, D),$$

where

- S is an alphabet of states,
- E is an alphabet of events,
- D is a transition function, $D : S \times E \rightarrow S \cup \{\lambda\}$,

and λ is used to indicate an undefined transition.

Such DES is also called the untimed (logical) DES to distinguish it from the system where the event occurrence time is taken into account.

A discrete-event process is introduced through a sample path of the DES that is given by an event sequence $e_1 e_2 \dots e_k \in E^*$.

3 Decision Support System

Consider a natural system affected by endogenous and exogenous activities. Depending on the insight into the problem being solved, suppose a finite number of possible states or integral characterizations of the system's behaviour in elementary time intervals. To describe the behaviour in an extended interval of time, the distinguished situations are interpreted as discrete events and the corresponding event sequence is considered. In this way, a time development of the behaviour is represented by a sample path, where an equidistant timing is supposed.

To support the analysis and forecasting of the system's behaviour, the problem is formulated as follows.

Let a sufficiently long history of the system's behaviour be represented by the sample path $e_1 e_2 \dots e_i$. Now, assuming the behaviour of the system in an interval (i_1, i_2) represented by the event sequence $e_{i_1} \dots e_{i_2}$, we require some description and/or characterization of the behaviour in the defined interval (k_1, k_2) . Further, let a union of intervals instead of the interval (i_1, i_2) be possible as well.

The underlying idea of the method supporting the decision making reflects, in fact, human reasoning and experiences. In our approach, a formalization of those is introduced using an objective framework based mainly on the notions of the discrete events and their distances. Indeed, they make possible to utilize a-priori information concerning the process and, on the other hand, to view the process with a variable selectivity.

As any event occurrence time is not taken into account, the untimed $DES = (S, E, D)$ and the sample path $e_1 e_2 \dots e_i \in E^*$ are considered. For the prescribed event subsequences, $e_{i_1} \dots e_{i_2}$ in (i_1, i_2) , the considered method looks for all occurrences of the same or the similar subsequences in the considered sample path. To find those, the numerically valued distance of the event subsequences based on a-priori defined event-to-event operations is utilized. The next development of the found subsequences in (k_1, k_2) is extracted and a clustering based on the nearest neighbour rule is used to get a partition of this set, Lu and Fu (1978). The subsequences clustered into the same partition class are characterized by a reference subsequence and by associated absolute and relative frequencies corresponding to a probability space. Finally, as these reference subsequences and frequencies characterize the development of the behaviour in the required time interval, the results are summarized to give an insight into the structural relations among the events in the context of the process development.

Rhythmical components of activities affecting the system may be revealed. To respect them, only particular periods of the considered sample path can be taken into account.

As particular events represent the process usually at short time intervals, one may object to the usefulness of those especially for long-range forecasting. To face it, the considered method employing the weighted distance introduces, in effect, a new process representation derived from the original one and based on macro-events.

As the notion of the weighted distance is based on the event-to-event operations, there is a possibility to handle noisy, uncertain, or incomplete events. Following the structural approach to pattern recognition, the real number associated with each event operation can be viewed as a measure of possible event occurrence and a transformation of the original sample path into a prototype one can be considered.

4 Application

The proposed method based on the length-preserving transformation of the event sequences is really utilized for the analysis and the forecasting of the atmospheric circulation, Pík and Bružek (1989). It is a part of the computer-aided decision support system for the long-range weather forecasting in the Czech Institute of Hydrometeorology.

In this application, the updated Hess and Brezowsky's standardization (GWL symbols) of the pressure field over the Atlantic-Europe region is considered, Hess and Brezowsky (1969). Twenty-nine well defined non-numerical types of the daily configurations of the pressure fields are distinguished, moreover, another type is added to represent an exceptional configuration.

Starting from 1881 the considered time series contains about 40,000 symbols constituting a sample path. There are attempts to utilize the standardization to the weather forecasting: e.g., Mares and Mares (1982), where the Markov chain theory is taken into account. States of the Markov chain are labelled using the alphabet of the GWL symbols and the corresponding transition matrix is computed. The obtained results are very briefly outlined and it is concluded that the considered Markov process is "...a first good approximation..., but a better approximation may be obtained often by fitting with a higher order autoregressive.", Mares and Mares (1982).

In our model, the set of event sequences of the given length over the alphabet of the GWL symbols Σ_{GWL} is reduced using the weighted distance. To compute it, we prepared two sets of the event-to-event operation weights. The weights of the former set follow a physical analogy of the pressure fields and are as follows

$\Sigma_{GWL} = \{C, S, W, A, B, H, V, X, Z, Y, T, R, J, I, F, E, M, O, N, D, 1, 2, 3, 4, 5, 6, 7, 8, 9, U\}$, $\sigma_1 = \{C, S, W\}$, $\sigma_2 = \{A, B\}$, $\sigma_3 = \{H\}$, $\sigma_4 = \{V, X, Z, Y, T, R\}$, $\sigma_5 = \{J, I\}$, $\sigma_6 = \{F, E, M, O\}$, $\sigma_7 = \{N, D\}$, $\sigma_8 = \{1, 2, 3, 4, 7, 8, 9\}$, $\sigma_9 = \{5, 6\}$, $\sigma_{10} = \{U\}$,
 $w(a, b) = c_1$ iff $a, b \in \sigma_i$ for some $i \in \{1, 2, \dots, 10\}$,
 $w(a, b) = c_2$ iff $a \in \sigma_i$, $b \in \sigma_j$, $i, j \in \{1, 2, \dots, 10\}$ and $i \neq j$, $c_1 < c_2$.

The latter set represents a more complex case as the weights depend on the correspondence between the weather and the standardization and, in effect, the twelve sets of the monthly weights are introduced.

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