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Predicting Nonlinear Processes for Manufacturing Automation: Case Study through a Robotic Application

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Abstract

The manufacturing environment is rife with nonlinear processes. In this context, an intelligent production controller should be able to predict the dynamic behavior of various subsystems as they react to transient environmental conditions, the varying internal condition of the manufacturing plant, and the changing demands of the production schedule. This level of adaptive capability may be achieved through a coherent methodology for a learning coordinator to predict nonlinear and stochastic processes. The system is to serve as a real time, online supervisor for routine activities as well as exceptional conditions such as damage, failure, or other anomalies. The complexity inherent in a learning coordinator can be managed by a modular architecture incorporating case based reasoning. In the interest of concreteness, the concepts are presented through a case study involving a knowledge based robotic system.

Keywords: Manufacturing automation, nonlinear prediction, multistrategy learning.

INTRODUCTION

Nonlinear processes constitute an inherent component of the manufacturing environment. In this context, an intelligent production controller should be able to predict the dynamic behavior of various subsystems as they react to transient environmental conditions, the vary-

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ing internal condition of the manufacturing plant, and the changing demands of the production schedule. This level of adaptive capability may be achieved through a coherent methodology for a learning coordinator to predict nonlinear and stochastic processes.

The next generation of manufacturing systems should incorporate adaptive capabilities to accommodate to transient environmental conditions as well as the changing goals of the operator and the dynamic condition of the factory itself. For instance, an automated guided vehicle (AGV) must take into account strategic knowledge such as prior information on the available routes and their characteristics. Since the enormous space of potential situations cannot be foreseen and enumerated in advance, the coordinating system should incorporate versatile learning capabilities. A further advantage of such adaptive capacity lies in the potential for steady improvement. By drawing on its accumulating experience, the system should yield enhanced performance over time, even in the absence of exceptional conditions which would stretch the boundaries of its knowledge base.

A complex system such as a mobile robot operates in a highly dynamic environment. Environmental disturbances may be caused by physical phenomena such as mechanical failure, or human activity such as passing workers, or automated systems such as moving shuttles. Due to the intrinsic complexity of automating the operation of autonomous mobile robots, control systems which have been fielded to date address only specific tasks or limited environmental scenarios. Moreover, exceptional conditions such as damage or failure of components have been handled with limited prowess: for instance, a sudden failure of the brakes in a manned vehicle invokes no automated response but rather relies on the swift reflexes of the driver and the invocation of manual procedures such as the use of the handbrake.

The complexity of the domain and the uncertainties which are often its derivatives limit the effectiveness of traditional control methods. Fortunately, this situation can be remedied by an adaptive control methodology using knowledge integration (Kim, 1994a).

Over the past decade, a popular methodology for implementing learning controllers has lain in the neural network. Despite its many advantages such as autonomous learning in specific contexts, the neural approach has its limitations. Among the limitations are the slow rates of learning and perhaps even more importantly, the implicit nature of the learned skill. More specifically, a neural network may yield the correct response to a query but it cannot explain the result or justify its "reasoning" (Kim, 1994b; etc.).

More extant control systems are islands of automation, each of which performs a simple regulatory function. An example in this vein is found in the cruise control system, which regulates only the speed of the vehicle; its regulatory behavior ignores the status of other subsystems, except for manual intervention such as the pressing of the brakes causing the controller to disengage. In general, having a portfolio of disparate systems leads to the problem of suboptimization: in a nonlinear context such as the realm of vehicle control, the union of local optima determined by the respective controllers is unlikely to lead to the globally optimum action.

The need for joint optimization applies not only to systems at a given level of operation, as exemplified by control modules for balancing speed against safety on a slippery road, but at different level of supervision, such as navigation versus collision avoidance. The limitations of existing control techniques may be transcended by an integrated approach. The approach tasks the form of a generalized framework for learning control which accommodates a portfolio of software and hardware technologies acting in concert (Kim, 1990). In the realm of software, the framework may be implemented through the declarative techniques of artificial intelligence as well as the procedural methods of traditional computing. The software methods range from rule bases and frames to object oriented programming and case based reasoning. The approach can accommodate not only the methods of declarative logic, but procedural methods such as those from nonlinear adaptive control theory.

Among complex systems, chaotic processes are perhaps the most difficult to predict (Farmer, 1982; Grassberger, 1983; Shaw, 1981). Even so, knowledge based methods have been used successfully for prediction in domains ranging from economics and finance to science and engineering (Scheinkman and LeBaron, 1989; etc.). This paper investigates the utility of the case based approach to the manufacturing environment.

BACKGROUND

The intelligent control of autonomous entities has been a subject of extensive investigation, especially over the past decade or two. One relevant project is the Autonomous Land Vehicle (ALV). Although the ALV program has not yet met the expectations of its sponsors or commentators, its successes and failures are instructive, as in any advanced-technology project. Perhaps the main stumbling block in this project has been the lack of an adequate technology base to support pattern recognition and image understanding in a complex landscape.

A fundamental limitation of classical methods of adaptive control lies in their vulnerability to instability in the face of unmodeled dynamics and unmeasurable disturbances. Even with improved algorithms such as enhancements to model reference adaptive control (MRAC), only local stability can be guaranteed under imperfect knowledge of system dynamics and disturbances. Moreover, such algorithms can lead to impractical computational burdens, as exemplified by the adaptive procedure for which a Cyber 205 supercomputer was inadequate to respond in real time to a simulated plant (Athans, 1988).

These limitations can be circumvented with the use of nonlinear models of the plant. The use of declarative methods of control obviates the need for developing an exhaustive model of the plant dynamics. This is especially advantageous in the interest of accelerated control system development, or in cases where the physical dynamics of the plant are unknown. Even in the down-to-earth task of fabricating composites for aircraft, the effects of production parameters such as temperature and humidity on the final characteristics of the cured part are imperfectly understood; yet knowledge based systems have been successfully developed for such production control applications (Kim, 1991).

METHODOLOGY

Adaptation refers to the modification of behavior patterns over time. such adaptive behavior is useful for dealing with unknown factors in current or future activities. More specifically, they are effective in applications where (a) predictive knowledge of the underlying process is incomplete, and (b) variations in inputs or environmental conditions may exceed the predetermined range of values, or may be even assume wholly unexpected characteristics (Kim, 1990). The framework and concepts for learning systems have been tailored to applications in various domains.

A learning system should make increasingly useful decisions as it accumulates experience. This is the express goal of the work in case based reasoning (CBR). Perhaps the most important advantage of CBR is the affinity to human learning and the ease of enhancing system performance. The knowledge in a particular domain can be stored in formats which are conventional for that domain. This is in contrast to other knowledge level representations such as production rules, in which the system developer is required to extricate the pertinent decision rules used by a human.

Case reasoning requires the retrieval of past experience in the form of cases. In this task, two types of difficulties can arise. The matching problem refers to the task of associating a new problem to pertinent prior cases. More specifically, a target case is matched against prior cases as indicated in Figure 1. A key issue lies in retrieving prior cases which are similar to the new problem in substantive rather than superficial ways. This relates in part to the issue of indexing, which

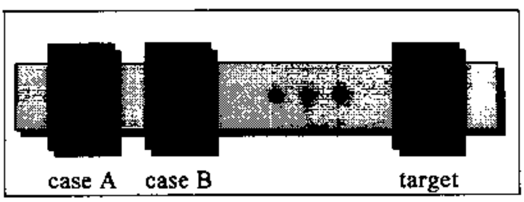

Figure 1. General scheme for case based reasoning.

deals with the organization of the case base.

To automate the task of matching in CBR, previous cases can be organized in some fashion to enable to the rapid identification of potentially relevant cases. To this end, previous solutions can be indexed by their key attributes and the features which distinguish them from other cases. The indexing problem refers to the task of storing cases for effective and efficient retrieval. In terms of efficacy, the subsides are accuracy - finding only relevant cases - and completeness - identifying all relevant cases.

In forecasting a univariate time series, the task of CBR is to predict the subsequent state $T+1$ at time T based on delay vectors of the form $x_t \equiv (x_t, x_{t-1}, \cdots, x_{t-k})$. Each delay vector x_t represents a case in the context of univariate forecasting. The basic structure of inputs and outputs for the CBR approach is presented in Figure 2.

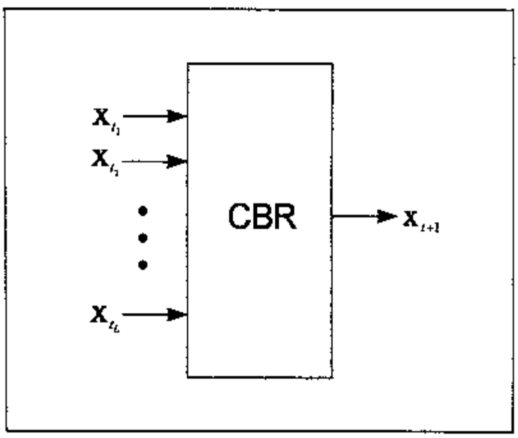

Figure 2. General structure of the case based reasoning method. In the study, the number of neighbors was $L = 5$

In the current study, the length of each delay vector was 5; that is, $k \equiv 4$. Moreover, the number of neighbors was $L \equiv 5$. The procedure for employing the CBR method is listed in Figure 3.

Step 1. Begin with current case $x(t)$.

Step 2. Seek the J neighboring cases $x(t_i)$ in the past which are closest to $x(t_i)$ according to the distance function :

$$d_i \equiv d[x(t_i), x(t)]$$

Step 3. Compute the sum of weights :

$$d_{TOT} = \sum_{i=1}^{J} d_i$$

Step 4. Determine the relative weight of i^{th} neighbor :

$$W_i = \frac{1}{J-1}[1 - \frac{d_i}{d_{TOT}}]$$

Step 5. Find the successor $x(t_i+1)$ of each case $x(t_i)$ in the set of neighbors.

Step 6. Calculate the forecast for t+1 as the weighted sum of successors :

$$\hat{x}(t+1) = \sum_{i=1}^{J} W_i x(t_i+1)$$

Figure 3. Procedure for case based reasoning using composite neighbors (Kim, 1995).

In many practical contexts, predictions must be made in domains rife with casual factors which are poorly understood. Even so, the explanatory factors must be incorporated into some model if predictions are to be accurate. Comparison-based planning (CBP) is one approach to addressing this challenge (Klein, 1986). In making a prediction for the target case, the designer first examines previous cases which incorporate many of the causal factors in the current situation. The information in one of these analogous cases is then used to make a prediction for the target case by examining the significant differences between the analogous precedents and the target case.

A learning system, to be effective, must have the ability to draw on knowledge from diverse sources. The diversity can take the form of different formats for encoding knowledge as well as multiple modules within a single representation format. The synergism of diverse formats is exemplified by the integration of production rules with the output of neural networks. The second major category of integration relates to the enhancement of performance through the fusion of new information with the old in an existing knowledge base.

APPLICATION OF METHODOLOGY

A general framework for learning systems has been developed for control automation in various domains (Kim, 1990). Information from the environment is acquired through sensors and from directives from humans; the input streams are processed by a learning coordinator in conjunction with dynamic trip requirements and decisions of the user. The actions from the system, implemented through the activators, modify the external environment - such as the clearance of an obstruction where appropriate - or the internal environment - such as the replacement of a malfunctioning unit by a redundant one. In this arrangement, the reasoning phase of observation, prediction, action, and evaluation proceed for each top-level module as well as its subsystems in turn.

A versatile learning system must incorporate input from multiple sources. To illustrate, consider the realm of sensor fusion for vehicles. The functional requirements on sensor systems for a mobile system may be broadly classified into internal and external categories. Internal functions deal with proprioceptive tasks such as monitoring for homeostasis and malfunctions. External sensory functions, on the other hand, include navigation, object detection, object identification, and verification. Any sensory modality exhibits a unique set of advantages and limitations, such as resolving capacity or attenuation in the atmosphere. Moreover, any physical device is also susceptible to malfunction or failure. For this reason, the likelihood of accurate perception is increased by integrating the input from multiple modalities as well as multiple physical units within a single modality. An example of the effective fusion of several modalities lies in the use of passive as active modes of infrared and radio frequency emissions for detecting objects.

A learning controller must supervise and coordinate the activities of many subsystems. The coordination of multiple decision making units has been investigated through various techniques, including game theory and team theory (Kim, 1994). The utility of coordinative and competitive heuristics to the coordination of mobile robots, for instance, has been validated through simulation studies (Egilmez and Kim, 1992).

CASE STUDY

For the sake of concreteness, the adaptive methodology has been applied to a robotic application. The basic motivation behind the case study is presented in Figure 4.

Figure 5 shows the scenario for the simulation study. The robot R travels with speed V in response to service calls from flexible machine cells F1, F2 and F3. It must navigate its way despite the potential obstruction of two slow-moving shuttles, S1 and S2, which convey workpieces from one location to another. Because the alleys allow for the passage of only one platform (robot or shuttle) at a time, the robot might reach its destination more quickly by selecting a roundabout route rather than a direct one.

The architecture for the robotic reasoning system is given in Figure 6. The system architecture has been used extensively in the past for the design of intelligent systems (Kim, 1990).

Premise

- Manufacturing system performance can be enhanced through learning techniques.

Case Study

- The context is a manufacturing system with multivariate inputs.
- The performance criterion for prediction and planning pertains to accuracy and response time. An example is a mobile robot which responds swiftly to service requests from a flexible manufacturing cell.

Simulation Format

- Simulation model consists of several modules with information hiding: only the inputs and outputs for each module are observable and/or controllable.
- The behavior of each module tends to be nonlinear, and the internal model is unavailable to the other modules.

Learning Methodology

- The learning robot observes system behavior using case based reasoning and generates regulatory rules to improve system performance.

Figure 4. Highlights of the study.

The simulation software was written in the C language and run on a Pentium PC. The input data in the form of Lorentz and Henon processes were generated on an Excel

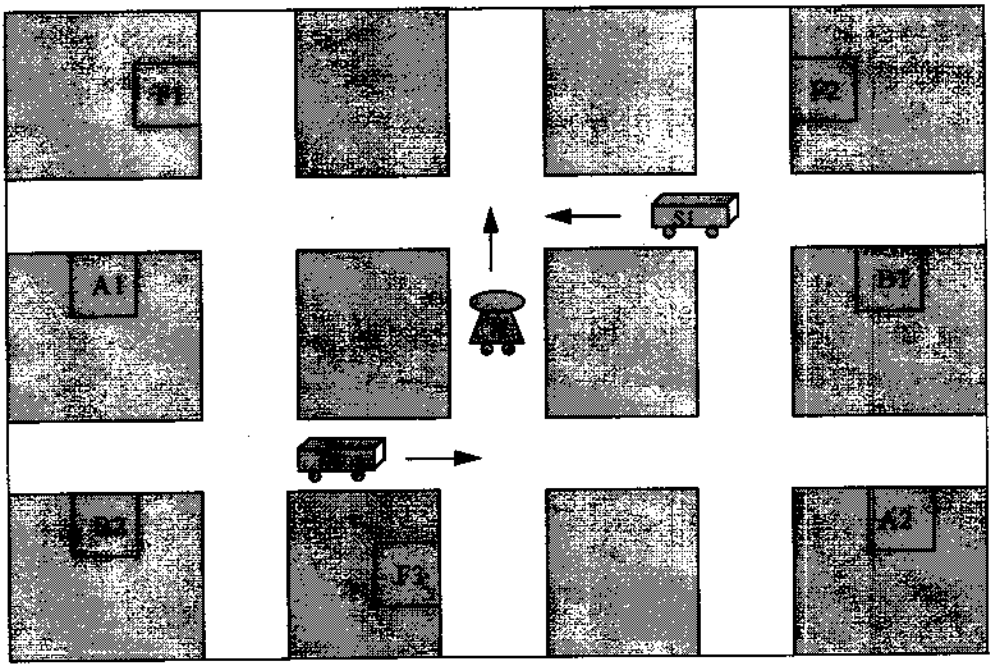

Figure 5. Simulation scenario. Robot R travels with speed V and responds to calls for service from flexible machine cells F1, F2, and F3. Each shuttle Si delivers workpieces from source A_i to destination B_i, traveling at speed C_i (much less than V). Each alley has room for two vehicles.

spreadsheet using equations described below.

The alternative models for the simulation experiments are given in Table 1. The service calls from each workcell are assumed to be chaotic.

The functions of the robot relate to prediction or planning. In the predictive task, the goal of the robot is to characterize the service calls in terms of the probability distribution of interarrival times. For the planning task, the objective of the robot is to generate a trajectory which will ensure minimal travel times with high probability.

A principal model of a chaotic process is the Lorentz system characterized by continuous variables (Lorentz, 1963). The discrete version of the model takes the following form.

$$x_{t+1} = (1-\sigma\,\Delta t)x_t + (\sigma\,\Delta t)y_t$$
$$y_{t+1} = (1-\Delta t)y_t + (r-z_t)\,\Delta t x_t$$
$$z_{t+1} = (1-b\,\Delta t)z_t + x_t y_t\,\Delta t$$

The system of equations exhibits chaotic behavior when the parameter values are $\sigma = 10$, $\Delta t = 0.025$, $r = 28$, and $b = 8/3$.

Another model of a chaotic process is the Henon system which involves discrete variables (Henon, 1976).

$$x_{t+1} = 1 - Ax_t^2 + y_t$$

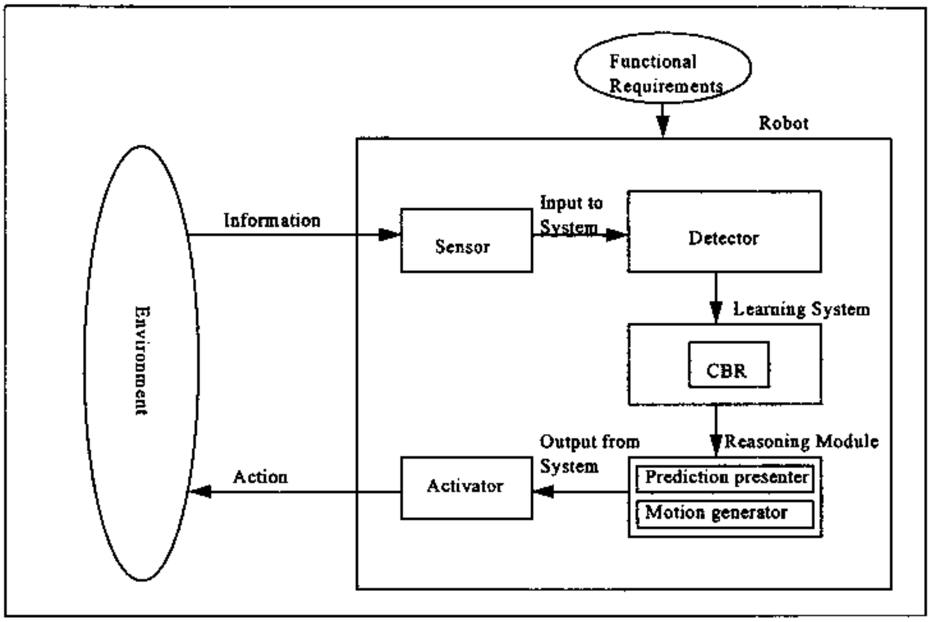

Figure 6. System architecture for a learning robot. The manufacturing environment involves a nonlinear model. The learning robot records historical information, and autonomously learns to adapt to its external environment.

Table 1. Simulation experiments. The interarrival times for service calls may be stochastic or deterministic (chaotic). The service calls arise from F_i for the robot, as well as B_i for shuttle S_i. In either the stochastic or deterministic milieu, the task of the robotic agent can be categorized as simple prediction (while remaining stationary), or planning (generation and execution of a trajectory).

	Lorentz model	Henon model
Prediction	Predict interarrival times with Probability distributions	Predict interarrival times with probability distributions
Planning	Generate a probabilistic trajectory	Generate a probabilistic trajectory

$y_{t+1} = Bx_t$

The model yields chaotic behavior for the parameter values of $A = 1.4$, and $B = 0.3$

The Lorentz and Henon models were implemented in our simulation software. The simulation utilized case based reasoning (CBR) for forecasting the process. In the CBR approach, previous patterns of events - in terms of time and location - are stored in a case base. This database of prior events is then used to forecast future events. The predictions are utilized by the robot and shuttles to make decisions geared toward minimizing response delays.

The average response delay of the system under a Lorentz model of interarrival times is shown in Figure 7. The corresponding chart for the Henon model is presented in Figure 8. The average response delay is computed as the arithmetic mean of response delays for the first 300 events in the simulation run.

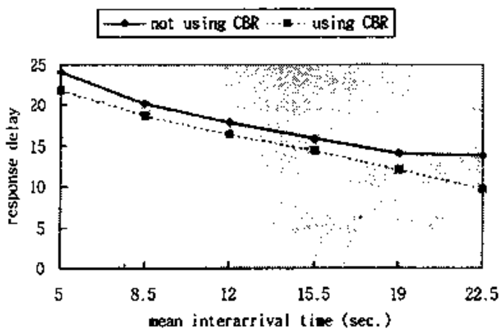

Figure 7. Performance under the Lorentz model. Solid line indicates the response delay of the system without any prediction module, while the dashed line indicates system behavior using CBR as the prediction technique.

According to the figures, the average response delay is improved by using the learning technique regardless of the Lorentz or Henon interarrival times. Further, the improved performance is evident at any of the mean interarrival times tested.

Under the null hypothesis of equal performance, the outcome of one approach is as likely to supercede or to underperform the other approach. In this context, the Wilcoxon test may be applied to determine the level of significance for the disparity in performance for the two methods. The resulting calculations for the Lorentz model are shown in Table 4. The sum of signed ranks is $T_+ = 21$ and $T_- = 0$. Consequently the test statistic is $T = \min\{T_+, T_-\} = 0$. According to widely available tables, the

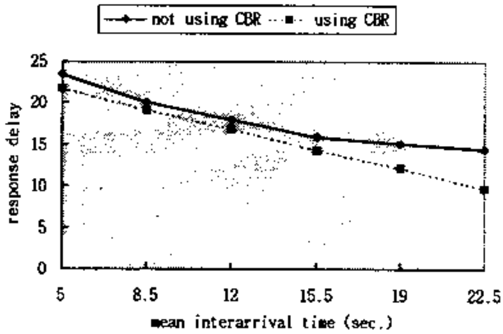

Figure 8. Performance under the Henon model. Solid line indicates the response delay of the system without any predictive module, while the dashed line indicates system behavior using CBR as the prediction technique.

Table 2. Wilcoxon test for the Lorentz model. Method A denotes the lack of CBR, while method B incorporates CBR.

	Method A	Method B	Difference	Rank of difference	Signed rank
1	24.08	21.88	2.20	5	+5
2	20.20	18.78	1.42	3	+3
3	17.77	16.36	1.41	2	+2
4	15.89	14.51	1.38	1	+1
5	14.11	12.17	1.94	4	+4
6	13.77	9.79	3.98	6	+6

Table 3. Wilcoxon test for the Henon model. Method A represents the lack of CBR, while method B includes CBR.

	Method A	Method B	Difference	Rank of difference	Signed rank
1	23.43	21.75	1.68	4	+4
2	20.08	19.17	0.91	1	+1
3	17.95	16.97	0.98	2	+2
4	15.86	14.36	1.50	3	+3
5	15.10	12.24	2.86	5	+5
6	14.46	9.81	4.65	6	+6

significance level is $p < 0.05$.

A similar test is outlined for the Henon model in Table 3. The disparity in performance is again significant at level $p < 0.05$. Consequently, the use of CBR improved results at a statistically significant level.[1]

CLOSURE

This paper has explored the premise that system performance can be improved by using learning techniques such as CBR. The approach was validated through a case study involving a robotic system.

A self-learning predictive methodology is applicable to any autonomous entity, whether an automated taxi, underwater surveyor, or a flying drone. The technology of a highly intelligent control system will be useful to the automation of complex plants ranging from the supervision of an automated factory, the management of energy in an office building, or the regulation of a public utility. Other applications include resource management in communication networks as well as monitors for ship operations or as controllers for automated shuttles.

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1) The Wilcoxon test takes into account the magnitude of the observations and is therefore more powerful than the sign test. The latter test uses the same null hypothesis of $p = 1/2$; however, it considers only whether the result of one method is larger or smaller than that of the other approach while disregarding magnitudes. For $n = 6$ observations, the appropriate p-value is $P(k = 6 \mid n = 6,\ p = 1/2) = (1/2)^6 = 0.0156$. Hence the null hypothesis can be rejected at a significant level of $p < 0.02$ using the sign test.

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