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AN ALGORITHM FOR DETECTING CHANGES IN BATTLE SCENARIO
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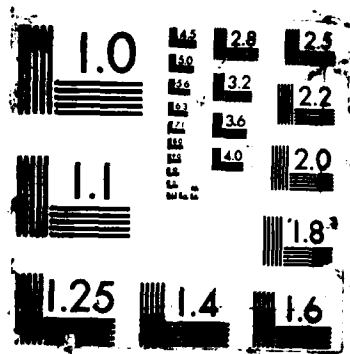
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UVA/325415/EE88/109 N00014-86-K-8742

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A Technical Report
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Submitted to:

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National Research Laboratory
Washington, D. C. 20375

Attention: Code 2627

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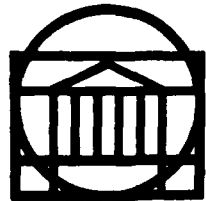
P. P. Kazakos
Professor

R. K. Bansal
Graduate Assistant

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Copy No. _____

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REPORT DOCUMENTATION PAGE

1a. REPORT SECURITY CLASSIFICATION Unclassified		1b. RESTRICTIVE MARKINGS None	
2a. SECURITY CLASSIFICATION AUTHORITY		2. DISTRIBUTION / AVAILABILITY OF REPORT Approved for public release, distribution unlimited.	
2b. DECLASSIFICATION / DOWNGRADING SCHEDULE			
4. PERFORMING ORGANIZATION REPORT NUMBER(S) UVA/525415/EE88/109		5. MONITORING ORGANIZATION REPORT NUMBER(S)	
6a. NAME OF PERFORMING ORGANIZATION University of Virginia Dept. of Electrical Engineering	6b. OFFICE SYMBOL (If applicable)	7a. NAME OF MONITORING ORGANIZATION Office of Naval Research Resident Representative	
6c. ADDRESS (City, State, and ZIP Code) Thornton Hall Charlottesville, VA 22901		7b. ADDRESS (City, State, and ZIP Code) 818 Connecticut Ave., N.W. Eighth Floor Washington, DC 20006	
8a. NAME OF FUNDING / SPONSORING ORGANIZATION Office of the Chief of Naval Research	8b. OFFICE SYMBOL (If applicable)	9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER N00014-86-K-0742	
8c. ADDRESS (City, State, and ZIP Code) 800 N. Quincy Street Arlington, Virginia 22217-5000		10. SOURCE OF FUNDING NUMBERS	
		PROGRAM ELEMENT NO.	PROJECT NO.
		TASK NO.	WORK UNIT ACCESSION NO.
11. TITLE (Include Security Classification) An Algorithm For Detecting Changes in Battle Scenaria			
12. PERSONAL AUTHOR(S) P. P. Kazakos; R. K. Bansal			
13a. TYPE OF REPORT Technical	13b. TIME COVERED FROM 9/1/86 TO 8/31/87	14. DATE OF REPORT (Year, Month, Day) 1987 October	15. PAGE COUNT 7
16. SUPPLEMENTARY NOTATION			
17. COSATI CODES		18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number)	
FIELD	GROUP	SUB-GROUP	
19. ABSTRACT (Continue on reverse if necessary and identify by block number) We propose an algorithm for the speedy detection of change in battle scenaria. The algorithm is sequential, numerically efficient, and asymptotically optimal, and can be either deployed in an automated fashion or can be implemented by trained human subjects.			
20. DISTRIBUTION / AVAILABILITY OF ABSTRACT <input checked="" type="checkbox"/> UNCLASSIFIED/UNLIMITED <input type="checkbox"/> SAME AS RPT <input type="checkbox"/> DTIC USERS		21. ABSTRACT SECURITY CLASSIFICATION Unclassified	
22a. NAME OF RESPONSIBLE INDIVIDUAL R. N. Madan		22b. TELEPHONE (Include Area Code) 202-696-4217	22c. OFFICE SYMBOL

I. Introduction

In distributed tactical decision making, commanders make decisions based on data generated by their local territory as well as on decisions and information communicated to them by other commanders. The timely aspect of the decisions is controlled by the rate with which the commanders receive data, which is in turn controlled by the deployed transmission algorithms, (such as those in [3] and [4]). The accuracy of the decisions, on the other hand, depends heavily on the way that the decision makers perceive their environment. This perception corresponds to a number of alternative models, where the latter are a priori developed based on the various battle scenarios. Each such model is associated with an appropriate decision mode. Furthermore, a model (or battle scenario) may shift to another such model, at a random time. In the event of such a shift, it is thus crucial that the commander be alerted, for adaptation to the appropriate decision mode. In this paper, we describe an algorithm which can be deployed in an automatic fashion, to alert the commanders about changes in battle scenarios.

II. The Algorithm

Each battle scenario is modelled by a stochastic process. Let the various battle scenarios be indexed, say from 1 to M. Then, the i th battle scenario is represented by a distribution $F_i(x_1, \dots, x_n, \dots)$, where x_1, \dots, x_n, \dots are the data outputs observed. Let us assume that the above distributions possess density functions, and let then $f_i(x_n | x_1, \dots, x_{n-1})$ denote the density of the datum x_n , given the data x_1, \dots, x_{n-1} , and given that the i th battle scenario is present.

Let the j th battle scenario be known to be present at time zero. Our objective is to decide if a change in this scenario occurs, and if the answer is yes, then to decide what is the new scenario. Furthermore, if a change does occur, we wish to decide affirmatively as soon from the instant of its occurrence as possible. Let us define,

$$g_{ij}(x_1, \dots, x_n) = \log \frac{f_i(x_n | x_1, \dots, x_{n-1})}{f_j(x_n | x_1, \dots, x_{n-1})} \quad (1)$$

$T_{ij}^{(n)}$ such that,

$$T_{ij}^{(0)} = 0$$

(2)

$$T_{ij}^{(n+1)} = \max(0, T_{ij}^{(n)} + g_{ij}(x_1, \dots, x_{n+1}))$$

A set $\{\delta_{ij}, 1 \leq i \leq M\}$ of positive thresholds, where δ_{ij} is associated with the sequence $\{T_{ij}^{(n)}, n \geq 1\}$

(3)

The thresholds $\{\delta_{ij}, 1 \leq i \leq M\}$ are determined a priori based on false alarm and correct decision criteria. The algorithmic decision is then as follows:

Decide that scenario j shifted to scenario k , the first time n , such that $T_{kj}^{(n)} \geq \delta_{kj}$, while for each i different than k , the value $T_{ij}^{(n)}$ is still below its threshold δ_{ij} .

The above algorithm is clearly sequential, and numerically very efficient. Furthermore, as proven in [1], it is also asymptotically optimal; that is, there is no other algorithm that can detect a change in model faster than the above algorithm. In addition, if there is lack of confidence in some of the observed data or ambiguity in the models of the battle scenario, then the algorithm can be easily modified, to basically maintain its performance characteristics, (see [2]).

III. Example

Let the observed data be binary and independent, and let us consider two scenarios, I and II. Let it be known that under scenario I, a bit has value 1 with probability p , and has value 0 with probability $1-p$. Let it also be known that under scenario II, a bit has value 1 with probability q , and has value 0 with probability $1-q$. Let scenario I be initially present, and let x_1, x_2, \dots , denote the observed binary sequence. Then, for detecting a change to scenario II, the algorithm easily reduces as follows:

Select some threshold δ positive.

$$\text{Set } T_0 = 0 \text{ and } T_n = \max(0, T_{n-1} + x_n + \frac{\log \frac{1-q}{1-p}}{\log \frac{q(1-p)}{p(1-q)}})$$

Decide that scenario I shifted to scenario II, the first time n such that $T_n \geq \delta$.

Here, we will study the nonasymptotic performance of the algorithm. In particular, given the threshold, δ , we will analyze the false alarm and the power characteristics induced by the algorithm. Let us define.

$P_{r,\delta}(n)$: The probability that the threshold, δ , is first crossed, at the time instant, n , under the condition that the p to q change actually occurred just after the datum x_r . (4)

The probabilities, $\{P_{\infty,\delta}(n); n \geq 1\}$, represent then a false alarm set, while the probabilities, $\{P_{0,\delta}(n); n \geq 1\}$, represent a power set. Indeed, the former probabilities show how probable is the crossing of the threshold, at different time instants, n , when the p to q change never occurs. The latter probabilities correspond, instead, to threshold crossings, at different time instants, n , when the "alarming", parameter- q , process is active, since after time zero. We note that when the threshold, δ , is finite, it is eventually crossed with probability one, even when the p to q change never occurs. The false alarm curves, $\{P_{\infty,\delta}(n); n \geq 1\}$, and the power curves, $\{P_{0,\delta}(n); n \geq 1\}$, can be only computed numerically. For efficiency in such computations, we

apply an approximation. In particular, we approximate the constant, $\frac{\log \frac{1-q}{1-p}}{\log \frac{q(1-p)}{p(1-q)}}$ by the ratio of two integers. That is, we write,

$$\frac{\log \frac{1-q}{1-p}}{\log \frac{q(1-p)}{p(1-q)}} \approx -\frac{l}{s} \quad (5)$$

; where $l < s$, and l and s are both natural numbers.

Then, we write the algorithm in the following equivalent form, where, without lack in generality, the threshold, t , in the latter is a natural number.

Select the threshold, t . Decide the change has occurred, at the first time, n , such that: $T'_n \geq t$, where:

$$T'_0 = 0, T'_n = \max(0, T'_{n-1} + y_n) \quad (6)$$

$$y_n = s x_n - l \quad (7)$$

Clearly, the updating step, y_n , in (7) is an integer. It is equal to $-l$, when $x_n = 0$, and it is equal to $s - l > 0$, when $x_n = 1$. Let us denote by, $P_{r,t}(n)$, the probability in (4), as applied to the modified algorithm in (6) and (7). It is then possible to obtain recursive expressions for the computation of the probabilities, $\{P_{r,t}(n); n \geq 1\}$, via a Markov chain formulation. The key element in the latter formulation is the probability, $P_{r,t}(n,j)$, that $T'(x^k) < t$; $\forall k < n$ and $T'(x^n) = j$, given that the p to q change occurs just after the datum, x_r . Indeed, we find,

i. If, $t - 1 \geq s > l + 1$:

$$P_{r,t}(n,0) = (1-v) \sum_{i=0}^l P_{r,t}(n-1, i)$$

$$P_{r,t}(n,j) = (1-v) P_{r,t}(n-1, j+l); 1 \leq j < s - l \quad (8)$$

$$P_{r,t}(n,j) = (1-v) P_{r,t}(n-1, j+l) + v P_{r,t}(n-1, j-s + l); s-l \leq j \leq t-l-l$$

$$P_{r,t}(n,j) = v P_{r,t}(n-1, j-s+l); t-l-l < j \leq t-1$$

ii. If, $t - 1 \geq s = l + 1$:

$$P_{r,t}(n,0) = (1-v) \sum_{i=0}^l P_{r,t}(n-1, i)$$

$$P_{r,t}(n,j) = (1-v) P_{r,t}(n-1, j+l) + v P_{r,t}(n-1, j-1); 1 \leq j \leq t-1-l$$

$$P_{r,t}(n,j) = v P_{r,t}(n-1, j-1); t-1-l < j \leq t-1$$

; where,

$$v = \begin{cases} p; & \text{if } n \leq r \\ q; & \text{if } n > r \end{cases} \quad (10)$$

$$P_{r,t}(n) = v \sum_{j=t-s+1}^{t-1} P_{r,t}(n-1, j); \quad t-1 \geq s \geq t+1 \quad (11)$$

The recursive expressions in (8) and (9) allow for the efficient computation of the probability, $P_{r,t}(n)$ in (11), for every r , and every n .

The false alarm probabilities, $\{P_{\infty,t}(n); n \geq 1\}$, and the power probabilities, $\{P_{0,t}(n); n \geq 1\}$, evolve as a special case of the probabilities, $\{P_{r,t}(n)\}$, and they can be also computed recursively then. Let us now define the following two quantities.

$$\alpha(p,q,n,t) = \sum_{i=0}^r P_{\infty,t}(i) \quad (12)$$

$$\beta(p,q,n,t) = \sum_{i=0}^n P_{0,t}(i) \quad (13)$$

The quantities, $\alpha(p,q,n,t)$ and $\beta(p,q,n,t)$, are the probabilities that the threshold, t , is crossed by the algorithm in (6) and (7), before or at the time instant, n , given that all the data are respectively generated by the p -parameter and the q -parameter process. Thus, $\alpha(p,q,n,t)$ and $\beta(p,q,n,t)$ are respectively the false alarm curve and the power curve induced by the algorithm in (6) and (7). Those two curves represent the nonasymptotic performance of the algorithm. We computed those curves for $p = .01$ and $q = .05$, and for various choices of the threshold, δ . In our computations, we applied the rational approximations represented by expression (5) and the algorithm in (6) and (7), and we used the recursions in (8) and (9). Our results are shown in Figure 1. From this figure, the powerful nonasymptotic characteristics of the algorithm are evident. For relatively small sample sizes, it simultaneously attains both low false alarm and high power. The choice of the threshold, δ , will be determined from the specific false alarm and power requirements, and it will depend on where the emphasis (power versus false alarm) is placed. When the probabilities, p and q , are further apart from each other, than the pair, $p = 0.1$ and $q = .05$, then the false alarm and the power curves are drawn further apart, than those in Figure 1. The performance characteristics of the algorithm are then further improved. Studies similar to those in this example can be performed, when dependent binary data structures are instead considered, (see [5]), or when Gaussian data are present.

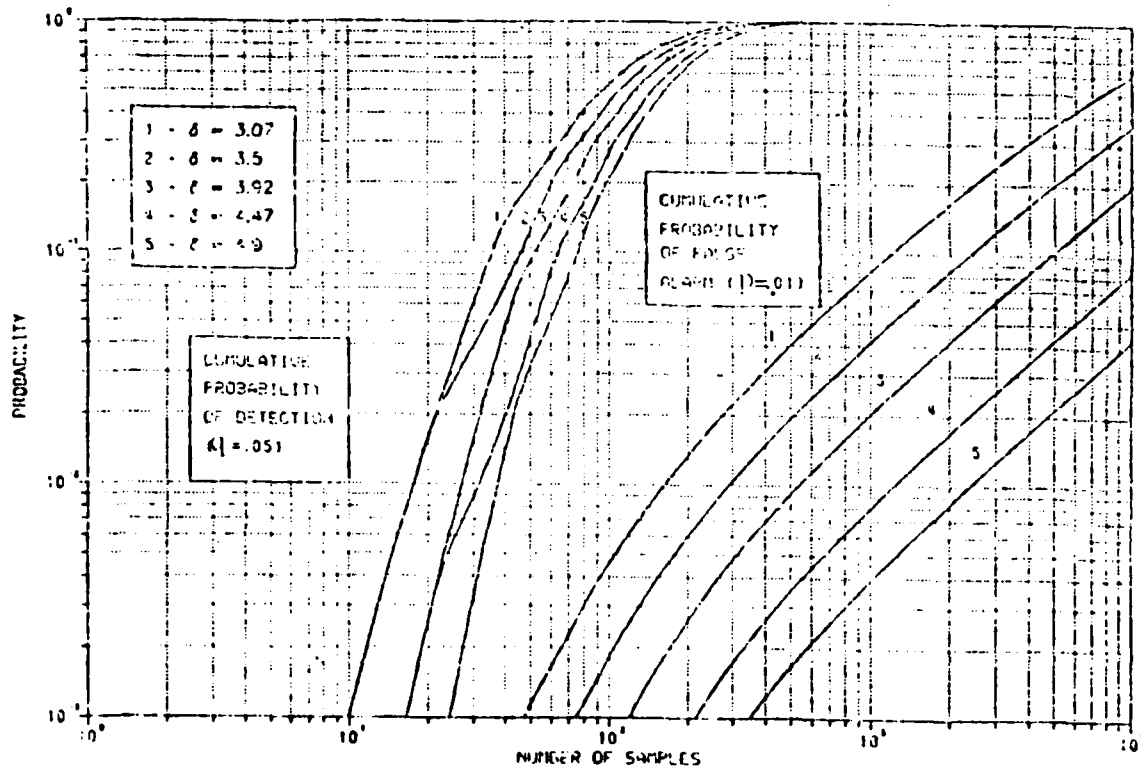


Figure 1

IV. CONCLUSIONS

In this paper, we exhibited a simple sequential algorithm which we have previously fully analyzed, (see [1] and [2]), and which can be deployed to detect changes in battle scenaria. The algorithm can be implemented in an automated fasion. At the same time, it would be interesting to see how closely can trained human subjects approximate the algorithmic operations and how fast can they react to the algorithmic alerts. We propose that experiments along those lines be performed by the researchers on human factors, within the DTDM program.

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