Functional Characterization of Fault Tolerant Integration in Distributed Sensor Networks

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Abstract— **Fault-tolerance is an important issue in network design because sensor networks must function in a dynamic, uncertain world. A functional characterization of the fault-tolerant integration of abstract interval estimates is proposed. This model provides a preliminary version for a general framework that is hoped to develop to address the general problem of fault-tolerant integration of abstract sensor estimates. It is further proposed that a scheme for narrowing the width of the sensor output in a specific failure model and give it a functional representation. The main distinguishing feature of our model over the original Marzullo's model is in reducing the width of the output interval estimate significantly in most cases where the number of sensors involved is large.**

I. Introduction

In RECENT years, the increasing sophistication of surveillance systems and tracking mechanisms has generated a great deal of interest in the development of new computational structures and strategies for detecting and tracking multiple targets, using data from many sensors.

The design of spatially distributed target-detection-and-tracking systems involves the integration of solutions obtained by solving subproblems in data-association, hypothesis-testing, data-fusion, etc. [13]. This must include the cooperative solution of problems by a decentralized and loosely coupled collection of processors, each of which integrates information received from a cluster of spatially distributed sensors into a manageable and reliable output for further integration at a higher level. Integration of information at the sensor level requires techniques to be developed to abstractly represent and integrate sensor information. Further these techniques have to be robust in the sense that even if some of the sensors are faulty, the integrated output should still be reliable. For details on multisensor integration and fusion in intelligent systems, see [5]–[11], [14].

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The aim of this paper is to present a fault-tolerant computational model for sensor integration in distributed sensor networks (DSN).

A DSN consists of spatially distributed sensors that detect and measure a certain phenomenon via its changing parameters. These readings are sent at regular intervals of time to processing units that *integrate* the readings from clusters of sensors and give outputs whose nature is much the same as the inputs of the sensors. Outputs from processors representing clusters of sensors are later integrated to get a complete picture of the spatially distributed phenomenon. However, before integration is performed at the processor level, it is necessary to have reliable estimates at each processor. Each sensor in a cluster measures the same set of parameters. It is possible that some of these sensors are faulty. Hence it is desirable to make use of the redundancy of the readings in the cluster to obtain a correct estimate of the parameter being read. In short, a *fault-tolerant* technique of sensor integration to obtain the correct estimate is sought.

A. Scope of This Paper

This paper has two objectives: The first is to propose a functional characterization of fault-tolerant integration of abstract interval estimates considered by Marzullo [4]; the second is to propose a modified computational scheme of integration carried out by Marzullo [4] in the case when the number of sensors is large, wherein it is possible to improve the accuracy of the integrated output.

The main distinguishing feature of our model over the original Marzullo's model is in reducing the width of the output interval estimate significantly in most cases where the number of sensors involved is large.

Elsewhere we intend to generalize Marzullo's approach to the cases when the sensor outputs are subsets of an abstract parameter space. The functional characterization of the fault-tolerant integration of abstract interval estimates described in this paper hints at an abstract framework. We hope to develop for addressing the general problem of fault-tolerant integration of sensor outputs.

B. Organization of the Paper

In Section II, we describe Marzullo's work on sensor integration and other related work. Our abstract model functional characterization is detailed in Section III and is an extension of the model proposed by Marzullo. In Section IV, we motivate the need for a new failure model and present the information

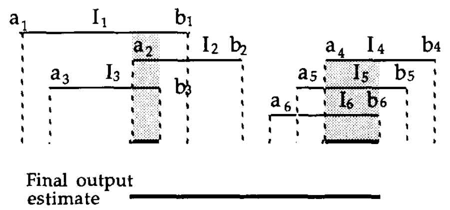

Fig. 1. Integrated interval estimates (*a la* Marzullo) ($a_1 < a_3 < a_2 < b_3 < b_1 < b_2 < a_6 < a_5 < a_4 < b_6 < b_5 < b_4$).

integration algorithm with a specific example. Finally, we close the paper with concluding remarks and future directions this research would take.

II. Related Work

Marzullo [4] considers the case of a processor receiving input from several sensors whose outputs are connected intervals. He gives a fault-tolerant integration algorithm that takes as input the intervals representing the sensors and gives as output of the processor a connected interval representing the sensor values. More precisely: Let there be n sensors, each of which yields an interval as its output. These sensors measure a certain physical value and their intervals contain the physical value unless they happen to be faulty sensors.

Thus, a correct sensor is one that contains the actual physical value in its interval. Any two correct sensors must overlap since they both contain the physical value being measured.

Marzullo considers the case when most f sensors are faulty and gives an algorithm that yields a connected interval as the output of the processor, containing the physical value.

If at most f of the n sensors are faulty, then it follows that at least $n - f$ sensors are correct. Marzullo considers all possible nonempty $(n - f)$-intersections of the n-sensors. A sensor that does not belong to any of the $(n - f)$-cliques is faulty since a correct sensor overlaps with at least $(n - f - 1)$ other correct sensors. One and only one of the $(n - f)$-intersections contains the physical value. Since it is not possible to decide which intersection has the physical value (which is as yet unknown to us) and since the processor output is required to be a connected interval, the smallest connected interval containing all the $(n - f)$-intersections is taken to be the output of the processor. It is easy to see that it contains the actual physical value. The wider this interval is, the lesser the accuracy of the processor output. Marzullo proves the existence of bounds for the width of this interval in terms of f.

The example described in Fig. 1 provides a description of integration process, where we have the intervals $I_j = [a_j, b_j]$ $1 \le j \le 6$. Overlapping one another according to the strict chain of inequalities given previously. Here $f = 3$ and $n = 6$. So, taking all possible $(n - f)$ intersections gives us the intervals $[a_2, b_3]$ and $[a_4, b_6]$. Then enclosing these intervals in the smallest possible connected interval, we have the integrated output interval I_p given by $I_p = [a_2, b_6]$.

In the statistical literature, the popular methods for combining the point estimates of several (possibly faulty) sensors into a single point estimate come under the designation of robust estimation. This family includes the median, Huber function based methods, least median square methods, etc. [1], [2] Some of these methods have been applied to the sensor fusion problem in [3].

However, in methods like the median, there is no easy way of including the additional information such as "at most f out of n sensors are faulty." Moreover, all of these methods are geared to the generation of point estimates whereas our paper concentrates on the interval estimates.

The main thrust in our paper is in the derivation of computational schemes for narrowing the width of the processor output in a specific failure model and give it a functional representation.

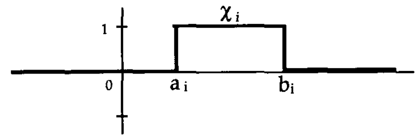

Fig. 2. Representation of intervals.

A. Interval Representation of Sensor Readings

A sensor reads a physical variable and gives a number as its output. However a sensor is prone to inaccuracies and there may be some uncertainty in the value of its output. The simplest modeling of this is achieved by looking upon sensor outputs as connected intervals on the real line rather than as points. The actual value representing the physical variable being measured is taken to be contained in the interval associated with the sensor if the sensor is not faulty. No assumptions are made about the width of these intervals or their position on the real line. Thus each sensor value is represented by an interval estimate. We make this notion precise in the following definitions that are useful in characterizing one model of sensor integration.

Definition 1: An *abstract sensor* is a sensor that reads a physical parameter and gives out an abstract interval estimate I_s, which is a bounded and connected subset of the real line $\mathbf{R}$.

Definition 2: A *correct sensor* is an abstract sensor whose interval estimate contains the actual value of the parameter being measured. If the interval estimate does not contain the actual value of the parameters being measured, it is called a *faulty sensor*.

Definition 3: Let sensors $s_1, \cdots, s_n$ feed into a processor P. Let the abstract interval estimate of s_j be I_j $1 \le j \le n$, where I_j is the closed interval $[a_j, b_j]$ with endpoints a_j and b_j. Define the *characteristic function* χ_j of the jth sensor s_j $1 \le j \le n$ as follows:

$$\chi_j : \mathbf{R} \to \{0, 1\}$$

$$\chi_j(x) = \begin{cases} 1 & \forall\, x \in I_j \\ 0 & \forall\, x \notin I_j \end{cases} \quad \forall\, 1 \le j \le n.$$

Section III addresses the question of how the abstract sensors or abstract estimates are combined to yield new abstract estimates.

III. The Problem of Fault-Tolerant Sensor Integration

Fault tolerance is a crucial requirement to be satisfied by a distributed sensor network for it to be reliable in a situation where one or more of its sensors fail and yield faulty readings. Fault tolerance in a distributed sensor network thus implies that the values of the parameters measured by the network are reliably reflected in its output even though some of the sensors may be faulty. We propose to introduce fault tolerance into the distributed sensor network by providing a method of integration of sensor values that yields a reliable output that reflects the correct values of the parameters being measured with high fidelity.

Recall that our definition of a faulty sensor is one whose abstract sensor estimate (interval estimate) does not contain the actual physical value being measured.

The problem of fault-tolerant sensor integration is the integration of the I_j $(1 \leq j \leq n)$, to obtain an abstract interval estimate $I_p = [a_p, b_p]$, which is a "reliable" and "fairly accurate" estimate of the region in which the physical sensor value lies. This integration should be fault-tolerant in that its reliability should not be severely affected by some of the sensors being faulty. In other words, we seek to obtain a functional relationship between the characteristic function χ_p of $I_p = [a_p, b_p]$ and the $\chi_j 1 \leq j \leq n$: $\chi_p(x) = f(\chi_1(x), \cdots, \chi_n(x))$ such that $\chi_p^{-1}(1)$ is a fault-tolerant interval estimate of the physical value being measured.

We now go about obtaining a functional representation of the integrated output estimate under the integration scheme of Marzullo. In order to do this we need to introduce a few relevant operations and functions. The following definition provide such operations for our integration problem:

Definition 1: If $f(x)$ is a real-valued function, define $\|f\| = \sup\{|f(x)| \mid x \in \mathbf{R}\}$ (norm of f). Here sup stands for the supremum. That is, $\|f\|$ is the smallest real number α such that $f(x) \leq \alpha \; \forall \; x \in \mathbf{R}$.

Definition 2: If $f(x)$ is a real valued function define $\mathrm{Supp} f = \{x \mid f(x) \neq 0\}$ (support of f).

Definition 3: Let $O(x) = \sum_{j=1}^{n} \chi_j(x)$ be the "overlap function." For each $x \in \mathbf{R}$, $O(x)$ gives the number of intervals in which x lies or the number of intervals overlapping at the point x.

If $\chi_i(x)$ and $\chi_j(x)$ are characteristic functions of intervals I_i and I_j then the characteristic function of the interval $I_i \cap I_j$ denoted $\chi_{I_i \cap I_j}(x)$ is given by the product $\chi_i(x)\chi_j(x)$.

If $\chi_i(x)$ is the characteristic function of I_i, then the characteristic function of I_i^c (the complement set of I_i) is given by $(1 - \chi_i(x))$.

Marzullo [4] assumes that there are at most f faulty sensors among n sensors, and considers the intersections of $(n-f)$ or more sensors as the regions in which the correct physical value lies. An interval that does not participate in any $(n-f)$-intersection is taken to be the estimate of a faulty sensor. The output is the smallest interval that contains all $(n-f)$ or more intersections.

A. Computational Characterization

We now obtain a functional characterization of the $(n-f)$ intersections and this integrated output estimate as described in the previous section. More precisely, we give an explicit expression for this characteristic function of the $(n-f)$ intersection in terms of the characteristic function of the intervals corresponding to the sensor estimates.

Remark 2: If at most f sensors are faulty, then we need to consider only those I_j's for which $\|\chi_j O\| \geq (n-f)$. Thus the characteristic function of the set of all points lying in $(n-f)$ or more intersections of the intervals I_j $(1 \leq j \leq n)$ is given by

$$S(x) = \chi_{[n-f,\infty]}(0(x)).$$

Now the correct physical value belongs to $\mathrm{Supp}(S(x))$, i.e., to one of the intervals constituting it. Marzullo proposes the smallest connected interval containing $\mathrm{Supp}(S(x))$ for the integrated output.

More precisely the output interval estimate I_p is given by

$$I_p = [\min\{x|S(x) = 1\},\ \max\{x|S(x) = 1\}].$$

Proof: Indeed $\chi_{[n-f,\infty]}^{(y)} = 1 \Leftrightarrow y \geqslant n - f$

$$\therefore \chi_{[n-f,\infty]}(0(x)) = 1 \Leftrightarrow 0(x) \geqslant n - f$$

$(0(x)) \geqslant n - f \Leftrightarrow n$ lies in the intersection of $n - f$ or more intervals, and

$$\therefore \chi_{[n-f,\infty]}(0(x)) = 1$$

iff x lies in the intersection of $n-f$ or more intervals.Q.E.D.

The previous integration technique does indeed give a connected interval within which the actual physical value lies. It however includes points that do not belong to the intervals constituting $\mathrm{Supp}(S(x))$. Furthermore, if the intervals constituting $\mathrm{Supp}(S(x))$ are widely scattered over $\cup_{i=1}^{k} I_j$, then there are wide gaps between these intervals that do not contain the physical value and yet are included in the output estimate. This results in the width of the smallest interval containing $\mathrm{Supp}(S(x))$ being comparable to the smallest interval containing $\cup_{i=1}^{k} I_j$ (see Fig. 1) and this is of little value from the point of accuracy. We need to evolve a criterion by which we can pick only a few of the intervals constituting $\mathrm{Supp}(S(x))$ with a fair amount of certainty that they enclose the correct physical value. The rest of our analysis is in this direction.

IV. A New Failure Model with Sharper Output Interval Estimates

We propose a failure model in which it is possible to choose in most cases a subset of $\mathrm{Supp}(S(x))$ as the region of correct sensor value instead of the whole of I_p as defined previously. A sensor may fail *wildly*, in which case there is no correlation between the actual physical value being measured and the interval estimate of the faulty sensor. On the other hand, a sensor may fail *tamely*, in which case although the faulty sensor's interval estimate does not contain the actual physical value, the interval estimate lies significantly close to the value in a certain sense. For example, mechanical vibrations may induce a tame fault in dials and meters by shifting the needles' fluctuations to a region that does not contain the correct value but lies close to it. Since we do not know the actual physical value, we cannot detect the tameness of a fault directly. However tamely faulty sensor estimates tend to overlap with correct sensor estimates because of their proximity to the actual physical value. We consider the case when the number of sensors to be integrated is very large and assume that most of the faulty sensors are tamely faulty. In this case, we observe that correct sensors have a relatively larger number of intervals overlapping with them as compared to undetected faulty sensors participating in the $(n-f)$-intersections, since tamely faulty sensors overlap with correct sensor estimates. Thus the number of sensor estimates overlapping with a given sensor estimate is a good index of its correctness. We make use of this observation to narrow our output interval estimate, namely I_p.

Let $\text{Supp}(S(x)) = \cup_{i=1}^{k} L_i$ where $L_i = [\alpha_i, \beta_i]$ with $\beta_i < \alpha_{i+1}\ \forall\ 1 \leq i \leq k-1$. We now perform an evaluation of the L_i's in order to attach a weight to each of them and choose those L_i's with maximum weight to be the intervals that have a high likelihood of containing the correct physical value. We then again enclose these L_i's of maximum weight by the smallest possible interval and take it to be the output estimate.

Remark 3: Let $\chi_{Li}(x)$ be the characteristic function of L_i. Then we can define the *popularity* of the jth sensor to be the number $P_j = \sum_{k=1}^{n} \|\chi_k \chi_j\| - 1$. P_j gives the number of sensor intervals overlapping with the j^{th} sensor interval.

Proof: Indeed

$$\|\chi_k \chi_j\| = \begin{cases} 1 & \text{if } I_k \cap I_j \neq \phi \\ 0 & \text{if } I_k \cap I_j = \phi \end{cases}.$$

Thus $\sum_{k=1}^{n} \|\chi_k \chi_j\| - 1$ gives the number of intervals (apart from I_j) intersecting with I_j. Q.E.D.

A. Narrowing of the Output Interval Estimate Width

The L_i's are $(n-f)$ intersections. The reliability r_i gives a measure of the clustering of sensors around the L_i. Our assumption that most of the faulty sensors are tamely faulty implies that the L_i with maximum clustering around it is most likely to contain the correct physical value measured by the sensors. The sum of the popularities of the sensors involved in the formation of L_i is a good index of the clustering of sensors about L_i.

Hence, we would like to take the sum of the popularities of all sensors involved in the formation of L_i, and call it the *reliability* r_i of L_i.

Consider the set function $W(L_i) = \sum_{j=1}^{n} \|\chi_{Li} \chi_j\| P_j$, $1 \leq i \leq k$ defined on each L_i. $W(L_i)$ gives the sum of the number of intervals overlapping with each sensor estimate in the $(n-f)$-or-more clique L_i. i.e., $r_i = W(L_i)\ \forall\ 1 \leq i \leq k$.

Let $r = \max\{r_i \,|\, 1 \leq i \leq k\}$, $m = \min\{i \,|\, r_i = r\}$ and $M = \max\{i \,|\, r_i = r\}$. Consider the interval $[\alpha_m, \beta_M]$. We take $I_p^* = [\alpha_m, \beta_M]$ as the integrated output estimate.

It is clear that $\beta_M - \alpha_m = |I_p^*| \leq |I_p|$, where $|I|$ is the width of the interval I. Thus in our failure model we have in general a way of narrowing the output estimate I_p to I_p^*. However if the number of wildly faulty sensors are as many as the tamely faulty ones, and if they happen to cluster somewhere else on I_p, then it is possible that $|I_p^*| = |I_p|$. Thus the worst case for I_p^* is I_p. The chances that wildly faulty sensors mimic the clustering behavior of tamely faulty sensors are remote. Also if the number of sensors is very small, it is possible that $|I_p^*| = |I_p|$.

For example, consider the case of three input sensor estimates $I_1 = [2.4, 3.2]$, $I_2 = [2.9, 4]$, $I_3 = [3.6, 5]$. In this case $I_p = [2.9, 4]$. Here $L_1 = [2.9, 3.2]$ and $L_2 = [3.6, 4]$, but they both have the same reliability. Hence $I_p^* = I_p$ here.

B. The Algorithm

We now present the algorithm as follows.

Algorithm:

Input: Intervals $I_1, I_2, \cdots, I_n, f$ (parameter denoting maximum number of allowable faults).

Output: Integrated output estimate.

begin

1) **Take** all $(n-f)$-intersections of the intervals to yield Intervals $L_1, \cdots, L_k$, each of which is an $(n-f)$-intersection: $\{L_j = [a_j, b_j]\}$;
2) **For** each i $(1 \leq i \leq k)$
   a) **Count** the number of intervals intersecting each of the intervals I_j $(1 \leq j \leq n)$ having nonempty intersection with L_i;
   b) **Add** these numbers up to obtain a number $r_i\{r_i$ gives the sum of the number of intervals intersecting with intervals involved in the formation of the L_i. a is a measure of the reliability of $L_i\}$;
3) **Choose** the maximum of the r_i $(1 \leq i \leq k)$ and call it r;
4) **Let** $m = \min\{i \,|\, r_i = r\}$ and $M = \max\{i \,|\, r_i = r\}$;
5) **Assign** $I_p^* = [a_m, b_M]$ to be the integrated output estimate;

end.

C. A Comparison of Performance

In this new model, we find that when the number of sensors is very large, by taking the clustering of the tamely faulty sensors into consideration, we reduce the output intervals width greatly, as compared to Marzullo's [4] output interval estimate.

Fig. 3 illustrates the superior performance of our model clearly. The numbers near each interval estimate gives the number of intervals overlapping with it. Here $n = 13$ and f (maximum number of fault intervals allowed) $= 10$. The thick lines in Fig. 3 are the intervals L_i with the numbers on them indicating their reliabilities. We may pick either the interval with higher reliability or define a range for reliabilities and pick intervals that fall in these limits. The thick line of the bottom indicates the output interval estimate for this case in Marzullo's model.

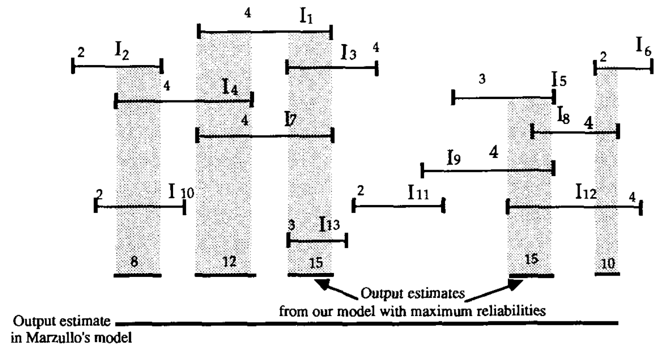

Fig. 3. A comparison of output estimates from Marzullo's method of integration and our method. The shaded strip illustrates overlapping regions of three or more interval intersections, where $n = 13$, $f = 10$, and $n - f = 3$.

TABLE I
POPULARITIES OF INTERVALS

Interval	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9	I_{10}	I_{11}	I_{12}	I_{13}
Popularity	4	2	4	4	3	2	4	4	4	2	2	4	3

The essential gain in the model proposed previously is that the $(n - f)$-intersections are assigned weights that are in the previous mentioned sense reliability estimates of these intersections. We may now impose any convenient rule for choosing these segments according to their reliabilities.

In Table I, we have each interval assigned a numbering that is its popularity.

The $(n - f)$ or more intersections (i.e., 3 to 4 intersections here) that form the output have reliabilities 8, 12, 15, 15, 10.

Thus, the advantage here is that we have the intersection weighted to help us judiciously choose the output intervals. We may employ any convenient rule depending upon our faith in the tameness of the faults to pick these intervals and enclose them by a connected interval. For instance, we may choose only those intervals with maximum reliability (in this case, the intervals with reliability 15) and enclose them by a connected interval. It is clear that the worst possible width for the final output interval estimate is the smallest interval containing all intersections irrespective of their weights.

So far, we have treated f as a fixed number. It is clear that as f increased, the output interval width increased, and as f decreased, output width decreased. This is so because output intervals are intersections of $(n - f)$ or more intervals. To improve performance, it is better to treat f as a parameter and perform integration for different values of f simultaneously and use only that f, for which outputs are within bounds.

D. Narrowing Widths of Intervals in the Case of Nonuniform Distributions

So far we have assumed that a sensor does not give any information about the probability distribution of the correct physical value over the interval (abstract sensor estimate) that represents it. In this case, we assume that each value in this interval is equally likely, i.e., we assume a uniform distribution of the physical value over each interval estimate. However, in the event of the sensor giving a unimodal probability distribution of physical value over its interval estimate, say, for example, a normal distribution, then we may use this additional information to narrow the interval widths beforehand by resorting to confidence interval estimates of the physical value. The resulting subset of this estimation is a connected interval whose width is less than the original interval. More precisely, if S is a sensor with its interval estimate $I = [a, b]$ and $p(x)$ is a unimodal probability distribution on I of the physical value measured by the sensor, and further if $(1 - \alpha)$ is a high probability, we need to compute numbers $L(\alpha), U(\alpha)$ such that

$$\begin{aligned} P[x \in [L(\alpha), U(\alpha)]] &= 1 - \alpha \\ &= \int_{L(\alpha)}^{U(\alpha)} p(x)\, dx \end{aligned}$$

where $[L(\alpha), U(\alpha)]$ is called $100(1 - \alpha)\%$ confidence interval for the physical value x, and $(1 - \alpha)$ is called the level of confidence associated with the interval.

Now, $[L(\alpha), U(\alpha)] \nsubseteq [a, b]$ if $\alpha \neq 0$ with a high probability of containing the physical value (if S is not faulty) and if is narrower than the original interval $[a, b]$. It is obvious that the widths of the L_i decrease if the width of one or more of the input intervals decrease. Thus the narrowing of the intervals before integration when possible increases the accuracy of the output.

V. CONCLUSION

In order to address the general problem of fault-tolerant sensor integration for a large class of sensors, it is necessary to evolve a broad-based computational framework that can accommodate a wide range of sensors and a variety of fault tolerant integration techniques depending upon the phenomenon being sensed and the method of sensing. We intend to develop a calculus of sensor integration by regarding the sensor estimates as subsets of an abstract parameter space and obtaining functional representations of the characteristics of these estimates. We then intend to obtain rules for combining these functions to get functions describing the characteristics of the output according to the kind of integration that is required to be performed. This paper is a preliminary exercise in concert with this effort. We have recast the fault-tolerant integration of abstract interval estimates *a la* Marzullo [4] in a computational framework, and considered a failure model wherein we could reduce the width of the output interval estimate significantly in most cases where the number of sensors involved is large.

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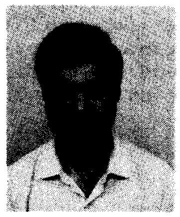

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