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N72-25381

NOISE ELIMINATION BY PIECEWISE CROSS CORRELATION OF PHOTOMETER OUTPUTS

by

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ABSTRACT

A piecewise cross correlation technique has been developed to analyze the outputs of remote detection devices. The purpose of this technique is to eliminate the noise from optical background fluctuations, from transmission fluctuations and from detectors by calculating the instantaneous product of the detector output and a reference signal. Each noise component causes positive and negative oscillations of the instantaneous product and may thus be cancelled by an integration of the instantaneous product. The resultant product mean values will then contain the desired information on the spatial and temporal variation of emission, absorption and scattering processes in the atmosphere.

The piecewise correlation technique differs from previous digital analyses of stationary time series by separating statistical and temporal variations of product mean values. The statistical variations describe the amount of still uncancelled noise. The range of these variations is calculated by determining the frequency band width of the noise from the decrease of an accumulative statistical error with integration time. The temporal variations of the product mean values describe a change in the meteorological boundary conditions. They are indicated by the calculated errors which exceed the range of statistical variations that is expected for the given noise band width. Furthermore, such temporal variations set a level of irreducible noise components since the uncancelled noise cannot be distinguished from the temporal variations of the meteorological boundary conditions. However, the change of these boundary conditions may very often be suppressed by suitable normalization and trend removal techniques.

The accomplishments to date provide for automatic piecewise changes of gain factors and coordinate shifts which eliminate intolerable temporal variations of meteorological boundaries provided the signals do not exceed the dynamic range of the amplifier or the tape recorder.

Our recommendations are to continue the present studies on noise elimination in the presence of time dependent boundary conditions. Particular emphasis should be given to the temporal variations of product mean values which are caused by changes in aerosol concentrations, optical background fluctuations, variations of wind speed and changes of wind direction. Future development of piecewise correlation techniques should concentrate on noise elimination and interpretation of rapid scanning remote detection devices such that optical and meteorological phenomena might be monitored in real time.

1. INTRODUCTION

A new "piecewise" correlation technique has been developed to eliminate noise in photometer outputs. The need for such a program became apparent in crossed beam field tests [Montgomery, 1969, this Vol.] where temporal variations of meteorological boundary conditions sometimes produced irreducible noise components which were fatal. The new correlation techniques have subsequently isolated and eliminated temporal variations of meteorological boundary conditions by piecewise normalization and detrending procedures. The same techniques could also be applied to any other remote detection device or any other set of meteorological data.

The noise elimination is based on the integration of a lagged product between the photometer output and a reference signal. Section 3 gives a review of the usual noise elimination by product integration which is used for stationary time series where the boundary conditions are time invariant [Bendat and Piersol, 1966]. The piecewise correlation was developed to extend this classical product mean value calculation to meteorological boundary conditions which are time dependent. In this case, the calculated product mean values will be subject to both statistical and temporal variations. In theory, temporal and statistical variations could be separated by analyzing a large group of imaginary experiments which should all have identical time dependent boundary conditions [Crandall and Mark, 1963]. This theory is reviewed in Section 4. However, it cannot be applied directly, since meteorological conditions cannot be controlled to give many realizations of the same phenomenon. The best one can hope for is that temporal variations of meteorological conditions are of such a type that suitably modified portions of one long record could be treated as independent realizations. The conditions of stationarity and the results of this approximation are discussed in Section 5.

Our program is new in that the variations between different piecewise estimated time averages are used to calculate accumulative statistical errors which should depend on the number of processed pieces in a universal way if the replacement of realizations with pieces is justified. Conversely, deviations from this behavior can be used to determine deviations from stationarity as discussed in Section 6. Temporal variations of meteorological boundary conditions restrict the noise elimination to the level of the temporal variations, since one cannot distinguish between statistical and temporal variations of product mean values. Fortunately, suitable normalization and trend elimination procedures are often sufficient to remove the temporal variations of boundary conditions. Piecewise variable ordinate shifts and gain factors have been proposed for trend elimination and normalization [Jayroe and Su, 1968]. The experience to date indicates that these piecewise modifications of photometer records were sufficient to remove temporal variations of boundary conditions and thereby increase the ability of noise elimination. The results are summarized in Section 7. Conclusions and recommendations are given in Section 8.

2. NOTATION

a. Independent Variables

t	observation time
T	integration time
ΔT	piece length
i	piece number $(t/\Delta T)$
m	accumulation number $(T/\Delta T)$
f	frequency
τ	time lag between photometer output and reference signal
$\tau_M = 1/6\ \Delta T$	maximum time lag
$k = 1, 2, \ldots N$	number of imaginary realizations.

b. Dependent Variables

I	d.c. coupled photometer output
i	a.c. coupled photometer output
$x = i_A$	output from photometer A
$y = i_B$	reference signal or output from photometer B
σ	root mean square value of i
R	product mean value of x and y

ΔR — statistical error of product mean value

$\delta R = \frac{\Delta R}{\sigma_x \sigma_y}$ — normalized statistical error of product mean value

P — power inside frequency interval

$$-\frac{1}{4\tau_M} \leq f \leq \frac{1}{4\tau_M}$$

$\bar{s}_i = {}_\tau\bar{R}_i$ — ordinate shift for piece i.

c. Operators

( ) Statistic

$$\overline{(\ )}_i = \frac{1}{\Delta T} \int_{(i-1)\Delta T}^{i\Delta T} (\ )\, dt \quad \text{piecewise mean}$$

$$\overline{\overline{(\ )}}_m = \frac{1}{m} \sum_{i=1}^{m} \overline{(\ )}_i \quad \text{accumulative mean}$$

$$\Delta\overline{\overline{(\ )}}_m = \frac{1}{m-1} \sum_{i=1}^{m} \left(\overline{(\ )}_i - \overline{\overline{(\ )}}_m\right)^2 \quad \text{piecewise statistical error}$$

$$\Delta\overline{\overline{(\ )}}_m = \frac{\Delta\overline{(\ )}_m}{m} \quad \text{accumulative statistical error}$$

$$E[\overline{(\ )}] = \frac{1}{N} \sum_{k=1}^{N} (\ )^{(k)}$$

sample of expected value or ensemble average for one group of N realizations

$$(\sigma^{(1)})^2 = \frac{1}{N-1} \sum_{h=1}^{N} \left(\overline{(\ )}^{(h)} - E[\overline{(\ )}]\right)^2$$

sample of variance between realizations

$$_\tau\overline{\overline{(\ )}} = \frac{1}{2\tau_{max}} \int_{-\tau_{max}}^{+\tau_{max}} \overline{(\ )}\, d\tau \quad \text{average over time lags.}$$

d. Subscripts

i	time interval $(i - 1)\Delta T \leqq t \leqq i\Delta T$
m	accumulation over all pieces up to i = m
x	from record x
y	from record y
a	straight time integration
w	weighting with piecewise variable gains
d	detrending with piecewise variable
c	ordinate shifts
C	combined piecewise shifts and gains.

3. NOISE ELIMINATION BY INTEGRATION OVER PRODUCTS

The subdivision of two data records into signal and noise components and the subsequent elimination of the noise are both based on the integration of instantaneous products. This is illustrated in Fig. 1 in terms of an idealized physical model that is used for the interpretation of crossed beam results [Krause, 1967]. Two data records, $I_A(t)$ and $I_B(t)$, are obtained by monitoring the fluctuations of the radiative power which is received inside the narrow field of view of the two telescopes, A and B. Each time history, I, accounts for all sources of radiative power along the entire line of sight. The temporal changes of emission, scattering, or absorption processes will cause a fluctuation, i, in the recorded time history, I, which may be calculated by subtracting the mean value, $\bar{I}$, that is obtained for a certain recording period, ΔT.

$$x(t,\ldots) = I_A(t) - \frac{1}{\Delta T} \int_{t_1}^{t_1+\Delta T} I_A(t)\, dt = I_A(t) - \bar{I}_A(t)$$
$$y(t,\ldots) = I_B(t) - \bar{I}_B(t) \qquad (1)$$

In our experiments this subtraction is done automatically by using a.c. coupled amplifiers. In this case ΔT is proportional to the time constant of the a.c. coupling element ($\approx$ 100 seconds).

Local information from the area of minimum beam separation is retrieved from the two signals, x and y, by determining statistically which modulations are "common" to both beams. The concept of "common" signals has been developed in the analysis of communication signals and random vibrations [Bendat, Piersol, 1966] and is based on "lagged product calculations." The two modulations, x and y, are analyzed for common signals by multiplying them with each other and

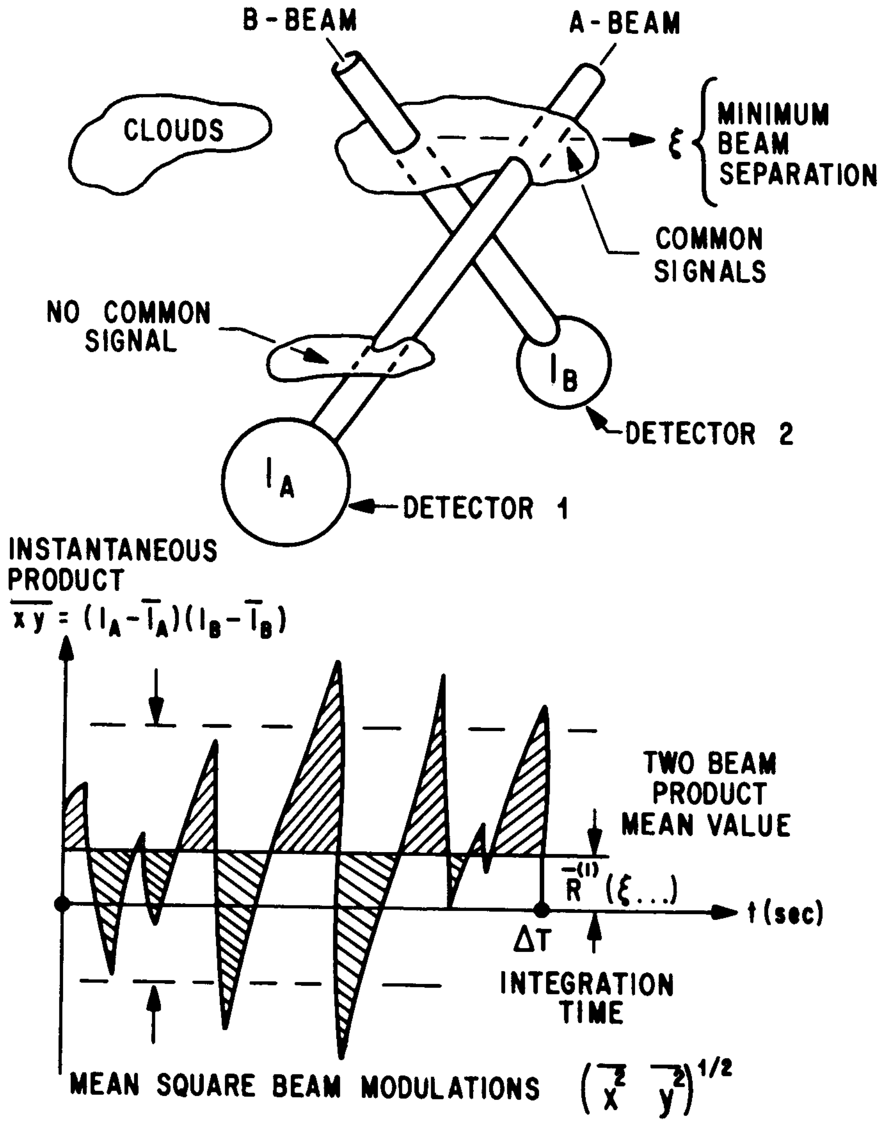

Figure 1. Retrieval of Common Signals.

by averaging this instantaneous product over time. This gives a "two-beam product mean value:

$$\bar{R}^{(1)}(t_1; \Delta T; \ldots) = \overline{x(t; \ldots)y(t; \ldots)}^{(1)} = \frac{1}{\Delta T} \int_{t_1}^{t_1+\Delta T} xy \, dt. \tag{2}$$

The instantaneous product oscillates between positive and negative values and these oscillations will cancel each other, at least partially, when the product is averaged by integrating it over time, as illustrated in Figure 1. Two beams are said to have no common modulations if the two-beam product mean value vanishes. This complete cancellation will occur when the increase or decrease of radiative power in one beam is independent of the power changes in the other beam in the sense that the change in the other beam may be positive or negative with equal likelihood. Typical examples for such independent beam modulations are the combined source and detector noise and any cloud which traverses only one beam without hitting the other beam. The partial cancellation of the oscillations of the instantaneous product is used to split a given time history, $x(t)$, into a "noise" component, x_N, and a "common" component, x_c. Both components are defined only with respect to a second reference signal, y. The noise component, x_N, of the first record, x, is that component which vanishes when multiplied with the reference signal

$$\overline{x_N\, y}^{(1)} = 0. \tag{3}$$

Conversely, the "common" component,

$$x_c = x - x_N, \tag{4}$$

is that component of signal, x, which is responsible for the finite value of the product mean value:

$$\overline{x\, y}^{(1)} = \overline{(x_c + x_N)\, y}^{(1)} = \overline{x_c\, y}^{(1)}. \tag{5}$$

The second signal could also be split into a common component, y_c, and a noise component, y_N, by taking the first signal, x, as the reference signal:

$$y = y_c + y_N. \tag{6}$$

Substituting Eq. (6) into Eq. (5), one finds that the product mean value is made up only of the common signals.

$$\overline{x\, y}^{(1)} = \overline{x_c\, y_c}^{(1)}. \tag{7}$$

The integration of the instantaneous product has thus eliminated the "noise" components and the resultant product mean value is contributed only by the signal component which is common to both data records, x and y. However, the word "common" does not mean that the components x_c and y_c are identical. It refers only to physical processes which produce a change simultaneously in both signals in such a way that the signs of these changes are either equal or opposite. A cloud which traverses two lines of sight (see Fig. 1) is a good example of such a physical process. Although this cloud will cause common changes in both photometer records x and y, these changes will be quite different since the two lines of sight intersect different portions of the same cloud.

4. TEMPORAL AND STATISTICAL VARIATIONS OF PRODUCT MEAN VALUES

The value of a product mean value, $\bar{R}$, will depend in general on both the position, t, of the integration period and on the length, ΔT, of the period. The variation with t reflects a temporal variation of the meteorological boundary conditions such as a change of wind speed and direction or a new type of lag in the area which is common to both lines of sight. The dependence on ΔT may also reflect a temporal variation of the common signals. However, it is often more likely that the change is produced by the noise components which are not completely cancelled since any finite integration period will have over a finite number of oscillations of the instantaneous product. Such incomplete cancellation of extraneous noises reflects a change which may be classified as statistical, since it is associated with the uncontrollable change of physical phenomena other than the common physical process, i.e., a random change in boundary conditions. Both temporal and statistical variations will mostly occur simultaneously and are therefore very difficult to separate.

A detailed description of temporal and statistical variations of product mean values is possible, in theory, by treating the actual conducted experiments as one sample of a population of imaginary experiments which are all recorded for identical time dependent boundary conditions. Assume that k = 1, 2, 3,... N realizations of the atmospheric field have been observed. Statistical averages may then be established by averaging over the different realizations instead of averaging over time. This "ensemble" average shall be denoted by the operator and will be called the "expected value":

$$E[(\ )] = \frac{1}{N} \sum_{k=1}^{N} (\ )^{(k)}. \tag{8}$$

Let $x^{(k)}(t)$ and $y^{(k)}(t)$ denote the photometer records of the k-th realization. The expected value of the product mean value would then be

$$E[\overline{x\ y}] = \frac{1}{N} \sum_{k=1}^{N} \frac{1}{\Delta T} \int_{t_1}^{t_1+\Delta T} x^{(k)}(t)\ y^{(k)}(t)\ dt = \frac{1}{N} \sum_{k=1}^{N} \overline{x^{(k)}\ y^{(k)}} = \bar{R}. \tag{9}$$

The temporal variations of this ensemble average can be determined, since the time dependence of $\bar{R}(t_1; \Delta T, \ldots)$ is not cancelled when integrating across the ensemble.

The statistical variations of the experimentally accessible product mean value $\bar{R}^{(1)}$ can also be established by analyzing the variations between the individual realization, k, and the expected value. The "expected" statistical variation of $\bar{R}^{(1)}$ is provided by a mean square error calculation or "variance":

$$\text{Var}\ \overline{(\ )}^{(1)} = \frac{1}{N-1} \sum_{k=1}^{N} \left\{ (\ )^{(k)} - E[(\ )] \right\}^2 . \tag{10}$$

A sample of the variance between individual product mean values is thus given by

$$\text{Var}\ \bar{R}^{(1)} = \frac{1}{N-1} \sum_{k=1}^{N} \left\{ \overline{x^{(k)} y^{(k)}} - E[x\ y] \right\}^2$$

$$= \frac{1}{N-1} \sum_{k=1}^{N} \left\{ \frac{1}{\Delta T} \int_{t_1}^{t_1+\Delta T} x^{(k)}(t)\ y^{(k)}(t)\ dt - \bar{R} \right\}^2 . \tag{11}$$

The associated standard deviation, $(\text{Var}\ \bar{R}^{(1)})^{1/2}$, describes one likely variation between the individual realization, $\bar{R}^{(k)}$, and the expected value, $\bar{R}$. Other variations will occur with other probabilities. Fortunately, the practical implications of the central limit theorem imply that the probability of mean value variations ought to follow the normal distribution. Knowing such a universal distribution, one can then calculate a certain limit, $t_p(\text{Var}\ \bar{R}^{(1)})^{1/2}$, which will not be exceeded by the individual variations $\bar{R}^{(1)} - \bar{R}$ for the fraction p of all N realizations. These limits provide a confidence interval for the statistical variation between a single realization, k = 1, and the expected product mean value. The 80 percent confidence interval would be

$$\bar{R}^{(1)} - t_{0.90}(N)\ (\text{Var}\ \bar{R}^{(1)})^{1/2} \leq \bar{R} \leq \bar{R}^{(1)} + t_{0.90}(N)(\text{Var}\ \bar{R}^{(1)})^{1/2} . \tag{12}$$

The "percentile factors" of the normal distribution, t_p, are listed in Table 1.

Equation (12) gives the desired estimate for the expected statistical variations of individual product mean values. The associated confidence interval could be calculated if Var $\bar{R}^{(1)}$ were accurately known. However, Eq. (11) gives only one sample of this variance. A new group of N realizations would give a different sample of Var $\bar{R}^{(1)}$. The accurate description of the statistical variations should therefore consider not only the variations between individual realizations of a single group but also the variation between different groups of realizations. Let $(\bar{\sigma}^{(1)})^2$ denote the "population variance", which is calculated by taking the arithmetic mean of all samples of

TABLE 1

Percentile Factors and Confidence Intervals for Stationary Records

Student's t Distribution			χ^2-Distribution			
m	$t_{.90}$	$1/\sqrt{m}$	$\chi^2_{.90}$	$\chi^2_{.10}$	$\chi_{.90}/m$	$\chi_{.10}/m$
2	3.08	.707	2.71	.0158	.823	.063
3	1.89	.578	4.61	.211	.716	.153
4	1.64	.500	6.25	.584	.625	.191
5	1.53	.447	7.78	1.06	.558	.206
6	1.48	.408	9.24	1.61	.507	.211
7	1.44	.378	10.6	2.20	.465	.212
8	1.42	.353	12.0	2.83	.433	.210
9	1.40	.333	13.4	3.49	.407	.208
10	1.38	.317	14.7	4.17	.383	.204
12	1.35	.288	17.3	5.58	.347	.201
14	1.34	.267	19.8	7.04	.318	.190
16	1.33	.250	22.3	8.55	.295	.183
18	1.33	.236	24.8	10.1	.277	.179
20	1.32	.222	27.2	11.7	.261	.174
25	1.32	.200	33.2	15.7	.230	.160
30	1.31	.183	39.1	19.8	.028	.150
61	1.30	.128	74.4	46.5	.142	.112
$m \to \infty$	1.28	$1/\sqrt{m}$	m	m	$1/\sqrt{m}$	$1/\sqrt{m}$

Accumulative Means

$$\overline{\overline{(\ )}}_m - t_p \overline{\overline{\Delta(\ )}}_m \leq E[\overline{(\ )}] \leq \overline{\overline{(\ )}}_m + t_p \overline{\overline{\Delta(\ )}}_m \ .$$

Normalized Accumulative Error

$$\frac{\chi_{.10}}{m\sqrt{B\Delta T}} \leq \delta\overline{\overline{R}}_m \leq \frac{\chi_{.90}}{m\sqrt{B\Delta T}} \ .$$

Var $\bar{R}^{(1)}$, i.e., the mean over all groups. The relative variation between the variance estimate from a single group and the average over all groups could then be expressed by the new variable,

$$\chi^2 = \frac{N \text{ Var } \bar{R}^{(1)}}{(\bar{\sigma}^{(1)})^2} . \tag{13}$$

The probability distribution of this variable is given by another universal distribution function, the χ^2-distribution. Knowing this distribution, one can calculate a lower limit, $\chi^2_{0.10}(N)$, which will be exceeded by the χ^2 samples of all but 10 percent of the admitted groups. One can also calculate an upper limit, $\chi^2_{0.90}(N)$, which will exceed 90 percent of all χ^2 samples. Both limits together then give a confidence interval for the statistical variation of variance estimates between different groups of realizations. The 80 percent confidence interval would be

$$\frac{N \text{ Var } \bar{R}^{(1)}}{\chi^2_{0.90}(N)} \leqq (\bar{\sigma}^{(1)})^2 \leqq \frac{N \text{ Var } \bar{R}^{(1)}}{\chi^2_{0.10}(N)} . \tag{14}$$

The percentile factors $\chi^2_{0.10}$ and $\chi^2_{0.90}$ are also listed in Table 1. For $N \geqq 30$ they may be calculated from the equation [Spiegel, 1961]

$$\chi^2_p = \frac{1}{2} \left(z_p + \sqrt{2(N-1) - 1}\right)^2 = N\left(1 - \frac{3}{2N}\right)\left(1 + \frac{z_p}{\sqrt{2N-3}}\right)^2 . \tag{15}$$

In summary, we find that a single group of N realizations can provide the following samples:

(a) The expected product mean value $\bar{R}$, Eq. (9).

(b) One sample, Var $\bar{R}^{(1)}$, for the desired statistical variations between the individual product mean values from different realizations, Eqs. (11) and (12).

(c) The confidence interval for the statistical variations of variance estimates between different groups of N realizations, Eq. (14).

All of these samples are based on universal distribution functions, which are independent from the particular physical process that produces the common signals. This universal behavior may therefore be used to separate the universal statistical variations of product mean values from specific temporal variations of these product mean values. One such possibility is discussed in Section 6.

5. STATISTICAL ERROR CALCULATION FOR STATIONARY DATA

Unfortunately, the results of the last section cannot be applied directly to experimental data, since meteorological boundary conditions cannot be adjusted to obtain many realizations of the same meteorological conditions. The alternative is then to assume that the meteorological boundary conditions are sufficiently time invariant during one experiment such that individual pieces of a long record represent statistically independent realizations of these invariant boundary conditions. For this purpose, a long record of length T is subdivided into $i = 1,2, \ldots m$ pieces of length $\Delta T = T/m$. The time average over one of these pieces may be expressed by

$$\overline{(\ )}_i = \frac{1}{\Delta T} \int_{t=(i-1)\Delta T}^{t=i\Delta T} (\ )\, dt. \tag{16}$$

Each of these piecewise estimates is then treated as if it came from a new realization. This means that the summation over realizations is replaced with a summation over pieces

$$\overline{\overline{(\ )}}_m = \frac{1}{m} \sum_{i=1}^{m} \overline{(\ )}_i = \frac{1}{m\Delta T} \int_{o}^{m\Delta T} (\ )\, dt = \frac{1}{N} \sum_{k=1}^{N} \overline{(\ )^{(k)}} = E[\overline{(\ )}]. \tag{17}$$

The following conditions [Bendat and Piersol, 1960] must be met to justify this replacement of realizations with pieces:

(a) The time history of the statistic "( )" is a self-stationary process.

(b) The autocovariance function $z(\tau)$ of this time history meets certain integrability conditions.

(c) The individual piece length ΔT exceeds the time lag range within which the autocovariance $z(\tau)$ has become negligibly small.

Experimental data mostly meet the conditions (b) and (c). However, the condition (a) means that the replacement of realizations with pieces is only justified if the temporal variations of the product mean value are negligible. Such time histories are called stationary. For such stationary time series all remaining variations are statistical. This means that the variations between piecewise averages and the statistical variations between sets of pieces should all follow the universal probability distributions given in the last section. The "fit" of these distributions may thus be used as a criterion for stationarity. One such criterion is developed in the remainder of this section.

The desired criterion for stationarity considers the variations of "accumulative" averages which were defined in Eq. (17). The accumulative average of product mean values is derived by substituting Eq. (17) into Eq. (9).

$$\bar{\bar{R}}_m = \frac{1}{m}\sum_{i=1}^{m}\overline{(xy)}_i$$

$$= \frac{1}{T}\sum_{i=1}^{m}\int_{(i-1)\Delta T}^{i\Delta T} x(t)\ y(t)\ dt$$

$$= \frac{1}{N}\sum_{k=1}^{N}\overline{x^{(k)}\ y^{(k)}} = \bar{R}. \tag{18}$$

The statistical variations of these accumulative averages are derived from the differences between pieces. A sample for the expected variance, $(\bar{\sigma}^{(1)})^2$, between any two pieces might be derived by substituting Eq. (17) into Eq. (10). This gives

$$\text{Var } \bar{R}^{(1)} = \frac{1}{(N-1)}\sum_{k=1}^{N}\left\{\overline{x^{(k)}\ y^{(k)}} - \bar{R}\right\}^2$$

$$= \frac{1}{(m-1)}\sum_{i=1}^{m}\left\{\overline{(x\ y)}_i - \bar{\bar{R}}_m\right\}^2 \tag{19}$$

$$= \frac{1}{(m-1)}\sum_{i=1}^{m}\left\{\bar{R}_i - \bar{\bar{R}}_m\right\}^2 = (\Delta\bar{R}_m^{(1)})^2.$$

The associated standard deviation, $\Delta\bar{R}_m^{(1)}$, will be called the piecewise error. Any new group of m pieces or m realizations would give another sample of the piecewise error. A confidence interval for the statistical variations of piecewise errors between different groups of pieces is derived by substituting Eq. (19) into Eq. (14).

$$\frac{m(\Delta\bar{R}_m^{(1)})^2}{\chi^2_{0.90}(m)} \leq (\bar{\sigma}^{(1)})^2 \leq \frac{m(\Delta\bar{R}_m^{(1)})^2}{\chi^2_{0.10}(m)} . \tag{20}$$

The statistical error of the accumulative mean, $\Delta\bar{\bar{R}}_m$, should be much smaller than the error of a piecewise mean, $\Delta\bar{R}_m$, since the statistical variations between pieces will partially cancel each other during the summation. For stationary data the reduction will be equal to 1/m, since the cancellation accounts for m independent realizations of the same experiment. A sample of the mean square error of an accumulative mean is thus given by:

$$\overline{\overline{(\Delta(\ )_m)^2}} = \frac{1}{m}\,\overline{(\Delta(\ )_m)^2}$$

$$= \frac{1}{m(m-1)}\sum_{i=1}^{m}\left\{\overline{(\ )}_i - \overline{\overline{(\ )}}_m\right\}^2 . \qquad (21)$$

The associated standard deviation, $\Delta\overline{\overline{R}}_m$, will be called the "accumulative error." Any new group of m pieces or m realizations would give a new sample of the accumulative error. A confidence interval for the statistical variations between these groups is derived by substituting Eq. (21) into Eq. (20) and by dividing with m. The result is

$$\frac{m(\Delta\overline{\overline{R}}_m)^2}{\chi^2_{0.90}(m)} \leq \frac{(\bar{\sigma}^{(1)})^2}{m} \leq \frac{m(\Delta\overline{\overline{R}}_m)^2}{\chi^2_{0.10}(m)} . \qquad (22)$$

In most applications the accumulative error is normalized with the product of the accumulative root mean square values

$$\delta\overline{\overline{R}}_m = \frac{\Delta\overline{\overline{R}}_m}{\overline{\overline{(X^2)}}_m^{1/2}\ \overline{\overline{(y^2)}}_m^{1/2}} \qquad (23)$$

The confidence interval for the normalized accumulative errors follows by dividing Eq. (23) with the product of the accumulative root mean square values:

$$\frac{m(\delta\overline{\overline{R}}_m)^2}{\chi^2_{0.90}\ (m)} \leq \frac{(\bar{\sigma}^{(1)})^2}{m\overline{\overline{(x^2)}}_m^{1/2}\ \overline{\overline{(y^2)}}_m^{1/2}} \leq \frac{m(\delta\overline{\overline{R}}_m)^2}{\chi^2_{0.10}\ (m)} . \qquad (24)$$

Expressing the population variance of piecewise means in terms of a "noise" band width, B,

$$(\bar{\sigma}^{(1)})^2 = \frac{\overline{\overline{(x^2)}}_m\ \overline{\overline{(y^2)}}_m}{B\Delta T} , \qquad (25)$$

and substituting this definition into the last inequality, one finds

$$\frac{m(\delta\overline{\overline{R}}_m)^2}{\chi^2_{0.90}\ (m)} \leq \frac{1}{BT} \leq \frac{m(\delta\overline{\overline{R}}_m)^2}{\chi^2_{0.10}\ (m)} . \qquad (26)$$

However, the two factors, $m/\chi^2_{0.90}$ and $m/\chi^2_{0.10}$, both asymptotically approach the value, 1, according to Eq. (14). Therefore, Eq. (25) gives the well known result that the relative statistical error of a product mean value should decrease with the inverse square root of integration time.

$$\delta\bar{\bar{R}}_m = \frac{\Delta\bar{\bar{R}}_m}{\overline{\overline{(x^2)}}_m^{1/2}\overline{\overline{(y^2)}}_m^{1/2}} \rightarrow \frac{1}{(BT)^{1/2}} . \tag{26a}$$

Direct calculations of the accumulative statistical error, $\Delta\bar{\bar{R}}_m$, may thus be used to determine the noise band width, B, from the asymptotic decrease of this error with the inverse square root of integration time. Furthermore, the knowledge of this band width can then be used to calculate the confidence levels for the relative accumulative error. Rearranging the two inequalities of Eq. (26), one gets

$$\frac{\chi_{0.10}(m)}{m\sqrt{B\Delta T}} \leq \delta\bar{\bar{R}}_m \leq \frac{\chi_{0.90}(m)}{m\sqrt{B\Delta T}} . \tag{27}$$

Figure 2 illustrates such a direct calculation of the confidence interval that is expected for stationary data. This example employs product mean values from a crossed beam test in a supersonic jet. The abscissa is given by the inverse square root of integration time, T, or accumulation number, $m = T/\Delta T$. The ordinate gives the relative statistical error which was calculated from Eq. (21). The actual data follow a straight line through the origin very closely as predicted by Eq. (26a). The slope of this line gives a noise band width of B = 22,276 cps. This noise band width has been used to calculate the confidence intervals according to Eq. (27) and Table 1. All directly calculated statistical errors fall into this interval. One can thus say that the probability is better than 80 percent that the entire record was stationary.

By processing m = 14800 pieces, it was also possible to reduce the statistical error $\Delta\bar{\bar{R}}_m$ of the accumulative product mean value, $\bar{\bar{R}}_m$, to 0.2 percent of the mean square value of the actually recorded integrated signals. This demonstrates the surprising power of digital correlation techniques to retrieve very small signals out of noise. The successful development of the associated "piecewise" correlation computer program and the success of crossed beam detection of wind profiles and turbulence parameters in subsonic and supersonic jets [Fisher, Krause, 1967] with the program provided the basis and the starting point for extending crossed beam measurements into the atmosphere.

6. DEVIATIONS FROM STATIONARITY AND IRREDUCIBLE NOISE

Fluctuation measurements with winds, humidity, and temperature sensors on meteorological towers indicate that the power spectra of these fluctuations may contain significant energy for frequencies down to 0.01 cps, i.e., for periods as long as 2 minutes. The length of one piece should be two to five times larger than this period if such pieces are to be treated as independent realizations of the same meteorological conditions. We chose a piece length

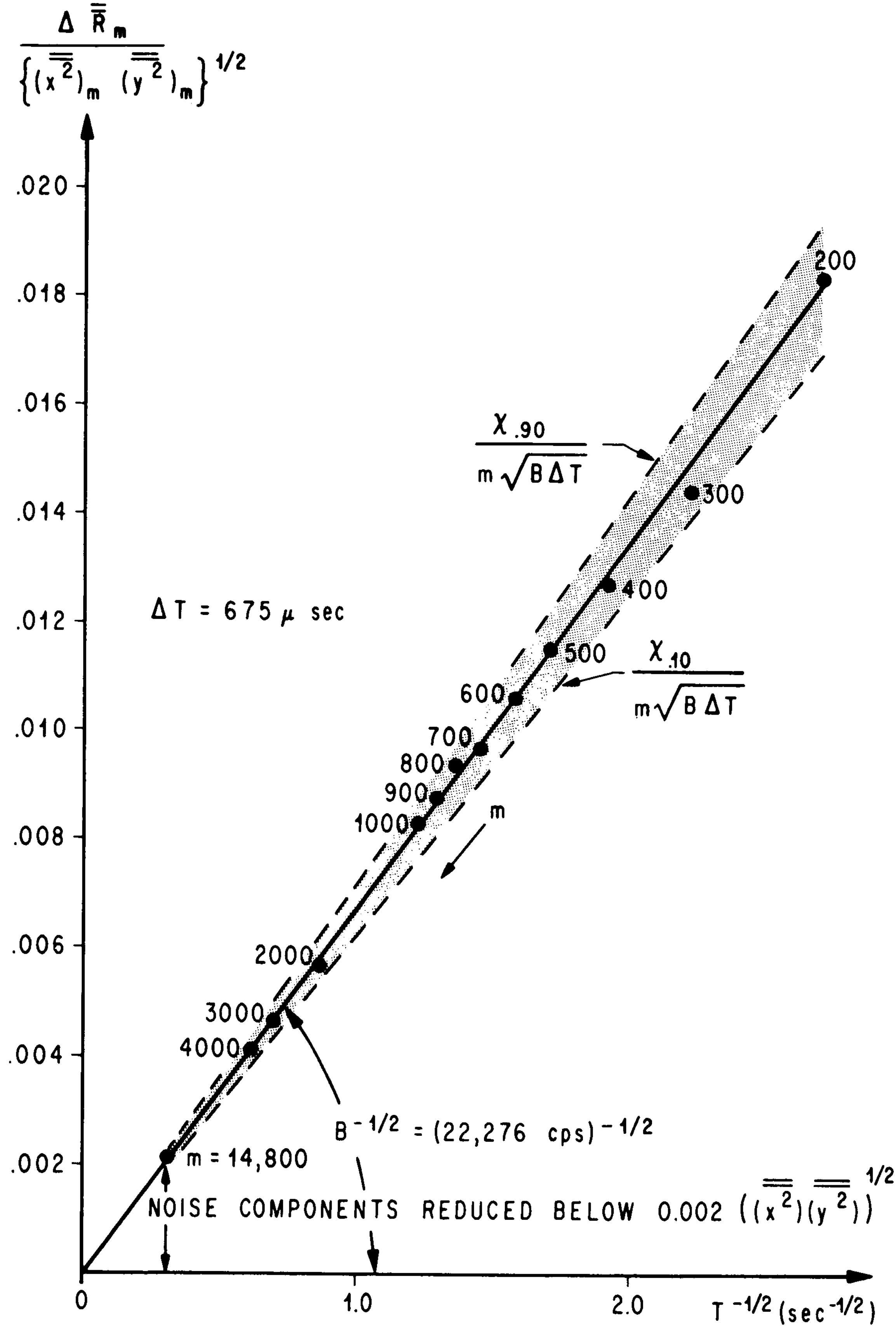

Figure 2. Noise Elimination for Stationary Wind Tunnel Data.

of ΔT = 450 sec = 7.5 minutes for most of our work. At least 5 different realizations of a physical phenomenon are then required to establish the level or irreducible noise components and nonstationarities from the statistical variations between these pieces.

We have chosen to illustrate the noise and stationarity analysis for a marginal case where only 6 pieces are available. The test conditions and the photometer records x(t) and y(t) are shown in Fig. 3. The piecewise means of photometer output "A", $\bar{x}_i$, are shown in Fig. 4a together with the accumulative mean, $\bar{\bar{x}}_6$, of these means. Furthermore, the statistical error of the individual piecewise mean, $\Delta\bar{x}_6$, is added and subtracted from each piecewise mean. The striking observation is that the mean of piece 6 makes a sudden jump which is so large that it exceeds the statistical errors. In case of stationary data, the different values of the piecewise means should stay within the confidence interval given by Eq. (12). The observed large jumps fall, however, outside such an interval; therefore, it is unlikely that these jumps are of a statistical origin. One should rather anticipate sudden changes in the meteorological boundary conditions.

The deviation from stationarity, which is anticipated because of the large jump of the sixth piecewise mean, is clearly indicated by the accumulative error of these means. These errors were calculated according to Eq. (21) and plotted against $T^{-1/2}$ as shown in Fig. 4b. The expected stationary process was then defined by fitting the calculated points with a straight line through the origin. The slope of this line gives a noise band width of B = 0.19 cps, which is then used to calculate the 80 percent confidence interval according to Eq. (27). However, the directly calculated errors increase suddenly between pieces 5 and 6 and exceed the confidence interval. This exceedance illustrates clearly the deviation from stationarity that was anticipated from the above visual inspection of Fig. 4a.

The exceedance of the confidence interval can be used to define and analyze a deviation from stationarity in many different ways. Fig. 4b illustrates the most simple of all classifications which completely disregards the shape of the actual error curve. A period of a record is called stationary if the accumulative error falls within the 80 percent confidence interval of the expected stationary process. Conversely, a period of a record is called non-stationary if the calculated errors exceed the expected confidence interval. The experience which was gained with this classification is summarized in Table 2.

The second important aspect of the accumulative error curves is the estimate of the irreducible amount of noise. Such an analysis is based on the results of the last section, which should apply within a period of stationarity. According to the discussion of equations (9) and (11), the accumulative statistical error will be contributed predominantly by the uncancelled noise components, since the meteorological boundary conditions are time invariant in a period of stationarity. The finite extent of the period of stationarity means, therefore, that an irreducible amount of noise exists which is equal to the lower limit of the accumulative statistical error inside the given period. The calculation of statistical error curve, $\Delta\bar{\bar{R}}_m(T)$, will therefore provide a direct estimate of the irreducible noise for each period of stationarity as illustrated in Fig. 4b.

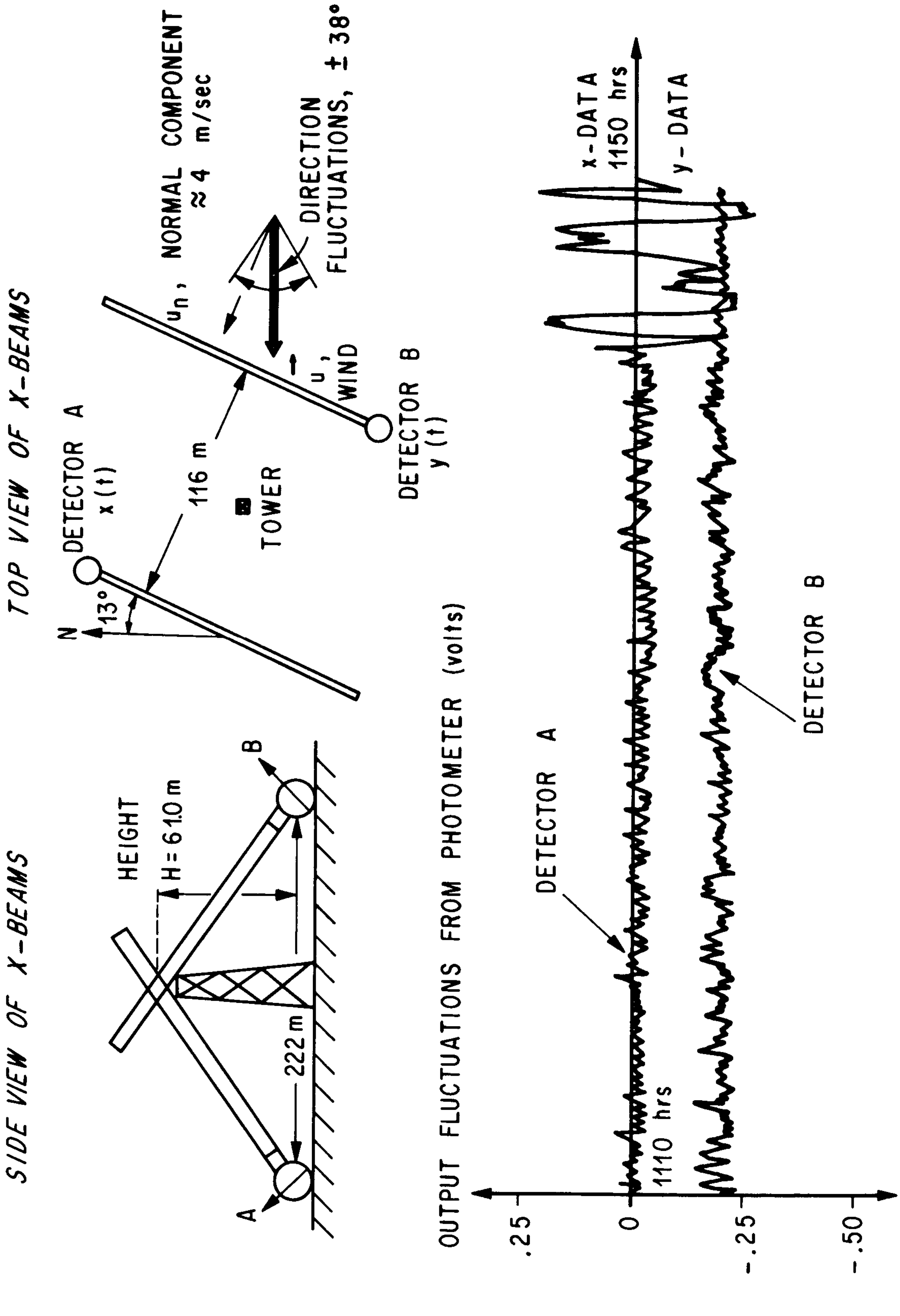

Figure 3. Example of Cross-Beam Experiment.

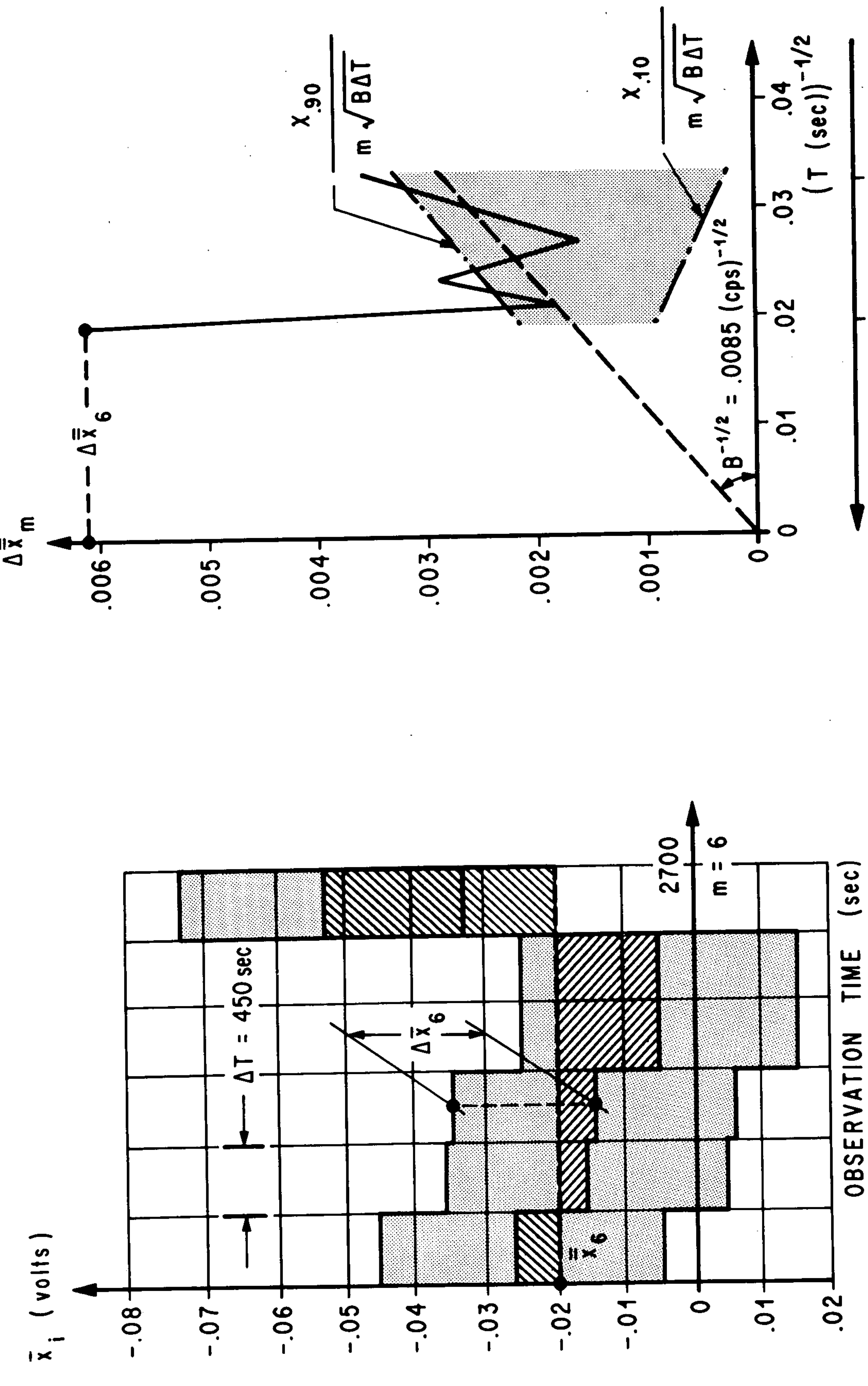

Figure 4. Piecewise Means (a) and Accumulative Statistical Error (b) of Photometer Output x.

Table 2

Preliminary Experience on Temporal Product Mean Value Variations

			Straight Time Integration				Piecewise Gain Change			
Run	T_{max} (sec)	B (cps)	T_1 (sec)	T_2 (sec)	$\frac{T_1-T_2}{T_{max}}$ (%)	$(\delta R)_{min}$	T_1 (sec)	T_2 (sec)	$\frac{T_1-T_2}{T_{max}}$ (%)	$(\delta R)_{min}$
A	6750	.063	NA	NA	0	NA	0	6750	100	.050
B	4050	.044	NA	NA	0	NA	0	4050	100	.067
C	4500	.045	3600	4500	20	.078	0	4500	100	.052
D	7200	.063	2250	7200	62	.060	0	7200	100	.046
E	3240	.063	NA	NA	0	NA	0	3240	100	.065
F	4950	.012	0	4950	100	.060	450	4950	91	.045
G	4500	.111	NA	NA	0	NA	0	4500	100	.044
H	10350	.250	NA	NA	0	NA	0	10350	100	.019
I	2700	.063	NA	NA	0	NA	0	2700	100	.040

T_1 = start of stationary period

T_2 = end of stationary period

$\frac{T_2-T_1}{T_{max}}$ = percentage of stationarity

NA = not applicable.

7. PARTIAL REMOVAL OF TEMPORAL VARIATIONS BY PIECEWISE ORDINATE SHIFTS AND GAIN FACTORS

The existence of an irreducible amount of noise would be fatal to crossed beam experiments if this irreducible noise exceeds the small levels of the common signal. However, the results of the last section imply that the "irreducible" amount is inversely proportional to the length of the period of stationarity. If one could partially remove the temporal variations of the meteorological boundary conditions, then the amount of "irreducible" noise might be further reduced by allowing a longer period of stationarity. In other words, the term "irreducible" applies only to a straight time integration as described by Eq. (16). Averaging procedures other than time integration might provide smaller "irreducible" noise levels by removing the time dependence of boundary conditions through suitable normalization and trend elimination procedures. Jayroe and Su proposed the concept of "accumulative" means which differ from straight time integration by employing piecewise variable ordinate shifts and gain factors [Jayroe and Su, 1968]. The applications of these shifts and gains will now be discussed for the same test run that has already been used.

A piecewise variable ordinate shift may be described as an attempt to remove large scale (i.e., low frequency) trends. Consider lagged product mean values which differ from the product mean values of Eq. (2) only by delaying signal x relative to signal y:

$$\bar{R}_i(\tau) = \overline{x(t-\tau)\ y(t)}_i = \frac{1}{\Delta T} \int_{(i-1)\Delta T}^{i\Delta T} x(t-\tau)\ y(t)\ dt. \qquad (28)$$

This lagged product mean value (or temporal correlation function) is calculated for equally spaced time lags and truncated at a time lag

$$\tau_{max} = \frac{1}{6} \Delta T.$$

Figure 5a shows such a piecewise estimated correlation function for piece 1 of our test run (Fig. 3). The ordinate of this correlation curve shall then be shifted by an amount $\bar{P}_i(0)$ which makes the area under the shifted curve vanish.

$$\bar{P}_i(0) = \frac{1}{2\tau_{max}} \int_{-\tau_{max}}^{+\tau_{max}} \bar{R}_i(\tau)\ d\tau. \qquad (29)$$

This ordinate shift is equal to the cross power inside the narrow frequency band

$$-\frac{1}{4\tau_M} \leqq f \leqq \frac{1}{4\tau_M} :$$

$$\Delta f \cdot S(f \rightarrow 0) = \frac{1}{2\tau_M} \cdot \lim_{f=0} \int_{-\infty}^{+\infty} \bar{R}_i(\tau)\ e^{-i2\pi f\tau}\ d\tau$$

$$= \frac{1}{2\tau_M} \int_{-\infty}^{+\infty} \bar{R}_i(\tau)\ d\tau = \bar{P}_i(0). \qquad (30)$$

The ordinate shift $\bar{P}_i(0)$ therefore removes all power at frequencies below $1/4\tau_M$, i.e., all slowly varying trends. The ordinate shift may thus be

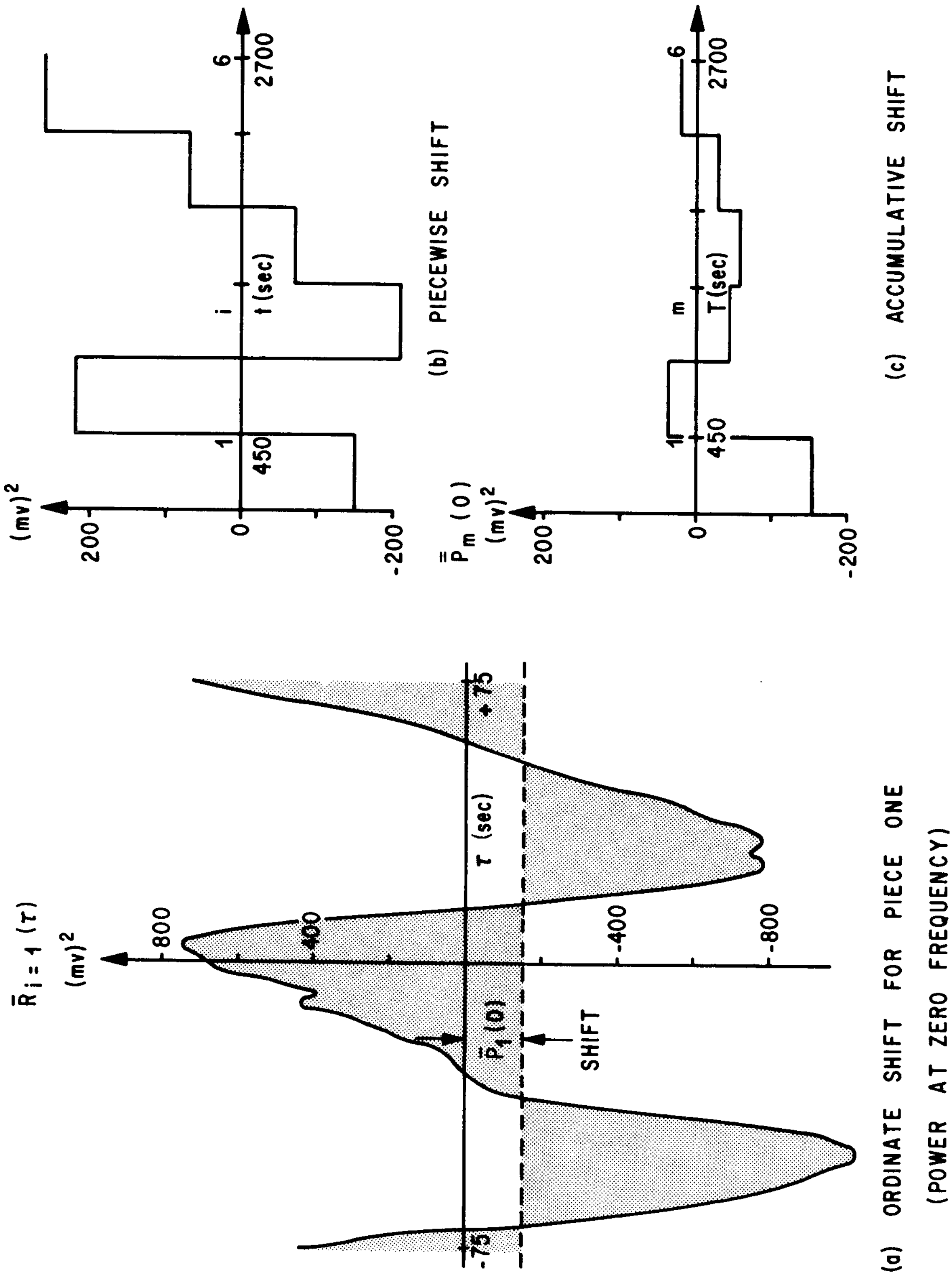

Figure 5. Removal of Low Frequency Components Through Piecewise Ordinate Shifts.

described as a piecewise trend elimination method. The application of this detrending procedure leads to the following accumulation average:

$$(\bar{\bar{R}}_m)_d = \frac{1}{m} \sum_{i=1}^{m} (\bar{R}_i - \bar{P}_i(0)). \tag{31}$$

Figure 5b shows the ordinate shifts, $\bar{P}_i(0)$, which have been calculated for the six pieces of our test run. These shifts oscillate between positive and negative values in such a way that the accumulative shift, $\bar{\bar{P}}_m(0)$, stays very small. Apparently, the temporal variations of product mean values (Fig. 5c) may be insignificant, although the temporal variations of the mean values (Fig. 4a) are large.

Piecewise ordinate shifts are effective in removing trends. However, in many cases the temporal variations of the boundary conditions will also cause changes at higher frequencies. One change that was observed often is a piecewise jump of fluctuation amplitudes. The average fluctuation amplitude, σ, for a piece is given by the root mean square value

$$\bar{\sigma}^2_{xi} = \frac{1}{\Delta T} \int_{(i-1)\Delta T}^{i\Delta T} x^2 dt. \tag{32}$$

Temporal variations of fluctuation amplitude are then indicated by the variations of this root mean square value. Figure 6 illustrates this variation for the test run. The temporal variation of the boundary condition that was discovered (Fig. 4b) also, apparently, causes a large jump of the amplitude between pieces 5 and 6. However, the effect of this jump could be minimized by normalizing with the associated root mean square value. This would reduce the fluctuations of the normalized signal $x/\bar{\sigma}_{xi}$ to the level of the previous pieces. The opposite would be true with a piece that is characterized by a sudden decrease of fluctuation levels. Temporal variations of signal amplitudes can thus be suppressed effectively by using a piecewise bariable gain factor which is proportional to $1/\bar{\sigma}_i$. Such a nondimensional gain factor has been defined by multiplying $1/\bar{\sigma}_i$ with the accumulative root mean square value

$$\bar{\bar{\sigma}}^2_m = \frac{1}{m} \sum_{i=1}^{m} \bar{\sigma}^2_i. \tag{33}$$

The application of this gain, $\bar{\bar{\sigma}}/\bar{\sigma}$, leads to a new type of accumulative average which may be denoted by

$$(\bar{\bar{R}}_m)_w = \frac{\bar{\bar{\sigma}}_{xm} \bar{\bar{\sigma}}_{ym}}{m} \sum_{i=1}^{m} \frac{\bar{R}_i}{\bar{\sigma}_{xi} \bar{\sigma}_{yi}}. \tag{34}$$

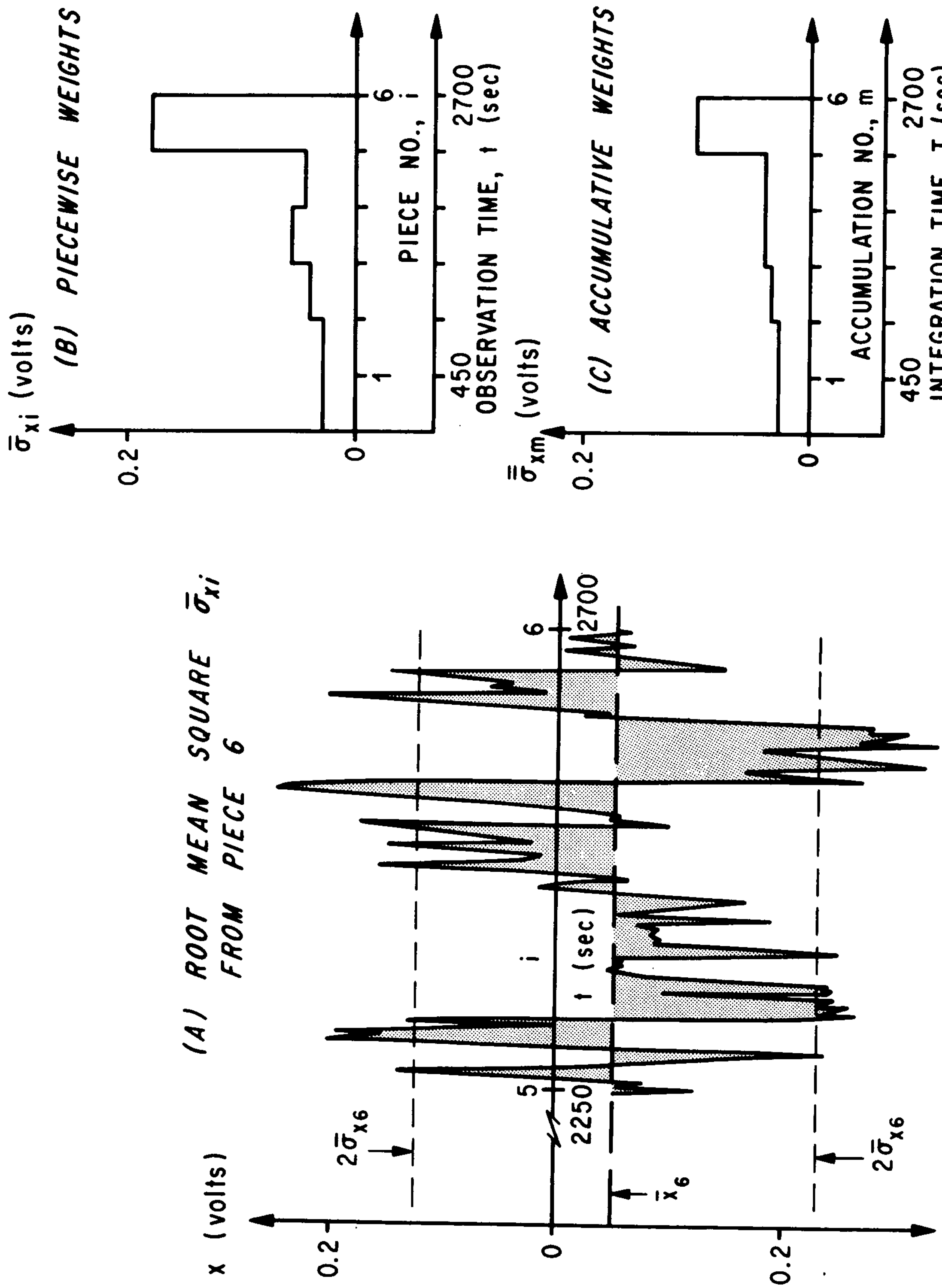

Figure 6. Piecewise gains.

Combined weighting and detrending gives a fourth type of accumulative average:

$$(\bar{\bar{R}}_m)_c = \frac{\bar{\bar{\sigma}}_{xm}\,\bar{\bar{\sigma}}_{ym}}{m} \sum_{i=1}^{m} \frac{\bar{R}_i - \bar{P}_i(0)}{\bar{\sigma}_{xi}\,\bar{\sigma}_{yi}}. \tag{35}$$

All of these different accumulation procedures may be summarized by the use of a unified accumulative average,

$$\bar{\bar{R}}(\tau;\ m;\ \ldots) = \frac{\bar{\bar{\sigma}}_{xm}\,\bar{\bar{\sigma}}_{ym}}{m} \sum_{i=1}^{m} \frac{\bar{R}_i - \bar{s}_i}{\sigma_x\,\sigma_y}, \tag{36}$$

which allows for a free choice of gain factors, $\bar{\bar{\sigma}}/\bar{\sigma}$, and ordinate shifts, $\bar{s}$. The various options that have been tried to this date are characterized by the following choices:

Straight time integration: subscript a

$$\sigma_x = \bar{\bar{\sigma}}_{xm}; \quad \sigma_y = \bar{\bar{\sigma}}_{ym}; \quad \bar{s}_i = 0.$$

Piecewise detrending: subscript d

$$\sigma_x = \bar{\bar{\sigma}}_{xm}; \quad \sigma_y = \bar{\bar{\sigma}}_{ym}; \quad \bar{s}_i = P_i(0).$$

Piecewise weighting: subscript w

$$\sigma_x = \bar{\sigma}_{xi}; \quad \sigma_y = \bar{\sigma}_{yi}; \quad \bar{s}_i = 0.$$

Combined detrending and weighting: subscript c

$$\sigma_x = \bar{\sigma}_{xi}; \quad \sigma_y = \bar{\sigma}_{yi}; \quad \bar{s}_i = P_i(0).$$

The value of these choices may be judged from the behavior of the associated accumulative statistical error,

$$(\delta\bar{\bar{R}}(\tau;\ T;\ m)^2 = \left(\frac{\Delta\bar{\bar{R}}(\tau,T,m)}{\bar{\bar{\sigma}}_{xm}\,\bar{\bar{\sigma}}_{ym}}\right)^2 = \frac{1}{m(m-1)} \sum_{i=1}^{m} \left\{\frac{\bar{R}_m - \bar{s}_i - (\bar{\bar{R}}_m - \bar{\bar{s}}_m)}{\bar{\sigma}_x\,\bar{\sigma}_y}\right\}^2 . \tag{36}$$

The desired accumulation procedure should suppress the temporal variation of meteorological boundary conditions. According to section 6, this suppression may be judged by fitting the tail (m large) of the error curve with a straight line. The best accumulation procedure is the one that gives the best fit. Furthermore, the slope of that line gives the noise band width, B, of the piecewise modified noises and can be used to calculate the confidence interval for the entire error curve from Eq. (27). The whole procedure is illustrated in Fig. 7 for the test run and differs from the illustration given in Fig. 4 in the following aspects:

(a) The statistical error refers to product mean values, not mean values.

(b) The time lag dependence of the product mean value has been cancelled by integration:

$$ {}_{\tau}\delta\overline{\overline{R}}^2(T;m) = \frac{1}{2\tau_{max}} \int_{-\tau_{max}}^{+\tau_{max}} \delta\overline{\overline{R}}^2(\tau;\ T;\ m)\ d\tau \tag{37} $$

(c) Four different error curves have been calculated using the different options for piecewise shifts and gains that were identified above by the subscripts a, d, w and c.

The straight time integration, curve a, indicates that both the beginning and the end of the record are strongly affected by temporal variations of the boundary conditions. These variations cannot be described by low frequency trends since the piecewise detrending, curve d, is not effective to alter the shape of the error curve. Only the use of piecewise gains produces error curves (c and a) which approximate a straight line through the origin. The slope of this line gives a bandwidth B = 0.063 cps, which in turn is used to calculate the confidence interval $X/m\sqrt{B\Delta T}$. Both curves w and c fall into this interval; i.e., the piecewise modified photometer records are stationary with a probability exceeding 80 percent. The smallest error of these curves, ${}_{\tau}\delta\overline{\overline{R}} \approx 0.075$, gives then the irreducible amount of noise that is left after accumulating over a period of T = 45.00 = 2700 seconds. A further noise reduction would require a longer record.

The use of piecewise gains proved to be a very powerful tool in cases where the meteorological boundary conditions were known to be highly time invariant. One of the more dramatic changes of meteorological conditions under clear skies is the change of wind direction. Fig. 8 provides an example of piecewise gain changes for moderate fluctuations of wind directions (± 22°, run H). Without piecewise gains we get a curve that fits the confidence interval; however, this curve does not exhibit the desired straight line fit. The use of piecewise gains improves the approximation of a stationary record significantly and also slightly improves the noise elimination. Figure 9 provides an example for extreme temporal variations of boundary conditions (±180°, run A). The wind was blowing from all directions during the

SYMBOL	ACCUMULATION METHOD
●	STRAIGHT TIME INTEGRATION $\overline{(\ )}_i = \bar{R}_i$, $\sigma = \overline{\overline{(x^2)}}_m^{1/2};\ \overline{\overline{(y^2)}}_m^{1/2}$
□	PIECEWISE GAINS $\overline{(\ )}_i = \bar{R}_i$, $\sigma = \overline{(x^2)}_i^{1/2};\ \overline{(y^2)}_i^{1/2}$
■	PIECEWISE SHIFTS $\overline{(\ )}_i = \bar{R}_i - \bar{P}_i(0)$, $\sigma = \overline{\overline{(x^2)}}_m^{1/2};\ \overline{\overline{(y^2)}}_m^{1/2}$
▲	COMBINED PIECEWISE GAINS AND SHIFTS $\overline{(\ )}_i = \bar{R}_i - \bar{P}_i(0)$, $\sigma = \overline{(x^2)}_i^{1/2};\ \overline{(y^2)}_i^{1/2}$

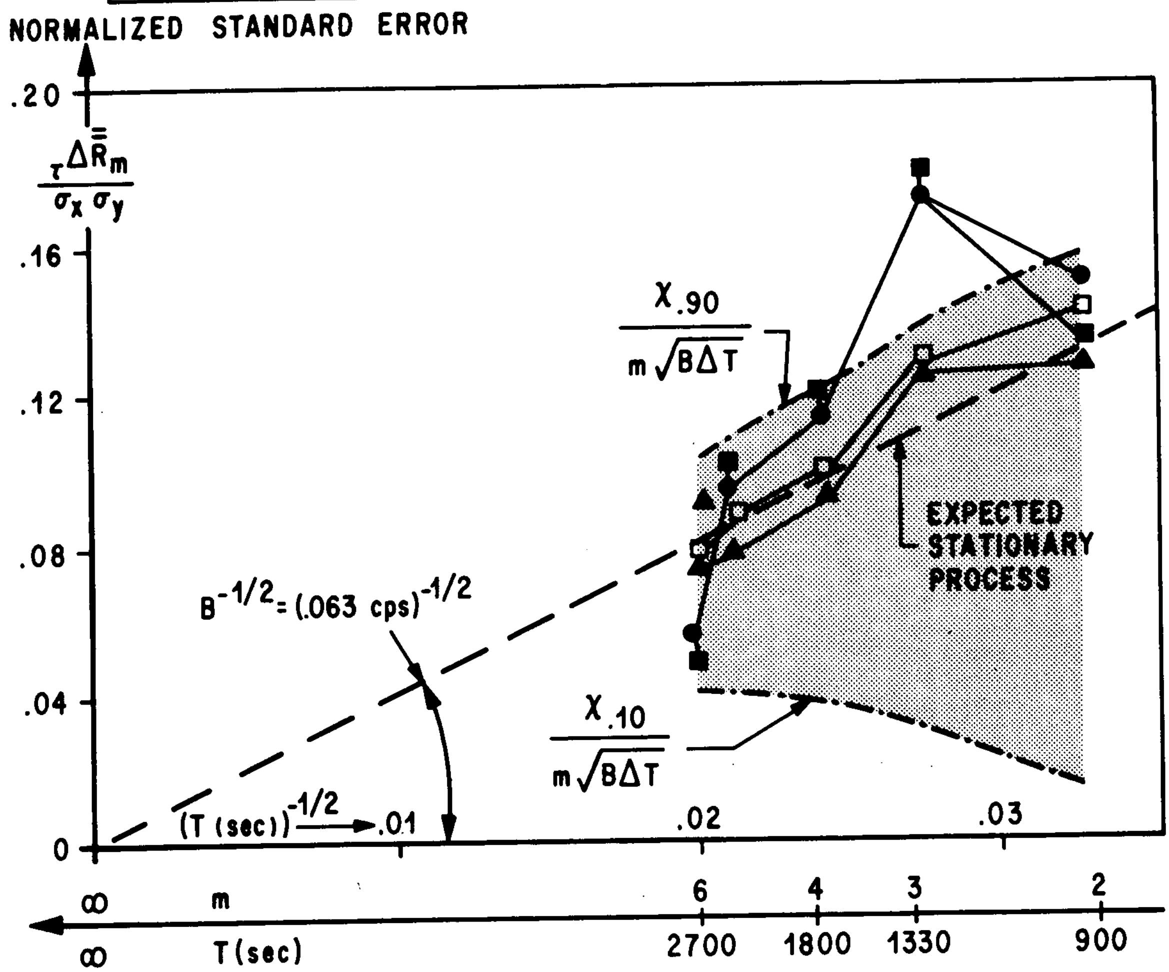

Figure 7. Application of Piecewise Shifts and Gains to Test Runs.

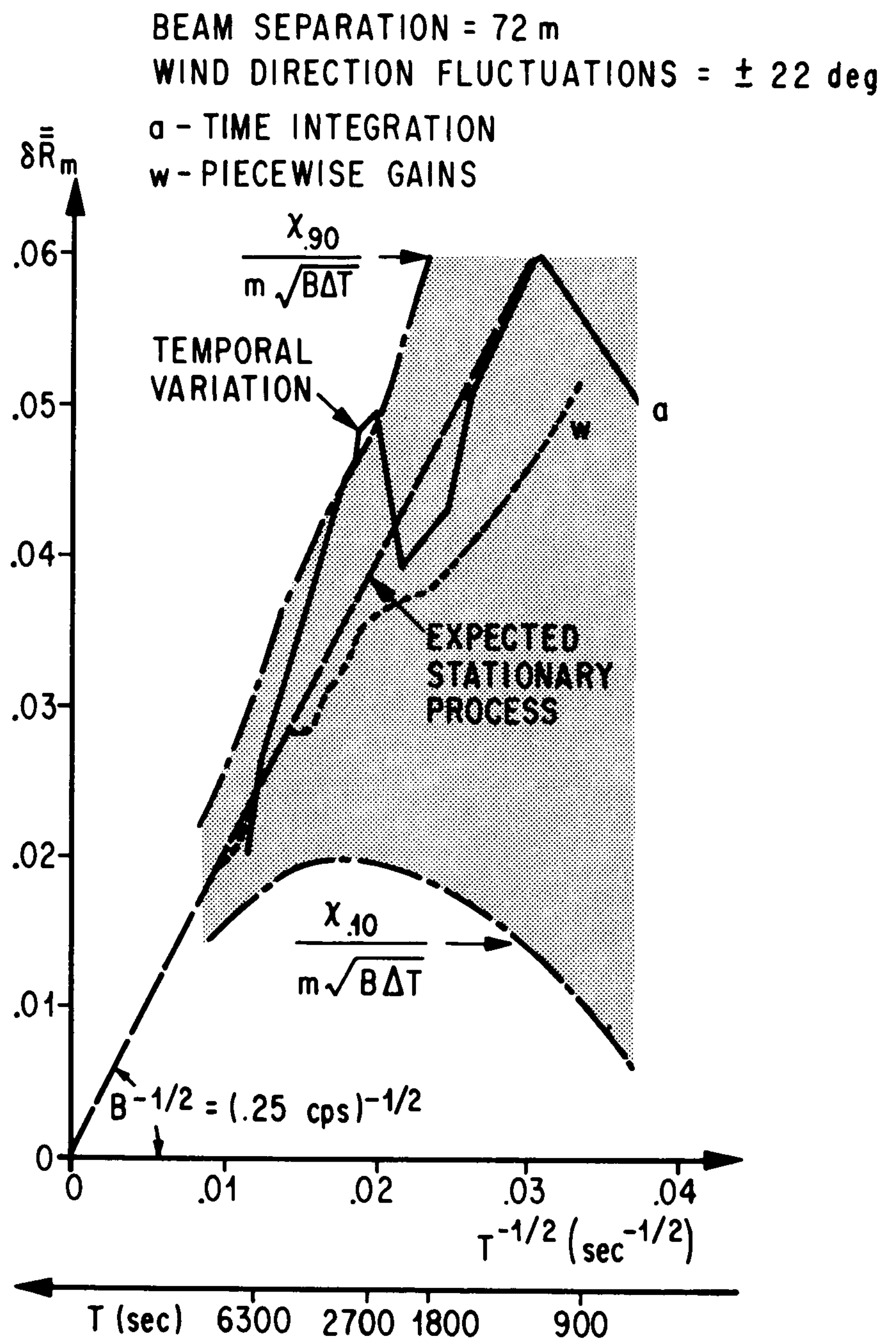

Figure 8. Removal of Temporal Product Mean Value Variations with Piecewise Gains (Run H).

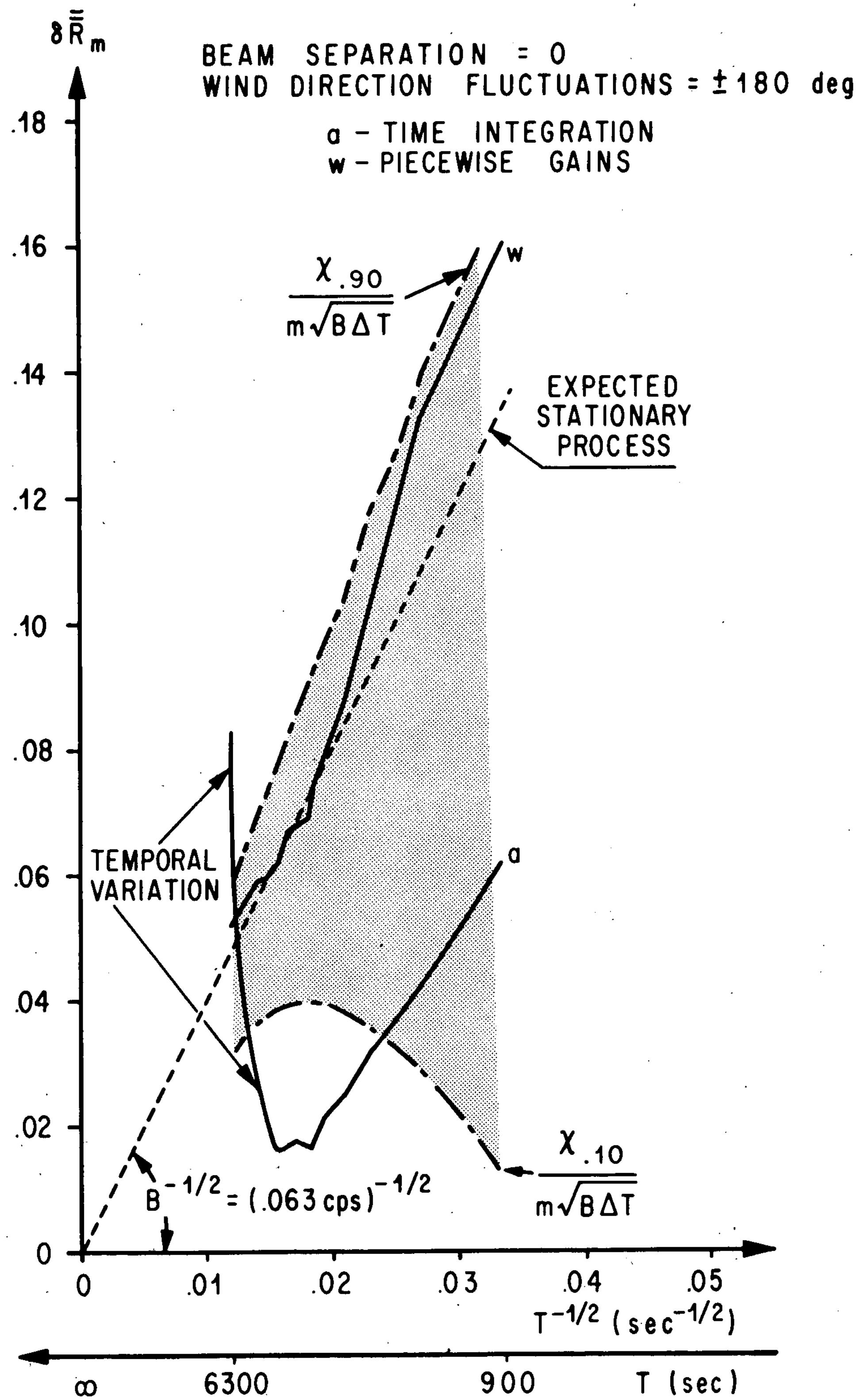

Figure 9. Removal of Temporal Product Mean Value Variations with Piecewise Gains (Run A).

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recording period. In this case, the straight time integration produces an error curve which does not resemble a stationary process at all. However, even in this extreme case the use of piecewise gains proves sufficient to eliminate the temporal fluctuations of product mean values.

Our preliminary experience with the application of piecewise correlation methods indicates that temporal variations of product mean values occur quite frequently for observation periods between 1/2 and 2 hours. Table 2 gives a summary of the first 9 runs where statistical and temporal product mean value variations were separated. In six out of nine runs the temporal variations of stationarity did not exist at all. Two of the six cases are illustrated in Figs. 7 and 9.

For record lengths up to 2 hours, the use of piecewise gains and ordinate shifts has always been sufficient to remove temporal variations of product mean values provided that the amplifier or tape recorder is not driven into saturation by these temporal variations. Saturation by a large temporal variation of meteorological conditions however always occurred and was the dominant factor which determined the maximum record length, T. Elimination of this saturation problem should allow longer recording times and thereby contribute to a further reduction of noise below the values of $(\delta R)_{min}$ that are listed in Table 2.

8. CONCLUSIONS AND RECOMMENDATIONS

The piecewise correlation technique was developed to eliminate noise in the output of remote detection devices. The noise is reduced by multiplying the photometer output with a reference signal and by integrating this instantaneous product over time. This method is quite common for stationary time series where the boundary conditions of the experiment are time invariant. The piecewise correlation technique is new by extending this elimination of noise to meteorological boundary conditions which are time dependent. The simple time integration of products cannot reduce the noise level below the level of temporal variations, since one cannot distinguish between statistical and temporal variations of the product mean value.

The mathematical theory of product mean value variations is based on the difference between a large group of imaginary experiments, all of which have the same time dependent boundary conditions. This theory cannot be applied directly since meteorological conditions cannot be controlled to repeat themselves many times. However, individual pieces of a long record may often be normalized and detrended in such a way that the resultant piecewise modified data behave as if they belonged to independent realizations of the same meteorological boundary conditions. Piecewise correlation techniques are thus based on the premise that one can, in most cases, find suitable piecewise modifications of the photometer outputs and the reference signal which produce two new signals that are stationary although the experiment itself is quite nonstationary.

The effect of piecewise modifications of the photometer outputs may be judged by curve fitting the resultant accumulative error curve with a straight line. The modifications have been successful if the accumulative error decreases linear with the inverse square root of integration time. The slope of the straight line fit gives the frequency band width of the noise components which one wishes to suppress. Knowing this band width, one can also calculate a confidence interval that should contain most of the calculated statistical errors. Temporal variations of product mean values are then indicated by those errors which fall outside this confidence interval.

The experience gained with piecewise correlation techniques indicates that significant temporal variations of product mean values do occur quite frequently (50 percent of all runs). However, these temporal variations have been removed successfully by employing piecewise changes of gain factors and piecewise ordinate shifts. The proposed automatic changes of gains and ordinates are thus suitable piecewise modifications. They have successfully reduced the temporal variations of product mean values below the level of the statistical variations in all cases where the temporal variations of the meteorological boundary conditions did not drive the amplifier or the tape recorder into saturation.

The piecewise correlation technique provides a new tool that can distinguish between statistical and temporal variations of product mean values. The statistical variations are due to the still uncancelled noise and the temporal fluctuations are caused by a temporal change in meteorological boundary conditions. We recommend continuing the present studies of noise elimination in the presence of time dependent meteorological boundary conditions. Particular emphasis should be given to the temporal variations of product mean values which are caused by changes in aerosol concentrations, optical background fluctuations, variations of wind speeds and changes of wind direction.

The above recommendation is based on the technical problems that were encountered in our first cross beam field tests. These problems and the proposed solutions may be described as follows.

Temporal variations of local scattering process were frequently observed under clear skies which are so large that both the a.c. amplifiers and tape recorders are driven into saturation. Amplifier saturation is being reduced by installing a new coupling circuit with a stepwise variable time constant that is triggered by the incoming signal. Tape recorder saturation will be eliminated by replacing the analog recorder with an on-line digital data logging system.

Temporal variations of the optical background radiation were caused by distant clouds and haze which drift through the photometer's field of view. The associated background noise far exceeds the signal contributions from the desired target layers and may be so large that it cannot be reduced sufficiently by integration of products. In crossed beam tests these background fluctuations have been suppressed by pointing the telescopes to the horizon beneath the cloud level. Infrared photometer systems are now being assembled which should suppress the background fluctuations by setting the monochromator bandpass to a spectral region where the optical path length terminates below the cloud level.

Temporal variations of wind speeds have often caused the dominant temporal variations of product mean values. One promising approach to eliminate noise in the presence of speed fluctuation is to replace the photometer output with its time derivative. The correlation of time derivatives is presently being employed to retrieve the probability density of wind component fluctuations.

Large temporal variations of wind directions change the altitudes where the common signals originate. A single-beam fan arrangement is being assembled which sets a fan of six narrow fields of view by mounting a plurality of photodiodes in the focal plane of the collector optics. A new piecewise correlation program is being coded for multichannel operation to process the output from several detectors simultaneously. The fan system will then be used to study the altitude distribution of the common signals and the restrictions on altitude resolution that are imposed by large wind direction changes.

A successful elimination of noise in the presence of time dependent meteorological boundary conditions would provide an opportunity to extend remote detection techniques to the description of dynamic phenomena such as winds and turbulence. In particular, the theory of a rapid scanning crossed beam system [Krause, et al., 1966] indicates that wind and turbulence profiles could conceivably be monitored in real time with a single flyby. Furthermore, a crossed beam system which is mounted on an airplane or a satellite moves so rapidly that temporal variations of wind speed and wind direction should no longer interfere with the noise elimination [St. John and Blauz, 1968]. Our recommendation for future studies is therefore to develop piecewise correlation techniques and onboard computer systems for rapid scanning remote detection devices such that space and time variations of optical and meteorological phenomena might be monitored in real time in regions where balloons are not available.

We hope to continue our present field test programs to collect design information that could be used for the development of rapid scanning remote detection devices. The long range objective of these field tests is to isolate the space time variations of local emission, absorption and scattering processes at various altitudes and to determine the irreducible amount of noise which is imposed by the variations of the meteorological boundary conditions. The design of airplane instrument packages and of on-line computer systems should be initiated as soon as the results of the continued field tests indicate the feasibility of such a step.

ACKNOWLEDGEMENTS

The development of the piecewise correlation program would have been impossible without significant contributions from our colleagues at the Marshall Space Flight Center (MSFC) and the Nortronics-Huntsville Division (N-H). Analog data acquisition systems were provided by J. P. Heaman, MSFC. Software and analog digital conversion systems were made available by J. A. Jones, MSFC. Computer operations and development of program options were provided by J. Pooley, N-H. The concepts of piecewise ordinate shifts and piecewise gain factors have been contributed by R. R. Jayroe, MSFC, and M. Y. Su, N-H. Most experimental data were collected by V. A. Sandborn, Colorado State University.

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