

AD-A185 746

A COMPUTER DECISION-MAKING PROCESS FOR THE ELIMINATION  
OF NOISE FROM DATA(U) AIR FORCE GEOPHYSICS LAB HANSCOM  
AFB MA R O BERTHEL 27 MAR 87 AFGL-TR-87-0118

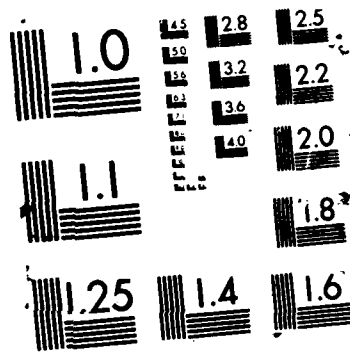
1/1

UNCLASSIFIED

F/G 12/5

NL





12

AD-A185 746

AFGL-TR-87-0118  
ENVIRONMENTAL RESEARCH PAPERS, NO. 972

DTIC FILE COPY

# A Computer Decision-Making Process for the Elimination of Noise From Data

Robert O. Berthel



27 March 1987

DTIC  
ELECTE  
OCT 15 1987  
S C D



Approved for public release; distribution unlimited.

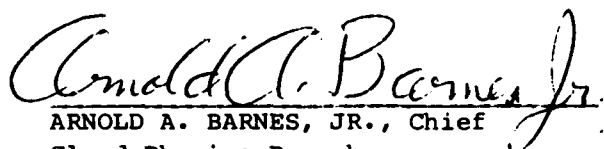


ATMOSPHERIC SCIENCES DIVISION Project 6670  
**AIR FORCE GEOPHYSICS LABORATORY**  
HANSCOM AFB, MA 01731

87 10 6 060

"This technical report has been reviewed and is approved for publication"

FOR THE COMMANDER

  
ARNOLD A. BARNES, JR., Chief  
Cloud Physics Branch

  
ROBERT A. McCLATCHEY, Director  
Atmospheric Sciences Division

This document has been reviewed by the ESD Public Affairs Office (PA) and is releasable to the National Technical Information Service (NTIS).

Qualified requestors may obtain additional copies from the Defense Technical Information Center. All others should apply to the National Technical Information Service.

If your address has changed, or if you wish to be removed from the mailing list, or if the addressee is no longer employed by your organization, please notify AFGL/DAA/LYC Hanscom AFB, MA 01731-5000. This will assist us in maintaining a current mailing list.

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE

AD-F-2

REPORT DOCUMENTATION PAGE

1a. REPORT SECURITY CLASSIFICATION <b>Unclassified</b>		1b. RESTRICTIVE MARKINGS	
2a. SECURITY CLASSIFICATION AUTHORITY		3. DISTRIBUTION/AVAILABILITY OF REPORT <b>Approved for public release; Distribution unlimited</b>	
2b. DECLASSIFICATION/DOWNGRADING SCHEDULE			
4. PERFORMING ORGANIZATION REPORT NUMBER(S) <b>AFGL-TR-87-0118 ERP, No. 972</b>		5. MONITORING ORGANIZATION REPORT NUMBER(S)	
6a. NAME OF PERFORMING ORGANIZATION <b>Air Force Geophysics Laboratory</b>	6b. OFFICE SYMBOL <i>(If applicable)</i> <b>LYC</b>	7a. NAME OF MONITORING ORGANIZATION	
6c. ADDRESS (City, State and ZIP Code) <b>Hanscom AFB Massachusetts, 01731-5000</b>		7b. ADDRESS (City, State and ZIP Code)	
8a. NAME OF FUNDING/SPONSORING ORGANIZATION	8b. OFFICE SYMBOL <i>(If applicable)</i>	9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER	
8c. ADDRESS (City, State and ZIP Code)		10. SOURCE OF FUNDING NOS	
		PROGRAM ELEMENT NO	PROJECT NO
		TASK NO	WORK UNIT NO.
11. TITLE (Include Security Classification) <b>A Computer Decision-Making Process (cont.)</b>		<b>62101F</b>	<b>6670</b>
		<b>12</b>	<b>09</b>
12. PERSONAL AUTHOR(S) <b>Berthel, Robert O.</b>			
13a. TYPE OF REPORT <b>Scientific, Interim</b>	13b. TIME COVERED FROM _____ TO _____	14. DATE OF REPORT (Yr. Mo. Day) <b>1987 March 27</b>	15. PAGE COUNT <b>26</b>
16. SUPPLEMENTARY NOTATION			
17. COSATI CODES		18. SUBJECT TERMS (Continue on reverse if necessary; and identify by block number)	
FIELD	GROUP	Artificial intelligence	
	SUB GR	Precipitation	
		Data analysis	
		Data reduction	
19. ABSTRACT (Continue on reverse if necessary; and identify by block number) <p>➤ Data acquired in many scientific and engineering activities are contaminated by "noise" or extraneous readings that are superimposed on base-line values. Automated data-analysis routines normally resort to some form of numerical averaging to suppress noise with the assumption that the smoothed values will closely approximate the base data. There are, however, circumstances where averaging may not produce acceptable results such as in situations of severe noise that are biased in magnitude and polarity.</p> <p>The Air Force Geophysics Laboratory was faced with this problem in the analysis of snow weight/rate data because of wind-induced extraneous readings. Various automated analytical schemes were tried in an attempt to reproduce the base-line data but all failed to give approximations within acceptable error boundaries. It was then noted that the base values could be very closely replicated by a hand-drawn, "best guess" line on the plotted, noisy-raw data. This revelation prompted the development of a computer process that, by mimicking the logic of human reasoning, can eliminate extraneous readings and (cont.)</p>			
20. DISTRIBUTION/AVAILABILITY OF ABSTRACT UNCLASSIFIED/UNLIMITED <input checked="" type="checkbox"/> SAME AS RPT <input type="checkbox"/> DTIC USERS <input type="checkbox"/>		21. ABSTRACT SECURITY CLASSIFICATION <b>Unclassified</b>	
22a. NAME OF RESPONSIBLE INDIVIDUAL <b>Robert O. Berthel</b>		22b. TELEPHONE NUMBER <i>(Include Area Code)</i> <b>(617) 377-2945</b>	22c. OFFICE SYMBOL <b>LYC</b>

A

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE

11 (cont. ).

for the Elimination of Noise From Data

Block 19 (cont. )

reconstruct the base-line data to a very close approximation. As such, this computer decision-making procedure may be classified as a form of artificial intelligence that may be applicable to other analytical routines.

This report discusses the problems associated with extraneous or noisy data and describes the technique that was developed to eliminate superfluous readings from snow weight/rate measurements.

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE



- 1. INTRODUCTION
- 2. PROBLEM DEFINITION
- 3. ANALYTICAL LOGIC
- 4. PROBLEM RESOLUTION
- 5. CONCLUSIONS
- REFERENCES

Accession For	
NTIS CRA&I	<input checked="" type="checkbox"/>
DTIC TAB	<input type="checkbox"/>
Unannounced	<input type="checkbox"/>
Justification	
By	
Distribution /	
Availability Codes	
Dist	Avail and/or Special
A-1	

### Contents

- 1
- 5
- 7
- 8
- 14
- 21

### Illustrations

- 1a. Extraneous Readings Having Symmetry in Magnitude and Polarity Superimposed Upon Constant Base-Line Data 2
- 1b. Extraneous Readings Having Random Magnitude and Symmetrical Polarity Superimposed Upon Constant Base-Line Data 2
- 1c. Extraneous Readings Having Symmetry in Magnitude and Random Polarity Superimposed Upon Constant Base-Line Data 3
- 1d. Extraneous Readings Having Both Random Magnitude and Polarity Superimposed Upon Constant Base-Line Data 3
- 2. Photograph of Snow Rate Meter 5

## Illustrations

3.	One Hour of Snow Weight Data Taken on 10 Dec 1982 at Camp Grayling, Mich., During the SNOW-ONE-B Field Experiment	6
4.	A 20-Min Segment of the Noisy Data From Figure 3	8
5.	A 20-Min Segment of the Noisy Data From Figure 3 With the Hand-Drawn "Best Guess" Estimates of the Actual Snow Weights	9
6.	A 20-Min Segment of the Noisy Data From Figure 3 With a 1-Min Running-Mean Average	10
7.	A 20-Min Segment of the Noisy Data From Figure 3 With a 5-Min Running-Mean Average	11
8.	A 20-Min Segment of the Noisy Data From Figure 3 With the Computer-Generated Estimates of the Actual Snow Weights	14
9.	Flow Diagram Describing the Logic of the Computer Decision-Making Process	15
10a.	A Base-Line Curve Superimposed on Assumed Computer-Generated, Noisy Data That Varied Randomly in Both Magnitude and Polarity	16
10b.	The Assumed Noisy Data of Figure 10a With the Computer Approximation Using the Noise Elimination Procedure and a 20-Point Running-Mean Line	16
11.	Basic Program of the Noise Elimination Procedure Used to Plot the Computer Approximation in Figure 8	18-19

## A Computer Decision-Making Process for the Elimination of Noise from Data

### 1. INTRODUCTION

Data analysis is often complicated by the problem of determining true values of measurements from those contaminated by extraneous signals normally referred to as "noise." The most common method of alleviating this problem is to average the raw data over some period of time so that the resulting mean values approximate the true readings. This approach is effective in many cases especially when the noisy signals are symmetrically superimposed upon a data base in both magnitude and polarity. Data averaging may also be effectively employed on random noise if the data are averaged over long time periods. Extraneous random readings do not exhibit a preference in their deviations from a data base and will, over a suitably long time period, tend to cancel one another to give accurate mean values. However, if the extraneous signals are biased in magnitude and/or polarity, averaging may, in turn, produce biased results no matter how many points are included in the averaging interval. Short-term averaging, on the other hand, can be used confidently only in cases where the superfluous readings are symmetrical in nature.

The four plots in Figure 1 illustrate the problems associated with averaging data that have extraneous signals superimposed on base-line data. In each case,

---

(Received for publication 26 March 1987)

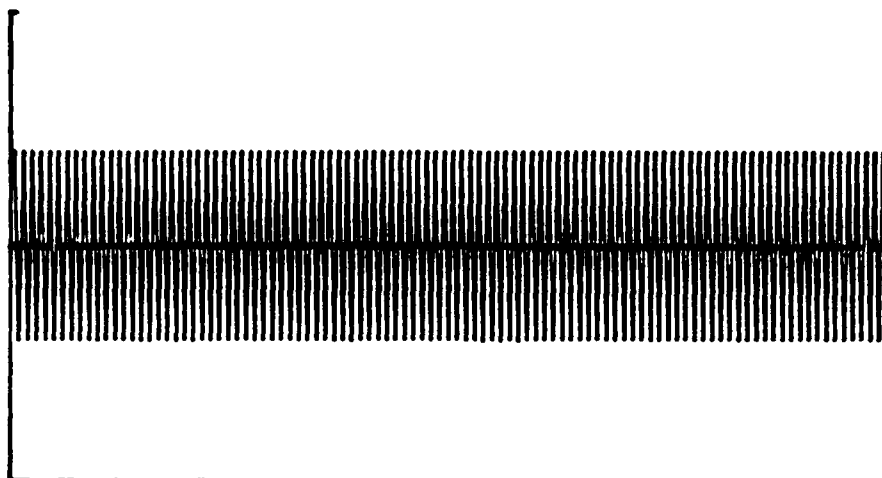


Figure 1a. Extraneous Readings Having Symmetry in Magnitude and Polarity Superimposed Upon Constant Base-Line Data. A 20 point running-mean average is indicated by the straight-solid line and the base data by the dashed line. The averaged line corresponds exactly to the base-line data

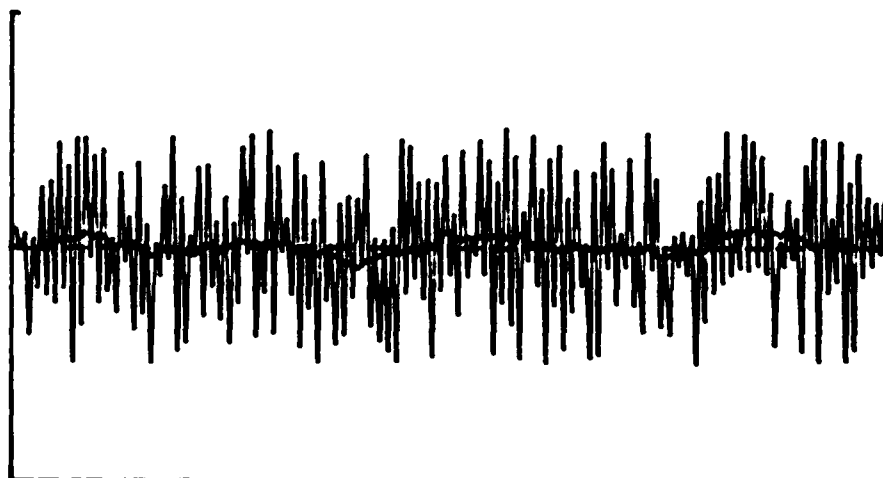


Figure 1b. Extraneous Readings Having Random Magnitude and Symmetrical Polarity Superimposed Upon Constant Base-Line Data. A 20 point running-mean average is indicated by the smoothed line and the base data by the dashed line

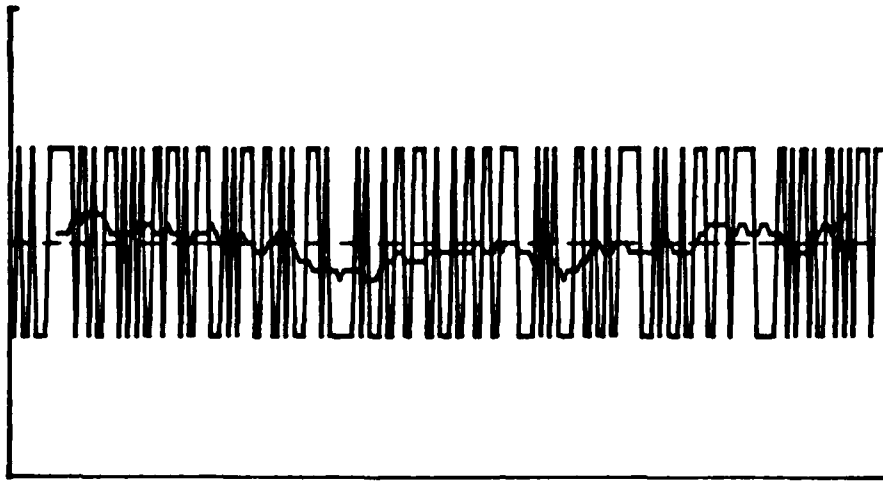


Figure 1c. Extraneous Readings Having Symmetry in Magnitude and Random Polarity Superimposed Upon Constant Base-line Data. A 20 point running-mean average is indicated by the smoothed line and the base data by the dashed line

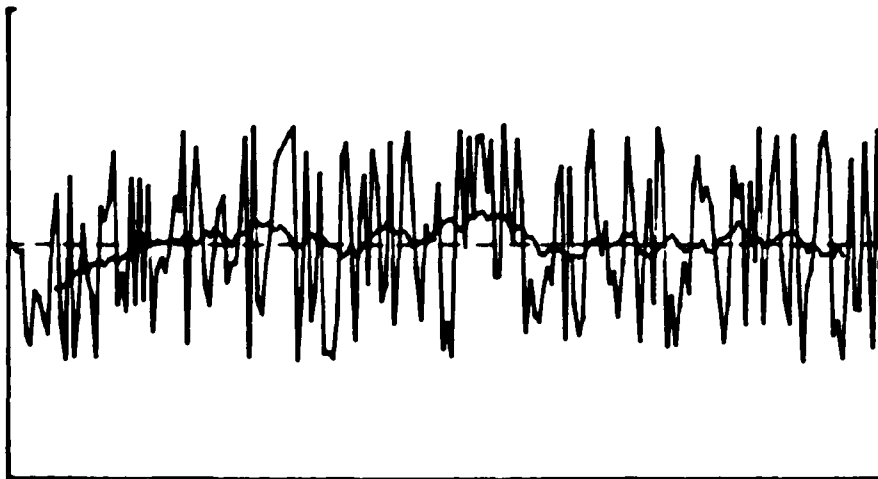


Figure 1d. Extraneous Readings Having Both Random Magnitude and Polarity Superimposed Upon Constant Base-line Data. A 20 point running-mean average is indicated by the smoothed line and the base data by the dashed line

the base data consists of 200 constant readings as indicated by the horizontal dashed lines. Also, in each case, the mean value of the total 200 points (long-term averaging) agrees with the base readings. The smoothed lines are the results of a 20 point, running-mean average (short-term). Plot 1a shows the superfluous readings being symmetrically displaced in both magnitude and polarity from the base line. The short-term, 20 point average corresponds exactly to the base readings. Plot 1b has symmetry in the polarity of the noise (alternately + and - the base data) with the magnitude of the deviation selected randomly. The 20 point averaged line shows small departures from the base-line readings. Plot 1c shows the extraneous signals having a constant deviation from the base data with a random polarity, whereas 1d has both random magnitude and polarity. The short-term averaged lines in both these cases show a larger deviation from the base line than that of 1b and seem to show that the effects of signal polarity can be more important than signal magnitude.

In 1980, the Cloud Physics Branch of the Air Force Geophysics Laboratory designed and constructed an instrument to determine the rate of falling snow.<sup>1, 2</sup> The operation of this prototype device is based on accurate and sensitive weight measurements from an electronic balance that are converted into mass and associated with time in the subsequent calculation of snow rate.<sup>3</sup> The acquisition of naturally-falling snowflakes requires the use of an open collection container (Figure 2) that, in conjunction with the high-resolution weighing device, makes the instrument responsive to the effects of wind action. Because of the ever-changing nature in the periodicity of wind gusts and the variability of wind velocities, the raw-weight data display periodic fluctuations of varying magnitude. Several automatic reduction schemes were tried in the analysis of these data, but none could be found that would produce results within acceptable error limits. The problem was finally resolved with the development of a technique that instructed a computer to conduct an analysis using a format akin to human reasoning. Because the computer makes decisions based on particular characteristics of the data set and adjusts parameters to produce optimum results, the analytical routine may be con-

1. Gibbons, L.C., Matthews, A.J., Berthel, R.O., and Plank, V.G. (1983) Snow Characterization Instruments. AFGI-TR-83-0063, AD A131984.
2. Plank, V.G., Matthews, A.J., and Berthel, R.O. (1983) Instruments used for snow characterization in support of SNOW-ONE-A and SNOW-ONE-B, Proceedings of SPIE Technical Symposium East 83, Session "Optical Engineering for Cold Environments." Sub-session "Optical Hardware in the Cold," Vol. 414, pp. 29-34.
3. Berthel, R.O., and Plank, V.G. (1985) Data reduction techniques used in the determination of precipitation rates from electronic weight measurements, Proceedings of Correction of Precipitation Measurements, Zurich, Switzerland, pp. 31-35.

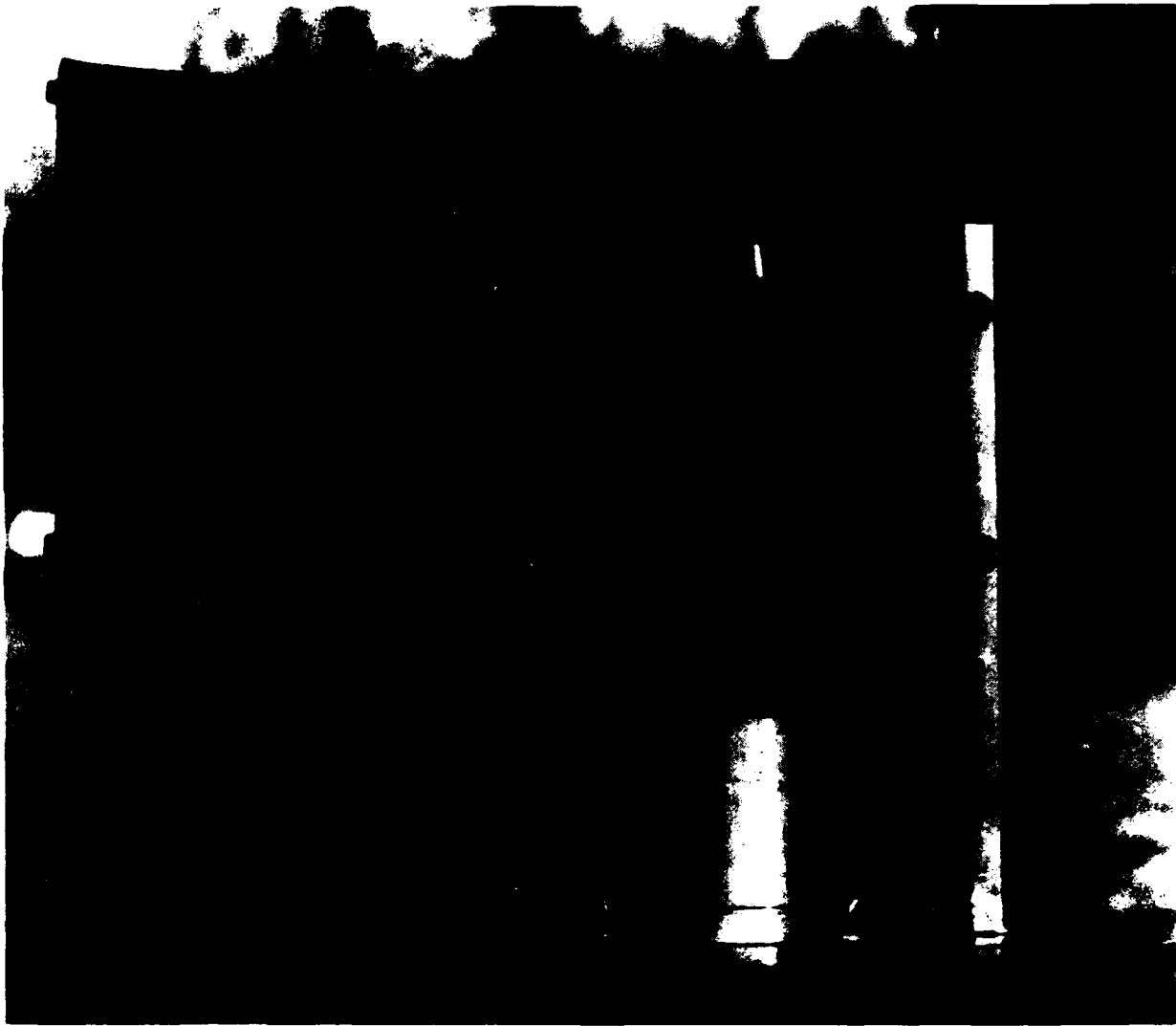


Figure 2. Photograph of Snow Rate Meter. The outer hinged metal wind shield is shown in the open position to expose the inner plastic shield and collection bucket

sidered as a form of artificial intelligence. Therefore, this technique may have beneficial applications in other analytical and reduction procedures.

The following sections define the logic that led to the development of this technique and describe the procedure used in resolving the problem.

## 2. PROBLEM DEFINITION

The data recognition problem referred to in the preceding section became apparent from the analysis of snow weight/rate data. Thus, it is only fitting that this type data be used to define the problem and the subsequent solution.

Figure 3 shows one hour of snow weights as recorded on 10 Dec 1982 during

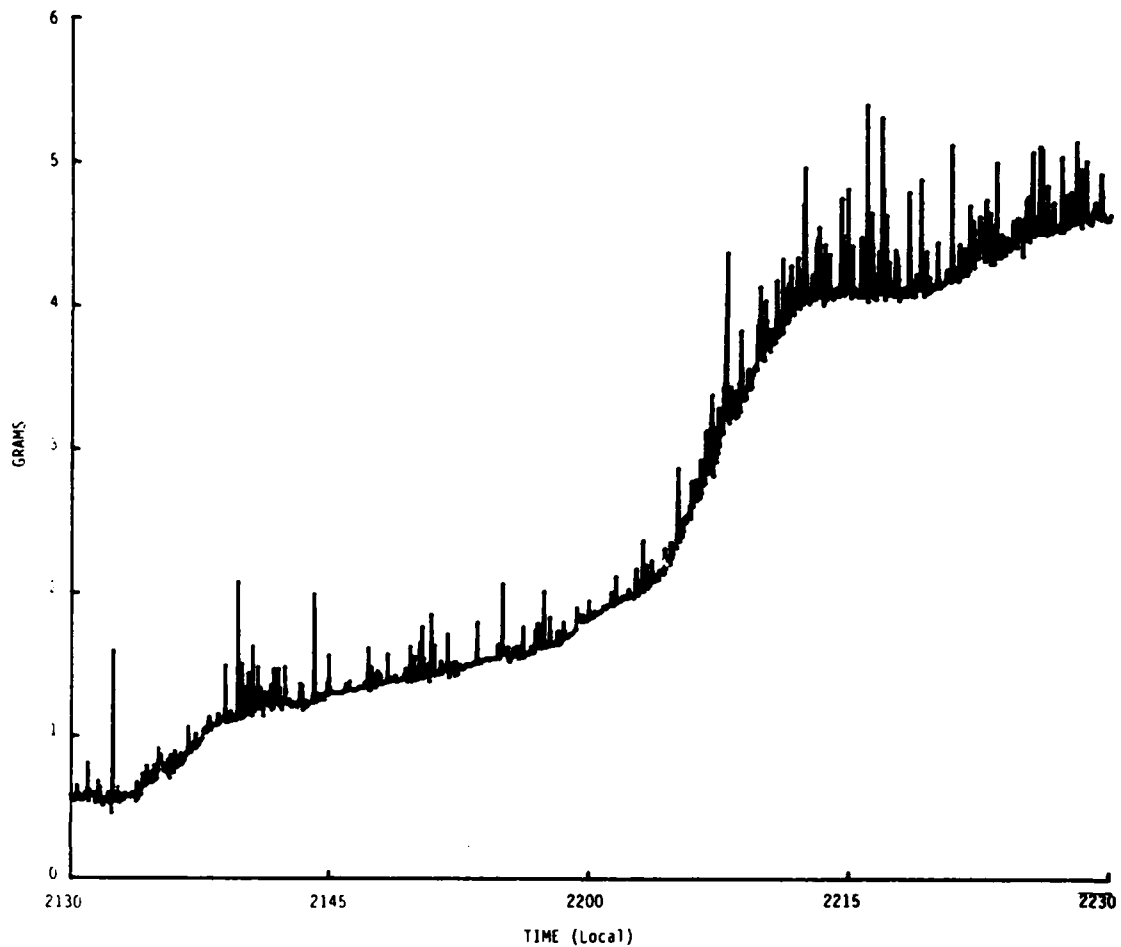


Figure 3. One Hour of Snow Weight Data Taken on 10 Dec 1982 at Camp Grayling, Mich., During the SNOW-ONE-B Field Experiment

the SNOW-ONE-B field experiment at Camp Grayling, Mich.<sup>4</sup> This plot consists of 1200 weight readings, one every 3 sec, as measured by an electronic balance having a 0.01 g sensitivity. The nature of these measurements, where the balance is weighing the accumulation of naturally-falling snowflakes, dictates that the weight readings will remain constant in the absence of snowfall and will increase during periods that snow is falling. The only allowable deviation from these rules, assuming a stable instrument environment and no zero drift, is a decrease in weight because of sublimation or the evaporation of snow from the collection container that is evidenced by gradually declining weight readings over long periods of

4. Bates, R.E., and Bowan, S.L., Eds. (1983) SNOW-ONE-B Data Report, U.S. Army Corps of Engineers, Special Report 83-16.

time. Sudden increases or decreases in weights that subsequently return to the base line (data spikes) are illogical in this type measurement and are classified as being extraneous or data noise. The base curve from the weights of accumulated snowfall in Figure 3 is readily distinguishable as are the major positive and the minor negative spikes that are superimposed on the curve. These extraneous readings are the effects of wind action on the open collection container. The differences in the magnitude of the spikes above and below the data base line are attributed to a shielding mechanism that serves to dampen the negative readings.<sup>5, 6</sup> The problem, obviously, is one of determining the actual data from this combination of weight and noise readings.

### 3. ANALYTICAL LOGIC

The individual raw-data readings are more definable in the 20 min (2200 to 2220) plot in Figure 4. This time segment was chosen as it illustrates slightly increasing weights with little or no noise (initial period), increasing noise and weights (central period) and high noise with little or no increase in weight (latter period). The small fluctuations during the initial quiet period constitute the normal variations of these data. By identifying similar quiet periods between wind gusts and drawing a connecting line through them, a "best guess" weight curve may be determined as indicated by the smoothed, hand-drawn line in Figure 5. This is a perfectly acceptable method of eliminating the superfluous readings caused by the wind effects, but it is labor intensive, time-consuming, and, above all, it is not processed in an automated reproducible manner.

Data smoothing by computer processing is generally accomplished by some form of data averaging. It is apparent from the discussion in Section 1 that the averaging of these highly biased, snow-weight data will not produce adequate results. Figure 6 shows the weight readings from Figure 4 with a superimposed 1-min, running-mean line. The averaged data points agree favorably during the initial 3 min of little or no wind action, but show considerable deviation for the remainder of the time period. Lengthening the averaging period will result in further smoothing as evidenced by the 5-min, running-mean averaged line in Figure 7, but the values will never match the true weights during periods exhibiting strong

5. Berthel, R.O., Plank, V.G., and Main, B.A. (1983) Analyses of snow characterization data acquired at SNOW-ONE-A and B, Snow Symposium III, CRREL, Hanover, N.H.
6. Berthel, R.O., Plank, V.G., and Main, B.A. (1983) AFGL snow characterization measurements at SNOW-ONE-B: Preliminary report, SNOW-ONE-B Data Report, U.S. Army Corps of Engineers, CRREL Special Report 83-16, AFGL-TR-83-0174, AD A130556, pp. 197-208.

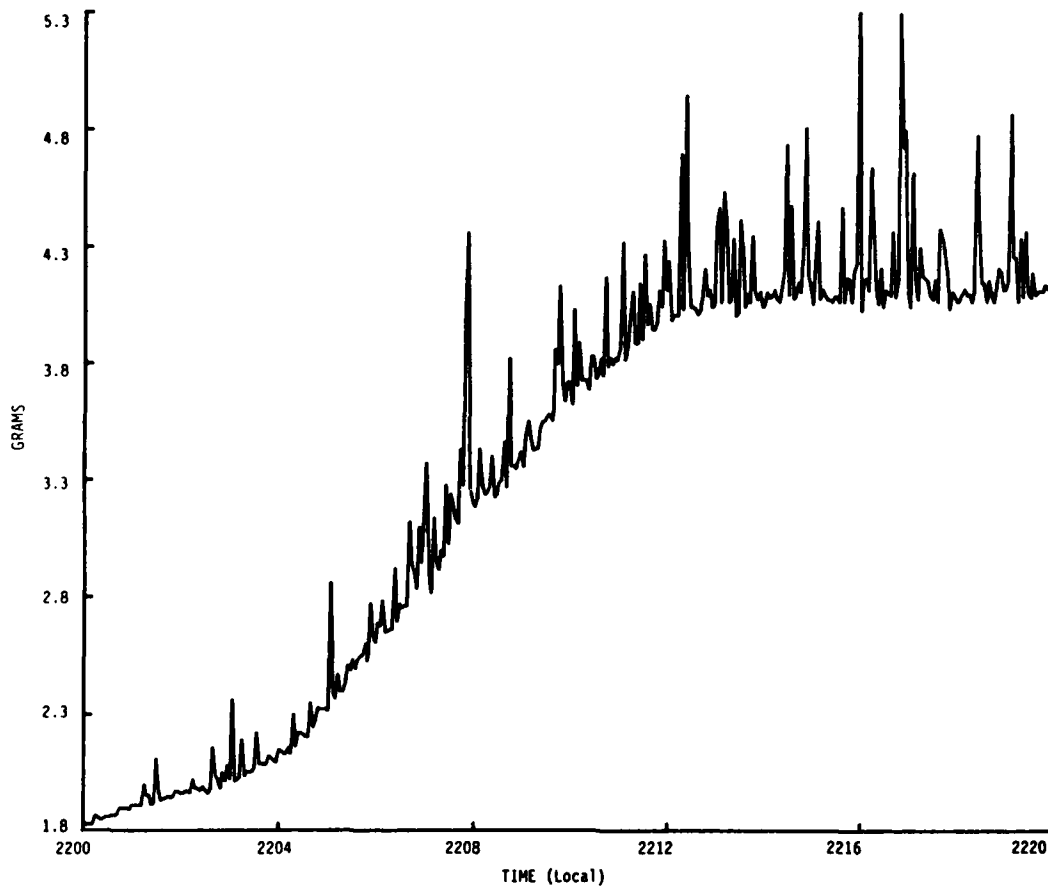


Figure 4. A 20-Min Segment of the Noisy Data From Figure 3

noisy signals. Long averaging periods also tend to blunt or mask small changes in the base data.

The most obvious solution to this problem is to have the computer apply an analytical process similar to the human reasoning used to construct the "best guess" line in Figure 5. To do this, the computer has to be instructed to find the sections of the raw-data curve where wind effects were minimal or not present. A straight-line connection of these quiescent periods should then approximate the hand-drawn line.

#### 4. PROBLEM RESOLUTION

The successful implementation of this technique depends entirely upon the computer determination of quiescent periods (QPs); therefore, two critical elements of a QP must be defined before this type of analysis is conducted. The first element is the minimum time duration or minimum number of data points that con-

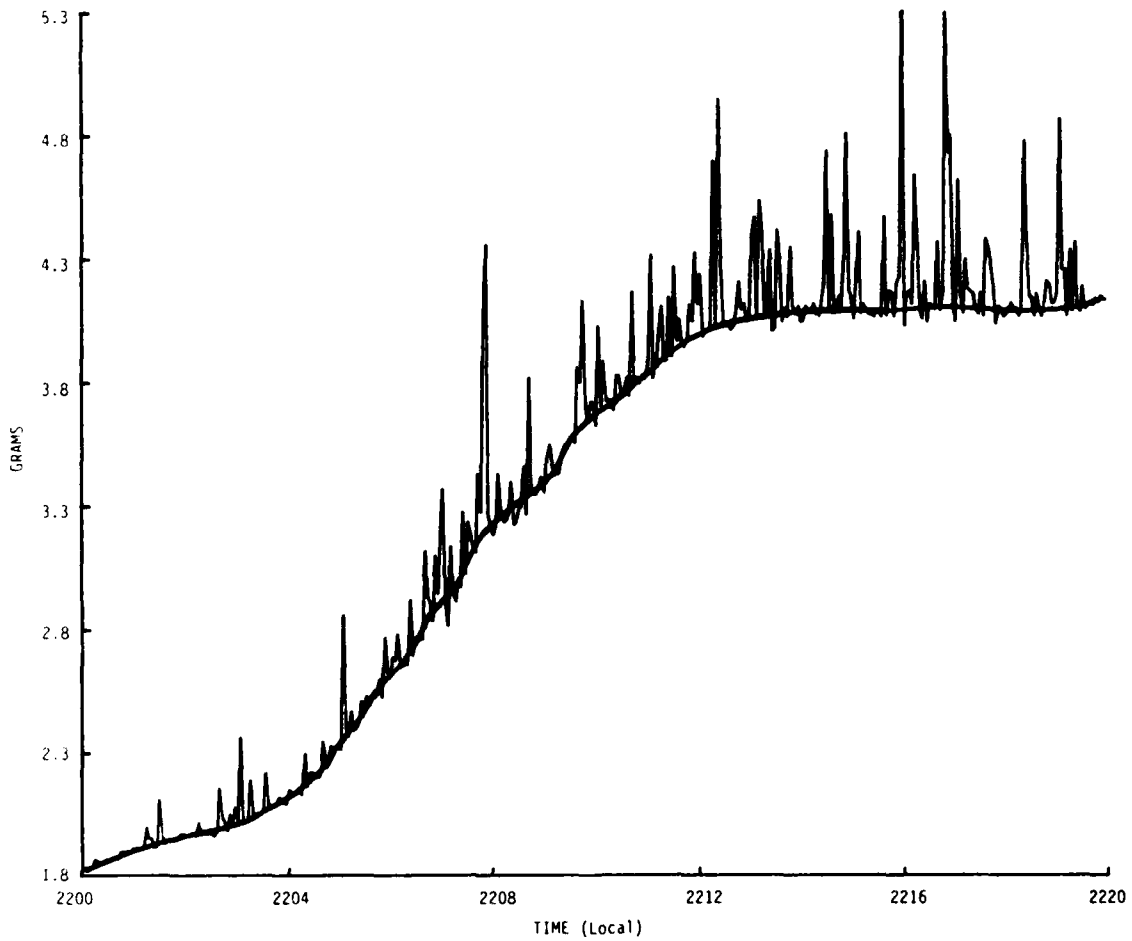


Figure 5. A 20-Min Segment of the Noisy Data From Figure 3 With the Hand-Drawn "Best Guess" Estimates of the Actual Snow Weights

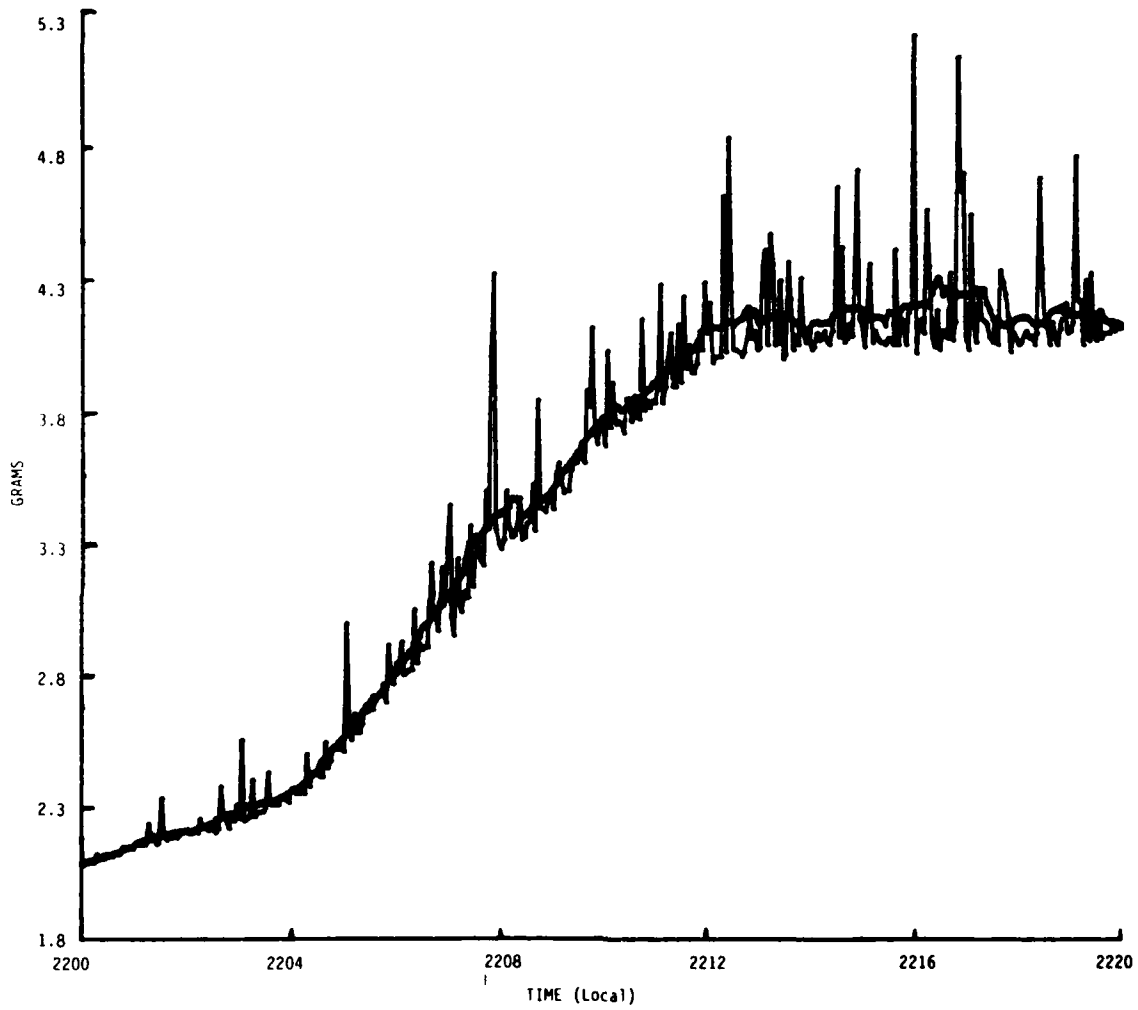
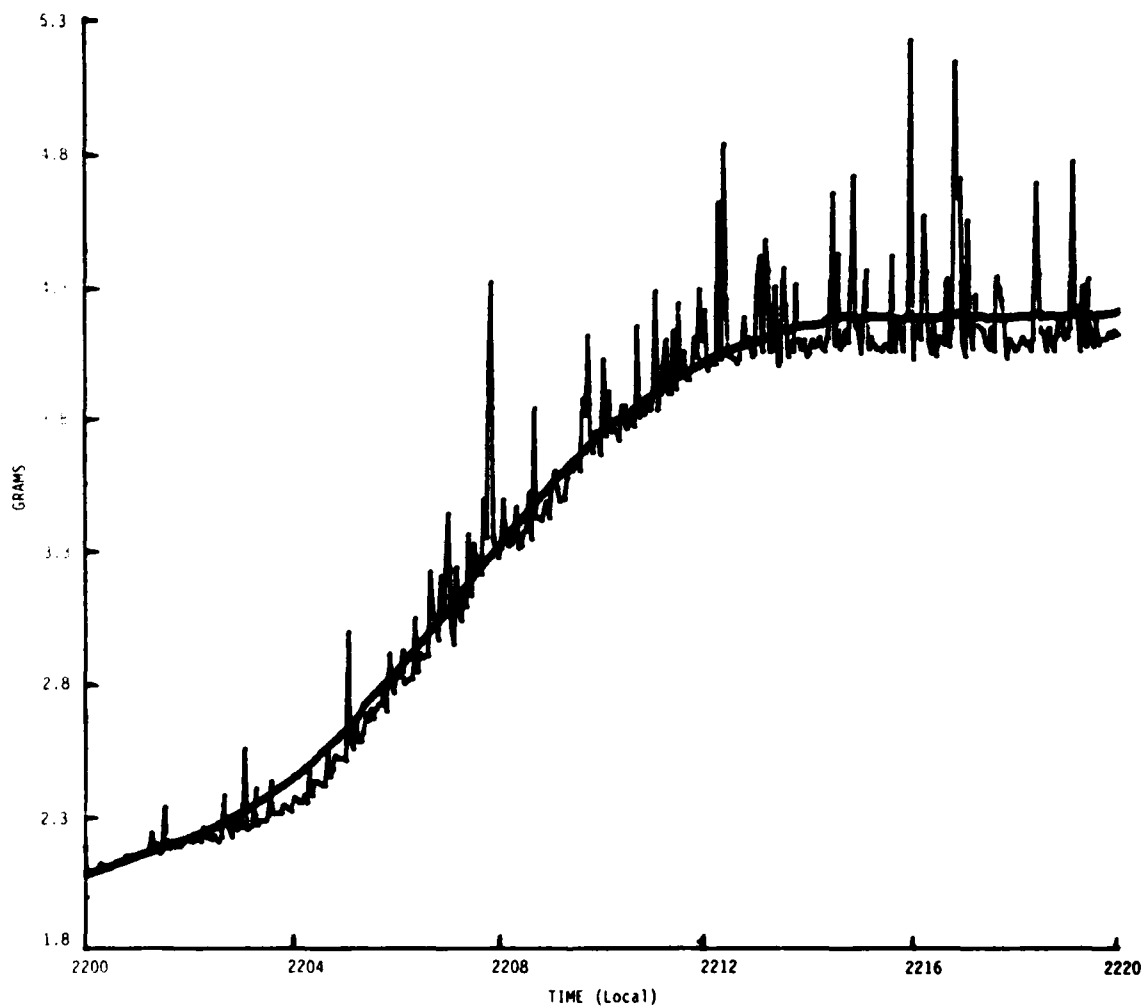


Figure 6. A 20-Min Segment of the Noisy Data From Figure 3 With a 1 -Min Running-Mean Average



**Figure 7. A 20-Min Segment of the Noisy Data From Figure 3 With a 5-Min Running-Mean Average**

stitute a QP, and the second is the magnitude of the natural variation that could be experienced in a situation without noise. Both are characteristics of the raw data. Thus, different types of measurements will require different definitions.

A close scrutiny of the raw snow-weight data shows that the extraneous values (wind effects) normally exhibit substantial changes in magnitude and polarity in adjacent weight readings. Two noisy readings with only small differences between them may occur infrequently, but three adjacent noisy points with approximately the same weight have not been found. Three adjacent weight values showing little or no change indicate that no extraneous readings are present. The minimum duration of a QP was therefore defined as three points over a 9-sec time period.

The electronic balance used in these measurements had a resolution of 0.01 g. During a 3-point period of no snow and little or no wind, three adjacent readings would have three identical weights or two of the same with the third showing +/- 0.01 g. Therefore, the natural variation of the data allows weight differences of at least +/-0.01 g within a QP. This magnitude difference is referred to as a weight limit.

Establishing these criteria enables the computer to begin analyzing the data. The first programmed instruction is to step through the raw data and search for a QP. This is done by averaging the weight ( $W$ ) at a particular data point number ( $N$ ) with the preceding weight at  $N - 1$  and the following at  $N + 1$  as

$$\bar{W} = \frac{W_{N-1} + W_N + W_{N+1}}{3} \text{ g.} \quad (1)$$

The mean weight ( $\bar{W}$ ) is then compared to each of the three constituent weights. If any of the three is found to be more than the designated weight limit from the value of  $\bar{W}$ , the point is rejected and the computer steps ahead by one point in the raw data and repeats the process. When all three readings are within the weight limit from  $\bar{W}$ , a QP has been found.

At this time, the computer must determine whether this period is, in fact, the next valid sequential quiet region or if there should be one or more QPs defined by a larger weight limit between the QP just defined and the last previously found QP. This judgment is necessary so that the weight limit may be adjusted to account for increases (or decreases) in the base-line data. For example, if the base data are changing in increments of 0.01 g between points, a magnitude limit of 0.01 g will detect a QP. However, if the incremental change were 0.05 g, then a 0.05 g limit would be required.

The judgment procedure will also serve to adjust the weight limit to account for changes that may occur in the natural variation.

The weight difference between a particular QP and the preceding one determines if a limit adjustment is required. If this differential weight is larger than the magnitude limit, there is a strong possibility that the base data, at some period or periods in the intervening region, is increasing in steps larger than the designated limit. If the weight differential is within the magnitude limit, that possibility does not exist.

Therefore, when a quiet period has been found using a particular weight limit, the computer determines the weight difference between that period and the preceding one. If the difference is within the designated limit range, the period is considered valid. If not, the limit is increased by 0.01 g and the search for a QP is begun anew. This iteration is repeated until the weight difference between quiet regions is within the magnitude limit used to define the second QP.

Upon determining the weight of a valid quiet period ( $W_Q$ ) at some data point number ( $N_Q$ ), the computer is then instructed to construct a straight-line approximation from the preceding quiet period  $W_{Q-1}$  at point number  $N_{Q-1}$ . This operation assigns an interpolated value to each discarded reading between the adjacent QPs and essentially reconstructs the data curve minus the noisy points.

The first step in this process is the determination of the incremental weight difference ( $\Delta W$ ) that is to be applied between data points by

$$\Delta W = \frac{W_Q - W_{Q-1}}{N_Q - N_{Q-1}} \text{ g.} \quad (2)$$

The individual intervening points are then assigned a weight ( $W_N$ ) as

$$W_N = \frac{N_Q}{N_Q - 1} W_{Q-1} + \Delta W (N - N_{Q-1}) \text{ g.} \quad (3)$$

(In this description, the weight readings are associated with data point numbers since the 3-sec time increments between readings may possibly cause confusion if the weights were based on a time reference.)

When the raw data from the 2200 to 2220 time period were subjected to the above analysis, a computer-generated approximation of the true data curve was constructed as shown by the superimposed line in Figure 8. The difference in this line and the "best guess" line of Figure 5 are minor and few. One can only speculate as to which approximation is more exact. The hand-drawn line tends to be smoother as some slight dips and rises can be detected in the computer version.

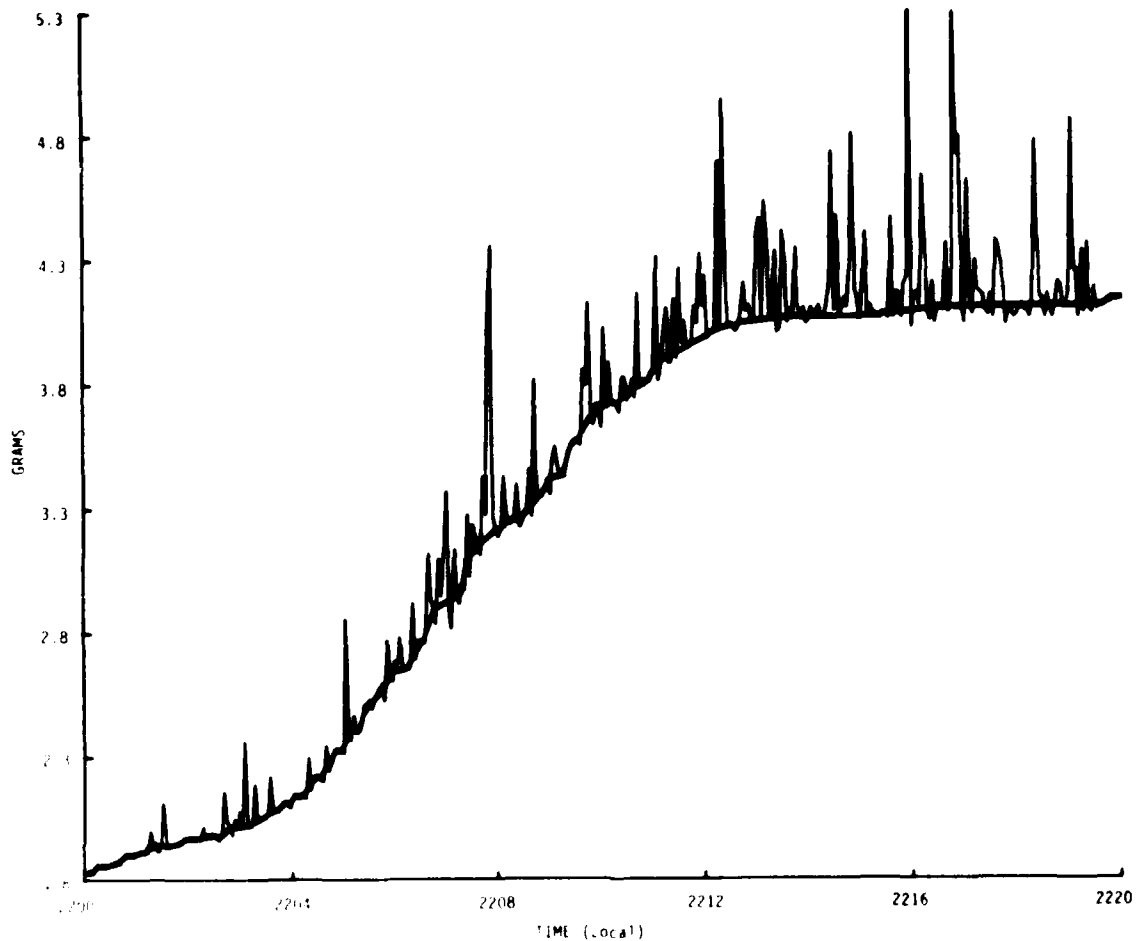


Figure 8. A 20-Min Segment of the Noisy Data From Figure 3 With the Computer-Generated Estimates of the Actual Snow Weights

## 5. CONCLUSIONS

The computer decision-making process discussed herein and described in the flow diagram of Figure 9 was purposely designed to eliminate wind-induced extraneous readings from weight measurements used in the determination of snow rate. It must be emphasized that the application of this procedure to other type measurements imposes two requirements on the raw data. First, the data must be recorded or stored since iteration may be necessary, and, second, the data must periodically approximate the base-line readings or, in other words, must have quiet or minimal noisy periods.

In addition, it may be advantageous to designate a particular point limit in the search for QPs. In most cases, the QP validity check, where the differences in QP values are required to conform to the magnitude limit, will act to restrict the

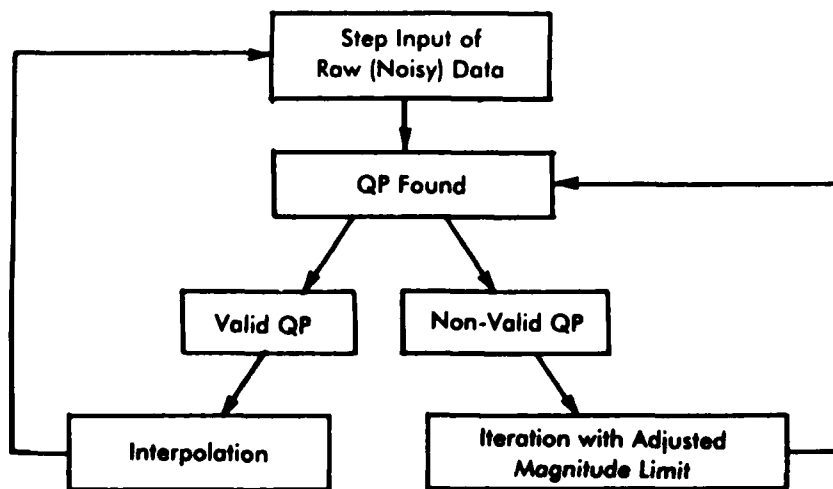


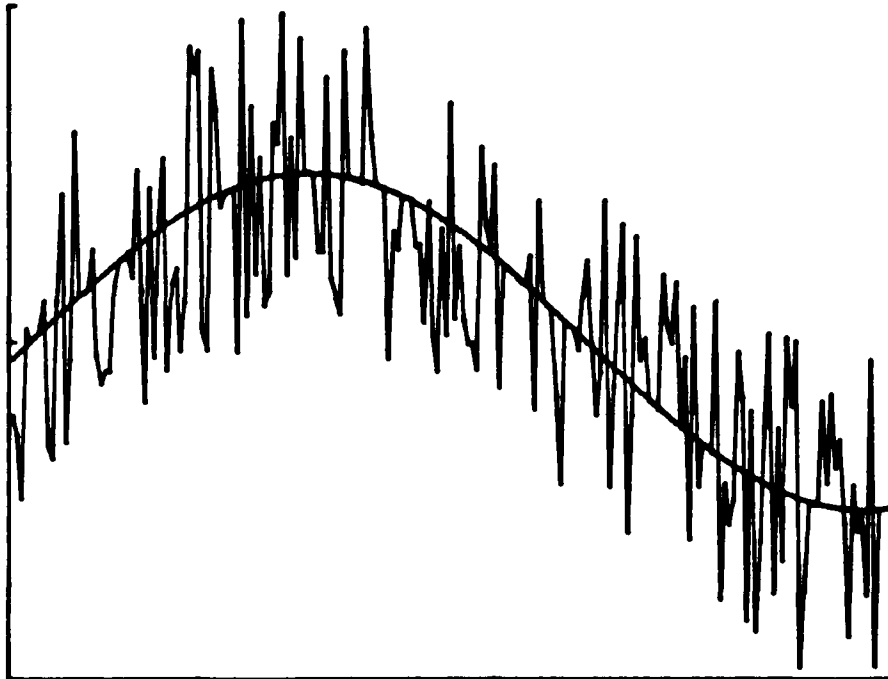
Figure 9. Flow Diagram Describing the Logic of the Computer Decision-Making Process. Definitions of terms are found in Section 4

number of points in the search for a QP because of changing base-line data. However, in certain situations of heavy noise and a slowly changing base line, a data set may conceivably be described by one straight-line extrapolation over a large number of points. This circumstance is alleviated by designating a maximum time duration or maximum number of points in the search for a QP. This designation is referred to as a "search limit."

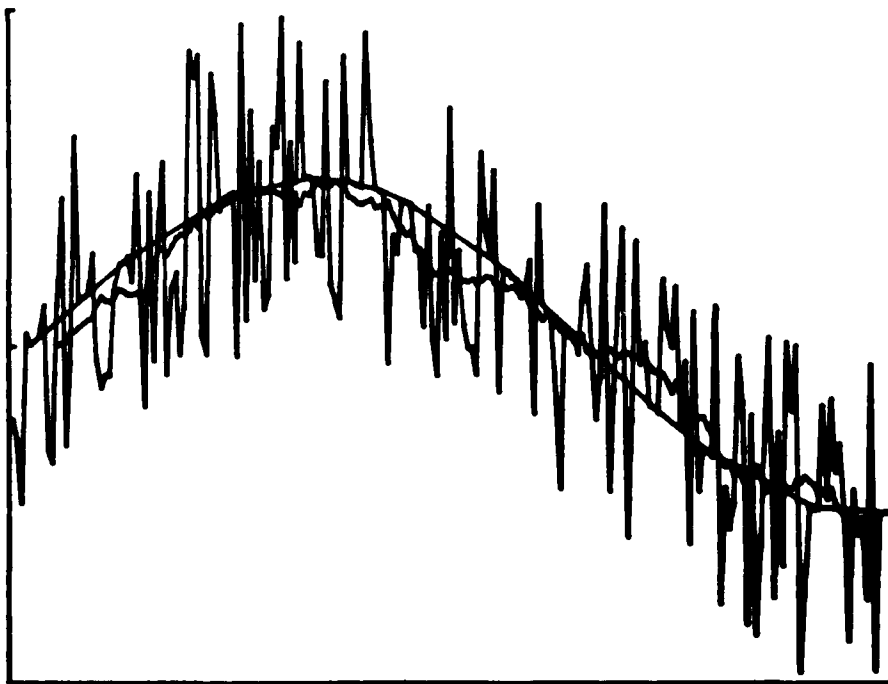
Upon reaching the number of points in the search limit, it is assumed that any and all intervening quiet periods have larger deviations than that of the current magnitude limit. This limit is then increased and the search restarted.

Snow weight data generally show quiet regions occurring periodically in  $\sim 1$  to  $\sim 4$  min intervals. A 5-min or 100-point search limit was included in the snow rate analysis program and in the noise elimination process used to produce the computer generated approximation in Figure 8. However, the limit was not required in this 20-min segment as the maximum search period encompassed 85 points (4.25 min).

The noise elimination process has not been applied to measurements other than snow weights, although it has proved successful in tests using computer-generated assumed data. For example, Figure 10a shows 200 points of base-line data in the form of a partial sine wave with superimposed assumed noisy "raw data." The extraneous readings are random in both magnitude and polarity. Also, the QPs were randomly dispersed at intervals of  $< 30$  points, thus imposing a 30-point search limit. The computer approximation of the base data is shown in Figure 10b along with a 20-point running-mean average of the assumed raw data.



**Figure 10a.** A Base-Line Curve Superimposed on Assumed Computer-Generated, Noisy Data That Varied Randomly in Both Magnitude and Polarity



**Figure 10b.** The Assumed Noisy Data of Figure 10a With the Computer Approximation Using the Noise Elimination Procedure and a 20-Point Running-Mean Line

The procedure described in this report is straightforward in logic and application. Because of this, it may prove useful in the analysis of other types of measurements. The entire process requires a relatively simple, short computer routine as demonstrated by the 27-line basic program in Figure 11. This program was used to determine the values of the computer-generated approximation shown plotted in Figure 8.

D(n) = Data (raw) array  
 X(n) = Point number array for plotting  
 Y(n) = Weight array for plotting  
 A = Average of 3 points  
 L = Magnitude limit  
 N = Number of plotting points  
 P = Point number at start of QP search  
 W = Weight at preceding QP  
 W1 = Delta weight between adjacent QPs

```

100  N=1
110  P=1
120  L=.01
      (Iteration)
130  For I=P+1 to 399
140  A=(D(I-1)+D(I)+D(I-1))/3          (Eq. 1)
150  For J=I-1 to I+1
160  If A-D(J)>L then 350              (check search limit)
170  If D(J)-A>L then 350              (check search limit)
180  Next J
      (QP found)
190  If N>I then 230                    (validity check)
      (initial plotting point)
200  X(N)=I
210  Y(N)=A
220  Goto 320                            (continue sampling)
      (Validity check)
230  If A-W>L then 260                  (valid QP)
      (Increasing magnitude limit)
240  L=L+.01
250  Goto 130                            (iteration)
      (Valid QP)
260  W1=(A-W)/(I-P)                    (Eq. 2)
      (Interpolation)
270  For J=P+1 to I
280  N=N+1
  
```

Figure 11. Basic Program of the Noise Elimination Procedure Used to Plot the Computer Approximation in Figure 8

```

290   N(N)=J
300   Y(N)=W-W1*(J-(P-1))   (Eq. 3)
310   Next J
      (Continue sampling)
320   P=1
330   W=A
340   L=.01
      (Search limit)
350   If 1-P > 100 then 240   (increase magnitude limit)
360   Next I

```

Figure 11 (cont.). Basic Program of the Noise Elimination Procedure Used to Plot the Computer Approximation in Figure 8

## References

1. Gibbons, L. C., Matthews, A. J., Berthel, R. O., and Plank, V. G. (1983) Snow Characterization Instruments. AFGL-TR-83-0063, AD A131984.
2. Plank, V. G., Matthews, A. J., and Berthel, R. O. (1983) Instruments used for snow characterization in support of SNOW-ONE-A and SNOW-ONE-B, Proceedings of SPIE Technical Symposium East 83, Session "Optical Engineering for Cold Environments," Sub-session "Optical Hardware in the Cold," Vol. 414, pp. 29-34.
3. Berthel, R. O., and Plank, V. G. (1985) Data reduction techniques used in the determination of precipitation rates from electronic weight measurements, Proceedings of Correction of Precipitation Measurements, Zurich, Switzerland, pp. 31-35.
4. Bates, R. E., and Bowan, S. L., Eds. (1983) SNOW-ONE-B Data Report, U. S. Army Corps of Engineers, Special Report 83-16.
5. Berthel, R. O., Plank, V. G., and Main, B. A. (1983) Analyses of snow characterization data acquired at SNOW-ONE-A and B, Snow Symposium III, CRREL, Hanover, N. H.
6. Berthel, R. O., Plank, V. G., and Main, B. A. (1983) AFGL snow characterization measurements at SNOW-ONE-B: Preliminary report, SNOW-ONE-B Data Report, U. S. Army Corps of Engineers, CRREL Special Report 83-16, AFGL-TR-83-0174, AD A130556, pp. 197-208.

END

12-87

DTIC