Bionic Self-Adaptive Data Compression

BARRY K. POWELL*
The Bendix Corporation, Southfield, Mich.

The increased complexity in spacecraft systems and experiment packages has resulted in large quantities of data to be processed and transmitted to ground stations, often in remote locations. The automatic removal of redundant information before transmission would allow more efficient use of the communication link, as well as yield a reduction in the net amount of information to be processed on the ground. This paper describes a proposed self-adaptive approach to data compression, and a method of extending the approach to a multichannel data compression system.

Problem Statement and Scope

THE increased sophistication of spacecraft computing and communication systems has resulted in a great deal of scientific data that must be processed or analyzed and generally transmitted to remote locations. The recent growth in data volume has increased interest in the development of methods for automatic data reduction. The removal of redundant information by analyzing data before transmission would be an effective method of data compression.[1] Such a reduction scheme would result in a lower average transmission rate which, in turn, would reduce weight and power requirements, conserve the radio frequency spectrum, improve efficiency of data processing on the ground, and minimize the data requiring human evaluation.

One approach to the data reduction problem is to perform a careful data analysis to ascertain the information content of each signal source of a multichannel or multidata system. Although this approach would likely result in effective data reduction, it would require a special information analyzer for each input sensor. An alternative method of data reduction is to pass the signal through a compression system with a fixed compression algorithm. The basic disadvantage of such a system is that the nonstationary nature of the signal sources would make it quite difficult to develop an algorithm capable of continually optimizing the tradeoff between data compression and data accuracy. This implies the need for a self-adaptive data reduction algorithm.

This paper describes a self-adaptive approach to the basic problem of removing redundant data caused primarily by oversampling. Such a process permits less data to convey the same message, yielding a corresponding increase in the average information per unit of data and per unit of power and bandwidth.

The self-adaptive concept presented is based on the use of probability state variable (PSV), or bionic devices as optimal control elements. These elements are learning control mechanisms which contain a probability structure that is adjusted to reflect the probability of a specific control law successfully regulating the system in the given control situation. This paper contains the details of a proposed self-adaptive data reduction approach, and a method of extending the proposed approach to a multichannel data compression system.

Redundancy Reduction

Generally, if a signal source is sampled at a rate much higher than the Nyquist rate, the signal from the source will be slightly obscured by quantization, reconstruction, and instrumentation errors. If the input is under-sampled, excessive errors due to aliasing (frequency overlap) will result. Thus, there is an optimal sampling rate at which the signal error is minimized. The effective variation in sampling rate may be achieved by removing redundant samples from an oversampled source.

Redundancy reduction by a prediction or interpolation algorithm[2,3] is an adaptive process for eliminating data samples. Eliminated samples can be implied by examination of preceding or succeeding samples, or by comparison with an arbitrary reference pattern with predetermined error constraint.[4] Polynomials and sine waves are useful functions for this purpose since real data can often be accurately approximated by such functions.

A redundancy reduction system using prediction or interpolation can be implemented by locating an information processing system between the channel sample/encode units and the transmitter, as shown in Fig. 1. The redundancy reduction approach offers the possibility of time-sharing a central information processing unit. In this type of system, the key design problem is the selection of an error criterion that determines which samples are redundant. An adjustable criterion is necessary in order to yield good compression and fidelity, as a fixed algorithm cannot adapt to the stochastic nature of the signal source, system errors, and buffer condition.[5]

Since the output rate of the data compressor is not constant, a buffer is required to make the compression system compatible with a pulse code modulator (PCM) telemetry system. A data compression approach based on buffer control has been implemented[6] by use of an adaptive compression error criterion to control the queue length of the buffer. Although moderate success was realized with this technique, an adaptive aperture based on buffer queue length or rate of change of queue alone can sometimes result in unnecessary degradation of pertinent data.[7]

A compromise must be made between compression ratio and data fidelity. It is desirable to simultaneously maximize compression ratio and fidelity, and to regulate the buffer condition. Such a system could learn the optimal relationship

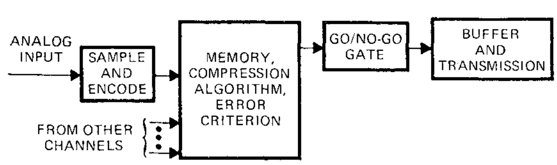


Fig. 1 Redundancy-reduction system.

Received February 11, 1971; presented as Paper 71–232 at the AIAA Integrated Information Systems Conference, Palo Alto, Calif., February 17–19, 1971; revision received September 15, 1971. The author acknowledges R. M. Centner and S. I. Lieberman for their technical advice, and the technical editing by W. C. Meahan.
Index categories: Spacecraft Communications Systems; Data Sensing and Presentation or Transmission Systems.

* Senior Staff Mathematician, Systems Synthesis Department, Bendix Research Lab.

between the signal, source system error, and buffer condition in a particular time interval. A bionic self-adaptive[8] compression system intended to satisfy these requirements is described below. The system contains bionic learning devices that regulate the system behavior. Since the control elements are learning devices, a performance measure is provided to regulate the learning trends according to desired behavior.

Optimum System Behavior

In order to synthesize the self-adaptive system, the optimal behavior, in the form of a performance index, must be determined. Optimal behavior may be understood, to some extent, by examining a complex relationship between compression ratio (CR) and reconstruction error or root mean square (rms) error. Compression ratio is defined as the ratio of the number of samples of a highly oversampled source to the number of remaining samples after periodic deletion of samples by a data compression system.

The quantization of a highly oversampled analog signal and and the subsequent use of a redundancy reduction algorithm lead to a general relationship between quantization and compression errors in the presence of instrumentation noise. The compression system behaves as a digital filter and the compression ratio can be maximized for a particular rms error. The relationship is represented in Fig. 2 (Ref. 1), for a first-order interpolation with an error tolerance E_i.

Examination of Fig. 2 reveals that the functional relationship between CR and error depends on the error tolerance of the reduction algorithm. The envelope encompassing the curve set in the CR-error plane is defined as the optimum filter path. It is optimal in the sense that given an rms error, an error tolerance exists that maximizes the compression ratio. It is a filter path because the variable error tolerance serves as a digital filter to the quantized analog samples. The minimum error tolerance is determined by the quantization level. The no-filter condition shown in the CR-error plane is the general behavior one might expect for a system that uses an adaptive sampling compression concept.

The function representing any particular curve also depends upon the type of data activity present at any particular time. The signal source may change at any time. Therefore, the CR-error curves may change or they may not be exactly as shown. However, the functional relationship in the CR-error plane illustrate the complexity of the problem and aid in the selection of variables to be controlled.

It is desirable at all times to have a compression ratio and over-all rms error represented by a point on the optimum path. To achieve the optimal state, it is necessary to determine the present state of the system and decide when it is optimal. The device used to accomplish this is described as the performance index or performance measure.

The performance index should reflect bandwidth compression in the form of a compression ratio, perhaps determined over a relatively short time interval, and data fidelity after compression in the form of rms error or other error function. A short term compression ratio is likely to be a variable function of time. The compression ratio is distinct from the buffer readout rate, which is a constant.

The measure of over-all system error can assume many forms, depending on the fidelity acceptance level of the type of information being transmitted. In any case, it is desirable to use a fidelity metric that reflects the error introduced by high-frequency measurement noise, sampling and encoding equipment, the compression algorithm, and reconstruction. Until better methods are developed for measuring data fidelity, peak and rms errors will likely have to suffice.

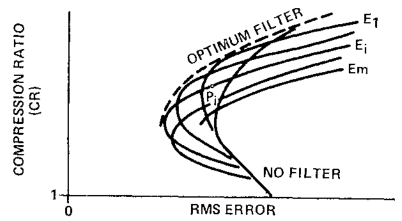


Fig. 2 Compression vs rms error for various error tolerances.

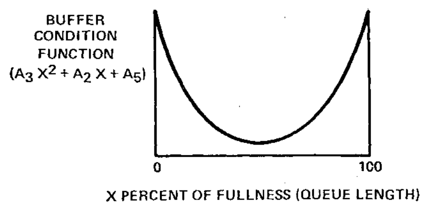


Fig. 3 General representation of the buffer condition.

Since it may be desirable to avoid onboard data reconstruction in order to determine the rms error, an estimate may be used from the actual data samples. For example, when a first-order fan interpolation algorithm is employed, an error estimate may be synthesized by continuously comparing the instantaneous sample value X_i with the value on the line representing all samples L_i over N samples as

$$f(\varepsilon) = \sum^{N} (L_i - X_i)^2/N$$

The point L_i is actually halfway between two bounds of the fan in this algorithm, since some line in this region will ultimately be used. Even though the bounds will approach each other in time, there still will likely be an error from the line to each sample because of the error tolerance variable.

In addition, a system that monitors the data activity will provide a fast decay of peak buffer queue[1,7] and will not allow the buffer to become filled with the unnecessary data resulting from low activity periods. It is also necessary to prevent buffer underflow. This is important from the stand-point that it is not efficient to store low-information-content signals just to prevent buffer underflow. When the condition of underflow is detected, the reduction system could be bypassed in order to transmit confidence samples.

The condition of the buffer could be represented by a quadratic function of a variable representing the percent of buffer that is filled. This is illustrated in Fig. 3 where the weighting parameters in the quadratic yield the curve shown.

Thus, the performance index equation would contain a measure of the short term compression ratio, rms error (or other error function), and the buffer condition. The outputs of the performance index system would be reward and/or punish pulses or other incremental adjustment signals supplied to the self-adaptive compression control elements.

One form of a proposed index of performance computed over a specific subinterval ΔT might be

$$PI = a_1(1/CR_f) + a_2 f(\varepsilon) + a_3 X^2 + a_4 X + a_5$$

All of the parameters a, are provided to allow flexibility in determining the proper PI weighing.

Choice of Control Variables

Since it is desirable to have the system behavior characterized by the optimal filter path, it is necessary to determine the system parameters or variables to be used for control. The choice is aided by examination of typical system behavior. The functional relation between the error tolerance and the resulting compression ratio is not available in closed mathematical form. That is, the behavior of the over-all system error for a particular error tolerance is not an explicit function. Consequently, the assignment of a fixed error tolerance could result in any value of CR or over-all error.

Let a particular control sequence in a data compression system begin with a choice of error tolerance E_i; as a result of this choice, there is a particular CR and rms error for the system represented by point P_i on the E_i curve as illustrated in Fig. 2. The compression ratio is a function of information content and E_i. If the system does not incorporate some method of regulating CR, the resulting value of CR will not necessarily be that which minimizes error. In fact, the system could have a very large rms error. However, the input information content cannot be directly controlled.

The next event in the control sequence might be to change the error tolerance E_i in an effort to minimize rms error. Unless there is a great deal of known information concerning the behavior of the signal source, ascertaining a preferred direction of change of the error tolerance is difficult. Either a decrease or an increase in error tolerance could cause the behavior of the system to be worse than presently exhibited. The ability to force the system to any particular state in the CR-error plane by variations in error tolerance alone could prove to be very unsatisfactory. This implies the need of another control variable.

The additional control variable must allow the freedom necessary to seek any point in the CR-rms error plane. The information presented in Fig. 2 is obtained by the periodic deletion of data samples, which implies that a new control variable is obtained by the insertion of a gate logic element which regulates the buffer input. The buffer input is now analogous to a compression ratio, denoted as CR', that would be obtained from adaptive sampling.

The periodic deletion of data samples may be accomplished by first dividing a specified sampling interval by the number of desired samples yielding the desired time between samples. Since adaptive sampling is not employed, this is the minimum time between samples at a logic gate input to the compression system. The error measure in this instance is the simple expression

$$f^*(\varepsilon) = \sum^{N} (K_i - X_i)^2/N$$

where the K_i are on a straight line between successive samples and X_i are the intermediate deleted values. The total error used in data reduction may be the weighted sum of the two error estimates.

This method differs from adaptive sampling in that sampling logic is regulated by an optimal control law from a bionic element and not by simple feedback from an error measuring device. However, the method is similar to adaptive sampling in that the optimal law is the one that yields the minimum rms error for a given error tolerance.

For a given error tolerance E_i, control over the buffer input alone would force the system to assume the state shown by the point P_i in Fig. 2. At this point, it is possible that another error tolerance E_k exists that would yield a lower rms error with appropriate adjustment of the compression ratio CR'. Therefore, control of both of the variables CR' and E is used to optimize the system behavior.

Control Law Mechanization

Given the two control variables CR' and E, it is desirable to determine the relationship between them such that the state of the system is always described by the optimal filter path shown in in Fig. 2. The self-adaptive system that accomplishes this end is shown in more detail in Fig. 4. The basic approach is to have a control system that learns the best control choice for each control situation. The control situation is determined from whatever variable measurements are necessary to obtain a good approximation of the system state. Control law readjustment or learning is accomplished by reinforcement of the probability of choosing a particular control for a given control situation.

The function of bionic element A is to control the error tolerance E_i and hence the buffer input CR. The function of bionic element B is to control the regulatable compression ratio CR' by dictating the average number of samples per second or the number per given time interval ΔT. The partitioning of the control measurements and the behavior of each of the bionic elements is the subject presented forthwith.

With use of the two bionic elements, the state of the system can be described at any time by the variables CR, CR', E, and rms error. The variable CR' defines the control situation or measurement space for bionic element A. Similarly, the measurement space of element B is specified by E_i. It may be desirable to quantize or partition each measurement space into regions representing control situations. This would obviate the necessity for the large storage required to accommodate all possible situations. The quantization process yields regions in the state space that will have similar characteristics and will thus require similar control choices. The partitioning of each measurement space into various control situations could also be performed by a learning controller.[4] This approach would result in additional memory savings as no quantization would occur in regions where measurements cannot occur.

After quantization of the measurement space, the variables are submitted to each of the bionic elements. Bionic element B receives the variables E_i. Element A receives CR (and possibly the rms error). The learning is accomplished by establishing a stimulus-response relationship between the control situation space and control law space. That is, if a controlled law is used in a given interval and the performance index indi-

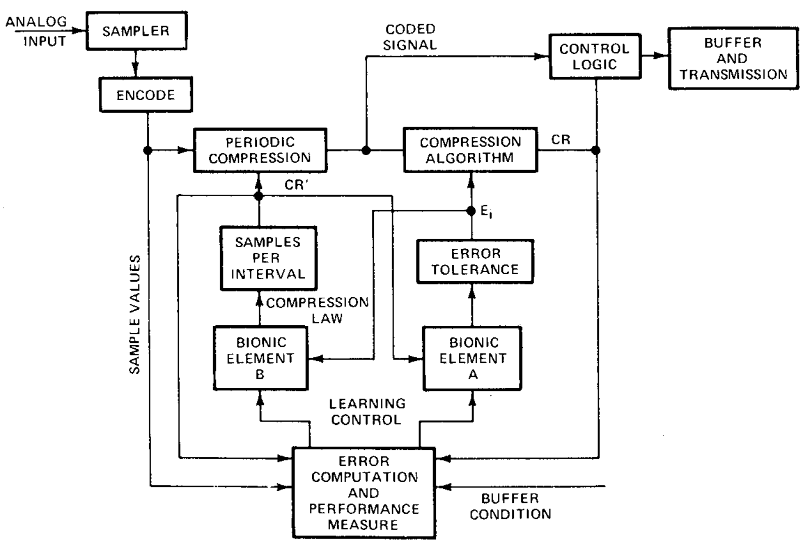


Fig. 4 Self-adaptive compression control.

cates unsatisfactory control, the learning device must be told to choose another law. The best control law choice is considered the same for all members in one control situation region. Since the bionic elements A and B are similar in nature, a general description of the behavior of either one will suffice. For this purpose, a discussion of element B follows.

The Bionic Element

For the development of a control law which regulates the compression ratio CR', the control situation is represented by the error tolerance E (and possibly its corresponding compression ratio CR). For this description, assume that the variables E (and CR) have been quantized in such a manner that any particular control situation represented by an error tolerance E corresponds to the variable S_j, where j is equivalent to an ordered pair (n, m). The purpose of bionic element B is to regulate the compression ratio by operating on the system state defined by the variable S_j. That is, given control situation S_j, produce the control law u_i that has the highest probability of improving the system performance.

The probability state space of the two random variables S_j and u_i is presented in Fig. 5. The control law u_i is a pulse train or other such function necessary to regulate the periodic compression logic. The probability P_{ij} is the probability of using control law u_i with control situation S_j. The probability adjustments are based upon the past performance of the control law. For a control situation S_j, the law used in any time interval is the one with the highest P_{ij}. If a law u_i is used for situation S_j and the system performance improves, the probability P_{Ij} is increased. The process of adjusting the probabilities to improve system performance is called reinforcement. For this method, it is necessary to have a learning algorithm which decides which probability is to be incremented and by how much.[4]

The adjustment of the probability is based upon a weighted average percentage improvement in the performance index over a given subinterval. That is, while employing the control law for a given control situation with the highest probability of success, the performance index improvement is computed in a separate bank (matrix). Let the percentage improvement in the index over the present interval be given by

$$\Delta = \delta PI/(PI + \delta PI)$$

where δPI is the index change. The previous computation for the weighted average percentage change in the index can be synthesized by examining a sequence of intervals. In the first two intervals, the average change is

$$\Delta_2' = (\Delta_1 + \Delta_2)/2$$

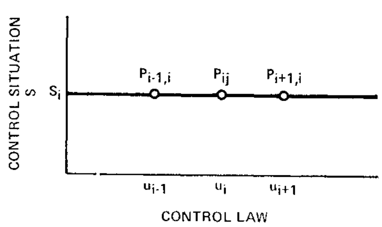
In the first three intervals

$$\Delta_3' = \frac{\Delta_1 + \Delta_2 + \Delta}{3} = \frac{2(\Delta_1 + \Delta_2)/2 + \Delta}{3} = \frac{2\Delta_2' + \Delta}{3}$$

and so on until, in the c'th interval

$$\Delta_c' = [(c-1)\Delta_{c-1}' + \Delta]/c$$

Fig. 5 Probability state space.



Thus, if c_{ij} represents the number of times u_i is associated with S_j, and rT represents the sample interval over which u_i is used with S_j, then the general expression for the weighted average percentage improvement is given by

$$\Delta_{ij}(rT) = \frac{[c_{ij}(rT) - 1]\Delta_{ij}[(r-1)T] + \Delta}{c_{ij}(rT)}$$

where $c_{ij}(rT)$ is an integer that is sequentially incremented to a given value J. The integer J is employed to help keep the learning flexible. That is, if J is very large, $\Delta_{ij}(rT)$ achieves a heavily damped state of statistical equilibrium, and adjustment is difficult. If J is very small, Δ_{ij} changes rapidly and may be very sensitive to noise or rapidly changing data.

Bionic reinforcement is determined by first comparing the Δ_{ij} to determine the largest one for a given S_j denoted by Δ_{Ij}. The probability associated with u_I will be reinforced even though another control law is presently being used for situation S_j.

The amount of reinforcement is given by a learning parameter θ where $0 < \theta = 1$ and the probabilities are influenced according to

$$P_{Ij}' = \theta P_{Ij} + (1 - \theta),\ P_{ij} = \theta P_{ij}$$

If θ is large, learning is very slow, and if θ is small, learning is very rapid. The method of determining θ as suggested in Ref. 8 is to first examine the quantity:

$$\alpha = (1/2) \underset{\substack{i = 1, \ldots \\ i \neq I}}{\text{minimum}} |\Delta_{Ij} - \Delta_{ij}|$$

This quantity indicates the degree of improvement resulting from using control law u_I. If α is large, u_I is a very good choice in subsequent time intervals. In this instance, rapid learning is desired. Thus,

$$\theta = 1 - (\alpha)^{1/2}$$

where the square root tends to accelerate the learning process. The complete process is represented in Fig. 6.

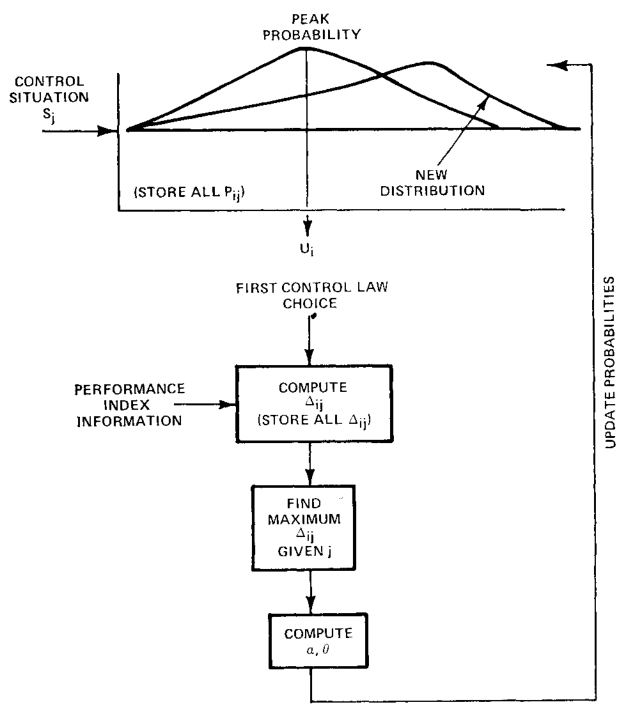


Fig. 6 Sequential computation for PSV algorithm.

The workings of a PSV bionic device are akin to a statistical sequential estimator which tends to improve control law choices given a situation in some time interval. Because of the stochastic nature of the control problem, new laws must be tried for the same control situation.

The method of regulating the probability state variable space variable space can be viewed in other ways. For example, the probability P_{ij} is analogous to the conditional probability of using control law u_i with control situation S_j. As the learning process proceeds, P_{ij} approaches unity for the u_i that gives the best performance, and P_{kj}, $k = 1$ approaches zero.

There are many methods of visualizing the behavior of the bionic elements. However, the general nature of the control device is such that if it is presented with any of several inputs, it learns to develop the output that tends to optimize the system. The bionic element that regulates the algorithm and tolerance is similar to the previously described device. An explanation of the behavior of the compression system in a function space is the subject of the following section.

Compression System Operation in a Function Space

The behavior of the probability devices as elements of the data compression system can be illustrated by transforming the control variables into a new function space. If can be observed from Fig. 2 that for any particular error tolerance and compression ratio, only one value of rms error will result. If the CR-error plane is mapped into the plane of compression ratio and error tolerance, with rms error as a parameter, it would appear as Fig. 7. The understanding of the behavior of each of the PSV devices can be appreciated by a simple example.

Suppose that an initial condition is chosen for the compression system such that E_1 results in CR_1. A perturbation in E_1, ΔE_1 could conceivably result in any of several paths in the plane shown in Fig. 7, e.g., paths a, b, or c. The difficulty is a result of the fact that E_1 is the only variable that has been changed. This condition is overcome by the introduction of a PSV device to control the over-all system output compression ratio CR', as well as a PSV device to regulate the error tolerance E, used for data compression. The tracing of a desired solution path in the CR-E plane is illustrated in Fig. 8.

Consider the initial condition represented by point a. Bionic element B will attempt to generate another compression ratio that tends to decrease rms error for the same compression error tolerance. This is represented in Fig. 8 by path ab'. At any particular point b' along the path ab, bionic element A will seek another error tolerance E_c that gives the same rms error for the given compression ratio. This is represented by the path $b'c'$. The process continues in increments $c'c$, controlled by element B, and cd, controlled by element A, until rms error has been minimized at the point 0.

Points P and P' in Fig. 8 represent the points that the system would seek on the optimal filter path in the event that the

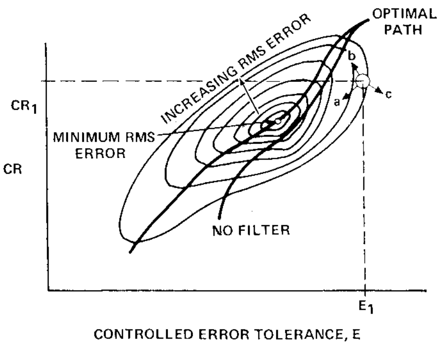


Fig. 7 Functional relationship with rms error as a parameter.

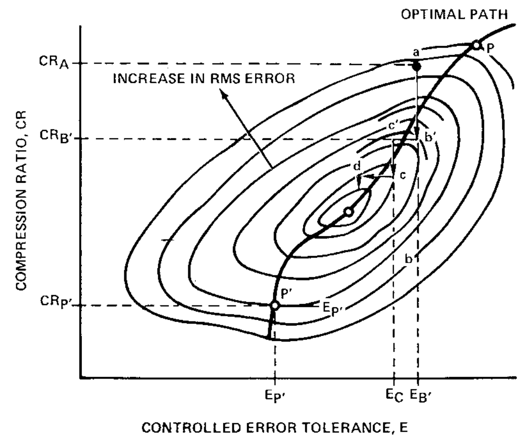


Fig. 8 System behavior in a function space.

buffer was close to overflow (point P) or underflow (point P').

Geometrically, for a given required compression ratio, the minimum rms error is represented by the rms curve tangent to the line parallel to the E axis in the function space. In fact, this is how the optimal path is constructed. This condition is represented in Fig. 8 by the tangent line at P', and the resultant rms error E_p'.

Multichannel System

It is desirable to extend the previously developed concepts to the multichannel situation, which will introduce some additional complexity. The most straightforward, but also more costly, approach is to have a compression system which separately optimizes each individual channel. In this case, the over-all system would be optimized by using an rms-error criterion and a pair of PSV devices for each channel. Equipment requirements are directly proportional to the number of channels and thus can become excessive for a system having many channels. By using a different approach based on some degree of equipment-sharing, greater hardware efficiency can be realized for the multichannel system.

The latter approach uses one central processing unit to accomplish a first degree of compression for all channels combined. This is followed by a second degree of compression on a per-channel basis. The performance index monitors the over all system behavior in such a manner that loss of significant data cannot occur. This concept is discussed in detail in the remainder of this section, and is shown schematically in Fig. 9.

The first degree of compression of the multichannel system is a direct extension of the self-adaptive concept for a single channel. The basis difference is that the pulse train from the sampler contains information from several signal sources, not just one source. The first degree of compression is applied to this pulse train in a manner analogous to the single-channel case.

Consider the pulse train coming from the sampler, which is sampling at a rate of nF samples per second. In this expression, F is the frame rate and n is the number of analog channels. This pulse train can be viewed as samples resulting from the sampling of the analog signal with highest frequency component $f_c = nF/2$. In fact, it is theoretically possible to reconstruct this analog signal with an ideal, sharp-cutoff filter with cutoff at f_c. It is the function of the primary compression system to perform the self-adaptive compression operation on this signal. The primary compression system is illustrated in Fig. 10 where a 1-to-n sample delay is provided to aid the interpolation process. Also shown in the figure is the secondary compression system which is discussed subsequently.

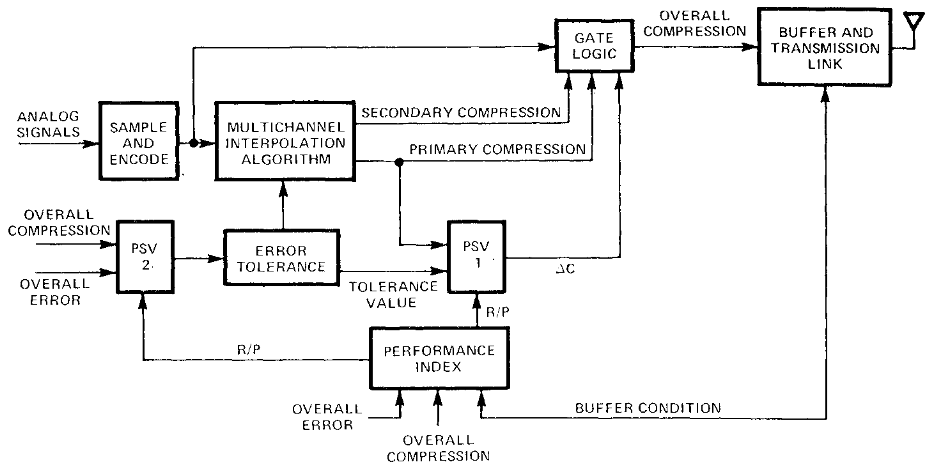


Fig. 9 Multichannel self-adaptive compression.

The generation of the optimal compression proceeds in a manner similar to the single-channel case. In this system, the performance index uses an rms error, a compression ratio, and a buffer condition that reflect the over-all multichannel system behavior. That is, the system compresses one signal which contains all the information of all of the n channels. It is realized that compression data in this manner does not always remove all of the redundant samples, because optimal data compression is not being performed on a per-channel basis. The main advantage of using the primary compression method is that it will remove a great deal of redundant data while employing one central processing unit for all channels.

Since the primary compression does not necessarily remove all of the redundant samples all of the time, a secondary system is designed to remove redundant samples missed by the primary system. The secondary system involves a minor amount of additional equipment. This secondary compression function is illustrated in the following example. Let the sampler output be as illustrated in Fig. 11 for a four-channel system. Below each sample is a number which represents the channel from which the sample was taken.

The secondary compression system shown in Fig. 10 consists of a prediction or interpolation algorithm, an error tolerance, and a 1-frame delay. The 1-frame delay allows compression in this part of the system on a per-channel basis. For the example illustrated in Fig. 11, all the samples, except perhaps the first four or eight,† will be removed.

The error tolerance used in secondary compression could be the same as the tolerance used in primary compression, since it is dictated by the performance index which monitors the rms error. Possibly, a more efficient compression could be realized at this point if an error sequence were used, each term of which corresponds to a particular channel. The adjustment of the sequence could be accomplished by the determination of the expected error in each channel. However, this adds a certain amount of complexity.

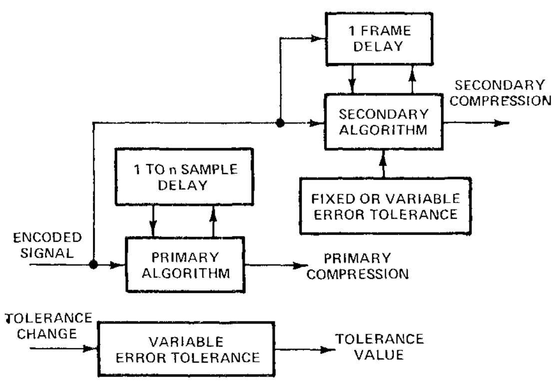


Fig. 10 Multichannel interpolation algorithm.

Fig. 11 Pulse train for four channels.

Function of Gate Logic

The output of the secondary compression system is connected to the gate logic shown in Fig. 9. The gate is simply a combination of two-position switches that prevent or allow the samples from the sampler to pass on to the buffer. The gate receives, as inputs, GO or NO-GO signals from the primary and secondary compression systems. In addition, the gate receives a control signal in the form of the pulse train from PSV 1.

The basic function of the logic gate is described by the function $A' \cup A''$, where A' is the primary compression output as a GO or NO-GO signal and A'' is the secondary compression output. In addition, the PSV-supplied pulse train has the capability of overriding this function as dictated by system considerations. That is, if the performance of the system is such that more compression is required, the gate will not allow the passage of samples to the buffer. If less compression is required, the gate allows more samples to pass to the buffer.

The over-all system performance is monitored by the performance index. The performance index receives signals equivalent to over all rms error, the short-term compression ratio input to the buffer, and a measure of buffer condition. The performance index is the primary regulator of the entire compression system. Hence, the design of a good system performance measure for the system will result in a great deal of data compression for a multichannel system and, at the same time, will prevent unnecessary loss of significant data. A survey of the information concerning data compression indicates that the self-adaptive data compression concept presented in this paper posses several technological advantages over present data compression methods.

† The number removed depends on the details of the reduction algorithm.

Summary

The proposed system is truly self-adaptive in the sense that it continually removes redundant information regardless of the changing nature of the analog inputs. The self-adaptive system also minimizes the over-all system error and provides an effective means of buffer control. The use of bionic elements removes the necessity of explicit a priori knowledge of the relationship between system compression and over all error. The reason is that the system behavior is continuously monitored by a performance measure.

It is believed that direct control of the compression error tolerances will result in more uniform compression with respect to time. This not only simplifies the output buffer design, but also allows a more exact computation of the required bandwidth for transmission. The result would be a significant improvement in bandwidth utilization. The proposed concept represents an immediate solution to a large portion of the increasing problems in data handling. The technology of data compression and bionic devices has progressed sufficiently to permit the proposed technique to be icorporated with confidence into a telemetry system for study.

References

[1] Weber, D. R., "A Synopsis on Data Compression," *National Telemetering Conference Proceedings*, Instrument Society of America, 1965, pp. 9–16.

[2] Berkowitz, M., "An Adaptive Data Sampling System," TR 62SD587, Nay 1962, Missile and Space Div., General Electric Co., Philadelphia, Pa.

[3] Kortman, C. M. "Redundancy Reduction—A Practical Method of Data Compression," *Proceedings of the IEEE*, Vol. 55, No. 3, March 1967, pp. 253–262.

[4] Lucy, R. W., "Adaptive Redundancy Removal in Data Transmission," *Bell System Technical Journal*, Vol. 47, No. 2, April 1968, pp. 549–573.

[5] Massey, J., "An Experimental Data Compressor," *National Telemetering Conference Proceedings*, Instrument Society of America 1965, pp. 25–28.

[6] Simpson, R. S. "Buffer Control in Data Compression Systems for Non-Stationary Data," *National Telemetering Conference Proceedings*, 1964, pp. 1–7.

[7] Medlin, J. E., "The Prevention of Transmission Buffer Overflow in Telemetry Data Compressors," *IEEE Convention Record*, Pt. I, March 1967, pp. 132–197.

[8] Waltz, M. D. and Fu, K. S., "A Heuristic Approach to Reinforcement Learning Control Systems," *IEEE Transactions on Automatic Control*, Vol. AC-10, No. 4, Oct. 1965 pp. 390–398.