

GLOBAL RATE ALLOCATION AND CONTROL

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ABSTRACT

The Galileo mission to Jupiter is now faced with extreme limitations in its communication downlink capability as a result of the inability of ground controllers to open its main antenna. Consequently, the rate that the Galileo spacecraft will be able to acquire data will exceed its capability to transmit it back by several orders of magnitude. Several proposed low-cost missions to go to the outer planets are faced with similar constraints.

Because of the very large disparity between collection data rate and downlink data rate for such missions, data must be accumulated in mass memory for later transmission. This paper addresses the situation when the total transmitted bits (downlink data rate x total downlink time) is far less than the accumulated data bits stored in mass memory. This is a data compression problem in which the data set is *all the stored data* (which may be from multiple sources) and the goal is to maximize *the total value* of all returned data using a specified (but limited) number of bits.

Typically, this problem is not simply a manyfold duplication of the more familiar compression problem to maximize the value (quality) of smaller data sets (e.g., single images or subsets of images). Instead, a basic assumption is that almost everything that matters can vary over the span of, and the period of communication of, stored data: data characteristics, user priorities, data rate, fidelity requirements, scientific value, etc.

This paper concentrates on stored data bases containing primarily image data, which has historically been the dominant data source for deep-space missions. Practical *"Global rate allocation and control"* strategies are developed which basically tie together all the data compression operations that might be performed on all subsets of the stored data, *such that a fixed number of bits are used overall*. The control structures developed here are not static, allowing for continuous adjustments during communication to accommodate variations in compression performance, unexpected changes to data characteristics, autonomous discovery such as from pattern recognition and feature extraction, and user intervention. In doing so, these strategies attempt to reassign the distribution of unused bits to data subsets where they will do the most good. Many present day compression algorithms can fit directly within this rate control structure with little modification.

I. INTRODUCTION

The Galileo mission to Jupiter is now faced with extreme limitations in its communication capability as a

result of the inability of ground controllers to open its main antenna.¹ Consequently, the rule that the Galileo spacecraft will be able to acquire data will exceed its capability to transmit it back by several orders of magnitude. Several proposed low-cost missions to the outer planets are faced with similar constraints.

This paper addresses situations like these in which data must be accumulated in mass memory for later transmission. This results in a unique data compression problem where the data set is *all the stored data* (which may be from multiple sources) and the goal is to maximize the total value of all returned data using a specified (but limited) number of bits. Subsequent sections will further develop this problem under the assumption that the stored data bases contain primarily image data (historically the dominant data source for deep-space missions). Using the Galileo problem as a model, rate allocation and control strategies are developed which tie together the data compression operations which might be performed on small subsets of the stored data, *such that a fixed number of bits is used overall*.

II. PROBLEM DEVELOPMENT

Partitioning Sequences/Images

Consider the diagram in Fig. 1, which partitions sequences of images into various entities we will want to discuss. It shows one or more sequences of images (presumably different camera views or camera pointings) being stored in mass memory as a "composite" sequence of K square L by L images (although images do not generally need to be square). An image is then shown as partitioned into m x m sub-pictures. For example, subpictures of size 80 x 80 would partition an 800 x 800 Galileo image into 100 square regions.

The General Problem

For Galileo and many proposed missions, large image data bases can be generated and then must be retained because the data rate to return images is far less than the rate at which they are acquired. In Galileo's case the downlink capability may be anywhere from 10 bits/s to 100 bits/s¹, whereas images can actually be acquired at up to 800 Kbits/s.

The disparity in acquisition and downlink rates is not always a problem. For example, a planetary flyby mission would generate a single image data base. If that data base can *all* be completely returned in a few months there is really no problem. There is a problem however, if that return would take several years.

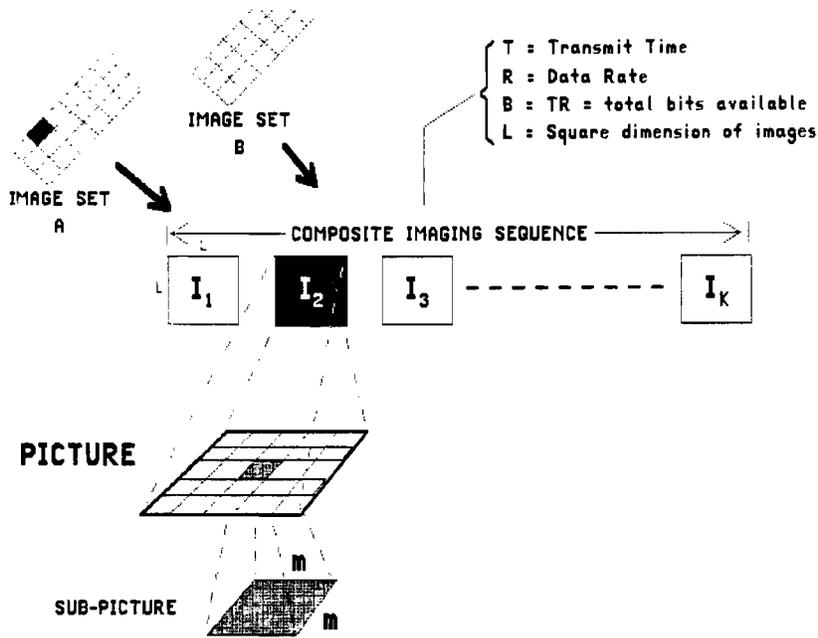


Fig. 1. Image Sequence

An orbiter mission like Galileo results in a different situation. There are multiple encounters and thus multiple image data bases generated. Data from one encounter must be removed from mass memory to ready it for the next. Data from one encounter may also influence plans for the next. Ultimately, this means that the communication of a stored image data base (and we will introduce other data later) is time constrained and therefore bit constrained. Subsequent discussions will focus on such scenarios.

Then, referring to Fig. 1, to transmit the complete imaging sequence in T seconds at R bits/s allows

$$B = TR \text{ bits} \quad (1)$$

We're after the most effective and intelligent way to use those few bits when

$$B \ll \text{Total Data Base} \quad (2)$$

General Approach/Assumptions

We begin our discussion by looking at the desirable features and characteristics of a compressor that represents the data of small areas of images (sub-pictures).

Sub-picture Compression. Suppose we have the sub-picture image compressor as shown in Fig. 2.

The sub-picture coder function is designated by $C(\cdot)$ and produces the coded $C(S_i, \hat{r}_i, \tilde{p}_i)$ when applied to sub-picture S_i with control inputs \hat{r}_i and \tilde{p}_i .

$C(\cdot)$ can be presumed to contain one or more algorithms that operate as follows:

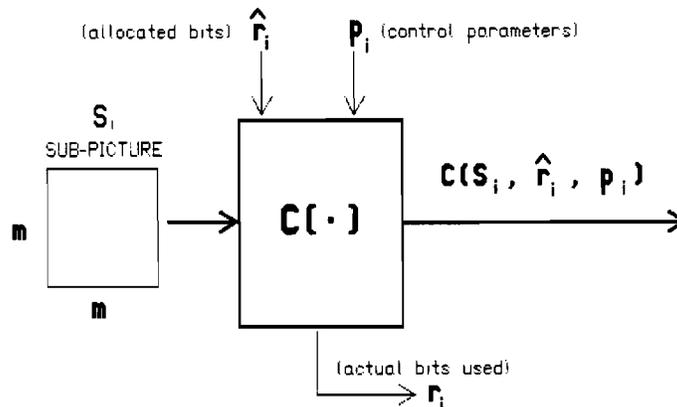


Fig. 2. Sub-picture Coder, $C(\cdot)$

Except for special circumstances controlled by parameters \tilde{p}_i , $C(\cdot)$ will seek to represent S_i using \hat{r}_i bits. The actual bits used are designated by r_i , where $r_i \approx \hat{r}_i$.

In general, the inverse $C^{-1}(\cdot)$ cannot reconstruct a compressed sub-picture precisely. The relationship between bits used and resulting quality of reconstruction (after decompression) follows the graph in Fig. 3 where r_i has been normalized to \bar{r}_i bits per picture element (bits/pixel). For discussion purposes an assumption of 8 bits/pixel will be assumed for uncompressed image data.

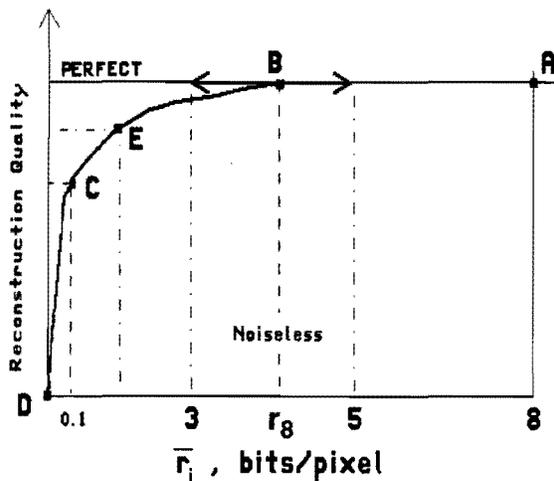


Fig. 3. Ideal Sub-picture Rate/Quality Tradeoff

Point A on this graph corresponds to uncompressed, original data. Point B corresponds to a "noiseless" or "lossless" representation which allows for perfect reconstruction while achieving some compression. The range of rates for "Galileo lossless coding" is probably from 3 bits/pixel to 5 bits/pixel (out of 8 bits/pixel), depending on scene activity.

The appropriate near optimum adaptive lossless coding algorithms for Galileo can be found in Refs. 2-8. Some of these techniques apply to the efficient coding of other forms of data as well, including transform coefficients from lossy compressors. For direct application, the most recent references describe algorithms similar to those used internally to BARC⁸ but with reduced computational requirements. They have recently been implemented separately as VLSI chips by both JPL and the Mitro Electronics Research Lab now located at the University of New Mexico⁷. A second version of the JPL chips is expected to be used by CRAF/Cassini imaging and PWS instruments. Cassini magnetometer and a replacement for the Mars Observer Gamma Ray Spectrometer and TES instruments will use other software versions.

Rates below B in Fig. 3 can only be achieved by accepting some form of degradation in quality. There are a large number of approaches for achieving such "lossy" compression. The intent here is not to specify that approach or approaches but to characterize the tradeoffs that a good approach should provide.*

The way to interpret the graph in Fig. 3 is as follows: The sub-picture coder $C(\cdot)$ can represent a sub-picture with any number of bits/pixel from 0 (point D)** up to r_B . Beyond r_B , using any more bits would be wasteful, assuming $C(\cdot)$ included an efficient lossless coder as already noted. At any specific rate, say r^* , a compressed/decompressed sub-picture will be reconstructed with a quality of say q . Increasing the rate used for representing the sub-picture by ϵ (very small) bits/pixel would increase the reconstructed quality to $q + \epsilon'$ as illustrated in Fig. 4, which expands the scale from Fig. 3.

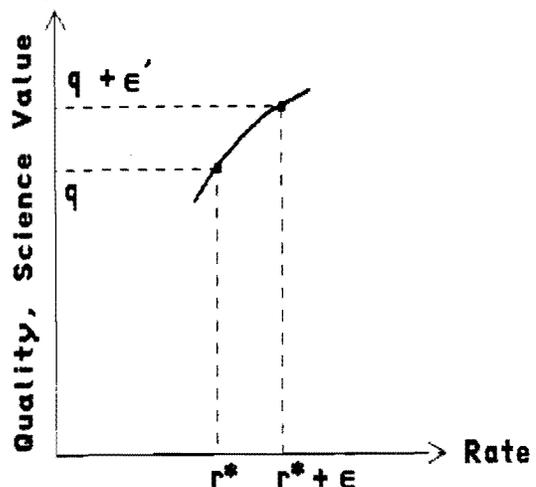


Fig. 4. Rate Quality, Expanded Scale

That is, using a few more bits should improve the preservation of some feature somewhere in the sub-picture. More bits should imply more quality, up to the point where exact reconstruction is achieved.

Clearly, for a given type of data and specific rate, one algorithm is better than another if it results in better quality. And what is quality? Such questions were the subject of earlier science value studies. Reasonably clear statements relating compression factor (or bits/pixel) and science content resulted for different investigations (assuming the specific sub-picture coder employed in the studies). This of course needs to be addressed as more is learned about desired features of existing and upcoming science data sets.

* Early science value studies looked directly at this problem in 1975⁹⁻¹¹ and 1980^{12,13}.

** Probably = 0 bits for header information.

However, the exact details of a sub-picture coder should not be of concern here. In fact, concern for such details would detract from important system issues. Out focus here is on maximizing science return over complete sequences (or the mission). It should suffice to note that a sub-picture coder with the general characteristics like those in Fig. 3 should be possible.^{11,14,15} So from now on we'll assume that C(-)

- a) Contains one or more algorithms that will approximate the performance characteristics in Fig. 3, coding sub-pictures with $r_i \approx \hat{r}_i$ bits when allocated \hat{r}_i bits to use.
- b) Includes special modes that can set internal quality parameters, and then represent the data with unspecified number of bits, depending on the data characteristics. Lossless coding of sub-pictures is an example of this.

All subsequent discussions will presume the existence of such a sub-picture coder. It will be later used as a tool to demonstrate how imaging scientists can maximize the total science return from each "bit constrained" imaging sequence as shown in Fig. 7.

Optimum Rate Allocation. Suppose that "replicas" of the imaging science team members could be placed on-board the spacecraft in the form of a knowledge-based system which included this sub-picture coder. Using it, their goal would be to most effectively use the "B" total bits to describe an imaging sequence. They would be allowed to look at all the images and use whatever processing necessary to determine "where to put the bits" most effectively. By most effectively we mean that they want to maximize the science that would be derived from the decompressed images by the real imaging team back on earth.

Then using all means at their disposal, this knowledge based system would effectively distribute bits (and hence quality) to all sub-pictures in the sequence. Key areas might receive enough bits to be represented error free whereas at the other end of the scale, areas of no interest (e.g., black space around a satellite or areas which only duplicate an already well defined science item) might receive zero bits. In-between, areas would vary in their bit allocation, taking into account the natural need for bits (e.g., more bits for detailed active areas compared to bland undetailed areas), the type of data and the level of detail needed to derive science from it,* and other factors. Ultimately, the resulting bit allocation to sub-pictures might look something like that in Fig. 5, where sub-pictures have been shaded according to the relative number of bits allocated, where

* Cloud data needed about 1/4 the average rate needed by cratered landscape data to achieve all science goals in previous science value studies.

$$\sum_{i=1}^{M'} \hat{r}_i = B \text{ bits} \quad (3)$$

and, assuming square images of dimension L

$$M' = K \cdot \left(\frac{L}{m}\right)^2 = \text{number of sub-pictures} \quad (4)$$

assuming square sub-pictures where m divides L.

In the figure, think of the shading as blocking the view of the data beneath. Dark shading implies a poor view and light areas a good view. Specifically, no shading at all would correspond to data of maximum quality (e.g., lossless coding is an example). The actual number of bits would vary as a function of data and type. Conversely, totally dark areas (opaque) would correspond to unimportant areas like black space or areas where editing is desired (virtually no bits required).

Thus the knowledge based system paints the image sequence in bits according to a presumed need, relative to the resources available. Subsequent sections will postulate various ways to approximate such a knowledge based system.

III. GLOBAL RATE ALLOCATION TWO PASS, AUTONOMOUS

In this and the following sections we will present several different versions of a process for distributing the B bits over an imaging sequence. We will also incorporate the impact of other science data as well.

The approach described here, beginning with Fig. 6, is the most fundamental and employs a two pass operation of mass memory and completely autonomous operation. Later we will convert this to a single pass approach and let the earth science team intervene as well (this also relates to the sequence planning phase).

Here the recorder first stores the K images from Fig. 1 (M' sub-pictures from Eq. 3), probably in uncompressed form.** On a first pass "information gathering" look at this data, images are read back from the recorder where image processing algorithms are applied to the sub-pictures to characterize them.

Phase I. Information Gathering

The output of this process is:

A) Maximum Rate

An estimate of the bits needed to represent each sub-picture with a specific set of quality parameters; (5)

** or perhaps using the lossless coding^{6,7}

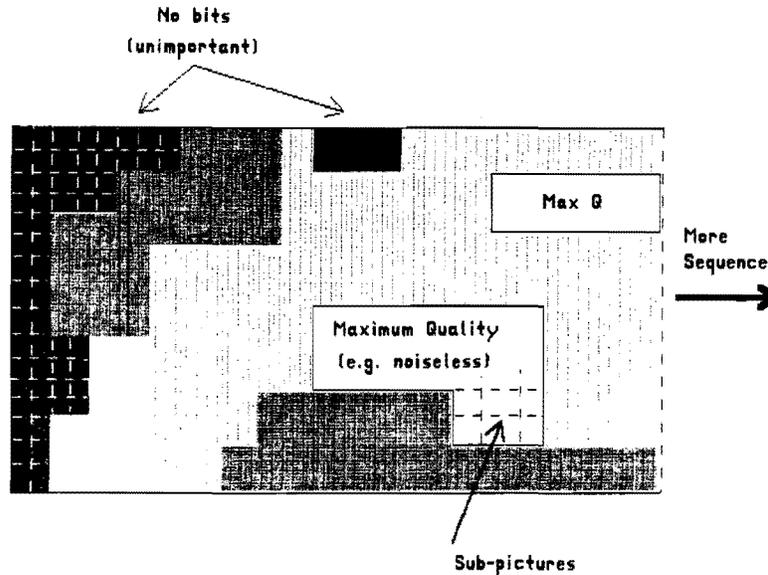


Fig. 5. Knowledge-based Rate Allocation over Imaging Sequence

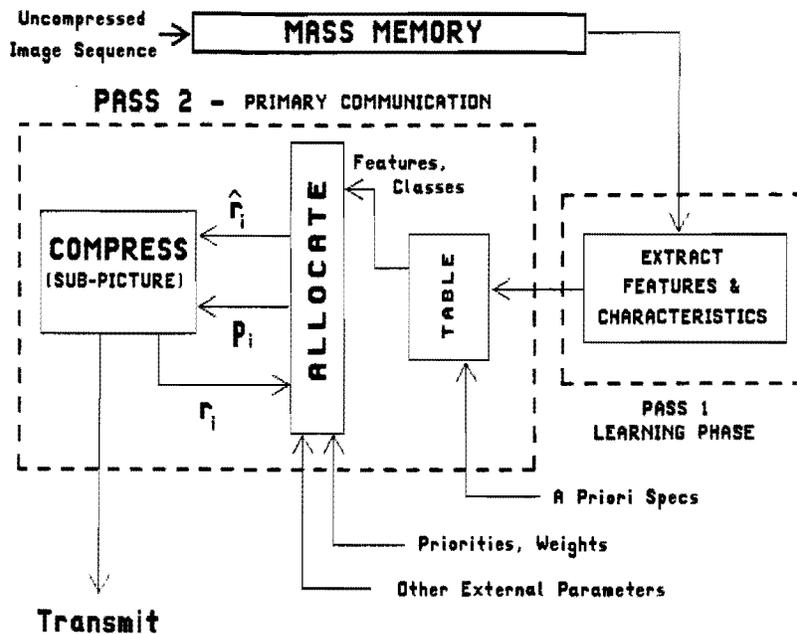


Fig. 6. Two Pass, Autonomous Rate Allocation and Coding

B) Classifications

One or more classifications of features that further distinguish the potential science content of the sub-picture. (6)

C) Transmitted Data

If the communication link is available during this process, selected compressed data would be communicated. That data would be flagged to avoid communicating it a second time during the primary communication phase. Communicated data could

be used to assist on-board classifications in B) and/or to alter priorities associated with rate control. (7)

Let's look at this further. One primary example of a maximum rate determination is a calculation of the bits needed to represent the sub-picture using lossless coding. This is computationally straightforward using the algorithms in Refs. 4-7.

In another example, suppose that it was determined that the maximum fidelity needed to achieve all science from cloud images was obtained from some lossy

algorithm with a fixed set of quality parameters (e.g., sub-sampled data followed by lossless coding, or transformed data with a specific set of quantization parameters and lossless coding). This would also produce a variable rate depending on the data as would the use of lossless coding alone. It might correspond to point E in Fig. 3.

Classification in its simplest form simply uses a priori information. For example, shots of cratered satellites are distinctly different than views of Jupiter itself. Such general classifications will almost certainly be known ahead of time, and are part of the sequence planning operations.

But on-board feature extraction and classification offer important possibilities where they are feasible. One such process should be the determination that a sub-picture is "black space" or mostly black space. For more sophisticated possibilities consult Ref. 16.

Other more sophisticated possibilities will determine how much on-board intelligence one can apply to the use of B bits/sequence. This needs investigation. What characteristics and features is it possible to determine without extraordinary computation requirements? What features would identify a sub-picture as one containing something you wouldn't want to miss (at a certain level of quality)?

Now assume that this initial step has been done and let

$$\hat{e}_i(0) = \text{lossless rate for sub-picture } i \quad (8)$$

Let*

$$C_i(j) = \begin{cases} 1 & \text{If feature or classification } j \text{ is} \\ & \text{associated with or present in} \\ & \text{sub-picture } i \text{ with high probability} \end{cases} \quad (9)$$

$$0 \quad \text{Otherwise}$$

Where $j = 1, 2, \dots, J$

$$\hat{e}_i(j) = \begin{cases} \text{Maximum rate (using any available} \\ \text{algorithms) to achieve maximum} \\ \text{desired quality if } j\text{th feature is} \\ \text{present alone } (\hat{e}_i(j) \leq \hat{e}_i(0)) \end{cases} \quad (10)$$

As an example, if small craters were present it might be desired to preserve the data perfectly under some conditions. Then $\hat{e}_i(j)$ would equal $\hat{e}_i(0)$ (lossless). A sub-picture which was determined to be all black space would only need some header information, so $\hat{e}_i(j) = 0$ bits. In between cases might include cloud shots (e.g., Jupiter). Based on prior science value studies, clouds might generally require a maximum fidelity setting that yielded rates of from 0.8 bits/pixel to 1.2

bits/pixel. But certain sub-pictures, say in a strip through the center of images might require a maximum fidelity setting that yielded rates ranging from 1.6 to 2.4 bits/pixel.

A sub-picture may contain more than one such feature, say

$$C_i(j_1), C_i(j_2) \dots$$

with corresponding

$$\hat{e}_i(j_1), \hat{e}_i(j_2) \dots$$

But the only rate of interest is

$$\hat{e}_i = \max \hat{e}_i(j) C_i(j) \quad (11)$$

Thus the algorithm settings for the most demanding fidelity requirements of a sub-picture determines the maximum rate \hat{e}_i . Usually, (11) would require only one calculation.

Without on-board processing, the max quality mode settings would be preplanned. That is, certain $C_i(j)$ would be preset, resulting in corresponding data dependent $\hat{e}_i(j)$. But if special features were discovered by processing, the max fidelity requirement might be raised, resulting in a higher \hat{e}_i in (11) as a result.

Allocation of Rate

All this so far only sets up the groundwork for the distribution of B bits. If all sub-pictures used \hat{e}_i bits, the total would be

$$B' = \sum_{i=1}^{M'} \hat{e}_i \text{ bits} \quad (12)$$

And each sub-picture would be reconstructed with a desired maximum quality. But it is far more likely that

$$B' \gg B \quad (13)$$

This is illustrated in Fig. 7 where

$$\bar{B}' = \frac{B'}{M'} \quad (14)$$

and

$$\bar{B} = \frac{B}{M'} \quad (15)$$

are corresponding sub-picture averages.

One natural way to allocate the \bar{B} bits per sub-picture is by scaling the distribution provided by the $\{\hat{e}_i\}$. The sub-pictures would then receive

$$\hat{b}_i = \hat{e}_i \left(\frac{B}{B'} \right) \text{ bits}, \sum \hat{b}_i = B \quad (16)$$

* In a more sophisticated representation $0 \leq C_i(j) \leq 1$ could reflect the likelihood or quantity of feature j.

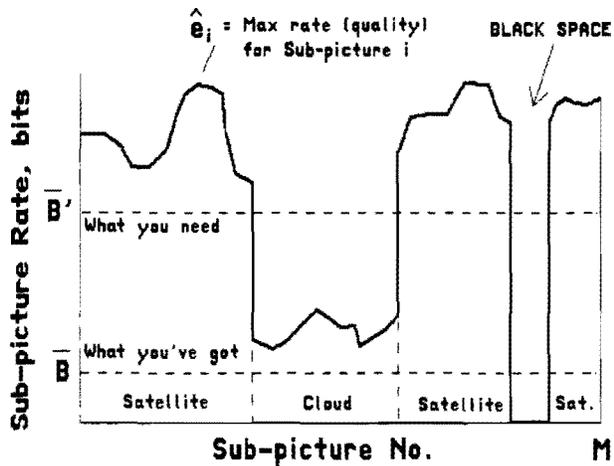


Fig. 7. Maximum Rates by Sub-picture

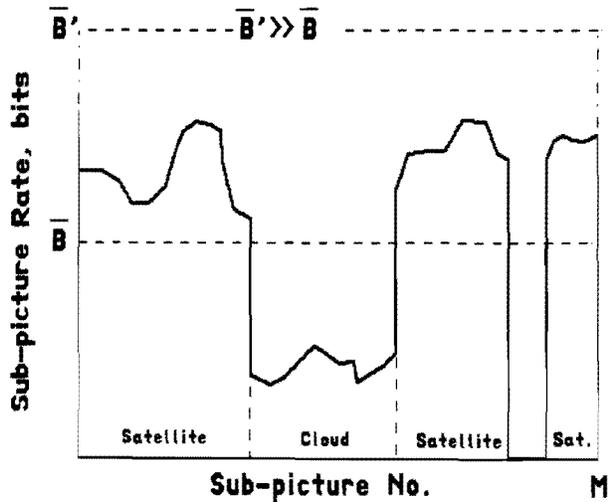


Fig. 8. Scaled Rate Distribution

instead, reflecting the natural need for bits. See Fig. 8. Basically, this is how the RM2 algorithm distributed rate within images in the example of Ref. 11 and for the science value studies.¹¹⁻¹³ In these cases, the $\{\hat{e}_i\}$ corresponded to the lossless rate for sub-pictures, $\hat{e}_i(0)$.

Weighting distribution. But this natural distribution may be easily modified to reflect science priorities and/or the detection of features which might be of great interest.

So let

$$\{\alpha_j\} \quad (17)$$

be a set of numbers which weight the relative importance in describing the data in a sub-picture when feature or classification j is present (a larger α_j implies more importance for feature j). On a recent

investigation of a multi-instrument imaging data system (OSL) simple iterative algorithms were defined for allocating rate that takes into account both the \hat{e}_i and the priority weightings in (17), and forced quality modes.

Basically, the weights in (17) would allow a modification to the scaled rate distribution in Fig. 8 to reflect changes and discoveries in the data, in much the same way that the "replica science team might do."

For example, suppose some key cloud features were detected in 10% of the cloud sub-pictures and 10% of the satellite images. Heavy weightings for such features would basically cause the rate allocation system to "rob" bits from the other sub-pictures to assure a higher quality. A possible hypothetical result is shown in Fig. 9. The result from Fig. 8 is shown also for comparison. What it shows is that when certain key features are detected, more rate (and hence quality, see Figs. 3 and 4) are applied at the expense of other regions which are not deemed as crucial. The rate used would never be greater than the maximum \hat{e}_i .

During phase two communication of compressed data, the actual rate used by a sub-picture will generally not precisely match its allocation. Thus allocations would be continuously scaled up or down to accommodate such variations as well as external parameter changes (see following discussion).

It should be noted that the application of additional rate in key areas could make the difference in doing substantial science or not (in those areas). Consider the sub-pictures corresponding to points A and B in Fig. 9. Point A might represent 4 bits/pixel and point B 1 bit/pixel for example. The improvement is a real 4:1 or 6 dB for the science occurring in those areas.

Other Advantages

Being able to focus rate (quality) in areas of discovery is the more obvious advantage of global rate control. But there are many other advantages in the design and maintenance of imaging sequences.

Sequence Parameters. Suppose it was desirable to add one more images to an already planned sequence of K images (or $M' = K(L/m)^2$ sub-pictures). This is instantly accommodated by the global rate allocation.

In the simplest case, assume uniform data type and equal rate assignments across the sequence. Each of the K images would be allocated B/K bits/image. Adding an extra image would reduce this to $B/(K+1)$ bits/image for each of $K+1$ images. Putting some numbers to this

Let
 $K = 100$ images
 and with $L = 800$
 $B/(800)^2 = 0.8$ bits/pixel

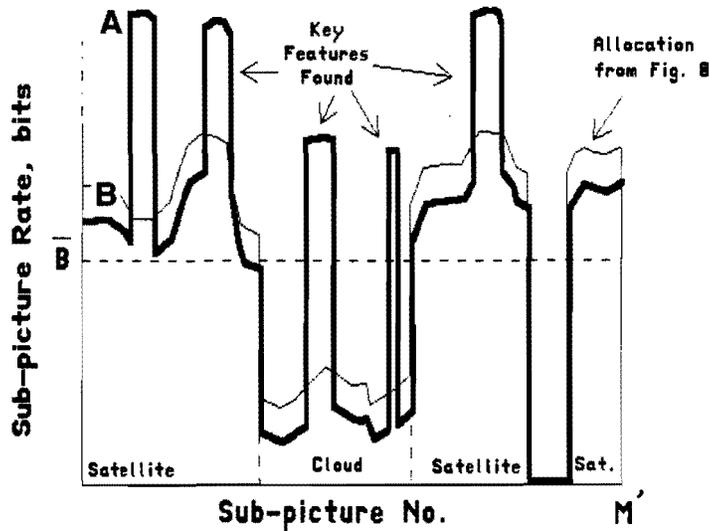


Fig. 9. Weighted Scaled Rate Distribution

corresponding to an average compression factor of 10:1. The new average rate would be

$$B/(K+1)(800)^2 \approx 0.79 \text{ bits/pixel}$$

This would correspond to an imperceptible "average" quality change throughout.

The same general effect would apply to a more sophisticated rate distribution such as the one in Fig. 9. Similarly, decreasing the number of images by a small amount would improve the average quality by a small amount.

Now force a single image to be represented losslessly, say at 4 bits/pixel, instead of the allocated 0.8 bits/pixel (or perhaps 10 sub-pictures scattered across different images). This would leave

$$\alpha = \frac{B - (800)^2(4)}{K-1}$$

for the remaining. Equivalently, this amounts to

$$\bar{\alpha} = \frac{B}{(K-1)(800)^2} - \frac{4}{(K-1)} \text{ bits/pixel}$$

$$> \frac{B}{K(800)^2} - \frac{4}{(K-1)}$$

If we originally had 0.8 bits/pixel for $K = 100$ images, then the remaining 99 would have

$$\bar{\alpha} > 0.8 - \frac{4}{99} \approx 0.76 \text{ bits/pixel.}$$

If the 10 special sub-pictures were set at a maximum quality mode corresponding to 2 bits/pixel (e.g. clouds), then

$$\bar{\alpha} > 0.78 \text{ bits/pixel}$$

Suppose the B bits allowed for a complete imaging sequence changes for any reason, prior to encounter and/or during encounter:

- a) Data rate capability available as a consequence of communication system upgrades.
- b) Longer, shorter time periods.
- c) Weather.
- d) Fluctuations in requirements of other instruments and engineering.
- e) Etc.

All these changes are instantly accommodated by the global rate allocation concept. If more bits are available, they are distributed where they are likely to do the most good.*

Fluctuations in non-imaging data rates.

Now suppose that other instruments have employed data compression that, as a group, generate a variable rate during the period of an imaging sequence. Provided this rate is a small fraction of the corresponding rate assigned to imaging, the global rate allocation could easily "absorb" the normal fluctuating rate or even the impact of special non-imaging events which might need more bits. As an example,

let

$$B_T = B_0 + b_0$$

* Large changes in B might call for a different weighting of science priorities.

where

B_T = total bits available to spacecraft during sequence

B_0 = a priori assignment to imaging sequence

b_0 = assignment to non-imaging group during imaging sequence period

and let

$$B_0 = 9 b_0$$

so that non-imaging constitutes 10% of the total allocation.

Now assume that special non-imaging events occur which require a 30% increase in b_0 to assure adequate definition (perhaps they have their own knowledge based system). Then

$$b_0' = b_0 + \Delta b_0 = b_0 + 0.3 b_0$$

so that

$$B_0' = B_0 - \Delta b_0 = 9b_0 - 0.3 b_0 = 8.7 b_0 = 0.967 B_0$$

a reduction of only 3.3%. That is, if the nominal imaging bit allocation B_0 corresponded to an average normalized rate of

0.8 bits/pixel

a 30% increase in non-imaging rate would reduce this to about

0.77 bits/pixel

Such a change in non-imaging rate might be simply the result of a priori considerations or autonomous detection of events during playback. In either case, the global rate allocation would quickly scale the distribution of bits to fit.

One case for a 30% fluctuation might simply be the variable output of a lossless coder (or some other fixed quality mode). Imaging could simply absorb those fluctuations, simplifying implementations for those instruments. Variations of that size or larger resulting from an event detection probably would require weighted priority considerations between competing disciplines in much the same way as the global image rate allocation between sub-pictures. With the ability to scale the distribution of rate, such considerations should no longer be impossible to discuss.

IV. GLOBAL RATE ALLOCATION ONE PASS, AUTONOMOUS

The previous section and Fig. 6 implied a two-pass mass memory operation: the first to access the overall imaging sequence as a set of sub-pictures and provide initial global rate distribution; the second, to perform the actual coding and adjustments to rate distribution. If the available processing speed is sufficient, the operations necessary to perform the first step may be accomplished simultaneously with the collection of data into mass memory. When this is not true, consideration for a simpler single-pass approach may be desirable. For example, a "single" pass approach would have a reliability advantage on Galileo because its mass memory is a tape recorder. The following provides some insight to performing these in a single pass. Consider the diagram in Fig. 10.

The upper part of the figure represents the imaging sequence in the mass memory. As sequence

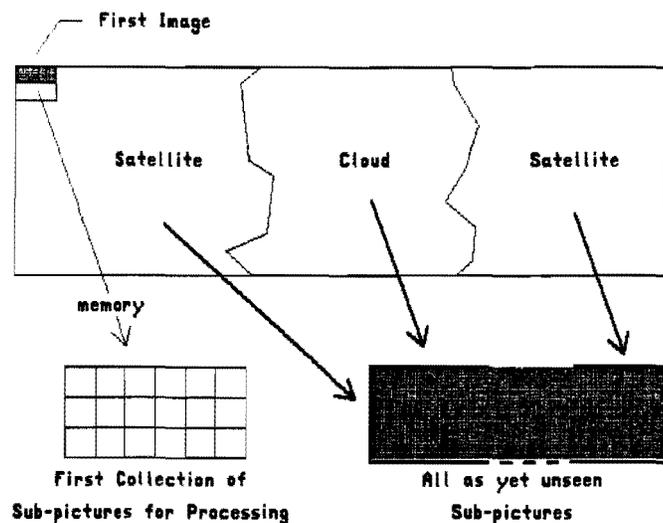


Fig. 10. Weighted, Scaled Rate Distribution

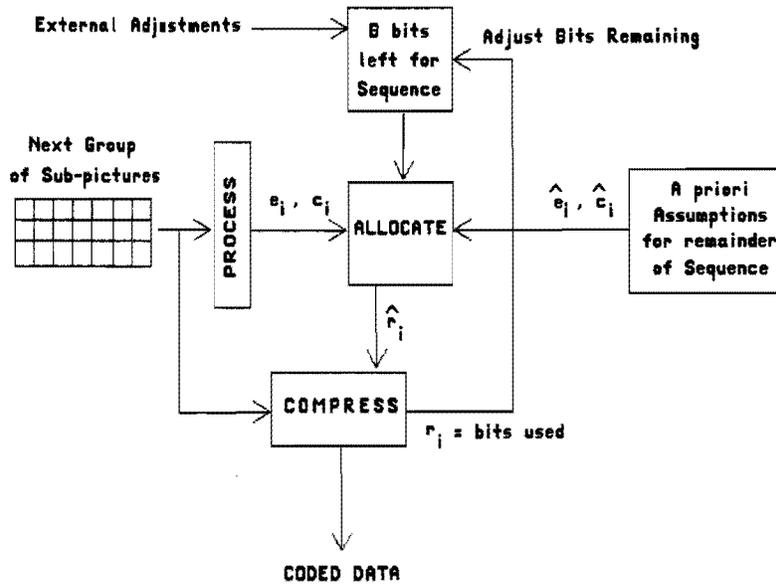


Fig. 11. Rate Allocation Process, Single Pass

transmission begins, the first set of sub-pictures from the first image are shown in memory on the left. Note the imaging sequence has been presumed to be partitioned into satellite images, followed by cloud images and then satellite images again.

Global Rate Allocation can proceed, using a priori assumptions about what lies ahead in the imaging sequence. This includes pre-established quality modes and estimated maximum rates for those modes (e.g., lossless and 4.0 bits/pixel for satellites, and perhaps a mode yielding an expected 1.0 bits/pixel for clouds).

The processing/coding process is illustrated in Fig. 11.

At the start, the "Next Group of Sub-pictures" would actually be the first group, as in Fig. 10 and the "B bits remaining" for the sequence would correspond to the initial total at the start of the sequence.

The sub-pictures in memory are processed by whatever means available (as in the two-pass approach) to characterize their contents. A global Rate Allocation then generates the rate assignment to these sub-pictures currently being processed. The actual rate numbers for sub-pictures to follow need not be generated. But the a priori assumptions on their expected characterization and coding are used in the allocation. Finding something very important that requires improved fidelity would then receive extra bits as in the two pass approach.

When the current group of sub-pictures is completed, the total bits allowed for the remainder of the sequence, B, is adjusted by the actual bits used to code the sub-pictures. B might also be adjusted for other reasons during this period (see previous discussion on variations caused by non-imaging instruments). Thus, the imaging sequence seen by the rate allocation and

coding system becomes effectively shorter and shorter as each group of sub-pictures is completed.

The fundamental difference between the single pass and two-pass rate allocations is the extent of intelligence that one can apply when something surprising occurs.

For example, in the two pass system, if exciting things happen only at the end of a sequence (i.e., events that desire extra quality) bits can be robbed from a relatively uninteresting first part of the sequence to achieve the desired result. In the single pass approach this couldn't be done because allocations to the first part of a sequence would have already been fixed (i.e., the data would have already been transmitted).

There are a number of other scenarios one can concoct where the two-pass would provide similar benefits. But the reliability advantage and simplicity of the one-pass approach may be the dominant issue.

V. GLOBAL RATE ALLOCATION NON-AUTONOMOUS

Modifications During Transmission

For data link constrained spacecraft, such as Galileo, an imaging sequence will be communicated back quite slowly, regardless of the compression process and other communication improvements. Presumably, the imaging team (and other science disciplines) will be carefully monitoring the returned data as it is reconstructed. Such observations might call for a change in the way the remaining imaging sequence is coded. For example,

- a) More bits for satellite images than clouds and vice versa.

- b) More bits in certain sub-pictures to come.
- c) Zero bits for certain sub-pictures (e.g., making smaller images, editing out images).
- d) More bits for non-imaging science.
- e) Fewer bits for the remaining sequence so it finishes sooner, leaving time for subsequent earth commanded special re-transmissions.

Such changes could easily be accommodated by transmitting a few parameters.

Note that earth observers could have access to the same parameters and features of sub-pictures yet to be transmitted as the on-board allocation system.

- During the first of two passes, feature and maximum rate information is communicated.
- In a one-pass approach, rate control only has access to current data.

Thus any adjustments to rate distribution parameters could be visually tested, and perhaps iterated on, before sending adjustments.

VI. IMPLEMENTATION NOTES

Note that the basic structure for global rate allocation is not computationally demanding. Consider that individual calculations for features, maximum rates and allocations are associated with sub-pictures. At a size of 80 x 80, this amounts to one number per 6400 pixels. None of these need to be extremely precise. Some of the desirable feature extractions and classifications will be easy to do, some will be predetermined and some will be computationally demanding and perhaps not possible for some missions.

VII. SUMMARY

This paper addresses situations like that now faced by the Galileo spacecraft as it approaches Jupiter where large science data bases, containing mostly images must be transmitted over extremely limited communication channels. Practical "global rate allocation and control strategies" are developed which tie together all the data compression operations that might be performed on small subsets of all the data, *such that a fixed number of bits is used overall*. In doing so, important rate control characteristics for image compressors are identified.

Even the most basic form of such "smart systems" has the potential for providing a science team with almost unlimited flexibility to distribute bits (quality) across the potential science targets – and to change that assignment at a moment's notice (within the constraints of communication turn around time for deep-space missions).

The on-board intelligence provided by the autonomous detection of specific events would additionally provide added power to avoid wasting bits on uninteresting subjects and allow them to be placed where they do the most good.

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