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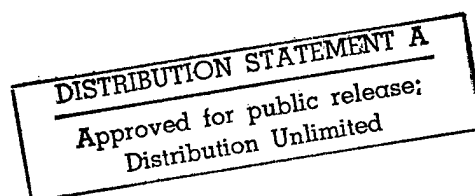
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Inventor John A. Antoniadis
 Mark M. Baumbach
 Jeffrey H. Bowles
 John M. Grossman
 Daniel G. Haas
 Peter J. Palmadesso

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Inventors: Antoniadou, et al.

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**COMPRESSION OF HYPERDATA WITH ORASIS MULTISEGMENT PATTERN
SETS (CHOMPS)**

This is a continuation in part of Application Serial Number 08/679,085, attorney docket number 77,409, filed July 12, 1996, and which is currently pending.

BACKGROUND OF THE INVENTION

1 The present invention relates generally to processing signals, and more particularly to
2 a system for the rapid compression of hypersensor data sets that contain objects, substances, or
3 patterns embedded in complex backgrounds. A hypersensor is a sensor which produces as its
4 output a high dimensional vector or matrix consisting of many separate elements, each of which
5 is a measurement of a different attribute of the system or scene under construction. A
6 hyperspectral imager is an example of a hypersensor. Hypersensors based on acoustic or other
7 types of signals, or combinations of different types of input signals are also possible.

8 Historically there have been three types of approaches to the problems relating to the
9 detection of small, weak or hidden objects, substances or patterns embedded in complex
10 backgrounds.

11 The first approach has been to use low dimensional sensor systems which attempt to
12 detect a clean signature of a well known target in some small, carefully chosen subset of all
13 possible attributes, e.g., one or a few spectral bands. These systems generally have difficulty
14 when the target signature is heavily mixed in with other signals, so they typically can detect
15 subpixel targets or minority chemical constituents of a mixture only under ideal conditions, if

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1 at all. The target generally must fill at least one pixel, or be dominant in some other sense as
2 in some hyperspectral bands. Also, the optimal choice of bands may vary with the observing
3 conditions or background (e.g. weather and lighting), so such systems work best in stable,
4 predictable environments. These systems are simpler than the high dimensional sensors
5 (hypersensors), but they also tend to be less sensitive to subdominant targets and less adaptable.

6 The second approach has been to employ high dimensional sensor systems which seek
7 to detect well known (prespecified) targets in complex backgrounds by using Principle
8 Components Analysis (PCA) or similar linear methods to construct a representation of the
9 background. Orthogonal projection methods are then used to separate the target from the
10 background. This approach has several disadvantages. The methods used to characterize the
11 background are typically not 'real time algorithms'; they are relatively slow, and must operate
12 on the entire data set at once, and hence are better suited to post-processing than real time
13 operation. The background characterization can get confused if the target is present in a
14 statistically significant measure when the background is being studied, causing the process to
15 fail. Also, the appearance of the target signature may vary with the environmental conditions:
16 this must be accounted for in advance, and it is generally very difficult to do. Finally, these
17 PCA methods are not well suited for detecting and describing unanticipated targets, (objects or
18 substances which have not been prespecified in detail, but which may be important) because the
19 representation of the background constructed by these methods mix the properties of the actual
20 scene constituents in an unphysical and unpredictable way. PCA methods are also used for
21 compression schemes however they have many of the same shortcomings. Learned Vector

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1 Quantization (LVQ) is also used for compression. Current LVQ schemes use minimum noise
2 fraction (MNF) or average patterns of PCs to compress the data, or various iterative methods
3 which are slow and require a priori knowledge of sensor characteristics.

4 The more recent approach is based on conventional convex set methods, which attempt
5 to address the 'endmember' problem. The endmembers are a set of basis signatures from which
6 every observed spectra in the dataset can be composed in the form of a convex combination, i.e.,
7 a weighted sum with non-negative coefficients. The non-negativity condition insures that the
8 sum can sensibly be interpreted as a mixture of spectra, which cannot contain negative fractions
9 of any ingredient. Thus every data vector is, to within some error tolerance, a mixture of
10 endmembers. If the endmembers are properly constructed, they represent approximations to
11 the signature patterns of the actual constituents of the scene being observed. Orthogonal
12 projection techniques are used to demix each data vector into its constituent endmembers.
13 These techniques are conceptually the most powerful of the previous approaches, but prior
14 methods for implementing the convex set ideas are slow, (not real time methods) and cannot
15 handle high dimensional pattern spaces. This last problem is a serious limitation, and renders
16 these methods unsuitable for detecting weak targets, since every constituent of a scene which
17 is more dominant than the target must be accounted for in the endmember set, making weak
18 target problems high dimensional. In addition, current convex set methods give priority to the
19 constituents of the scene which are dominant in terms of frequency of occurrence, with a
20 tendency to ignore signature patterns which are clearly above the noise but infrequent in the
21 data set. This makes them unsuitable for detecting strong but small targets unless the target

patterns are fully prespecified in advance.

When operating in high dimensional pattern spaces massive quantities of data must be managed which requires hundreds of millions of computations for each pixel. Thus the need to compress massive quantities of data for storage, download, and/or real time analysis becomes increasingly important and equally elusive.

SUMMARY OF THE INVENTION

Accordingly, it is an object of this invention to compress multispectral data, while preserving the spectral information for the detection of objects or substances embedded in complex backgrounds.

Another object of this invention is accurate and quickly compress multidimensional data sets from chemical, acoustic or other types of hypersensors capable of handling multidimensional analysis.

Another object of this invention is to process signals and compress data with a fast set of algorithms which provide a greatly reduced computational burden in comparison to existing methods.

Another object of this invention is to compress hyperspectral or multispectral data in a system employing parallel processing which offers true real time operation in a dynamic scenario.

These and additional objects of this invention are accomplished by the structures and processes hereinafter described.

1 The Compression of Hyperdata with ORASIS Multisegment Pattern Sets,
2 (CHOMPS), system is a collection of algorithms designed to optimize the efficiency of multi
3 spectral data processing systems. The CHOMPS system employs two types of algorithms,
4 Focus searching algorithms and Compression Packaging algorithms. In a preferred
5 embodiment CHOMPS system is integrated into the Intelligent Hypersensor Processing
6 System (IHPS). IHPS is a system for processing high dimensional data employing a
7 prescreener module to reduce the size of the data set received from the sensor and
8 employing Gram Schmidt/Salient methods to reduce the dimensional space necessary to
9 describe what the hypersensor detects with a minimal loss of useful information. The IHPS
10 prescreener reduces the size of the data set by comparing the incoming data from the sensor
11 with previously sampled data, called exemplars, and excludes the incoming sensor data the
12 prescreener characterizes as redundant.

13 The Focus algorithms employed by CHOMPS reduce the computational burden of
14 the prescreening process by reducing the number of comparisons necessary to determine
15 whether or not data is redundant, by selecting only those exemplars which are likely to
16 result in the exclusion of the incoming sensor data for the prescreener comparisons.
17 The CHOMPS system also employs Compression Packaging algorithms, which compress the
18 volume of the data necessary to describe what the sensor samples. In the preferred
19 embodiment these algorithms employ the Prescreener, the Demixer Pipeline and the
20 Adaptive Learning Module Pipeline to construct a compressed data set. The compression is
21 realized by constructing the data set from the exemplars defined in the prescreening

1 operation and expressing those exemplars in wavespace with the necessary scene mapping
2 data, or further processing the exemplars through the adaptive learning pipeline and
3 expressing the exemplars in terms of endmembers, to facilitate the efficient storage,
4 download and the later reconstruction of the complete data set with minimal deterioration of
5 signal information.

6 **BRIEF DESCRIPTION OF THE DRAWINGS**

7 Figure 1. is a representation of the data cube and the orientation of the spatial and
8 wavelength information in X , λ and T coordinates.

9 Figure 2. is a block diagram of an embodiment of IHPS showing the system's parallel
10 structure.

11 Figure 3. is a logic flowchart of the operation of the prescreener

12 Figure 4. is a representation of the plane created by V_1 and V_2 during Gram-Schmidt
13 operations.

14 Figure 5. is a representation of the orthogonal projections V_{10} and V_{20} during Gram-
15 Schmidt operations.

16 Figure 6. is a representation of the Salient vector and plane defined by V_{10} and V_{20} .

17 Figure 7. is a representation of the 3-dimensional spanning space defined during Gram-
18 Schmidt/Salient operations.

19 Figure 8. is a representation of the 3-dimensional spanning space showing the salient
20 vectors.

21 Figure 9. is a representation of a hypertriangle convex manifold.

1 Figure 10a. is a representation of a minimized hypertriangle defined using shrink wrap
2 method 1.

3 Figure 10b. is a representation of a minimized hypertriangle defined using shrink wrap
4 method 2.

5 Figure 11. is a representation of a minimized hypertriangle defined using shrink wrap
6 method 3.

7 Figure 12. is a logic flowchart of the operation of the adaptive learning module.
8 Figure 13. is a flowchart of the operation of the demixer module.

9 Figure 14. is a block diagram of the ALM processor pipeline employing
10 multithreaded operation.

11 Figure 15. is a representation of a reference vector and its exemplar projections.

12 Figure 16. is a logic flowchart of the Pop-up Stack search method.

13 Figure 17. is a representation of the Single Bullseye search method in vector space.

14 Figure 18. is a representation of the Double Bullseye search method in vector space.

15 Figure 19. is a logic flowchart of the CHOMPS wavespace compression mode.

16 Figure 20. is a logic flowchart of the CHOMPS endmember compression mode.

17
18 **DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENTS**
19

20 The Compression of Hyperdata with ORASIS Multisegment Pattern Sets,
21 (CHOMPS), system is a collection of algorithms designed to optimize the efficiency of multi

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1 spectral data processing systems. The CHOMPS system employs two types of algorithms,
2 Focus searching algorithms and Compression Packaging algorithms. In a preferred
3 embodiment CHOMPS system is integrated into the Intelligent Hypersensor Processing
4 System (IHPS). IHPS is a system for processing high dimensional data employing a
5 prescreener module to reduce the size of the data set received from the sensor and
6 employing Gram Schmidt/Salient methods to reduce the dimensional space necessary to
7 describe what the hypersensor detects with a minimal loss of useful information.

8 In the preferred embodiment CHOMPS is integrated into IHPS employed on an
9 aircraft or spacecraft. As the craft flies over or in close proximity to an area of interest, a
10 hypersensor scans the scene or area of interest by taking successive snapshots of the scene
11 below. Each snapshot constitutes a frame of spectral data. The spectral data is scanned
12 frame by frame and displayed as variations in intensity. In the optical example, a frame is
13 the diffracted image on a two dimensional focal plane of a narrow slit which accepts light
14 from a narrow linear strip of the scene. Variations of the sensor layout are possible.

15 Figure 1 is a representation of the data cube and the orientation of the spatial and
16 wavelength information. IHPS forms a series of pattern vectors through the concatenation
17 of the outputs of multiple sensors. Each sensor measures a different attribute of the system
18 being observed, and has a consistent relationship to all the other sensors.

19 Each frame 210 comprises multiple lines 205; each line 205 being the spectral
20 characteristic for a specific point in the scene which correlates to a specific coordinate of the
21 area scanned. Each frame 210 is configured such that the spatial information is expressed

1 along the X axis and wavelength information is contained in the λ direction. Data cube 200,
2 as illustrated in Figure 1, is created by the concatenation of successive frames 210 (different
3 spatial strips) and represents the observed spectral data of the scene provided by the
4 hypersensor. The observed spectral data, which is used to create data cube 200 is expressed
5 in vector form, and processed one spatial pixel, i.e. one spectrum, at a time. Each pixel is
6 fed into a preprocessor (not shown) which performs normalization and purges bad spectral
7 data, bad spectral data being data corrupted or otherwise useless due to incomplete spectral
8 information.

9 Referring now to figure 2, which shows a block diagram of the basic IHPS system
10 architecture, the data from the sensors **d** 200 is entered into a processing system 100 which
11 employs a parallel-pipeline architecture. Hypersensor 10 collects data and simultaneously
12 transmits the collected data **d** 200 through two separate processor pipes, one for demixing
13 140, and one for adaptive learning operations 150. In demixer pipeline 140, demixer
14 module 20, decomposes each pattern vector into a convex combination of a set of
15 fundamental patterns c_k which are the constituents of the mixture. The decomposition is
16 accomplished using projection operations called 'Filter Vectors' F_j generated in adaptive
17 learning pipeline 150, by adaptive learning module 30.

18 Prescreener 50 constructs a survivor set/exemplar set by extracting exemplars, or
19 data collected by hypersensor 10 which may contain new or useful information. The
20 signature pattern of a weak constituent or an unresolved small target is separated from
21 background patterns which may hide the target pattern in the unmixed data. A priori

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1 knowledge about the signatures of known targets can be used, and approximate signatures of
2 unknown constituents are determined automatically. Information detailing the composition
3 of the demixed data patterns is sent to Output Module 40, along with information about the
4 fundamental patterns and Filter Vectors. Learning module 30, performs minimization
5 operations and projects the exemplar set information into a reduced dimensional space,
6 generating
7 endmembers and filter vectors.

8 For other types of hypersensors, the spectral vectors produced by the sensor array
9 would be replaced by a vector of other types of data elements, such as the amplitudes of
10 different frequencies of sound. The organization of input data vectors may also vary
11 somewhat depending on the type of sensor. Aside from these sensor-dependent variations in
12 the type and organization of the input data, the operation, capabilities, and output of the
13 processing system would remain the same.

14 The parallel processing architecture illustrated in the figure 2 is a preferred structure,
15 however, this system, algorithms and hardware contained herein may be employed in a
16 system with a traditional architecture. The demixer processor pipeline 140 comprises
17 demixer module 20 which decomposes each data vector $\mathbf{d}_k$ into a convex combination of a set
18 of fundamental patterns, which are endmembers or constituents of the mixture. The
19 decomposition is accomplished using projection operators called 'Filter Vectors' generated by
20 the adaptive learning module 30.

21 The filter vectors are the column vectors of minimum magnitude constituting matrix

E such that:

$$\mathbf{E}^T \mathbf{E} = \mathbf{I}$$

I is the identity matrix, and E is the matrix whose columns are the endmember vectors. If the vector space defined by the endmembers is N dimensional, and each data vector **d** is a convex combination of the endmembers plus a noise vector **N**, then:

$$\mathbf{d} = c_1 \mathbf{E}_1 + c_2 \mathbf{E}_2 + \dots + c_n \mathbf{E}_n + \mathbf{N}$$

Where $c_1, c_2, \dots, c_n$ are real, non-negative, numbers, and $\mathbf{E}_1, \mathbf{E}_2, \dots, \mathbf{E}_n$ are the endmember vectors of the system. Stated alternatively:

$$\mathbf{d} = \mathbf{E} \mathbf{c} + \mathbf{N}$$

Where **c** is the column vector whose elements are $c_1, c_2, \dots, c_n$.

Filter vectors allow the signature pattern of a weak constituent or unresolved small target to be separated from background patterns which may hide the target pattern in the spectral data. Filter vectors demix the spectrum by projecting out one endmember at a time.

CHOMPS is not limited to filter vector manipulations to demix the spectrum. There are several methods known in the art to demix the spectrum, such as the use of spectral matched filters (SMF) or pseudoinverses, any of which may be suitable for compression use.

Information vector **c** detailing the composition of the demixed data spectrum is sent to Display/Output module 40 from the demixer module through the demixer pipeline 140, along with endmembers **E** about the fundamental spectra patterns, and filter vectors from adaptive learning module 30 via the adaptive learning pipeline 150. Display/Output module

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40, displays the distribution of the constituents of the scene, transmits, or stores the demixed data for later analysis.

The adaptive learning pipeline 150 comprises prescreener 50, and adaptive learning module 30. The object of prescreener 50, is to generate the exemplar set $\{S\}$ to a user specified precision by comparing each incoming spectral vector $\mathbf{d}$ to the updated exemplar set $\{S\}$.

Referring now to figure 3 which shows a logical flowchart for the operation of prescreener 50, once the prescreener 50 receives data vectors $\mathbf{d}$ from preprocessor (not shown), prescreener 50 generates a reduced set of vectors or exemplar ensemble called the survivor or exemplar set 55. Exemplar set 55 is then transmitted to adaptive learning module 30. Prescreener 50 reduces the amount of data processed by discarding spectral signatures which contain redundant information. This reduces the computational burden on the other elements of the learning pipeline. The exemplar set 55 is generally less than 1% of the total input stream, but its size varies depending upon the conditions and applications.

In CHOMPS, prescreener 50 is implemented in several different ways, depending on the application's timeliness requirements and the processing system hardware. In a preferred embodiment the prescreener module is implemented using multithreaded or messaging multiprocessor operation. Referring now to figure 14 which shows a block diagram of ALM processor pipeline 150 employing multithreaded operation, data generated by sensor 10 passes through multiple processor pipes 49. The data set is segmented so that each prescreener 50 processes a different section of the input stream. Prescreeners 50 are coupled

1 to allow each prescreener 50 to share exemplar set information, updating and receiving
2 updates from the other prescreeners. This allows each prescreener 50 to build a complete
3 exemplar set $\{S\}$ which reflects the exemplars extracted from vector data set $\{d\}$ by each
4 prescreener 50. In multithreaded operation the prescreeners 50 can also be decoupled, for
5 independent operation. In this mode, each prescreener 50 processes the complete data set ,
6 and a separate software module (not shown) reconciles the output of the parallel prescreeners
7 into a single exemplar set.

8 The complete and updated exemplar set $\{S\}$ is then passed to the ALM 30 for
9 endmember generation. The endmember data and filter vectors are passed to the output
10 module.

11 CHOMPS is thus able to quickly and efficiently sample a very large data set and
12 generate a exemplar set by prescreening large "chunks" of the data set $\{d\}$ simultaneously.
13 Coupled with the CHOMPS compression and computational management techniques
14 discussed throughout this text, the ability to employ parallel processing at the prescreener
15 level results in a substantial improvement in the efficiency of IHPS, significantly extending
16 the real time operation envelope.

17 The multiprocessor configuration illustrated in figure 14 may also be employed using
18 multiple prescreeners distributed in a network of machines. CHOMPS is also capable of
19 being employed using a single threaded operation, where each vector is processed
20 sequentially by a single processor.

21 Referring now to Figure 3, which illustrates a flowchart of the logical operation of

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prescreener 50, prescreener 50 constructs the exemplar set $\{S\}$ by comparing 54 the data spectra of the most recent pixel sampled with existing members of the exemplar set 55. The exemplar set is generated by performing dot operations in accordance to the relation:

$$\mathbf{d}_i \cdot \mathbf{S}_j > 1 - \epsilon$$

where, $\mathbf{d}_i$ is the i th newly sampled data vector, $\mathbf{S}_j$ is the j th existing exemplar set vector, and ϵ is variable controlling threshold sensitivity. Here, the vectors $\mathbf{d}_i$ and $\mathbf{S}_j$ are assumed to be normalized to unit magnitude. Thus, the condition $\mathbf{d}_i \cdot \mathbf{S}_j = 1$ means that the two vectors are identical and the condition $\mathbf{d}_i \cdot \mathbf{S}_j > 1 - \epsilon$ means that they are almost identical if ϵ is small. Vectors for $\mathbf{d}_i$ which meet the above condition 57 for any exemplar $\mathbf{S}_j$ are discarded 52 and the next vector is examined. Discarded vectors are not included in the exemplar set. The rejection count for each exemplar is stored in an array for future recall. The value of ϵ , which is set by the operator or a control system, is a function of the exemplar set size desired, memory length for exemplar set values, desired thruput of data and the noise in the signal 56. Generally, as the value of ϵ is increased, the sensitivity of the system is decreased. The pruner 51 is a memory management device which determines when a exemplar set vector $\mathbf{S}_j$ should be purged from the memory. Pruner 51 monitors the exemplar set 55, and adjusts the control parameters to control exemplar set size. This is accomplished by setting the value for ϵ 54, and the maximum allowed age of a exemplar, which determines the threshold for additions to the exemplar set and the time a exemplar is

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1 allowed to remain in the exemplar set $\{S\}$ without being regenerated.

2 Exemplar set vector, S_j , used in the $d_i \cdot S_j > 1-\epsilon$ comparison is preferably chosen
3 via the use of a structured search technique to minimize the number of dot operations while
4 offering thorough analysis of the exemplar set 55. This may be accomplished by comparing
5 54 the newly sampled data vector d_i with the most recent vectors entered into the exemplar
6 set $\{S\}$. Other search methods which minimize the number of operations necessary for
7 thorough matching are also suitable. CHOMPS employs several such structured techniques
8 designed to minimize the number of operations necessary for effective prescreener operation
9 discussed in detail below.

10 The computational management techniques employed by CHOMPS is referred to as
11 Focus searching. Focus searching includes priority searching and zone searching which
12 generally relate to focusing the comparisons of the incoming data vector d_i to the exemplars
13 S_j so that relevant exemplars can be quickly located, and to reduce the number of exemplar
14 comparisons necessary, before a determination can be made as to whether a new data vector
15 d_i is similar to an existing exemplar S_j .

16 In a priority search CHOMPS will assign a higher priority to some exemplars than
17 others on the basis of an exemplars age, past comparisons or some other statistical basis.
18 The exemplars designated with the higher priority are initially used in the $d \cdot S > 1-\epsilon$
19 prescreener comparison. Exemplars with a lower priority are used later, if necessary.

20 In a preferred embodiment, one such computational management technique CHOMPS
21 employs is in the form of a priority search technique called a Pop-up test. The pop up test

1 uses a data structure called a pop up stack. The pop-up stack is a subset of the exemplar set
2 $\{S\}$ containing only the exemplar vectors S_j that most recently rejected an incoming
3 spectral data vector d_i . The pop up stack is comprised of the most recent exemplar entry,
4 and the exemplar that most recently rejected a candidate exemplar. When a data vector is
5 determined to be dissimilar from the other exemplar set members it is entered into the pop
6 up stack.

7 Referring now to figure 16, which shows a flowchart of the pop up stack test,
8 prescreener first receives a data vector d_N from the sensor 556, where N is just the order in
9 which the vector is received. Prescreener then performs the standard dot product
10 comparison to determine if d_N is similar to S_j . If the condition in the inequality is met, d_N is
11 rejected as similar to S_j or repetitive data 565 and the next data vector d_{N+1} is retrieved,
12 566. S_j is then placed at the top of the stack 567, resulting in the next data vector sampled
13 being compared to S_j first. If the condition is not met, the prescreener retrieves the next
14 exemplar in the stack S_{j-1} 555, and repeats the $d_N \cdot S_j > 1-\epsilon$ comparison 564 where $S_j =$
15 S_{j-1} . If the condition is met, prescreener again rejects d_N as similar 565, places S_{j+1} at the
16 top of the stack 567 and retrieves the next data vector d_{N+1} for comparison 566, 556. If the
17 condition is not met, the prescreener will go on to the next text 570.

18 The pop up stack thus gives priority to the last exemplar to reject a data vector as
19 similar. Called a rejector, this exemplar is statistically more likely to be similar to the next
20 incoming data vector than an exemplar with a more distant rejection history. Thus the pop
21 up test improves the chances of quickly classifying a vector as similar with a single

1 comparison operation. Other variations of the pop up stack are possible, for instance the
2 newest rejector may not be assigned highest priority (used in first comparison), it may just
3 be given a higher priority the majority of the other exemplars.

4 Preferably, the pop up test is performed for no more than 2 or 3 cycles, however,
5 multiple iterations of the pop up test may be performed. In the preferred embodiment, after
6 2 or 3 cycles, CHOMPS next performs a Zone search.

7 In a zone search CHOMPS chooses a point of reference, and defines the exemplar set
8 $\{S\}$ and the incoming data vectors d according to their relation to the reference. The
9 exemplar data set $\{S\}$ is labeled and stored according to some defined relationship with the
10 reference point structured to allow the prescreeener to quickly recall exemplars S_j which meet
11 parameter in relation to data vector d_i . Thus CHOMPS can use the incoming data vectors
12 relation to the reference point to define a zone of exemplars to compare with d_i and
13 determine whether the incoming data vector d_i contains new information.

14 In a preferred embodiment CHOMPS designates a vector as a reference point. These
15 vectors are referred to as reference vectors. The reference vector is used as a reference point
16 from which the vectors of the exemplar set $\{S\}$ and data set $\{d\}$ are defined. Reference
17 vectors may be arbitrary, however a further reduction in the number of computations
18 necessary is achieved if the reference vectors are selected such that the exemplar projections
19 yield the maximum possible spread in each reference direction. Reference vectors may be
20 chosen as approximations to the largest principal components of the current exemplar set.
21 Alternatively, the reference vector may be initially chosen arbitrarily. This would likely be

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1 so immediately after the system has started up: at that time, the endmembers are themselves
2 arbitrary and thus using them to form the reference vector would have no value. Once the
3 prescreener constructs the exemplar set, CHOMPS would preferably use a Principal
4 Components Analysis to designate one or more reference vectors. This is done by
5 inspecting the values of each component of each endmember, and form the reference vector
6 from the largest value of each component, e.g. for the n elements of the endmembers, inspect
7 the first element of each endmember and making the largest the first element of the
8 reference vector, and do the same for the second, third, etc., element until the reference
9 vector is formed. If one wishes plural reference vectors (e.g. the embodiment of figure 18,
10 discussed below), one can repeat this for the second largest components, third largest, etc.

11 In the Principal Components Analysis, CHOMPS uses the exemplar vectors as well
12 as the rejection count for each exemplar to estimate the covariance matrix. As more image
13 pixels arrive, the reference vectors are updated, based on mission requirements and
14 considerations as to whether an update is beneficial. In CHOMPS, the data vectors are
15 addressed on the basis of their projection onto the reference vector.

16 Referring now to figure 15 which illustrates a reference vector R and exemplar set
17 vectors S_x projected onto it, the angle θ_x between the reference vector and each incoming
18 data vector is computed. The reference angle for each exemplar is stored in an array or
19 table along with a notation designating which vector the angle θ_x represents for future
20 recall.

21 In a preferred embodiment the exemplar set data, the exemplar number and its

1 orientation to the reference vector is contained in a linked list or hash table, known in the
2 art, such that each exemplar can be quickly located and recalled by the prescreener as a
3 function of the reference angle θ_N . A hash table is a list consisting of a tabulation of angular
4 bins spanning the angular range into which all data vectors $\mathbf{d}$ will lie, e.g. 360 degrees, each
5 bin being, e.g. several degrees. Associated with each bin is a list of exemplar vectors whose
6 angles with respect to the reference fall within the bin. Thus, the actual reference angle
7 need not be stored, the reference angle is determined as a function of which address the
8 entry occupies. As new entries to the linked list are made the address pointers are changed,
9 rather than shuffling and reloading the entire array each time an exemplar is changed. In
10 particular, as each new data vector $\mathbf{d}$ arrives, its angle with respect to the reference is
11 determined, and the bin corresponding to that angle identified. To determine whether vector
12 $\mathbf{d}$ matches any exemplar vector, one need only compare $\mathbf{d}$ with the exemplars associated with
13 that bin, not all exemplars, making the search more efficient.

14 A preferred embodiment of CHOMPS also uses a form of the Bullseye test to locate
15 the exemplars in the current exemplar set which are likely to reject the new data vector $\mathbf{d}$ as
16 similar.

17 In the Bullseye test, CHOMPS uses the data vectors projection on the reference
18 vector in concert with the exemplars projection on the reference vector to eliminate all
19 existing exemplars that could not possibly match the incoming vector. CHOMPS
20 accomplishes this by constructing a cone which defines the zone in which possible matches
21 may occur and excluding exemplars which do not fall within that range.

1 The bullseye test uses the angle defined by the new data vector and the reference
2 vector to locate all exemplars in the current set that match the new spectral vector to the
3 specified angular precision θ_ϵ about the reference where $\theta_\epsilon = \cos^{-1}\epsilon$. Those exemplars are
4 then used by the standard prescreener comparison inequality $(\mathbf{d}_i \cdot \mathbf{S}_j > 1-\epsilon)$ to make a
5 determination as to whether $\mathbf{d}_i$ is similar to $\mathbf{S}_j$.

6 Figure 17 illustrates reference vector $\mathbf{R}$ 600 and cone 610 defining a range in which a
7 possible match (rejecting exemplar) may occur. Only exemplars within match zone, 620-
8 622 will be compared to the new data vector. These exemplars, contained in match zone 650,
9 which form an annulus having a center at $\mathbf{q}_i$ 660 with maximum thickness $2*\epsilon$, are
10 representative of those vectors which have similar projections onto the reference vector
11 within the selected precision. If an exemplars projection does not fall into the match zone,
12 there is no need to compare that exemplar the to data vector $\mathbf{d}_i$ because there the data
13 vector $\mathbf{d}_i$ cannot be similar within the desired precision, defined by the thickness of match
14 zone 650.

15 In the bullseye test CHOMPS determines which vectors lie within the annulus by
16 keeping an indexed list of entries in the exemplar table, ordered by angle to the reference
17 vectors, e.g. a hash table, link-list, or other appropriate search structures. Once the zone is
18 computed (i.e. θ_ϵ), a zig-zag search is performed where the candidate vector is compared to
19 the exemplars with angles starting at θ_0 . To perform this search, one addresses the angle
20 bin in the hash table corresponding to vector $\mathbf{d}$'s angle with the reference vector, and tests
21 whether $\mathbf{d}$ and any of the exemplars $\mathbf{S}$ associated with that bin match. If not, the exemplars

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1 in the next adjacent bins are sumularly addressed. This continues, addressing bins above and
2 below the first addressed bin, and further away from the first addressed bin, i.e. bins
3 associated with angles which differ from **d**'s angle by increasingly large amounts. In this
4 manner, **d** is compared first to exemplars with the highest likelihood of a match, based on
5 the relative angular orientation of **d** and the exemplars, making it likely that, if there is a
6 match, it will show up quickly, thus increasing computational efficiency. If the entire zone
7 does not produce a match the vector is determined to contain new information, designated as
8 a new exemplar and added to exemplar set **{S}**.

9 Thus through the use of reference vector **R** and the bullseye test, the number of
10 comparisons necessary to test the entire exemplar set are reduced from several thousand, to
11 something on the order of 20, on the average.

12 In an alternative embodiment of the bullseye test a substantial increase the precision
13 and speed of the search is realized by designating multiple reference vectors, each one
14 having its own associated bullseye. One such embodiment is depicted in figure 18, which
15 shows what may be described as a double bullseye cone. A first cone 610 is defined in
16 relation to reference vector **R** and the second cone 710 is defined in reference to second
17 reference vector **R₂**, 700. Exemplars that are candidates to match the new data vector are
18 located within the intersection of the match zones for each reference vector 777* and 888.
19 Through the use of multiple bullseyes defined by multiple reference vectors, the "hot zone"
20 or area in which a likely matching exemplars must reside is reduced. Only the vectors
21 which simultaneously occupy both match zones are possible matches and need be compared

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1 to the new data vector. Referring to the figure 18, the only vector which meets this test
2 requirement is exemplar 620. In effect, one generates separate hash tables (or the
3 equivalent) for the exemplars with respect to each reference vector. One then tests d against
4 exemplars which are within a preselected angular distance from both references, e.g. by the
5 zig-zag procedure or equivalent. Thus, CHOMPS is able to conclude that all exemplars in
6 the data set are not rejectors (dissimilar to data vector d), with the possible exception of
7 exemplar 620. By employing CHOMPS and a variation of the bullseye test, the prescreener
8 is able to *exclude* the majority of the exemplar set from the prescreener's comparison test
9 (every exemplar except exemplar 620), and designate the incoming data vector as similar or
10 dissimilar to the exemplar set exemplars after a comparison of the data vector to exemplar
11 620, a single comparison.

12 Excluding the 2 or 3 comparisons for the pop-up stack, the only one dot product
13 operation need be processed before the prescreener can determine whether the new data
14 vector contains new data and should be added to the exemplar set.

15 Alternative embodiments of the zone type test may be employed to minimize the
16 computational load on the prescreener depending on mission requirement and the precision
17 desired. For example an avatar bullseye test may be employed. In the avatar bullseye test,
18 only the exemplars with the highest vector rejection totals are used rather than the complete
19 exemplar set.

20 In yet another version of the bullseye test, the match zone width can be diminished
21 by a significant factor with minimal generation of redundant exemplars but with an increase

1 of algorithm speed. For a candidate exemplar which makes an angle θ_0 with the reference
2 vector the width of the match zone is given by δ where:

$$\delta = 2 \sin \theta_0 \sqrt{1 - \epsilon^2}$$

3 The data set describing a scene may be processed using either of three modes which
4 include the Automatic scene segmentation mode, the Full scene mode or the
5 Adaptive/continuous mode.

6 In the Automatic scene segmentation mode, the scene is divided into a series of
7 segments and is processed by the prescreeener one segment at a time. One way to perform
8 such a segmentation would be to partition data at points where the data has caused a
9 decidedly "sharp" or "large" change in system dimensionality, i.e. the number of system
10 Endmembers.. Segment size is determined as a function of the exemplar set size. This
11 variation offers several advantages, particularly when attempting to resolve dynamic scenes.
12 With a dynamic or complex scene, in general, a larger exemplar set is required to maintain a
13 specified precision. As the number of exemplars increases, the processing time increases
14 very steeply and the compression ratio decreases. Automatic segmentation may also increase
15 compression efficiency because the dimensionality and the exemplars added into a scene
16 segment in a complex setting, only affect the segment that produced them, and not the
17 possibly simpler segments that follow.

18 The full scene mode is identical to the Automatic segmentation mode, except that a
19 scene is treated as one continuous dataset rather than a number of smaller segments.

1 While operating in the single or multiple segmentation modes, the prescreener feeds the
2 exemplar set to the Adaptive Learning Module (ALM) for endmember computation at the
3 end of each segment or block of data.

4 In the Adaptive mode the same efficiency is accomplished by injecting a finite but
5 renewable lifetime to the exemplars, that is, they are pushed to long term system memory, if
6 they have not produced a spectral match with new vectors for predefined time/frame
7 intervals. The lifetime of the individual exemplars depends on their relationship to the
8 endmembers and the priority assigned to the importance of their spectral patterns. For
9 example, exemplars that contain important subpixel objects are assigned longer lifetimes
10 than ones containing variations of background substances.

11 In the adaptive/continuous mode an ALM cycle is triggered when new exemplars
12 change the dimensionality of the enclosing subspace or when a new exemplar is defined that
13 lies outside the subspace defined by the current endmember set or other criteria, which are
14 mission dependent.

15 When a new exemplar is found, it can be projected into the orthogonal basis set
16 produced by the ALM, to confirm whether the new spectrum produced a subspace
17 dimensionality change. A projection in the endmember space, utilizing the current matched
18 filter vectors, indicates whether the subspace has expanded past the bounds of the current
19 space, determined by the shrinkwrap component of the ALM. Either test will signal a
20 trigger to the ALM. Additional criteria, such as the number of image frames since the last
21 ALM, are used to avoid triggering excessive numbers of learning cycles.

1 Referring again to figure 2, the exemplar set data, as computed by prescreener 50 is
2 input 58 into adaptive learning module 30. Learning module 30, computes from the
3 exemplar set, a set of endmembers $\{E\}$ which together span the current scene. Endmembers
4 are a set of fundamental patterns (vectors) from which any pattern vector in the data set can
5 be reconstructed as a convex combination in reduced dimensional space, to within an error
6 determined by the noise or other error criteria. The requirement that all of the observed
7 spectral vectors d_k be representable as convex combinations of conventional basis vectors,
8 insures that the decomposition makes sense as a physical mixture of constituents, since any
9 such mixture must have this property. The resulting patterns conform as closely as possible
10 to signatures of actual constituents of the scene.

11 Referring now to figure 12, learning module 30, may employ an ordered Gram-
12 Schmidt analysis using salients to construct a reduced dimensional spanning space 125,
13 while retaining the spectral information contained in the exemplar set. The spanning space is
14 constructed based on a spectral uniqueness hierarchy. The observed spectra of the exemplar
15 set, expressed as vector data are then projected into the spanning space 126. A pixel purity
16 determination algorithm may also be employed to define a subset of the salients, followed by
17 a Gram-Schmidt analysis to complete the set. Computation of the endmembers is performed
18 by learning module 30 by projecting the exemplar set data into a reduced dimensional
19 spanning space using a Gram-Schmidt/Salient analysis of the exemplar set data, and
20 employing shrink wrap minimization 127, to minimize the spanning space volume defined
21 using Gram-Schmidt/Salient analysis. The endmembers are defined by the vertices of the

1 hyper triangle defined by the minimized spanning space 128, as illustrated in figure 8.

2 **Gram-Schmidt/ Salient Analysis**

3
4 The spanning space is defined by using a Gram-Schmidt / Salient analysis of the
5 exemplar set vectors. In the parameter vector space which contains the exemplar set data,
6 one first determines the two vectors which are furthest apart in the space, then, in the plane
7 formed by these two vectors, select two mutually orthogonal vectors which lie in the plane.
8 These mutually orthogonal vectors are for convenience called basis vectors, for reasons made
9 apparent below. Next, select the vector in the data cube which is furthest from the plane and
10 identify the hyperplane in which the basis vectors, and the newly selected vector, lie, and
11 select a third basis vector such that it lies in the hyperplane and is mutually orthogonal to
12 the other two basis vectors. This process is repeated, and one accumulates more and more
13 mutually orthogonal basis vectors, until the most distant remaining vector is found to be
14 within a preselected distance of the hyperplane containing all the basis vectors. At this point,
15 the exemplar set vectors are projected onto the reduced dimensional space defined by these
16 basis vectors.

17 Through the reduction of the dimension of the vector space in which one must work,
18 CHOMPS correspondingly reduces the number of operations one must do to perform any
19 calculation.

20 Since none of the data vectors lie very far outside the hypervolume spanned by the basis
21 vectors, projecting the vectors into this subspace will change their magnitude or direction
22 very little, i.e. projection merely sheds components of each vector which were small already.

1 Furthermore, because such components are necessarily too small to correspond to significant
2 image features, these components are disproportionately likely to be noise, and discarding
3 them will increase the system's signal to noise ratio.
4
5

6 Gram-Schmidt \ Salient analysis of the exemplar set data is performed in accordance
7 with the following algorithm:
8

9 a) Designate the two exemplar vectors farthest apart, V_1 and V_2 . Figure 4 illustrates
10 the orientation of V_1 and V_2 and the plane that V_1 and V_2 define.
11

12 b) Generate a 2 dimensional orthogonal set of basis vectors from V_1 and V_2 labeled
13 V_{10} and V_{20} in the plane defined by V_1 and V_2 , labeled as PV_{012} as illustrated in Figure 5.
14

15 c) Determine the salient vector (vector displaced farthest from plane) in relation to
16 plane PV_{012} , defined in Figure 6 as $\sim S_1$.
17

18 d) The salient $\sim S_1$ can be represented as a sum of vectors $S_{1\perp}$ and $S_{1\parallel}$, where $S_{1\perp}$ is
19 orthogonal to the plane PV_{012} and $S_{1\parallel}$ lies in the plane. Use the Gram-Schmidt procedure
20 to find $S_{1\perp}$, and call this V_{30} . V_{10} , V_{20} and V_{30} now define a subspace in 3 dimensions. See
21 the figure 7. representation of the subspace created by this step.
22

23 e) Select the salient $\sim S_2$ which is the exemplar vector farthest from the subspace
24 defined by step (d).
25

26 f) Generate a new orthogonal direction from $\sim S_2$ defined as V_{40} . V_{40} coupled with V_{10} ,
27 V_{20} , and V_{30} now defines a subspace of 4 dimensions.
28

g) Steps (e) and (f) are repeated to define a spanning space of N dimensions. The distance out of the current subspace of the salient selected at each step is the maximum residual error which would be incurred by projecting all of the exemplars into the subspace. This decreases at each stage, until the remaining error is within a specified error tolerance. At this point the subspace construction process is complete. The value of N is the number of dimensions necessary to allow the projection of the exemplar set data vectors into the subspace while at the same time preserving important but infrequent signatures.

The Gram-Schmidt \ Salient analysis is the preferred subspace determination for CHOMP, however CHOMP is not limited to the Gram-Schmidt \ Salient method for subspace determination. Other methods known in the art may be employed including but not limited to PCA methods, and Pixel Purity methods.

Shrink Wrap

Once the N -dimensional spanning space is defined, a convex manifold in the form of a hypertriangle within the spanning space is generated using shrink wrap minimization. Shrink wrap minimization of the spanning space is a simple optimization operation, that maintains the condition that all of the data vectors projected into the reduced dimensional space are contained within the hypertriangle. The vertices of the hypertriangle are the endmembers, and the volume defined by the hypertriangle itself is the locus of all possible mixtures (convex combinations) of endmembers. The shrink wrap process determines good

1 approximations of the physical constituents of the scene (endmembers), by insuring that the
2 shape and orientation of the hypertriangle conforms as closely as possible to the actual
3 distribution of the data vectors (exemplars). The exemplars are assumed to be mixtures of
4 the actual constituents. The number of endmembers is equal to the dimension of the
5 spanning space.

6 The salients may be used to guide the shrink wrap process. Referring to figure 8,
7 hypertriangle $T_{S_1S_2S_3}$ is defined by salient vectors, however, other vectors which include
8 data may not be within the spanning space which $T_{S_1S_2S_3}$ defines, as depicted in figure 9.

9 The shrink wrap operation must satisfy the condition that all of the data vectors projected
10 into the spanning space be contained within the volume defined by convex manifold $T_{E_1E_2E_3}$.

11 The shrink wrap operation starts with $T_{E_1E_2E_3} = T_{S_1S_2S_3}$ and then expands or contracts the
12 triangle $T_{E_1E_2E_3}$ by manipulating the vertices, E_1 , E_2 and E_3 , or by manipulating the
13 orientation of planes that define $T_{E_1E_2E_3}$, by the minimal amount to fulfill the above stated
14 condition.

15 For purposes of example, the method described above and the following methods
16 have been found effective, however, a combination of one or more of the disclosed methods,
17 or any other minimization method which maintains the condition that the majority of the
18 data vectors be contained within the minimized space is suitable.

19 Adaptive learning module 30 generates a set of filter vectors $\{F_i\}$ and endmembers
20 $\{E_1, E_2, E_3, \dots, E_N\}$ in accordance with one of the following procedures, or variants thereof:

21 Method 1

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1 With reference to figure 10a, find a set of endmembers $\{E_i\}$ such that each endmember E_i is
2 matched to a salient vector $\sim S_i$, and is as close as possible to its salient, subject to the
3 condition that all the data vectors are inside the hypertriangle with vertices $\{E_i\}$. I.e.,
4 minimize

$$C = \sum_{i=1}^{N_D} (E_i - S_i)^2$$

5 subject to the constraints $F_i \cdot d_k \geq 0$ for all i and k where N_D is the number of dimensions.

6 The filter vectors are computed from the candidate endmembers as described above. This
7 constraint condition means that all the coefficients of the decomposition of d_k into

8 endmembers are non-negative, which is equivalent to saying that all d_k are inside $T_{E_1 E_2 \dots E_N}$.

9 This is a nonlinear constrained optimization problem which can be solved approximately and
10 quickly using various iterative constrained gradient methods.

11 Method 2

12 Compute a set of filter vectors $\{F_{si}\}$ from the salients $\{\sim S_i\}$, using the formulas previously
13 provided. These vectors will not, in general satisfy the shrink wrapping constraints see

14 figure 10b. Find a new set of Filter vectors $\{F_i\}$ such that each Filter vector F_i is matched
15 to a salient Filter vector F_{si} , and is as close as possible to its salient filter, subject to the

16 condition that all the data vectors are inside the hypertriangle. I.e., minimize

$$C = (F_i - F_{si})^2$$

17 subject to the constraints $F_i \cdot d_k \geq 0$ for all k . This is a set of independent quadratic
18 programming problems with linear constraints, which can be solved in parallel using
19

1 standard methods. The decoupling of the individual filter vector calculations increases
2 computational efficiency. Manipulation of the Filter vectors instead of the endmember
3 vectors is equivalent to manipulating the plane faces of the triangle instead of the vertices.
4 Given solutions for the Filter vectors, find the endmembers using the same procedure used
5 to compute Filter vectors from endmembers (the defining relationships are symmetric except
6 for a normalization constant).

7 Method 3

8 With reference to figure 11, find an approximate centroid C_d of the set of exemplar vectors,
9 and then find the hyperplane of dimension one less than the dimension of the enclosing
10 space which is closest to the centroid. Hyperplane 120 divides the complete subspace into
11 two halves, and the minimization is subject to the constraint that all the exemplar vectors
12 d_k must be in the same half-space as the centroid $\{c_d\}$. The normal to the optimal
13 hyperplane 120, is F_1 , the first filter vector, and the condition that all the exemplars are in
14 the same half-space is equivalent to the constraint that $F_1 \cdot d_k \geq 0$ for all k . This process is
15 equivalent to finding a vector F_1 with a fixed magnitude which minimizes the dot product F_1
16 $\cdot C_d$ subject to the constraint $F_1 \cdot d_k \geq 0$ for all k . As such it is amenable to solution using
17 conventional constrained optimization methods. The hypertriangle T_{E1E2E3} can be
18 constructed out of a set of suitably chosen optimal (locally minimal distance to the centroid)
19 bounding hyperplanes which form the faces of the convex manifold. The normal to each face
20 defines the associated filter vector. Again, the endmembers can be determined from the Filter
21 vectors at the end of the shrink wrapping process.

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1 Referring to figure 12 and figure 2, once the endmembers and filter vectors are
2 computed adaptive learning module 30 stores this endmember and filter vector data, along
3 with data reflecting the exemplar set, and source vectors 33 for future recall. The adaptive
4 learning module 30 then searches the exemplar set for any changes 148. If the system
5 detects change in the exemplar set 99, the basis and shrink wrap processes are repeated 141.
6 This process allows the system to continually learn and adapt to changes in the
7 environment. Endmember data and the accompanying exemplar set and source data can be
8 labeled as being consistent with a particular threat or target allowing the system to learn
9 and remember the signature of specific targets in real time 34.

10 Again, referring to figure 2, the filter vectors and endmember data stream are
11 transmitted from learning module 30, to demixer module 40, for computation of the
12 endmember coefficients. The original data set from the sensor is also transmitted to
13 demixer module 20 through the first processor pipe.

14 Demixer module 20 may contain several processors, each of which convolves the
15 unprocessed data vector with a different filter vector. These operations could be performed
16 sequentially on a single fast processor, but in the best mode they are performed in parallel.
17 The output of demixer module 20, is a vector called the endmember coefficient vector, the
18 jth element of which indicates the fraction of the jth fundamental pattern which is present in
19 the unprocessed data vector. The endmember coefficients indicate the amplitude of the
20 signal from the associated endmember, in a mixed spectrum.

21 Demixer module 20 convolves the unprocessed data vector and computes the

1 endmember coefficient in accordance with the equation;

$$F_J \cdot d_k = \sum_{j=1}^n C_{jk} F_J \cdot E_j + F_J \cdot N_k \approx C_{jk}$$

2 where F_J = said filter vector, d_k = said data set, c_{jk} = said endmember coefficient, N_k =
3 noise vector, E_j = said endmember and n is the number of endmembers.

4 Demixer module 20 next computes the fraction coefficient 131, which tells what
5 percentage of the photons from the given pixel are associated with the endmember in
6 accordance to the equation:

$$C_{jk \text{ fraction}} = \frac{C_{jk} A(E)_j}{A(d_k)}$$

7 where $A(d_k)$ is the area under vector d_k , i.e. the sum of the elements of d_k .

8 Figure 13 illustrates the flowchart for demixer module operation including the
9 demixer module's 20 function in the system's learning process. If the pixel information
10 passed from the preprocessor indicates bad data or an unlearned spectrum 133, 134 demixer
11 module 20 routes that information to the display/ output module 40 with a notation of the
12 status of the pixel data 135, 136.

13 The spectral information, filter vectors, and endmember coefficients is passed to the

$$d_k = \sum_{j=1}^n C_{jk} E_j + N_k$$

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display/ output module 40 for display and further processing 138. The spectral characteristics of the data is stored, transmitted or displayed in terms of endmembers and endmember coefficients maintaining the relation:

where $\mathbf{d}_k$ = said data set, $\mathbf{c}_{jk}$ = said endmember coefficient and c is ≥ 0 , $\mathbf{N}_k$ = noise and $\mathbf{E}_j$ = said endmember.

CHOMPS feature three compression modes which provide significant compression of the massive data stream coming from the sensor. These compression modes in a preferred embodiment take advantage of the priority and zone searching techniques disclosed above.

In the first and most basic compression packaging mode, the CHOMPS algorithm employs the basic IHPS algorithm, using the computational management techniques described in this text, and produces a compressed data set which expresses the scene as, a set of fraction planes belonging to each endmember $\mathbf{E}$. Compression results from the low dimensional space in comparison to the number of bands employed by the sensor.

For purposes of example, assume a sensor operates in 200 bands, the data set produced by that sensor as input for IHPS will thus tend to have what approaches 200,000,000 scalar values. This assumes only 1,000,000 pixels in a scene. IHPS expresses the scene as fraction planes. The IHPS endmember form compresses the data stream by the ratio:

where N_B is the number of bands and N_E is the number of endmembers necessary to describe the scene.

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$$\frac{N_B}{N_E}$$

1 For many natural scenes at a reasonably small loss rate, IHPS requires on the order
2 of 10 endmembers to describe the scene which results in a compression ratio of 20:1 for a
3 200 band sensor.

4 Following each ALM cycle, all exemplars for the segment are either left
5 uncompressed, are projected into the orthogonal basis space or are projected to the current
6 shrinkwrap.

7 Referring to figure 19 which shows a simple logical flowchart of the second
8 compression packaging mode in which the data is expressed in terms of the exemplars and
9 two maps used for reconstruction of the data set **d**. The complete data set is received from
10 the sensor 701, containing for purposes of example approximately 200 million scalar values
11 describing a scene. CHOMPS next uses the prescreener to perform the prescreener
12 comparison 702, and reduces the complete data set to an exemplar set 703. The exemplar
13 set size can be adjusted by the user on the basis or the precision desired or other mission
14 requirements, but for purposes of example may be 10,000 vectors in size (2,000,000 scalars).
15 The data are stored in the form of (1) the exemplar which rejected, i.e. matched, it, typically
16 by an index associated with that exemplar, rather than the exemplar itself and (2) the
17 magnitude of **d**, because the exemplars will typically be normalized. For a high dimensional
18 space, the bits necessary to represent the total number of exemplars, and represent the
19 magnitude of a vector, is much less than the number of bits necessary to represent the

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1 vector directly, In this manner, the system compresses the data for convenient storage. The
2 number of times an exemplar **S** rejects a data vector **d** may be recorded also, for example to
3 be used in setting the amount of time an exemplar will be retained before being removed
4 from exemplar set **{S}**.

5 Thus the data stream of 200 million scalars is expressed as approximately 10,000
6 exemplars each having 200 elements and the map information, each map containing 1 scalar
7 for each of the 1 million data set vector, rather than the 200 scalar values for each data
8 vector. This represents a data set compression of the approaching 50:1 using the wavespace
9 mode.

10 The third compression packaging mode is similar to the foregoing, except that
11 CHOMPS projects the exemplars into endmember space for additional compression.
12 Referring to figure 20 which is a flowchart of the endmember compression mode, the data
13 set is received in the prescreeener from the sensor 555 and compared to the existing
14 exemplars 556, just as in the wavespace compression mode 700. The prescreeener builds the
15 exemplar set 557, rejector index 558, and an intensity map 559 identical to that in the
16 wavespace compression mode 700. However, in the endmember compression mode
17 CHOMPS sends the exemplar set to the ALM 560, for computation of endmembers 561.
18 The exemplar set is thus projected into endmember space 562, realizing additional
19 compression. The compressed exemplar set is expressed in endmember space, each exemplar
20 now expressed as 10 or so scalars rather than the 200 or so scalar values necessary in
21 wavespace, assuming a sensor having 200 bands. The endmembers expressed in wavespace

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1 are added to facilitate reconstruction of the scene. The rejector index and intensity map are
2 also output for reconstruction of the data set. Endmember compression realizes a 100:1
3 reduction in the data transfer necessary to describe a scene. The output packet of the
4 compressed segment data consists of the exemplar list in any of the projections above, the
5 endmembers or basis vectors and the two decoding maps. Additional information can be
6 injected, such as the number of vectors replaced by each exemplar.

7 CHOMPS thus uses the Adaptive Learning Module Pipeline to construct a
8 compressed data set, along with the necessary scene mapping data, facilitating the efficient
9 storage, download and the later reconstruction of the complete data set with minimal
10 deterioration of signal information.

11 In a preferred embodiment the CHOMPS employs the following algorithm:

- 12 a) Receive data vector $\mathbf{d}_i$ into the prescreener.
- 13 b) Designate priority exemplars from the existing exemplar set and perform priority
14 testing according to the relation $(\mathbf{d}_i \circ \mathbf{S}_j = 1 > \epsilon)$ of the data vector $\mathbf{d}_i$ using the exemplars $\mathbf{S}_j$
15 designated with the higher priority.
- 16
- 17 c) If priority testing generates a match condition go to (a), if no match condition
18 produced after N iterations, continue.
- 19
- 20 d) Select at least one reference point or reference vector.
- 21

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1 e) Designate at least one match zone and perform zone testing on data vector $\mathbf{d}_i$
2 according to the relation $(\mathbf{d} \circ \mathbf{S} = 1 > \epsilon)$ using only those exemplars $\mathbf{S}_j$ which are contained
3 (to the desired precision) within the match zone.

4
5 f) If zone testing generates a match condition go the step (a), if no match condition is
6 produced add $\mathbf{d}_i$ to the exemplar set and go get next data vector $\mathbf{d}_{i+1}$ exemplars are
7 exhausted.

8
9 g) Perform compression packaging via full IHPS mode, wavespace mode, exemplar mode
10 or a combination thereof.

11
12 Obviously, many modifications and variations of the present invention are possible in
13 light of the above teachings. For example this invention may be practiced without the use
14 of a parallel processing architecture, different combinations of zone and priority testing may
15 be employed, ie., zone testing may be employed without priority testing or standard
16 compression algorithms may be employed to compress the intensity map and rejectors index.

17 It is therefore understood that the invention
18 may be practiced otherwise than as specifically described.

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ABSTRACT

The Compression of Hyperdata with ORASIS Multisegment Pattern Sets, (CHOMPS), system is a collection of algorithms designed to optimize the efficiency of multi spectral data processing systems. The CHOMPS system employs two types of algorithms, Focus searching algorithms and Compression Packaging algorithms. The Focus algorithms employed by CHOMPS reduce the computational burden of the prescreening process by reducing the number of comparisons necessary to determine whether or not data is redundant, by selecting only those exemplars which are likely to result in the exclusion of the incoming sensor data for the prescreener comparisons.

The Compression Packaging algorithms employed by CHOMPS, compress the volume of the data necessary to describe what the sensor samples. In the preferred embodiment these algorithms employ the Prescreener, the Demixer Pipeline and the Adaptive Learning Module Pipeline to construct a compressed data set. The compression is realized by constructing the data set from the exemplars defined in the prescreening operation and expressing those exemplars in wavespace with the necessary scene mapping data, or further processing the exemplars through the adaptive learning pipeline and expressing the exemplars in terms of endmembers, to facilitate the efficient storage, download and the later reconstruction of the complete data set with minimal deterioration of signal information.