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METHOD AND APPARATUS FOR DETERMINING BASIS FUNCTIONS FOR DATA OBJECTS

Field of the Invention

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The present invention relates to determining basis functions for data objects in a database, for transforming data into a more suitable domain, for instance in signal/image processing applications, multimedia coding, digital watermarking applications, etc. The invention is particularly useful for determining suitable image basis functions to represent images in an image database.

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Background

Data manipulation, whether of audio, video, images or other data and whether for analysing, storing, encoding, altering or other actions, typically involves a transformation of the set of data, from one or the original data domain to another, usually more appropriate, domain. This allows the data to be more readily or efficiently manipulated. Such transformations are conducted using a transform, made up of a number of basis functions and coefficients. As such, basis functions are one of the most common and important tools in analysing audio, video and images in multimedia processing systems, amongst others. The audio or video in an original domain is known as "data", while the data produced in the transformed domain is known as "coefficients".

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Both analogue and digital versions of transforms are available. For example, the FFT (fast Fourier transform) and the DFT (discrete Fourier transform) are very often used in audio/speech signal processing. The DCT (discrete cosine transform) and the WT (wavelet transform) are widely used in image/video data processing.

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With audio-visual data, the purpose of a transform is to convert the data into a set of transformed data that is more amenable to further manipulations, such as compression, noise removal, etc. The choice of basis function is important as the properties of the basis function decide the characters of the coefficients.

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The FFT or DFT is used to transform one-dimensional audio/speech signals from the time domain into different frequency bands, where each frequency band usually

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corresponds to a set of Fourier basis functions (sine and cosine functions in certain centre frequencies).

5 The DCT transforms two-dimensional images into coefficients representing the weights of two-dimensional regular and periodic patterns with different frequencies. The image/video data can then be organised in a base of energy-in-frequency.

10 The WT transforms one-dimensional data into a high-pass and a low-pass frequency range in the manner of subsequent 2-to-1 sub-sampling. The kernel function used in WT gives the basic properties of the transformed data and the sub-sampling keeps the scalability of such a transform.

15 The basis function and the coefficient are the two components in a transform, but the basis function is the dominant factor to determine a transform in the above classical transforms. In other words, such a transform is fixed if and only if its appropriate basis functions are determined. The coefficients are produced or changed according to the audio-visual data to which the function is applied. Therefore, when such a transform is mentioned, reference is actually made to its one basis function or a coupled pair of basis functions. For fixed basis transforms such as DCT, FFT and WT, the simplicity of
20 the basis function is their most important advantage. The disadvantage is that any basis function is only best fit to certain types of data.

A more-recently developed transform is the independent component analysis (ICA) transform. The ICA technique uses a signal processing method that transforms a
25 signal to mutually independent components in the complete statistical sense. The ICA transform is a transform to convert audio-visual data that is usually much correlated to statistically independent coefficients. In image processing, the image coefficients obtained from one ICA feature (transform) are statistically independent from those from other ICA features. In other words, each ICA feature (transform), consisting of an
30 analysis filter and a synthesis filter, uniquely and accurately represents a particular common shape in the image very well, and in a way which is very different from other features. This kind of transform gives a set of features with the least representation redundancy among them.

35 ICA originates from the criterion of statistical independence among signal components, i.e. the coefficients, so the dominant factor in the ICA transform is the

independent coefficients obtained from audio-visual objects. In other words, the only fixed factor in the ICA transform is the property of independence between coefficients. In order to meet the independence criterion, the basis functions need to be changed for every supplied audio-visual object accordingly. The ICA basis functions also have some special properties, such as: localisation, orientation, and frequency bandpass.

Although the ICA transform picks out many kinds of different ICA features from each individual image, they all have in common that the features are spatially orientated, band-passed, and localised both in the spatial and frequency domains. In other words, they are some edges and bars with certain angles, widths and lengths. These are actually the essential elements or significant shapes in 2D images.

As the characteristics of a component in the visual field closely match the properties of features in the ICA transform, most ICA image features obtained by ICA transforms represent the edge-like or bar-like details that are the most essential elements in images: perceptually significant components. Figures 1A and 1B are illustrations of certain properties of an ICA image: localisation 12, orientation 14 and band-pass 16. Figure 1A illustrates a part of a transform W for a typical image, and Figure 1B illustrates the Fourier transform of it. In both cases amplitude values are represented as grey-scale values. In Figure 1A high amplitudes are light, whereas in Figure 1B high amplitudes are dark.

DCTs and WTs use only a single set of basis functions for all kinds of audio-visual data representations, but they are easy and simple to manipulate. A set of adaptive basis functions is generated for every particularly considered audio-visual object, so that the coefficients have the required independent distribution and the basis function preserves the detailed ICA features for each object. This overcomes the limitations associated with DCT and WT of one basis function for all images, since the ICA has an individual basis function for every image, that is adaptive basis functions for each individual set of audio-visual data objects for its particular representation. On the other hand, the ICA features are troublesome to learn and there are practical problems, such as huge storage requirements, since ICA requires the storage of basis functions for every object, and time-consuming computation. For each set of data, the generation of basis functions has to be carried out before using them in analysing the data. The basis functions can also be a burden to be transmitted or stored with audio-visual objects for subsequent processing.

Summary

According to one aspect of the invention, there is provided a method of
5 determining basis functions for data objects in a set of data objects. The method
comprises: generating a plurality of sets of common basis functions for said objects and
analysing and grouping the objects. The objects are grouped among the sets of
common basis functions, with a plurality of objects grouped to individual ones of the sets
of common basis functions.

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The various steps of generating basis functions, and analysing and grouping the
objects may be repeated in a plurality of iterations.

According to another aspect of the invention, there is provided a method of
15 determining common basis functions for images in an image database. The method
comprises: classifying the images into image groups, determining whether to at least
one of: split an image group and merge two or more image groups, learning revised sets
of common basis functions, determining if the process is converging, and repeating
these steps if the process is determined to be converging or stopping, otherwise. The
20 images are classified into image groups associated with different sets of common basis
functions. Splitting an image group splits it into two or more smaller image groups.
Merging two or more image groups merges them into a larger image group. The revised
sets of common basis functions are learned based on the current groupings of images
in image groups.

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According to a third aspect of the invention, there are provided basis functions
generated according to the method of either the first two aspects.

According to a fourth aspect of the invention, there is provided a plurality of basis
30 functions for transforming images of an image database. The plurality of basis functions
comprise a plurality of sets of common basis functions. Individual images of the image
database are associated with individual ones of the sets of common basis functions, a
plurality of images with each one of the sets of common basis functions.

According to a fifth aspect of the invention, there is provided encoded data comprising image data transformed using one or more transforms based on basis functions according to the third or fourth aspect.

5 According to a sixth aspect of the invention, there is provided apparatus comprising a processor and memory means and programmed to operate according to the method of either of the first two aspects.

10 According to a seventh aspect of the invention, there is provided computer software for determining basis functions for data objects of a set of objects. The computer software comprises computer code means for each of: generating a plurality of sets of common basis functions for said objects; analysing said objects; and grouping the objects among the sets of common basis functions, with a plurality of objects grouped to individual ones of the sets of common basis functions.

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In the above aspects, the basis functions may be ICA basis functions.

Introduction to the Drawings

20 The invention will be further understood from the accompanying description of non-limitative examples, with reference to the accompanying drawings, in which:-

Figures 1A and 1B are illustrations of certain known properties of ICA basis functions;

25 Figure 2 is a schematic illustration of an image database, its clustering groups and their corresponding sets of common basis functions produced according to an embodiment;

Figures 3A to 3D illustrate the iterative process employed in an embodiment of the invention;

30 Figures 4A and 4B are illustrations of signal dependence measurements by mutual information (MI) between two signals;

Figure 5 is a schematic illustration of various MI values of a single image to different common basis functions in a database;

Figure 6 is an illustration of how confidence values can vary between images apparently belonging to the same image group;

35 Figures 7A to 7C illustrate various situations where a splitting process may be required;

Figure 8 is a flowchart of an exemplary process for learning ICA features;

Figure 9 is an overview flowchart of an exemplary approach to generating a set of common ICA basis functions for a particular image database;

Figures 10A to 10C are exemplary images in a database;

5 Figure 11 are the final sets of ICA common basis functions for the images in Figures 10A to 10C, once grouped; and

Figure 12 is a schematic representation of a computer system suitable for performing the techniques described with reference to Figures 1 to 11.

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Detailed Description

The described embodiments of the present invention are described with reference to ICA basis functions. Those are preferred as ICA provides what is currently
15 the most useful approach to encoding data into mutually statistically independent components. However, other basis functions may be useful with the present invention, for instance principal component analysis (PCA), factor analysis (FA), protection pursuit analysis (PPA), etc.

20 A preferred embodiment of the present invention provides a semi-ICA basis function technique, which generates a fixed set of ICA common basis functions with a small set number for a large database (e.g. an image database, such as for a movie). Such a technique keeps some of the merits of both the adaptive basis features in ICA and the simple basis function of the DCT and WT.

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An exemplary embodiment of the invention uses an evolutionary technique to generate one or more sets of common image basis functions by having a mutual-information (MI) based image classification and an ICA learning process. This technique can be used for generating one or more sets of common basis functions,
30 especially suitable for a particular image database, e.g. a movie, or one or more sets of general-used common basis functions for image representations for certain image categories. The work domain of this technique can be generalised to audio data.

There are two basic components in this technique in the described exemplary
35 embodiment: (1) image classification, (2) ICA learning, both of which occur in most or all of a series of iterations. Image classification is used to cluster the images in a database.

into several groups. These groups are identified by the smallest dependence value among the image's ICA coefficients. Images are thereby classified into certain common groups with similar ICA basis properties: orientation, bandpass frequency, etc. An ICA learning algorithm is used to learn the set of ICA basis functions for each image group.

- 5 Thus, a common ICA basis is learnt for each common group, using an ICA learning programme. The ideal image classification involves new techniques and approaches, whereas the ICA learning can be pure ICA learning, using existing techniques.

- Generation of common basis functions involves a system of learning common
 10 basis functions by repeating image classification and basis learning until there is convergence of one or more selected criteria. The exemplified technique is based on an evolutionary approach: clustering images into groups based on a classification criterion, such that an image is classified into the group whose ICA basis functions can represent that particular image in the best way among all groups. This may involve
 15 relating the similarity of a group's ICA basis functions to a fixed basis function; evolving image groups by competing-splitting-merging techniques; generating ICA common basis functions of image groups for next-step evolution (that is the next iteration); and gradually re-organising and fine-tuning the image groups until the clustering is converged. The ICA basis functions produced at the final stage are the expected
 20 common basis functions. Figure 2 schematically illustrates the relationship between an image database 20, individual image groups (clusters) 22 and common basis functions 24.

- In classification, the measurement used for judging how to cluster images is
 25 referred to herein as the mutual-information (MI) value, which is a dependence level among ICA coefficients obtained from a data object, such as an audio-visual data object, by a particular set of ICA basis functions. A smaller MI value means that the particular set of ICA basis functions is matched with the image to produce ICA coefficients that are more independent. The smallest MI value amongst all the MI
 30 values between an image and the different common basis functions indicates the degree to which the image belongs to the relevant basis function (its belongingness).

- Based on MI values, a confidence parameter is computed to define how close and how important the image is to its classified basis group from other groups. The
 35 bigger confidence value an image has, the more important and closer that image is to the group's common basis. The confidence parameter is adopted here as a condition to

choose images for split/merge processes. This approach is performed dynamically as the image groups may be split or merged under various circumstances so that the system is not trapped at local minima.

ICA basis learning is performed on the full set or a sub-set of images in each formed group. The confidence parameter is also used to judge which images are to be used for learning, so that only closely related or important images are chosen.

The MI value and the confidence parameter are two important parameters in the exemplary approach. The thresholds of the confidence parameter, used in splitting processing and learning processing, play key roles in determining the final outcomes of image clustering and basis functions.

Evolving

Evolving refers to the whole dynamic evolution from an initial state to an end state. The initial state can be a given set of classified images or a given set of common basis functions or any set of basis functions/images. The end state may be finally classified images and common basis sets. Evolution occurs via a number of iterations repeating the processes of image competing, group splitting and merging, and basis learning.

These processes at each evolving step (iteration) may change the number of classified groups and the images in the groups. Images that move between groups or that are split or merged to another group are considered as changed images. The number of these changed images is a parameter to measure the stability of image group clustering in the previous iteration. This parameter can be used as a cost function for measuring the convergence of the entire evolution. The evolution is considered as stable or converged when this parameter is below a certain threshold. Figures 3A to 3D illustrate the iterative process in a parallel learning scheme, in which common basis functions are learnt for all the images in parallel. Figure 3A represents the initial groupings at the beginning of the process. Figure 3B represents the groupings after one iteration. Figure 3C represents the groupings at one iteration before the final stage. Figure 3D represents the final groupings.

Within each evolutionary iteration, the approach as exemplified contains three basic processes:

- 1) *competing*: image classification judged by using the dependence measurement, mutual information (MI);
- 2) *splitting/merging*: split some large groups to remove some images to form more groups and/or merge images or small groups into one to reduce the number of image groups and enlarge diversity within that group; and
- 3) *learning*: learn basis functions from each formed group.

1. Competing

Competing is the process by which the basis group that an image belongs to is determined. This involves finding out which set of common basis functions of an image has the best ICA representation. This process uses a measurement based on ICA criteria for determining image belongingness. The parameter used in this embodiment is the signal dependence measure, mutual information (MI), which is the ultimate goal of achieving statistical independence in ICA.

In general, the MI measures the dependence (in the complete statistical sense) between signals with the same dimensions. In image feature representation, the MI is defined as a measure of the dependence among all n^2 ICA coefficients, $\mathbf{C}$, of a plurality of $n \times n$ image patches from an image (where, for example, $n = 8$). The coefficients, $\mathbf{C}$, are the result of analysing the image patches, $\mathbf{X}$, through ICA weight functions, $\mathbf{W}$, that is:

$$\mathbf{C} = \mathbf{W}\mathbf{X}.$$

The relation between the MI and the signal dependence is illustrated in Figures 4A and 4B. Figure 4A and 4B show an example of observation data having two components, as respective time series. Figure 4A shows two similar components. Figure 4B shows two dissimilar components. Where the two signals are similar, as in Figure 4A, they are more dependent, so the MI is higher. Where the two signals are dissimilar, as in Figure 4B, they are more independent, so the MI is lower. Images with small MI values form an image group, and a unique ICA basis learnt from the group is its common basis.

To determine the MI measurement of n^2 ICA coefficients of $n \times n$ image patches, this embodiment uses an approach developed by Alex Kraskov et al. [References 1-3] based on the k-nearest neighbour distance measure to estimate the mutual information. Software available at "www.fz-juelich.de/nic/cs/software", on 24 November 2004 and earlier, referred to therein as Mutual Information Least-dependent Component Analysis, is suitable for determining the relevant MI measurements. Specifically, the embodiment uses the estimator $I^{(2)}(X,Y)$ whose derivation is described in Reference 1, in particular in section C, on pages 5 and 6 of Reference 1. The estimator $I^{(1)}(X,Y)$ whose derivation is described in Reference 1, in particular in section B, on pages 4 and 5 may be used instead. These approaches are hereby incorporated by reference. Other ways of determining MI may also be used, as appropriate.

For mutual information among objects (in the main embodiment, the objects being images) X , Y , and Z , $MI(X, Y, Z) = MI((X, Y), Z) + MI(X, Y)$, that is the MI between three objects X , Y , and Z is equal to the sum of the MI between X and Y plus the MI between Z and the combined object XY . Thus, the MI can be decomposed into hierarchical levels. By iteration, one can decompose $MI(X_1, X_2, \dots, X_{n-1}, X_n)$ for any $n^2 > 2$ and for any partitioning of the set of $MI(X_1, X_2, \dots, X_{n-1}, X_n)$ into the MI between elements within one cluster and the MI between clusters.

Kraskov's approach provides the $MI(X,Y)$, where X and Y can be scalar or vector elements, so the preferred embodiment uses this decomposition rule to generate $MI(X_1, \dots, X_n)$ by recursively using $MI(X,Y)$. For 8×8 image patches, the optimal neighbour parameter (k in Reference 1) is set at 10, the additive noise (mentioned in Reference 1, in the implementation section, on page 6) is set at $1e-10$, the number of data points set at 1000 (the higher, the more time consuming in exponential way), and image patches with variance greater than 0.15 are selected for measurement.

Assume there are P images in a database and currently Q sets of common basis functions. For an image p , Q sets of ICA coefficients can be generated from the image's patches by using their common basis functions. Each set of coefficients can have its MI value calculated. The relevant MI of a set of coefficients is called MI_{pq} , which is the mutual information of ICA coefficients generated from image p by using the set of common basis functions, q ($q = 1, 2, \dots, Q$). The degree to which image p belongs in all Q common basis groups, that is the belongingness of image p to all Q common basis functions, is determined by the smallest value among all MI_{pq} ($q = 1, 2, \dots, Q$).

The smallest MI value for image p is referred to herein as $MIpq_1$, and the second smallest MI value as $MIpq_2$, where q_1 and q_2 are the corresponding common basis functions, respectively. In this simple scheme, an image can always find the most suitable set of common basis functions as the q_1 among all the available common basis functions. The images with the same suitable set of basis functions are clustered in a group.

Figure 5 schematically illustrates an image p plotted on an image database 20, amongst individual image groups 22 and common basis functions 24. Assuming lines drawn between the image p and the different common basis functions 24, the length of these lines represent the MI value $MIpq$ to each respective common basis 24. In this instance, the image p belongs to the group with the smallest $MIpq_1$ measure equal to l_1 , indicated by a solid line. The second smallest $MIpq_2$ is indicated by l_2 with a dashed line, the third smallest $MIpq_3$ is indicated by l_3 , also with a dashed line and so on.

Another parameter, confidence d , is computed as the normalised distance between the smallest and second smallest MI values $MIpq_1$ and $MIpq_2$:

$$d = (MIpq_2 - MIpq_1) / MIpq_1.$$

Parameter d defines how well the image p can be suitably represented by the common basis set q_1 against other basis sets. A large confidence value d indicates a strong belongingness of image p to the basis set q_1 , and a small belongingness to other basis sets. A small confidence value d shows a weak belongingness of image p to the basis set q_1 . The image p may, for instance, be at the boundary between the group q_1 and q_2 or others, or it may belong to another new basis set. This parameter d is also important for defining how well the entire image classification in this image database has gone and how robust the belongingness of an image to a common basis in the future application will be, through a convergence measure mentioned later.

Figure 6 is a schematic illustration helpful in understanding the effect of different image-basis closeness relationships on the confidence value. As is indicated by the boundary of common basis 1, all three images **a**, **b** and **c** belong to a first common basis 42, and have their smallest MI values as l_{a1} , l_{b1} , and l_{c1} . For the adjacent group, with a second common basis 44, the images **a**, **b** and **c** have their second smallest MI values, as l_{a2} , l_{b2} and l_{c2} . Image **a** has a larger MI difference ($l_{a2} - l_{a1}$) than image **b**'s ($l_{b2} - l_{b1}$).

This means that image **a** is closer to the first common basis 42 than image **b** is. However, assuming that image **c**'s MI difference ($I_{c2} - I_{c1}$) is the same as **a**'s ($I_{a2} - I_{a1}$), then the normalised MI differences provide further information. The normalised MI difference for **c** is:

$$(I_{c2} - I_{c1}) / I_{c1}.$$

The normalised MI difference for **a** is:

$$(I_{a2} - I_{a1}) / I_{a1}.$$

Comparing the normalised MI differences for **a** and **c**

$$(I_{c2} - I_{c1}) / I_{c1} < (I_{a2} - I_{a1}) / I_{a1}$$

- 10 since I_{a1} is smaller than I_{c1} Thus the normalised MI difference shows image **a** is the closest one to the first common basis 42 among the three images **a**, **b** and **c**.

15 In Figures 2, 3, 5 and 6, the lines dividing the groups are not drawn as centre lines between each relevant pair of bases as measurements between different groups are not comparable in Figure 2. The scale of measurement to different groups is different because the common basis functions at each group are different. It can happen that all images have small MI values to one certain group but large values to another group.

- 20 Figure 6 further contains a threshold line 46 which is explained later in the portion on learning.

The overall confidence measure, e.g. the average confidence value or the lowest confidence value of all images in the database, is another parameter to be checked for convergence of the evolution. The evolution can be considered converged when the average confidence value or minimum confidence value is above a threshold value, or the average confidence value from one iteration to another changes within only a small range.

30 2. Splitting and Merging

Splitting is where a single image group is split into two or more smaller image groups. Splitting is performed when the number of image groups is too few to represent the image clustering in the database well. There are a number of possible situations where splitting may be useful or necessary. Several examples of such situations are shown in Figures 7A, 7B and 7C:

Figure 7A - one or more image groups 52 is sufficiently big as to contain several sub-groups, with the images 54 in the big image group 52 such that the sub-groups 56a, 56b, 56c would be of generally equal competence; the set of learnt common basis functions 58 is then a compromise from all these sub-groups.

Figure 7B - one or more image groups 62 is sufficiently big as to contain several sub-groups, with the images 64 in the big image group 62 such that the sub-groups 66a, 66b would be of generally uneven competence; the set of learnt common basis functions 68 is dominated by the major sub-group.

Figure 7C - one or more image groups 72 has very versatile or widely distributed images 74; the current image group 74 is not good enough to represent image clustering around the common basis 78.

Most of the images 54, 60, 66 in the large image groups 52, 58, 64 in Figures 7A to 7C have small confidence values as they are far from the set of learnt basis functions 58, 68, 78, whereas images with high confidence values are always close to the basis. So, a simple criterion to choose the images to split from the current group is the confidence value. Those images with a confidence value d lower than a threshold, t_s , are split away. As the split could be into more than two groups, the images with the same second closest group q_2 in a split image group form a new same image group.

The frequency with which to execute such group splitting can be adjusted. The time for splitting should ideally be set when the evolution is locally stable, e.g. (1) every a few iterations after a splitting, (2) when the change of image-group belongingness is very small, or (3) when the average confidence value change from step to step is very small.

Merging: refers to reducing the number of clustering groups during evolution. It can happen implicitly or explicitly. There are several situations where the merging process tends to happen:

(1) During the *competing* process, it may implicitly happen that all images in a group fall into other one or several groups after calculating and comparing their MI values, so the unused groups vanish.

(2) During the *learning* process, all images in a group have confidence values below a learning threshold, so a common basis learnt for this group does not exist. In the next *competing* process, these images will be merged into other groups. This happens when several image groups have similar basis functions.

(3) In a large image database, one group can be merged explicitly with other groups when the current group has too few images, e.g. only 1 or 2 images.

3. Learning

The common basis of an image group is learnt by passing a subset or full set of images in this group into an ICA learning programme. The subset is preferably selected by a threshold of confidence value, t_l , as some images with small confidence values may not be key images for common basis learning. The threshold line 46 in Figure 6 indicates that the image **a** is located within the subset for learning; the image **b** at the edge of this group and the image **c** in the far area of this group are excluded from the subset for learning.

An exemplary procedure of adaptive ICA feature learning is illustrated in the flowchart of Figure 8, where the left side of the figure gives the process steps and elements on the right side of the figure illustrate typical results of those steps.

3.1. Image Patches Pre-processing

In step 21, An image, such as image 100, is used to generate patches 102, at step S202. These patches are 8x8 pixel arrays randomly selected from the image 100. Twelve such patches 102 are shown in Figure 8, but in practice, there would tend to be more, preferably a large number, such as thousands of 8 x 8 image patches randomly selected from the image. The patches 102 are selected randomly in order to cover all kinds of image shapes in the image. For patches with an 8x8 size, each group has a set of 64 common basis functions. An alternative to generating the patches randomly is to obtain the patches regularly block-by-block, e.g. by selecting blocks in turn adjacently from left to right and top to bottom, one by one without overlap. This alternative way is to avoid learning the blocky effect caused by JPEG/MPEG compression in the learnt basis functions.

The rest of the learning process is then carried out on these patches 102. Patches with variance less than a threshold, e.g. 0.1, may be kept out from the following steps, as they may not have enough contrast to present features.

The 8x8 patches 102 are each vectorised into respective 64 x 1 column vectors, at step S204, and the vectors are used as respective columns in a data matrix $\mathbf{X}$. Thus the matrix $\mathbf{X}$ is 64 elements high and has a number of elements in the lateral direction equal to the number of patches 102. Thus, the matrix $\mathbf{X}$ has a number of columns equal to the number of patches.

The rows and columns of the matrix $\mathbf{X}$ are processed, at step S206, by: (i) subtraction from each of the elements of each row of the respective mean of that row, to form a modified matrix; (ii) then subtraction from each of the elements of each column of the modified matrix of the respective mean of that column. This results in a matrix of "pre-processed image patches" in which each of the rows or columns has a zero mean.

3.2. "PCA Pre-Whitening"

"PCA pre-whitening" is carried out, at step S208, in which the data matrix $\mathbf{X}$ of "pre-processed image patches" is pre-whitened by performing a principal component analysis (PCA) to remove any row-wise correlation. Specifically, the covariance matrix $\text{Cov} = \mathbf{X} \times \mathbf{X}^T$, which is a 64x64 matrix, is obtained, and from this the 64 eigenvectors of the covariance matrix. The eigenvectors form a whitening matrix $\mathbf{V}$ with the eigenvectors as respective rows. In statistics this process is called 2nd-order de-correlation. The data matrix $\mathbf{X}$ is processed using $\mathbf{V}$ to form a new matrix $\mathbf{X}'$ given by $\mathbf{X}' = \mathbf{V} \times \mathbf{X}$.

3.3. "ICA learning"

"ICA learning" is carried out, at step S210, e.g. by the algorithm called fastICA by Aapo Hyvarinen [4]. This ICA learning uses the data matrix $\mathbf{X}'$ to form a demixing matrix, $\mathbf{dW}$. The rows of an output matrix $\mathbf{Y}$ given by $\mathbf{Y} = \mathbf{dW} \times \mathbf{X}'$ are as independent as possible when the system is convergent. The matrix $\mathbf{dW}$ is orthogonal because the input is 2nd-order uncorrelated.

3.4. "ICA feature forming"

"ICA feature forming" is carried out, at step S212, to produce a matrix $\mathbf{W}$ (the "ICA transform") and a matrix $\mathbf{A}$ (the "inverse transform"). Matrix $\mathbf{W}$ is given by $\mathbf{W} = \mathbf{dW} \times \mathbf{V}$. The rows of the matrix $\mathbf{W}$ represent 64 ICA weight functions of the image 100. The
 5 inverse matrix $\mathbf{A}$ is given by $\mathbf{A} = \mathbf{W}^{-1}$ (or equivalently $\mathbf{A} = \mathbf{V}^{-1} \times \mathbf{dW}^T$). The columns of the matrix $\mathbf{A}$ represent the corresponding 64 ICA basis functions. Each of the matrices $\mathbf{A}$ and $\mathbf{W}$ is a 64x64 matrix.

10 Figure 9 is a flowchart illustrating the entire evolutionary approach, including the three above-mentioned processes: competing, splitting/merging and learning.

A determination is made, at step S302, of what the initial condition of the image database is, the choice being between having some existing sets of common basis
 15 functions available, and not having them (although the choice could set a minimum threshold for existing sets of common basis functions).

Assuming there are some existing sets of common basis functions available, a *competing* process is performed, at step S304, to compute and compare the MI values
 20 for each image, and classify images into groups according to their minimal MI values. During the competing step (S304), confidence values for the images are also computed. A determination is made of whether the system is locally stable, at step S306, that is whether the group classification has few or no changes between consecutive iterations (e.g. the number of groups is kept the same – although the definition may change
 25 according to the actual situation). If the system is locally stable, the *splitting / merging* process is performed, at step S308, to rearrange the image groups according to confidence values. In this way image groups are determined.

After the image groups are determined the ICA *learning* process is performed, at
 30 step S310, on those image groups that have different image contents from the last iteration to compute a new common basis set for each such group.

If there were no (or insufficient) existing sets of common basis functions available at set S302, some image groups are initiated, at step S312, containing a part
 35 of or all the images in the database. Initialisation can occur in various ways. One option is to generate initial groupings randomly, for example by deciding on a number of

groups and allocating some of the images, one image to each group, with no image appearing in more than one group. The initial number of groups is usually selected within the range of from 1/10 to 1/5 of the number of images in the database. The selection of the initial number of groups and allocation of some of the images is followed
 5 by the ICA *learning* process (step S310) to obtain initial sets of common basis functions.

Likewise, if the system is determined as not being locally stable (step S306), the ICA *learning* process is performed, at step S310, on those image groups that have different image contents from the last iteration, to compute a new common basis set for
 10 each such group.

After the learning process, a determination is made of whether the system is converged, at step S314. Convergence may be defined in various ways. One approach is to set a threshold on the number of images that change group in a single iteration. If
 15 the number of moves in a single iteration is equal to or below that threshold, e.g. 0 or 1, the evolution is considered converged. Another possibility is to use the confidence measure mentioned earlier in the section on *competing*. If the system is considered to be converged, the process stops; otherwise, the process goes back to the *competing* process (step S304) for the next evolutionary iteration. And so the process continues
 20 until the system is considered to be converged.

In this embodiment, two threshold parameters, t_s and t_l , are the keys to controlling the image clustering. All images with a confidence value $d < t_s$, need to be considered for splitting. All images with a confidence value $d > t_l$, are used for basis
 25 learning. The larger the splitting threshold value, t_s , that is set, the more images with small confidence values can be split from the current group; thus, more image groups will be created. The larger the learning threshold value, t_l , that is set, the fewer images in the group can be used for basis learning. This results in the difference between basis sets being wider, and thus image groups are less likely to be merged. So, larger t_s and
 30 t_l may result in more different image groups and common basis sets, and the classification is diverged. On the other hand, smaller t_s and t_l may cause classifications to converge and to have less different image groups and common basis sets.

If the splitting threshold t_s is larger than the learning threshold t_l , there will be a
 35 gap between t_s and t_l , within which some images may fall, meaning they will be misclassified into requiring both splitting and learning processes. This would be a

contradictory situation, given that images for splitting are meant to be those that do not belong to a particular group, whilst images for learning are meant to be those that strongly belong to a particular group. If the splitting threshold t_s is much smaller than the learning threshold t_l , the system may be unstable as the small splitting threshold t_s leads to convergent image grouping but the large learning threshold t_l leads to divergent grouping. Further, the image classification may not be robust, as there will usually be many images with confidence values lying between t_s and t_l . If the two thresholds are set at the same value or the splitting threshold t_s is a bit smaller than the learning threshold t_l , this will provide a rather stable splitting/learning processes and a robust image classification.

At the end of this technique, a final set of ICA common basis functions for this image database is obtained. For any images in this database or any images in the category this database represents, the *competing* process can be used to find the corresponding basis set that is most suitable for representing this image in an ICA way.

Many image processing methods may change the image details, such as lossy image compression, image filters. The classification in the technique based on MI measurement is very robust. The *competing* process can find the same corresponding basis set from common basis sets even when an image is slightly modified or distorted. As an example, images can be correctly classified into the same basis sets when they are compressed by JPEG with quality between 50 and 100 (quality less than 50 causes large distortion in image quality).

For an image with a high confidence value, a single corresponding basis set is good enough. However, a low confidence value indicates that the image can be represented using more than one basis set. The confidence value formula can be extended to compute the closeness between the second and the third minimal MI values, the third and the fourth, and so on: $d_1 = (Mlpq_2 - Mlpq_1) / Mlpq_1$, $d_2 = (Mlpq_3 - Mlpq_2) / Mlpq_2$, $d_3 = (Mlpq_4 - Mlpq_3) / Mlpq_3$, etc. The thresholds t_s and t_l can be used to judge confidence values to determine which other basis sets can also be treated as suitable for ICA representation for different images.

An example of the process of grouping is now discussed with reference to Figures 10A to 10C and Figure 11. Figures 10A to 10C together show twenty images in an image database.

The images in the database are not important to the process, but in this example the images are:

- image 1 - a mosaic of stars and regular polygons on the inside of a dome;
- 5 image 2 - a wall mosaic of ancient Arabic characters with drawing of patterns in lines, squares, crosses, circles, et al.;
- image 3 - a painting of an Indian court scene;
- image 4 - a close up mosaic of patterns in spire, squares, trapezoids, circles and other irregular spaces with Arabic characters inside;
- 10 image 5 - a painting of a flying avatar carrying lotus blossoms;
- image 6 - view of an American football ground and game from one corner, at a first angle and magnification;
- image 7 - view of an American football ground and game from one corner, at a second angle and first magnification;
- 15 image 8 - view of an American football ground and game from one corner, at a third angle and first magnification;
- image 9 - view of an American football ground and game from one corner, at a fourth angle and first magnification;
- image 10 - view of an American football ground and game from one corner, at a second angle and second magnification;
- 20 image 11 - a silhouette of some mountain peaks;
- image 12 - view along the side of a snow-covered mountain ridge, with peaks in the distance;
- image 13 - view of snow covered mountain peaks;
- 25 image 14 - view along a snow-covered mountain ridge with two climbers in the fore-ground;
- image 15 - view along a snow-covered mountain ridge, with peaks in the distance and two climbers in the middle distance;
- image 16 - view over a calm sea towards shore;
- 30 image 17 - view over a calm sea over a reef;
- image 18 - view over a lake with a single bird swimming in the middle distance;
- image 19 - view over a calm sea over a reef; and
- image 20 - view over a lake with a group of birds swimming in the middle distance.

35

Initial stage:

Initialisation: Four groups are initialised by randomly selecting one image for each group.

Group 1: image 6;

Group 2: image 15;

5 Group 3: image 18;

Group 4: image 13.

Learning: ICA basis functions are learnt for each group. Bases 1, 2, 3 and 4 are the four sets of common basis functions at the initial stage (one for each group).

Convergence: Not converged as the grouping is at its initial stage.

10

1st Iteration:

Competing: For each image, four sets of ICA coefficients are computed, using the four sets of common basis functions. Their respective MI values are then computed. The minimum MI value determines the image's belongingness. The image groups are re-classified. Images are ordered according to their confidence values as given in parentheses.

15

Group 1: image 6 (0.16), 7 (0.11), 9 (0.09), 10 (0.05), 16 (0.02)

Group 2: image 17 (0.20), 2 (0.19), 15 (0.19), 19 (0.16), 1 (0.11), 5 (0.09), 3 (0.07), 4 (0.04)

20

Group 3: image 18 (0.10), 20 (0.09), 8 (0.04)

Group 4: image 13 (0.25), 14 (0.10), 11 (0.09), 12 (0.02)

Locally stable: the number of images that change their belongingness is 16, and the system has just begun to keep track of the number of groups. It is not locally stable.

25

Learning: t_i is set at 0.1. New sets of ICA common basis functions are learnt by using images with confidence value greater than t_i .

Convergence: the number of images that change their belongingness is 16. It is not converged

30 2nd Iteration:

Competing: The ICA coefficients, MI values and confidence values are computed for each image. The new image groups are re-classified as:

Group 1: image 16 (0.10), 6 (0.04), 10 (0.01)

Group 2: image 1 (0.19), 4 (0.17)

35

Group 3: image 8 (0.12), 18 (0.07), 9 (0.07), 20 (0.05), 7 (0.01)

Group 4: image 13 (0.64), 12 (0.54), 15 (0.31), 14 (0.25), 11 (0.23),

5 (0.15), 3 (0.15), 17 (0.08), 2 (0.03), 19 (0.01)

Locally stable: the number of images changing belongingness is 8, and the number of groups is kept at 4 for 1 iteration. It is not locally stable.

Learning: New sets of ICA common basis functions are learnt accordingly.

5 **Convergence:** the number of images changing belongingness is 8. It is not converged

3rd Iteration:

Competing: The new image groups are:

10 Group 1: image 11 (0.16), 6 (0.14), 5 (0.13), 10 (0.10), 7 (0.04),
18 (0.02), 16 (0.02), 9 (0.02)

Group 2: image 4 (0.34), 1 (0.22), 19 (0.00)

Group 3: image 20 (0.10), 8 (0.06)

15 Group 4: image 12 (0.22), 13 (0.19), 2 (0.16), 15 (0.16), 14 (0.15),
3 (0.14), 17 (0.11)

Locally stable: the number of images changing belongingness is 6, and the number of groups is kept at 4 for 2 iterations. It is not locally stable.

Learning: New sets of ICA common basis functions are learnt accordingly.

20 **Convergence:** the number of images changing belongingness is 6. It is not converged.

4th Iteration:

Competing: The new image groups are:

25 Group 1: image 16 (0.28), 11 (0.24), 5 (0.20), 8 (0.15), 9 (0.15),
6 (0.10), 7 (0.10), 10 (0.08), 20 (0.07), 18 (0.06)

Group 2: image 1 (0.13), 4 (0.10)

Group 3:

Group 4: image 14 (0.11), 13 (0.10), 17 (0.09), 19 (0.09), 2 (0.08),
15 (0.06), 12 (0.04), 3 (0.03)

30 **Locally stable:** the number of images changing belongingness is 3, the number of groups is reduced to 3. It is not locally stable.

Learning: New sets of ICA common basis functions are learnt accordingly.

Convergence: the number of images changing belongingness is 3. It is not converged.

35

5th Iteration:

Competing: The new image groups are:

Group 1: image 16 (0.84), 6 (0.59), 10 (0.57), 7 (0.52), 9 (0.41),
18 (0.39), 8 (0.33), 20 (0.26), 11 (0.20), 5 (0.18)

Group 2: image 4 (0.16), 1 (0.16), 19 (0.02)

5 Group 3: image 13 (0.17), 14 (0.14), 3 (0.12), 2 (0.11), 12 (0.09),
15 (0.07), 17 (0.03)

Locally stable: the number of images changing belongingness is 1, less than 3.
It is considered locally stable. The splitting process is activated.

10 **Splitting:** images with confidence values less than t_s are split, $t_s = 0.1$. Images
split from the same group form a new group and images split from different
groups form different new groups. Thus there is a total of 5 groups in the new
classification.

Group 1: image 16 (0.84), 6 (0.59), 10 (0.57), 7 (0.52), 9 (0.41),
18 (0.39), 8 (0.33), 20 (0.26), 11 (0.20), 5 (0.18)

15 Group 2: image 4 (0.16), 1 (0.16)

Group 3: image 13 (0.17), 14 (0.14), 3 (0.12), 2 (0.11)

Group 4: image 19 (0.02)

Group 5: image 12 (0.10), 15 (0.07), 17 (0.03)

Learning: New sets of ICA common basis functions are learnt accordingly.

20 **Convergence:** Because of splitting, it is not converged.

6th Iteration:

Competing: The new image groups are:

25 Group 1: image 7 (0.51), 10 (0.48), 6 (0.46), 9 (0.32), 18 (0.31),
16 (0.30), 20 (0.29), 8 (0.26), 5 (0.08), 11 (0.06)

Group 2: image 4 (0.28), 1 (0.17)

Group 3: image 2 (0.24), 3 (0.09), 15 (0.03)

Group 4: image 19 (0.32), 17 (0.18)

Group 5: image 12 (0.11), 13 (0.11), 14 (0.04)

30 **Locally stable:** the number of images changing belongingness is 4, the number
of groups is kept at 5 for 1 iteration. It is not locally stable.

Learning: New sets of ICA common basis functions are learnt accordingly.

Convergence: the number of images changing belongingness is 4. It is not
converged.

35

7th Iteration

Competing: The new image groups are:

Group 1: image 6 (0.50), 10 (0.43), 7 (0.36), 9 (0.33), 16 (0.28),
20 (0.27), 18 (0.26), 8 (0.21)

Group 2: image 4 (0.21), 1 (0.20)

5 Group 3: image 2 (0.14)

Group 4: image 17 (0.22), 19 (0.20)

Group 5: image 13 (0.66), 11 (0.62), 12 (0.45), 15 (0.35), 14 (0.23),
5 (0.21), 3 (0.06)

10 **Locally stable:** the number of images changing belongingness is 4, the number of groups is kept at 5 for 2 iterations. It is not locally stable.

Learning: New sets of ICA common basis functions are learnt accordingly.

Convergence: the number of images changing belongingness is 4. It is not converged.

15 8th Iteration

Competing: The new image groups are:

Group 1: image 10 (0.48), 7 (0.46), 6 (0.40), 18 (0.34), 20 (0.29),
9 (0.28), 16 (0.27), 8 (0.17)

Group 2: image 1 (0.31), 4 (0.26)

20 Group 3: image 2 (0.18)

Group 4: image 17 (0.15), 19 (0.14)

Group 5: image 13 (0.70), 12 (0.48), 11 (0.41), 15 (0.34), 5 (0.23),
14 (0.20), 3 (0.12)

Learning: New sets of ICA common basis functions are learnt accordingly.

25 **Convergence:** the number of images changing belongingness is 0. It is converged.

30 The final sets of ICA common basis functions for these twenty images of Figures 10A to 10C, once grouped using an embodiment of the invention, are shown in Figure 11.

35 If an image database is large enough for certain image categories, the set of semi-ICA common basis functions may be good enough for general use in applications for such an image category, or its use may even be widened to more general usage, for instance to any image application.

The processes described above may be implemented using just hardware, with circuits dedicated for the required processing, or by a combination of hardware and software modules, even if the hardware is just that of a conventional computer system.

5 A module, and in particular the module's functionality, can be implemented in either hardware or software. In the software sense, a module is a process, program, or portion thereof, that usually performs a particular function or related functions. In the hardware sense, a module is a functional hardware unit designed for use with other components or modules. For example, a module may be implemented using discrete
10 electronic components, or it can form a portion of an entire electronic circuit such as an Application Specific Integrated Circuit (ASIC). Numerous other possibilities exist.

Figure 12 is a schematic representation of a computer system 400 suitable for performing the techniques described with reference to Figures 1 to 11. A computer 402
15 is loaded with suitable software in a memory, which software can be used to perform steps in a process that implement the techniques described herein. Simulation programs can be executed, and simulation results obtained using such a computer system 400. This computer software executes under a suitable operating system installed on the computer system 400.

20 The computer software involves a set of programmed logic instructions that are able to be interpreted by a processor, such as a CPU, for instructing the computer system 400 to perform predetermined functions specified by those instructions. The computer software can be an expression recorded in any language, code or notation,
25 comprising a set of instructions intended to cause a compatible information processing system to perform particular functions, either directly or after conversion to another language, code or notation.

The computer software is programmed by a computer program comprising
30 statements in an appropriate computer language. The computer program is processed using a compiler into computer software that has a binary format suitable for execution by the operating system. The computer software is programmed in a manner that involves various software components, or code means, that perform particular steps in the process of the described techniques.

The components of the computer system 400 include: the computer 402, input and output devices such as a keyboard 404, a mouse 406 and an external memory device 408 (e.g. one or more of a floppy disc drive, a CD drive, a DVD drive and a USB flash -memory drive) and a display 410, as well as network connexions for connecting to the Internet 412. The computer 402 includes: a processor 422, a first memory such as a ROM 424, a second memory such as a RAM 426, a network interface 428 for connecting to external networks, an input/output (I/O) interface 430 for connecting to the input and output devices, a video interface 432 for connecting to the display, a storage device such as a hard disc 434, and a bus 436.

The processor 422 executes the operating system and the computer software executing under the operating system. The random access memory (RAM) 426, the read-only memory (ROM) 424 and the hard disc 434 are used under direction of the processor 422.

The video interface 432 is connected to the display 410 and provides video signals for display on the display 410. User input, to operate the computer 402 is provided from the keyboard 404 and the mouse 406.

The internal storage device is exemplified here by a hard disc 434 but can include any other suitable non-volatile storage medium.

Each of the components of the computer 402 is connected to the bus 436 that includes data, address, and control buses, to allow these components to communicate with each other.

The computer system 400 can be connected to one or more other similar computers via the Internet, LANs or other networks.

The computer software program may be provided as a computer program product. During normal use, the program may be stored on the hard disc 434. However, the computer software program may be provided recorded on a portable storage medium, e.g. a CD-ROM read by the external memory device 408. Alternatively, the computer software can be accessed directly from the network 412.

In either case, a user can interact with the computer system 400 using the keyboard 404 and the mouse 406 to operate the programmed computer software executing on the computer 402.

5 The computer system 400 is described for illustrative purposes: other configurations or types of computer systems can be equally well used to implement the described techniques. The foregoing is only an example of a particular type of computer system suitable for implementing the described techniques.

10 The present invention can be used to achieve many advantageous and useful effects. These exemplary effects include:

- (1) generating a fixed set of ICA common basis function sets from a particular image database for analysing and synthesising images in the database;
- (2) generating a fixed number of ICA common basis functions for image
15 analysis and synthesis in almost any image application;
- (3) classifying an image database into image groups based on dependence measure among ICA coefficients;
- (4) changing the one-to-one relation in the pure ICA transform to a one-to-many relation between basis and image in this semi-ICA transform;
- 20 (5) reducing the storage space and computational expense required for the fixed number of common ICA basis sets;
- (6) allowing the common ICA basis sets need to be transferred or shared once between two sides of communication channels for further image analysis and synthesis;
- 25 (7) providing an evolutionary approach to classifying images and learning ICA basis functions in a parallel manner is a dynamic process for a large image database;
- (8) the evolutionary approach has fewer local minima by using the evolving process and splitting/merging process;
- 30 (9) the competing process classifies images into groups by using the dependence measure – mutual information (MI);
- (10) the splitting and merging processes help to grow and shrink the image groups dynamically;
- (11) defining a confidence parameter to measure the closeness between the
35 image and the basis set, to be used in splitting and learning processes for image selection;

(12) providing two thresholds for splitting and learning processes, which can easily control the convergence/divergence of image classification and basis learning; and

(13) providing an image classification based on MI measurement which is very robust to some small distortions. The same basis set can be associated with an image compressed by JPEG with quality 50.

Thus the described embodiment of the invention can be used to generate sets of common ICA basis functions for analysing and representing all images in an image database. Each set of common basis functions is used to cover a subset of images in the database. The basis function sets are distinguished from each other in the properties of ICA features' location, orientation and frequency. The number of basis function sets is controlled by some parameters, such as confidence, to limit at a small and reasonable value. A group of several sets of common ICA basis functions are more versatile than classical DCT or Wavelet with only one set of basis functions. Common ICA basis functions require much less computation and storage than pure adaptive ICA basis functions in practical image applications.

While the preferred embodiments of the invention have been described in detail above, it will be understood that various new constrained parity-check codes fitting to different data storage systems can be designed by those skilled in the art based on the techniques described herein.

While the invention has been particularly shown and described with reference to the preferred embodiments, it will be understood by those skilled in the art that various changes and modifications in form and detail may be made therein without departing from the scope of the invention.

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CLAIMS

1. A method of determining basis functions for data objects in a set of data objects, comprising:
 - 5 a) generating a plurality of sets of common basis functions for said objects;
 - b) analysing said objects; and
 - c) grouping the objects among the sets of common basis functions, with a plurality of objects grouped to individual ones of the sets of common basis functions.
- 10 2. A method according to claim 1, wherein the objects comprise images in an image database.
3. A method according to claim 1 or 2, wherein generating a plurality of sets of common basis functions comprises learning basis functions for a previously formed
15 group of objects.
4. A method according to claim 3, further comprising repeating steps a) to c) a plurality of times, with the generation of common basis functions in step a) of the individual iterations dependent on the grouping of objects in step c) of the preceding
20 iteration.
5. A method according to claim 4, wherein generating common basis functions in iterations of step a) comprises revising the common basis functions for those groups that have different image contents from the previous step a).
- 25 6. A method according to any one of the preceding claims, wherein analysing said objects in step b) comprises determining dependence measurements for individual objects relative to a plurality of the sets of common basis functions.
- 30 7. A method according to claim 6, wherein grouping the objects in step c) is based on the dependence measurements determined in the analysing step.
8. A method according to claim 7, wherein an object is grouped with the set of common basis functions which produces the dependence measurement indicative of
35 least dependence.

9. A method according to claim 8, wherein an object is grouped with the set of common basis functions which produces the lowest dependence measurement for that object.
- 5 10. A method according to any one of claims 6 to 9, wherein the dependence measurement comprises a mutual information value.
- 10 11. A method according to any one of the preceding claims, wherein analysing said objects in step b) further comprises determining a confidence value for individual objects, representing how well the object is suitably represented by the set of common basis functions with which it is grouped.
- 15 12. A method according to claim 11, wherein determining a confidence value for an object comprises comparing a first dependence measurement, being the dependence measurement for the object with the set of common basis functions with which the object is grouped, and a second dependence measurement, being the dependence measurement for the object with a neighbouring set of common basis functions to the set with which the object is grouped.
- 20 13. A method according to claim 12, wherein determining a confidence value for an object further comprises dividing the difference between the first and second dependence measurements with the first dependence measurement.
- 25 14. A method according to any one of claims 11 to 13, wherein a higher confidence value represents greater confidence that the object is suitably represented by the set of common basis functions with which it is grouped.
- 30 15. A method according to any one of the preceding claims, wherein generating a plurality of sets of common basis functions in step a) is based upon a subset of the plurality of objects.
- 35 16. A method according to claim 15 when dependent on at least claim 11, wherein generating a plurality of sets of common basis functions in step a) comprises comparing the determined confidence values with a first threshold and basing learning basis functions on the objects for which the confidence value is a first side of the first threshold.

17. A method according to claim 16, wherein the first side of the first threshold is greater than the first threshold.

5 18. A method according to claim 4 or 5 or according to any one of claims 6 to 17 when dependent on at least claim 4, further comprising determining an overall confidence value for the set of objects and stopping repeating steps a) to c) if the overall confidence value is a first side of a second threshold.

10 19. A method according to claim 18, wherein the first side of the second threshold is greater than the second threshold.

20. A method according to claim 18 or 19 when dependent on at least claim 11, wherein the overall confidence value for the set of objects comprises an average of the
15 confidence values of a plurality of objects for the current groupings.

21. A method according to claim 20, wherein the overall confidence value for the set of objects comprises an average of the confidence values of all of the objects of the plurality of objects.

20

22. A method according to claim 18 or 19 when dependent on at least claim 11, wherein the overall confidence value for the set of objects comprises the lowest determined confidence value for the current groupings.

25 23. A method according to any one of the preceding claims, further comprising determining whether the groupings are stable.

24. A method according to any one of the preceding claims, further comprising splitting each of one or more existing first groups into a plurality of second groups and
30 regrouping the objects previously grouped with the one or more first groups with the plurality of second groups.

25. A method according to claim 24 when dependent on at least claim 11, wherein splitting occurs based on the confidence values of the objects of the one or more
35 existing first groups.

26. A method according to claim 24 or 25 when dependent on at least claim 23, wherein splitting occurs when the groupings are determined to be stable.
27. A method according to any one of the preceding claims, further comprising
5 merging two or more existing third groups into a single fourth group and regrouping the objects previously grouped with the two or more third groups with the single fourth group.
28. A method according to claim 27 when dependent on at least claim 11, wherein
10 merging occurs based on the confidence values of the objects of the two or more existing third groups.
29. A method according to claim 27 or 28 when dependent on at least claim 23, wherein merging occurs when the groupings are determined to be stable.
15
30. A method of determining common basis functions for image objects in an image database, comprising a process of:
- a) classifying the images into image groups associated with different sets of common basis functions;
 - 20 b) determining whether to at least one of: split an image group into two or more smaller image groups and merge two or more image groups into a larger image group;
 - c) learning revised sets of common basis functions based on the current groupings of images in image groups;
 - d) determining if the process is converging; and
 - 25 e) (i) returning to step a) if the process is determined to be converging; or
e) (ii) stopping, otherwise.
31. A method according to any one of the preceding claims, wherein the basis functions are transforms for encoding the objects into mutually independent
30 components.
32. A method according to claim 31, wherein the basis functions comprise ICA basis functions.
- 35 33. Basis functions generated according to the method of any one of the preceding claims.

34. A plurality of basis functions for transforming images of an image database, comprising a plurality of sets of common basis functions; wherein individual images of the image database are associated with individual ones of the sets of common basis functions, a plurality of images with each one of the sets of common basis functions.
35. A plurality of basis functions according to claim 34, generated according to the method of any one of claims 1 to 32.
36. Encoded data comprising image data transformed using one or more transforms based on basis functions according to any one of claims 33 to 35.
37. Apparatus comprising a processor and memory means and programmed to operate according to the method of any one of claims 1 to 32.
38. Computer software for determining basis functions for a set of a plurality of objects, comprising:
- computer code means for generating a plurality of sets of common basis functions for said objects;
 - computer code means for analysing said objects; and
 - computer code means for grouping the objects among the sets of common basis functions, with a plurality of objects grouped to individual ones of the sets of common basis functions.
39. Computer software according to claim 38, operable according to the method of any one of claims 1 to 32.