A Metadatabase System for Semantic Image Search by a Mathematical Model of Meaning

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Abstract

In the design of multimedia database systems, one of the most important issues is to extract images dynamically according to the user's impression and the image's contents. In this paper, we present a metadatabase system which realizes the semantic associative search for images by giving keywords representing the user's impression and the image's contents.

This metadatabase system provides several functions for performing the semantic associative search for images by using the metadata representing the features of images. These functions are realized by using our proposed mathematical model of meaning. The mathematical model of meaning is extended to compute specific meanings of keywords which are used for retrieving images unambiguously and dynamically. The main feature of this model is that the semantic associative search is performed in the orthogonal semantic space. This space is created for dynamically computing semantic equivalence or similarity between the metadata items of the images and keywords.

1 Introduction

In recent years, the design and implementation of metadatabase systems is one of the key issues in the field of multimedia database research. In the design of the metadata for images, the important issues are how to define and represent the metadata items of images and how to extract images dynamically according to the user's impression and the image's contents.

There are many approaches to image retrieval. Two major approaches are direct retrieval using partial pattern matching and indirect retrieval using abstract information of images. We use the latter approach for extracting images.

In this paper, we present a new method and a metadatabase system for extracting appropriate images according to the user's impression and the image's contents. In this method, the images are selected by using our proposed mathematical model of meaning[4, 5] which realizes the semantic associative search. The semantic interoperability for multidatabases is the important issue in the research field of multidatabase systems[1, 10, 11]. This model has been applied to support the semantic interoperability for multidatabase environments[5]. In this paper, the mathematical model of meaning is extended as a fundamental framework for representing the metadata and extracting images.

The mathematical model of meaning is a new model for realizing the semantic associative search and extracting information by giving a keyword and its context words which explain the context of the keyword. This model can be applied to extract images by giving the keyword and its context words which represent the impression and contents of the images.

The extended mathematical model of meaning consists of:

1) A set of m words is given, and each word is characterized by n features. That is, m by n matrix is given as the data matrix.

2) The correlation matrix with respect to the n features is constructed. Then, the eigenvalue decomposition of the correlation matrix is computed and the eigenvectors are normalized. The orthogonal semantic space is created as the span of the eigenvectors which correspond to nonzero eigenvalues.

3) Images and keywords are characterized by using the specific features(words) and representing them as vectors.

4) The images and keywords are mapped into the orthogonal semantic space by computing the Fourier expansion for the vectors.

5) A set of all the projections from the orthogonal semantic space to the invariant subspaces (eigen spaces) is defined. Each subspace represents a phase of meaning, and it corresponds to a context or situation.

6) A subspace of the orthogonal semantic space is selected according to the user's impression or the image's content, which is given as a context represented by a sequence of words.

7) The closest image to the keyword in the user's impression and the image's contents is extracted in the selected subspace.

Several information retrieval methods, which use the orthogonal space created by mathematical procedures like SVD (Singular Value Decomposition), have been proposed. Our model is essentially different from those methods using the SVD (e.g. the Latent Semantic Indexing (LSI) method [3]). The essential difference is that our model provides the important function for semantic projections which realizes the dynamic recognition of the context. That is, in our model, the context-dependent interpretation is dynamically performed for computing the distance between words and images by selecting a subspace from the entire orthogonal semantic space. In our model, the number of phases of the contexts is almost infinite (currently 2^{800}, approximately). Other methods do not provide the context dependent interpretation for computing equivalence and similarity in the orthogonal space, that is, the phase of meaning is fixed and static.

We present three methods for representing the metadata items for images which are mapped into the orthogonal semantic space. Furthermore, we present basic functions which extract the appropriate images from the orthogonal semantic space.

2 Metadatabase System

2.1 The overview of the metadatabase system

The metadatabase system selects appropriate images for requests of database users by using metadata items and basic functions. This system consists of the following subsystems:

(1) Image Selection Subsystem: This subsystem supports the facilities for selecting appropriate images by using the extended mathematical model of meaning. Three methods are provided for representing the metadata items for images.

(2) Metadatabase Management Subsystem: This subsystem supports the facilities for keeping metadata consistent in the orthogonal semantic space.

(3) Metadata Acquisition Subsystem: This subsystem supports the facilities for acquiring metadata from the database storing the source images.

2.2 Basic functions and metadata for images

The metadatabase system is used to extract image data items corresponding to the words which represent the user's impression and image's contents. Each metadata item of images are mapped in the orthonormal semantic space. This space is referred to as "orthogonal metadata space" or "metadata space." The mathematical model of meaning is used to create the orthogonal metadata space. The mathematical model of meaning gives the machinery for extracting the associated information to the keyword according to the context which explains the keyword.

In extracting images, context words that represent the user's impression and the image's contents are given as the context. According to these context words, a semantic subspace is selected dynamically. Then, the keyword is given and the closest image to the keyword is extracted in the semantic subspace.

Metadata items are classified into three different kinds. The first kind of data items are used for the creation of the orthogonal metadata space, which is used as a search space for semantic image retrieval. These data items are referred to as "data-item for space creation."

The second kind of metadata items are used as the metadata items of the images, which are the candidates for semantic image retrieval. These metadata items are referred to as "metadata for images."

The third kind of metadata items are used as the keywords and context words, which represent user's imagination and impression in image retrieval. These metadata items are referred to as "metadata for keywords."

The basic functions and metadata structures are summarized as follows:

1. Creation of metadata space:

   To provide the function of semantic associative search, basic information on m data items ("data-items for space creation") is given in the form of a matrix. Each data item is provided as fragmentary metadata which is independently represented one another. No relationship between data items is needed to be described. The information of each data item is represented by its features. The m basic data items is given in the form of an m by n matrix M. For given m basic data items, each data item is characterized by n features. By using this matrix M, the orthogonal space is computed as the metadata space $\mathcal{MDS}$.

2. Representation of image data items in n-dimensional vectors

   Each of the image data items is represented in the n-dimensional vector whose elements correspond to n features used in 1. These vectors are used as "metadata for images". The image data items become the candidates for the semantic associate search in this model. Furthermore, each of the keywords and context words, which are used to represent the user's impression and the image's contents in semantic image retrieval, is also represented in the n-dimensional vector. These vectors are used as "metadata for keywords."

3. Mapping data items into the metadata space $\mathcal{MDS}$.

   Metadata items (data-items for space creation, metadata for images and metadata for keywords) which are represented in n-dimensional vectors are mapped into the orthogonal metadata space. Those data items are used as keywords, context words, and target image data items which are extracted according to users' requests.

4. Semantic associative search

   When a keyword and a sequence of context words which determine the user's impression and the image's contents are given, the corresponding metadata for images is extracted from a set of metadata items for images in the metadata space.

2.3 Creation methods of metadata for images

We present three methods for creating metadata for images. In these methods, the metadata is represented as an n-dimensional vector.

2.3.1 Method-1

Each image data item is explained by using the n features of the data matrix M as the metadata of the image. In this explanation, the impression of the image is represented by using these features. Then, each image data item is represented as an n-dimensional vector in which the non-zero value is assigned to the corresponding elements of the vector to these features.

The image P is explained and defined by using some of the words which are used in n features. Then, the image is represented as an n-dimensional vector.

$$P = (w_{i1}, w_{i2}, \ldots, w_{in}). \tag{1}$$

Each metadata item is mapped into the metadata space by computing Fourier expansion for the vector corresponding to the image data item itself.

2.3.2 Method-2

The image P consists of t objects $\mathbf{o}_1, \mathbf{o}_2, \ldots, \mathbf{o}_t$, where each object is defined as a t dimensional vector:

$$\mathbf{o}_i = (o_{i1}, o_{i2}, \ldots, o_{it}), \tag{2}$$

which is characterized by t specific features.

Namely, we define the image P as the collection of t objects which appear in the image.

$$P = \{\mathbf{o}_1, \mathbf{o}_2, \ldots, \mathbf{o}_t\}. \tag{3}$$

Moreover, we define the operator union $\bigoplus$ of objects $\mathbf{o}_1, \mathbf{o}_2, \ldots, \mathbf{o}_t$, to represent the metadata for the image P as a vector as follows:

$$\bigoplus_{i=1}^{t} \mathbf{o}_i \equiv (\mathrm{sign}(o_{\ell_1 1}) \max_{1 \le i \le t} |o_{i1}|, \mathrm{sign}(o_{\ell_2 2}) \max_{1 \le i \le t} |o_{i2}|, \ldots, \mathrm{sign}(o_{\ell_n t}) \max_{1 \le i \le t} |o_{it}|), \tag{4}$$

where $\mathrm{sign}(a)$ represents the sign (plus or minus) of "a" and $\ell_k, k = 1, \ldots, t$, represents the index which gives the maximum, that is:

$$\max_{1 \le i \le t} |o_{ik}| = |o_{\ell_k k}|. \tag{5}$$

2.3.3 Method-3

In this method, the metadata for images is automatically created by using the image data items themselves. This method is implemented by using image processing facilities which are studied in the field of image processing. That is, this method is based on using the media-dependent metadata.

If we consider the case that the impression which we obtain from an image can be estimated from the elements composing the image, we can derive the following formula:

$$P = \sum_{i=1}^{N} a_i I_i, \tag{6}$$

where P is an impression vector of an image itself, N is a number of elements composing the image, a_i is some kind of coefficient for element i in the image, and I_i is an impression vector of the element i. Each impression vector is expressed as follows:

$$I_j = (w_{j_1}, w_{j_2}, ..., w_{j_m}), \quad (7)$$

where w_{j_i} is a word expressing an impression, and m is the number of features for expressing the impression. The actual value of w_{j_i} is the weight of that word.

In this method, we consider the case that the colors used in the image can derive the impression of the image, that is, the color is the dominant factor which decides the impression of the image[2, 7]. Images and colors are described by expression words such as 'warm', 'bright' and so on.

The coefficient a_i of the formula is the percentage of the region of specific color, and I_i is the impression vector of that color, that is, its elements correspond to colors. The impression vector of the image P, that is, the metadata for the image, can be expressed as follows:

$$P = (c_{p_1}, c_{p_2}, ..., c_{p_m}), \quad (8)$$

where c_{p_i} is a color used on the image. Actual value of c_{p_i} is the weight of that color in the image. In the case that only the area size of each color is considered, c_{p_i} should be calculated by the following formula:

$$c_{p_i} = k \frac{A_{c_{p_i}}}{A}, \quad (9)$$

where k is a constant value, A_{c_i} is the unit area of a color c_i, and A is the unit area of the whole image. Note that c_i must be within $[0, 1]$. Similarly, the word w_i, metadata for a keyword, is expressed as follows:

$$w_i = (c_1, c_2, ..., c_m). \quad (10)$$

As the result, the distance between images and words can be measured.

We use the Munsell color system to express colors, which is much more familiar to the human sense than that of CIE such as XYZ color system or RGB color system. The correspondence of names of colors and actual color in the Munsell color system is defined by ISCC[1] and NIST[2]. The names of colors defined in this standard are used as the features.

We can use the results of psychological experiments, as many word association tests have been done on the relation between colors and psychological effects, e.g. showing a single color and asking the reminded words. According to the results, there seems to be an association between words and colors. For instance, from the color 'strong orange' (e.g. 5YR7/14), the word 'warm' is likely to be associated with it. Naturally, the association between colors and words is not one-to-one correspondence, but many-to-many.

[1]Inter-Society Color Council.

[2]National Institute of Standards and Technology.

3 Creation of a Metadata Space and Basic Functions

In this section, we introduce a creation method of a metadata space for systematically storing fragmentary metadata and implementing the semantic associative search for images. The overview of the creation of a metadata space and semantic search for metadata items is shown.

3.1 Creation of a metadata space

The semantic associative search for images is realized by extending the mathematical model of meaning [4, 5] which we have proposed. For the data items for space creation, a data matrix M is created. When m data items for space creation are given, each data item is characterized by n features $(f_1, f_2, \cdots, f_n)$. For given $\mathbf{d}_i (i = 1, \cdots, m)$, the data matrix M is defined as the $m \times n$ matrix whose i-th row is $\mathbf{d}_i$. Then, each column of the matrix is normalized by the 2-norm in order to create the matrix M.

Figure 1 shows the matrix M. That is $M = (\mathbf{d}_1, \mathbf{d}_2, \mathbf{d}_3, \cdots, \mathbf{d}_n)^T$.

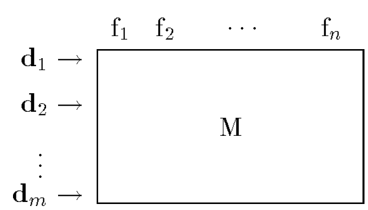

Figure 1: Representation of metadata items by matrix M

1. The correlation matrix $M^T M$ of M is computed, where M^T represents the transpose of M.

2. The eigenvalue decomposition of $M^T M$ is computed.

$$M^T M = Q \begin{pmatrix} \lambda_1 & & & \\ & \ddots & & \\ & & \lambda_\nu & \\ & & & 0 \cdot \cdot 0 \end{pmatrix} Q^T,$$

$0 \leq \nu \leq n$.

The orthogonal matrix Q is defined by

$$Q = (\mathbf{q}_1, \mathbf{q}_2, \cdots, \mathbf{q}_n)^T,$$

where $\mathbf{q}_i$'s are the normalized eigenvectors of $M^T M$. We call the eigenvectors "semantic elements" hereafter. Here, all the eigenvalues are real and all the eigenvectors are mutually orthogonal because the matrix $M^T M$ is symmetric.

3. Defining the metadata space $\mathcal{MDS}$.

$$\mathcal{MDS} := span(\mathbf{q}_1, \mathbf{q}_2, \cdots, \mathbf{q}_\nu),$$

which is a linear space generated by linear combinations of $\{\mathbf{q}_1, \cdots, \mathbf{q}_\nu\}$. We note that $\{\mathbf{q}_1, \cdots, \mathbf{q}_\nu\}$ is an orthonormal basis of $\mathcal{MDS}$.

3.2 The set of the semantic projections Π_ν

The projection P_{λ_i} is defined as follows:
$P_{\lambda_i} \stackrel{\mathrm{d}}{\Longleftrightarrow}$ Projection to the eigenspace corresponding to the eigenvalue λ_i,
i.e. $P_{\lambda_i} : \mathcal{MDS} \to span(\mathbf{q}_i)$.
The set of the semantic projections Π_ν is defined as follows:

$$\Pi_\nu :=$$

$$\begin{aligned}\{\ 0\ ,\ & P_{\lambda_1}, P_{\lambda_2}, \cdots, P_{\lambda_\nu}, \\ & P_{\lambda_1} + P_{\lambda_2}, P_{\lambda_1} + P_{\lambda_3}, \cdots, P_{\lambda_{\nu-1}} + P_{\lambda_\nu}, \\ & \vdots \\ & P_{\lambda_1} + P_{\lambda_2} + \cdots + P_{\lambda_\nu}\}.\end{aligned}$$

The number of the elements of Π_ν is 2^ν, and accordingly it implies that 2^ν different phases of meaning can be expressed by this formulation.

3.3 Semantic operator

The correlations between each context word and each semantic element are computed by this process. The context word is used to represent the user's impression and the image's contents for images to be extracted. A sequence

$$s_\ell = (\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{u}_\ell)$$

of ℓ context words and a positive real number $0 < \varepsilon_s < 1$ are given, the semantic operator S_p constitutes a semantic projection $P_{\varepsilon_s}(s_\ell)$, according to the context. That is,

$$S_p : T_\ell \longmapsto \Pi_\nu$$

where T_ℓ is the set of sequences of ℓ words and $T_\ell \ni s_\ell$, $\Pi_\nu \ni P_{\varepsilon_s}(s_\ell)$. Note that the set $\{\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{u}_\ell\}$ must be a subset of the words defined in the matrix M.
The constitution of the operator S_p consists of the following processes:

1. Fourier expansion of $\mathbf{u}_i (i = 1, 2, \cdots, \ell)$.
The inner product of $\mathbf{u}_i$ and $\mathbf{q}_j$ u_{ij} is computed, i.e.

$$u_{ij} := (\mathbf{u}_i, \mathbf{q}_j)\ ,\ for\ j = 1, 2, \cdots, \nu.$$

We define $\widehat{\mathbf{u}}_i \in \mathcal{I}$ as

$$\widehat{\mathbf{u}}_i := (u_{i1}, u_{i2}, \cdots, u_{i\nu}).$$

This is the mapping of the context word $\mathbf{u}_i$ to the metadata space $\mathcal{MDS}$.

2. Computing the semantic center $\mathbf{G}^+(s_\ell)$ of the sequence s_ℓ.

$$\mathbf{G}^+(s_\ell) := \frac{\left(\sum_{i=1}^{\ell} u_{i1}, \cdots, \sum_{i=1}^{\ell} u_{i\nu}\right)}{\|\left(\sum_{i=1}^{\ell} u_{i1}, \cdots, \sum_{i=1}^{\ell} u_{i\nu}\right)\|_\infty},$$

where $\|\cdot\|_\infty$ denotes infinity norm.

3. Determining the semantic projection $P_{\varepsilon_s}(s_\ell)$.

$$P_{\varepsilon_s}(s_\ell) := \sum_{i \in \Lambda_{\varepsilon_s}} P_{\lambda_i} \quad \in \Pi_\nu,$$

where $\Lambda_{\varepsilon_s} := \{\ i \mid |(\mathbf{G}^+(s_\ell))_i\ | > \varepsilon_s\}$.

3.4 Dynamic metric

A dynamic metric $\rho(\mathbf{x}, \mathbf{y}; s_\ell)$ for $\mathbf{x}, \mathbf{y} \in \mathcal{MDS}$ is introduced to compute the similarity between keyword and metadata items for images. This metric changes dynamically depending on the context. This metric is designed in order that the model faithfully reflects the change of the context. The metric $\rho(\mathbf{x}, \mathbf{y}; s_\ell)$ is defined as follows:

$$\rho(\mathbf{x}, \mathbf{y}; s_\ell) = \sqrt{\sum_{j \in \Lambda_{\varepsilon_s}} \{c_j(s_\ell)(x_j - y_j)\}^2},$$

where the weight $c_j(s_\ell)$ is given by

$$c_j(s_\ell) := \frac{\sum_{i=1}^{\ell} u_{ij}}{\|\left(\sum_{i=1}^{\ell} u_{i1}, \cdots, \sum_{i=1}^{\ell} u_{i\nu}\right)\|_\infty},$$

$$j \in \Lambda_{\varepsilon_s}.$$

4 Semantic Associative Search for Metadata for Images

The proposed system realizes the semantic associative search for metadata items for images.

The basic function of the semantic associative search is provided for context-dependent interpretation. This function performs the selection of the semantic subspace from the metadata space. When a sequence s_ℓ of the context words for determining a context are given to the system, the selection of the semantic subspace is performed. This selection corresponds to the recognition of the context, which is defined by the given context words. The selected semantic subspace corresponds to a given context. And then, when a keyword for the semantic associative search is given with the semantic subspace, the metadata items for images with the closest meaning to the keyword in the selected semantic subspace are extracted from the specified image data item set $\mathcal{W}$. By using the dynamic metric defined in Section 3, the function finds the image data item with the equivalent or closest meaning to the given keyword in the selected semantic subspace. This semantic associative search is performed by the following procedure:

1. When a sequence s_ℓ of the context words for determining a context(the user's impression and the image's contents) are given, the Fourier expansion is computed for each context word, and the Fourier coefficients of these words with respect to each semantic element are obtained. This corresponds to seeking the correlation between each context word and each semantic element.
2. The values of the Fourier coefficients for each semantic element are summed up to find the correlation between the given context words and each semantic element.
3. If the sum obtained in the step 2 in terms of each semantic element is greater than a given threshold ε_s, the semantic element is employed to form the semantic subspace $P_{\varepsilon_s}(s_\ell)\mathcal{MDS}$. This corresponds to recognizing the context which is determined by the given context words.
4. The Fourier expansion of the given keyword is executed and the Fourier coefficients are computed with respect to each semantic element involved in the selected semantic subspace. This corresponds to seeking the correlation between the given keyword and each semantic element of the semantic subspace.
5. The metadata item for the image with the closest meaning to the given keyword is selected among the candidate metadata items for images in $\mathcal{W}$ in the selected semantic subspace. This corresponds to finding the image with the closest meaning of the given keyword from $\mathcal{W}$ in the given context.

5 Implementation for the Metadata Space Creation

To clarify the feasibility of the semantic associative search for images in the metadatabase system, the metadata space for the Methods-1 and 2 has been actually created. To create the metadata space, we have used "General Basic English Dictionary [9]" in which 850 basic words are used to explain each English definition. Those 850 basic words are used as features, that is, they are used for characterizing fragmentary metadata as the features corresponding to the columns in the matrix M. Two thousand data items are used as fragmentary "data items for space creation" to create a metadata space$\mathcal{MDS}$. Those data items are used as the basic words in the English dictionary "Longman Dictionary of Contemporary English [8]." Those data items are explained by using the features and correspond to the rows in the matrix M. The procedure for the creation of the metadata space is as follows:

1. Each data item for space creation corresponds to a row of the matrix M. In the setting of a row of the matrix M, each column corresponding to the features which appear in the explanation of the data item is set to the value "1". If the feature is used as a negative meaning, the column corresponding to it is set to the value "-1". And, the other columns are set to the value "0". This process is performed for every data item. And then, each column of the matrix is normalized by the 2-norm to create the matrix M.
2. By using this matrix M, the metadata space is created as described in Section 3. This space represents the semantic space for computing contexts and meanings of the metadata items.

To automatically create the data matrix M from the dictionary, we have implemented several filters which remove unnecessary elements (words), such as articles and pronouns, and transform conjugations and inflections of words to the infinitives. Those elements are removed from the features characterizing each data item. The unnecessary words are not used as features in the data matrix M.

(filter-1) This filter eliminates the unnecessary elements, such as articles and pronouns.

(filter-2) This filter transforms conjugations and inflections to the infinitives.

(filter-3) This filter transforms the large characters to the small ones.

(filter-4) This filter transforms clipped form words to the corresponding original words.

(filter-5) The rows of the matrix M is created for each data item by using the filtered features which characterize the data item.

Each metadata item (metadata item for images, metadata item for keywords) is mapped into the metadata space, by computing Fourier expansion for the n-dimensional vector representing the metadata item itself. These metadata items are defined as fragmentary metadata by using the n features. These metadata items are used as keywords, context words, and candidate image data items for realizing the semantic associative search according to the user's impression and the image's contents.

6 Examples of Creating Metadata

6.1 Method-1

We currently have 850 basic words from "General Basic English Dictionary" as the features. To create the metadata as vectors for images by using those 850 words, the creator of metadata looks at an image and checks features that correspond to the image. If the feature corresponds to the image, the value 1.0 is put for that feature. If it does not correspond to the feature, the value 0.0 is put., and if it negates the image, the value -1.0 is put. Although the cost is very expensive, the simplest way is to check for 850 features one by one for each image. A vector is created for each image, and mapped into the metadata space which is created as shown in Section 5.

6.2 Method-2

As the previous method, the same features from "General Basic English Dictionary" are used. This method creates metadata by referring to objects composing the original image. The names of the objects which appear in the image are referred to from "General Basic English Dictionary," and the explanatory words for each object are used as features, and the value for each feature is calculated by the operator union defined in Section 2.3.2.

6.3 Method-3

This method doesn't use the features from "General Basic English Dictionary." The color names defined by ISCC and NBS are used as the features.

The creation of the metadata for images can be done automatically, as the color of the image in the CIE color system can be obtained easily and can be transformed to the Munsell color system. Then, the value for corresponding color is put in the range of 0.0 and 1.0 according to some rule such as the area size of colors. The creation of the metadata can be done automatically.

However, the difficulty of this method is how to correspond the colors with explanatory keywords, that is, how to create the metadata for keywords. To solve this difficulty, the results of psychological experiments can be used, because many word association tests had been done on the relation between colors and psychological effects, e.g. showing a single color and asking for the reminded words.

7 Conclusion

In this paper, we have presented a metadatabase system for extracting image data items according to the user's impression and the image's contents. This system provides several functions for performing semantic associative search for images. Those functions are realized by using the extended mathematical model of meaning. This model is used as a basic computational system for extracting appropriate images.

We are currently implementing our proposed metadatabase system to clarify its feasibility and effectiveness. As our future work, we will extend this system for realizing a multimedia metadatabase environment. The system will support multimedia data retrieval for video, and audio data. This system will be integrated in the distributed multimedia database system[6].

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