Classification-Driven Feature Space Reduction for Semantic-based Neuroimage Retrieval

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Abstract. This paper summarizes our work on volumetric pathological neuroimage retrieval under the framework of classification-driven feature selection. The main effort concerns image feature space reduction for the purposes of reducing computational cost during image retrieval as well as improving image indexing feature discriminating power.

1 Motivation

Medical images form an essential and inseparable component of diagnosis, intervention and patient follow-ups. It is therefore natural to use these images as a front-end index to retrieve medically relevant cases from digital patient databases. Common practice in the image retrieval and pattern recognition community is to map each image into a set of numerical and/or symbolic attributes called *image indexing features*. Thus each image corresponds to a point in a multidimensional image feature space. Existing "content-based" image retrieval (CBIR) systems [1, 6], depend on general visual features such as color and texture to classify diverse, two-dimensional (2D) images. These general visual cues alone, however, often fail to be effective discriminators for image sets taken within a single domain, where images have subtle, domain-specific differences. Furthermore, these global statistical color and texture measures do not necessarily reflect or have proven correspondence to the meaning of an image, i.e. the image semantics.

2 Our Approach

We have explored various issues in medical image retrieval [3, 5, 2, 4] using a neuroimage database composed of clinical volumetric CT image sets of hemorrhage (blood), bland infarct (stroke) and normal brains. The image semantics in this context is expressed as the image pathology. For example, *normal*, *right basal ganglion acute bleed* or *frontal lobe acute infarct*. Figure 1 shows a framework of our approach. The three major components in this scheme are (1) **Feature extraction** maps each volumetric image into a multi-dimensional image feature space; (2) **Feature selection** determines the relative scale of the feature space and the best metric for image comparison; and (3) **Adaptive image retrieval** captures user intention by choosing the most suitable image similarity.

For each given image database **B** and a set of potential image features F_B extracted from each image in the database, we define two basic parameters:

1. the **fundamental dimension** of the database which is the lowest feature subspace dimension excluding irrelevant and redundant features;

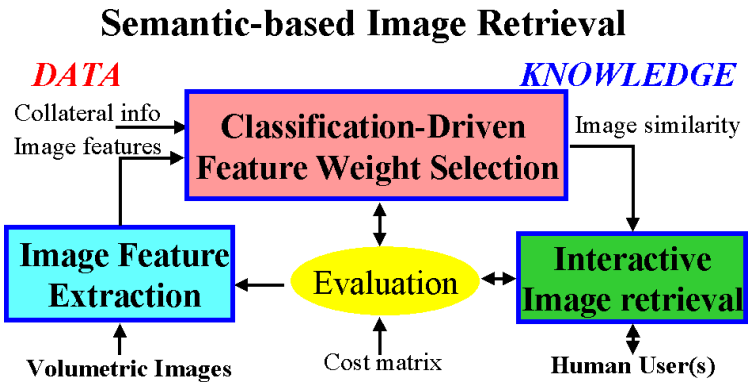


Fig. 1. Overview of a semantic-based classification-driven image retrieval framework.

2. the semantic class **separability** within the database which is a quantitative measure for how-well image classes are separated.

Our research goal is to construct a systematic framework to learn these two parameters through classification-driven semantic-based image feature space reduction. The net result of the feature space reduction in image retrieval application includes: (1) reduced computational cost during image retrieval; and (2) improved discriminating power for finding similar images at retrieval time.

3 Classification-Driven Feature Space Reduction

We use a novel midsagittal plane method for 3D pathological neuroimage alignment [2]. Global and local statistical image features are extracted for describing brain asymmetry [4], geometry and texture properties. These features form the initial, high dimensional feature space. There are many existing feature space reduction approaches, not all of which are appropriate for image retrieval. We are looking for methods that can truly reduce computational cost by explicitly weighting each feature dimension (so that we can discard unnecessary feature dimensions during retrieval). Principal component analysis, for instance, though it gives an estimate of the fundamental dimensions, does not meet this standard. Artificial neural networks do not provide the explicit weightings desired for image retrieval either.

Table 1 records the results from feature space reduction using three different methods: memory based learning, classification trees and discriminant analysis. All the experiments are carried out on an image dataset containing 48 3D brains with three broad pathology classes: normal (26), blood (8) and stroke (14). The initial feature space is 46 dimensions composed of statistical measurements describing human brain asymmetry [4, 2].

Memory Based Learning In [4] we have reported in detail our initial effort on finding the most discriminating feature subset(s) using a memory-based learning approach, Bayes classifier, Parzen windows and a non-deterministic search engine. The average precision rate for image retrieval across different pathologies is

Feature Space Reduction Method	Initial Feature SpaceDimension	Reduced Feature SpaceDimension (fold)	CR Improved
MemoryBasedLearning (holdout)	46	5 - 10 (5-10)	15%
ClassificationTree (holdout)	46	2-4 (12-24)	8%
ClassificationTree (LOO)	46	3-5 (9-15)	5%
Discriminant Analysis (holdout)	46	6-10 (5-7)	19%
Discriminant Analysis (LOO)	46	12-15 (3-4)	29%

Table 1. This table shows the feature space dimension reduction rates after feature selection, in actual dimensions and in fold. Also shown is the classification rate (CR) improvement over the original feature space. Here *holdout* means separating the original dataset into a training set (2/3 data) and a *holdout* test set (1/3 data), training the classifier on the training set and evaluating results using the test set. LOO = *leave one out* strategy, it uses each data point as a test set once.

near 80%. **Classification Trees** A binary classification tree is used by finding the best binary split among the features at each step [7]. Based on a multinomial probability model, we define a *deviance* for the tree: $D = \sum_i D_i$ where $D_i = -2 \sum_k n_{ik} \log p_{ik}$ as a sum over leaves. The 'best' split is the maximum reduction in *deviance* over all leaves. The tree grows until the leaf is homogeneous enough (its deviance is less than certain value). We randomly divided the dataset 50 times into 2/3-1/3 training-testing pairs. A tree was grown on each of the 50 training sets. Results are listed in Table 1. **Discriminant Analysis** A combination of forward selection [7] and linear discriminant analysis is used with two different criteria for selecting features: (1) the augmented variance ratio, which compares within-group and between-group variances and penalizes features where class means are too close together, and (2) Wilks' lambda, which measures dissimilarity among groups. Results on feature space reduction over 50 randomly divided training-testing pairs are in Table 1.

4 Conclusion

Under our classification-driven semantic-based image retrieval framework, image classification is used as a tool for feature space reduction. We have shown, quantitatively, an initial feature space with 46 dimensions can be reduced to 2-15 dimensions (3-24 fold) with increased discriminating power (better classification rates). Our effort in looking for the best automated methods for feature space reduction distinguishes our work from most image retrieval practice where the image indexing features are determined by human system designers. These selected feature dimensions form the basis for on-line image indexing at retrieval time. Our method provides the generality and potential to scale up to much larger image databases. Figure 2 demonstrates a JAVA image interface for our adaptive classification-driven neuroimage retrieval system.

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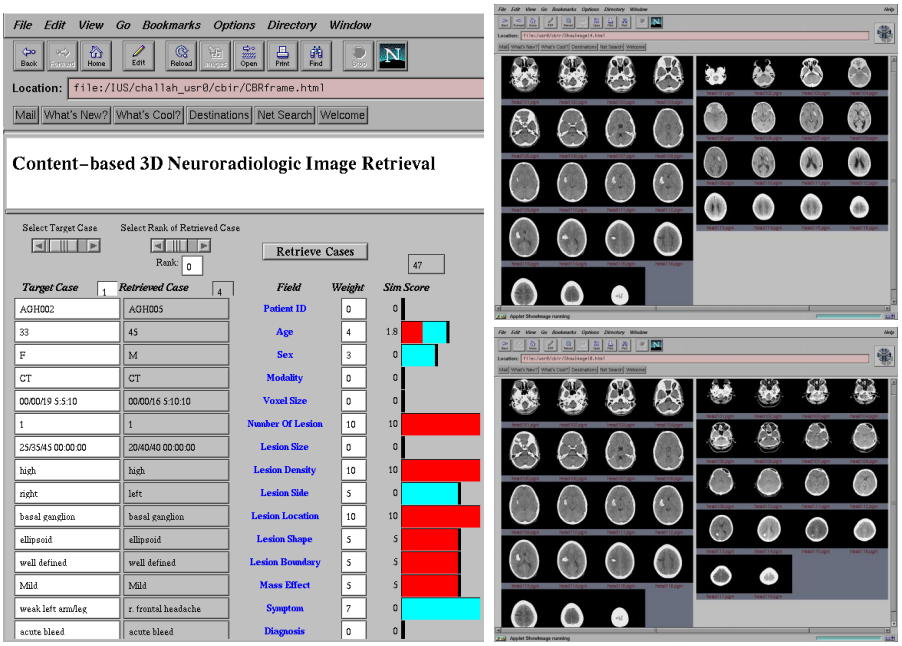


Fig. 2. Left panel: a JAVA user interface of our semantic-based 3D Neuroimage Retrieval System, under development by Dr. Liu et al at the Robotics Institute of Carnegie Mellon University. Two right panels: the netscape screens show one query image on the left with *right basal ganglion acute blood* (shown as a set of 2D slices), the most similar image on the right (top panel)) and the second most similar image (bottom panel) retrieved from an image database of more than 100 pathological, volumetric neuroimages.

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