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Histology Based Image Retrieval in Multifeature Spaces

D.Sudha, J.Priyadarshini, A.Ranjidha

Abstract— ***Content-based histology image retrieval systems have shown great potential in supporting decision making in clinical activities, teaching, and biological research. In content-based im-age retrieval, feature combination plays a key role. It aims at en-hancing the descriptive power of visual features corresponding to semantically meaningful queries. It is particularly valuable in his-tology image analysis where intelligent mechanisms are needed for interpreting varying tissue composition and architecture into histological concepts. This paper presents an approach to auto-matically combine heterogeneous visual features for histology im-age retrieval. The aim is to obtain the most representative fusion model for a particular keyword that is associated with multiple query images. The core of this approach is a multiobjective learn-ing method, which aims to understand an optimal visual-semantic matching function by jointly considering the different preferences of the group of query images. The task is posed as an optimization problem, and a multiobjective optimization strategy is employed in order to handle potential contradictions in the query images associated with the same keyword. Experiments were performed on two different collections of histology images. The results show that it is possible to improve a system for content-based histology image retrieval by using an appropriately defined multifeature fu-sion model, which takes careful consideration of the structure and distribution of visual features.***

Index Terms— ***Content-based image retrieval (CBIR), feature fusion, histology image retrieval, multiobjective optimization.***

I. INTRODUCTION

Histology is a fundamental tool that provides information on structure and composition of tissues at microscopic level. Nowadays, images of tissue slides are often digitized to document procedures and to support findings. These collections are often huge in size and thus hide a latent source of information that can be greatly exploited if suitable mechanisms are available for accessing the data.

II. VISUAL FEATURE EXTRACTION AND ANALYSIS

To extracting several commonly used visual features, analyzing their characteristics, and deriving their normalization functions.

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D.Sudha received the M.E degree in computer science from Anna University, Chennai in 2012, and the B.E. degree in computer science and information engineering from Anna University, Chennai, India.

Dr.J.Priyadarshini received the B.E. degree in computer science from the Anna university in 2006 and the M.E. degree in computer science from the Anna University, India.

A.Ranjidha received the M.E degree in computer science from Anna University, Chennai in 2012, and the B.E. degree in computer science and information engineering from Anna University, Chennai, India.

A. Feature Extraction

It is to develop an approach for automatically combining low-level visual features for retrieval of histology images according to their fundamental tissue types. Therefore, the extraction and analysis of useful visual features in histology images.

Gabor textures (GT): Gabor filters possess an outstanding ability of filtering in the spatial and frequency domain. The Gabor transform is a set of directional filters; thus, it is shift invariant

Tamura textures (TT): Tamura proposed six texture fea-tures corresponding to human visual perception: *coarse-ness, contrast, directionality, line-likeness, regularity*, and *roughness.*

Zernike moments (ZMs): ZMs have many desirable prop-erties, such as rotation invariance, robustness to noise, ex-pression efficiency, fast computation, and multilevel rep-resentation for describing the shapes of patterns.

Scale-invariant feature transform (SIFT)-based dictio-nary: SIFT feature is known for its ability in handling intensity, rotation, scale and affine variations. A histogram of SIFT converts each patch to 128-D vector.

Discrete cosine transform (DCT) dictionary: DCT his-tograms are invariant to translation and rotation. In this paper, each block is represented by the coefficients of the DCT, applied to each channel of the RGB color space.

Gray-level co-occurrence matrix (GLCM): GLCM tex-tures are obtained by a tabulation of how often different combinations of pixel brightness values occur in an im-age.

MPEG-7 edge histogram (EH): EH describes the local edge distribution of an image. The descriptor is scale in-variant and supports rotation invariant and rotation sensi-tive matching operations.

MPEG-7 Homogeneous textures (HT): An HT descriptor provides a quantitative representation using 62 numbers, including the image intensity average, standard deviation (SD) of the image pixels, energies of the 30 partitioned frequency channels based on the human visual system, and energy deviations of these 30 channels.

B. Distance Calculation and Normalization

In this feature distances have to be calculate using a specifically defined distance metric of each feature space. The goal of normalization is to guarantee the appropriateness of comparing different measurements that differ in scale and domain.

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Distri-bution	$\Theta =$	PDF	Mean	Standard deviation
Normal	(μ, σ)	$\frac{1}{\sqrt{2\pi\sigma^2}} exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$	μ	σ^2
Gamma	(k, θ)	$x^{k-1}\frac{exp(-x/\theta)}{\Gamma(k)\theta^k}$	$k\theta$	$k\theta^2$
Laplace	(μ, b)	$\frac{1}{2b} exp\left(-\frac{\lvert x-\mu\rvert}{b}\right)$	μ	$2b^2$
Log-norm	(μ, σ)	$\frac{1}{x\sqrt{2\pi\sigma^2}} exp\left(-\frac{(ln\, x-\mu)^2}{2\sigma^2}\right)$	e^{μ}	$\left(e^{\sigma^2}-1\right)e^{2\mu+\sigma^2}$
Rayleigh	(σ)	$\frac{x}{\sigma^2} exp\left(\frac{-x^2}{2\sigma^2}\right)$	$\sigma\sqrt{\frac{\pi}{2}}$	$\frac{4-\pi}{2}\sigma^2$
Expo-nential	(λ)	$\lambda exp\left(-\lambda x\right)$	$\frac{1}{\lambda}$	$\frac{1}{\lambda^2}$

PDFS IN THE SET OF POSSIBLE APPROXIMATIONS FOR EACH DISTANCE DISTRIBUTION

III. MULTIFEATURE BASED HISTOLOGY IMAGE RETRIEVAL

The proposed approach to multifeature-based histology im-age retrieval relies on the MOL method that is able to automat-ically learn a suitable multifeature model from a representative group containing multiple query images as a visual representa-tion for the keyword.

A. Representative Query Images

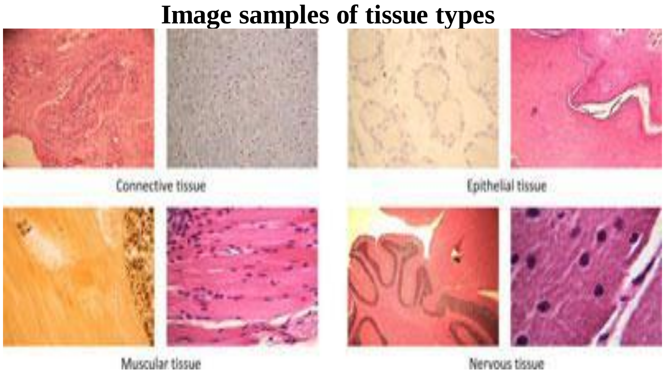
To define a suitable combination model for each keyword related to the histology database, multiple query images are employed in a query process. Due to the complex and varying visual appearance in different keywords, it is unrealistic to as-sume that there exist a single image query giving an optimal representation of a semantic keyword

B. Optimization of Multifeature Model and Histology Image Retrieval

The aim of MOL method is to define a suitable multifeature model for the visual representation of a specific histological keyword. The core of this method is a learning process toward an optimal combination model by assigning each involved low-level feature space F_j a proper weight α_j . This can be achieved by optimizing an objective function or a set of objective func-tions for variable α.

C. Multiobjective Optimization

Image samples of tissue types



In comparison to the single-objective-based optimization schemes, the advantage of employing the proposed MOL method is that each representative sample and its correspond-ing objective function are treated separately in an optimization process. The interest of each representative sample is taken into account while the overall interest is being satisfied. MOO is used to find the solution that can achieve a balanced local optimum for each objective, without compromising the other objectives.

HISTOLOGY IMAGE RETRIEVAL IN OPTIMIZED MULTIFEATURE SPACES

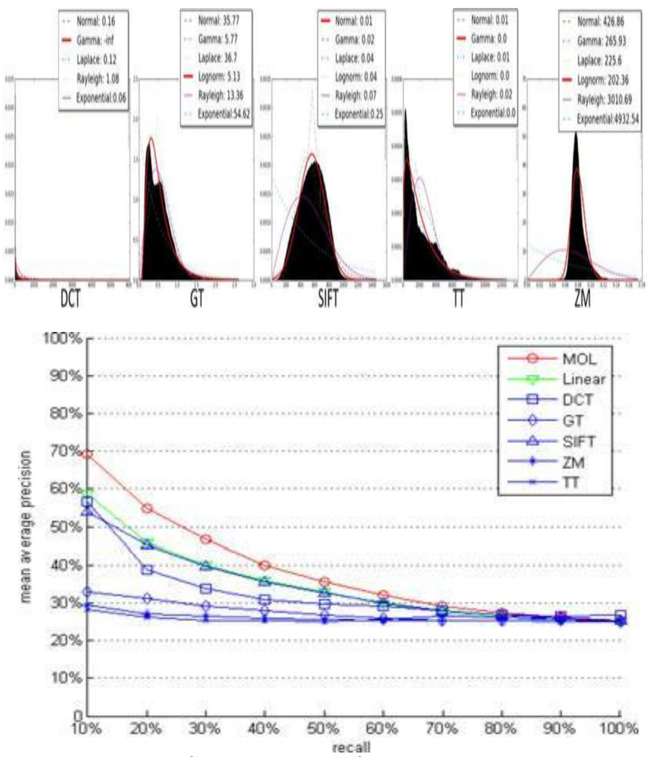


Fig. 2. Distribution of distances in each feature space. Plot labels show the KL-divergence scores for each PDF. The best fit PDF with minimum score is shown in a bold-continuous curve.

TABLE II
NORMALIZATION PARAMETERS

	PDF	Parameter I	Parameter II
DCT	Gamma	$k = 0.087$	$\sigma = 3124.743$
Gabor Textures	Log-norm	$\mu = -0.799$	$\sigma = 0.601$
SIFT	Normal	$\mu = 556.950$	$\sigma = 181.939$
Tamura Textures	Gamma	$k = 1.241$	$\sigma = 1712.942$
Zernike Moments	Log-norm	$\mu = -2.531$	$\sigma = 0.131$

TABLE III
EXPERIMENT I: RETRIEVAL EVALUATION OF FOUR TISSUE TYPES USING AN MOL APPROACH ACROSS FIVEFOLDS, MEAN AND SD VALUES REPORTED

Tissue types	AP		R-prec		Prec 20	
	Mean	SD	Mean	SD	Mean	SD
Connective	0.378	0.024	0.354	0.014	0.830	0.249
Epithelial	0.467	0.018	0.409	0.020	0.840	0.188
Muscular	0.338	0.024	0.303	0.045	0.760	0.167
Nervous	0.584	0.032	0.525	0.020	0.930	0.027

TABLE IV
EXPERIMENT I: RETRIEVAL EVALUATION OF THE PROPOSED RESULTS COMPARED TO SINGLE FEATURES AND LINEAR FUSION MODEL ACROSS FIVEFOLDS, MEAN VALUES REPORTED

Feature	mean AP	R-prec	Prec 20
GT	0.296	0.290	0.383
TT	0.272	0.255	0.313
ZM	0.273	0.267	0.343
SIFT	0.352	0.357	0.658
DCT	0.328	0.325	0.675
All features linear comb.	0.402	0.356	0.748
MOL feature comb.	**0.442**	**0.398**	**0.840**

In the same training set. The performance measures presented included mean and SD values across fivefolds in average pre-cision (AP); R-precision (R-prec), which was obtained at the point where precision and recall got the same value; and preci-sion after the first 20 retrieved samples (Prec 20), as shown in Table III.

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As presented in Table III, among the four different tissue types, some results are better compared to the others. For in-stance, the muscular tissue results are relatively less accurate than the other three. There are probably two reasons for that. First, the number of muscular tissue images is less than the oth-ers. There are 484 connective, 804 epithelial, 514 muscular, and 1026 nervous tissue samples in the evaluation dataset of exper-iment I. The task of retrieving images of a less popular query concept is usually more difficult than popular ones. Second, each different tissue type has its unique visual characteristics and patterns. Some of them may be trickier to recognize and differentiate from the others.

Table IV shows mean retrieval performance across four con-cepts, and using each of the five single features, and two dif-ferent feature fusion models. All features linear comb is the direct linear combination model of all the five features with the same importance weights for each feature space. This fu-sion model follows a direct linear combination approach. MOL feature comb. represents the results using the proposed MOL feature combination model. As it can be observed in Table IV, the proposed MOL method performed the best out of the seven different retrieval methods.

To further analyze the results, a statistical significance test was performed based on binomial testing. Given the null hypothesis that the MOL-based feature fusion model does not improve the retrieval AP on top of the second best approach—the linear fusion model, the *P*-value was calculated to be 0.003. This means that we can confidently reject the null hypothesis and declare that our approach has shown a statistically significant improvement in the experiment compared to the linear fusion model.

It represents the mean average precision–recall curves cor-responding to MOL model-based multifeature retrieval, a linear fusion model for multifeature retrieval, and retrieval using each of the considered single features. This figure shows that MOL multifeature retrieval has shown a clear advantage in the perfor-mance over the retrievals relying on direct linear combination or single features. Moreover, direct linear fusion multifeature retrieval did not bring significant improvements in the retrieval performance based upon SIFT feature.

In three vectors are GT, GLCM, and ZM, and two MPEG-7 texture features: EH and HT. As experiment II aims at demonstrating that the proposed approach for fusion model learning is independent of selected features, we replaced three features (ZM, SIFT, and DCT) in ex-periment I with three other texture features—GLCM, EH, and HT. The other two features, GT and TT which had relatively poor performance in experiment I, were kept and used again in experiment II. GLCM feature also uses the same Euclidean distance metric in (12). For the two MPEG-7 features, EH and HT, their recommended distance metrics in MPEG-7 standard were used.

After the feature extraction and distance calculation steps, the same distance normalization process was performed fol-lowing the same steps as described in experiment I. Here, the PDF parameters were estimated based on a combined set of all images in both two experiments, because the number of images in experiment II may not be big enough for acquiring appropriate estimations of parameters. Similar normalization results were obtained but are not presented here due to the space limitation.

For each keyword, a representative group was randomly se-lected based on the ground-truth annotations, and the rest of image in the dataset were used for testing. For this experiment, a comparison of results are shown in Table V,based on five single features, the linear fusion model and the MOL-based fusion model. Similarly, three evaluation scores for each tissue concept, MAP, R-prec, and Prec 20, are presented.

An average precision–recall curve is presented for this set of experiment results in Fig. 4. In Table V and Fig. 4, a similar observation from experiment I can be obtained that the proposed MOL feature fusion model outperformed the other models or single features. This observation conforms our assumption that the proposed feature fusion approach is independent of the set of testing features.

V. CONCLUSION

This paper proposes a strategy for multifeature-based retrieval in histology image databases. The multifeature fusion model is obtained using a MOL method, which automatically derives a suitable model for feature combination based on multiple query images that are associated with the keyword in concern. The advantage of the proposed feature fusion approach is that it considers a fusion model for each keyword individually. Two different histology image datasets and different sets of low-level features were considered in the experiments. Experimental per-formance of the proposed approach, as well as a comparison to retrievals relying on single features and other similar fusion models, were presented and analyzed. The evaluation of re-sults showed that, in the used experimental setups, the proposed strategy was able to provide more precise retrieve results based on semantic keywords that were each represented by a set of query images.

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D.Sudha received the M.E degree in computer science from Anna University, Chennai in 2012, and the B.E. degree in computer science and information engineering from Anna University, Chennai in 2010. She has been with the Faculty of the Department of Computer Science and engineering, Tagore Institute Of Engineering and Technology since 2012, where She is currently a Assistant Professor. Her current research interests include Automated Predictions in image Processing .

Dr.J.Priyadarshini received the B.E. degree in computer science from the Anna university in 2006 and the M.E. degree in computer science from the Anna University, in 2008 and Ph.D. degree in computer engineering from MIT University in 2012. She was a Teaching Research Associate, in I.T Department of MIT Campus from 2008 to 2012. Her current research interests include database design, data structures, and image processing. At Present she was working Associate Professor in VIT University, Chennai campus.

A.Ranjidha received the M.E degree in computer science from Anna University, Chennai in 2012, and the B.E. degree in computer science and information engineering from Anna University, Chennai in 2010. She has been with the Faculty of the Department of Computer Science and engineering, Tagore Institute Of Engineering and Technology since 2012, where She is currently a Assistant Professor. Her current research interests include in digital image Processing .

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