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MR IMAGE CLASSIFICATION USING WKNN AND E-LTrP

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Abstract— Image classification is one of the important steps in image annotation. Features extracted from the image serves as the base for image classification. For medical images local features have more discriminative power than global features. Enhanced Local Tetra Patterns (E-LTrP) of medical images are extracted for constructing the feature set of training images together with the perceptual features. But matching features with base images alone does not have good outcome in the context of image annotation. Hence images need to be further classified using a classifier. This paper compares the outcome of results without a classifier and using a classifier. Two types of classification employed in annotation are supervised and unsupervised. The method employed in this work is supervised image classification using Weighted K-NN classifier and classification using E-LTrP features.

Index Terms— Classification, Medical Image Annotation, K-NN classifier, LTrP, MR images

1 INTRODUCTION

IMAGE annotation is the process of assigning text to images for describing its context, content or purpose. The annotated and indexed images enable effective search and retrieval of images [1], [2]. Manual annotations of images are fraught with inaccurate details and mostly error prone. Moreover it is also time consuming and labor-intensive work [3], [4], [5]. Hence computer aided systems are needed to automate the process of annotation. Automatic image annotation, which is usually formulated as a multi-label classification problem, is one of the major tools used to enhance the semantic understanding of web images [6].

Classification is a general process related to categorization, the process in which ideas and objects are recognized, differentiated and understood. This is a major machine learning area which in course of time is renewed due to the applications like data mining, financial forecasting, organization and retrieval of multimedia and bioinformatics. Image classification refers to assigning a class label to each image which globally describes the image. This includes a broad range of decision-theoretic approaches to the identification of images. All classification algorithms are based on the assumption that the image in question depicts one or more features and that each of these features belongs to one of several distinct and exclusive classes. The classes may be specified a priori by an analyst (as in supervised classification) or automatically clustered (i.e. as in unsupervised classification) into sets of prototype classes, where the analyst merely specifies the number of desired categories.

Feature extraction phase serves as the initial step for classification. A feature is defined to capture a certain visual property of an image, either globally for the entire image or locally for a small group of pixels. In global extraction, features are computed to capture the overall characteristics of an image [7]. The advantage of global extraction is its high speed for both extracting features and computing similarity. But global features are often too rigid to represent an image. Specifically, they can be oversensitive to location and hence fail to identify important visual characteristics. To increase the robustness of spatial transformation, the second approach to form signature is by local extraction and an extra step of feature summarization. In local feature extraction, a set of features are computed for every pixel using its neighborhood (e.g., average color values across a small block centered on the pixel).

Medical image annotation (MIA) involves annotating medical images for the purpose of diagnosis, study and future reference. MIA is of two types pathological and anatomical. Pathological annotation deals with identifying the disease in the medical images whereas anatomical annotation involves identifying the body parts or regions found in the images. Magnetic Resonance (MR) imaging is a safe and economic method employed in disease diagnosis. The domain of study in this paper involves MR images.

2 RELATED WORKS

The nonparametric K-nearest neighbor classifier was used in [8] to automatically detect and classify melanoma. Automated image annotation based on nonparametric density estimation was proposed in [9]. Under this framework very simple global image properties like color and texture, can yield reasonable annotation accuracies. The image signatures were compared using Earth Mover's Distance (EMD) measure. Image annotation performance largely depends on three issues: (1) automatic image feature extraction; (2) a semantic image concept modeling; (3) algorithm for semantic image annotation. Wang and Khan in [10] proposed weighted feature selection

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algorithm as a solution to this problem. For a given cluster, relevant features were determined based on histogram analysis and greater weight is assigned to relevant features as compared to less relevant features. Visual tokens were linked with keywords based on clustering results of K-means algorithm. In [11] in order to address the first issue, multilevel features are extracted to construct the feature vector, which represents the contents of the image. To address second issue, domain-dependent concept hierarchy is constructed for interpretation of image semantic concepts. To address third issue, automatic multilevel code generation is proposed for image classification and multilevel image annotation. In [12] discriminative cue integration, based on support vector machines was addressed to tackle the problem. K-Nearest Neighbour (KNN) classifier is used to classify medical images in two classes abnormal and normal based on statistical textural features of images in [13]. In [14] adaptive nonparametric approach using KNN is proposed for annotation followed by contextual smoothing. An open challenge for automatic annotation of medical images is that images that belong to the same visual class might look very different, while images that belong to different visual classes might look very similar. The challenge described above is known in the medical image annotation literature as the inter-class vs intra-class variability problem.

3 Proposed Method

Image annotation or image tagging is the process of giving keywords to an image identifying its domain or purpose. From the image search point of view it gives index to an image which aids in faster retrieval of images. Efficient retrieval of images is possible if annotations are proper and valid. To begin with a small set of training images was taken from the open source database, European Society of Radiology (EURORAD). The images acquired may contain noises. Hence noise removal is important as the presence of noise may degrade the accuracy of results. MR images have usually noises added to them during image acquisition. These noises were usually added in frequency domain and are of Gaussian and Rayleigh distribution. The most appropriate filter to remove these noises is Gaussian filter.

3.1 Feature Extraction

Image features provide the main signature of an image. Features of image can be broadly categorized as global and local features. Global features give the description of image as a whole, whereas local features give the fine details of the image. The collection contained mainly monochrome or gray level medical images with specific layout. There are at least five factors need to be considered in quality characteristics which include contrast, blur, noise, artifacts and distortion [15]. The accuracy of the classification system depends greatly on the representation of these low-level visual features. The more discriminative the low-level features, the more accurate the classification or annotation [16]. Texture features generally capture the information of image characteristic with respect to the changes in certain direction and scale of the image. This information gives benefit for regions or images with homogeneous texture. Among popular texture descriptor methods that have been used for medical image indexing and retrieval are co-occurrence matrices, wavelets and Fourier transform [17].

The feature vector is framed using the texture features and local features. Tamura textures were calculated based on the co-variance matrix (COM) which includes contrast, coarseness, directionality and skewness. Local features were calculated using LTrP [18] and E-LTrP. Local Tetra Patterns (LTrP) which describes the spatial structure of the local texture using the direction of the center gray pixel g_c. The first order derivatives were calculated along 0° and 90° directions.

3.2 Enhanced Local Tetra Patterns (E-LTrP)

The proposed method uses LTrP and further enhances the number of features. Using LTrP, all patterns are separated into four parts based on the direction of the center pixel. Finally tetra patterns of each part are converted to three binary patterns. Thus 12 (4 x 3) binary patterns are obtained. The 13th pattern is the magnitude, calculated from magnitudes of horizontal and vertical first order derivatives.

If we shift an image, the output image is same but for the shift applied [19] and it is observed in [18] that increase in number of features will increase the accuracy of image retrieval. These are the reasons which induced the idea to use the shift operation for generating additional features. Circular right shift is applied on the binary patterns four times to generate additional 13 features. Textural features like coarseness, contrast, directionality and busyness were also calculated. Thus a total of 30 features were obtained. Histograms of original binary patterns and shifted patterns are calculated.

3.3 Classification

Feature extraction phase constructs a feature vector of training and test images. Apparently there is a wide semantic gap between the search image and retrieved image, if we consider only the image content. In order to overcome this problem the features were further classified using K-NN classifier.

3.3.1 Building classifier model

One of the widely used methodologies in automatic image annotation is the classification approach, where image is classified according to predefined classes and class label is considered as image label. In traditional classification problems usually a text or image is classified as member of a single class. However in the semantic domain a text or image can be member of more than one class. Image semantics is represented by multiple entities in the image and the relationship between them.

3.3.2 KNN Classifier

K-nearest Neighbor rule (KNN) has been one of the most well-known supervised, nonparametric learning algorithms in pattern classification, since it was first introduced [20]. The entire training dataset is retained during learning and each query is assigned a class represented by the majority label of its k-nearest neighbors in the training set. The simplest form of KNN is the Nearest Neighbor rule where k=1. Main advantages of KNN are: (1) It is robust to noisy data, (2) Target function for a whole space may be described as a combination of less complex local approximations, (3) Learning is very simple, (4) Can work with relatively little information.

It has been found that the asymptotic error rate of KNN approaches the optimal Bayes error rate R* when the number of samples N and the number of neighbors k tend to infinity and $k/N \to 0$, and the error rate of NN is bounded above by twice the optimal Bayes error rate 2R* [21].

K-Nearest neighbor classifier requires three things: (1) Set of sorted records, (2) Distance metric to compute distance between records, (3) The value of k, the number of nearest neighbors to retrieve.

The KNN algorithm works using a distance measure. WKNN is employed here as the nearest distance images were more likely to belong to the class of query image than those farther from it. The value of k is taken as square root of the number of classes.

3.3.3 Algorithm of WKNN

Let $T = \{(x_i, y_i)\}_{i=1}^{N}$ denote the training set, where, $x_i \in R^m$ is training vector in the m-dimensional feature space, and y_i is the corresponding class label. Given a query x′, its unknown class y′, is assigned by the steps: (1) Compute distance of other training records with that of x′, (2) Identify k nearest neighbors, (3) Use class labels of nearest neighbors to determine the class label of unknown record by taking the majority vote.

3.3.4 Determining the majority vote

In order to boost the classification results, calculation of majority vote of WKNN is modified in this work. The textural features of the query image x′, is further compared with that of nearest matching class's (y_i) range of values, that is, if the image's feature values are in between the possible maximum $(x_{ij_{max}})$ and minimum $(x_{ij_{min}})$ values of the class images, where j is the feature value, then a weight (w_{ij}') of 1 is assigned to that feature, if not weight is zero. Weight of the class (y_i) is then calculated as:

$$w_i' = \sum_j w_{ij}' \quad (1)$$

The classification result of the query is made by the majority weighted voting:

$$y' = \arg\max_y \sum_{(x_i^{NN}, y_i^{NN}) \in T'} w_i' \times \delta(y = y_i^{NN}) \quad (2)$$

where, x_i^{NN} is the ith nearest neighbor, and y_i^{NN} is the class label for i. $\delta(y = y_i^{NN})$, is the Dirac delta function which takes the value of one if $y = y_i^{NN}$ and zero otherwise.

4 Results and Discussions

The MR images are classified into one of the 12 classes as given in tables 1, 2 and 3. Table 3 shows that images are classified with higher accuracy and recall when WKNN classifier is used with E-LTrP features than when classification is done individually by E-LTrP features alone or with WKNN classifier alone.

TABLE 1
PERFORMANCE MEASURES OF CLASSIFICATION USING E-LTRP ALONE

Class Name	Accuracy	Error Rate	Recall	Precision
Alzhemiers	0.86	0.14	0.50	0.50
Normal	0.74	0.26	0.17	0.14
Glioma	0.74	0.26	0.00	0.00
Cavernous Angioma	0.90	0.10	0.67	0.67
Motor Neuron	0.90	0.10	0.67	0.67
Herpes Encephalitis	0.86	0.14	0.50	0.50
Multiple Sclerosis	0.81	0.19	0.17	0.25
Abnormal	0.76	0.24	0.83	0.88
Degenerative	0.81	0.19	0.58	0.70
Inflammatory	0.67	0.33	0.33	0.40
Stroke	0.93	0.07	0.83	0.71
Tumor	0.74	0.26	0.00	0.00
Average	**0.81**	**0.19**	**0.44**	**0.45**

TABLE 2
PERFORMANCE MEASURES OF CLASSIFICATION USING WKNN

Class Name	Accuracy	Error Rate	Recall	Precision
Alzhemiers	0.90	0.10	0.33	1.00
Normal	0.81	0.19	0.67	0.40
Glioma	0.98	0.02	0.83	1.00
Cavernous Angioma	1.00	0.00	1.00	1.00
Motor Neuron	0.90	0.10	0.83	0.63
Herpes Encephalitis	0.90	0.10	0.67	0.67
Multiple Sclerosis	0.93	0.07	0.67	0.80
Abnormal	0.81	0.19	0.83	0.94
Degenerative	0.81	0.19	0.58	0.70
Inflammatory	0.83	0.17	0.67	0.73
Stroke	1.00	0.00	1.00	1.00
Tumor	0.98	0.02	0.83	1.00
Average	**0.90**	**0.10**	**0.74**	**0.82**

TABLE 3
PERFORMANCE MEASURES OF CLASSIFICATION USING WKNN WITH E-LTRP

Class Name	Accuracy	Error Rate	Recall	Precision
Alzhemiers	1.00	0.00	1.00	1.00
Normal	0.98	0.02	0.83	1.00
Glioma	0.95	0.05	0.83	0.83
Cavernous Angioma	0.98	0.02	1.00	0.86
Motor Neuron	1.00	0.00	1.00	1.00
Herpes Encephalitis	0.98	0.02	0.83	1.00

Multiple Sclerosis	1.00	0.00	1.00	1.00
Abnormal	0.98	0.02	1.00	0.97
Degenerative	1.00	0.00	1.00	1.00
Inflammatory	0.98	0.02	0.92	1.00
Stroke	0.98	0.02	1.00	0.86
Tumor	0.95	0.05	0.83	0.83
Average	**0.98**	**0.02**	**0.94**	**0.95**

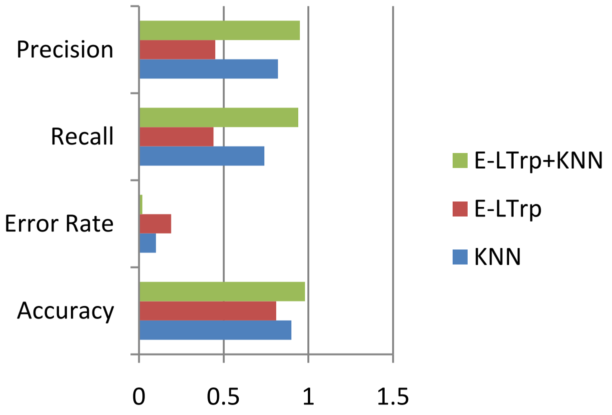

Fig. 1. Comparison chart of performance measures using E-LtrP, KNN and E-LTrP with KNN

5 Conclusion

Fig. 1 shows that classification results are better when E-LtrP features are combined with weighted KNN classifier. The classifier performed with 98% accuracy with an error rate of 2%. Further work aims to improve the accuracy by including semantic knowledge base for classification.

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