2012 International Conference on Information and Network Technology (ICINT 2012)
IPCSIT vol. 37 (2012) © (2012) IACSIT Press, Singapore

Multi Label Boosting for Image Classification

Bhuvaneswari Perumal and ChitraKala Gopalan +
CSE Dept, Easwari Engineering College

Abstract. In this paper we present a new object recognition system named Multi Label Boosting which learns from multi-label data through boosting and improves the performance of Multi Instance Learning. In an image the instance may belongs to several classes. The main challenge of this problem is that usually classes are overlapped and correlated. In single instance the correlation among instance is not taken into account. The correlations among different tags can significantly help predicting precise labels for improving the performance of image classification. The proposed framework comprises an input image which can be partitioned into image patches and features can be extracted. It proposes Multi Label Boosting, breaks the original training set into several disjoint clusters of data and k means clustering is used to perform automatic instance cluster. Kernel canonical Correlation analysis can be made between disjoint clusters to know exact correspondence between image patches. The SVM classifier used to classify the image based on domain specific. Multi label boosting is one potential solution to address the issue of huge inter-concept visual similarity and improve the classification accuracy. Applications of image classification are computer vision, object recognition, pattern recognition, computer graphics, medical imaging.

Keywords: multi label boosting, instance clustering, huge inter concept similarity, correlation analysis.

1. Introduction

Image data are typically Multi Instanced, each image belongs to several classes. In Single instance where classes are mutually exclusive and most approaches treat a learning task as multiple binary classification tasks. These way potential correlations among the labels are not taken into account. However, in Multi Instance Learning approaches that attempt to take correlations into account. The major issues are huge inter concept similarity, huge intra concept diversity. But in Multi-label where classes are not mutually exclusive and an instance that may belong to several classes simultaneously. The main challenge of this problem is that usually classes are overlapped and correlated. Multi Label boosting consider the correlations among different tags can significantly help predicting precise labels for improving the performance of image classification. The above problem has stimulated us to propose a system to classify image based by using Multi Label Boosting. It significantly improves the classification accuracy.

The rest of this paper is structured as follows. Section 2 presents background information on image classification, Section 3 reviews related work on image classification, while Section 4 introduces the proposed approach. Section 5 describes the setting of the empirical study and Section 6 presents and discusses the results. Finally, section 7 concludes this work and points to future research directions.

2. Related Work

The effective multi-label classification methods such as Multi-label boosting strategy which learning the correlation between image segments and the text tag in a set of training images. SVM based multi-label active learning model is explored for image classification [3].

+ Corresponding author. Tel.: + 9444182150.
E-mail address: ckgops@gmail.com.

Multi-instance learning (MIL) based image classification takes the relations between labels and regions into account. In this paradigm, an image is regarded as a bag consisting of multiple instances (i.e., regions). MIL allows of only labeling images at the Image level, instead of labeling at region level, when building classifiers. For a specific semantic label, a bag is labeled positive if at least one instance has the corresponding semantic meaning; otherwise, it is negative [1]. SVM based multi-label active learning model is explored for image classification. It considers the Correlation of words among the semantic keyword of images. It minimize the classification error are different due to the inherent label correlations [6]. Multi label classification considers correlation among labels. Problem transformation (PT) and algorithm adaptation (AA) to convert multiple binary classifications into single label classification. Adapt binary classification [2]. The critical problem remained in the existing approaches is how to exploit the correlations between class labels. Multi Label Boosting is proposed to identify correlation among image patches can take in to account to classify images based on domain specific. It improves the image classification accuracy.

3. System Architecture

An Automatic Instance Clustering and correlation analysis is performed for identifying exact correspondence between image instances. Each image region is treated as one instance and multimodal visual features are extracted. The region-based visual features are Colors, Edges and Textures (Contourlet). Contourlet transform improve the performance of edge detection in initial stage. In Multi label boosting identify the exact correspondence between image patches it improves the classification accuracy. The functional architecture for proposed system is given in Fig.1 It has the following modules, Feature Extraction, Multi Instance Learning and Classifier. The input image can be segmented into image patches. Each image region is treated as one instance and multimodal visual features are extracted from each image instance.

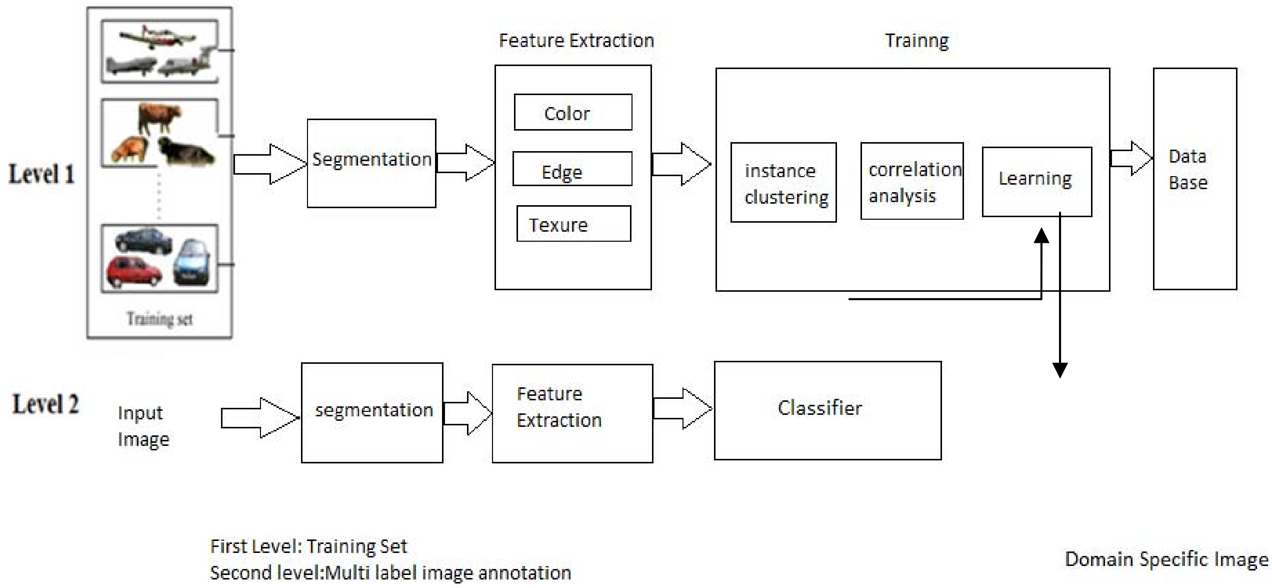

Fig. 1: Functional Architecture for Image Classification by Multi Label Boosting

There are two well-accepted approaches for classifier training: discriminative approach and generative approach. The major weakness of the discriminative approach is that it cannot tackle the issue of huge inter-concept visual similarity effectively. The major weakness of the generative approach is that it cannot handle the high-dimensional multimodal visual features effectively. It is very attractive to integrate them to tackle the issues of huge intra-concept visual diversity and huge inter-concept visual similarity more effectively. To address these two challenging issues more effectively, a Multi Label Boosting is developed in this paper to achieve more accurate training of classifiers.

3.1. Feature extraction

Each multi label image can be partitioned into set of image instances/image regions Each image region is treated as one instance and multimodal visual features are extracted from each image instance to characterize its various visual properties more sufficiently. The following region-based visual features are extracted are colours, shape, texture (contour let).Contourlet Transform (CT) addresses this problem by providing two additional properties viz., directionality and anisotropy.

Contourlet feature extraction. Contourlet transform is a multi scale and directional image representation that uses first a wavelet like structure for edge detection. Contourlet transform can be divided into two main steps: Laplacian pyramid (LP) decomposing and directional filter banks (DFB). Fig.2 shows sparse expansions for typical images having smooth contours.

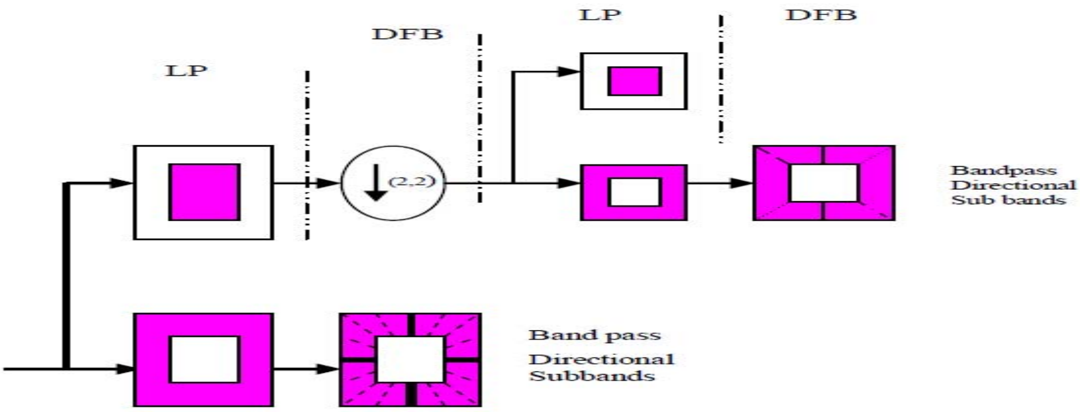

Fig. 2: Double Filter Bank Decomposition of Contourlet Transform

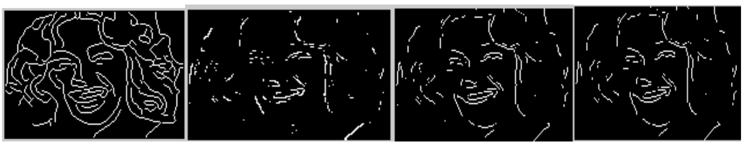

Fig. 3: a) Canny b) Roberts c) Sobel d)Prewitt

3.2. Multi instance learning

The Image Instances in the positive bags and the negative bags are first partitioned into multiple clusters according to their visual similarity contexts. Inter-cluster correlation analysis is further performed for identifying the exact correspondences between multi labels and the image instances The proposed system proposes k-means algorithm for automatic instance clustering and perform correlation analysis between those two clusters. Multi label boosting algorithm for Multi Instance learning. It improves the image classification accuracy.

K-Means clustering. Clustering is the process of partitioning or grouping a given set of patterns into disjoint clusters. In K mean method the number of k clusters, here k _is assumed to be fixed. Let the k prototypes $(w_1,.....w_k)$ be initialized to one of the n input patterns $(i_1,.......i_n)$. The followings steps are,

Each cluster C_j is associated with prototype w_j.

Repeat for each input vector $i_{1,}$ where $l \in \{1,.....n\}$, do Assign $i_{1,}$ to the cluster C_j *, with nearest prototype w_{j*} for each cluster C_j, where $j \in \{1,.....k\}$,do Update the prototype w_j to be the Centroid of all samples currently. In C_j, so that

$$w_j = \sum_{ij \in C_j} i_1 / |C_j| \quad (1)$$

Compute the error function:

$$E = \sum_{j=1}^{k} \sum_{i_1 \in C_j} |i_1 - w_j|^2 \quad (2)$$

Until E does not change significantly or cluster membership no longer changes. It shows a high level description of the k-means clustering algorithm for automatic instance clustering and performs correlation analysis between those clusters.

Multi label boosting algorithm. Documents which are consistently labelled correctly decrease in training significance exponentially while documents which are consistently annotated incorrectly increase in training significance. Also, those which are consistently annotated incorrectly with the same words increase in training significance exponentially. The proposed system proposes Multi Label Boosting Algorithm for multi instance learning. It improves the performance of image classification.

Input: Documents $\langle (x_1, Y_1), ..., (x_N, Y_N) \rangle$ with labels $Y_i \subset Y = 1, ..., k$ with distribution D over the documents. Integer T specifying number of iterations and training speed constant K.

Initialize the weight vector: $w^1_{i,y} = 1$,for t=1 to T do

Set:

$$W^T{}_i = \sum_{y \notin Y} w^t{}_{i,y} = 1\,;\, q_t(i, y) = \frac{w^t{}_{i,y}}{W^t{}_i} \tag{3}$$

For $y \notin Y_i$; and set :

$$D_t(i) = \frac{W_i^t}{\sum_{i=1}^{N} W^t{}_i} \tag{4}$$

Call MultiWeakLearn, providing it with the distribution D_t and label weighting function q_t ; get back hypothesis $h_t : X \times Y \rightarrow [0,1]$.

Set ε_t equal to the pseudoloss of h_t , Set

$$\beta_t = \frac{\varepsilon_t}{(1 - \varepsilon_t)} \tag{5}$$

Produce an annotation set A_i for each x_i where $|A_i| = |Y_i|$ and contains the most likely labeling elements y with regard to h_t . Set the new weights vector to be

$$w^{t+1}_{i,y} = \begin{cases} K w^t_{i,y} & y \in A_i \odot Y_i \\ \dfrac{w^t_{i,y}}{K} & otherwise \end{cases} \tag{6}$$

Output the hypothesis:

$$h_{f(x,y)} = \sum_{t=1}^{T} (\log \frac{1}{\beta_t}) h_t(x, y) \tag{7}$$

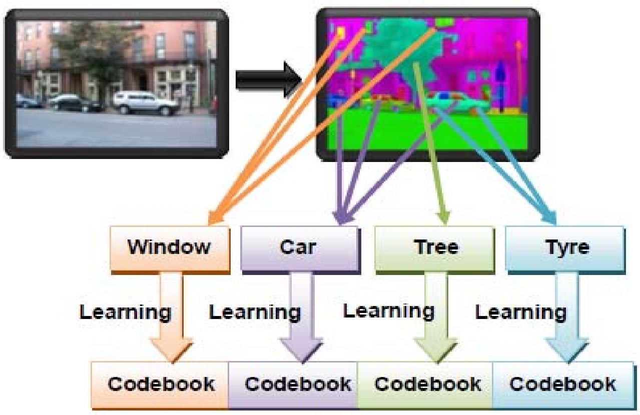

Fig. 4: Multi Instance Learning

3.3. Image classification

It is used to identify the object classes and image concepts from the test images. It automatically clusters the image instance and performs correlation analysis on different cluster to know exact correspondence between image instances. Multi label boosting is used to improve the classification performance. The test image is first segmented into multiple image regions or multiresolution image patches. Each image region or image patch (image instance) is first classified into the most relevant object class Ck on the visual concept network, which has the maximum value of the confidence score. The confidence scores for the inter-related object classes are further calculated to determine the potential classification paths. If the confidence scores for some of these inter-related object classes are above a given threshold $\delta_2 = 0.65$ .The relevant classification paths are selected. Otherwise, the relevant classification paths are terminated. The test image is matched with the database and produces the domain specific images.

4. Experiments and Results

The corel dataset is a popular benchmark for image classification. It is based on 5000 Corel images, 4500 of which are used for training and the rest 500 for testing. The Proposed system uses the contourlet transform is used for the initial edge based it improve the performance of classification. It is compared with edge based technique like canny, Sobel, Prewitt, Roberts. The results shown for all edge based approaches are given in Fig. 3. The results are shown the performance classifier is compared based on domain specific images based on precision and recall. It significantly improves the performance of classification accuracy.

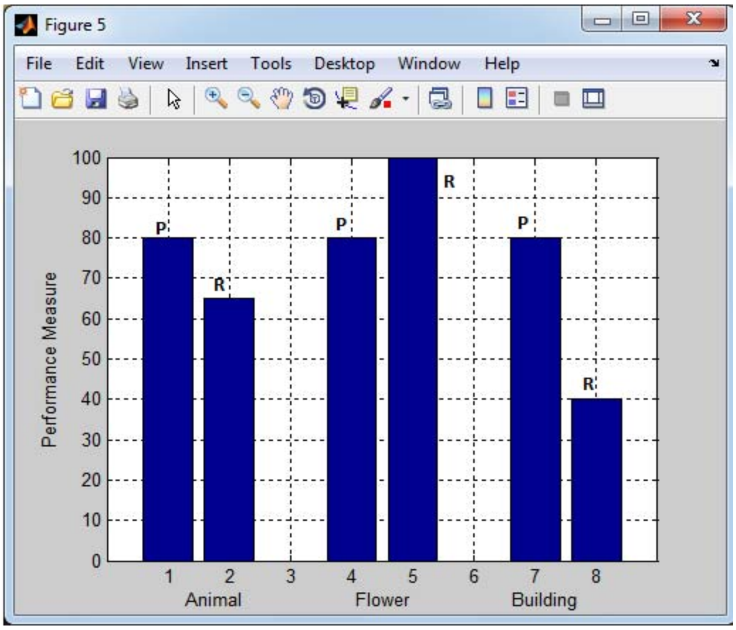

Fig. 5: performance measure of precision and recall

Table. 1: Domain sample values for precision and recall

Domain Name	Precision	Recall	Fscore
Animal	1	0.090	0.1651
Flower	1	0.51	0.4
Building	1	0.53	0.42
Animal	0.98	0.056	0.56
Flower	0.0982	0.067	0.58
Building	0.0889	0.087	0.30
Animal	0.0999	0.078	0.169
Flower	0.0877	0.067	0.76
Building	0.0867	0.056	0.56

5. Conclusion

In this paper, a Multi Label Boosting algorithm is developed to improve the performance of multi instance learning. K means clustering is used to achieve automatic Instance clustering and perform correlation analysis for identifying correspondence between the image instances. The visual concept network is constructed for characterizing the inter-concept visual similarity contexts more accurately in the high dimensional multimodal feature space and determining the inter-related learning task directly in feature space.

6. References

[1] Zheng-Jun Zha, Xian-Sheng Hua, and Jingdong Wang. Joint Multi-Label Multi-Instance Learning for Image Classification. Computer Vision and Pattern Recognition.2008, 1 -8.

[2] G.Nasierding and A.Z Kouzani. Empirical Study of Multi-label Classification Methods for Image Annotation and Retrieval. Digital Image computing.2010, 617-622.

[3] Matthew Johnson and Roberto Cipolla. Improved Image Annotation and Labelling through Multi-label Boosting.Machine Learning.1-6.

[4] J.Kumar, J.Pillai and D.Doermann. Document Image Classification and Labeling using Multiple Instance Learning. Document Analysis and Recognition (ICDAR). 2011,1059 – 1063.

[5] Y.Chen and J.Wang. MILES: Multiple instance learning via embedded instance selection. Pattern Anal. Mach. Intell. 2006,28:1931-1947.

[6] Guo-Jun Qi, Xian-Sheng Hua, and Yong Rui. Two-Dimensional Multi-label Active Learning with an Efficient Online Adaptation Model for Image Classification. Image processing.2010,31:1-6 .