IJISET - International Journal of Innovative Science, Engineering & Technology, Vol. 1 Issue 9, November 2014.
www.ijiset.com
ISSN 2348 – 7968

An Efficient Image Classification Using Class Imbalance in High-Dimensional Data

[1]R.Deepa, [2]K.Jeyalakshmi

[1]Research Scholar, PG & Research Department of Computer Science,
Hindusthan College of Arts & Science,Coimbatore, India
[2]Assistant Professor, PG & Research Department of Computer Science,
Hindusthan College of Arts & Science,Coimbatore, India

Abstract: The image classification based on large scale learning is widely used for commercial domain. The image clarity is one of the issues in Voter ID. This issue can be solved by large scale image classification based on Class imbalance method by increasing the competitive performance. The proposed work takes single image and several processes are carried out to obtain the final result. The proposed work is tested with two different datasets with different categories. The SIFT (Scale Invariant Feature Transform) extraction method finds the key points and descriptors of imbalance input images are considered to find the Depth of object orientation location of each image and then preprocessing method is the next step to detect the majority and minority class sampling allowing the system to receive the training instances as if they belonged to a well-balanced data sets. Imbalance Classification measure which is related two classes are to be labeled or unlabeled is calculated in third step and final method is the SVM (Support Vector Machine) method which is used to integrate the class imbalance classification methods result to obtain the result of accuracy of image and the classification is also measured. Thus the result is obtained with good classification quality. The proposed system helps various domains such as satellite, Medical industry and in rural areas, for capturing the images clearly which is used for further process.

Keywords: Image Mining, Artificial Neural Network (ANN), support vector machine (SVM), Bag Of Visual Words (BOV), Nearest Neighbor (NN), Scale Invariant Feature Transform (SIFT),Class imbalance, Singular Value Decomposition(SVD),The Homogeneous Texture descriptor(HTD

I. INTRODUCTION

The World Wide Web is regarded as the largest global image repository. Advances in mining and storage technology have led to tremendous growth in significantly large and detailed image databases. An extremely large number of image data such as satellite images, medical images, and digital photographs are generated every day. These images, if analyzed, can reveal useful information to the human user[2]. There is a lack of effective tools for searching and finding useful patterns from these images. Image mining systems that can automatically extract semantically meaningful information (knowledge) from image data are increasingly in demand. The fundamental challenge in image mining is to determine how low-level, pixel representation contained in a raw image or image sequence can be efficiently and effectively processed to identify high-level spatial objects and relationships.

The image mining deals with the extraction of implicit knowledge, image data relationship, or other patterns not explicitly stored in the image databases. It is an interdisciplinary endeavor that essentially draws upon expertise in computer vision, image processing, image classification, data mining, machine learning, database, and artificial intelligence[6][1]. While some of the individual fields in themselves may be quite matured, image mining, to date, is just a growing research focus and is still at an experimental stage.

The image database containing raw image data cannot be directly used for mining purposes. Raw image data need to be processed to generate the information that is usable for high-level mining modules [3]. An image mining system is often complicated because it employs various approaches and techniques ranging from image classification and indexing schemes to data mining and pattern recognition. A good image mining system is expected to provide users with an effective access into the image repository and generation of knowledge and patterns underneath the images. Such a system typically encompasses the following functions: image storage, image processing, feature extraction, image indexing and classification, patterns and knowledge discovery.

At present, it can distinguish two kinds of frameworks used to characterize image mining systems: function-driven versus information-driven image mining frameworks. The prior focuses on the functionalities of different component modules to organize image mining systems while the latter is designed as a hierarchical structure with special emphasis on the information needs at various levels in the hierarchy.

Object recognition has been an active research focus in field of image processing. Using object models that are known a priori, an object recognition system finds objects in the real world from an image. This is one of the major tasks in image mining. Automatic machine learning and meaningful information extraction can only be realized when some objects have been identified and recognized by the machine[7]. The object recognition problem can be referred to as a supervised labeling problem based on models of known objects. An object recognition system typically consists of four components, namely, model database, feature detector, hypothesizer and hypothesis verifier. The model database contains all the models known to the system. These models contain important features that describe the objects. The detected image primitive features in the Pixel Level are used to help the hypothesizer to assign likelihood to the objects in the image.

Image Classification 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 (e.g., geometric parts in the case of a manufacturing classification system, or spectral regions in the case of remote sensing, as shown in the examples below) and that each of these features belongs to one of several distinct and exclusive classes[10]. 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[18]. (Classification and segmentation have closely related objectives, as the former is another form of component labeling that can result in segmentation of various features in a scene.)

In this research, the Image Classification (using the minimum (mean) distance classifier), will consider a remote sensing or real sensing application. Here, a collection of multi-spectral images (i.e. images containing several bands, where each band represents a single electro-magnetic wavelength or frequency) of the planet Earth collected from a satellite. To classify each image pixel into one of several different classes (e.g. water, city, wheat field, pine forest, cloud, etc.) on the basis of the spectral measurement of that pixel.

It would be very difficult to find a threshold, or decision surface, with which to segment the images into training classes (e.g. spectral classes which correspond to physical phenomena such as cloud, ground, water, etc.). It is often the case that having a higher dimensionality representation of this information (i.e. using one 2-D histogram instead of two 1-D histograms) facilitates segmentation of regions which might overlap when projected onto a single axis, as shown for some hypothetical data in Figure 1.

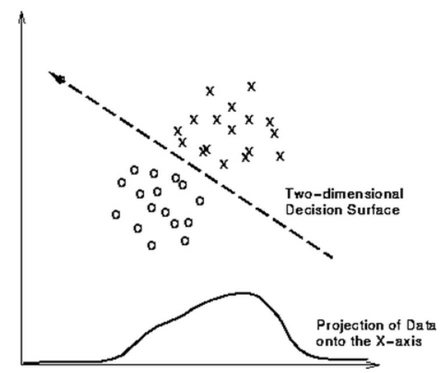


Figure 1: 2-D feature space representation of hypothetical data

II. RELATED WORK

The most important part of the research is Large-Scale Learning for Image Classification technology and methods used to retrieve color and texture information[9]. Therefore, in this chapter, the studies are focus on some basic concepts of image classification and also discuss recent techniques and methods being applied in existing multimedia application which uses classification. The study is carried out with the existing example of Image classification system and to understand how they work.

Image Classification is the process of assigning data to one of a set of pre-determined class labels. Let the input data, denoted by X, be a sample in some high-dimensional data space R^N where N is presumed large. For example, X might be samples of a digitized camera image. It is always assumed that X is the *original* data. That means that no processing that might result in meaningful information loss has been made to the data. The so-called C -ary classification problem is that of assigning X to one of C classes. The statistical hypothesis that class H_j is true is denoted by H_j , $1 \le j \le C$.

The image Classification is a fundamental problem that has to be solved if machines are to approximate the human functions of recognizing sounds, images, or other sensory inputs. This is why classification is so important for automation in today's commercial and military arenas. Many of us have first-hand knowledge of successful automated recognition systems from cameras that recognize faces in airports to computers that can scan and read printed and handwritten text, or systems that can recognize human speech[14]. These systems are becoming more and more reliable and accurate. Given reasonably clean input data, the performance is often quite good. But many of these systems fail in applications where clean, uncorrupted data is not available or if the problem is complicated by variability of conditions or by proliferation of inputs from unknown sources. In short, they often fail in difficult problems where skilled human operators perform very well.

Image classification is the problem of assigning one or multiple labels to an image based on its content. This is a standard supervised learning problem: given a training set of labeled images, the goal is to learn classifiers to predict labels of new images. Large-scale image classification has recently received significant interest from the computer vision and machine teaching communities [8], [16], [12]. This goes hand-in-hand with large-scale datasets being available. For instance, ImageNet (www.image-net.org) consists of more than 14M images labeled with almost 22K concepts [13], the Tiny images data set consists of 80M images corresponding to 75K concepts and Flickr contains thousands of groups (www.flickr.com/groups) with thousands (and sometimes hundreds of thousands) of pictures, that can be exploited to learn object classifiers, [19].

III. PROPOSED SYSTEM

The proposed system addresses the problem of the one-versus-rest method classification of large-scale learning images with multiple imbalanced classes and very high dimensionality. Using stochastic gradient descent, it can scale the training to millions of images and thousands of classes. Class imbalance classification is handled by re-sampling the data set, whereas SIFT is applied to reduce the number of spectral bands. The proposed system, also show that learning through cross-validation the optimizing the imbalance parameter in one-versus-rest strategy is a must for competitive performance. This is a preliminary study that pursues to investigate the benefits of using together these two techniques, and also to evaluate the application order that leads to the best classification performance. Our approach is evaluated on the 100 largest classes of ImageNet and Caltech 101 datasets.

A. Scale Invariant Feature Transform (SIFT)

Scale Invariant Feature Transform (SIFT) is an image descriptor for image based matching developed by David Lowe (1999, 2004). This descriptor as well as related image descriptors is used for a large number of purposes in computer vision related to point matching between different views of a 3-D scene and view based object recognition. Experimentally, the SIFT descriptor has been proven to be very useful in practice for image matching and object recognition under real world conditions.

The SIFT descriptor comprised a method for detecting interest points from a grey level image at which statistics of local gradient directions of image intensities were accumulated to give a summarizing description of the local image structures in a local neighborhood around each interest point, with the intention that this descriptor should be used for matching corresponding interest points between different images. Later, the SIFT descriptor has also been applied at dense grids (dense SIFT) which have been shown to lead to better performance for tasks such as object categorization, texture classification, image alignment and biometrics . The SIFT descriptor has also been extended from grey level to color images and from 2-D spatial images to 2+1-D spatio-temporal video.

B. Image Content Descriptors

The image content may include both visual and semantic content. Visual content can be very general or domain specific. General visual content include color, texture, shape, spatial relationship, etc. Domain specific visual content, like human faces, is application dependent and may involve domain knowledge [17]. Semantic content is obtained either by textual annotation or by complex inference procedures based on visual content. This chapter concentrates on general visual contents descriptions. Later chapters discuss domain specific and semantic contents. A good visual content descriptor should be

ISSN 2348 – 7968

invariant to the accidental variance introduced by the imaging process (e.g., the variation of the illuminate of the scene). However, there is a trade-off between the invariance and the discriminative power of visual features, since a very wide class of invariance loses the ability to discriminate between essential differences. Invariant description has been largely investigated in computer vision (like object recognition), but is relatively new in image classification [1].

C. Homogenous Texture Description

The Homogeneous Texture descriptor (HTD) [17] provides a quantitative representation that is useful for similarity classification. The feature extraction is done as follows. Image is first filtered with a bank of orientation and scale turned filters (modeled using Gabor functions). The first and second moments of energy in the frequency bands are then used as the components of the descriptor. The number of filters used is 5x6=30 where 5 is the number of scales and 6 is the number of orientations used in the multi-resolution decomposition using Gabor functions. The HTD feature vector is then given by:

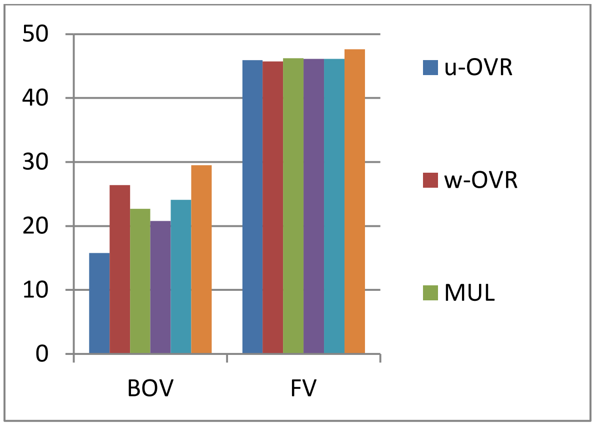
$$TD=[f_{DC}, f_{SD}, e_1, e_2, \ldots\ldots, e_{30}, d_1, d_2, \ldots d_{30}]$$

IV. EXPERIMENTAL RESULTS

From the results of our synthetic and real data experiments, it is, therefore, difficult to argue for the merits of one classifier or the other for denser or sparser data sets. The research work, provide a comparison of the OVR, MUL, RNK, and WAR SVMs.

Table 1: Comparison of Class imbalance-OVR, u-OVR, w-OVR, MUL, RNK, and WAR

	u-OVR	w-OVR	MUL	RNK	WAR	Class imbalance-OVR
BOV	15.8	26.4	22.7	20.8	24.1	29.5
FV	45.9	45.7	46.2	46.1	46.1	47.6



VI. CONCLUSION

In this paper, the SVM and class imbalance techniques was motivated by our interest in image mining, and the need for the methods, which can accomplish this task based on relational input data. This paper has presented new methods for visual classification on a large scale, i.e., when have to deal with a large number of classes, a large number of images and high-dimensional features. Two main conclusions have emerged from our work. The first one is that, despite its theoretical sub optimality, class imbalance-one-versus-rest is a very competitive training strategy to learn SVMs. Class imbalance is often reported as an obstacle to the induction of good classifiers by machine learning algorithms. However, for some domains, machine learning algorithms are able to achieve meaningful results even in the presence of highly imbalanced datasets.

In this research work, a systematic study using a set of artificially generated datasets aiming to show that the degree of class overlapping has a strong correlation with class imbalance. This correlation, to the best of our knowledge, has not been previously analyzed elsewhere in the machine learning literature. A good understanding of this correlation would be useful in the analysis and development of tools to treat imbalanced data or in the (re)design of learning algorithms for practical applications.

REFERENCES

[1] E.L. Allwein, R.E. Schapire, and Y. Singer, “Reducing Multiclass to Binary: A Unifying Approach for Margin Classifiers,” Proc. Int’lConf. Machine Learning (ICML), 2000.

[2] P.L. Bartlett, M.I. Jordan, and J.D. McAuliffe, “Convexity Classification, and Risk Bounds,” Proc. Conf. Neural Information Processing Systems (NIPS), 2003.

[3] Y. Bengio, A. Courville, and P. Vincent, Representation Learning: A Rev. and New Perspectives.

[4] A. Beygelzimer, V. Dani, T.P. Hayes, J. Langford, and B. Zadrozny, "Error Limiting Reductions between Classification Tasks," Proc. Int'l Conf. Machine Learning (ICML), 2005.

[5] Y.-L. Bourreau, F. Bach, Y. LeCun, and J. Ponce, "Learning Mid-Level Features for Recognition," Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2010.

[6] G. Burghouts and J.-M. Geusebroek, "Performance Evaluation of Local Colour Invariants," Computer Vision and Image Understanding, vol. 113, pp. 48-62, 2009.

[7] K. Crammer and Y. Singer, "On the Algorithmic Implementation of Multiclass Kernel-Based Vector Machines," The J. Machine Learning Research, vol. 2, pp. 265-292, 2002.

[8] G. Csurka, C. Dance, L. Fan, J. Willamowski, and C. Bray, "Visual Categorization with Bags of Keypoints," Proc. ECCV Workshop Statistical Learning in Computer Vision Workshop, 2004.

[9] J. Dean, G. Corrado, R. Monga, M. Devin, Q. Le, M. Mao, M. Ranzato, A. Senior, P. Tucker, K. Yang, and A. Ng, "Large Scale Distributed Deep Networks," Proc. Conf. Neural Information Processing Systems (NIPS), 2012.

[10] J. Deng, A. Berg, K. Li, and L. Fei-Fei, "What Does Classifying More Than 10,000 Image Categories Tell Us?" Proc. 11th European Conf. Computer Vision (ECCV), 2010.

[11] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, "Imagenet: A Large-Scale Hierarchical Image Database," Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2009.

[12] T. Deselaers and V. Ferrari, "Visual and Semantic Similarity in Imagenet," Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2011.

[13] J. Farquhar, S. Szedmak, H. Meng, and J. Shawe-Taylor, "Improving Bag-of-Keypoints Image Categorisation," technical report, Univ. of Southampton, 2005.

[14] V. Franc and S. Sonnenburg, "Optimized Cutting Plane Algorithm for Support Vector Machines," Proc. Int'l Conf. Machine Learning (ICML), 2008.

[15] Y. Gong and S. Lazebnik, "Comparing Data-Dependent and Data-Independent Embeddings for Classification and Ranking of Internet Images," Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2011.

[16] H. Je´gou, M. Douze, and C. Schmid, "Product Quantization for Nearest Neighbor Search," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 33, no. 1, pp. 117-128, Jan. 2011.

[17] T. Joachims, "Training Linear SVMs in Linear Time," Proc. 12th ACM SIGKDD Int'l Conf. Knowledge Discovery and Data Mining, 2006.

[18] A. Krizhevsky, I. Sutskever, and G. Hinton, "Image Classification with Deep Convolutional Neural Networks," Proc. Conf. Neural Information Processing Systems (NIPS), 2012.

[19] H. Je´gou, F. Perronnin, M. Douze, J. Sa´nchez, P. Pe´rez, and C. Schmid, "Aggregating Local Image Descriptors Into Compact Codes," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 34, no. 9, pp. 1704-1716, Sept. 2012.

BIOGRAPHIES

Ms.R.Deepa, Pursuing Mphil Research Degree in Hindusthan college of Arts & Science at Coimbatore. She received her PG degree MCA in Navarasam Arts & Science College for Women at Erode and also her UG Degree B.Sc (Mathematics) in Bharathidasan University. She had 2 years of Experience as an Assistant Professor in Sasurie College of Arts & Science.

Mrs.K.Jeyalakshmi Pursuing Ph.d in Bharathiar University. Currently she is working as an Assistant Professor of PG & Research Department of Computer Science in Hindusthan college of Arts & Science at Coimbatore. She received her PG degree MCA in Madurai Kamaraj university and also her UG Degree B.Sc (CS) in Bharathiar University. Totally she has 11 years and 4 Months of Experience in Teaching Field.