Need of Hubness for Object Recognition

Sneha Prakash Sumare, Rasika M. Kaingade

Abstract— **One of the essential troubles in image processing is recognition of object and semantically feature extraction. In this paper, we mainly concentrated on KNN methods, which are frequently applied in large number of algorithms and less frequently used in data type like image. In recent times data with high dimensionality exhibit property of high hubness, which effectively means that some data points from data set are very influential treat as most nearest neighbor of other data points, so these type data points are point out as hubs. In this paper we also see that hubs play a vital role in process of KNN classification. We study the hubness of various image data sets, below multiple different image local feature representations.**

Index Terms—**Hubness; object recognition; nearest neighbors; high dimensionality; image classification**

I. Introduction

Now a day importance of image processing increased more and more. Since the amount of applications is increasing constantly. Object detection and recognition is the most concentrated tasks in image analysis. That's why here we going focus on object recognition, for which many existing machine learning classification algorithms can be used. To analyze an image segment, an appropriate representation of the image must be chosen, and that depends on which task has to be done. This representation of image is normally contains process like extracting information contained into pixel color of image, gradient of image, texture involved into visual information of image data, edges of objects from image, or any information that found in image semantics which we feel may be important while capturing. This information and its representation may call as features. All such features are of two main types – local image features and global image feature. If we intended to summarize the mean properties of an interested segment we will use global image features, and in other hand the information from local features represent of imaged retrieved from neighborhoods of some sampling points [40]. Following are some different types of local image features.

A. Feature Types.

Many image feature types can be retrieved from image data. For the purpose generic object recognition we have choose three types of features that all have been successfully applied in algorithms.

1. Haar Features:

Haar filters work on gray level images and their value feature representation is represented by the difference of sums computed over rectangular areas. The areas have the same shape and size and are vertically or horizontally neighboring. We have used the two types of features: two-rectangular and three-rectangular as shown in Figure 1:

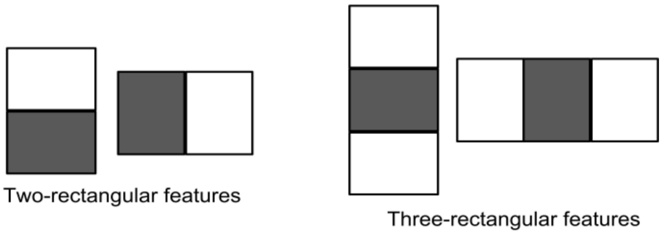

Figure. 1. Example of Haar filters

There is much difference between sums of pixels from two rectangular (the white and black regions) areas and value of a two-rectangular feature. The regions have the same shape and size and are horizontally or vertically adjacent. A 3 rectangular feature retrieved the addition within two outside rectangle areas subtracted from the addition in center rectangle area. The integral representation of an image is used to become more and more fast calculation of values of feature.

2. Histogram of oriented gradient (HoG) features:

The HoG representation was successfully used in purpose of classification in [36] and later extended to generic object recognition [9].

Following are steps of process for constructing the HoG comprises:

- Gradient computation
- Spatial/orientation binning
- Normalization and descriptor blocks

3. SIFT (Scale Invariant Feature Transform) features:

The SIFT technique for object recognition or visual scene comparison has been introduced by [22] and extended by [23] that is applied a fast KNN algorithm to invariant key points and get a robust object recognition technique. The main steps are as follow.

- To detect candidate ROI points, the difference between Gaussians will use. And these ROI points have property scale invariant and orientation invariant.
- Stability measure of ROI and selection of location of ROI key point.
- When we compare descriptor of every key point with respective orientation, we will get rotation invariant representation.
- By considering distortion in shape and illumination change invariance we will get final key point representation.

In this paper, we try to discover how the concept of hubness causes impact on image classification. The hubness is used in many data sets of images with different image

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lower and global features, both quantized as BoW (Bag of Words) of visual information as well as the non-quantized visual representations. Also, we find that many algorithms developed algorithms based on KNN consider hubness.

II. RELATED WORK

The algorithm KNN is a mostly used in classification method. It is easy, yet powerful method. It is based on an instinctive idea that same instances usually split the same label, i.e. belong to the similar object class. Since real world data set is usually noisy and very sparse and there is also a probability of partly cover between classes of different types and categories. This KNN algorithm was first time introduced in [10].

Many additional modifications and extensions has been done over the initial algorithm have been implemented over the years. These modifications have been targeted at different practical shortcomings of the algorithm. From these modifications some were general changes and some changes target particular domain. Attribute Based weighting was introduced in [13] and adaptive based distances in [20]. Fuzzy based labels were too measured [17] [18] [15]. Some algorithms with advanced methods have been studied recently, this includes KNN classifier with large margin which studied the Mahalanobis distance matrices with the help of semi definite programming [24].

Recently, techniques which exhibit the phenomenon of hubness by studying from recent occurrences [23] have been proposed. Hub points are appears in data sets of high dimensionality, as will be explained in Section II. They were first find use in collections of music [2] [3] [19] [22]. Some authors find that there were some music which were same to many other musics. This topical similarity, however, did not show the perceptual similarity. In other some words, these songs acts as hub and were an artifact of the high-dimensional song demonstration. Similar to this Images are also exhibited high-dimensional, so hubs are probability to appear in collections of images as well.

III. THE HUBNESS PHENOMENON

As we stated before, the phenomenon of skewness is occur in hubness with the k-occurrences distribution(occurrences in k-neighbor sets) which cause the effect of hubs as representative point points, which will be more similar to many other data points, in effect of this hubness hub points will treat as centroids or medoids of clustering process. This hubness phenomenon was detailed studied in . The concentration of distances concept is much similar phenomenon of hubness is closely related to what is usually referred to as, which is yet another interesting property of high dimensional spaces [1], [11]. As defined in theory of High dimensionality, the number of dimensions of data points from data set increases, the Euclidean distances between any two data points get relatively more and more similar so that it we cannot distinguish the data points and distance between them. This cause difficulty in further clustering or classification process. This normally due to variance remains contents while increase in value of the expected (mean) distance. That's why the concept of KNN in high dimensional feature spaces was questioned.

Suppose D = $(x_1, y_1), (x_2, y_2), ..(xn, yn)$ be the data set,

Where $x_i \in Rd$ and $y_i \in c_1, c_2, ..cc$ are the labels

The each x_i of D locate in some high-dimensional feature space.

$N_k(x_i)$ is the count K of occurrences of a data point $x_i \in D$. This occurrence is calculated in KNN sets of other points from D.

Roughly speaking, there are, two types of $Nk(x_i)$

- the good k-occurrence ($GN_k(x_i)$)
- the bad k-occurrence ($BN_k(x_i)$),

This comes to $Nk(xi) = GNk(xi) + BN_k(x_i)$.

The occurrence of data point xi in a KNN of other data point xj is said to be"good" if it satisfies the concision $y_i = y_j$. This means that, the respective labels of data points get matched. When the label of data points are not get matched then it will called as bad hubness $BN_k(x_i)$. All the points from data set which have large value for BNk will be called as bad hubs. They always show influence at the time of classifying process with the help of KNN rule. The first method for removing bad hubness and bad hub points in KNN was a scheme with weighting method, which is proposed in , and we will use to this technique and algorithm with notation as hw- KNN.

Our experiments mainly used 500 features (visual words) for Caltech101 database and 100 words for ImageNet in Haar quantized representation, as well as 400 in the SIFT quantized representation.

IV. HUBNESS IN IMAGE DATA

Data description:

We use our hybrid algorithm for 2-class and multi-class object recognition.

A. *Non-quantized feature representations:*

For 2-class we use pedestrian datasets in purpose of object recognition to analyze the proposed algorithm. In this we retrieve Haar features, HoG features and SIFT features for same dataset [25] , the for dataset form Daimler pedestrian [7].

B. *Bag of visual words (BoW) representation:*

In purpose of object recognition with help of multi-class we have retrieve Haar features and SIFT features for Caltech101 dataset [8] and ImageNet (http://www.imagenet.org/) subsets.

Our experiments mainly used 500 features (visual words) for Caltech101 database and 100 words for ImageNet in Haar quantized representation, as well as 400 in the SIFT quantized representation. For ImageNet datasets, we summaries the quantized SIFT feature representation with 16-bin color histograms retrieved from the dataset images. Both parts of the hybrid feature representation of images were scaled separately to perform 2 probability distributions, the former pertaining of representation to the quantized local feature information and then to the global color information representation. As we assign similar weight to the both parts of the feature representation is away from optimal, as we can see in to the result analysis, but we intended to see what goes on in such cases and whether both the hubness-based nearest neighbor method and KNN method are equally affected.

V. CONCLUSION

We have find that of hubness phenomenon is present in data types like images, with different image feature representations. Not all feature representations have the same quantity of hubness. We need to account this difference for any kind of NN method is to be used, whether for clustering or classification. When we found skewness is high in the k- occurrence distribution, hub points emerge and they can sometimes exhibit a detrimental influence on NN algorithms.

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