Neurocomputing 207 (2016) 71–77

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Asymmetric hashing with multi-bit quantization for image retrieval

Zhenyu Weng, Ziqiang Sun, Yuesheng Zhu*

Communication and Information Security Lab, Institute of Big Data Technologies, Shenzhen Graduate School, Peking University, China

ARTICLE INFO

Article history:
Received 1 March 2016
Accepted 18 April 2016
Communicated by Mingli Song
Available online 26 May 2016

Keywords:
Image retrieval
Asymmetric hashing
Multi-bit quantization

ABSTRACT

In the hashing approaches with multi-bit quantization, each projected dimension is divided into multiple regions indexed with multiple bits to preserve the neighborhood structure of the data. However, the query is processed in binary, and the distances between the adjacent regions are usually assumed to be equal, resulting in the accuracy loss of the computed distance between the data and the query. To tackle the above problems, in this paper an approach is proposed to process the query and the data asymmetrically. By representing the data with the expectation value of the region where the data belong and preserving the query in original form, the distance between the query and the data can be computed accurately. A specific asymmetric approach with non-parametric multi-bit quantization is further developed for the PCA (Principle Component Analysis) hashing method. With the special consideration of PCA characteristic, every projected dimension is adaptively divided into a certain number of the regions according to the minimal variance. The results of the experiments have shown that the better performance can be obtained in the asymmetric hashing approach with multi-bit quantization than that in the other approaches, and can be improved further in the specific asymmetric approach with non-parametric multi-bit quantization with respect to the PCA hashing method.

1. Introduction

Recently, the explosion in the scale of the data brings a challenge to the large scale retrieval tasks, such as image retrieval [1]. As image descriptors are usually high-dimensional vectors, it is difficult for the conventional methods [2,3] to perform efficient similarity search. Considering about the memory cost and the computational cost, the research on learning compact binary codes to compress the image descriptors [4–13] has attracted considerable attention. By transforming the high-dimensional vectors into the compact binary codes, a large number of binary codes can be stored in the RAM, and the Hamming distance between the binary codes can be computed efficiently.

The goal of the hashing methods is to map the high-dimensional vectors into compact binary codes such that the similar data points in the original space have similar binary codes. As mentioned in [14], to avoid directly computing the best binary codes for a given data set, which is an NP-hard problem, in most of existing hashing methods a two-stage strategy is adopted, i.e., projection stage and quantization stage. To generate a c-bit binary code, there are c projection functions generated to map the high-dimensional data point into a real vector with c components, and then each component is quantized to a bit according to a threshold. For locality sensitive hashing (LSH) [15] and its variants [16], random projection vectors drawn from a multidimensional Gaussian distribution with zero mean and identity covariance matrix are used in the projection functions. To achieve a good precision, however, the length of binary code is usually long in the LSH methods. To generate the compact codes, the learning-based hashing methods are used. In the spectral hashing (SH) [17] data-dependent projection functions are learnt by spectral graph partition. In the PCA hashing (PCAH) [18] principal component analysis method is adopted to take eigenvectors from the covariance matrix of the training data as the projection vectors. In the iterative optimization (ITQ) [19] the quantization error between the PCA-projected data and the vertices of the hypercube is minimized by rotating the PCA-projected data. In these hashing methods, various projection functions are based on symmetric distance with single-bit quantization.

On the one hand, since each projected dimension is quantized as one bit, the faraway points may be quantized as the same bit value, which violates the neighborhood structure of the data. The multi-bit quantization approaches [14,20] can preserve the neighborhood structure of the data well. By dividing the dimension space into multiple regions indexed by multiple bits, the points at the close positions will have the near indices in the dimension space, and vice versa. Thus, the neighborhood structure

* Corresponding author.
E-mail address: zhuys@pku.edu.cn (Y. Zhu).

http://dx.doi.org/10.1016/j.neucom.2016.04.037
0925-2312/

of the data in each projected dimension can be preserved well. Since the approaches just replace the single-bit quantization with the multi-bit quantization, they are applicable to a variety of hashing methods. They also have the benefits of the hashing methods with the single-bit quantization both on the storage and the search, since the data are still stored in binary and the search is efficient. But the query is processed in binary yet. And in these approaches, they assume that the distance of every pair of data points respectively from adjacent regions is equal, and the distance between the adjacent regions is set to "1" in each dimension. Since the distance between the query and the data is compressed too much, the accuracy of the distance computation would be lost.

On the other hand, the query might be ambiguous when the different binary codes share the same Hamming distance to the query. To alleviate the ambiguity, in the asymmetric approaches [18,21] the query and the data are processed asymmetrically, i.e., only the data are quantized as binary codes, while the query is preserved. The distance between the query and the data in each dimension is represented as a real-value rather than a binary value, thus the query is not ambiguous. In [18,21], it is demonstrated that the asymmetric approaches can be applicable to a variety of hashing methods including LSH, PCAH and ITQ. As the data points are still stored in binary, and the distance computation is efficiently performed by look-up table, the asymmetric approaches have the benefits on the computation and the storage. However, since the asymmetric approaches use the single bit quantization, they still violate the neighborhood structure of the data.

In this paper, in order to enhance the search accuracy a new asymmetric hashing approach with multi-bit quantization is proposed. In the new approach the neighborhood structure of the data can be preserved well, also the query and the data are processed asymmetrically to avoid much information loss. By representing the data with the expectation value of the region where the data belong, and preserving the query in the original form, the distance between them can be computed accurately, leading to the improvement of the search accuracy. It is applicable to a variety of hashing methods. Furthermore, with the special consideration of the characteristic of the PCAH method, a novel specific asymmetric hashing approach with non-parametric multi-bit quantization for the PCAH method is proposed to adaptively divide each dimension space into a certain number of regions according to the minimal variance. The experiments show that a better search accuracy of our asymmetric hashing approach with multi-bit quantization can be gained, than that of other approaches, and is improved further in the specific asymmetric approach with non-parametric multi-bit quantization with respect to the PCAH method.

2. Asymmetric hashing with multi-bit quantization

In this section, two asymmetric hashing approaches with multi-bit quantization are proposed: one is applicable to a variety of binary hashing methods, and the other one is specific for the PCAH method with adaptively determining the number of the quantization levels in each dimension.

2.1. Multi-bit quantization

The projection and the quantization are two important stages used in a variety of hashing methods [14]. Denote the data points as $\{x_1, x_2, \dots, x_n\}$ that form the columns of data matrix $\mathbf{X}$. Suppose

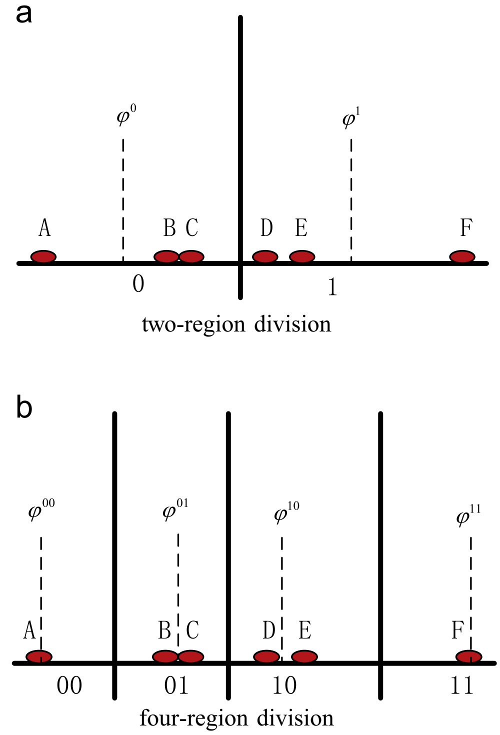

Fig. 1. The visualization of the region division.

that the data have zero-mean. In the projection stage, the kth projection function $g_k(\cdot)$ is defined as

$$g_k(x_i) = w_k^T x_i \tag{1}$$

where w_k is a projection vector generated by the hashing method. And in the quantization stage, the quantization function is defined as

$$y_k(x_i) = \sigma(g_k(x_i) + b_k) \tag{2}$$

where

$$\sigma(x) = \begin{cases} 0 & x < 0 \\ 1 & x \geq 0 \end{cases} \tag{3}$$

and b_k is a threshold and is usually set to zero as the data have zero-mean. Since only one bit is generated by each quantization function, the quantization process is called the single-bit quantization process.

In the multi-bit quantization approach, l bits are allocated to each projected dimension, and the space in each projected dimension is divided into 2^l regions. The indices of each region are encoded by natural binary code (NBC) [14], i.e., the real-valued index is transformed to the binary index. If l is equal to 1, that is single-bit quantization as shown in Fig. 1(a), and the space of the projected dimension is divided into 2 regions $\{0, 1\}$. When l is equal to 2, the space of the projected dimension is divided into 4 regions $\{0, 1, 2, 3\}$ as shown in Fig. 1(b). And then the indices are encoded as $\{00, 01, 10, 11\}$ respectively. Thus, Eq. (3) can be rewritten as

$$\sigma(x) = \{0, 1\}^l \tag{4}$$

where l is the number of the bits allocated for each dimension.

From Fig. 1, we can find that when more bits are allocated to the dimension, the space will be divided into smaller regions, and the neighborhood structure of the data can be represented better.