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Contents

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Application of Image Retrieval Algorithm based on Sports Events

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Abstract: Sports image feature description and indexing mechanism is the key of content-based image retrieval based on, for mass sports image data, this paper presents improved sports image retrieval algorithm based on, when indexing mechanism in the query time, to ensure that the recall rate and accuracy of the query result and improve the candidate reverse chain index, which has led to an increase in the distance calculation and query time. The experimental results show that the algorithm has achieved good results in the massive image data capture based on sports events, and has practical value.

Keywords: Sports image; Catch; Image retrieval

1. Introduction

Locality-Sensitive Hashing (LSH) and the inverted index based on are the index methods that can better cope with the “dimension disaster” in recent years [1-3]. Although LSH can deal with the high-dimension feature data in a certain extent, it increases the storage space of indexing by several times, which makes it difficult to adapt to the massive database retrieval [4-8]. And while the vocabulary tree based on BOF can save the indexing space greatly relative to LSH, it still can not meet the performance demands of the massive image retrieval. On the basis of VLAD, Jegou and others make use of the methods of Product Quantization and Asymmetric Distance Computation to realize the Inverted File with Asymmetric Distance Computation and build index for massive image library . But only under the 20 byte image coding can this approach ensure the query efficiency which is higher [9].

For the massive image data and the problem of “dimension disaster”, this paper proposes the based image retrieval improved algorithm, and combines with VLAD and soft assignment it generates the soft assignment local aggregation descriptor which has a better ability to resist the dimension reduction and a higher recognition rate. When the index mechanism IVFADC is at query time, to ensure the recall ratio and precision rate of the result, the candidates inverted index chain are increased, which leads to the problems of distance calculation and the query time’s increasing. For this point, in the index phase, the scattered distribution is carried out aiming at the database vector, which reduces the burden of distance calculation, and improves the quality of the query results at the same time.

2. The Soft Assignment based on Local Aggregation

The calculation of the membership weight adopts the membership function in the fuzzy k-means method. In the fuzzy k-means, the error sum of squares between the vectors in the clustering and the center of the clustering is required to be the smallest, it usually uses the criterion function to measure. And the criterion function is as follows:

$$sk_i = \sum \frac{1}{t_i(s)}(s - t_i) \tag{1}$$

The fuzzy clustering method demands that the sum of the membership degrees of each local feature vector relative to each cluster to be 1. It is shown as follow:

$$sk = (sk_1, \ldots, sk_1, \ldots sk_i) \tag{2}$$

Get the minimum value of i_n in the case that the sum of the membership degree is 1, and set the partial derivative of i_n relative to t_i and $t_i(k_x)$ to be 0, the obtained necessary condition is as follows:

$$D_i = \frac{\sum_{j=1}^{m}\left[t_i(k_x)\right]^2 t_i}{\sum_{i=1}^{m}\left[t_i(k_x)\right]^2}, i = 1, 2, \ldots, n \tag{3}$$

Thus, the membership function of t_i in the i cluster $t_i(k_x)$ is gained.

Based on k clusters to carry out the aggregation of the local feature vector to generate the SA-VLAD descriptor, the detailed steps are as follows:

(1) Initialize SA-VLAD to the zero vector s_v with the dimension of $m \times n$. m is the number of the cluster centers and n is the dimension of the image’s local feature vector.

(2) Through the near search, the local feature vector S of each image finds out t cluster centers that have the clos-

est distance with the feature vector in the entire cluster center.

$$D_i = \frac{\sum_{j=1}^{m}\left[t_i\left(k_x\right)\right]^2 t_i}{\sum_{i=1}^{m}\left[t_i\left(k_x\right)\right]^2}, i = 1, 2, \ldots, n \quad (4)$$

In the formula, $s(k)_e$ represents the h close cluster center vector with the vector s. The difference between s and $s(k)_e$ reflects the distribution of s after the mapping of the cluster center, and codebook is the code book vector formed by the aggregation of all the vectors in the cluster center.

Calculate the membership weights of feature vector S in the t closest clusters, and use the membership weights to calculate the difference between S and the t closest cluster centers. The collection of the differences between all the local feature vectors in one image and their closest cluster center is namely the SA-VLAD descriptor of the image. sk_i is the vector of d dimension, which stands for the sum of differences of the image's SA-VLAD descriptor in the i cluster center position. The value of sk_i is as follows:

$$t_i\left(k_x\right) = \frac{\left(1 - \left\|t_i - d_i\right\|^2\right)^{\frac{1}{(c-1)}}}{\sum_{k-1}^{c}\left(1/\left\|t_i - d_i\right\|^2\right)^{\frac{1}{(c-1)}}}, i = 1, 2, \ldots, m, i - 1, 2, \ldots n \quad (5)$$

sk is the SA-VLAD feature value of the image.

3. The Inverted Index Mechanism based on Scattered Assignment

The index mechanism in the core of the content-based image retrieval, DA-IVFAD index mechanism makes up for the inadequacy of IVFADC mechanism, realizes the simplified coding, effective distance calculation and high-efficient inverted chain storage of the feature vector.

In the IVFADC index mechanism, during the indexing phase the database vector is only assigned to a certain chain table after the quantization. Because the quantitative method will inevitably produce errors, in order to ensure the recall ratio of the results, it is needed to increase the value of the candidate chain list at query time to result in the increasing of the calculation amount and the calculation time. Thus, in IVFADC there are some contradictions between the high recall ratio of the results and the fast query speed. While scattered assignment can effectively solve this problem and reduce the query time in the case of guaranteeing the recall ratio.

The query process of DA-IVFADC is similar to its indexing process, it also has the process of overall quantification, but there is only product quantification for the database vectors, no product quantification for the residual vectors of the query vectors is carried out. The distance calculation between the vectors after quantification and the vectors without quantification is called the asymmetric distance computation, as shown in Figure 1.

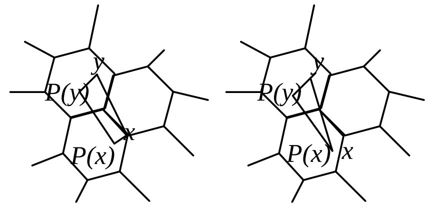

Figure 1. The symmetric distance computation (Left) and the asymmetric distance computation (Right)

4. The Simulation Experiment and Analysis

The software and hardware environments uses in the experiment are as follows: the hardware environments are Intel(R) Core(TM) 2Quad CPU Q8230@ 2.34GHz, 4GB memory; the operating system is Windows XP; the coding environments are Matlab 7. 10.1(R2012a) Microsoft Visual Studio 2007.

In order to validate DA-IVFADC and SA-VLAD, two databases are prepared for DA-IVFADC. Each database contains three subsets, the training set, indexing data set and query data set.

4.1. The effects of product quantification parameters m and f' on the Results

The two important parameters of product quantification are subspace number m and the cluster number of product quantification f', which determine that the coding bit of the vector is $Lcode = m \times Log2f'$.

ADC and SDC are two different calculation ways, which respectively constitute two different index mechanisms combined with product quantification. The non-overall quantification process carries out the product quantification for the original vectors directly, and the candidate result is the whole database rather than a similar data that falls into the candidate w chain tables in the DA-IVFADC mechanism. Under the query mechanism without introducing the inverted table, the effects of m and f' on the results recall@ R can be seen clearly. Based on SIFTSMALL, Figure 2 and Figure 3 are respectively the experimental results figures of recall@100, when there are $m = \{1, 2, 5, 7, 18\}$ and $f' = \{26, 28, 30\}$ in the ADC and SDC index mechanisms.

4.2. The Effects of f^*, m and f', w on the Results in DA-IVFADC

w is the number of the candidate chain tables at query time, m is the number of the product quantification subspaces, f' is the number of the cluster centers of each subspace, and $f*$ is the number of the clusters during the overall quantification, namely the number of the chain tables.

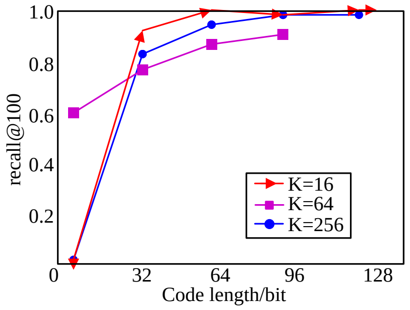

Figure 2. Effects of parameter settings on recall@100 in ADC index mechanism

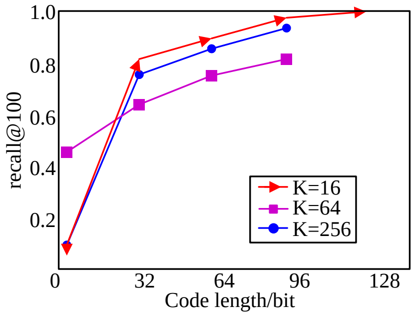

Figure 3. Effects of parameter settings on recall@100 in SDC index mechanism

Figure 4 shows the recall@100 data of the SIFT database, the data are recorded when the subspace cluster centers in the DA-IVFADC product quantification are $f'=256$, $m=\{1,2,5,7,18\}$, $f*=\{1024,4096\}$, $w=\{1,4,8,64\}$, the parameter of scattered assignment is $n=2$, and the distance threshold is $\alpha=1000$.

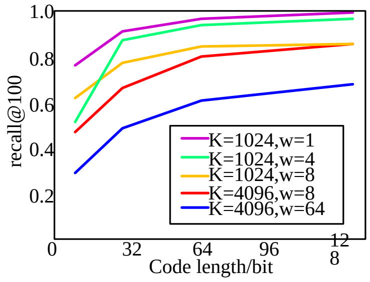

Figure 4. Effects of the parameters on recall@R in DA-IVFADC index mechanism

It can be seen from the curve changes of figure 4 that when the values of $f*$ and w are determined, the increasing of the code bits cannot obviously improve the query efficiency, and the curve approaches to gentle after the value of m is up to 8, the length of code reaches at 64 bits. The reason is that after the value of $f*$ is determined, the database objects in each chain table have already been determined, and after the value of w is confirmed, the candidate result objects are confirmed too. When the value of m increases to a certain degree, all the similar objects fall into w chain tables have already returned, and the rest of the neighbor objects in the database have already been filtered out after the confirmation of m, for not falling into any one of the w chain tables, which makes the curve gradually gentle. When the value of $f*$ is determined, the greater the value of w is, the higher the recall ratio will be, and the recall@100 increases correspondingly. But it is not the bigger w value the better, because with a bigger value of w, there will be a bigger time cost when calculating the distance between the residual vectors in the object subspace and the cluster center of the candidate chain table subspace, which will have impact on the query efficiency. The greater the value of $f*$ is, the finer the partition of the database vectors will be, and to ensure the quality of the results, the value of w must be increased. If the value of $f*$ is too small, it will degrade to ADC query, which makes it cannot give full play to the finer classification overall quantification and the accelerated query function of the inverted chain. Therefore, the parameters of DA-IVFADC need to be designed according to the actual circumstances of the database.

4.3. The comparison between DA-IVFADV and IVFADC

Figure 5 is the recall@100 comparison diagram of IVFADC and DA-IVFADC when there are $m=8$, $f'=256$, $Lcode=68bits$, $f*=65$, $w=\{1,2,10,16\}$ in RANDOM test library, because the curve basically has no changes after the value of R is greater than 20, only the part when the value of R is less than 20 is drawn. Figure 6 is the corresponding query time comparison diagram. It can be seen by combining the two figures that with the same value of w, the difference of query time is very little, but the accuracy of DA-IVFADC is obviously higher than that of IVFADC. When there are $w=16$, $time=13.1$, the value of recall@20 is 0.99 in IVFADC, and when there are $w=10$, $time=8.4$, the value of recall@20 is more than 0.98 in DA-IVFADC.

Figure 7 and Figure 8 is the recall@ 22 comparison diagram of IVFADC and DA-IVFADC when there are $m=8$, $f'=256$, $Lcode=68bits$, $f*=1024$, $w=\{1,2,8,16\}$ of the SIFT feature vectors in the 1MB test library, and figure 11 is the corresponding query time comparison diagram. Figure 9 counts the query time of the 500 retrieval objects, while figure 11 counts the average query time of 10000 retrieval objects. It can be seen by combining the two figures that DA-IVFADC still has a better performance than IVFADC under the condition of large amount of data.

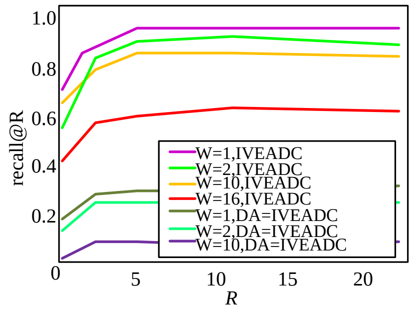

Figure 5. The value of recall@ R in RANDOM database

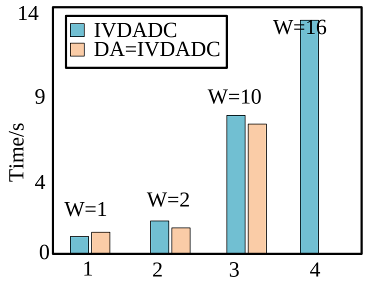

Figure 6. The query time diagram of 500 retrieval objects in RANDOM

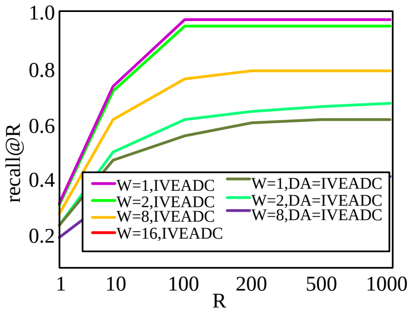

Figure 7. The value of recall@ R in SIFT database

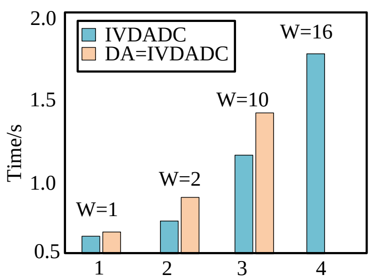

Figure 8. The average query time diagram of SIFT database

4.4. The Results of the Soft Assignment Based Local

The gap of the query time between SA-VLAD and VLAD is time difference for the retrieval object to generate the aggregated vector. By statistics, the average gap of each object's query time is 0.09ms, which shows that when SA-VLAD and VLAD remain the same in not having obvious increasing of query time and storage space, SA-VLAD improves the accuracy of the query results.

Figure 9 is the typical drawing of the query results combined by VLAD and DA-IVFADC. And Figure 10 and Figure 11 is the typical drawing of the query results combined by SA-VLAD and DA-IVFADC. In the two figures, the first images in each column are the retrieval images, and each retrieval image returns four query results.

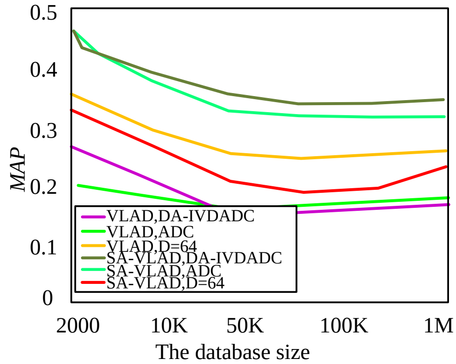

Figure 9. The average accuracy of SA-VLAD and VLAD under different index mechanisms

Figure 10. The typical drawing of query results combined by VLAD and DA-IVFADC

Figure 11. The typical drawing of query results combined by SA-VLAD and DA-IVFADC

5. Conclusion

Aiming at the problem of massive image data and “dimension curse”, this paper proposes the BOF-based image retrieval improved algorithm. Through the experiment it is verified that the improved algorithm in this paper improves the image query performance of the database.

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