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Research on Tagging Recommendation Algorithm Based on Relevance and Diversity

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Abstract. The traditional recommendation algorithms of image tagging ignore the diversity between the visual content information and the tags recommended, which causes the recommended results have the problem of tag ambiguity, tag redundancy and so on. Therefore, this paper proposes the recommendation algorithm of image tagging based on relevance and diversity. The algorithm defines the relevance and diversity of a label set, and selects a label set which can reasonably balance the relevance and diversity to recommend to the user. The experimental results show that this algorithm improves the relevance between the recommended results and the image, and makes the recommended results be able to reflect the image content thoroughly at the same time.

Keywords: Relevance, Tagging, Vision distance, Topic coverage

1 Introduction

The number of the images on the Internet presents an explosive growth. In order to effectively organize and control such massive scale of the image resources, the image retrieval technology emerges at this historic moment, and has been widely studied. Since the 1990s, the content-based image retrieval has been developed constantly, but due to the existence of the “semantic gap” between the image’s low-level visual features and the high-level semantic concepts, the retrieval performance of CBIR is difficult to be satisfactory [1-3]. Therefore, the current commercial image retrieval engines (Google Image, Bing Image) still adopt the Text-based Image Retrieval (TBIR) approach, which creates index through the text information of the image, and uses the mature text retrieval algorithm to provide image retrieval service to the user, its retrieval performance is dependent on the quality of the image’s relevant text [4].

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2 The Image Tag Recommendation Algorithm

Combine the above relevance between the tag and the image with the visual distance between the tags, this section introduces the image tag recommendation algorithm that combines the relevance and the diversity. The relevance and diversity of a label set are defined firstly, and then use the greedy search algorithm to find the tag set that can reasonably balance the relevance and the diversity. At the end, treat the tag set as the final recommended result.

A. The Relevance and Diversity of the Tag Set

In the previous image tag recommendation algorithm, the problem of the tag recommendation tends to be converted into the problem of tag ranking according to the relevance between the tag and the image, and the algorithm recommends the tag with a high ranking to the users. While the image tag recommendation algorithm proposed in this paper takes the interrelation between the recommended tags, thus the goal of the algorithm is to recommend a tag set with a specified size.

Combine with the contents introduced in the previous section, given a target image I. For a candidate tag set s_t with a size of N, the average relevance between the tags in S T and the image I is defined as the index for measuring the relevance $\mathrm{Re}l\left(s_t\right)$ of s_t.

$$\mathrm{Re}l\left(s_t\right)=\frac{\sum_{i\in s_t} r\left(i,t\right)}{N} \quad (1)$$

The definition of $r\left(i,t\right)$ is shown in formula (10), the average visual distance between the two tags in s_t is defined as the index for measuring the diversity $Div(s_t)$ of s_t.

$$Div(s_t)=\frac{\sum_{t_i,t_j\in s_t} D\left(t_i,t_j\right)}{C_m^1} \quad (2)$$

$$C_m^1=\frac{M\left(M-1\right)}{2}$$

The definition of $D\left(t_i,t_j\right)$ is shown in formula (11). Further, treat the weighted sum of the two indexes as the score of the balance degree $h\left(s_t\right)$ between the relevance and diversity of s_t, and it is as follows:

$$h\left(s_t\right)=\lambda\,\mathrm{Re}l\left(S_t\right)+\left(1-\lambda\right)Div\left(s_t\right) \quad (12)$$

Parameter $\lambda\left(0\prec\lambda\prec1\right)$ is used to control the score proportion of the relevance and the diversity when calculating the scores.

B. Algorithm Description and Time Complexity

In the process of image tag recommendation, the algorithm proposed in this paper hopes to find a tag set that can reasonably balance the relevance and the diversity. Given the target image I and its initial tag set m_i , the algorithm chooses the tag set with a highest score of the balance degree between the relevance and the diversity in the remaining tags, and recommends it to the users. And it is as follows:

$$k_m^* = \arg\max h(s_t), s_t \subset M / M_i \quad (3)$$

M represents the collection of all tags in the data set. The solution of the formula (15) is a typical problem of non-linear integer programming, which belongs to the problem of optimization combination of NP-Hard class, and there is no accurate algorithm within the polynomial time. Thus, the greedy search algorithm is used to find out the near-optimal solution to the problem, and the solving process is shown in algorithm 1.

Initially, k_m^* is initialized to an empty set (line 1). First of all, the algorithm finds out the tag m_i with the highest relevance with the image in the remaining tags except of tag m_i, and treats m_i as the first tag to join in k_m^* (line 2 –line 3). Then, the algorithm iteratively finds out the remaining $m-1$ tags. In each round of the iteration, finds out the tag m_r in the remaining tags except of m_i and k_m^*, which is the tag that can make the current k_m^* become the tag with the highest score after its join, adds m_r into k_m^* (line 4 – line 7). Finally, the set k_m^* contains m tags, and return the k_m^* as the recommended result.

Before the start of the recommendation algorithm, first of all, train out the VLM of each tag in the data set offline, and calculate the co-occurrence similarity and visual distance between any two tags. The time complexity of algorithm 1 is $o(mn_2)$. In which, m is the expected number of the recommended tags, and m is the total number of the tags in the data set. In the actual calculation, the value of n is generally small ($N = 10$ in the experiment), thus the running time of the algorithm mainly depends on the total number of the tags in the data set. The algorithm that can effectively improve the running efficiency is the one that will rank all the tags according to its relevance with the image in the first place when computing, and then in the basis of the performance requirements, select a number of tags which are in the top of the ranking, to continue the calculation in algorithm 1.

Algorithm 1 Tag Recommendation Algorithm Based on Greedy Search

Input: all the tags T in the training set, an image I, the initial tag set

Output: the recommendation tag set k_m^* with a size of m

1) Initialize $k_m^* = \Omega$;

2) T_i of i, the expected number N of the recommended tags

3) $k_m^* = k_m^* \cup \{t_i\}$

4) For $i = 2$ to N do

5) Select tag $T / \{T_i \cup k_m^*\}$ from t_i, t_j satisfy:

$t_r = \arg\max_{t_r} R(i, t_r)$;

6) $k_m^* = k_m^* \cup \{t_r\}$;

7) End for

8) Return k_m^*.

3 Conclusion

For the traditional image tag recommendation algorithm ignores the diversity between the visual content information of the image and the recommended tags, which leads to the recommendation results have the problem of tag ambiguity, tag redundancy and so on, the image tag recommendation algorithm based on the relevance and diversity is proposed in this paper. The algorithm solves the problem of tag ambiguity and tag redundancy in the traditional algorithm, defines the relevance and the diversity of a tag set, and selects a tag set which can reasonably balance the relevance and the diversity to recommend to the users. The experimental results show that the algorithm proposed in this paper improves the relevance between the recommended results and the image on the one hand, and on the other hand makes the recommended results be able to reflect the image content thoroughly.

References

1. S. Li, Y. Geng, J. He, K. Pahlavan,Analysis of Three-dimensional Maximum Likelihood Algorithm for Capsule Endoscopy Localization, 2012 5th International Conference on Biomedical Engineering and Informatics (BMEI), Chongqing, China Oct. 2012 (page 721-725)
2. J. He, Y. Geng and K. Pahlavan, Modeling Indoor TOA Ranging Error for Body Mounted Sensors, 2012 IEEE 23nd International Symposium on Personal Indoor and Mobile Radio Communications (PIMRC), Sydney, Australia Sep. 2012 (page 682-686)
3. J. Naereddine, J. Riihijarvi, P. Mahonen. Transmit power control for secondary use in environments with correlated shadowing. IEEE, ICC2011 Proceedings, 2011 pp. 1-6
4. Y. Geng, J. He, H. Deng and K. Pahlavan, Modeling the Effect of Human Body on TOA Ranging for Indoor Human Tracking with Wrist Mounted Sensor, 16th International Symposium on Wireless Personal Multimedia Communications (WPMC), Atlantic City, NJ, Jun. 2013.

