A Modified Semantic Learning Space and Radial Basis Function

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Abstract

This paper introduces an improvement to the methods discussed in [1]. We use a radial basis function and semantic learning space to construct a CBIR system. We run experiments on the Corel and Flickr image databases, and attach the experimental results.

1. Introduction

Current CBIR research seeks to narrow the semantic gap between low-level features and high-level meaning. Thus, relevance feedback is studied in detail.

However current CBIR systems have limitations such as space limitations, and intricacies that make the construction very difficult[1].

To address this issue an earlier paper introduced a semantic learning space (SLS) and applied a radial basis function (RBF) based relevance feedback technique based on user inputs[1].

This paper seeks to introduce a modification that gives improvement to the complexity of the previous approach by modifying the RBF, by simplifying it. We also modify the composite learning to simplify the overall approach.

2. Related Work

Our work is directly related to and derived from [1] "A Radial Basis Function and Semantic Learning Space Based Composite Learning Approach to Image Retrieval" by Konstantin Shkurkol and Xiaojun Qi.

3. Proposed Approach

We modify the RBF of the previous approach to be the Euclidean distance of the low-level features of the query image to each other image. Then we form the SLS query and high-level distance as in [1] except that we do not allow the same image to be returned in a given query more than once so that we get more information on each query. Then, we combine these scores and return the smallest totals and the user classifies each image as relevant or not, we then modify the query low-level vector to be the mean of all the positive images, and the high-level query vector as in [1]. We then repeat 10 times to get a better analysis. Finally, we run this for each training image.

4. Experimental Results

We have tested our CBIR system on 2000 images from Corel and Flickr initially to find out which percentage of training data gives better results. These images are from 20 distinct categories, 100 images each. We further tested our system after determining that a 10% training data was superior on the 6000 Corel database. These images are from 60 categories, 100 images each. Next, we tested our system on the 8000 Corel+ Flickr database. We then repeated all these experiments with a 5% noisy feedback to simulate a user giving incorrect input 5% of the time. We always ran 10 iterations, and at each iteration, the top 50 results were returned.

Experiment 1: We used a 2%, 5%, and 10% training data and a 2000 Corel database, and the 2000 Flickr database. We filled the SLS tables with these training data and compared their

precisions. We determined that a 10% training rate is better, it gives a better computational cost and better storage cost. Tables 1 and 2 illustrate this.

Flickr 2000	
2 percent training	0.7434
5 percent training	0.7692
10 percent training	0.9581

Table 1: Flickr Comparison

Corel 2000	
2 percent training	0.8916
5 percent training	0.9295
10 percent training	0.9830

Table 2: Corel Comparison

Experiment 2: We filled the SLS with 10% again, but this time used the 6000 Corel database. We used 10 iterations as before, and our accuracy is near 90%. As shown above, a 10% training data gives better results than 5 percent or 2 percent.

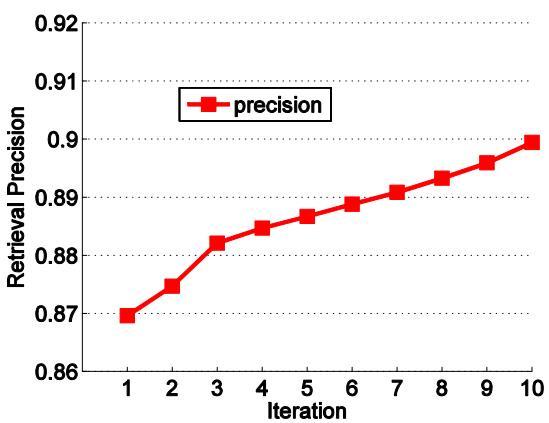

Figure 1: 6000 corel 10 percent training, no noise.

Corel 6000 precision 10% Training	
Iteration 1	0.8696
Iteration 2	0.8747
Iteration 3	0.8821
Iteration 4	0.8847
Iteration 5	0.8867
Iteration 6	0.8888
Iteration 7	0.8908
Iteration 8	0.8933
Iteration 9	0.8959
Iteration 10	0.8994

Experiment 3: Optimal filling of 8000 Corel + Flickr databases with 10% training. We use 10 iterations and the top 50 results are returned each iteration as before. This gives approximately an 80% precision.

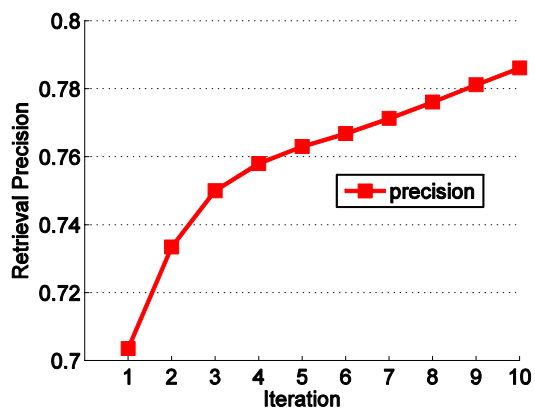

Figure 2:8000 corel and flickr combined 10 percent training no noisy feedback

Combined Flickr 2000 + Corel 6000 precision 10% Training	
Iteration 1	0.7035
Iteration 2	0.7334
Iteration 3	0.7500
Iteration 4	0.7580
Iteration 5	0.7630
Iteration 6	0.7668
Iteration 7	0.7713
Iteration 8	0.7761
Iteration 9	0.7812
Iteration 10	0.7862

Experiment 4: Again we filled the SLS of the 6000 Corel database. However, this time we used a 5% noisy feedback, that is the user returned the incorrect answer 5% of the time. Figure 3 shows that with a 5% feedback the errors compound themselves and we end up with about 60% precision after 10 iterations.

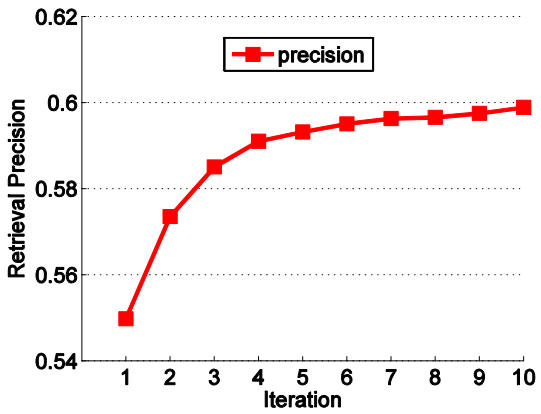

Figure 3: 6000 Corel 10 percent training 5 percent noisy feedback

Experiment 5: Again filling the SLS with 5% noisy feedback. This time we used the 8000 combined 6000 Corel and 2000 Flickr databases. We continued to use 50 returned images per iteration, and 10 iterations per query. Figure 4 shows the results, about 49% accuracy. We continued to use 10% training data because of the fairly low storage costs.

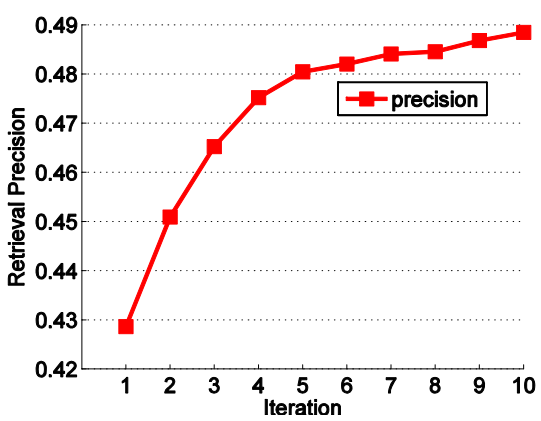

Figure 4:6000 corel +2000 flickr 10 percent training, 5% noisy feedback

5. Conclusions and Future Work

A novel combination of RBF and SLS was proposed for a CBIR system. The contributions are that 1) Ten percent training data is better than two percent or five percent. 2)Learning the semantic meaning using the SLS and RBF. 3) Learning that errors compound themselves in a CBIR system. 4) That this system does not achieve results as good as its predecessor.

In the future we hope to combine the learning from this and previous research done in [1] and reduce the compounding error from user input, also possibly reducing the overall complexity of the system.

6. References

[1] K. Shkurko and X. Qi, "A Radial Basis Function and Semantic Learning Space Based Composite Learning Approach to Image Retrieval," ICASSP, pp945-948, 2007.