Egyetemi doktori (PhD) értekezés tézisei

IMPROVING THE PERFORMANCE OF RECOMMENDER SYSTEMS USING A PARALLEL CBIR METHOD

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1 Introduction

An everlasting goal of the computerized systems has been providing users with a more desirable experience using the system. This goal has driven many researches in a vast area of science. Recommender systems are among the most valuable components that can improve the user experience with a more general system considerably when embedded inside that system. Since the mid-nineties and slightly after that, when the term "recommender system" coined by Resnick and Varian, researchers have conducted huge studies on this topic and the methods and approaches they have found are various and sundry.

The majority of recommender systems research papers are related to movie, shopping, document, book, TV program, music, and suchlike [1]. Putting together concepts of knowledge and collaborative filtering, Carrer-Neto et al. conducted a study [2] which presents a hybrid system that allows suggestions to be made based on the semantic linkage between contents and users' preferences, as well as inheriting recommendations from the users' social network. In order to capture implicit preference information, Lee et al. [3] have proposed a new CF-based recommendation methodology for mobile Web music, called CoFoSIM. Yu et al. [4] have proposed a method to merge users' profile in order to provide recommendations about TV programs. The rationale behind this decision has been the fact that people usually watch TV together. Their strategy to achieve program recommendation merges all user profiles to construct a common user profile as its first step, and then uses a recommendation approach to generate a common program recommendation list for the group according to the merged user profile. Valdéz et al. [5] have conducted a research to define and capture some parameters which helped them to analytically find correlations between explicit and implicit feedback on recommender systems. They have provided a more advanced method for taking feedback from users of electronic books which captures their preferences implicitly instead of explicitly rating which may hinder the users' experience. Serrano-Guerrero et al. [6] have proposed a fuzzy linguistic recommender system as tool for communicating researchers interested in common research lines based on the Google Wave[1] capabilities which suggests automatically several researchers and useful resources for each wave. Their proposed recommender system utilizes information related to user preferences and resource description along with wave description, which are provided by the systems users and the administrators of the waves. Zaiane [7] has suggested a recommender system for e-learning purposes. The author has used data mining techniques in order to build a software agent which is able to recommend on-line learning activities or shortcuts in a course web site based on learners' access history. The aim of system is to improve users' experience through providing them the ability to better navigate the on-line materials by finding relevant resources faster and assisting the online learning process. Castro et al. [8] have proposed a fuzzy logic based recommender system which provides the users with knowledge about the existing relationships among the attributes that describe a given product category. Their system is applicable to Business-to-Consumer (B2C) portals. They have developed a prototype of a B2C e-commerce portal to demonstrate the benefits of their proposed system.

A big part of data around us is in image format and people use these images in many of their decisions. The popularity of an item, in many cases, depends highly on its visual quality. For instance, the shape of a car has a significant influence on the attitude of potential customers toward it. Recommender systems try to provide people with recommendations resulted from an automatic process which is aimed at giving the users a better experience working with system, and perhaps improve the system owner's sales. As images are quite important in users' decisions, in this research we have proposed a parallel distributed method to take images into account when trying to give the user a recommendation, which despite its apparent

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advantages has not found a fair amount of attention so far. The main reason that we have proposed a distributed method that is implemented on a distributed architecture is that the time complexity of measuring the similarity between images compared to other operations of a recommender system are huge. Therefore, this is an excellent use case of distributed and parallel processing. We have conducted various experiments to prove the effectiveness of our proposed method. The results of the experiments show that the proposed method will increase the performance of the recommender system significantly, without a non-tolerable computational overhead.

2 Proposed methods

2.1 Proposed CBIR method

Images, despite their undeniable effect on users' decisions and desirability and acceptability of a computer system which works on data that has at least a visual part, have not taken enough attention from the researchers who work on recommender systems. To address this issue, we have proposed a method to take the image part of each item's information into account in order to propose the most desirable items to users.

One of the main parts of the system is storage part which is constituted from some distributed databases that contain three main entities of the system; users (stored in UDB), items (stored in IDB) and users' ratings (stored in RDB). IMDB contains the image part of each item, while the DDB contains the other features of an item. Our proposed method, which falls into the hybrid recommender systems category. The resulting system is comprises of a CF component and a CBF component, which are modified properly to work with items that have an image part. This modification is made in the definition of the similarity metric used for item-item comparisons. We define the similarity of two items i_1, i_2 using the following formula [9]:

$$Sim(\mathrm{i}_1,\mathrm{i}_2) = \alpha.grSim(\mathrm{i}_1,\mathrm{i}_2) + \beta.trSim(\mathrm{i}_1,\mathrm{i}_2)$$

where *grSim*(.) refers to a function which measures the similarity of two items based on their graphical feature, which is the only picture of the item in our case, *trSim*(.) refers to a function which measures the similarity of two items based on their text-based features, and α and β are two weighting parameters chosen from the interval [0,1]. We have assumed that each item has a graphical feature set (images) and a text-based feature set (categorical, Boolean, numerical, etc.). It is worth to mention that we have assumed that each item has only one image.

In order to find the quantitative similarity of two items, first we categorize numerical features; then simple matching coefficient (SMC) in order to measure the similarity of two items:

$$SMC(i_1,i_2) = \frac{\text{Number of matching attributes beween } i_1 \text{and } i_2}{\text{Number of textural attributes}}$$

Let X and Y denote the intensity values of two $M \times N$ images. In order to find the qualitative similarity of images, we have used the method introduced in [10] called IMNCC[1] :

$$IMNCC(X,\mathrm{Y}) = \frac{\sum_{i=1}^{MN}\sum_{j=1}^{MN} g_{ij} x_i y_j}{\sqrt{\sum_{i=1}^{MN}\sum_{j=1}^{MN} g_{ij} x_i x_j \sum_{i=1}^{MN}\sum_{j=1}^{MN} g_{ij} y_i y_j}}$$

where g_{ij} is defined as in IMage Euclidean Distance (IMED) [10]:

$$g_{ij} = \frac{1}{2\pi\sigma^2}\exp(\frac{-dist(\mathrm{P}_i,\mathrm{P}_j)^2}{2\sigma^2})$$

where $dist(\mathrm{P}_i, \mathrm{P}_j)$ denotes the spatial distance between the pixels i and j.

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[1] IMage Normalized Cross-Correlation

The proposed method was implemented on 4 machines running Hadoop on them. Each machine has 4GB RAM DDR 2, an Intel Core 2 due CPU and 500GB HDD. Considering the lack of a sensible general purpose dataset, we decided to generate our dataset which contains all the information required for both running the system and evaluating it. In this regard, we gathered information of 10000 houses from some local real estate agents and online real estate websites and asked 250 different people to give 500 items a rank from 1 to 5 based on the pictures and other features of the house with overlaps in items they have ranked. The education level, occupation and gender of the evaluators were intentionally quite different, to reflect a more realistic evaluation.

In order to evaluate the accuracy of the proposed method we have used the Root Mean Square Error (RMSE) metric. A subset of items was represented to a set of new users and their ratings were recorded. It is worth mentioning that some users had already have rated the items, but in cases that the item was new to the users, they were asked to rate it. This process repeated exactly using the proposed method and the ratings were recorded, with the exception that each item's rating was calculated anew by the recommender system even if the user's rating was available in the dataset. Then RMSE was calculated using the following formula.

$$RMSE = \sqrt{\frac{1}{|\mathrm{U}_{test} \times \mathrm{I}_{test}|} \sum_{(u,i) \in \mathrm{U}_{test} \times \mathrm{I}_{test}} (\hat{r}_{u,i} - r_{u,i})^2}$$

We used NRMSE metric to evaluate the precision of our proposed method in combining image part of item with its other features when used by a recommender system. The NRMSE is simply RMSE normalized by the range of the ratings, i.e. r_{max}-r_{min}. Lower NRMSE corresponds to more accurate recommender systems. In the above formula, $r_{u,i}$ denotes the rating given to the item i by user u and $\hat{r}_{u,i}$ denotes the rating predicted by the system for user u and item i.

$$NRMSE = \frac{RMSE}{r_{\max} - r_{\min}}$$

In the following picture Graphical is same as our proposed approach without considering the text-based features, and Text-based is same as our approach without considering the image of an item.

Figure 2.1 NRMSE value for each method.

So far, the results have shown the significant improvements due to introducing images into recommender systems, which proves that considering images explicitly in these systems is quite promising (Figure 2.1).

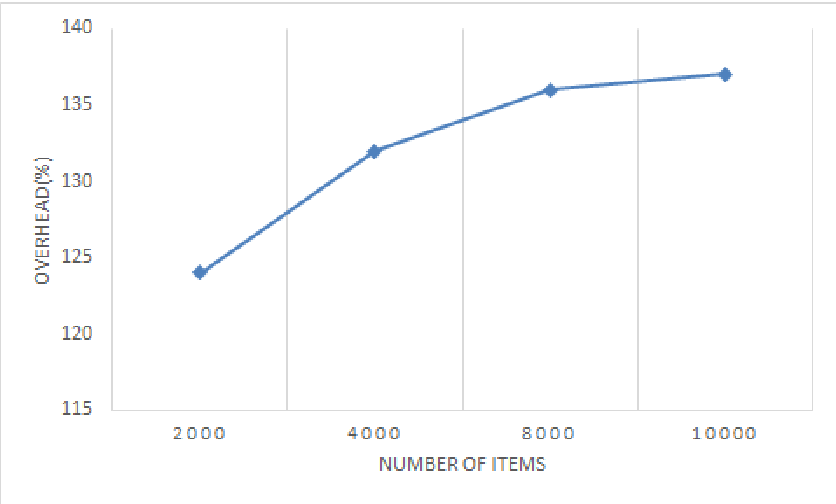

Figure 2.2 The overhead due to measuring the qualitative similarity, i.e., considering the images explicitly.

Indeed, the results show that using the distributed parallel approach that we have proposed for comparing the images of items still the system is fully practical, and the overhead has never exceeded 140 percent (Figure 2.2).

In order to show the effectiveness of our distributed similarity computation approach, we have implemented the whole system again, and the only difference is that the search method that used to retrieve the similar images is exhaustive search. The results are depicted in the Figure 2.3.

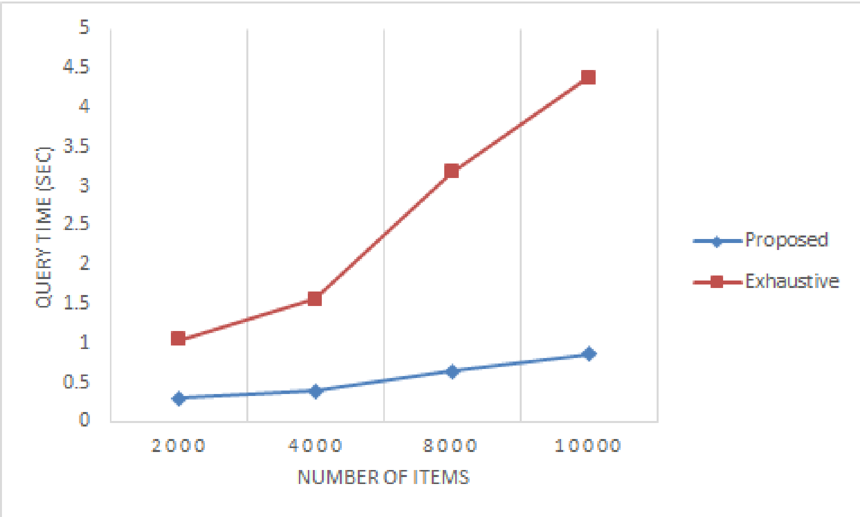

Figure 2.3 Comparison of query time between proposed method and exhaustive search-based method for different number of items.

This plot shows that the distribution of similarity measurement process that is proposed in this dissertation has a considerably positive effect on the processing time of each query. It should be noted that in the Exhaustive approach we did not use the Kd-Tree structure as well.

2.2 Proposed image retrieval methods

2.2.1 The first proposed image retrieval method

Our proposed method [11] is comprised of two main parts. The first part determines how the filter bank should be implemented and applied to decompose the input image into layers, and the second part proposes a method to extract features from each layer. The block diagram which illustrates how these layers are extracted has been depicted in Figure 2.4.

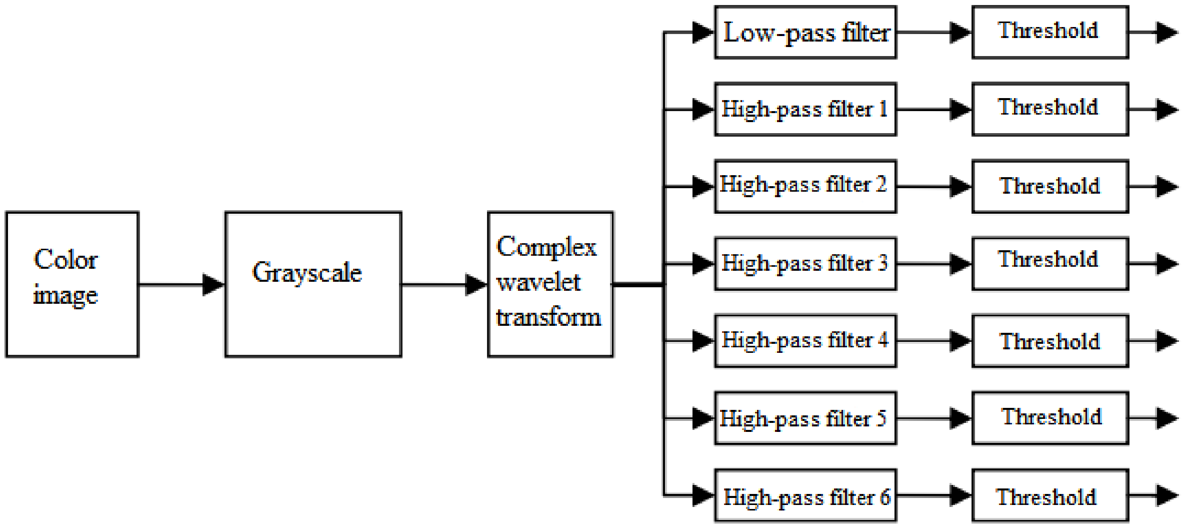

Figure 2.4 The block diagram of the layer extraction system.

With the extraction of these layers, each layer represents a different range of spatial frequency. The first layer determines the regions with low-frequency which correspond to backgrounds or the interior regions of objects, while the other 6 layers represent the regions which include more details in. If the variation range of the value of the pixels after the application of wavelet transform filters are set to be in the interval [0,1], all the threshold can be set to 0.5. For the first layer, the pixels whose value is lower than 0.5 and for the rest of the layers the pixels whose value is higher than 0.5 are taken into account and the other pixels are neglected.

In order to evaluate the proposed method, it has been implemented using Matlab running on a PC with an Intel CORE 2 Due 2.20 GHz processor and 4GB of RAM, on which the extraction of features from an image takes about 2 seconds. A collection including 3000 images borrowed from Hamshahri dataset was used in our experiments. The main reason for using this dataset was the fact that this dataset is extracted from an online news website so the images have come with very precise details about the category or categories the image belong to and each image is supported with a list of keywords which describe its contents. This gave us the ability to precisely verify the effectiveness of the proposed method. Although the Hamshahri dataset includes 36 main categories with many more sub-categories, we used 5 main categories in our evaluations including sports, buildings, animals, weather forecast, and accidents.

Two common metrics, namely precision, and recall have been used to evaluate the proposed method. We have used the definitions given in [12]:

$$P_j = \frac{\text{Number of retrieved and relevant elements in the first j positions}}{\text{j}}$$

$$R_j = \frac{\text{Number of retrieved and relevant elements in the first j positions}}{\text{Total number of relevant elements in the collection}}$$

We have used the aforementioned tags provided for each image in order to verify whether the image is relevant to the query or not. According to above equations, P_j shows an almost decreasing behavior when j increases while the opposite is true for R_j. As we mentioned before, color correlogram is one of the best methods in CBIR, so we have compared our proposed method with this method. The results have been shown in Table 2.1.

Table 2.1 The results of experiments conducted using the proposed method (Pr) and the color correlogram (CC) method.

Category	P_5	P_{10}	P_{15}	P_{20}	R_5	R_{10}	R_{15}	R_{20}	Method
Sports	1	1	1	0.94	0.22	0.47	0.79	0.8	Pr
	1	0.94	0.81	0.84	0.17	0.39	0.71	0.78	CC
Buildings	1	1	1	1	0.14	0.33	0.59	0.63	Pr
	0.89	0.74	0.86	0.86	0.12	0.28	0.45	0.57	CC
Animals	1	0.99	0.99	0.98	0.1	0.21	0.31	0.46	Pr
	1	0.96	0.83	0.76	0.09	0.21	0.25	0.9	CC
Weather Forecast	1	0.99	0.99	0.87	0.14	0.22	0.32	0.37	Pr
	0.96	0.92	0.85	0.86	0.15	0.19	0.28	0.31	CC
Accidents	0.98	0.98	0.98	0.98	0.04	0.09	0.21	0.29	Pr
	0.81	0.82	0.89	0.85	0.03	0.06	0.11	0.14	CC

As it is implied from the above table the proposed method shows a consistent superiority over the color correlogram method which is a competent method in the domain of CBIR.

2.2.2 The second proposed image retrieval method

In this proposed method [13], the query vector is broken into several multi-query vectors in regard to every feature space to perform the short-term learning. Initially, the user feeds the system with a query image Q, then, the features of the query image are extracted- these features are illustrated in the following section. The extracted feature vector is then used by the similarity function to retrieve P relevant images from the stored images. The images are then partitioned into two categories by the user: the relevant images, and the irrelevant images. At the next stage, the multi-query approach is used. This is done by clustering the images that are categorized as relevant, and using each cluster centre as a new query. Subsequently, the minimum distance of each image from the cluster centres is considered as its similarity to the query. We have used the WPGMC[1] algorithm to perform the clustering.

In order to combine the results of the retrieval based on each feature i, the ranking of each image in the database is computed when images are retrieved based solely on that feature. This ranking is then used to adjust the weight of each feature. Suppose we have N images in the database, and we offer the user only the M first retrieved images. First, the rankings of each of these M images are added together. Then according to the difference between the summation achieve at the stage t and the stage t+1 the new weights are computed. It should be noted that initially the weight of all the features are equal.

In order to evaluate the proposed method, it has been implemented using Matlab running on a PC with an Intel CORE 2 Due 2.20 GHz processor and 4GBs of

[1] Weighted Pair Group Method Centroid

RAM. A collection composed of 20000 JPEG formatted images borrowed from the Hamshahri2 dataset was used in our experiments [14]. Furthermore, 50 query images chosen from 50 different semantic groups were examined in the experiments. Each of these 50 images was used in a scenario wherein the image was given to the user as the query image, then the system offered the user a predefined number of images as the relevant images. Thereafter, the user was asked to provide a feedback and to decide which images were relevant and which ones were not. We have compared our proposed method with the CC[1], RR[2] and RGG[3] methods. The precision of the proposed method is compared to the precisions of the other methods and the results are depicted in Figure 2.5. It is worth mentioning that the results achieved at each iteration are averaged over all the categories. The following equation is used to compute the precision of each method:

$$\text{Precision} = \frac{\text{The number of the relevant images in the first j positions of the retrieved images}}{\text{j}}$$

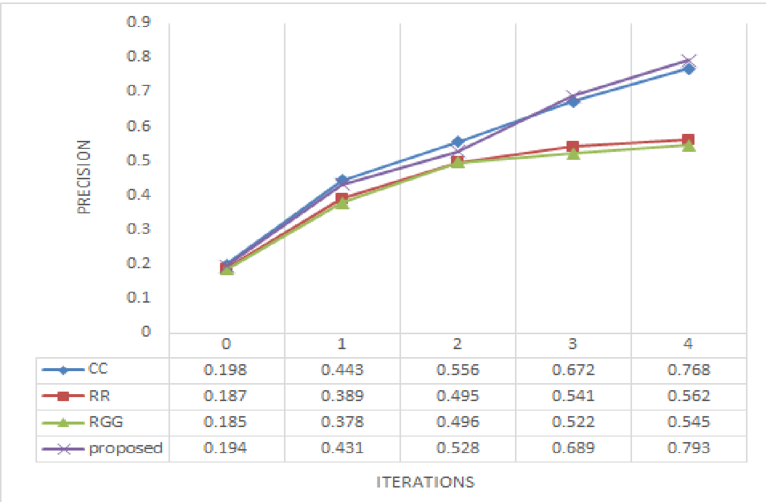

Figure 2.5 The average precision graph depicted for the top 20 retrieved images.

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[1] Classifier Combination, which is based on the multi-query approach.

[2] Uses the Rocchio's method [15] for the query vector refinement and the Rui's method [16] for the distance function refinement.

[3] Uses the Rocchio's method [15] for the query vector refinement and the method proposed by Guldogan & Gabouj [17] for the distance function refinement

The average time for the retrieval of images by means of each method is shown in Figure 2.6.

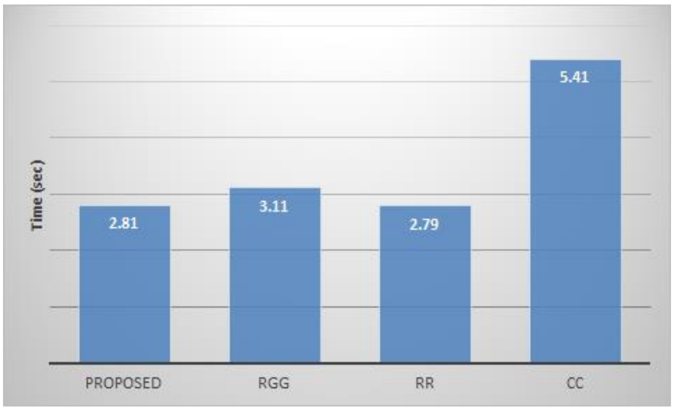

Figure 2.6 The average time taken for the retrieval of images by different methods.

It can be alluded from the above results that the proposed method not only produces more accurate results, but also achieves the results in a reasonable time.

Furthermore, the precisions of each method for some randomly selected semantic groups are shown in Table 2.2. The best result is shown by bold face for each case in which the proposed method outperforms the other well-known methods in most cases.

Table 2.2 Comparison of the precision of the proposed method with other methods for the top 20 retrieved images.

Semantic group	CC	RR	RGG	proposed
Sports	0.8185	0.5643	0.5912	**0.9261**
Buildings	0.7203	0.6485	0.7943	**0.8527**
Animals	**0.9918**	0.9561	0.8924	0.9840
Weather Forecast	0.5470	0.7511	**0.7519**	0.7455
Accidents	0.4149	0.2206	0.2418	**0.5613**
Cars	0.8651	0.8769	0.8133	**0.8774**

2.3 Utilization of the Image retrieval (IR) Methods

Besides the advantages in using the proposed methods solely in the image retrieval domain, they can be utilized to improve the proposed method illustrated in the previous chapter. In this section the application of these methods in our novel method introduced and discussed in the previous chapter is presented. Indeed, we avoid repeating the materials and just focus on the experiments carried out with and without the methods proposed in this chapter. The settings and the results of the experiments are presented after the illustration of the mechanism required to adopt each of the information retrieval methods so as to be used in the proposed recommender system.

There are some commonalities between the mechanisms required to apply the image retrieval methods presented in this chapter into our recommender system. In fact the general framework to make this work is the same for both methods, however, due to the process of relevance feedback there are some steps that are specific to the second method.

In the previous chapter we used the equation **Error! Reference source not found.**) in order to measure the similarity of the items, which was calculated in order to find the most similar items to some specific items which we call the proposal set $R = \{i_1, ..., i_N\}$. In order to use the proposed image retrieval methods, this scenario should be slightly changed. Indeed, the items having most similarity to the items of the proposal set regarding just the graphical features are retrieved using the IR method. In this step, the items are manipulated as they are just images and the text-based features are simply neglected. It should be mentioned that for each item i_j , *n* items are retrieved. From the items retrieved according to the item i_j , *m* items having the maximum similarity regarding just the text-based features are selected. In this approach the parameters *n* and *m* play almost the same role as the parameters α and β.

In order to apply the second method to our recommender system, the items should be categorized into some semantic groups. To avoid the unintended bias and achieve the most realistic results, the users that participate in the process of providing the feedbacks should be distinct from the users of the recommender system.

Some adjustments carried out to make an equal condition for all the experiments are as listed below:

- All the implementations are carried out using the Matlab software running on a PC with an Intel CORE 2 Due 2.20 GHz processor and 4GBs of RAM.
- We first create a grayscale equivalent for each image and normalize it so as to have the dimensions of 256×256.
- None of the users participated in the RF process of the second proposed IR method have taken part in any process of the proposed recommender system.
- A database containing 2300 houses from some local real estate agents and online real estate websites were used for the evaluations. In order to make sure the ratings reflect the view points of the users more realistically, the people participated in the process of rating the houses were real customers.
- The database of users contains 178 users each of which have rated at least 8 items and at most 58 items. The average number of ratings provided by each user is almost 21.
- As we have not yet proposed the parallel version of the methods discussed in this chapter, despite the fact that some parts of each method can be simply performed in a parallel fashion, no parallelization is carried out on any of the methods which are mentioned in this section.
- There are 5 semantic groups considered for the items which correspond to the different kinds of the properties existed in the data set of items.

In order to measure the effectiveness of the proposed methods presented in this chapter, the quality of the recommendations is measured in terms of *NRMSE* metric introduced in the chapter 6.

Figure 2.7 NRMSE metric measured for different approaches.

In Figur 2.7, M1 and M2 denote utilization respectively the first IR method and the second IR method, while ch6 denotes the approach discussed in chapter 6. According to the results it is clear that using either of the methods illustrated in this chapter has a positive effect on the overall quality of the recommender system.

3 Suggestion and future works

Our main focus in this study was on suggesting a new practical approach to improve the performance of recommender systems that work on the items containing images that describe them or have a considerable impact on the users' attitude towards the items. We believe that this study can be a considered as the starting point a significant variety of researches in the future, from which we mention some:

- Trying to improve the quality of the system using similarity measures that take the shapes into account;
- Extending the proposed method to the case that items have more than one descriptive image attached to them;
- Generating a data set which contains millions of items with images associated to them, along with the user’s rankings and testing the proposed method using this data set to achieve an even better evaluation.

References

[1] D.H. Park, H.K. Kim, I.Y. Choi, J.K. Kim, "A literature review and classification of recommender Systems research", Expert Systems with Applications 39, 10059–10072, 2012.

[2] W. Carrer-Neto, M.L. Hernández-Alcaraz, R. Valencia-Garcı´a, F. Garcı´ aSánchez, "Social knowledge-based recommender system, Application to the movies domain". Expert Systems with Applications 39, 10990–11000, 2012.

[3] S.K. Lee, Y.H. Cho, S.H. Kim, "Collaborative filtering with ordinal scale-based implicit ratings for mobile music recommendations", Information Sciences 180, 2142–2155, 2010.

[4] Z. Yu, X. Zhou, Y. Hao, J. Gu, "TV program recommendation for multiple viewers based on user profile merging", User Modeling and User-Adapted Interaction 16, 63–82, 2006.

[5] E.R. Núñez-Valdéz, J.M. Cueva-Lovelle, O. Sanjuán-Martı´nez, V. Garcı´a-Dı´az, P. Ordoñez, C.E. Montenegro-Marı´n, "Implicit feedback techniques on recommender systems applied to electronic books", Computers in Human Behavior 28, 1186–1193, 2012.

[6] J. Serrano-Guerrero, E. Herrera-Viedma, J.A. Olivas, A. Cerezo, F.P. Romero, "A google wave-based fuzzy recommender system to disseminate information in University Digital Libraries 2.0.", Information Sciences 181,1503–1516, 2011.

[7] O. Zaiane, "Building a recommender agent for e-learning systems", in: Proceedings of the International Conference on Computers Education (ICCE'02), vol. 1, pp. 55–59, 2002.

[8] Z. Huang, D. Zeng, H. Chen, "A comparison of collaborative filtering recommendation algorithms for e-commerce", IEEE Intelligent Systems 22, 68–78, 2007.

[9] M. Azodinia, A. Hajdu. *A recommender system that deals with items having an image as well as quantitative features*. The 9th IEEE international symposium on intelligent signal processing (WISP 2015), Vol. 1, pp. 1-6, 2015.

[10] A. Nakhmani, A. Tannenbaum. “A New Distance Measure Based on Generalized Image Normalized Cross-Correlation for Robust Video Tracking and Image Recognition”. Pattern recognition letters, Vol. 34(3), pp. 315-321, 2013.

[11] M. Azodinia, A. Hajdu. “A method for image retrieval using combination of color and frequency layers”. International journal of computer applications (IJCR), Vol. 118(3), pp. 10-13, 2015

[12] H. Muller, W. Muller, D.M. Squire, S. M. Mailent and T. Pun. “Performance evaluation in content-based image retrieval: overview and proposals”. Pattern Recognition Letters, Vol. 22, pp.593-601, 2001.

[13] Azodinia, M., Hajdu, A. “A novel combinational relevance feedback content-based image retrieval method. Acta Polytech. Hung. [Megjelenés alatt], 2016.

[14] A. AleAhmad, H. Amiri, E. Darrudi, M. Rahgozar and F. Oroumchian. “Hamshahri: A Standard Persian Text Collection. Knowledge-Based Systems”, Vol. 22(5) pp. 382-387, 2009.

[15] P. Ciaccia, M. Patella, and P. “M-tree: An Efficient Access Method for Similarity Search in Metric Spaces”, The 23rd International Conference on Very Large Data Bases, pp. 426-435, Athens, Greece, 1997.

[16] Rui, Y., Huang, S., Ortega, M., Mehrotra, S. “Relevance feedback: a power tool for interactive content-based image retrieval”. IEEE Transactions on Circuits and Video Technology, Vol. 8(5), pp. 25-36, 1998.

[17] Guldogan, E. & Gabbouj, M. “Dynamic feature weights with relevance feedback in content-based image retrieval”. 24th International Symposium on Computer and Information Science, pp. 56-59, 2009.

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List of publications related to the dissertation

Foreign language Hungarian book chapters (1)

1. **Azodinia, M.**, Farrokhi, V., Hajdu, A.: Constant time median filtering of extra large images using Hadoop.
   In: Proceedings of the 9th International Conference on Applied Informatics January 29 - Februar 1, 2014. Eger, Hungary Volume I [elektronikus dokumentum]. Ed.: by Kovács Emőd, Kusper Gábor, Kunkli Roland, Tómács Tibor, Eszterházy Károly Főiskola, Eger, 93-101, 2015.
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Foreign language international book chapters (1)

2. **Azodinia, M.**, Hajdu, A.: A recommender system that deals with items having an image as well as quantitative features.
   In: Proceedings of the 9th International Symposium on Intelligent Signal Processing (WISP), 2015 May 15-17, Siena, IEEE, [Piscataway], 1-6, 2015. ISBN: 9781479972524
   DOI: http://dx.doi.org/10.1109/WISP.2015.7139167

Foreign language scientific articles in Hungarian journals (1)

3. **Azodinia, M.**, Hajdu, A.: A novel combinational relevance feedback content-based image retrieval method.
   Acta Polytech. Hung. [Megjelenés alatt], p. [1-15], 2016. ISSN: 1785-8860
   IF: 0.544 (2015)

Foreign language scientific articles in international journals (1)

4. **Azodinia, M.**, Hajdu, A.: A method for image retrieval using combination of color and frequency layers.
   IJCA. 118 (3), 10-13, 2015. ISSN: 0975-8887.
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List of other publications

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5. **Azodinia, M.**, Hajdu, A.: A novel method to increase the performance of recommender systems using a parallel CBIR approach.
   IJCSIS. [Megjelenés alatt], p. [1-15], 2016. ISSN: 1947-5500.

Foreign language conference proceedings (1)

6. Mosavi, A**., Azodinia, M.**, Hewage, K. N., Milani, A. S., Yeheyis, M.: Reconsidering the multiple criteria decision making problems of construction workers with the aid of Grapheur.
   In: International ANSYS and EnginSoft Conference, Verona, Italy, 2011
   ENGINSOFT Newsletter. 8 (4), [1-5], 2011.

Total IF of journals (all publications): 0,544
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The Candidate's publication data submitted to the iDEa Tudóstér have been validated by DEENK on the basis of Web of Science, Scopus and Journal Citation Report (Impact Factor) databases.

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