Yu-yun *EURASIP Journal on Embedded Systems* (2017) 2017:14
DOI 10.1186/s13639-016-0050-x

EURASIP Journal on Embedded Systems

RESEARCH Open Access

Research on the fusion mechanism of cooperative embedded filtering and crowd content recommendation

Chen Yu-yun

Abstract

Internet simultaneous services of large-scale users will lead to server overload and information failure. Static content recommendation system cannot adapt to the dynamic similarity characteristics of users. So, how to perceive the high accuracy of recommendation scheme in dynamic environment becomes one of the key techniques in application of educational information and embedded application. We analyze the problem of low efficiency and high error of the recommendation technology based on the user's requirement. And, we proposed the cooperative filtering recommendation system based on the dynamic similarity of different users. In order to improve the prediction accuracy of cooperative filtering algorithm, the user's target content would be processed with crowd scheme. Then, the system is fused with the recommendation system. According to the weights of the fusion, the crowd recommended fusion scheme are proposed. The experimental results show that the fusion mechanism of cooperative embedded filtering and crowd content recommendation has obvious advantages in terms of content recommendation accuracy, reliability, and convergence speed.

Keywords: Cooperative embedded, Crowd content, Recommendation fusion, Filtering

1 Introduction

Internet applications can provide users with more and more information and services [1]. However, Internet users are faced with a lot of garbage information and meaningless data [2]. At the same time, Internet users who do not know how to get the information needed from the mass of network resources become a problem. Internet recommendation system [3] can be based on the needs of users to change [4] through information analysis and data mining to improve the efficiency and accuracy of the user's information.

On the one hand, Efatmaneshnik M et al. proposed the new positioning algorithm for localization of mobile networks, in general, that applies directly to vehicular networks [5]. The information-weighted consensus filter was utilized in article [6] to track space objects using multiple space-based optical sensors. A proposal was researched by Bacha A R A et al. [7] for a collaborative intelligent localization algorithm inspired from the Particle Swarm Optimization technique and applied to a highly dynamic road vehicle localization. According to the traditional fusion rules, Andre Lei et al. refer to them collectively as multiple-symbol differential (MSD) fusion rules [8]. For a kind of nonlinear bio mechatronics system, Quanbo Ge et al. [9] proposed a fifth-degree ensemble iterated cubature square-root information filter by combining many estimation schemes. A solution for the distributed information transfer and fusion among the participating platforms was presented in article [10]. The novel sample specific late fusion method was proposed in article [11] for considering the fact that each classifier may perform better or worse for different subsets of samples.

On the other hand, a user-content matrix update approach was proposed in article [12], which updates and fills in cold user-video entries to provide the foundations for the recommendation. An improved Jaccard similarity was proposed to improve the collaborative filtering recommendation quality [13].

Correspondence: yuyuncchen@sina.com
Guangxi Technological College of Machinery and Electricity, Nanning, Guangxi 530007, China

However, the fusion of cooperative filter and content recommendation is ignored in the above research results.

The content recommendation for video-related solutions was proposed in article [14], which ranged from IP television. A M-Learning Content Recommendation Service was provided by exploiting the mobile social interactions in article [15].

The rest of the paper is organized as follows. Section 2 describes the cooperative embedded filtering recommendation system. In Section 3, we discussed the crowd fusion mechanism for content recommendation. The algorithm analysis and verification has been shown in Section 4. Finally, the conclusions are given in Section 5.

2 Cooperative embedded filtering recommendation system

In the large data analysis and the application of complex network transmission, the recommendation technology shows the problem of low efficiency and high error. Because of the dynamic similarity of different users, it is recommended to reduce the accuracy by calculating the different user's needs. The similarity of the dynamic changes will lead to that the neighbor and the user demand is not consistent.

When the user needs have multiple target features, the mapping between the user similarity and the recommended content has a large deviation. Based on the mapping relationship matrix, the predicted project content leads to a poor prediction error, as shown in the formula (1).

$$\begin{cases} R_{\mathrm{A}} = \dfrac{R_{\mathrm{T}}}{\max E_{\mathrm{R}} f_{\mathrm{R}}} \\ M_{\text{R-O}} = \begin{bmatrix} \sum\limits_{i=1}^{k} \delta_{\mathrm{S}}{}^{k} R^{k} & \overline{\delta}_{\mathrm{S}} R_{\mathrm{A}} \\ \overline{\delta}_{\mathrm{S}} R_{\mathrm{A}} & \sum\limits_{i=k+1}^{n} \delta_{\mathrm{S}} R^{k} \end{bmatrix} \\ E_{\mathrm{F}} = \dfrac{\sum\limits_{i=1}^{n} \delta_{\mathrm{S}}{}^{k} R^{k}}{R \cdot R_{\mathrm{A}}} \end{cases} \tag{1}$$

Here, R_{A} indicates the accuracy of recommendation. $M_{\text{R-O}}$ represents the mapping between content and user requirements, which could satisfy the users' needs according to the content effectively. δ_S is the similarity weights. E_{F} indicates the prediction error. k represents the recommended relationship between the first set of user neighbors. n represents the number of users. R represents a collection of recommended content.

From formula (1), we found that the value of K determines the mapping between the matrix of the rank and the elements. k also determines the mapping between the best subset of the search neighbors and other users. When both k and n are increased, the $M_{\text{R-O}}$ will show the on-coordination and inconsistency.

To sum up, we will make the user needs and different users become the target. By setting up a multi-objective matrix, the co-adjustment between the target and the target is carried out. The purpose of the adjustment is to weaken the differences between goals and strengthen the consistency of the target.

The nearest neighbor was chosen to ignore the difference between the user's needs. The multiple objective matrix would be queried when predicting the recommended results. The main basis for choosing the nearest neighbor is the consistency and the similarity of the target. The recommended content for multi-object coordination is transparent. The transparency as shown in formula (2).

$$\begin{cases} P = \begin{bmatrix} R_1 \cdot \phi_1 & R_m \cdot \phi_m \\ R_t \cdot \phi_t & R_{n-m} \end{bmatrix} \cdot \phi_{n-m} \\ T_R = \log \left(\dfrac{\|P\|}{\sum\limits_{k=1} R^k} \right) \end{cases} \tag{2}$$

Here, ϕ is the transparency coefficient. The transparency of multi-object coordination is obtained through the calculation of the matrix P paradigm.

Transparent processing can predict the content of the project. The prediction is not related to the recommendation and mapping. Multi-objective cooperative process is as follows:

(1) The prediction of the target user needs is equivalent to a linear similar item set.
(2) Calculate the similarity of multiple targets. The nearest neighbor set of multiple targets would be reorganized with similarity.
(3) Search the nearest neighbor of a target in a particular item category.
(4) The data of these nearest neighbors would be sparse processed. Coordinate the nearest neighbor target structure, based on the similarity and reliability search for multi-objective optimization objectives.

Through the above process, the similarity and reliability of the combination of the best optimization objectives OP (T, R_{LI}) are as shown in the formula (3).

$$\mathrm{OP}(T, R_{\mathrm{LI}}) = \frac{\sum_{i=1}^{m} R_{\mathrm{LI}}{}^{i} T_{\mathrm{R}}{}^{i}}{\delta\sqrt{\sum_{i=1}^{n} R_{\mathrm{LI}}{}^{i}} + \phi\sqrt{\sum_{i=1}^{n} T_{\mathrm{R}}{}^{i}}} \quad (3)$$

The objective of the optimization is to be a linear result of the multi-objective evaluation. However, there is a certain degree of coupling after multiple target filtering. Coupling between objects can increase the diversity of users' requirements and the accuracy of the recommendation. This kind of interference will reduce the transparency. Therefore, we will construct the embedded filter according to the similarity and preference of the multiple targets. The method of formula (4) could reduce the coupling degree between multiple targets N_{C}. Target similarity between target user and neighbor user would be updated. The reliability of multiple targets is in the nearest neighbor combination. The minimum similarity content would be found by traversal search.

$$N_{\mathrm{C}} = \mathrm{OP}(T, R_{\mathrm{LI}}) \frac{\sum_{i=1}^{m} OP\left(T_i, R_{\mathrm{LI}}{}^{i}\right)}{\delta\phi\sqrt{\sum_{i=1}^{n} T_{\mathrm{R}}{}^{i} R_{\mathrm{LI}}{}^{i}}} \quad (4)$$

Then, the multi-objective near coupling is embedded into the multi-object similarity matrix of all users. From the low coupling objective, the traversal of the nearest neighbor set select the recommended content and, finally, the recommended content filtering. The similarity and reliability measures are given to the multi-objective matrix, and the nearest neighbor set is updated in real time. Through the multi-objective coordination and embedded recommendation, the best forecast goal is pushed to the upper level service. The recommendation system model includes the user group, multi-goal conversion module, comparability and reliability measure module, feedback module, nearly coupling degree measure module, recommended question processing module, and database module, as shown in Fig. 1.

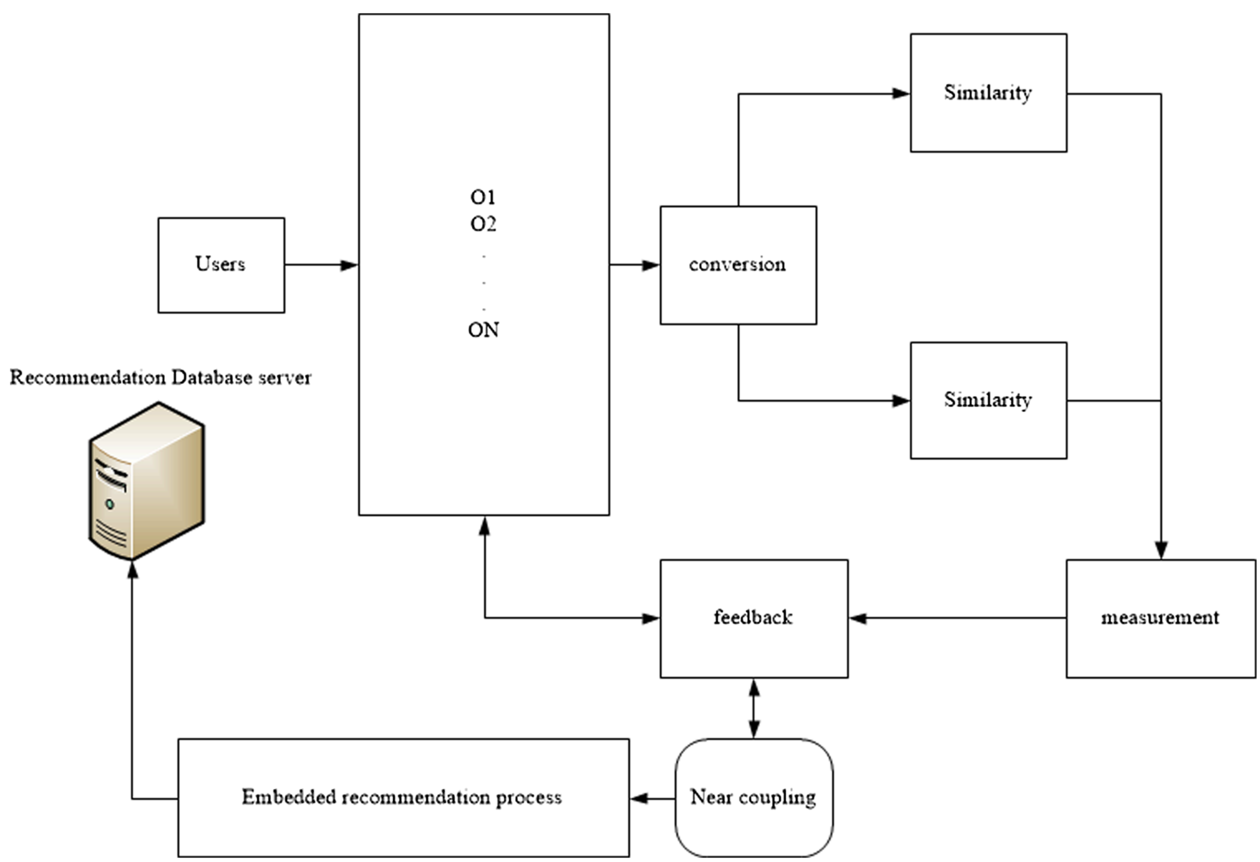

Fig. 1 Cooperative embedded filtering recommendation system

Table 1 Multi-objective coordination process

Users	Objects	Coordination	Optimal objective
1	R_1, R_2	Transparent	$OP(T,R_{LI})$
2	R_2, R_1,R_3		
3	R_1, R_4	R_3	
4	R_3	Transparent	

3 Fusion mechanism for crowd content recommendation

In order to improve the prediction accuracy of cooperative filtering algorithm, the user's target content is processed with crowd scheme, and then, the system is fused with the recommendation system. According to the weights of the fusion, the crowd fusion and the recommended fusion scheme are proposed.

Based on the multi-object coordination, the nearest neighbor set would be processed according to the recommended content. The fusion of nearest neighbor set and user requirements are completed. The coordination model would be optimized. Based on the user demand and similarity, the crowd processing of multi-objective matrix would be completed. The pseudo code is as follows.

Input: multiple object matrix R
Output: crowd content fusion matrix C_{CF}

1: While R
2: get the object from R
3: compute the crowd data with the object
4: IF $N_C > 1$
5: compute the crowd with RA based on Table 1
6: END IF
7: construct the matrix C_{CF}
8: return C_{CF}

The crowd content is measured and the similarity S_C between the crowd users, as shown in formula (5). Then, the optimal crowd neighbor set OP_L would be selected, as shown in formula (6).

$$S_C = \min_{R_A,n} \sum\nolimits_R \left\{ \|P\|\delta \sum_{i=1}^{n} R_A^i - \frac{\|M_{R\text{-}O}\|\phi}{\delta\phi\sqrt{\sum_{i=1}^{n} T_R{}^i R_{LI}{}^i}} \right\} \tag{5}$$

$$OP_L = \frac{\|P\|\delta \sum_{i=1}^{n} R_A^i}{\|M_{R-O}\|\phi \sum\nolimits_R \sqrt{\sum_{i=1}^{n} T_R{}^i R_{LI}{}^i}} \tag{6}$$

Based on the crowd fusion, recommendation fusion scheme was designed. Based on the formation of the C_{CF} data set through polling iteration, we could achieve convergence of recommended training. The similarity and reliability of different crowd objectives are analyzed. Based on the optimal target set, the final recommendation content would be obtained with crowd fusion. The user can get the N dimension of the recommended content vector $V_R = \left\{ v^{\delta\cos\phi}, v^{\delta\cos^2\phi}, \ldots, v^{\delta\cos^n\phi} \right\}$. Figure 2 shows the fusion process of crowd content recommendation.

4 Algorithm analysis and verification

Experiments used the WS-DREAM data set. The data set of 120×180 of the sample formed a user service matrix $M_{R\text{-}O}$. Each item in the matrix represents a target. One hundred eighty target users are divided into two

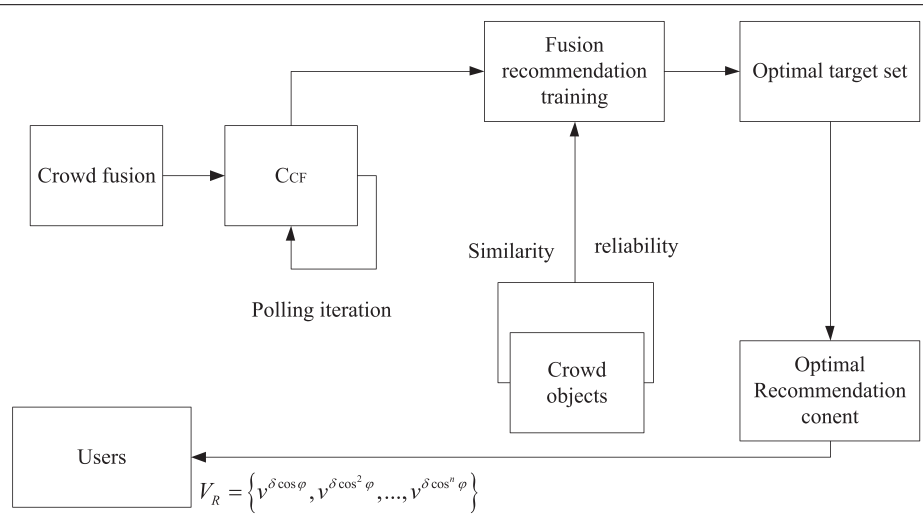

Fig. 2 Fusion mechanism for crowd content recommendation

groups randomly in the user service matrix. The first set is used as a training sample set. The second group is the recommended content user set. The target number of the training sample set is obtained by formulas (1) and (2). In order to analyze the influence of the similarity and transparency on the performance of the algorithm, the similarity measure between the multiple targets is weakened by the proportion from 0.1 to 1. The target number of the recommended content user set varies from 10 to 100. On the basis of the analysis, the prediction accuracy and reliability of the algorithm are analyzed. In addition, due to the need for collaborative embedded filtering and crowd content recommendation fusion, the recommended content user set according to formula (5) and (6) definition of the conditions for segmentation. The convergence of the algorithm is easy to be solved.

Figure 3 shows the recommendation accuracy with transparent fusion comparison results of the proposed fusion mechanism of cooperative embedded filtering and crowd content recommendation (FCECR) algorithm and recommendation algorithm based on ant colony (RAAC). Figure 4 shows the recommendation accuracy with non-transparent fusion comparison results.

Due to the dynamic similarity between the training samples and the training samples in each cycle, the accuracy of the recommendation is changed with the change of the national model of the training sample set. When the number of users increased from 60 to 80, the recommendation accuracy of the algorithm based on ant colony algorithm became smaller. And, when the number of users is 90, the accuracy of the recommendation algorithm based on the ant colony algorithm has been unable to achieve the prediction of the recommended content. However, FCECR can well adapt to the changes in the number of training users and always maintain a high recommendation accuracy. From Figs. 3 and 4, when the number of users is less than 60, the prediction accuracy of the two schemes is close. It shows that the prediction performance of the small-scale user recommendation system is mainly dependent on the multi-objective partitioning, and the multi-objective coordination performance is mainly reflected in the large-scale user recommendation system. The filtering accuracy of RAAC scheme is lower than one of FCECR scheme because of ignoring the fusion mechanism and crowd. So, the content recommendation effect of RAAC scheme is poor with large users and objects.

The reliability of the recommendation algorithm is analyzed through statistical user feedback. In this section, we use six kinds of different training samples set and user matrix of HPCN. The values were 0.1, 0.3, and 0.5. The values of δ were 45, 65, and 75 %, respectively. The reliability with transparent fusion and non-transparent

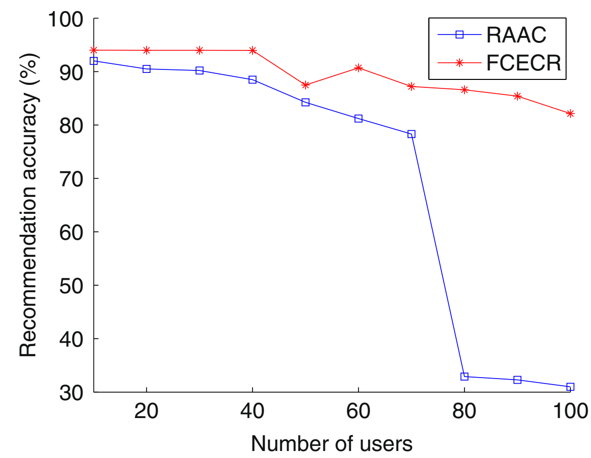

Fig. 4 Recommendation accuracy with non-transparent fusion

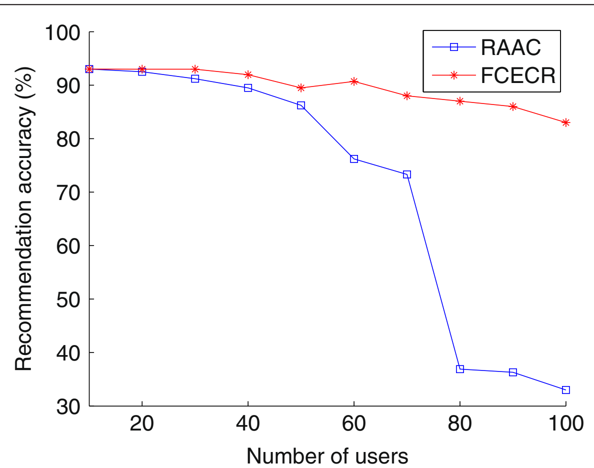

Fig. 3 Recommendation accuracy with transparent fusion

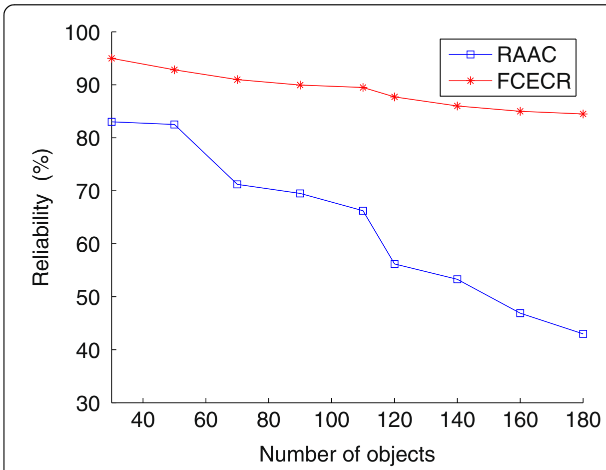

Fig. 5 Reliability with transparent fusion

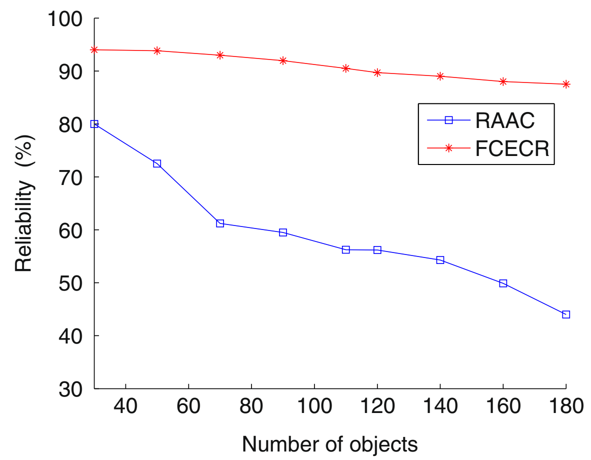

Fig. 6 Reliability with non-transparent fusion

fusion of the two algorithms are shown in Figs. 5 and 6. Because the FCECR algorithm will predict the target user, it needs linear equivalence for a similar item set. Then, according to the nearest neighbor set of the similarity of the multiple targets, finally, sparse processing is performed on the nearest neighbor target data so as to search for a multi-objective optimization with high reliability.

FCECR algorithm processed the recommended content with crowd scheme for multi-objective coordination of the nearest neighbor set. The nearest neighbor set and user needs have been fused, based on the optimal target set, the final recommendation content, so we can quickly converge with fewer iterations with transparent fusion and non-transparent fusion, as shown in Figs. 7 and 8.

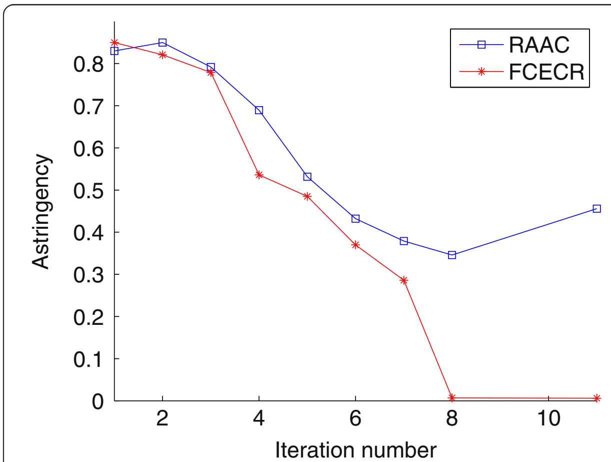

Fig. 7 Astringency with transparent fusion

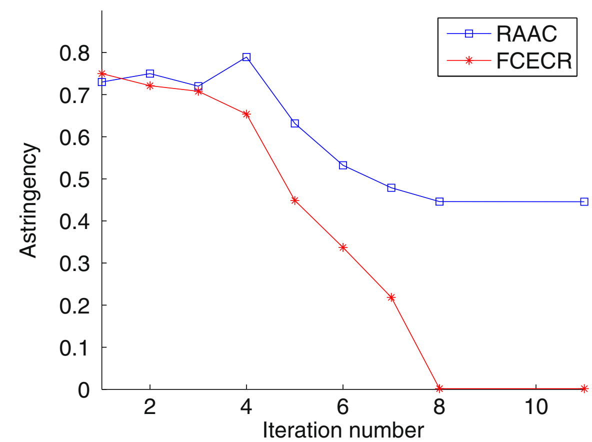

Fig. 8 Astringency with non-transparent fusion

5 Conclusions

To solve a large number of Internet garbage information and meaningless data reduce the user's Internet experience, according to the changing needs of users, the co-operative embedded filter crowd content recommendation mechanism was proposed to enhance the efficiency and accuracy of use information from the large amount of network resources. The mechanism will make the user needs and different user as objects. By setting up a multi-objective matrix, the co-adjustment between the target and the target is carried out. The purpose of the adjustment is to weaken the differences between goals and strengthen the consistency of the target. The multi-objective coordination of the nearest neighbor set of the recommended content would be processed with crowd embedded scheme. Based on the data set through the polling iteration, we could achieve crowd fusion recommendation content. Compared with the recommendation system based on ant colony algorithm, the proposed recommendation system has high precision, reliability, and efficiency.

Competing interests

The authors declare that they have no competing interests.

Received: 21 June 2016 Accepted: 20 August 2016
Published online: 30 August 2016

References

1. Chang HS, Liao YS, Huang YH, et al. (2010) *Seamless On-Line Service Upgrade for Transaction-Based Internet Services[C]//International Symposium on Parallel and Distributed Processing with Applications* . (pp. 319-326). IEEE Press.
2. Yung C, Syu JJ, Yang SY (2010). *A Graph-Based Algorithm of Mostly Incremental Garbage Collection for Active Object Systems[C]//Computer Symposium* (pp. 988–996). IEEE Press.
3. Putri AN, Akbar S, Sunindyo WD (2015) *Public Facilities Recommendation System Based on Structured and Unstructured Data Extraction from Multi-Channel Data Sources[C]//International Conference on Data and Software Engineering*. (pp. 185–190). IEEE Press.
4. F Steiner, RT Tarman, JC Ihl et al., *Learning from the Customer: Identifying Changing User Needs During Product Usage Through Embedded Toolkits for*

User Innovation[C]//Portland International Conference on Management of Engineering & Technology, 2009, pp. 706–716
5. M Efatmaneshnik, AT Balaei, N Alam et al., *A Modified Multidimensional Scaling With Embedded Particle Filter Algorithm for Cooperative Positioning of Vehicular Networks[C]//IEEE International Conference on Vehicular Electronics and Safety*, 2009, pp. 7–12
6. Jia B, Pham KD, Blasch E, et al. (2014). *Cooperative Space Object Tracking Using Consensus-Based Filters[C]//International Conference on Information Fusion* (pp. 1–8). IEEE Press.
7. Bacha ARA, Gruyer D, Mammar S (2013). *A New Robust Cooperative-Reactive Filter for Vehicle Localization: The Extended Kalman Particle Swarm 'EKPS'[C]// Intelligent Vehicles Symposium (IV), 2013 IEEE* (pp. 195-200). IEEE Press.
8. A Lei, R Schober, Multiple-symbol differential decision fusion for mobile wireless sensor networks[J]. IEEE Transactions on Wireless Communications **9**(2), 778–790 (2010)
9. Q Ge, T Shao, Q Yang et al., Multisensor nonlinear fusion methods based on adaptive ensemble fifth-degree iterated cubature information filter for biomechatronics[J]. IEEE Transactions on Systems Man & Cybernetics Systems **46**(7), 1–14 (2016)
10. D Akselrod, A Sinha, T Kirubarajan, Information flow control for collaborative distributed data fusion and multisensor multitarget tracking[J]. Systems Man & Cybernetics Part C Applications & Reviews IEEE Transactions on **42**(4), 501–517 (2012)
11. KT Lai, D Liu, SF Chang et al., Learning sample specific weights for late fusion[J]. IEEE Transactions on Image Processing A Publication of the IEEE Signal Processing Society **24**(9), 2772–2783 (2015)
12. Z Wang, L Sun, W Zhu et al., Joint social and content recommendation for user-generated videos in online social network[J]. IEEE Transactions on Multimedia **15**(3), 698–709 (2013)
13. Y Deng, T Lu, H Xia et al., *AOPUT: A Recommendation Framework Based on Social Activities and Content Interests[C]//IEEE, International Conference on Computer Supported Cooperative Work in Design*, 2013, pp. 545–550
14. JD Vriendt, N Degrande, M Verhoeyen, Video content recommendation: an overview and discussion on technologies and business models[J]. Bell Labs Technical Journal **16**(2), 235–250 (2011)
15. H Chao, C Lai, S Chen et al., A M-learning content recommendation service by exploiting mobile social interactions[J]. IEEE Transactions on Learning Technologies **7**(3), 221–230 (2014)