*International Journal of Latest Trends in Engineering and Technology*
*Special Issue SACAIM 2017, pp. 132-137*
*e-ISSN:2278-621X*

# A STUDY OF FASHION RECOMMENDER SYSTEM WITH HYBRID COLLABORATIVE FILTERING & FUZZY LOGIC

Janice J Fernandes[1] & Rhea Fernandes[2]

**Abstract- The information about the items preferred by the user are collected byRecommender system. This paper proposes clever form recommender system to choose the most relevant clothing configuration for a specific buyerin order to decide 'what to wear'. This sees the decision of garments in your wardrobe at home as a form of everyday decision making which could be supported by a variety of decision-support systems. Collaborative Filtering is a technique to suggest a thing chose by client, similar tendency based on similarity between users. Hybrid Collaborative Filtering presents a possibility to give precise proposals by considering the client preferences in multiple perspectives and a several strategies have been proposed for enhancing the exactness of these frameworks.**
**Keywords – Decision-support systems, Collaborative Filtering, recommender system**

## 1. INTRODUCTION

Today, as people emphasis on fashion, outfit select difficulty became a serious problemin daily life and as massive amounts of fashion items are available in markets and online, needs for efficient recommendation services has grown significantly. Recommender systems bolster clients in customized way for the identification of product based on the history of the user. Recommender Systems are the occurrences of personalization programming. Personalization worries with the adjusting to the individual needs, intrigue and inclinations of every client. It includes recommending, filtering and predicting.

Collaborative filtering looks for similar buying pattern among users. It keeps up the database of clients' evaluations of extensive variety of things. For a given client, it finds other comparable clients whose ratings firmly associate with the present client's ratings. It at that point prescribes things rated by these comparable clients despite the fact that they might not have been rated yet by the present client. Utilizing fuzzylogic procedures design characteristics, which incorporate style,shading,material,quality, mark, and regularity, to create mold traits work andattributes function adjustsusers evaluating grid parameters of collaborative filtering algorithm to enhance fashion recommendation system performance.

The primary aim of this paper is to design, develop, and evaluate a novel concept for managing the storage and wearing of clothes using user-centered methods and techniques. The paper explores ways in which combinations of technology can be used to support buying clothes and deciding what to wear and explores conceptual designs for a system to help people to decide what to wear by using different methods: By using a recommender system find a suitable outfit and by managing their wardrobe, via their computer or mobile phone, to find a suitable outfit or to add or remove clothes from the wardrobe

## 2. PERSONALIZED RECOMMENDATION SYSTEM MODEL BASED ON MODIFIED COLLABORATIVE FILTERING ALGORITHM

Personalized recommendation system (PRS) model based on modified collaborative filtering algorithm is as follows.

[1] Department of Software Technology, Aloysius Institute of Management and Information Technology, Mangaluru, Karnataka, India
[2] Department of Software Technology, Aloysius Institute of Management and Information Technology, Mangaluru, Karnataka, India

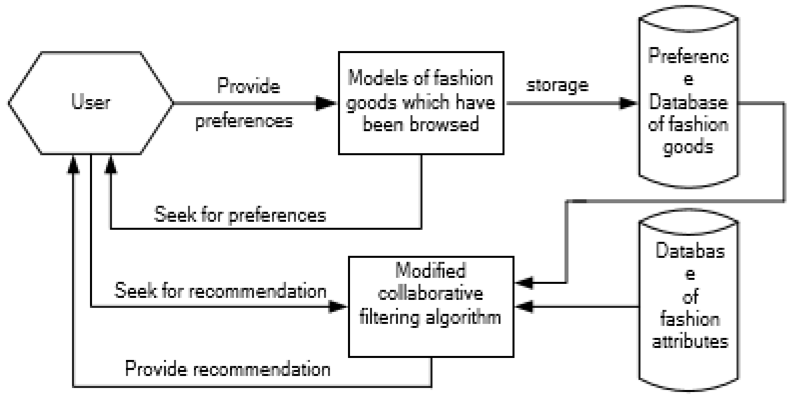


Figure 1. PRS Model based on Modified Collaborative Filtering Algorithm

Filtering consists of two core parts basically in PRS model based on modified collaborative. They are recommendation algorithm based on modified collaborative filtering and data refining procedure. Firstly, as indicated by the web which is accessed by users, to process and refine web data,data refining procedure is used. Secondly, altered collaborative filtering executes clustering items, implements and processesself-adaptive recommendation services.

## 3. USUAL COLLABORATIVE FILTERING RECOMMENDATION ALGORITHM

Following parts are mainly included inusual collaborative filtering recommendation algorithm.

The first step: In the recommendation system data resource is selected. As indicated by a few papers, data resource can be defined as follows:

Definition 1[10] Data resource function is D=f(U,I,R), where U=($User_1$,$User_2$,….,$User_m$) $\in Z_+^m$, $User_i$(i=1,…,m) is the i-th user, U is m users vector, I =($Item_1$, $Item_2$, ….,$Item_n$)$\in Z_+^n$, $item_j$(j=1,….,n) is j-th item , I is the n items vector, R is the matrix that vector U multiplies vector$I^T$ to produce ,$I^T$ is vector I transposition,The matrix R is as following formula(1):

$$R = \begin{pmatrix} r_{11} \dots & r_{1j} & \dots & r_{1n} \\ \cdot & & & \cdot \\ \cdot & & & \cdot \\ \cdot & & & \cdot \\ r_{i1} \dots & r_{ij} & \dots & r_{in} \\ \cdot & & & \cdot \\ \cdot & & & \cdot \\ r_{m1} \dots & r_{mj} & \dots & r_{mn} \end{pmatrix} \tag{1}$$

Where $r_{ij}$is that $User_i$appraises $Item_j$to produce value.

The second step: based on similaritycorrelation has to be computed.

Definition 2 Another name for correlation is Pearson similarity ,it is based on similarity, where sim(i, j) is correlation , $r_{(i,j)}$is $User_i$and $User_j$appraise elements ofvector $I_{(i,j)}$ to produce $r_{(i,j)}$, $I_{(I,j)}$□ □ I . sim(i, j) is as following formula (2) :

$$\mathrm{sim}(i,j) = -\frac{\sum_{k\in I(i,j)}(r_{ik}-\bar{r}_i)(r_{jk}-\bar{r}_j)}{\sqrt{\sum_{k\in I(i,j)}(r_{ik}-\bar{r}_i)^2}\sqrt{\sum_{k\in I(i,j)}(r_{jk}-\bar{r}_j)^2}} \tag{2}$$

Where $\bar{r}_i$is that$User_i$appraise elements of vector $I_{(i,j)}$to produce average score, $\bar{r}_j$ is $User_j$appraise elements of vector $I_{(i,j)}$to produce average score.

The third step: to produce recommendation.

As indicated by neighbors of special website users who are accessing theweb, two recommendation results , which include thattop-N recommendation set , can be computed and users predict arbitrary items to produce value.

(a) Users predict arbitrary items to produce value: according to user u to Appraise$I_u$, $P_{u,k}$is as following formula (3):

$$P_{u,k} = \overline{R_u} + \frac{\sum_{m=1}^{N}\mathrm{sim}\,(u,m)*(R_{m,k}-\overline{R_m})}{\sum_{m=1}^{N}\mathrm{sim}\,(u,m)} \tag{3}$$

Where $\overline{R_u}$is that user u has appraised item k ( k□$I_u$) to produce average score, sim(u,m) is similarity coefficient of user u and neighbors set N. $R_{m,k}$is that user m appraises item k ,which is not to be appraised by user u , to produce score ,$\overline{R_m}$ is user mappraises item m to produce score , N is neighbor numbers . If $P_{u,k}$value is more big,that states that users u more likes item k .

(b) Top-N recommendation set is produced : firstly,$P_{u,k}$is processed , then $P_{u,k}$valuescan be arranged from big to small , thirdly , $^{n}$items is selected according to$P_{u,k}$values arrangement , lastly , top-N recommendation set is produced .

In the E-commerce website some collaborative filtering recommendation algorithm can be used successfully, there is some faults .The key fault is asfollowing:

Data potential sparsity:Scope, users and goods numbers become larger with the development of E-commerce system application.User can only appraise small parts of goodsbased on interestof every user.In website, data potential sparsity is produced because these small parts of goods are1%-2% of total goods. Based on Data potential sparsityrecommendation efficiency of usual collaborative filteringrecommendation algorithm based on users appraising web goods score decrease.

**4. COLLABORATIVE FILTERING RECOMMENDATION ALGORITHM BASED ON FASHION ATTRIBUTES**

To improve recommendation efficiency of fashion website, to solve data potential sparsity of fashion website in some degree, modified collaborative filtering algorithm based on fashion attributes is researched.

Firstly, To create fashionattributes function uses fuzzy mathematics processes fashion attributes. In the paper, fashion attributes consist fashion style, fashioncolor, fashion quality,fashion material, fashion brand, and fashion seasonality. Letfashion style use fuzzy set $A_1$, fashion color use fuzzy set $A_2$, fashion material fuzzy useset $A_3$, fashion quality fuzzy use set $A_4$, fashion brand use fuzzy set $A_5$, fashionseasonality use fuzzy set $A_6$. Fuzzy sets $A_1$, $A_2$,$A_3$, $A_4$, $A_5$, $A_6$are as following formula(4-9).

$$A_1 = \frac{A_1(u_1^{(1)})}{u_1^{(1)}} + \frac{A_1(u_2^{(1)})}{u_2^{(1)}} + \cdots + \frac{A_1(u_{n1}^{(1)})}{u_{n1}^{(1)}} \tag{4}$$

$$A_2 = \frac{A_2(u_1^{(2)})}{u_1^{(2)}} + \frac{A_2(u_2^{(2)})}{u_2^{(2)}} + \cdots + \frac{A_2(u_{n2}^{(2)})}{u_{n2}^{(2)}} \tag{5}$$

$$A_3 = \frac{A_3(u_1^{(3)})}{u_1^{(3)}} + \frac{A_3(u_2^{(3)})}{u_2^{(3)}} + \cdots + \frac{A_3(u_{n3}^{(3)})}{u_{n3}^{(3)}} \tag{6}$$

$$A_4 = \frac{A_4(u_1^{(4)})}{u_1^{(4)}} + \frac{A_4(u_2^{(4)})}{u_2^{(4)}} + \cdots + \frac{A_4(u_{n4}^{(4)})}{u_{n4}^{(4)}} \tag{7}$$

$$A_5 = \frac{A_5(u_1^{(5)})}{u_1^{(5)}} + \frac{A_5(u_2^{(5)})}{u_2^{(5)}} + \cdots + \frac{A_5(u_{n5}^{(5)})}{u_{n5}^{(5)}} \tag{8}$$

$$A_6 = \frac{A_6(u_1^{(6)})}{u_1^{(6)}} + \frac{A_6(u_2^{(6)})}{u_2^{(6)}} + \cdots + \frac{A_6(u_{n6}^{(6)})}{u_{n6}^{(6)}} \tag{9}$$

According to segmentation of fashion style, fashion colour, fashion quality, fashion material, fashion brand, and fashion seasonality, domain $u_i^{(j)}(j \in [1,6], i \in [1,N])$and$A_j\left(u_i^{(j)}\right)(j \in [1,6], i \in [1,N])$are decided. Because segmentation of fashion attributes has notstandardized definition and we make programming become easy, uniform form of fuzzysets $A_1$, $A_2$,$A_3$, $A_4$, $A_5$and $A_6$are given .The explicit form is given in the experiment.

Recommendation efficiency which is produced by fashion attributes function named fashion recommendation efficiency function. In order to research function relationship among fuzzy sets $A_1$, $A_2$, $A_3$, $A_4$, $A_5$and $A_6$further , fashion recommendation efficiency function is defined according to the following way.

Definition 3 for$\forall(x_{i1}^{(1)}, x_{i2}^{(2)}, x_{i3}^{(3)}, x_{i4}^{(4)}, x_{i5}^{(5)}, x_{i6}^{(6)})$, there must be $\exists y_i$ to make$\left(x_{i1}^{(1)}, x_{i2}^{(2)}, x_{i3}^{(3)}, x_{i4}^{(4)}, x_{i5}^{(5)}, x_{i6}^{(6)}\right) \xrightarrow{f} y_i$. Where $x_{i1}^{(1)} \in A_1, x_{i2}^{(2)} \in A_2, x_{i3}^{(3)} \in A_3, x_{i4}^{(4)} \in A_4, x_{i5}^{(5)} \in A_5, x_{i6}^{(6)} \in A_6$.f is mapping between function $y_i$ and variables $\left(x_{i1}^{(1)}, x_{i2}^{(2)}, x_{i3}^{(3)}, x_{i4}^{(4)}, x_{i5}^{(5)}, x_{i6}^{(6)}\right)$

According to definition 3, function $y_i$ is as following formula (10)

$$y_i = \left(x_{i1}^{(1)}, x_{i2}^{(2)}, x_{i3}^{(3)}, x_{i4}^{(4)}, x_{i5}^{(5)}, x_{i6}^{(6)}\right) \tag{10}$$

Fuzzy sets $A_1$, $A_2$, $A_3$, $A_4$, $A_5$and $A_6$satisfy the following assumptions.

$$A_1\left(u_1^{(1)}\right) > A_1\left(u_2^{(1)}\right) > \cdots > A_1\left(u_{n1}^{(1)}\right) \tag{11}$$

$$A_2\left(u_1^{(2)}\right) > A_2\left(u_2^{(2)}\right) > \cdots > A_2\left(u_{n2}^{(2)}\right) \tag{12}$$

$$A_3\left(u_1^{(3)}\right) > A_3\left(u_2^{(3)}\right) > \cdots > A_3\left(u_{n3}^{(3)}\right) \tag{13}$$

$$A_4\left(u_1^{(4)}\right) > A_4\left(u_2^{(4)}\right) > \cdots > A_4\left(u_{n4}^{(4)}\right) \tag{14}$$

$$A_5\left(u_1^{(5)}\right) > A_5\left(u_2^{(5)}\right) > \cdots > A_5\left(u_{n5}^{(5)}\right) \tag{15}$$

$$A_6\left(u_1^{(6)}\right) > A_6\left(u_2^{(6)}\right) > \cdots > A_6\left(u_{n6}^{(6)}\right) \tag{16}$$

Fashion in current markets is defined as set C. Where $C = \{c_1, c_2, ..., c_n\}$, $c_i (i \in [1, n])$ means current market l1 –th type fashion whose attributes is in fuzzy sets $A_1$, $A_2$, $A_3$, $A_4$, $A_5$and $A_6$. Assuming l1 –th type fashion attributes values are $u_{j1}^{(1)}, u_{j2}^{(2)}, u_{j3}^{(3)}, u_{j4}^{(4)}, u_{j5}^{(5)}, u_{j6}^{(6)}$ and $u_{j1}^{(1)} \in A_1$, j1 $\in [1, n1]$, $u_{j2}^{(2)} \in A_2$, j2 $\in [1, n2]$, $u_{j3}^{(3)} \in A_3$, j3 $\in [1, n3]$, $u_{j4}^{(4)} \in A_4$, j4 $\in [1, n4]$, $u_{j5}^{(5)} \in A_5$, j5 $\in [1, n5]$, $u_{j6}^{(6)} \in A_6$, j6 $\in [1, n6]$.

Let $x_j^{(1)} = u_{j1}^{(1)}$, $x_j^{(2)} = u_{j2}^{(2)}$,$x_j^{(3)} = u_{j3}^{(3)}$,$x_j^{(4)} = u_{j4}^{(4)}$,$x_j^{(5)} = u_{j5}^{(5)}$,$x_j^{(6)} = u_{j6}^{(6)}$.

According to f definition, the l1 –th type fashion in the current markets is as following formula (17).

$$y_{l1} = \frac{1}{6}\left(x_{j1}^{(1)}, x_{j2}^{(2)}, x_{j3}^{(3)}, x_{j4}^{(4)}, x_{j5}^{(5)}, x_{j6}^{(6)}\right) \tag{17}$$

Using same calculation method, we can get to $c_{l1}(l1 \in [1, n]), c_{l2}(l2 \in [1, n]), ..., c_{ln}(ln \in [1, n])$ whose function are $y_{l1}, y_{l2}, ..., y_n . y_{lp}(lp \in n)$, which is ultimate value among$y_{l1}, y_{l2}, ..., y_n$, is computed according to the following formula (18).

$$y_{lp} = y_1 \cup y_2 \cup ... \cup y_n \tag{18}$$

Using $y_{lp}$ adjusts elements values of matrix $\hat{R}$according to the following formula (19).

$$\hat{R} = \begin{bmatrix} r_{11} \cup y_{lp} \ldots r_{1j} \cup y_{lp} \ldots r_{1n} \cup y_{lp} \\ \vdots \quad\quad \vdots \quad\quad \vdots \\ r_{i1} \cup y_{lp} \ldots r_{ij} \cup y_{lp} \cdots r_{in} \cup y_{lp} \\ \vdots \quad\quad \vdots \quad\quad \vdots \\ r_{m1} \cup y_{lp} \cdots r_{mj} \cup y_{lp} \cdots r_{mn} \cup y_{lp} \end{bmatrix} \tag{19}$$

The formula (19) is processed further, we can obtain formula (20).

$$\hat{R} = \begin{bmatrix} \widehat{r_{11}} \cdots \widehat{r_{1j}} \ldots \widehat{r_{1n}} \\ \vdots \quad \vdots \quad \vdots \\ \widehat{r_{i1}} \cdots \widehat{r_{ij}} \cdots \widehat{r_{in}} \\ \vdots \quad \vdots \quad \vdots \\ \widehat{r_{m1}} \cdots \widehat{r_{mj}} \cdots \widehat{r_{mn}} \end{bmatrix} \tag{20}$$

Where $\widehat{r_{ij}} = r_{ij} \cup y_{lp}$

According to formula (20) and (2), we can obtain $\widehat{sim_{(i,j)}}$ which is computed as following formula (21).

$$\widehat{sim_{(i,j)}} = -\frac{\sum_{k \in I_{(i,j)}} (\widehat{r_{ik}} - \widehat{\bar{r}_i})(\widehat{r_{jk}} - \widehat{\bar{r}_j})}{\sqrt{\sum_{k \in I_{(i,j)}} (\widehat{r_{ik}} - \widehat{\bar{r}_i})^2} \sqrt{\sum_{k \in I_{(i,j)}} (\widehat{r_{jk}} - \widehat{\bar{r}_j})^2}} \tag{21}$$

According to formula (21) and (3), we can obtain $\widehat{P_{u,k}}$ which is computed as following formula (22).

$$\widehat{P_{u,k}} = \widehat{\bar{R}_u} + \frac{\sum_{m=1}^{N} \widehat{sim(u,m)} * (\widehat{R_{m,k}} - \widehat{\bar{R}_m})}{\sum_{m=1}^{N} \widehat{sim(u,m)}} \tag{22}$$

Modified $\widehat{P_{u,k}}$ can reflect function relationship between current popular fashion attributes and users appraising in the markets. In the recommendation system values are arranged from big to small, we can get to n items from the first item to n-th item .The n items produce users recommendation set top-N.

## 5. EXPERIMENT RESULT AND ANALYSIS

### *5.1 Data Sets and Evaluation Criterion*

In order to test feasibility of modified collaborative filtering recommendation algorithm fused with fashion attributes, the fashion shopping website based on the algorithm is developed. Data sets are built on the following the rule.

Firstly, from users database 50 users' data is chosen. Secondly, 50 users appraised 30 kinds of fashion goods to produce according to first level to 5-th level rule, thus 1500 data is selected from users appraising database. Training data set consist 80% data, test data set consist of 20% data.

Appraising recommendation system test criterion is built on mean absolute error (MAE). MAE can test accuracy which is expected according to error between the first type of users who predict goods of web to produce score and the second type of users who actually appraise goods of web to produce score. The recommendation system efficiency is higher, if MAE value becomes smaller. Data set which is to expect goods of web to produce is $\{R_1, R_2, ..., R_n\}$ , data set which is to appraise goods of web to produce is $\{R_1', R_2', ..., R_N'\}$.MAE[11] is computed as following formula (23)

$$MAE = \frac{\sum_{i=1}^{N} \left| R_{ik}^{j} - \left(R_{ik}^{j}\right)' \right|}{N} \tag{23}$$

In the special test fashion website, there are two kinds of databases .The first kind ofdatabase is database of fashion goods attributes. Database of users evaluating fashion goods is the second type of database .The modified collaborative filtering recommendation algorithm to process the first kind of database and the second kind of database to producerecommendation results. Fashion attributes are as following tables.

**Table 1. Fashion Style Level**

| style level | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| meaning | very fashion | general fashion | fashion | old fashion | very old fashion |

**Table 2. Fashion Color Level**

| color level | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| meaning | very fashion color | general fashion color | fashion color | old fashion color | very old fashion color |

**Table 3. Fashion Material Level**

| material level | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| meaning | very fashion material | general fashion material | fashion material | old fashion material | very old fashion material |

**Table 4. Fashion Quality Level**

| material level | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| meaning | very good | general good | good | a little poor | poor |

**Table 5. Fashion Brand Level**

| brand level | 1 | 2 | 3 |
|---|---|---|---|
| meaning | very famous | general famous | usual brand |

**Table 6. Fashion Seasonality Level**

| seasonality level | 1 | 2 | 3 |
|---|---|---|---|
| meaning | very matching to current time | matching to current time | poor matching to current time |

According to Table 1 to Table 6, fashion attributes fuzzy mathematic programming formulae, which are based on formula (4-16), are as following formula (25-30).

$$A_1 = \frac{0.7}{1} + \frac{0.6}{2} + \frac{0.5}{3} + \frac{0.4}{4} + \frac{0.3}{5} \qquad (25)$$

$$A_2 = \frac{0.7}{1} + \frac{0.6}{2} + \frac{0.5}{3} + \frac{0.4}{4} + \frac{0.3}{5} \qquad (26)$$

$$A_3 = \frac{0.7}{1} + \frac{0.6}{2} + \frac{0.5}{3} + \frac{0.4}{4} + \frac{0.3}{5} \qquad (27)$$

$$\mathrm{A}_4 = \frac{0.8}{1} + \frac{0.6}{2} + \frac{0.4}{3} + \frac{0.2}{4} + \frac{0.1}{5} \qquad (28)$$

$$\mathrm{A}_5 = \frac{0.5}{1} + \frac{0.5}{2} + \frac{0.4}{3} \qquad (29)$$

$$\mathrm{A}_6 = \frac{0.8}{1} + \frac{0.5}{2} + \frac{0.2}{3} \qquad (30)$$

*5.2 Experiment Results and Analysis*

Two experiments can be designed to test the modified collaborative filtering recommendation algorithm fused with fashion attributes. Firstly, modified Pearson similarity fused with fashion attributes is how to effect the fashion recommendation system function .With the same test situation, cosine, Pearson similarity and modified Pearson similarity fused with fashion attributes are be tested separately. The outcomes are as per the following.

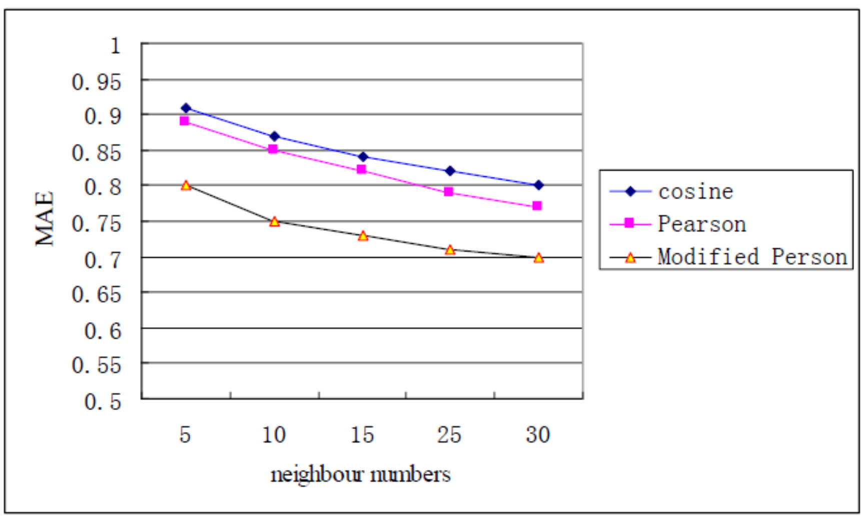


Figure 1. Three Similarity Computer Method Comparison

From Figure 1, MAE values of modified Pearson similarity fused with fashion attributes are smallest among MAE values of cosine, MAE of Pearson similarity and modified Pearson similarity. Therefore, modified Pearson function is best among cosine, Pearson, and modified Pearson.That means modified Pearson function can be adjusted by fashion attributes function effectively. Secondly, recommendation capability of modified collaborative filtering algorithm (MCFA) and usual collaborative filtering algorithm (UCFA) can be compared. The result is as follows.


Figure 2. Function between MCFA and UCFA

From Figure 2, with neighbor numbers increasing, with MAE values becoming more and more small, although that means two algorithms is feasible to process fashion goods recommendation in the fashion website recommendation system, MCFA function is better than UCFA function,because the reason is that MAE values of MCFA is smaller than MAE of UCFA.

## 6. CONCLUSION

A modified collaborative filtering algorithm fused with fashion attributes is researched under usual collaborative filtering algorithm. With using fuzzy mathematics to process fashion attributes parameters, fashion attributes function can be produced. Fashion attributes function adjusts R matrix of usual collaborative filtering recommendation algorithm to improve recommendation capability. With experiment results, the modified collaborative filtering algorithm is proved to be feasible to process fashion goods recommendation in fashion goods website.

## 7. REFERENCES


[1] [1] M.-H. Kuo, L.-C. Chen and C.-W. Liang, “Building and evaluating a location-based service recommendation system with a preference adjustment mechanism”, Expert Systems with Applications, vol. 36, Issue 2, Part 2, (2009) March, pp. 3543-3554.

[2] [2] S.-L. Wang and C.-Y. Wu, “Application of context-aware and personalized recommendation to implement an adaptive ubiquitous learning system”, Expert Systems with Applications, vol. 38, Issue 9, (2011) September, pp. 10831-10838.

[3] [3] Q. Yang and Z. Xin-Juan, “An apparel recommended system based on data mining”, Journal of Xi’an Polytechnic University, vol. 24, no. 4, (2010), pp. 438-443.

[4] [4] D. Miao, H. Kuang-Rong and D. Yong-Sheng, “Optimal Selection of Garment Sizes Expert System Based on Fuzzy Neural Networks”, Microcomputer Applications, vol. 26, no. 3, (2010), pp. 21-23.

[5] [5] H.-N. Kim, A.-T. Ji, I. Ha and G.-S. Jo, “Collaborative filtering based on collaborative tagging for enhancing the quality”, Electronic Commerce Research and Applications, vol. 9, Issue 1, pp. 73-83.

[6] [6] Y. Li, L. Lu and L. Xue-Feng, “A hybrid collaborative filtering method for multiple-interests and multiple-content recommendation in E-Commerce”, Expert Systems with Applications, vol. 28, Issue 1, (2005) January, pp. 67-77.

[7] [7] S. K. Lee, Y. H. Cho and S. H. Kim, “Collaborative filtering with ordinal scale-based implicit ratings for mobile music recommendations”, Information Sciences, vol. 180, Issue 11, (2010) June 1, pp. 2142- 2155.

[8] [8] C. Cechinel, M.-Á . Sicilia and S. Sánchez-Alonso, “Evaluating collaborative filtering recommendations inside large learning object repositories”, Information Processing & Management, vol. 49, Issue 1, (2013) January, pp. 34-50.

[9] [9] J. Bobadilla, F. Ortega, A. Hernando and J. Bernal, “A collaborative filtering approach to mitigate the new user cold start problem”, Knowledge-Based Systems, vol. 26, (2012) February, pp. 225-238.

[10] [10] T. Li, J.-D. Wang, F.-Y. Ye, X.-Y. Feng and Y.-D. Zhang, “Collaborative filtering recommendation algorithm based on clustering basal users”, system engineering and electronics, vol. 29, no. 7, (2007), pp. 1178-1182.

[11] [11] X. Li and Y. Yu, “Research on Self-adaptive Recommendation System Based on Implicit Feedback”, Computer Engineering, vol. 36, no. 16, (2010), pp. 270-275.