Calligraphy Style Correlation Discovery Based on Graph Model and Its Applications

Lu Weiming, Zhuang Yueting, Wu Jiangqin
The Institute of Artificial Intelligence, Zhejiang University, Hangzhou, 310027, P.R.China
Digital media Computing & Design Lab, Zhejiang University
E-mail: {luwm, yzhuang, wujq}@zju.edu.cn

***Abstract* — As more and more works of calligraphy exists in digital library, traditional browsing and searching are not satisfying. This paper presents an algorithm for calligraphy style correlation discovery based on graph model. We first segment calligraphy work into characters, extract their texture features through 64 Gabor channels, and estimate the calligraphy style using a probability multi-class SVM classifier. Then we compute the style similarity between each pair of characters and select the top k neighbors to generate a data graph. Finally we use random walk on the graph to discover the correlation among works and authors. Three experimental analyses show our proposed approach works well.**

***Index Terms* — Calligraphy Style, Correlation Discovery, Graph Model, Random Walk, Visualization.**

I. INTRODUCTION

Recently, data mining and information visualization have been widely studied for large scales of data. Knowledge discovery, decision making, user behavior analysis and customer relations analysis have all benefited from technology of data mining. Information visualization technology can transform the complex relationship hidden in information to visual form, which allows people to visually observe, explore, discover and understand massive data and find potential information hidden in data.

In China-US Million Book Digital Library (www.cadal.zju.edu.cn), there has been a lot of excellent works of calligraphy digitalized and preserved, such as Wang Xizhi's "Lanting Xu(兰亭序)". We can search and browse the works by metadata like name, dynasty and author, and the result can be viewed in a list. But such returned list loses internal style correlation between works. We need to discover the correlation among works and authors in order to make people browse them semantically.

The primary contribution of this paper is to propose a calligraphy style correlation discovery algorithm based on graph model, then three applications are implemented based on the algorithm: graph based style browser for calligraphy works, author writing style analysis and author recognition for calligraphy works.

The remainder of this paper is organized as follows. We discuss related work in Section 2. Section 3 presents the system architecture of our system and the calligraphy style correlation discovery algorithm. In Section 4, three applications are discussed. The conclusion is given in the last section.

II. RELATED WORK

A. Calligraphy Style Feature Extraction

Calligraphy style feature extraction and analysis are the key steps in computer aided calligraphy research. Character's contour feature was extracted for character retrieval in [1]. In [2], calligraphy features were extracted and a parametric representation of calligraphy was derived, and then constraint based reasoning was used to generate stylistic calligraphic characters. Individual stroke feature and spatial layout feature were extracted as character features in [3], and then a supervised learning based method was employed to explore the space of visually pleasing calligraphy. At last, a numeric grading method for judging the visually aesthetic quality was applied to make the character generated from [2] more beautiful. In [4], stroke's thickness and strokes order were extracted from an offline Chinese calligraphy writing through stroke analysis and structure analysis, and then a 3D visualization method was implemented to animate the character's writing process. In [5], a visual verification model for historical Chinese calligraphy works was presented by learning features that characterize an individual author's writing style. Texture analysis and structural information represented by a set of parameterized ellipses were combined in [7] to address the brush writing style classification problem for single-character Chinese calligraphic images.

All above researches only focus on feature extraction and modeling. Style association among calligraphy works and authors are not discussed until now.

B. Association Mining

There are lots of association algorithms such as LSA [6], spectral method [9]-[11], [21], and graph model [22], Canonical Correlation Analysis [13].

LSA maps high dimensional document vector to low dimensional space which is called Latent Semantic space, and reveal the relationship between documents and words in the latent semantic space. Spectral method can map high dimensional feature to low dimensional manifold space and still retain global or local topology of data. Spectral method falls into two categories: linear method such as PCA, ICA and nonlinear method such as MDS, ISOMap, LLE etc al. Linear method map high dimensional feature to linear space and nonlinear method map the feature to nonlinear space correspondingly. Cross-modal correlation between media was discovered using graph model in [22]. In the example of automatic image annotation, image, regions and annotated words are taken as nodes in MMG, and then find correlations across modalities (regions and words) by random walk to annotate images. Canonical Correlation Analysis (CCA) is used to measure the linear relationship between two multidimensional variables. The main idea of CCA is to find a base vector for each variable while keeping as much correlation as possible between two variables, then to find relationship between the two variables in mapping subspace.

C. Information Visualization

With the technology of visualization, massive data can be viewed in visual form. People can inspire their visual thinking ability, and find hidden rules in massive data in chaos, and provide support for decision making and knowledge discovery. Information visualization technology is widely used in many areas, such as finance, communication, business, scientific computing, and library.

In image retrieval area, the most common result presentation technique is based on a tabular (grid) disposition [8, 12]. The images are organized according to their similarity with the query image from left to right and from top to bottom. This presentation can allow users quickly browse the retrieved images, but lack the visual presentation between the retrieved images and the query image, and it also doesn't mine the correlation among the retrieved images. Two visualization techniques based on Spiral and Concentric Rings were presented in [14] to explore query results. The query image was at the center, and the retrieved images farther from the center were less similar than those near center. Semantic Image Browser [15] mapped image feature to MDS space, and disposed images according to the distance between two images in MDS space. Focus+context method and graph layout were combined in [16, 17]. Images were regarded as nodes in graph, and two correlative images were linked with the distance measure by the similarity. Focus+context visualization attempts to maximize the use of display space by displaying information of interest at a larger size than that of contextual information, and graph layout can reveal the contextual relations among images.

III. SYSTEM ARCHITECTURE AND ALGORITHM

This section proposes the calligraphy style correlation discovery algorithm and introduces the system architecture in detail.

A. Architecture

Fig. 1 gives an overview of our system architecture of calligraphy style correlation discovery based on graph model and its applications. Its infrastructure mainly includes Data generator, Data model converter, Style correlation discoverer and Applications.

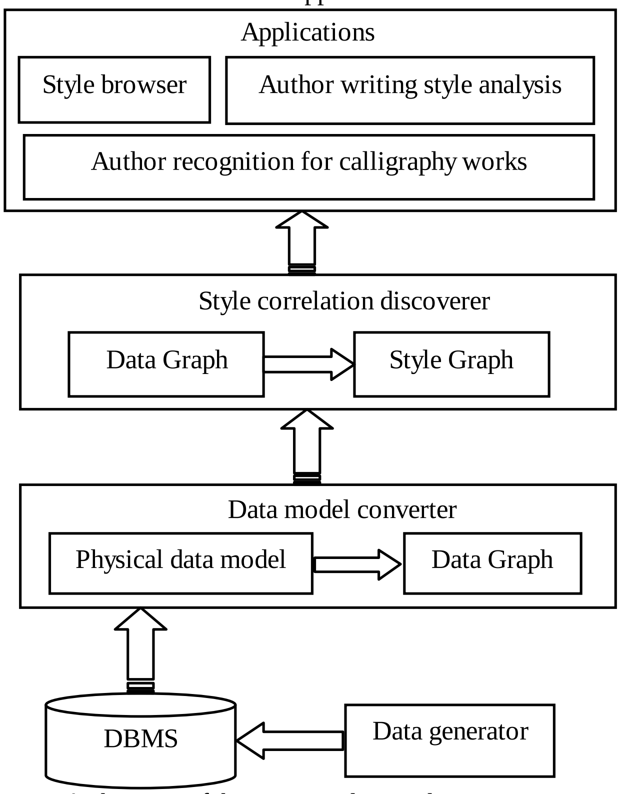

Fig.1. Architecture of the system and its applications

Data generator preprocesses the calligraphy resource, and store the result in database. The schema is like Fig.2.

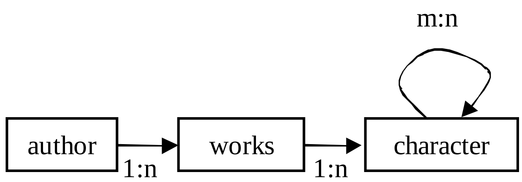

Fig.2. Schema of Calligraphy Database

Data model converter transforms the physical data model formed in the table to data graph for correlation mining. Four tables including Author, Work, Character and CharacterSim are in the database storing the information about author, work, character and the style

Author

AuthorID	Name
a1	王羲之
a2	米芾
a3	董其昌

Work

WorkID	Name	AuthorID
w1	快雪时晴帖	a1
w2	姨母帖	a1
w3	苕溪帖	a2
w4	逃暑帖	a2
w5	丙辰论书册	a3

Character

CharacterID	WorkID	StyleFeature	Label
c1	w1	0.0161519 0.087317 0.216585 0.191209 0.488737	山
c2	w2	0.00242149 0.0092693 0.098578 0.160238 0.72949	之
c3	w3	0.0033212 0.00219 0.0897423 0.163484 0.741262	时
c4	w3	0.0147136 0.079354 0.220038 0.150756 0.535138	徙
c5	w4	0.0154549 0.0949842 0.243474 0.169522 0.476566	获
c6	w5	0.0321947 0.0327678 0.388501 0.242719 0.303817	钵

CharacterSim

CharacterID1	CharacterID2	StyleSimilarity
c1	c5	0.997900
c1	c4	0.995612
c4	c6	0.995874
c2	c3	0.999863

Fig.3. Tables of Calligraphy in database

similarity between two characters. The example of tables is shown in Fig.3.

Style correlation discoverer runs random walk algorithm on data graph to mine the style correlation among works and authors.

In application layer, the style correlation mined from style correlation discoverer is used for three applications: graph based style browser for calligraphy works, author writing style analysis and author recognition for calligraphy works.

B. Data generator

The books named "Chinese Calligraphy Collections" have been scanned with 600dpi resolution in China-US Million Book Digital Library Project [18]. The pages were segmented into individual characters in the former work [19], and the calligraphy information was stored as Fig.3 in [19]. As the aim of the work [19] is to retrieve calligraphy character with similar shape, it only extract the contour feature. So in this layer, we should extract character style features and compute the style similarity between each two characters.

As [7], we extract character textual feature for computing the style feature. At first, we scale the character image to 64*64 in pixels. Then, we use 2D Gabor filter with (1) [20] to extract texture feature.

$$y_{u,v}(z) = \frac{\|k_{u,v}\|^2}{s^2} e^{(-\|k_{u,v}\|^2 \|z\|^2 / 2s^2)} [e^{ik_{u,v}z} - e^{-s^2/2}] \qquad (1)$$

where $z = (x, y)$, $\|\cdot\|$ means norm, $k_{u,v} = \begin{pmatrix} k_v \cos(j_u) \\ k_v \sin(j_u) \end{pmatrix}$, $k_v = 2^{-\frac{v+2}{2}} p$, $j_u = u\frac{p}{8}$, u and v are orientation and spatial frequency of the Gabor filter. The parameters with $u = 0,1,2,....7$ and $v = 0,1,2,3$ gives a total of 32 Gabor channels. Each character image is transformed through each channel, and the mean value and the standard deviation of the channel are chosen to present texture features. Thus, 64 features are extracted from a character image which form a 64-dimensional feature vector $G =< m_1, s_1, m_2, s_2, ...m_{32}, s_{32} >$.

Then we train a SVM classifier. Let G_i be the texture feature of the character V_i, and $< G_i, k >$ be the training sample where $k = 1, 2, ...K$ means style class label. After training, we get a probability multi-class SVM classifier [24].

All characters in the database are processed to extract the texture feature, and a style vector $\vec{G}_i =< g_{i1}, g_{i2}, ...g_{iK} >$ of character V_i is formed by estimating the probability with SVM classifier where g_{ij} is the probability of V_i belonging to class j. So the style similarity between character V_i and V_j can be defined as:

$$gSIM(V_i, V_j) = \vec{G}_i \bullet \vec{G}_j / \|\vec{G}_i\| \bullet \|\vec{G}_j\| \qquad (2)$$

Then, the value of StyleFeature is $\vec{G}_i$ and the value of StyleSimilarity is $gSIM(V_i, V_j)$ in Fig.3.

TABLE I

SVM CONFUSION MATRIX FOR STYLE CLASSIFICATION

	seal script	clerical script	standard script	semi-cursive script	cursive script
seal script	**0.8495575**	0.0619469	0.03539823	0.03539823	0.017699
clerical script	0.03539823	**0.7699115**	0.14159	0.035398	0.017699
standard script	0.0420168	0.05042	**0.6470588**	0.142857	0.117647
semi-cursive script	0.031746	0.05555556	0.126984	**0.555556**	0.2301587
cursive script	0	0	0.1171	0.26126126	**0.62162**

When training SVM classifier, we use the characters in book "Commonly used word dictionary with six styles" as labeled data and five styles are used for training and testing including seal script, clerical script, standard script, semi-cursive script and cursive script. There are 500 characters for each style, and half are used for training classifier and the other half are used for testing. After testing SVM confusion matrix is shown as Table I.

C. Data model converter

Data generator preprocesses the calligraphy resource, computes the style similarity between two characters and stores the data in the form of Fig. 3. In Data model converter, we transform the data from table to graph representation as shown in Fig. 4, which called data graph.

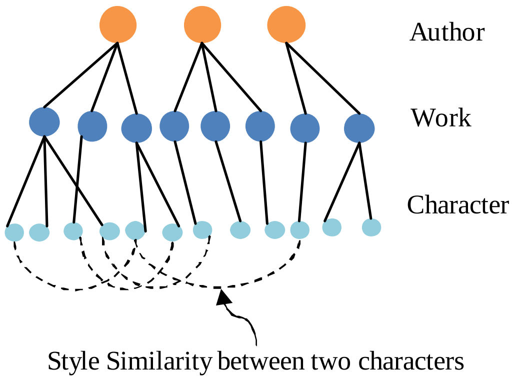

Fig. 4. Calligraphy Data Graph

Data graph takes author, work and character as nodes, and has two types of edges: object-relational edge and object-neighbor edge. Object-relational edges include edge between author and work and edge between work and character. If the author of work w is a, then edge (a, w) is added to the data graph with the weight of 1. In the same way, if work w contains character c, then edge (w, c) is added to the data graph. Object-neighbor edges only exist between characters. We choose k neighbors for each character with the similarity between each pair of characters which has been computed, and add the edges to the data graph with the weight accounting for the similarity.

D. Style correlation discoverer

Now we change the style correlation discovery to graph problem. In the paper, we use random walk with restart [22] to estimate the style correlation between two nodes in Fig. 4.

The random walk with restart algorithm operates as follows. In order to compute the correlation between node A and node B, consider a random walker starting from node A. The random walker iteratively transmits to its neighbors with the probability which is proportional to the weight of edge. Also at each step, the walker can return to the start node with the probability c. When at a steady state, we get the probability of walking to node B p_B which can be used to measure the style correlation between node A and node B.

Let matrix A be the relations among authors, matrix W be the relations among works, matrix C be the relations among characters, matrix AW be the relations between author and work, and matrix WC be the relations between work and character. Obviously, the elements of matrix A and W are initialized with 0, and the element of matrix C c_{ij} is assigned with the value of $gSIM(V_i, V_j)$ which measures the style correlation between character V_i and V_j. The element of matrix AW aw_{ij} denotes the relation between author a_i and work w_j. If the author of w_j is a_i then $aw_{ij} = 1$, else $aw_{ij} = 0$. The elements of matrix WC can be assigned in the same way. In this way, we get a $|A|+|W|+|C|$ -dimensional matrix M, where

$$M = \begin{bmatrix} 0 & AW & 0 \\ AW^T & 0 & WC \\ 0 & WC^T & C \end{bmatrix}.$$

The equation (3) defines the random walk with restart algorithm:

$$\vec{u}_A = (1-c)M\vec{u}_A + c\vec{v}_A \tag{3}$$

TABLE II

CALLIGRAPHY RESOURCE

Author	董其昌	米芾	邓石如	蔡襄	苏轼	王羲之	智永	顏真卿	王献之
Num of Work	7	27	6	4	5	24	1	13	1
Num of Character	885	1336	934	107	29	638	59	1445	10

The elements of vector $\vec{v}_A$ are initialized to zero except the corresponding dimension with the start node A which is initialized to 1. Vector $\vec{u}_A$ measures the probability of walking from node A to another node in a steady state. The correlation among authors, works and characters can be discovered through (3).

IV. APPLICATIONS AND ANALYSIS

This section mainly presents the three applications based on style correlation discovery algorithm as Fig.5.

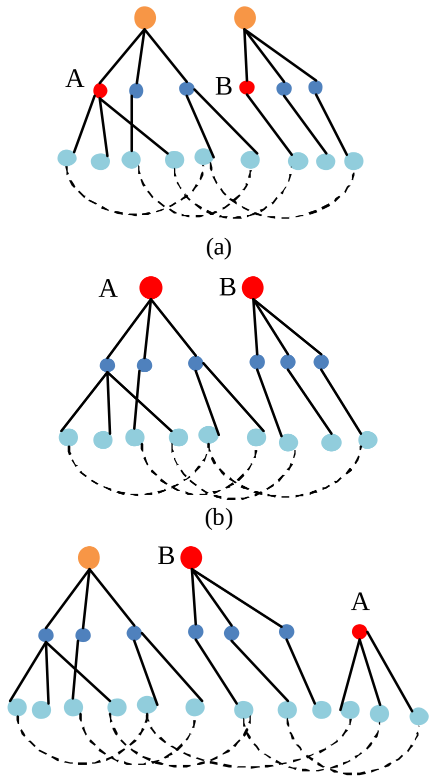

Fig.5. Graph model of three applications (a) Style browser for calligraphy works (b) Author writing style analysis (c) Author recognition for calligraphy works

As said in Data generator section, we obtained calligraphy resource of 9 authors, 87 works and 5443 characters from the project. The overall resource is shown in Table II, and the distribution of the number of characters from each work is shown in Fig.6.

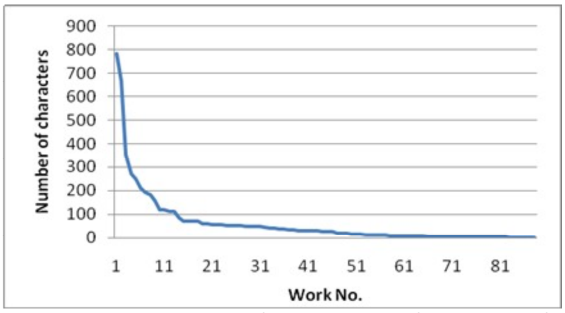

Fig. 6. The distribution of the number of characters from each work

A. Graph based style browser for calligraphy works

When the walker starts from work node A as shown in Fig. 5(a), we can get the style correlation between two works when only consider the dimensions of $\vec{u}_A$ corresponding to the works until reaching a steady state. The open source ToughGraph[23] was used as visualization tool in which the distance between two nodes denotes the style similarity between the two nodes. In the graph, we only link each node to their top k similar nodes with the distance is proportional to the style similarity. Fig.7 shows the relations between all works and Fig.8 shows the corresponding authors. We can find that the works of the same author are grouped together, which shows the style correlation discovery algorithm is useful for calligraphy works.

Style browser uses the mode of Fig.9 which only shows the current selected work and its correlative works. User can switch to the other correlative works easily.

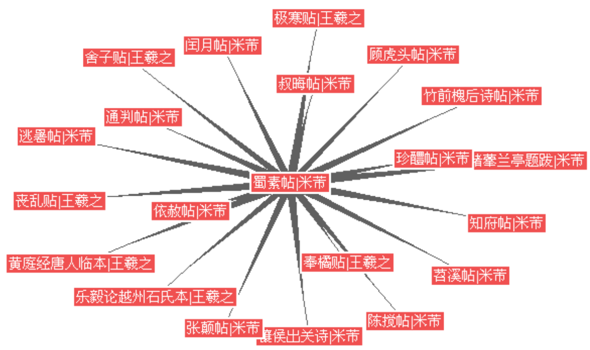

Fig.9. Work Style Graph with center of “Shu Su Tie(蜀素帖)”

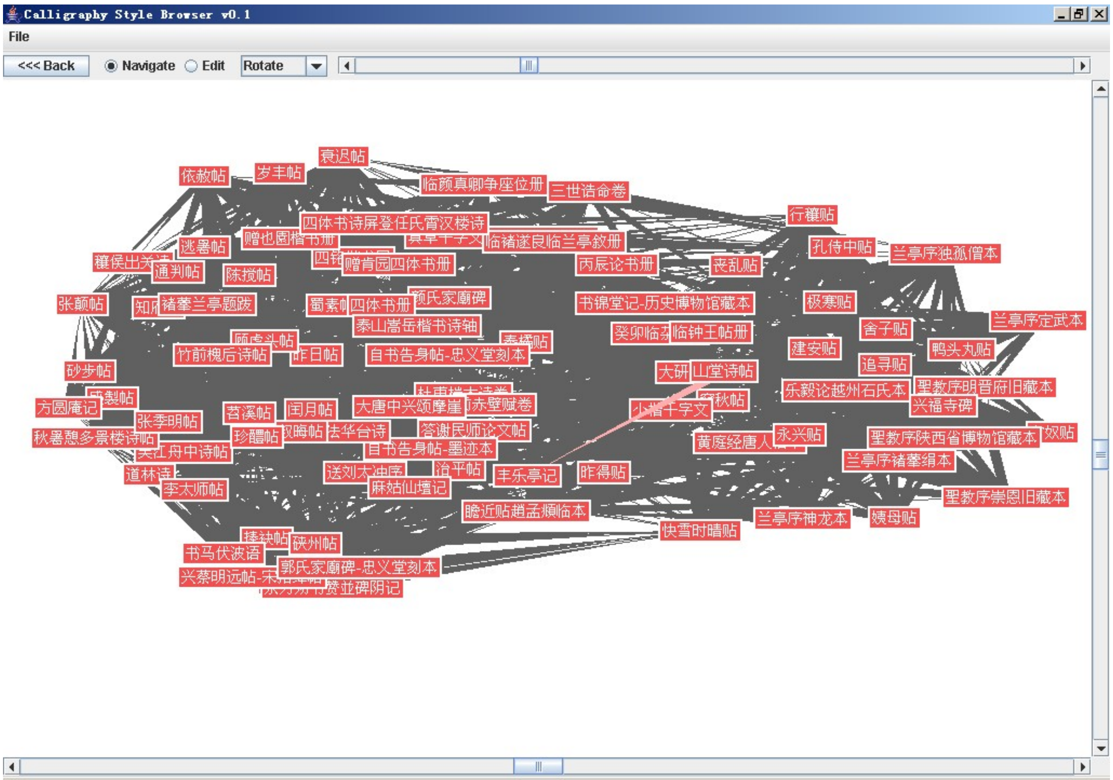

Fig. 7. K neighbor Works Style Graph ($k = 20$)

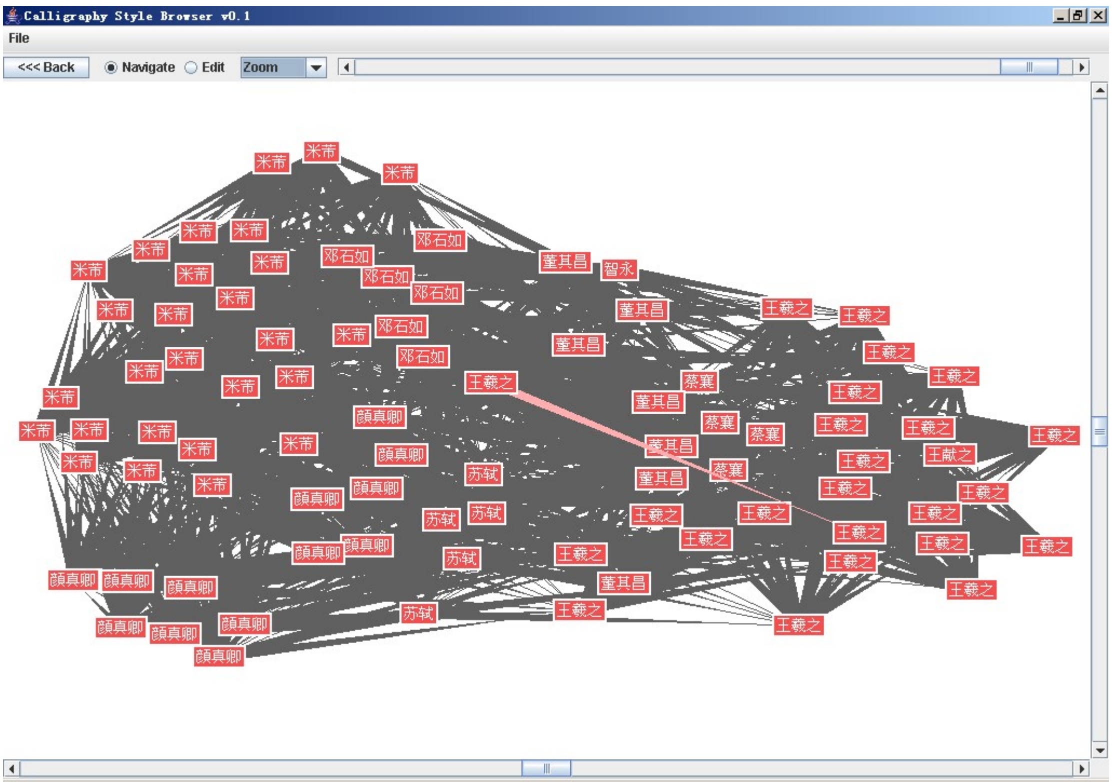

Fig.8. Corrsponding author for each work in Fig. 7

B. Author writing style analysis

When walker starts from work node A as shown in Fig. 5(b), we can get the style correlation between two authors when we only consider the dimensions of $\vec{u}_A$ corresponding to the authors until reaching a steady state. In the same way, ToughGraph based k neighbor author style graph is shown in Fig.10.

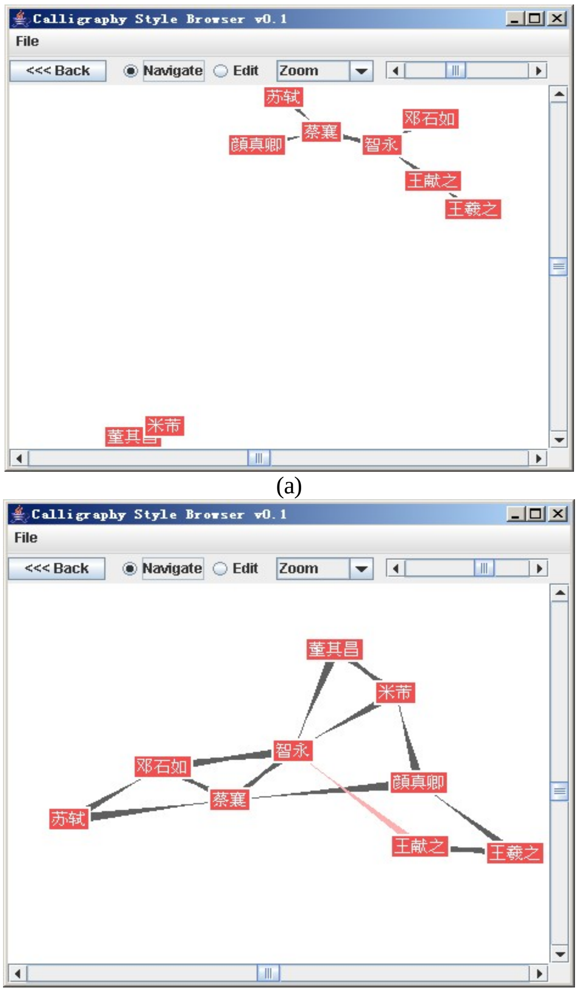

Fig.10. k neighbor author style graph (a) $k = 1$ (b) $k = 2$

Referring to [25,26,27], Wang Xianzi(王献之) and Zhi yong(智永) are both descendants of Wang Xizhi(王羲之), and they both learnt from WangXizhi excellently; Dong Qichang(董其昌) learnt from Li Yong(李邕) early, and then learnt from Mi Fu(米芾) who was Dong's goal. His style was about 20%-30% like Li and about 50%-60% like Mi; Cai Xiang(蔡襄) was expect at standard script, semi-cursive script and cursive script, and his style was civility and Biedermeier as Yan Zhenqing(颜真卿). These correlations are shown in Fig.10, which proves that the algorithm can discover the correlation between authors, and it can aid researcher in studying author's writing style.

C. Author recognition for calligraphy works

The verification problem of calligraphy has long been considered as a problem belonging to the field of the art, which is usually carried out by artists. But both work and author are needed in verification. If we can judge who wrote a piece of work only through the work itself, it may make a good guide for calligraphy verification.

Given a work for verification, we segment it into characters, and add them into data graph shown in Fig.5(c). Then the walker starts from work node A as before. We can get the style correlation between the work and authors in database. The work is more likely to be written by the corresponding author of the larger similarity.

We took 87 works whose authors are known in the experiment, and used Know Item Search to test the performance. Know Item Search simulates the process of finding a certain thing, and can get the rank in the return list. Each work can get the author list descending by the correlation between the work and each author. Then checking the rank of known author in the list, we used MRR (Mean Reciprocal Rank) to measure the performance. Random MRR which is 0.28 was used as baseline. Fig.11 shows MRR changes with the parameters k and c. We can see that the algorithm is much better than baseline, especially when $k = 14,16,18$. This is because when k is smaller, not enough similar characters were mined, and when k is larger, it introduced noise. Fig.12 shows the convergence time of Random Walk algorithm changing with the parameter c. The algorithm converged faster when c is larger.

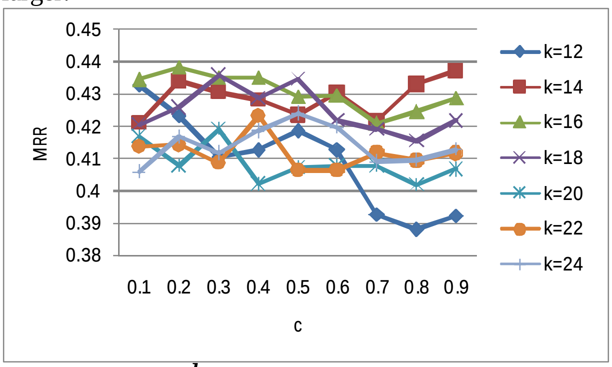

Fig. 11. MRR VS. k and c

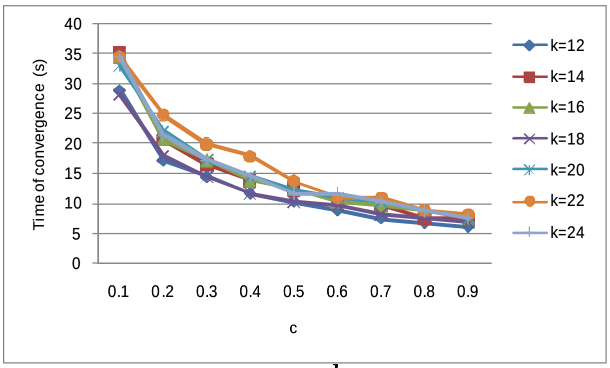

Fig. 12 the convergence time VS. k and c

V. CONCLUSION

This paper proposes a calligraphy style correlation discovery algorithm based on graph model, and three applications are designed based on this algorithm. It is very practical that texture feature is used as style feature. Though strokes may be more accurate to express calligraphy style, it is practically impossible to automatically extract strokes for highly cursive and severely distorted calligraphy character. Our future work is to extract more features such as stroke feature and structure feature which will make our calligraphy style correlation discovery more accurate.

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