ISBN 978-952-5726-02-2 (Print), 978-952-5726-03-9 (CD-ROM)
Proceedings of the 2009 International Symposium on Information Processing (ISIP'09)
Huangshan, P. R. China, August 21-23, 2009, pp. 352-355

An Engineering Drawings Retrieval Method based on Density Feature and improved Moment Invariants

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***Abstract*—A novel engineering drawings feature extraction and retrieval method is proposed in this paper which comprehensively utilizes density feature and improved moment invariants. This paper defines the density feature which can reflect the spatial information of objects in the engineering drawings and presents its extraction method. Improved moment invariants can describe the shape information of the objects from the whole aspect, with translation, rotation and scale invariance. The linear weighted method of multi-feature is proposed to calculate the integrated similarity, using density feature and improved moment invariants. The retrieval results which have the higher similarity scores are returned to the user. Compared with other retrieval methods, experimental results prove that this method is effective and has the better retrieval performance.**

***Index Terms*—engineering drawings, density feature, improved moment invariants, retrieval**

I. INTRODUCTION

With the rapid development of multimedia and internet technology, the application of engineering drawings is more and more extensive in the production department of the enterprises. How to retrieve the necessary information from the large amount engineering drawings quickly and efficiently needs to be solved urgently. Content-based retrieval of engineering drawings[1] arises, following with the deep study of image retrieval technology. In order to realize engineering drawings retrieval, to select the appropriate features of engineering drawings and to take the effective feature extraction methods are the sticking points. Engineering drawings is composed of a number of line and plane geometry such as. Therefore, density and shape features are comprehensively used to retrieve the engineering drawings in this paper. The shape feature is described by the improved moment invariants. Experimental results show that this method can effectively improve recall and precision of the retrieval of engineering drawings.

II. THE BASIC IDEA OF RETRIEVAL

In view of the current content-based retrieval of engineering drawings doesn't efficiently use of the spatial information, an engineering drawings feature extraction and matching method is presented in this paper which comprehensively utilizes density feature and improved moment invariants. First of all, in the establishment of engineering drawings database, density feature and improved moment invariants are extracted by analyzing the scanned engineering drawings to store in the features database. Then, in accordance with the query example of engineering drawings provided by the user, the multi-feature linear weighted method is utilized to calculate the integrated similarity. Finally, the retrieval results which have a certain similarity are returned to the user. In this paper, the retrieval process of engineering drawings is shown in Fig.1.

In order to reduce the storage capacity, the engineering drawings is binary image in this paper. Engineering drawings is expressed as $f(x, y)$, where x =1,2,…, I and y =1,2,… J . x and y respectively denote the column numbers and row numbers of engineering drawings. The value of $f(x, y)$ is 1 when the object is a black pixel, otherwise is 0.

III. DESIGN OF THE RETRIEVAL ALGORITHM

(1) Density feature and its extraction

In this paper, the concept of density is presented to describe the density degree of black pixels in the engineering drawings, that is, the proportion of the black pixels in the total pixels. Engineering drawings is two-dimensional distribution, so the black pixels denoting objects have different density situation in the spatial distribution. How to effectively improve the retrieval performance of engineering drawings strongly depends on finding a viable method of density feature extraction. In the study of the correlation algorithms[2], engineering drawings is divided reasonably into $M \times N$ sub-blocks, in this paper. Density feature vector is made by calculating the density feature of each sub-block.

In order to accurately reflect the density degree of the black pixel near a pixel, weighted point density[2] is used in this paper. Weighted point density is defined as (1):

$$d(x, y) = \frac{1}{dis(x, y) + 1}. \qquad (1)$$

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Where x =1,2,…, I and y =1,2,…, J . $dis(x,y)$ obtained by distance transform is the city distance of the

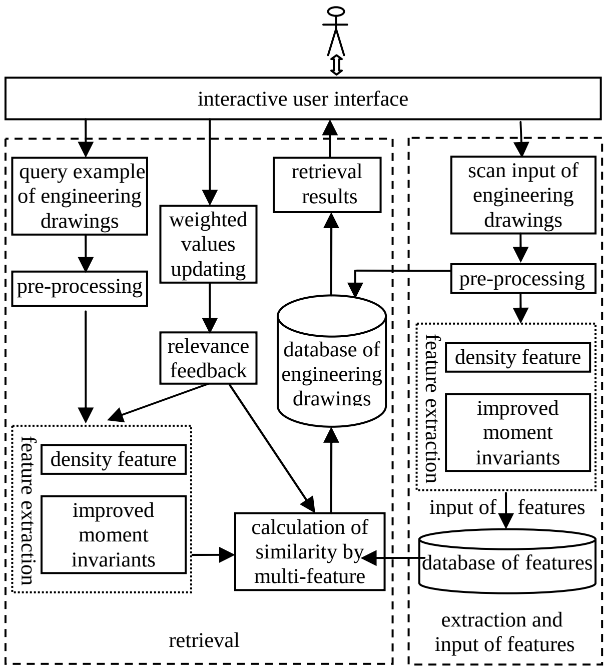

Figure 1. Retrieval process of engineering drawings

point (x,y) to the nearest pixel in the input image. The value of $dis(x,y)$ is 0, when the pixel is black. The total number of pixels in the k-th sub-block is defined as n_k after dividing the engineering drawings into $M \times N$ sub-blocks. With the above definition of the weighted point density, the density feature of sub-block can be defined as (2):

$$d_k = \frac{\sum_{x=0}^{I}\sum_{y=0}^{J} d(x,y)}{n_k} . \tag{2}$$

Where x =1,2,…, I , y =1,2,…, J , k =1,2,…, $M \times N$ and $d_k \in$ (0,1). The density features of sub-blocks are combined into feature vector, which is density vector. Density feature of engineering drawings is defined by (3), as follows:

$$D = (d_1, d_2, ..., d_{M \times N}) . \tag{3}$$

In this paper, density feature has translation, rotation and scale invariance.

(2)Improved moment invariants features and its extraction

Moment invariants[3] with translation, rotation and scale invariance is first proposed by K.M.Hu in 1962 for the image shape recognition. For the engineering drawings $f(x,y)$ of digital image, the (p+q)th-order moment is defined by (4):

$$m_{pq} = \sum_x \sum_y x^p y^q f(x,y) . \tag{4}$$

The (p+q)th-order central moment is denoted by (5):

$$\mu_{pq} = \sum_x \sum_y (x-\bar{x})^p (y-\bar{y})^q f(x,y) . \tag{5}$$

Central moment μ_{pq} has translational invariance. In order to have scale invariance, normalized central moment should be used, defined as (6):

$$\eta_{pq} = \frac{\mu_{pq}}{(\mu_{00})^{(p+q+2)/2}} . \tag{6}$$

Where $p+q$ =2, 3, … . η_{pq} is an invariant under the transformation of translation and scale, but will change when the objects are rotated. K.M.Hu structure seven moment invariants with translation, rotation and scale invariants by using of normalized second-order and third-order central moments, defined as follow (7):

$$\begin{cases} \phi_1 = \eta_{20}+\eta_{02} \\ \phi_2 = (\eta_{20}-\eta_{02})^2 + 4\eta_{11}^2 \\ \phi_3 = (\eta_{30}-3\eta_{12})^2 + (3\eta_{21}-\eta_{03})^2 \\ \phi_4 = (\eta_{30}+\eta_{12})^2 + (\eta_{21}+\eta_{03})^2 \\ \phi_5 = (\eta_{30}-3\eta_{12})(\eta_{30}+\eta_{12})[(\eta_{30}+\eta_{12})^2 - 3(\eta_{21}+\eta_{03})^2] \\ \qquad +(3\eta_{21}-\eta_{03})(\eta_{21}+\eta_{03})[3(\eta_{30}+\eta_{12})^2 - (\eta_{12}+\eta_{03})^2] \\ \phi_6 = (\eta_{20}-\eta_{02})[(\eta_{30}+\eta_{12})^2 - (\eta_{21}+\eta_{03})^2] + 4\eta_{11}(\eta_{30}-\eta_{12})(\eta_{21}+\eta_{03}) \\ \phi_7 = (3\eta_{21}-\eta_{03})(\eta_{30}+\eta_{12})[(\eta_{30}+\eta_{12})^2 - 3(\eta_{21}+\eta_{03})^2] \\ \qquad +(3\eta_{21}-\eta_{03})(\eta_{21}+\eta_{03})[3(\eta_{30}+\eta_{12})^2 - (\eta_{12}+\eta_{03})^2] \end{cases} \tag{7}$$

Scale factor can effect on the seven moment invariants in the discrete state. For the sake of having the translation, rotation and scale invariants, the seven moment invariants need to be re-structured.

(x', y') is assumed the coordinate distorted by the scale factor λ in the discrete state. (x', y') and the pre-distortion coordinates (x,y) satisfy the following equation (8):

$$\begin{cases} x' = \lambda x \\ y' = \lambda y \end{cases} . \tag{8}$$

According to (8), we can deduce the following equation (9), as in:

$$\begin{cases} x' - \bar{x}' = \lambda(x-\bar{x}) \\ y' - \bar{y}' = \lambda(y-\bar{y}) \end{cases} . \tag{9}$$

$(x' - \bar{x}')$ and $(y' - \bar{y}')$ are substituted into μ'_{pq}, the following formula (10) can be obtained:

$$\mu'_{pq} = \lambda^{p+q} \mu_{pq} . \qquad (10)$$

After substituting formula (10) into the normalized central moments, the following equation (11) can be gotten:

$$\eta'_{pq} = \frac{\mu'_{pq}}{(\mu'_{00})^{(p+q+2)/2}} = \frac{\lambda^{p+q} \mu_{pq}}{(\mu'_{00})^{(p+q+2)/2}} = \lambda^{p+q} \eta_{pq} . \qquad (11)$$

From (11), we can see that scale factor has an impact on η'_{pq}. The change of η'_{pq} is not only related to η_{pq}, but also related to the (p+q)th-order of moment. From the theory, we can prove that although seven moment invariants have scale invariance in the continuous state, don't establish in the discrete state.

See from (11), according to the relationship between the normalized central moments η_{pq} and η'_{pq} of pre-post scale transformation, the seven moment invariants vector with pre-post scale factor transformation can be expressed as (12):

$$\begin{cases} \phi'_1 = \lambda^2 \phi_1 \\ \phi'_2 = \lambda^4 \phi_2 \\ \phi'_3 = \lambda^6 \phi_3 \\ \phi'_4 = \lambda^6 \phi_4 \\ \phi'_5 = \lambda^{12} \phi_5 \\ \phi'_6 = \lambda^8 \phi_6 \\ \phi'_7 = \lambda^{12} \phi_7 \end{cases} \qquad (12)$$

On the basis of (12), improved moment invariants vector[4] with scale invariance in the discrete state can be defined as (13), as follows:

$$\begin{cases} \phi^*_1 = \phi'_1 \\ \phi^*_2 = \phi'_2 / \phi'^2_1 \\ \phi^*_3 = \phi'_3 / \phi'^3_1 \\ \phi^*_4 = \phi'_4 / \phi'^3_1 \\ \phi^*_5 = \phi'_5 / \phi'^6_1 \\ \phi^*_6 = \phi'_6 / \phi'^4_1 \\ \phi^*_7 = \phi'_7 / \phi'^6_1 \end{cases} \qquad (13)$$

Improved moment invariants not only have translation and rotation invariance, but also have scale invariance. Seven moment invariants have great varying range and possibly have negative. For purpose of the convenient calculation, the method of taking logarithm and then using absolute values of the seven moment invariants is adopted in the actual retrieval of engineering drawings. In this paper, the moment invariants actually used is defined by (14), as follows:

$$M_i = \left| \lg \left| \phi^*_i \right| \right| . \qquad (14)$$

Where $i = 1, 2, ..., 7$. The feature vector M of engineering drawings can be structured by the above-mentioned seven moment invariants M_i. In this paper, the definition of feature vector M is (15):

$$M = (M_1, M_2, ..., M_7) . \qquad (15)$$

Improved moment invariants M can describe the overall shape feature of the objects in the engineering drawings, and meets the important index of description, that is translation, rotation and scale invariance.

(3) Similarity calculation

The retrieval performance of engineering drawings not only depends on the extracted features, but also is closely related to the similarity calculation method that is utilized. In this paper, the linear weighted method of multi-feature is utilized to calculate the integrated similarity. Q and T respectively express the query example of engineering drawings and the candidate engineering drawings from the database, and the corresponding feature vectors are respectively denoted by H_q and H_t. After normalizing the corresponding density feature D and improve moment invariants M, Cosine Similarity[5] is utilized to calculate the similarity of the query example and the candidate engineering drawings from the database, the formula is (16), as follows:

$$S(H_q, H_t) = \frac{H_q^T H_t}{\left\| H_q \right\| \cdot \left\| H_t \right\|} . \qquad (16)$$

Where $\left\| H_q \right\| = (H_q^T H_q)^{1/2}$ and $\left\| H_t \right\| = (H_t^T H_t)^{1/2}$.

In the following formula (17), S_d denotes the similarity of the density feature, and S_m denotes the similarity of the improve moment invariants. The linear weighted method of multi-feature is utilized to calculate the integrated similarity, achieved by the following formula (17)

$$S = w_d S_d + w_m S_m . \qquad (17)$$

Where $w_d + w_m = 1$, w_d and w_m respectively denote the weighted values of density feature and improve moment invariants. The retrieval results with the highest similarity are returned to the user.

IV. EXPERIMENT RESULTS AND ANALYSIS

In the experiment, I have built the database of engineering drawings, including 200 engineering drawings of 640*480 pixels. The experiment has been carried out in the Microsoft Windows XP system in the Intel PC (1.99GHz CPU, 1.00GB of memory). In order to reduce the complexity of the retrieval, M and N are seted the values of 3.

In this paper, the graph of recall-precision rate[6] is adopted to evaluate the performance of the retrieval algorithm. $\mathrm{R(q)}$ expresses the number of engineering drawings related to query example in the database, and $\mathrm{A(q)}$ expresses the number of engineering drawings retrieved by the system. $\mathrm{R(q)} \cap \mathrm{A(q)}$ expresses the number of relevant and retrieved engineering drawings. Recall is calculated by the following equation:

$$\mathrm{Recall} = \left|\mathrm{R(q)} \cap \mathrm{A(q)}\right| / \left|\mathrm{R(q)}\right|. \tag{18}$$

Precision is calculated by the following equation:

$$\mathrm{Precision} = \left|\mathrm{R(q)} \cap \mathrm{A(q)}\right| / \mathrm{A(q)}\,\big|. \tag{19}$$

In the recall-precision graph, as shown in Fig.2, the higher curve shows the better retrieval performance. With the same recall rate, the higher curve illustrates the higher precision.

As can be seen from the Fig.2, the retrieval performance of Hu moment invariants is lower. In this paper, the retrieval performance of the improved moment invariants has greatly improved. The retrieval method integrating density feature and improved moment invariants has obvious superiority. By the above analysis and comparison, the method I have presented has the better retrieval performance, is a feasible retrieval method of engineering drawings.

V. Concluding Remarks

The method integrating density feature and improved moment invariants has been proposed to retrieve engineering drawings in this paper. The retrieval results put in order by the similarity are returned to the user, and the most relevant engineering drawings are put at the first place. The advantages of this retrieval method are that the density feature can combine the spatial distribution of objects in the engineering drawings, and the improved moment invariants can describe the overall shape feature. In this paper, the experimental results prove that this retrieval method has the better recall and precision. But the user participation isn't introduced to the retrieval process. In order to further improve the retrieval performance of engineering drawings, the relevance

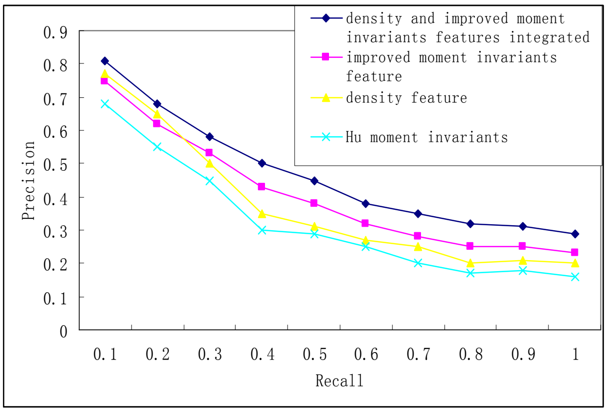

Figure 2. Comparison of Retrieval Performance

feedback[7] will be introduced in future research work, and to enable interactive retrieval process and properly express the subjective perception of the system users.

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