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FRAMEWORK FOR FORGERY DETECTION IN CONTENT BASED IMAGE RETRIEVAL SYSTEM

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ABSTRACT

Nowadays Image retrieval is becomes more challenged thing in many of the fields like medical diagnosis, crime prevention, military services, architectural and engineering design, geographical information, trade- mark matching, etc. So there is the necessitates of effectively retrieving relevant images when needed. Thus, content-based image retrieval systems (CBIR) have become very popular for browsing, searching and retrieving images from a large database of digital images. So in order to improve the retrieval accuracy, this paper will focus on to use content-based image retrieval systems with k-means as the clustering algorithm and B+ tree for speeding up the retrieval process. For representing the images, we extract their feature vectors of images using Daubechies' wavelets. Then we introduced the Zernike moments in the retrieved images with the reference image by that we find out the variations of the images. After that by comparing the images using Zernike moments and find out the forgery between the images.

Keywords: image retrieval, zernike moments, content based image retrieval, wavelet transformation, clustering.

1. INTRODUCTION

By the advancement of technology, people can highly involve to take pictures using digital cameras, camcorders, web camera videos and smart mobile phones anytime and anywhere. This phenomenon makes image databases get an explosive growth. Thus, users need to employ efficient and effective tools to search for the images they want in the huge image database [1]. Currently many of the top leading popular websites, such as Google and Yahoo, provide the function for image searching. The problem of image retrieval (IR) from huge image archives has been a subject of significant research in the recent past years. Basically, IR is defined by how the image archive is organized and how the search mechanism is used. Therefore, there is a need for advanced techniques to help in sorting out and easily searching the captured and stored images, including personal collections. Content-based classification, storage and retrieval is the only affordable effective technique that could meet the expectations of naive and professional users. Content-based image retrieval (CBIR) was introduced in the early 1980s. In CBIR, images are indexed by their visual content, such as color, texture, shapes. A pioneering work was published by Chang in 1984, in which the author presented a picture indexing and abstraction approach for pictorial database retrieval [2]. The pictorial database consists of picture objects and picture relations. To construct picture indexes, abstraction operations are formulated to perform picture object clustering and classification. The related works of a few commercial products and experimental prototype systems have been developed, such as QBIC [3], Photobook [4], Virage [5], VisualSEEK [6], Netra [7], SIMPLIcity [8]. Comprehensive surveys in CBIR can be found in Refs. [9, 10].

QBIC is well known and earliest CBIR systems. It works both with image and video databases. It uses content of the images and videos such as color, shape, layout and texture information. One of the most important properties of QBIC is that it supports content of the images and user drawn graphics in its queries. In other words, a query is not restricted with images themselves but their content can also be queried. For example, a user can enter a query image and search for the images who have texture features similar to the query image's texture. QBIC technology has been developed at IBM and it is currently used commercially.

The VIR Image Engine [11], developed by Virage Inc., is similar to QBIC in the sense that it supports querying by color, shape, layout and texture. As in QBIC, user drawn sketch queries are also supported. It provides a GUI where developers can sketch the images are make modifications on the images. It also supports integration of image keywords into the query. VIR Image Engine has been integrated into several databases; it is a component of the Oracle DBMS.

Multimedia analysis and retrieval system (MARS) [12] project was started at the University of Illinois to develop an effective multimedia database management system. As a first step in the project, they had developed an image retrieval system. In this retrieval project, image features are extracted from the content of the image and the textual annotation of the images. Content of the images are stored as global color histogram, a texture histogram and shape features. Shape features are obtained after segmentation of the image and applying Fourier descriptor to each of the segments. User can query for any combination of the image features. For example a user can enter a query which contains an image's color histogram and another image's shape feature.

Photobook project was developed at MIT. It uses features of the images for comparison. Features of the images contain information about the image's color, shape and texture. Features are compared according to any linear combination of the following distance measures: Euclidean, Mahalanobis, divergence, vector space angle, histogram, Fourier peak, and wavelet tree distances. Photobook also let developers to load their own distance measure.

WBIIS is a CBIR system developed by Wang *et al*. using Daubechies wavelet transformation. They first represent the Red (R), Green (G) and Blue (B) components of the images in a different domain which is based on RGB values of the original pixels to better reflect the human perception on the color distance.

Then, they apply 4-level and 5-level Daubechies wavelet transformation on the images and store the low frequency components of the resulting images as a part of the feature vector. They also find the standard deviation of the matrix which they obtained after 5-level wavelet transformation and store the deviation matrix as part of the feature vector. During the query phase they have 2 steps for distance calculation. They first compare the standard deviation of the images and if the difference between their standard deviations is high, the image is not considered to be a good match and no more distance calculations are done for it. In the second step, they find the distance between the query image and images that passed the first criteria using a weighted version of Euclidean distance comparison. They sort these results and return the closest images to the query image.

Wang *et al.* also developed SIMPLICITY, which is a CBIR system that covers different image types. An image is first segmented into its regions and classified as indoor–outdoor, textured–nontextured, city–landscape, with–without people, or graph–photograph image. These classes are manually defined and the feature extraction schema is decided according to the class label of the image. They defined a new similarity measure to find the distance between two images which are stored as a set that contains a feature vector for each individual region.

WaveQ [13] which was developed earlier by our research group at the University of Calgary is another CBIR system that uses Wavelets. WaveQ uses LUV color space where L is the luminance of a pixel, U is the red–green color value of a pixel and V is the blue– yellow color value of a pixel. First an image is classified as texture or non-texture according to the standard deviation of the U component and different feature vector extraction methods are used for these classes. After feature vectors are calculated, texture images and non-texture images are clustered into subgroups using the OPTICS algorithm. Then a representative feature vector is calculated for each cluster. When a query is entered, it is first classified and then the feature vector of the image is calculated. Then the similar images are retrieved from the closest cluster.

Kang *et al.* [14] developed a CBIR method that combines concept lattice and ensemble learning technique into a multi-instance ensemble learning model. Elalami [15] introduced an image retrieval framework based on a rule base system. His approach utilizes color and texture features to cluster the images; then the clusters are used to build a rule based classifier. Elalami [16] employed E. Yildizer *et al.* / Knowledge-Based Systems 31 (2012) 55–66 57 feature selection in order to utilize the most relevant features for CBIR. He showed how the reduced set of features could be used for precise image retrieval in a short time. Wang *et al.* [17] developed a texture based algorithm for palmprint recognition by combining 2D Gabor wavelets and pulse coupled neural network. The recognition is done by involving a support vector machine [18,19,20,21] based classifier. Lancieri and Boubchir [22] employed fuzzy logic and adaptive clustering to propose an automatic method capable of characterizing images by comparing unknown images. Sung and Hu [23] developed an icon driven image retrieval method which utilizes three characteristics of an icon, namely texture, color, and text attributes. Each characteristic leads to a similarity value and the combination of the three similarity values is used for identifying the final icon similarity by using a proven adaptive algorithm.

Generally, images are classified into two different classes, they are texture and non-texture. Texture images form an important class, where one pattern is repeated periodically throughout the image, for example in medical images such as X-rays, and topographic images are under this category. Non-texture images tend to have objects of interest clustered in one or more regions of an image. Most real world images that people are familiar with fall under this second category. In this paper, we mainly focus on the non-texture images; they are more challenging to handle. However, the same technique can be used to analyze texture images; we have left as future work to report test results on texture images.

Teague [38] has suggested the use of orthogonal moments based on a certain class of orthogonal polynomials to overcome the aforementioned shortcomings associated with the geometric moments. In particular, he has proposed to use the orthogonal moments defined in terms of the Legendre and Zernike polynomials. A number of studies on the Legendre and Zernike moments reconstruction and classification power has been carried out. Nevertheless, the error analysis and analytic characterization of the orthogonal moments have been rarely investigated. The Legendre moments, however, despite their good reconstruction properties, are not invariant to linear operations. The method of Zernike orthogonal moments, which are invariant to linear transformations, has been used as an attractive alternative.

In this paper, the images are retrieved based on the content and the retrieved images are compared with the query image for find out the forgery of the retrieved images. In Figure-1 the flow diagram of the proposed work. In module 1 Image acquisition is done. This module is to acquire the images from the user for query image and also to select the database images. Next is Feature Extraction. In this module the color and texture feature of the images are extracted first for the database images and

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the features are further processed for the classification. After getting the input from the user the features are extracted for this image and processed further.

Next one is K-Means clustering, In this module the same features of an image is grouped together using K-Means clustering for the database images and stored as .mat file. For the query image also the same task is performed but the values are not stored in .mat file. Next process is Image Retrieval, in this module the query image feature vector is compared with the feature vector of database images in .mat file. Then the similar images present in the database are retrieved. Then the final module is Forge Detection, In this module the forge in the retrieved image is compared with the query image. Initially, the saliency map of the image is calculated based on the thresholding and the hash vector is generated from the hamming distance of the saliency map. Then the forgery of image is detected based on the hash vector values.

2. IMAGE CLUSTERING

Clustering was widely used in image and video identification/ processing. It is the unsupervised classification of patterns into groups. Geographical tagging or title of photographs have been used for image retrieval or browsing applications. Never the less, the goal of feature classification and clustering in image processing and computer vision is how to deal with images for classification, in order to separate the images by low-level features such as color, texture, shape, or by high level semantics, or a combination of those features (Kuijperand Florack, 2005). A similarity measure using these features between images is one of the critical issues because it is still weak in partial occlusion, view translation, orientation and noise (Kuijperand Florack, 2002). Most classification approaches into three main categories; partition, division, and aggregation. One of the most popular methods in partition methodology is the k-Means method (Murthy *et al.* 2010), the division follows kd-tree method (Gao *et al.* 2008). Combining these two approaches is still a challenging research area. In the next section we present our method that add hierarchical layers exploiting 3D camera parameters and related poses. Brilakis *et al.* [24] developed a framework for managing digital images of construction sites.

The framework divides an image into clusters that represent different construction materials in the image and uses the cluster features to identify the material from a database of material signatures. Evaluation was performed by testing the correctness of identification of five different construction materials in terms of precision, recall and effectiveness. The researchers describe the high accuracy of the bottom–up clustering technique implemented in the method. In video image processing, several studies utilized clustering to develop a codebook – or dictionary – of actions and/or poses used for comparing, identifying and classifying motions of workers in a construction activity [25,26]. In both studies, K-means clustering was used to limit the multitude of possible actions into a fixed set of poses. For evaluation, a supervised learning algorithm was applied to classify the motions of workers on a test video based on the developed codebook, and performance was determined based on accuracy of classification.

3. PROPOSED FRAMEWORK

In this paper we proposed the system by using the content based image retrieval system. In CBIR we use K-means clustering algorithm and B+tree for speeding up the retrieval process. In this approach we make the feature extraction by using Daubechies' wavelets method. The proposed work is divided into three main divisions, they are Feature extraction, Clustering and query phase.

In feature extraction, we extract feature vectors of the images stored in the database. The image dataset that we work on consists of non-texture true-color images. Each true color (RGB) image is stored as a three-dimensional (m-by-n-by-3) Finally, we apply 1 more level transformation to each component and store these 8 _ 8 matrixes and their standard deviations as part of the feature vector. For each color channel, we are storing a 8 _ 8 and a 16 _ 16 matrixes, and the standard deviation of the 8 _ 8 matrix. The final size of our feature vector is (8 + 8 _ 8 + 16 _ 16) _ 3 which is equal to 984. This method was proposed by Wang *et al*. for the image retrieval project WBIIS [28].

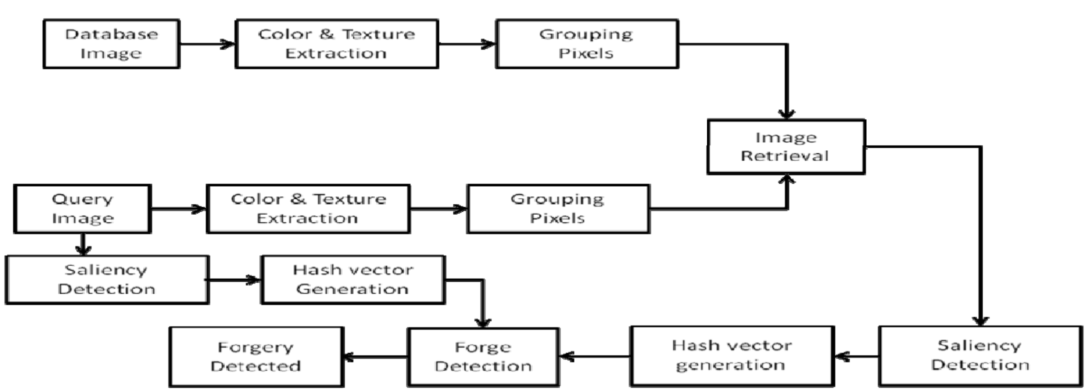

Figure-1. Flow diagram for the proposed framework.

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After the Daubechies' wavelet transformation is completed, the original matrix is divided into four sections, where the upper left part is the image passed through horizontal and vertical low filters. We know that low frequency bands represent the gross features of the image which we are interested in. Daubechies' wavelet transformation can be applied several times. When we say 4-level wavelet transformation, this means we apply transformation iteratively 4 times. In our approach, we apply 4-level wavelet transformation to all 3 components of the image; namely C1, C2, and C3. We store the upper left 16 _16 matrixes, which are also divided into its high and low frequency components, as part of the feature vector array where the first dimension represents the 'R' component, the second dimension represents the 'G' component and the third dimension represents the 'B' component of the image [27]. During the feature extraction step, we first preprocess the image by resizing it and then transforming it into a data space based on RGB values of the original image. Then we apply Daubechies' wavelet transformation to divide the image into its high and low frequency bands and construct feature vectors from the low-pass filtered image components.

The basic steps of the process can be found in the below algorithm.

Algorithm for feature extraction
Rescale the image using bilinear interpolation to size
128 _ 128
Transform the image to a data space different than RGB and
get components C1, C2, C3
R 0
for all Components of the image (C1,C2,C3) do
Apply 4-level Daubechies wavelet transform
X upper left 16 _ 16 matrix
Apply 5-level Daubechies wavelet transform
Y upper left 8 _ 8 matrix
Z standard deviation of Y
R+ = (X + Y + Z)
end for
RETURN R

In clustering phase, we construct a model from the images in the database and use this model for narrowing down the search space. However, while reducing the search space we must also consider not losing any relevant images. In this phase, different classification or clustering methods can be used. Once we classify or cluster the images in the database, we can find which class or cluster the query image belongs to and search for the most similar images in that class or cluster. For this purpose, we have tried different classification and clustering algorithms for model construction. After finding out that k-means clustering algorithm gives the most cost-effective results for reducing the search space and also for not losing any useful information, we proposed an approach that enhances the k-means clustering model. We decided to over-come the major shortcoming of k-means (i.e., specifying the number of clusters as input) by employing majority voting on the results obtained from cluster validity analysis indexes. We mainly applied these cluster validity indexes: Calinski, Db, Hartigan, Ratkowsky, Scott, Marriot, Ball, Trcovw, Tracew, Friedman, Rubin, Ssi, Avg Silwidth and Dunn [29, 30, 31, 32, 33].

We run k-means for a range of the number of clusters and if the majority voting reports the upper bound of the range as the appropriate number of clusters, we repeat the process for the next five values, i.e., we expand the range by five more values and check these five values in addition to the reported upper bound. This process is recursively applied until the number of clusters reported is less than the upper bound of the last tested range of values. Here it is worth mentioning that the integration of B+-tree index into the process indirectly lead to neglecting outliers. In other words, outliers are mostly located near the boundaries of the clusters and hence their distance from the centroid will be large and hence will not be retrieved as part of the query result.

After clustering the images in the database, when a new query image is entered to the system the common trend used in many existing CBIR systems is to find the closest cluster to the query image and search for similar images in that cluster. The query point falls into the red cluster while there are some blue data points which are very close to the query point. Therefore, narrowing down our search space to one cluster might filter out many relevant data points. Keeping this in mind, we can enhance our model as we will describe in the sequel. After clustering, we know images in each cluster and its centroid. For each image, we can calculate the distance between the image and the cluster center that the image belongs to.

Algorithm 2: Clustering

Call the k-Means algorithm combined with validity analysis
(output will be cluster centers and the cluster of each image
in the database)
for all Cluster i do
Initialize a B+-tree BTi
c cluster center i
for all Image j in cluster i do
d distance between cluster center i and feature vector of image j
Add (d, image name) to BTi where d is the key
end for
end for
All BTs

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In the query phase, we will use the query image's distance to cluster centroid and the queried image's distance to cluster centroid as our similarity measurement for reducing distance calculations. This will reduce distance calculations during the query phase. When we store those distances in a sorted order, we can also cut down the search space. The computed distance values are used to construct one B+-tree per cluster. This step is described in Algorithm 2.

At this point, one can ask why we are using B+-tree instead of any data structure which can store the images in sorted order according to their distance values. We could use a sorted linked list for this purpose as well. However, indexing schema of B+-tree enables us to reduce the total I/O cost which will be a bottleneck in large image databases. Moreover, dynamically changing the indexing data structure of B+-tree makes our system extensible. If the user of the database wants to add new images, this would be handled in an efficient way with the B+-tree as the index structure. Finally, it is worth mentioning that high dimensional index structures like VP-tree [34] or NAQ-tree [35] could be used as alternative to the whole process of clustering and constructing B+-tree index per cluster. However, high dimensional index structures are not very effective in handling dynamic databases. In other words, while the proposed clustering and B+-tree index model can effectively and smoothly deal with new images added to or dropped from the database, high dimensional index structures are mostly effective for dealing with static databases and would require rebuilding the whole structure in case any modifications are applied to the indexed database.

When a new query is entered to the system, first we find the feature vector of the image. Then, we find the closest cluster center to the query image. Most similar images will be most probably in that cluster. some similar images may also be in other clusters. Therefore, we do not only consider the closest cluster but also the other clusters in our search space. Here, it is worth noting that searching all clusters for similar images is not different from searching the whole database. However, we will be using the B+-trees we constructed in the previous step. From the triangle inequality, we know that the distance between two points must be greater than or equal to the difference between their distances to a third point.

a) Zernike moments

Here we introduced the Zernike moments for find out the difference between in the query image and the retrieved images. This algorithm is utilized for the forgery detection in the retrieved images. It calculates the hashing vector for the saliency map of the images. Based on the hashing vector values the type of forgery is detected. The types of forgery are:

- Enhanced objects
- Missed objects
- Replaced objects
- Inserted objects

Moment descriptors have been studied for image recognition and computer vision since the 1960s [22]. Teague first introduced the use of Zernike moments to overcome the shortcomings of information redundancy present in the popular geometric moments [13, 21]. Zernike moments are a class of orthogonal moments and have been shown effective in terms of image representation. Zernike moments are rotation invariant and can be easily constructed to an arbitrary order. Although higher order moments carry more fine details of an image, they are also more susceptible to noise. Therefore we have experimented with different orders of Zernike moments to determine the optimal order for our problem. The Zernike polynomials are a set of complex, orthogonal polynomials defined over the interior of a unit circle $x^2 + y^2 = 1$ [10, 11],

$$v_{nm}(x, y) = v_{nm}(\rho, \theta) = R_{nm}(\rho)e^{jm\theta} \tag{1}$$

$$R_{nm}(\rho) = \sum_{s=0}^{\frac{n-|m|}{2}} (-1)^s \frac{(n-s)!}{s!\left[\frac{n+|m|}{2}-s\right]!\left[\frac{n-|m|}{2}-s\right]!} \rho^{n-2s} \tag{2}$$

Where n is a non-negative integer, m is an integer such that $n-|m|$ is even and $|m| \leq n$, $\rho = \sqrt{x^2 + y^2}$, and $\theta = \tan^{-1}\frac{y}{x}$.

Projecting the image function onto the basis set, the Zernike moment of order n with repetition m is:

$$A_{nm} = \frac{n+1}{\pi}\sum_x\sum_y f(x, y)V_{nm}(x, y), x^2 + y^2 \leq 1 \tag{3}$$

It has been shown in [11] that the Zernike moments on a rotated image differ from those of the original un rotated image in phase shifts, but not in magnitudes. Therefore $|A_{nm}|$ can be used as a rotation invariant feature of the image function. Since $A_{n,-m} = A_{nm}$, and therefore $|A_{n,-m}| = |A_{nm}|$, we will use only $|A_{nm}|$ for features. Since $|A_{00}|$ and $|A_{11}|$ are the same for all of the normalized symbols, they will not be used in the feature set. Therefore the extracted features of the order n start from the second order moments up to the n^{th} order moments.

The selection of appropriate and optimal number of features is an important task for an effective image retrieval system. A small number of features do not provide satisfactory results, while the high numbers of features are prone to ''overtraining'' and reduce the computation efficiency. In addition, higher order ZMs suffer from numerical integration error and they are numerically unstable.

4. CONCLUSIONS

In this paper we focused on the development of CBIR system for non-texture image databases. In the proposed framework, we done the extraction based on the color and texture, then we grouped into the pixels. We eliminate the effect of outliers by using the distance to centroid based index structure. Then the by using CBIR system in which we use k-means as the clustering algorithm and B+ tree for speeding up the retrieval process. For representing the images, we extract their feature vectors using Daubechies' wavelets. Then we construct a model using k-means clustering and B+-tree. After that we find out the forgery between the query image and retrieved image by using the Zernike moments. In future the proposed framework will be implemented and calculating the accuracy of the framework.

REFERENCES

[1] M. Kokare, P.K. Biswas and B. N. Chatterji. 2006. Rotation-invariant texture image retrievalusing rotated complex wavelet filters, IEEE Transactions on Systems, Man andCybernetics-Part B: Cybernetics Vol. 36, no. 6, pp. 1273–1282.

[2] S.K. Chang and S. H. Liu. 1984. Picture indexing and abstraction techniques for pictorial databases, IEEE Trans. Pattern Anal. Mach. Intell. Vol. 6, no. 4, pp. 475–483.

[3] C. Faloutsos, R. Barber, M. Flickner, J. Hafner, W. Niblack, D. Petkovic and W. Equitz. 1994. Efficient and effective querying by imagecontent, J. Intell. Inf. Syst. Vol. 3, no. 3–4 pp. 231–262.

[4] A. Pentland, R.W. Picard and S. Scaroff. 1996. Photobook: content-based manipulation for image databases, Int. J. Comput. Vision Vol. 18, no. 3, pp. 233–254.

[5] A. Gupta and R. Jain. 1997. Visual information retrieval, Commun. ACM Vol. 40, no. 5, pp. 70–79.

[6] J. R. Smith and S. F. Chang. 1996. VisualSeek: a fully automatic contentbased query system, Proceedings of the Fourth ACM International Conference on Multimedia, pp. 87–98.

[7] W.Y. Ma and B. Manjunath. 1997. Netra: a toolbox for navigating large image databases, Proceedings of the IEEE International Conference on Image Processing, pp. 568–571.

[8] J.Z. Wang, J. Li and G. Wiederhold. 2001. SIMPLIcity: semantics-sensitiveintegrated matching for picture libraries, IEEE Trans. Pattern Anal. Mach. Intell. Vol. 23, no. 9, pp. 947–963.

[9] F. Long, H.J. Zhang and D.D. Feng. 2003. Fundamentals of content-based image retrieval, in: D. Feng (Ed.), Multimedia Information Retrieval and Management, Springer, Berlin.

[10] Y. Rui, T. S. Huang and S.-F. Chang. 1999. Image retrieval: current techniques, promising directions, and open issues, J. Visual Commun. Image Representation. Vol. 10, no. 4, pp. 39–62.

[11] J. Bach, C. Fuller, A. Gupta and A. Hampapur. 1996. B. Gorowitz, R. Humphrey, R. Jain, C. Shu, Virage image search engine: an open framework for image management. in: Proceedings of the SPIE Conference on Storage and Retrieval for Image and Video Databases IV, February, pp. 76–87.

[12] T.S. Huang, S. Mehrotra and K. Ramchandran. 1996. Multimedia analysis and retrieval system (mars) project, in: Proceedings of 33rd Annual Clinic on Library Application of Data Processing – Digital Image Access and Retrieval.

[13] R. Alhajj and D. Gebara. 2007. Waveq: combining wavelet analysis and clustering for effective image retrieval, in: 21st International Conference on Advanced Information Networking and Applications Workshops, Vol. 1, pp. 289– 294.

[14] X. Kang, D. Li and S. Wang. 2011. A multi-instance ensemble learning model based on concept lattice, Knowledge-Based Systems.Vol. 24, no. 8, pp. 1203–1213.

[15] M. E. Elalami. 2011. Supporting image retrieval framework with rule base system, Knowledge-Based Systems. Vol. 24, no. 2, pp. 331–340.

[16] M.E. Elalami. 2011. A novel image retrieval model based on the most relevant features, Knowledge-Based Systems. Vol. 24, no. 1, pp. 23–32.

[17] X. Wang, L. Lei and M. Wang. Palmprint verification based on 2D – Gabor wavelet and pulse-coupled neural network, Knowledge-Based Systems, in press. <doi:10.1016/j.knosys.2011.10.008>.

[18] C. Chang and C. Lin. Libsvm – A library for support vector achines.<http://ww.csie.ntu.edu.tw/cjlin/papers/guide/guide.pdf> (accessed 22.02.10).

[19] A. Gidudu, G. Hulley and T. Marwala. 2007. Image classification using svms: one-againstone vs one-against-all, in: Proceedings of the 28th Asian Conference on Remote Sensing.

[20] L. Wang. 2001. Support Vector Machines: Theory and Applications, Springer.

VOL. 10, NO. 9, MAY 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

[21] L. Wang and V. Kecman. 2005. Introduction to Support Vector Machines and Other Kernel-based Learning Methods, Springer.

[22] L. Lancieri and L. Boubchir. 2007. Using multiple uncertain examples and adaptive fuzzy reasoning to optimize image characterization, Knowledge-Based Systems Vol. 20, no. 3, pp. 266–276.

[23] S.Y. Sung and T. Hu. 2006. Iconic pictorial retrieval using multiple attributes and spatial relationships, Knowledge-Based Systems. Vol. 19, no. 8, pp. 687–695.

[24] I. Brilakis, L. Soibelman and Y. Shinagwa. 2005. Material-based construction site image retrieval, Journal of Computing in Civil Engineering. Vol. 19, no. 4, pp. 341–355.

[25] J. Gong and C. H. Caldas. 2011. Learning and classifying motions of construction workers and equipment using bag of video feature words and Bayesian learning methods, Proc. of the InternationalWorkshop on Computing in Civil Engineering, American Society of Civil Engineers, Miami, Florida, United States.

[26] V. Escorcia, M. Dávila, M. Golparvar-Fard and J. Niebles. 2012. Automated vision-based recognition of construction worker actions for building interior construction operations using RGBD cameras, Proc. of the Construction Research Congress 2012, American Society of Civil Engineers, West Lafayette, Indiana, United States.

[27] The MAthWorks website (accessed 15.03.10).

[28] J. Wang, G. Wiederhold, O. Firschein and S. Wei. 1997. Content-based image indexing and searching using Daubechies' wavelets, International Journal on Digital Libraries. Vol. 1, no. 4, p. 31328.

[29] T. Özyer and R. Alhajj. 2006. Clustering by integrating multi-objective optimization with weighted k-means and validity analysis, International Conference on Intelligent Data Engineering and Automated Learning, Vol. 4224, Springer- Verlag.

[30] T. Özyer and R. Alhajj. 2006. Combining validity indices and iterative multi-objective optimization based clustering, in: Proceedings of the International FLINS Conference on Applied Artificial Intelligence, World Scientific Press.

[31] J. Bezdek and R. Pal. 1998. Some new indexes of cluster validity, IEEE Transactions on Systems Man, and Cybernetics – Part B. Vol. 28, no. 3, pp. 301–315.

[32] M. Halkidi and M. Vazirgiannis. 2001. Validity assessment: Finding the optimal partitioning of a data set, in: Proceedings of IEEE International Conference on Data Mining, California, November, p. 187.

[33] D. Jiang, C. Tang and A. Zhang. 2004. Cluster analysis for gene expression data: a survey, IEEE Transactions on Knowledge and Data Engineering. Vol. 16, no. 11, pp. 1370– 1386.

[34] J.K. Uhlmann. 1991. Satisfying general proximity/similarity queries with metric trees, Information Processing Letters Vol. 40 pp. 175–179.

[35] M. Zhang and R. Alhajj. 2010. Effectiveness of naq-tree as index structure for similarity search in high-dimensional metric space, Knowledge and Information Systems. Vol. 22, no. 1, p. 12.

[36] Teh C. and Chin R.T. On Image Analysis by the Methods of Moments. IEEE Trans. on PAMI. Vol. 10, no. 4, pp. 496-513.

[37] Lipscomb J. S. A Trainable Gesture Recognizer. Pattern Recognition. Vol. 24, no. 9, pp. 895-907.

[38] Teague M. R. Image Analysis via the General Theory of Moments. Journal of the Optical Society of America. Vol. 70, no. 8, pp. 920-930.

[39] Khotanzad, A. and Hong, Y.H. Invariant Image Recognition by Zernike Moments. IEEE Trans. on PAMI. Vol. 12, no. 5, pp. 289-497.

[40] Khotanzad A. and Hong Y. H. Rotation Invariant Image Recognition using Features Selected via a Systematic Method. Pattern Recognition. Vol. 23, no. 10, pp. 1089-1101.