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A Multilayered Complex Network Model for Image Retrieval

Hadi Shakibian
Department of Computer Engineering
Faculty of Engineering, Alzahra University
Tehran, Iran
h.shakibian@alzahra.ac.ir

Nasrollah Moghadam Charkari*
Faculty of Electrical and Computer Engineering
Tarbiat Modares University
Tehran, Iran
moghadam@modares.ac.ir

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Abstract—**In this study, an image retrieval system is proposed based on complex network model. Assuming a prior image categorization, firstly, a multilayered complex network is constructed between the images of each category according to the color, texture, and shape features. Secondly, by defining a meta-path as the way of connecting two images in the network, a set of informative meta-paths are composed to find the similar images by exploring the network. The established complex network provides an efficient way to benefit from the image correlations to enhance the similarity search of the images. On the other hand, employing diverse meta-paths with different semantics leads to measuring the image similarities based on effective image features for each category. The primary results indicate the efficiency and validity of the proposed approach.**

Keywords: Component; Content based Image Retreival; Complex Networks; Meta-Path.

I. INTRODUCTION

A challenging problem in large image databases is to efficiently retrieve a set of images that are similar to a given image query [1]. The simplest way is to tag the images using some relevance texts and search the images by keywords [2]. Although, this has been the basis of many image retrieval systems, it suffers from time-consuming computations. Moreover, it is not feasible to reflect all the image semantics in terms of keywords. An alternative solution is to develop a content based image retrieval (CBIR) system that considers the image contents like color, texture, and shape to measure the image similarities. Such a system could be employed in a wide range of applications including medical diagnosis [3], e-commerce [4], and reverse image search [5].

In a CBIR system, the main issue is to describe the visual contents of the images in terms of some important features, denoted as image descriptors. Generally, two types of features as low-level and high-level features could be extracted from the images. The low-level features such as color, texture, shape, and salient points are defined in order to decrease the sensory gap between the real object and its visual descriptor [6]. On the other hand, the high-level features such as semantic templates, object ontologies, and relevance feedback are used to fill the semantic gap between the extracted semantical information from the images and the relevant interpretations. Since different people have their own specific perceptions from the visual contents of an image, employing high-level features as image descriptors is difficult. In this regard, the majority of studies in this area focus on introducing or employing low level image features than semantical features to properly retrieve the images [6].

The low-level image features usually compose of four types of visual information i.e. color [7-12], texture

* Corresponding Author

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[13-16], shape [17-21], and salient points. Despite the use of low-level features, deep convolutional neural networks has been successfully employed in image classification tasks [22, 23]. However, it has been shown that the features obtained from a convolutional neural network do not show superior performance compared to employing other features [24].

The current image retrieval systems that employ low-level feature are mostly rely on extracting a set of informative image features to accurately find the image similarities. However, there are some major concerns that need to be considered in future studies. Firstly, it is required to keep all the above mentioned features for the entire dataset. While it has high computational cost, it might generate redundant and useless information that makes the similarity search of images not to be effective nor accurate. Secondly, changing the order of employing the feature types are important. For example, using the color and then texture features would provide different results compared to a reverse order as well as using all the features simultaneously. However, this fact is omitted in the current systems. Finally, the system is weakly scaled up when the size of the dataset is increased.

In this study, a multilayer complex network model is proposed to address the above shortcomings in CBIR systems. The proposed approach, denoted as CNIR (Complex Network based Image Retrieval), comprises of three main steps in the training phase. Firstly, different image features are extracted based on the color, texture, and shape information. Then, assuming an image as a node, a multilayer complex network is constructed for each image category. Each layer is found based on a feature type. Next, a set of meta-paths (i.e. the way of connecting two images in the network) is defined over the constructed networks to explore the image similarities. The primary experimental results using some categorized image datasets show the accuracy and efficiency of CNIR based on the precision and recall scores.

The remainder of this paper is organized as follows. In section 2, the problem is defined formally. In section 3, the proposed CNIR system is introduced. In section 4, initial results on a benchmark dataset are reported. Finally, the last section is our concluding remarks.

II. Problem Definition and Assumptions

Assume a dataset $\Upsilon = \{X1, \dots, Xn\}$ is given where the i-th image is represented by a feature vector as $Xi = \{x_i^1, \dots, x_i^l\}$ and l is the total number of features [28]. We consider Υ in two distinct sets of Υ^t and Υ^p where $\Upsilon^t \cap \Upsilon^p = \emptyset$. Moreover, let us consider $Xq = \{x_q^1, \dots, x_q^l\} \in \Upsilon^p$ as a query image. The objective is to train a model f that finds the images with the same label to the given query.

We assume that Υ is divided into k categories as $\{\Upsilon 1, \dots, \Upsilon k\}$ with associated labels as $\{c1, \dots, ck\}$ such that:

$$\Upsilon = \cup_{i=1}^{k} \Upsilon_i \qquad \cap_{i=1}^{k} \Upsilon_i = \emptyset$$

III. Complex Network Model for Image Retrieval

The concept of complex network has been successfully studied in image analysis tasks. Shape boundary description [25, 26], large image segmentation [27], texture classification [28], and low level feature extraction based random-walk [29, 30] are among the most important works.

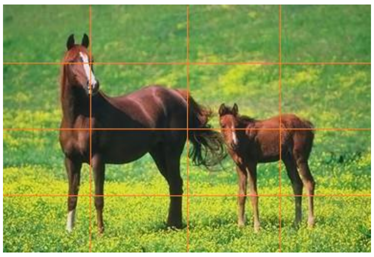

Fig 1. Representing each image as a set of image blocks.

The main achievement of the proposed complex network models for the above image processing tasks is to obtain an image analysis system that are robust, noise tolerant, scale and rotation invariant [25]. To the best of our knowledge, there is not any relevant studies in CBIR based on complex network analysis.

A. Proposed Approach

In this section a novel complex network based CBIR is introduced that consists of three main steps:

1. Feature Extraction: Various image features based on the color, texture, and shape are extracted for each image. The extracted features are employed to construct the complex network between the images.

2. Network Construction: For each image category, a complex network model is obtained using the extracted features in the previous step.

3. Similarity Measurement: This step is based on defining a number of meta-paths over the constructed networks and exploring the similarities obeying the meta-paths between the nodes (images).

Assuming each image $X \in \Upsilon$ on a grid of size $z \times z$, the image X would be presented with image blocks $X^{(1)}, X^{(2)}, \dots, X^{(z^2)}$. Figure 1 shows an image on a grid of size 4×4 with 16 image blocks. In the following subsections, the steps of the proposed CNIR system is described in more details.

1) Feature Extraction

The first part of the employed features are based on the color information. We have chosen color histogram [31] and dominant color [32]. To obtain the color histogram, at first, each color channel is equally divided into a number of bins within its allowed range. Then, the pixels are packed into the bins based on their intensities in that channel. The color histogram for each image block $X^{(i)}$ is obtained after counting the pixels in each bin as:

$$h^{(i)} =< h_1, \dots, h_\alpha > \qquad (1)$$

where α is the the number of bins, and h_r is defined as:

$$h_r = \sum_{j=1}^{z^2} \#\{I(p_j) \in [L_r, U_r)\} \quad (2)$$

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in which $I(p_j)$ is the intensity of the j-th pixel of $X^{(i)}$, and $[L_r, U_r)$ denotes the allowed range of the r-th bin. The Eq. (1) is applied on all the color channels and the corresponding histogram vector is obtained as:

$$\mathbf{h}^{(i)} =< h^{(i),1}, h^{(i),2}, \ldots > \qquad (3)$$

Calculating the color histogram for each color channel, defining the relevant dominant color would be straightforward:

$$d^{(i)} = max\{h_1, \ldots, h_\alpha\} \qquad (4)$$

which results in a vector as:

$$\mathbf{d}^{(i)} =< d^{(i),1}, d^{(i),2}, \ldots > \qquad (5)$$

To extract the texture information of the images, some important features could be employed directly [33] or used to define a number of statistical features based on them. In practical evaluations, wavelet features have been used which belongs to the second order statistical features [34].

Like color and texture, there are many shape descriptors to be employed [35]. However, we have proposed a graph based descriptor to extract a number of graph measures as the features. For this purpose, inspiring [25] and [26], a complex network is defined between the extracted interest points. The interest points could be determined using different descriptors such as SURF [21] or SIFT [20]. To have a computationally efficient detection method, Harris corner points has been employed [36]. The Harris points are detected according to the intensity variations of the pixels within a predefined window throughout the image block. Thus, the total number of Harris points for the blocks of an image would be almost equal to those points for the whole image.

When the interest points are extracted, a fully connected graph is formed between them. Afterwards, the link between any pair of interest points that their spatial distance is greater than a threshold λ is removed. The resulted graph is a complex network [28]. In Figure 2, the interest points of an example image and the corresponding complex network has been shown.

Finally, a number of network measure are calculated as the shape features including: assortativity [37], betweenness centrality [38, 39], clustering coefficient [40], average node degrees, density, flow coefficient [41], modularity [42], and pagerank [43]. In Figure 2, the interest points of an example image and the corresponding complex network has been shown.

2) Network Construction

Employing the extracted image features, a multilayered complex network is constructed for each category. The number of the network layers would be equal to the number of different feature types, i.e. three layers in CNIR. As mentioned before, each image is considered as a node. Thus, the network size equals to the number of the images in each category which are presented in all network layers. In following, creating the similarity links between the nodes (images) of each layer are described according to the corresponding feature type.

Color Layer. Let $\mathbf{c_X}$ and $\mathbf{c_Y}$ denote to the color feature vector of two images X and Y. The color similarity of two images could be created as a weighted color link (*cl*) as:

$$cl_{XY} = \sum_{i=1}^{z^2}\sum_{j=1}^{z^2} [\lambda(\mathbf{u}^{(ij)}.\mathbf{v}^{(ij)} + (1-\lambda)hst(\mathbf{X}^{(i)}, \mathbf{Y}^{(i)})]w^{(i)}w^{(j)} \qquad (6)$$

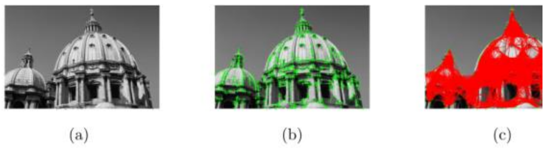

Fig 2. An example of the complex network model for shape description in CNIR: (a) Original image; (b) Harris points; (c) Complex network-based shape descriptor.

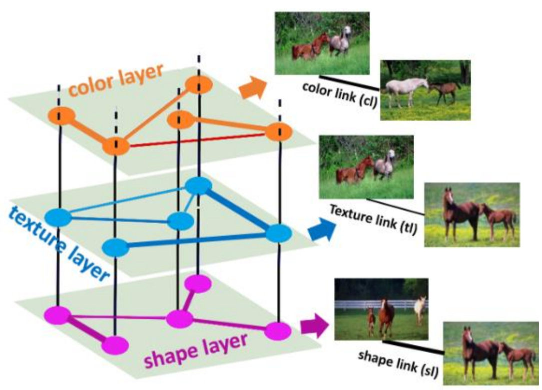

Fig 3. The schematic of the multiplex image network in CNIR system.

in which $\mathbf{u}$ and $\mathbf{v}$ are dominant color feature vectors, hst is the intersection of color histograms, and w is a weight to differentiate the importance of different image blocks.

Texture Layer. Similar to the color layer, the links in the texture layer is composed by calculating the link scores based on the texture features. Suppose the texture features for $\mathbf{X}^{(i)}$ and $\mathbf{Y}^{(j)}$ are denoted by $\mathbf{wav}_i$ and $\mathbf{wav}_j$ respectively. Then, the texture link (*tl*) is created as:

$$tl_{XY} = \sum_{i=1}^{z^2}\sum_{j=1}^{z^2} \frac{1}{\epsilon_1 + \|\mathbf{wav}_i - \mathbf{wav}_j\|} \qquad (7)$$

where $\mathbf{wav}_i$ and $\mathbf{wav}_j$ are the corresponding wavelet features, respectively, and ϵ_1 is a positive constant.

Shape Layer. Assume that $\mathbf{netf}_i$ and $\mathbf{netf}_j$ be the shape features, i.e. the network measures, of $\mathbf{X}^{(i)}$ and $\mathbf{Y}^{(j)}$, respectively. The shape link (*sl*) is created using:

$$sl_{XY} = \sum_{i=1}^{z^2}\sum_{j=1}^{z^2} \frac{1}{\epsilon_2 + \|\mathbf{netf}_i - \mathbf{netf}_j\|} \qquad (8)$$

where ϵ_2 is a positive constant. Creating the color, texture, and shape links between the images result in obtaining a multilayer complex network. In Figure 3, the schematic of the multilayer image network has been shown.

3) Similarity Measurement

A multilayer complex network could be explored by a meta-path to discover latent relationship between any node pairs [44, 45]. The concept of meta-path has been

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employed in a broad range of complex network applications such as link prediction in information networks [46, 47, 48], drug interaction prediction [49], similarity search [50], etc.

TABLE I. META-PATHS TYPES. THE ABBREVIATIONS I, C, T, AND S DENOTE TO IMAGE, COLOR, TEXTURE, AND SHAPE, RESPECTIVELY. EVERY IMAGE I HAS THREE NEIGHBORHOOD SETS RESPECT TO EACH LAYER. WE CALL THESE SETS AS C, T, AND S NEIGHBORS, RESPECTIVELY.

#. of Active layers	Example Meta-path	Semantic
1	ICI ITI ISI	Two images are similar if they have high color/texture/shape similarity
2	ITSTI	Two images are similar if their *T* neighbors show high shape similarity
3	ITSCSTI	Two images are similar if their *T* neighbors have some *S* neighbors with high color similarity

In the third step of CNIR system, the network is explored via a set of meta-paths to discover the image similarities. Accordingly, a meta-path connects two images through different network layers while carrying a specific semantic. In this regard, each meta-path investigates the image relationships by a combination of different types of image information, i.e. color, texture, and shapes. In Table 1, three classes of meta-paths have been introduced. The first class of meta-paths include only one layer of information, while the meta-paths in the second and the third classes employ two and three layers of information, respectively. Although it could be possible to define longer meta-paths, their effectiveness might be decreased [45] while computational time complexity is undesirably increased. However, a meta-path selection step might be required to select the best set of the possible meta-paths. To do this, every meta-path is applied on the training image dataset for each category and the meta-path with the highest precision rate is picked. In the next section, we define several instances of each meta-path type.

In classification phase, the meta-path similarity score is calculated for the new image by employing the associated meta-path(s) to each category. The meta-path similarity score is the summation of the visited link weights from the source image to the target one:

$$ss_{IX}^{P} = \sum_{p \in P} \sum_{link \in p} w_{link} \qquad (9)$$

where $I \in \Upsilon^{p}$ is the new image, $X \in \Upsilon^{p}$, and p is a path instance of the meta-path P. Finally, the most relevant images to the given query is sorted and the prediction accuracy in terms of the precision and recall is obtained.

IV. RESULTS

We have evaluated our primary results over the Wang dataset which comprises 1000 images in 10 different classes. In Figure 4, some instances of this dataset has been shown.

a) Prediction Accuracy

From each category, 10 images are selected randomly for the test and the rest of the images are used in the training stage. Also, precision and recall rates are chosen to show the classification accuracy of each meta-path as:

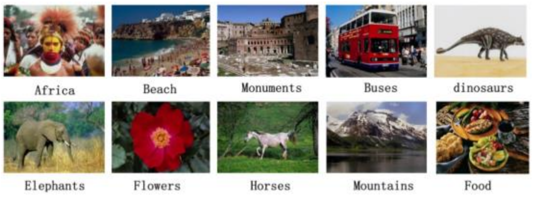

Fig 4. Samples of the Wang dataset.

TABLE II. THE PROPOSED META-PATHS IN CNIR SYSTEM.

ID	Meta-Path	ID	Meta-Path
MP1	ICI	MP10	ICTCI
MP2	ITI	MP11	ICSCI
MP3	ISI	MP12	ITCTI
MP4	ICCI	MP13	ITSTI
MP5	ITTI	MP14	ISCSI
MP6	ISSI	MP15	ISTSI
MP7	ICTI	MP16	ICTSI
MP8	ICSI	MP17	ITCI
MP9	ITSI	MP18	ITSCI

$$precision = \frac{TP}{TP+FP} \qquad (9)$$

$$recall = \frac{TP}{TP+FN} \qquad (10)$$

where TP and FP denote the number of the relevant and non-relevant retrieved images, respectively, and FN denotes the number of the relevant images that have not been retrieved.

Recalling Table 1, we have defined 18 meta-paths in Table 2 to explore the image similarities such that each layer of information is met at most twice. The obtained precision and recall rates have been reported in Table 3. Also, the average of Precision and Recall rates of different algorithms have been depicted in Figure 5. The results show competitive scores to the state of the art CBIR methods.

TABLE III. PRECISION/RECALL RATE COMPARISON.

Alg.	[60]	[59]	[58]	[51]	[53]	[57]	CNIR
Afr	0.725 0.145	0.726 0.161	0.741 0.148	0.831 0.166	0.850 0.170	0.730 0.173	**0.915** **0.212**
Bch	0.527 0.105	0.593 0.203	0.753 0.150	0.462 0.092	0.750 0.150	0.612 **0.221**	**0.995** 0.207
Bld	0.527 0.105	0.587 0.191	**0.758** 0.151	0.722 0.144	0.600 0.120	0.597 **0.197**	0.300 0.100
Bus	0.939 0.187	0.891 0.126	0.815 0.163	0.977 0.195	**1.000** **0.200**	0.890 0.132	0.900 **0.200**
Food	0.710 0.142	0.772 0.148	0.813 0.162	**0.894** 0.178	0.850 0.170	0.781 0.135	0.835 **0.185**
Din	0.994 0.198	0.993 0.109	**1.000** 0.200	0.990 0.198	**1.000** 0.200	0.990 0.113	**1.000** **0.220**
Elf	0.524 0.104	0.702 0.163	**0.967** **0.193**	0.643 0.128	0.800 0.160	0.713 0.159	0.615 0.136
Flw	0.866 0.173	0.928 0.129	0.932 0.186	0.954 0.190	**1.000** 0.200	0.916 0.134	0.940 **0.208**
Hrs	0.837 0.167	0.856 0.144	0.852 0.170	**0.924** 0.184	0.900 0.180	0.862 0.146	0.860 **0.191**
Mnt	0.431 0.086	0.562 **0.236**	0.804 0.160	0.478 0.095	**0.850** 0.170	0.573 0.229	0.625 0.174

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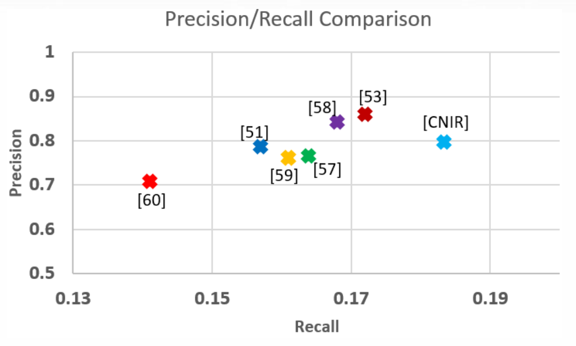

Fig 5. The comparison of average Precision/Recall rate of different algorithms.

b) Complexity analysis

The time complexity of the CNIR has been compared with some of the related studies in Table 4. The time complexity of CNIR is composed of the required time for constructing the network and then exploring the network using the meta-paths. The network construction is performed for each category where an adjacency matrix by size of $n^* \times n^*$ is created. On the other hand, the required features for each category is determined based on the selected meta-paths which is less than the total number of features. Thus, constructing the network of each category requires O($m^* \times n^{*2}$) while the network exploration needs O($l \times n^{*3}$). By approximating n^* as $\sqrt{n}$, the total time complexity of CNIR would be $O(mn\sqrt{n}) + O(ln^2)$ where l is the average meta-path length. However, as the network construction for each category is performed independently, CNIR could be easily speeded up using a parallel implementation.

V. Discussion and Concluding Remarks

In this paper, a novel complex network based model has been proposed for image similarity search. Defining and employing the meta-paths in a multi-layer network leads two important achievements:

- It provides a systematic way to investigate the effect of combining different feature types. Moreover, the importance of different features could be addressed by swapping the order of the visited layers.
- In each image category, some meta-paths, say as P, would show superior performance rather than the others. Thus, the feature types that are not appear in P would not be necessary to extract for that image category.

The obtained prediction accuracy of the proposed approach show promising results compared to its counterparts. However, some important challenges should be resolved in future. Firstly, the best meta-path for each category has been selected manually in training phase. While an automatic meta-path selection is required respect to the length, semantic, and the accuracy of the meta-paths. Secondly, constructing the network between all of the images might be time-consuming and unnecessary. Instead of that, the network could be constructed using a subset of the representative images in each category which we call them as hubs. Thirdly, we have employed a few

TABLE IV. Time Complexity Comparison. We Would Have $l \ll n$.

Algorithm	Time Complexity
Ref [51]	$\theta(n^3)$
Ref [52]	$\theta(n^3)$
Ref [53]	$\theta(n^2 \log n^2)$
Ref [54]	$\theta(n^3)$
Ref [55]	$\theta(n^2)$
Ref [56]	$\theta(n^2)$
CNIR	$\theta(ln^2)$

common features to construct each layer. As the calculated link scores would be strongly affected by those features, other well-known and more informative image features must be examined.

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Hadi Shakibian received his Ph.D. degree in Computer Engineering from Tarbiat Modares Univeristy, Tehran, in 2018. Currently he is with the Department of Computer Engineering at Alzahra University, Tehran. His main research interests include Complex Networks and Machine Learning.

Nasrollah Moghadam Charkari received his B.Sc. degree in Computer Engineering from Shahid Beheshti University, Tehran, Iran, in 1987, and his M.Sc. and Ph.D. degrees in Computer Engineering and Information System Engineering from Yamanashi University , Japan, in 1993 and 1996, respectively. His research interests include Robot Vision and Image Analysis, Image Mining, Complex Networks, Parallel Algorithms and Processing, Information Technology, Data Hiding and Water Marking.