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Interest Point Detection Using a Composite Index of Complex Networks

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Abstract. *In this letter, a new approach for interest point detection in images based on a composite index for key node detection in complex networks is proposed. First, we use a multi-neighbourhood gradient map of the target image to build a network. In this step, we use a set of thresholds and a Gaussian weighted function to reduce the complexity of the generated network as well as keep the local properties of the original image. Then, a composite index is used to detect key nodes in the network. Finally, the key nodes are mapped back to interest points in the image domain. Experiments show the effectiveness of the proposed methods.*
Keywords: Interest Points, Digital Image Analysis, Complex Networks, Composite Index

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1. **Introduction.** Interest points, namely the specific positions of some distinguishable points such as corners, edge points, or straight-line points, are usually served as the lowest-level features in a digital image. These points are commonly used as local features in many image applications such as content-based image retrieval, object recognition, image registration in stereo vision techniques and in 3D image reconstruction.

The best-known interest point detectors include the Moravec algorithm, Spin, Cross-correlation, the SUSAN detector, the Harris and Stephens algorithm, the multi-scale Harris operator, genetic-programming algorithms, and affine-adapted interest point operators [1]. The Moravec algorithm [2] defines the corner strength of a point as the smallest sum of squared differences (SSD) between the point patch and its neighbour patches. Spin image algorithm [3] and Cross-correlation algorithm [4] are based on brightness distribution. The SUSAN [5] detector is based on the minimization of local image region and uses the noise reduction method. Harris and Stephens detector [6] is a well-known interest point detector and plays an important role in low-level image feature detection algorithms. It computes the locally averaged moment matrix using the image gradients, and then combines the eigenvalues of the moment matrix to compute the strength of each corner. The multi-scale Harris detector works at different scales to produce a more robust detector which responds to interest points of varying sizes in the image domain.

This work introduces a novel approach to detect the interest points in a digital image using complex network analysis. We use a multi-neighbourhood gradient map of the target image to build a complex network. Then, a composite index is used to detect key nodes in the network. Finally, the key nodes are mapped back to interest points in the image domain.

2. **Computer Vision Problems using Complex Network Analysis.** There exist a lot of complex networks in our real world such as internet networks [7], social networks, scientific collaboration networks and biologic networks. In recent years, complex network has become an important research interest in many fields of science.

Some research topics using complex network to analyse computer vision can be found in literature [8, 9, 10]. A general framework to integrate the areas of vision research and complex networks was proposed in literature [11]. A local centrality algorithm based on a network to detect interest points [12] shows the value of using complex network analysis. This method uses morphological watershed method to create a sparse network. However, they do not make full use of the properties of the generated network. Also, there are problems about how to spot a pixel from a segmentation region of an image. Thus, this article will propose a new approach for interest point detection in images based on a composite index for key node detection in complex networks.

3. **Proposed Approach.** The main steps of the proposed approach are as follows. First, a multi-neighbourhood gradient map of the target image is computed to build a network. In this step, a Gaussian weighted function is applied to each pair of nodes to generate a sparse network. Then, a composite index is used to detect key nodes in the network. The key nodes are finally mapped back to interest points in the image domain.

The main disadvantage of the idea introduced in [11] is the heavy computational cost largely because the network is always a complete weighted graph. To avoid this disadvantage, we introduce a distance parameter r: the nodes associated to two pixels are connected by an edge only when the Euclidean distance between their corresponding pixels is no longer than r. As a result, the complexity of generated networks is largely reduced, and the local nature of the interest points detected can be guaranteed.

3.1. **Network Generation and Selection of Parameters.** From a mathematical point of view, a gray-level image I of size $N \times N$ is a non-negative matrix $I = (I_{xy}) \in M_{N\times N}$ such that every entry I_{xy} has an integer value (typically between 0 and 255 if we are dealing with 8-bit images), where x and y are the x-coordinate and y-coordinate of the special location of each pixel respectively. Therefore, the idea introduced in literature [11] consists in associating a network $G = (X, E)$ to each image I in such a way that we can analyse some properties of I from the structural and dynamical properties of G. If I is a gray-level image of $N \times N$ pixels, we can associate to it a weighted network $G = (X, E)$ with $|X| = N^2$ nodes, so that each node of the network corresponds to a pixel of I. The weight of each link $(i, j) \in E$ is $w(i, j) = \|\overrightarrow{f}_i - \overrightarrow{f}_j\|_2$, in which $\|\cdot\|_2$ denotes the Euclidean norm and $\overrightarrow{f}_i$ is a feature vector which describes some local visual properties about respective image pixels. Many of the classic algorithms for interest point detection are designed on the basis of an idea: the interest points are related to points with high gradient values compared to their surrounding pixels. To detect interest points, it is reasonable to build the network by setting the weight of each edge to be the luminance difference between two nodes. However, the computational complexity is very huge and it is meaningless if we consider each edge between any two nodes to generate a complete graph.

To avoid the disadvantages mentioned above, we try to generate an un-weighted incomplete graph for the target image by applying a Gaussian weighted function and setting series of threshold values. In other words, we first get a weighted complete graph by mapping each pixel into a node and mapping the luminance difference between each two nodes into the weight of each edge. For each edge, its weight is multiplied by a Gaussian function with the distance between its two nodes as independent variable. Then we generate an un-weighted incomplete graph by setting the threshold value of edge weight W and the threshold value of spatial distance D. The first threshold value W guarantees the interest points to be related to points with high gradient values. The second threshold value D guarantees the locality of the visual properties (global visual properties are insignificant for interest point detection). The use of Gaussian weighted function can give more emphasis on the edges between nodes with shorter distances and effectively reduce the number of links of the network. In summary, a multi-neighbourhood gradient map of the target image I is used to build an un-weighted incomplete graph G as the following steps.

- Map each pixel $P_i \in I$ into a node $X_i \in G$.
- Compute $W_{ij} = |I_i - I_j|$ (the luminance difference) and $d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$ (the spatial distance) between any two pixels P_i and P_j.
- Apply the Gaussian weighted function, i.e., $w_{ij} = W_{ij} \cdot e^{-d_{ij}^2/2\sigma^2}$, with σ being a specified parameter.
- If $w_{ij} > W$ and $d_{ij} < D$, connect X_i and X_j to form an edge E_{ij}.
- An un-weighted incomplete graph $G = (X, E)$ is obtained.

Actually, we can obtain different networks when setting different values for W, D and σ. According to our experiments, appropriate values of W, D and σ should be chosen based on the following principles.

- σ should be big enough, otherwise w_{ij} would decrease too rapidly as d_{ij} increases, leading to excessive elimination of edges when we apply weight thresholding. It should also be noted that the value of σ is dependent on the size of the image: a larger σ should be used for an image at large size. In this paper, we propose $\sigma = 2$ for an 128×128 image.

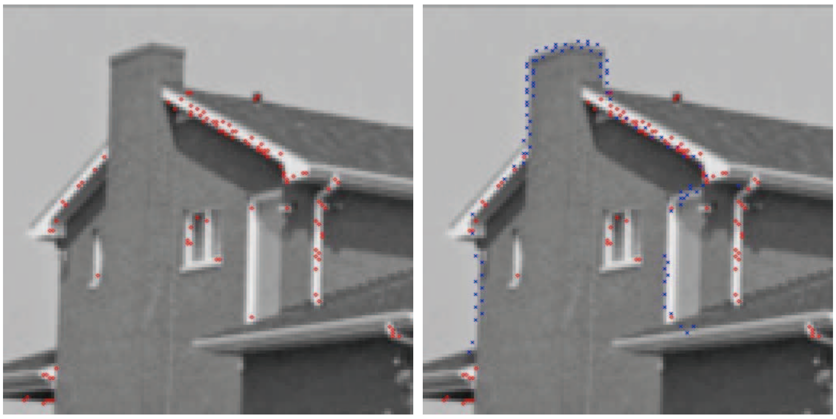
• W should be around half of the statistical mean of luminance difference according to our experiments. Since we also apply a Gaussian weighted function, we multiple W by the value of the function with $d_{ij} = 1$, therefore, $W = 0.5 \cdot e^{-1/2\sigma^2} \cdot \overline{w}$, where $\overline{w}$ is the statistical mean of $|I_i - I_j|$, for $1 \leq i < j \leq N^2$.

• D should be small enough to guarantee the locality of the visual properties. We have set D to 8, 10 and 12 for 128×128 images, and we did not notice any significant difference in results. Therefore, we chose 10 as the value of D in this paper.

3.2. **Key Nodes Detection using a Composite Index.** Many different methods have been proposed to detect key nodes in complex networks [13]. Most of these methods use the index of node degree, which is defined as the number of links incident upon a node. Degree is often interpreted in terms of the immediate risk of node for catching whatever is flowing through the network. Degree centrality (DC) is the simplest measures of centrality in a complex network, which is defined as follow.

• For a graph with n nodes, the degree centrality $C_D(v)$ for node v is: $C_D(v) = \mathbf{deg}(v)/(n-1)$, where $\mathbf{deg}(v)$ is the node degree of v.

By using $C_D(v)$, the importance of every node could be calculated. In FIGURE 1 (a), we map the first 0.5% important nodes back into the original image and mark the corresponding interest points as the symbol of red '∘'.



(a) (b)

FIGURE 1. (a): The first 0.5% important nodes detected by using the index of node degree only. (b): The first 1% important nodes detected by using both node degree and betweenness centrality.

In FIGURE 1 (a), we can see that we have detected some important points of the image. For example, the points on the two eaves, the windows and the pipe of the house are detected. They are calculated as important points because they have relatively high gradient values. However, some important points such as those on other edges of the image are not detected. This is because the key nodes detected by using $C_D(v)$ are the points with high gradient values in the image domain, which can lead to an incomplete detection result.

To solve this problem, we use not only the degree centrality, but also the betweenness centrality (BC). Betweenness is a centrality measure of a node within a graph. Nodes that lie on many shortest paths between other nodes have higher betweenness values.

For a node v, the betweenness centrality $C_B(v)$ is computed as follows.

• For each pair of nodes (s, t), compute all shortest paths between them.

• Determine the fraction of shortest paths that pass through node v.

• Sum this fraction over all pairs of nodes (s, t).

A faster algorithm for betweenness centrality [14] reduces the time complexity of calculation from $\mathbf{O}(n^3)$ to $\mathbf{O}(nm)$ for un-weighted networks and $\mathbf{O}(nm + n^2 \log n)$ for weighted networks, where n and m are the number of nodes and edges of the network, respectively.

In FIGURE 1 (b), we add the first 0.5% important nodes detected by using $C_B(v)$ as the symbol of blue '$\times$'. The final interest points are those marked as either '$\circ$' or '$\times$'. We can see that the nodes detected by using betweenness are good complements to the previous result. In other words, most of the edges of the image are detected.

4. **Experimental Results.** In this section, we use several images to test our detector and compare it with classic detector and other complex based approach. For the proposed method, we choose 0.5% nodes detected by using degree centrality and 0.5% nodes detected by using betweenness for all the test images.

4.1. **Visual Experimental Results of Comparison with Other Methods.** In the first experiment, visual experimental results are shown to compare the Harris interest point detector [6] and the DC detector [12] with our method in a direct way. The original images are 128×128, and we followed the principles proposed in section 2 to set the parameters, i.e., $\sigma = 2$, $D = 10$, and $W = 0.5 \cdot e^{-1/2\sigma^2} \cdot \overline{w}$.

(a) (b)

FIGURE 2. The results of (a) [12] and (b) our method.

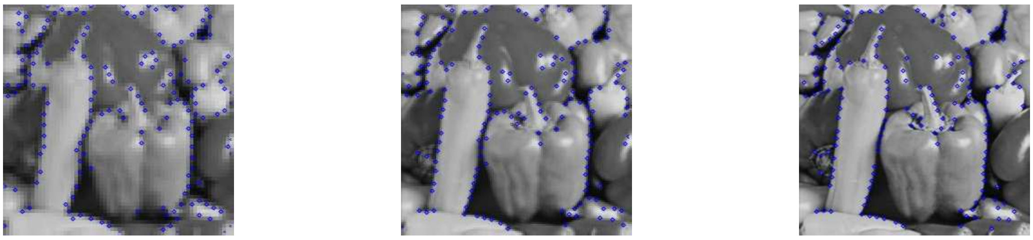
FIGURE 2 compares the result achieved by the DC detector proposed in [12] with the result of our method. The points detected in [12] are sparsely distributed around the edges, but our method can accurately spot the points on these edges.

(a) (b)

FIGURE 3. The results of (a) Harris and (b) our method.

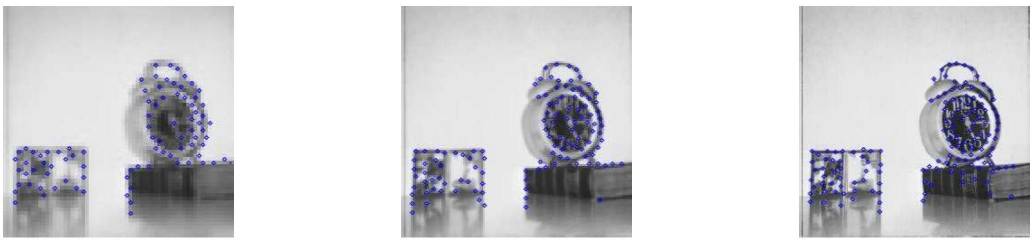
FIGURE 3 shows the result achieved by the Harris and the result of our method. The same number of points is detected. It can be seen that our method can detect some edge points that are not spot by the Harris detector, such as those on the edge of the man's left arm. Besides, we can see that the nodes detected by using degree centrality and those detected by using betweenness centrality are well complementary.

4.2. **Visual Evaluation of Scale Invariance.** In the second experiment, results on several test images in different resolutions are shown to evaluate the scale invariance our method visually. Images at lower resolutions are obtained by resizing the image at 256×256 using cubic interpolation. For an image at a spatial resolution of 64×64, we set $\sigma = 1$ and $D = 5$. These two parameters are multiplied by the scale factor for a image at different scales, and thus they become 2 and 10 for a 128×128 image and 4 and 20 for 256×256 respectively. The results of our method are shown in FIGURE 4 and FIGURE 5. From left to right, the resolution of the figure shown is 64×64, 128×128 and 256×256, and they are all resized to 256×256 for presentation. All interest points that detected by our method are marked as the same symbol of '$\circ$' for convenience.



(a) (b) (c)

FIGURE 4. Detection results of the test image PEPPERS at scale: (a) 64×64, (b) 128×128 and (c) 256×256.



(a) (b) (c)

FIGURE 5. Detection results of the test image CLOCK at scale: (a) 64×64, (b) 128×128 and (c) 256×256.

The results can show that the proposed method has very excellent performance under scale changes. For example, each of the two white regions in the upper-middle part of PEPPERS has exact two interest points in all of the three images in FIGURE 4 and the top part of CLOCK in FIGURE 5. Although these points may not be detected at the same position, they only have slight displacements in images at different scales.

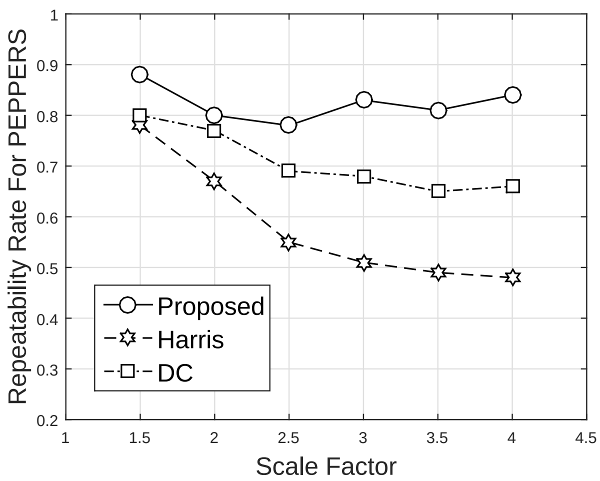
4.3. **Objective Evaluation of Scale Invariance.** In the last experiment, comparisons between the proposed method with the Harris detector [6] and the DC detector [12] are also presented for scale changes. To evaluate the scale invariance of the three approaches, we use the repeatability criterion introduced in [15]. The set of point pairs (x_1, x_i) which correspond with an ε-neighborhood is defined by:

$$R_i(\varepsilon) = \{(x_1, x_i)|dist(H_{1i} \cdot x_1, x_i) < \varepsilon\} \tag{1}$$

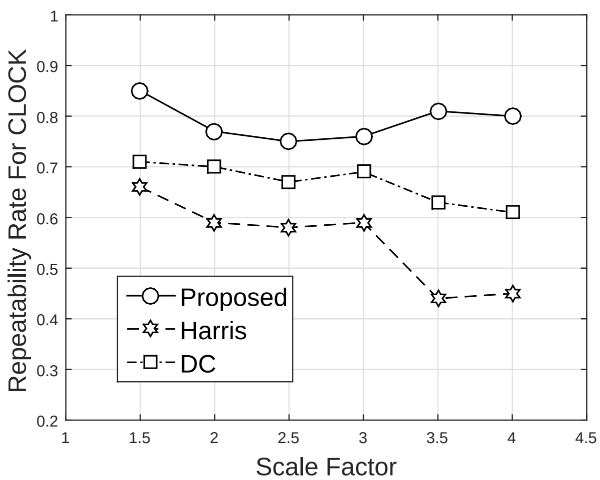
where x_1 is a point in image I_1 and x_i is its corresponding point in image I_i, I_i is the scaled version of I_1, and H_{1i} represents the projection from x_1 to x_i. The repeatability rate $r_i(\varepsilon)$ for image I_i is defined by:

$$r_i(\varepsilon) = |R_i|/\min(n_1, n_i) \tag{2}$$

where n_1 and n_i are the numbers of interest points detected in image I_1 and image I_i respectively. Since more interest points are detected on the high resolution image, only the minimum number of interest points can be repeated. Thus, we use the image at the resolution of 64×64 as the reference image when we calculate the repeatability rate.



(a)



(b)

FIGURE 6. Repeatability rates of the three detectors for different test images: (a) PEPPERS, (b) CLOCK.

FIGURE 6 shows the repeatability rates of the three detectors. The scale factor is determined by the square-root of the ratio of the numbers of pixels of the image being considered and the reference image. We use 1.5 as the value of ε. For the Harris detector [6], the value of k is 0.01, the size of the window for maximal suppression is 3×3, and we use the maximum of the response function multiplied by 0.01 as the threshold. For the DC detector, the parameters are the same as [12]. Evidently the Harris detector is very sensitive to scale changes, and its results are hardly usable. On the other hand, the repeatability rates of our method are mainly above 0.8, and are obviously higher than those of the DC detector.

5. **Conclusion.** In this Letter, a novel approach for interest point detection in digital images is proposed by using both node degree centrality and betweenness centrality of a network. The experiment shows results with high quality of proposed method. Also, this work presents a new use in computer vision based on the complex network analysis.

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