

## Interest Point Detection in Images by a Local Centrality Algorithm on Complex Networks

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**Abstract.** The field of Digital Image Processing offers an interesting framework for the application of the Complex Networks theory. Since images can be seen as organized data structures of adjacent pixels, it becomes natural to model and analyze them using complex network properties. We present a local centrality algorithm on a network with the aim detect the position and importance of interest points (i.e. corners) in a digital image. An spatial and weighted complex network is associated to the image and a new method for locating these feature points based on a local centrality measure of the corresponding network, is proposed.

*Keywords:* Interest Points, Image Analysis, Geometrical Networks, Local Centrality

### 1. Introduction

It is now well known that Feature Detection is an essential stage in many Image Analysis and Computer Vision systems [4]. Some of the most low-level features to be detected in an image are the specific positions of some distinguishable points like corners or edges that give very rich information about the nature of the image. These keypoints (usually, the corners which appear at the intersection of two or more image edges) present some interesting structural properties [9] such as:

- they have a clearly defined position in the image space,
- they are rich in terms of information content,
- they are also stable on local and global changes in the image domain.

In addition to this we must point out a crucial fact: these points (which are usually called *interest points*) are a set of pixels in an image which are characterized by a mathematically well-founded definition [8]. This deep property makes that interest points are commonly used as local features in many image applications like content-based image retrieval or object recognition. In particular, the corresponding feature points in overlapping images can be matched among them using stereo vision techniques for 3D image reconstruction. Moreover, these feature points can also be good indicators of object boundaries and occlusion events in image sequences.

Some of the most known interest point detectors are: Moravec algorithm, Harris and Stephens algorithm, multi-scale Harris operator, SUSAN detector, genetic-programming algorithms, and affine-adapted interest point operators, among others. [13] Moravec algorithm (1980) was one of the first proposed algorithms and it defines the corner strength of a point as the smallest sum of squared differences (SSD) between the point patch and its neighbors patches (horizontal, vertical and on the two diagonals). The Harris and Stephens detector computes the locally averaged moment matrix using the image gradients, and then combines the eigenvalues of the moment matrix to compute each corner “strength”. 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. The SUSAN operator (acronym for *Smallest Univalued Segment Assimilating Nucleus*) is highly robust to noise and it finds corners based on the fraction of pixels that are similar to the center pixel within a small circular region. Some authors [14] have introduced genetic programming (GP) methods to automatically synthesize image operators aimed to find the interest points in an image. These GP operators use fitness functions which measure the stability of the operators through the repeatability rate, and also promote the uniform dispersion of detected points. Finally, detector which add robustness to perspective transformations has also been proposed [9]. These affine invariant interest points can be obtained through an affine shape adaptation process where the shape of a smoothing kernel is iteratively warped to match the local image structure around the interest point. Schmid et al [10] have proposed different techniques to compare the interest point detectors.

The purpose of this work is to introduce a novel approach to computing the interest points of an image by using complex network analysis. We associate a weighted geometrical and fast-computable complex network to each image that gives some valuable information about the location of the interest points and we can rank the regions of an image according to its interest in the whole image. The use of complex networks with a spatial structure are usual in

several real-world applications [1], but this work presents a new use in the realms of Computer Vision. Since the classical mathematical definition of the interest points are mainly of local nature, we use local measures of the associated network and we discuss the use of other tools and properties of the weighted geometrical network.

## 2. Interest points: A complex networks approach

The recent developments in Computer Vision and Image Processing have been reached by the use of different results and techniques coming from a wide range of scientific areas, including partial differential equations [11], wavelets [12] or physic-based models [15]. One of these new multidisciplinary and emergent approaches deals with the use of techniques coming from complex network's analysis in problems related to Computer Vision [6] and that it is far from being well understood. The new fresh basic idea is to associate a complex network  $G = (X, E)$  to each image  $I$  in such a way that we can analyze some properties of  $I$  from the structural and dynamical properties of  $G$  (see, for example [6]). There are several alternative procedures to follow this idea and the use of each of them strongly depends on the specific Computer Vision problem considered. One of the first mathematical models related to this idea was introduced in [5]. If  $I$  is an gray-level image of  $N \times N$  pixels, we can associate to it a weighted network  $G = (X, E)$  of  $|X|=N^2$  nodes such that each node corresponds to each pixel of  $I$  and the weight of each link  $(i, j) \in E$  is:

$$w(i, j) = \|\vec{f}_i - \vec{f}_j\|_2,$$

where  $\|\cdot\|_2$  denotes the Euclidean norm and  $\vec{f}_i \in \mathbb{R}^m$  is a *feature vector* that describes some local *visual* properties about the respective image pixel [5]. The main disadvantages of this approach proposed in [5, 7] deal with the computational (time and space) complexity on such networks when the number of pixels is big, since the number of nodes of the associated network  $G$  is the same as that of the original image  $I$  and the weighted network is always a complete weighted graph, which implies inefficient computations (in time and memory).

In this work, we propose considering a complex spatial network  $G$  with less nodes and much less links (actually it is a sparse network) associated to each image  $I$  that gives a much better approach from a computational point of view. If we have an image  $I$  of  $N \times N$  pixels, such that for each of them  $p \in I$  we know its intensity value  $f(p) \in [0, K]$ , we first compute an *watershed-based segmentation*  $R = R(I) = \{r_1, \dots, r_k\}$  of  $I$  and we choose a set of pixels  $X(R) = \{p_1, \dots, p_k\} \subseteq I$  such that for every  $1 \leq j \leq k$ ,  $p_j \in r_j$ . By using

these pixels  $X(R) = \{p_1, \dots, p_k\}$  as nodes we construct a weighted, sparse and spatial network  $G(I) = (X(R), E)$  by defining each link weight  $w(p_i, p_j)$  as follows

$$w(p_i, p_j) = \begin{cases} |f(p_i) - f(p_j)| & \text{if } r_i \text{ and } r_j \text{ are adjacent regions in } R(I), \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

It is quite easy to check that the weighted associated network is, in general, sparse and its number of nodes  $k \ll N$ , which makes that the computations on such networks be much more efficient than those previously stated in the associated networks. Let us notice that the networks introduced in [5] or [7] can be also defined by using this model, simply by considering the appropriate *feature vector* describing some *visual* properties of each region  $r_j$ , by considering regions of only one pixel each.

Once we have associated a (weighted) complex network to each image, we want to analyze some visual properties of the image from the structural and dynamical properties of the corresponding network. More precisely, we will spot the interest points of an image  $I$  by using some structural properties of its associated network  $G(I)$ . The heuristics behind the proposed methods deal with the fact that the interest points are related to points with a high gradient values compared to their surrounding pixels. There several alternative classic algorithms for the detection of interest points (such as the the Harris and Stephens algorithms) and many of them are based on this idea, and therefore we should try to translate them into structural properties of the associated network. Under the perspective of discrete mathematics, having in mind that the associated network  $G(I)$  is a weighted network related to the difference of intensity between adjacent regions of the image, then points with high intensity gradient are related to points of high centrality in the associated network. Hence, we can spot the interest points of an image by computing the centrality of the corresponding nodes in the associated network.

There are many different centrality measures of the nodes of a network (see, for example [1]), each one of different nature and with different applications, but since the interest points are clearly of local nature we consider local centrality measures. Actually we will show that the interest points are related to nodes with high strength centrality. Let us remind that the *strength* of a node  $i \in X$  in a network  $G = (X, E)$  is the value

$$s(i) = \sum_{(i,j) \in E} w(i, j),$$

where  $w(i, j)$  is the weight of the link  $(i, j) \in E$ . After some normalization, this value allow us to rank the nodes of the network by a local criterium that helps to locate the interest points.

Fig. 1 compares the results on the usual "House" test image produced by our algorithm (right) when it is compared to the Harris and Stephens' interest point detection method (left). This image is in gray-levels with a  $256 \times 256$  spatial resolution. The results have been obtained by producing the same number of interest points (466) for both algorithms. In the case of Harris and Stephens' algorithm all the points (in red) appear more concentrated on the strongest edge regions of the image. For our algorithm, these points are ranked and colored into three categories according to their respective importance (red=high, blue=medium and green=low). Moreover, the points obtained by our algorithm are also located on the same regions that in the other algorithm but are also more sparsely distributed around the edge regions.

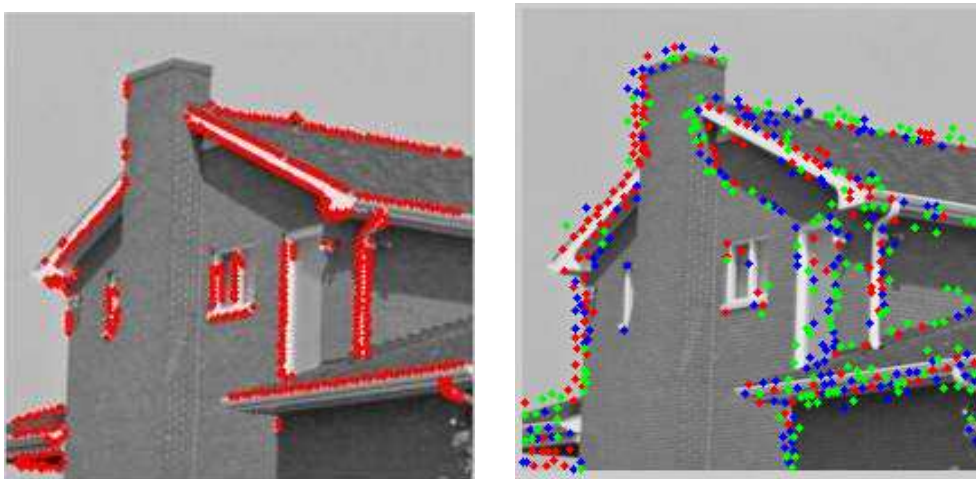


Figure 1: Visual comparison of the classic Harris interest point detector (on the left) with the new interest point detector obtained by using the centrality (on the right).

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