

Complex Networks: New Concepts and Tools for Real-Time Imaging and Vision

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This article discusses how concepts and methods of complex networks can be applied to real-time imaging and computer vision. After a brief introduction of complex networks basic concepts, their use as means to represent and characterize images, as well as for modeling visual saliency, are briefly described. The possibility to apply complex networks in order to model and simulate the performance of parallel and distributed computing systems for performance of visual methods is also proposed.

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I. INTRODUCTION

To a large extent, scientific advances have been constrained by the increasing complexity of the data and dynamics under analysis. Having initially tamed the simplest systems by using linear systems or linear approximations (and as a consequence missing the most interesting dynamics), science and engineering progressed inexorably towards the so-called *complex systems* and structures. Driven by challenging applications in areas such as biology and neurosciences, the developments in image processing and computer vision have been no exception to this rule. Along the last decades, not only has the availability of high resolution images increased substantially, but the problems under analysis have also become more and more intricate as implied by the underlying non-linear dynamics and spatial complexity. For instance, advances in biotechnology and image acquisition have allowed the capture of 4D images (3D plus time) identifying gene expression in presence of anatomical structures (e.g. [1]). High complexity visual data has also been continuously produced as results of simulations. While the capture and storage of such data implies their own technological demands, the concepts and methodologies required for the analysis and modeling of such results impose major challenges not only on the theoretical side, but also on developing computational resources capable to cope with the complexity of both data and algorithms. The latter is particularly critical because of the recent slow down of Moore's law. In this text we briefly overview how the area of *Complex Networks*, by incorporating many flexible and powerful concepts and tools, can provide the means for significant advances in real-time imaging science and technology.

II. COMPLEX NETWORKS

Complex networks and graph theory are closely intertwined areas. However, while the latter concentrates on combinatorics and mathematical theoretical formal-

ism, the former emphasizes dynamics, statistics, statistical physics, and applications. Yet, the eventual differences between these two areas should be considered for their potential to complement one another, and not as a divisive barrier. While random networks have been around for a long time (e.g. [2]), their applicability has been constrained by the fact that few structures and phenomena in nature seem to follow uniformly random organization [23]. It was mainly through the studies of small world properties of social networks (e.g. [3]), jointly with the more recent characterization of *power law* (or *scale free*) networks (e.g. [4]), that the area of complex networks gained momentum to become one of the most exciting modern fields of research. The success of complex networks stems from several factors, especially: (i) the generality of networks (and graphs) to model virtually any discrete structure; (ii) the fact that natural structures often present small world or scale free connectivity; and (iii) the possibility to relate the network topology and dynamics. Although relatively young, the applications of complex networks already extend from genetics to scientific citations. Complex networks have been reviewed in comprehensive surveys (e.g. [4, 5, 6, 7]) and books (e.g. [3, 8, 9]).

Of particular interest to imaging and vision are the special category of networks known by the name of *spatial* or *geographical*. Such networks are characterized by the fact that each constituent node has a specific, well-defined position within an embedding space. Examples of spatial networks include highways, air routes between airports, power distribution systems, among many others. Network representation of images are inherently spatial, as the position of pixels, regions or objects associated to the networks will have well-defined coordinates. A particularly interesting possibility is to consider spatial networks where the positions of the nodes vary along time, as is the case with mobile communications or video. In addition to their connectivity, spatial networks are also characterized by the spatial distribution of the nodes along space. Because of the adjacency imposed by the most immediate neighbors, spatial networks tend not to exhibit the small world property, unless long range connections are incor-

porated. At the same time, the strength of the interconnection between pairs of nodes usually tend to decrease with the distance between those points. A particularly interesting concept for analysis of the spatial structure of such networks is the Voronoi diagram (e.g. [10]).

III. COMPLEX NETWORKS FOR IMAGE REPRESENTATION

Image analysis and recognition involve the integration of information and clues from local properties of the pixels (e.g. gray-level, color) to neighborhoods, objects and scenes (e.g. [11]). In other words, the integration of the visual information takes place along several scales of space and time, from micro to macro, and vice-versa (e.g. [12]). While many shape and image analysis methods have relied on the use of pixels as basic elements (e.g. [11]), the representation of an image as a complex network allows the short, medium and long range relationships between pixels as objects to be explicitly represented and taken into account. Therefore, it would be interesting to conceive algorithms taking into account not only the raw image, but also its enhanced representation as a complex network.

There are several possibilities for transforming an image into a complex network. In this article we restrict our attention to the two following methodologies. In the first, each pixel is associated to a node, while edges are defined in terms of the similarities between the local properties of pixels [13, 14]. For instance, it is possible to associate every pair of pixels through an edge whose weight is inversely proportional to the difference between the respective gray-levels. Other local features such as gradient magnitude and orientation, local dispersion, and color, can also be considered for defining the similarities and weights. In order to simplify the otherwise densely networks obtained by such a methodology, it is often useful to establish a threshold for connections (i.e. only the most similar pixels are connected) and to consider for connections only those pixels lying within a fixed distance from the reference node (e.g. [15, 16]). The second methodology for converting an image into a graph involves the determination of tangent (or normal) fields along the image contours and interconnecting all pixels falling under the straight lines determined by such fields [17] (more detail in Section V).

IV. COMPLEX NETWORKS FOR IMAGE CHARACTERIZATION AND ANALYSIS

Once an image is represented as a complex network, it becomes possible to devise more comprehensive algorithms for its characterization and analysis which rely not only on local properties (i.e. pixels and respective neighborhoods), but also on medium to long range relationships. For instance, the node degree [24], as well as

many other measurements associated to individual nodes (e.g. clustering coefficient [4] and hierarchical measurements [18, 19, 20]) can be used as subsidy for identification of textures [13, 16] and even objects. Another example of a typical image analysis situation where complex networks presents promising performance is *image segmentation*, i.e. the task of identifying the parts of the image corresponding to the existing objects in the image. Of particular interest is the application of *community finding* algorithms. Loosely speaking, a *community* (e.g. [21]) is a portion of the network (a subnetwork) whose nodes are more intensely related one another than with the rest of the network. The problem of identifying communities in networks is challenging and closely related to problems in pattern recognition [11], sharing methodologies and limitations. Such algorithms can be applied to images represented as networks so that each community will, in principle, correspond to a segmented region [14]. Because the network representation typically supplies more information than just the pixels and their immediate neighborhood, it is expected that such algorithms may lead to enhanced performance when compared to traditional image segmentation methodologies.

V. COMPLEX NETWORKS FOR VISUAL SALIENCY DETECTION

In this section we illustrate the possibility of integrating the topological and dynamical properties of an image represented as a complex network [17]. First, the image is transformed into a complex network by representing the edge elements in the images as nodes and defining the network links as follows. For each high contrast pixels p (i.e. an edge) of the image, its orientation α (e.g. direction of the gradient at p) is estimated and used to define a straight line L throughout the image which passes through p and has orientation α . All other edge elements of the image which fall under the line L are connected bidirectionally to p . Now, a random walk is performed on the obtained network which proceeds as follows: being currently at node p , the next movement is determined at random between the edges emanating from p . The steady state solution of such a dynamics can be conveniently obtained in terms of the eigenvector equation $\vec{q} = W\vec{q}$, where W is the stochastic matrix associated to the Markov chain driven by the random walk and \vec{q} is the state occupancy at equilibrium. It has been shown [17] that the nodes with highest values of occupancy ratio tend to correspond to points of high saliency in the image. Actually, such a basic framework can be immediately extended to treat other situations in saliency detection such as those involving elementary, pre-defined, saliency indices associated to each object or point [17]. This example also illustrates how complex networks can be defined with nodes associated not to pixels, but to pre-defined regions or objects at larger spatial scales.

VI. COMPLEX NETWORKS FOR MODELING AND QUANTIFICATION OF PERFORMANCE

Another area where complex networks can provide valuable help for those working on real-time image processing and analysis concerns the characterization, modeling and simulation of the performance of real-time distributed systems. Distributed systems can be immediately mapped as complex networks – each processor as a node, with respective interconnections – and the effect of different interconnections models (e.g. random, small world, scale free, regular lattices) over the respective performance quantified through simulations. Such a possibility has been preliminary addressed regarding the performance of *grid* computing systems [22], where the performance while distributing computer tasks was quantified in terms of speed-up measurements. We are currently applying a similar methodology for investigating the performance of distributed systems interconnected through different network models while processing a stream of real-time video frames.

VII. CONCLUDING REMARKS

This article has overviewed the perspectives of the new area of complex networks for coping with the demands being imposed onto imaging and real-time processing as a consequence of ever increasing complex data and algorithms. It has been argued that, because of their generality for representation of discrete structures and emphasis on statistics and dynamics, complex networks can greatly contribute to advances in areas including image characterization and segmentation as well as the analysis of performance of real-time parallel and distributed systems. Illustrations of the potential of such a methodology have been provided with respect to several typical problems in real-time image processing and analysis, including image segmentation, texture characterization, saliency detection at varying spatial scales, and quantification and modeling of distributed systems for video processing. Because of the incipency of such applications, there is plenty of room for related developments and investigations.

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- [1] J. Huisken, J. Swoger, F. del Bene, J. Wittbrodt, and E. K. Stelzer, *Science* **305**, 1007 (2004).
 - [2] B. Bollobás, *Random Graphs* (Cambridge University Press, 2004).
 - [3] D. J. Watts, *Small worlds: The Dynamics of Networks between Order and Randomness* (Princeton University Press, 2003).
 - [4] R. Albert and A. L. Barabási, *Rev. Mod. Phys.* **74**, 47 (2002).
 - [5] M. E. J. Newman, *SIAM Review* **45**, 167 (2003), cond-mat/0303516.
 - [6] S. Boccaletti, V. Latora, Y. Moreno, M. Chavez, and D.-U. Hwang, *Physics Reports* (2006), accepted.
 - [7] L. da F. Costa, F. A. Rodrigues, G. Travieso, and P. V. Boas, cond-mat/0505185 (2005).
 - [8] A.-L. Barabási, *Linked* (Plume, 2003).
 - [9] S. N. Dorogovtsev and J. F. F. Mendes, *Evolution of Networks* (Oxford University Press, 2004).
 - [10] L. da F. Costa, *Physical Review E* **73**, 011913 (2006).
 - [11] L. da F. Costa and R. M. C. Jr., *Shape Analysis and Classification: Theory and Practice* (CRC Press, 2001).
 - [12] M. J. Tové, *An Introduction to the Visual System* (Cambridge University Press, 1996).
 - [13] L. da F. Costa, cond-mat/0403346 (2004).
 - [14] L. da F. Costa, cond-mat/0405022 (2004).
 - [15] L. Diambra and L. da F. Costa, *Bioinformatics* **21**, 3846 (2006).
 - [16] T. Chalumeau, L. da F. Costa, O. Laligant, and F. Meriaudeau, in *Machine Vision Applications in Industrial Inspection XIV* (SPIE, San Jose, USA, 2006).
 - [17] L. da F. Costa, physics/0603025 (2006).
 - [18] L. da F. Costa, *Physical Review Letters* **93**, 098702 (2004).
 - [19] L. da F. Costa and F. N. Silva, cond-mat/0412761 (2005).
 - [20] L. da F. Costa and L. E. C. da Rocha, *European Physical Journal B* (2004), accepted (also cond-mat/0408076).
 - [21] M. E. J. Newman, physics/0602124 (2006).
 - [22] L. da F. Costa, G. Travieso, and C. A. Ruggiero, *European Physical Journal B* **44**, 119 (2005), cond-mat/0312603.
 - [23] In a random network, the probability of connection between any pair of nodes is constant.
 - [24] The degree of a network node is equal to the number of edges connected to that node.