Identification and Mapping of Vehicle Robbery and Theft in Rio de Janeiro

Douglas Ferreira[1,2], Jennifer Ribeiro[2,3], Renato Freitas[2], André Pimenta[2], Valter Felix[2], and José Mendes[1]

[1] *Department of Physics, University of Aveiro, Aveiro, Portugal*
[2] *LISComp – Laboratory, Federal Institute of Rio de Janeiro, Paracambi, RJ, Brazil*
[3] *Department of Geophysics, National Observatory, Rio de Janeiro, RJ, Brazil*

Keywords: Complex networks; Crime; Rio de Janeiro, Nonextensive statistical mechanics

Among the various problems in human society, crime is one of the most worrying and harmful since it strongly interferes with the sustainable development of society. In a highly tragic way, Rio de Janeiro (Brazil) has alarming rates of crime and violence, of all possible types, from petty offenses to the most tragic cases of robberies and murders.

Empirical evidence shows that crime has a remarkable regularity of concentration in several dimensions that relate to the context (target, location, offender, etc.) and characteristics (spatial, temporal, type of crime, etc.) [1]. Thus, in the present work, the characterization of activities of robberies and theft of vehicles that occurred in the city of Rio de Janeiro was carried out to develop methods and models to evaluate spatial concentrations of crimes that collaborate in the search for existing patterns among the criminal activities that occurred.

Given the successful application of statistical physics methods in modeling and describing various social systems (such as interactions between individuals [2], epidemic propagation [3], and human cooperation [4]), in this work, we analyzed the behavior of crime from the point of the theory of complex networks, analyzing the spatial and temporal dynamics of crimes. It is worth mentioning that in complex systems, individual interactions between the system elements produce global behaviors that cannot be inferred only by individual analyses. It happens since the relationships between the system components create non-linear complex behaviors, which in many cases translate into long-range spatial and temporal interactions. Such methods have already proven effective in crime studies for certain political or geographical contexts [6,7]. In this way, we use complex network techniques for mining and analyzing criminal data, helping to understand important issues related to the "criminal phenomenon" and contributing to a clearer and broader view of the behavior of criminal activities and how they are related and/or evolve.

The data used in the present work have information on the neighborhood, the date, and the time when each crime occurred. Those data were provided by the Rio de Janeiro Public Security Institute (ISP-RJ). The types of crimes analyzed were classified as "vehicle theft" (VT) and "vehicle robbery" (VR). The data provided have information from 2010 to 2015, with 42,365 vehicle thefts and 69,330 vehicle robberies.

For the construction of crime networks, we will consider that each neighborhood in Rio de Janeiro will become a vertex of the network if it has at least one occurrence of the considered type of crime in the range from 2010 to 2015. The connections between the vertices will be carried out according to the following method. A time window of size W is defined and inserted in the chronologically organized data to connect all the vertices inside this window. The time window is inserted starting from the first vertex, causing this vertex to be connected to all vertices that are inside this window. After that, the window is moved forward, starting at the next occurrence. This second occurrence is then connected to all subsequent events that fall within the time window, after which the window is again moved forward to the next occurrence of the considered crime. This binding process is repeated until moving the window forward is no longer possible. This network construction model works as a temporal filter for the connections between vertices, allowing vertices that are close in time to be connected, regardless of whether they are immediately subsequent or not. Likewise, this model prevents the connection of vertices that are very distant in time and thus have a low probability of being correlated.

A fundamental step in creating the time window network is to define an "ideal value" for the window size, W, since, *a priori*, there is no preferred or pre-defined value. Thus, it is necessary to develop a methodology capable of finding the best value for W. To obtain this value, we use the concept of *community* and apply it directly to the data time series. We vary the time window value for each type of crime and observe that the number of communities reaches a maximum value for a specific time window value (Fig.1). This specific time window value was the one considered for constructing the networks for VT and VR occurrences.

Considering the network as *weighted*, where the weight of each link is the number of times a given link is repeated, in Fig. 2 we have the distribution of strengths for the VT and VR networks. The results present the characteristic of the behavior described by the non-extensive statistical mechanics [8], characterized by the emergence of probability distributions in q-exponential functions,

$$P(\geq s) = -e_q(\beta s) = [1-\beta(1-q)s]^{1/(1-q)}, \quad (1)$$

where s is the strength value of each vertex and β is the positive constant for each network.

Fig.3 shows how are distributed the connections between the vertices of the networks for both VT and VR crimes. In the network maps, the vertices have the geographic locations of each neighborhood, and only the edges with a strength greater than 50 are represented. It means that the edges shown on the map only refer to crimes that occurred at least 50 times between one neighborhood and another and within a time interval equal to or less than the time window, W.

The networks were also organized to allow groupings of neighborhoods by their respective regions. It was done to provide another perspective for visualizing the connections between neighborhoods. The results are shown in Fig.4, where only the 40 neighborhoods with the highest number of occurrences are highlighted.

Our results indicate that theft and robbery of vehicles have strong spatiotemporal correlations, meaning that each occurrence cannot be evaluated and analyzed as an isolated event. Furthermore, our study gives a first step to correlating criminal activities in different areas of Rio de Janeiro.

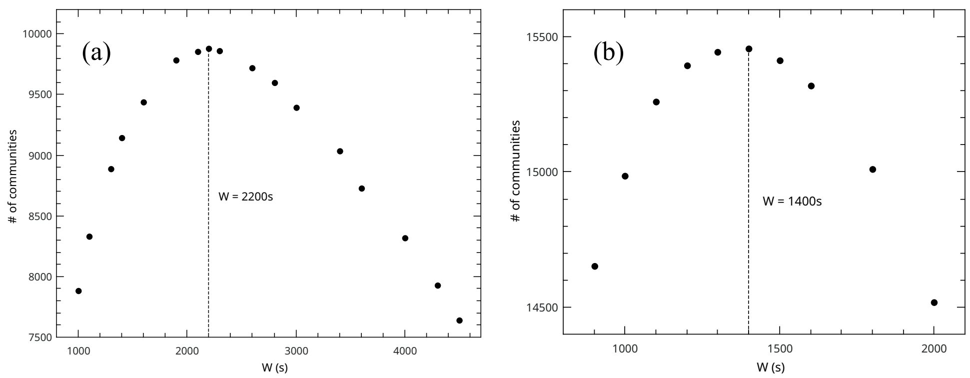

Fig.1- Number of communities for each time window value, W, for vehicle (a) theft and (b) robbery.

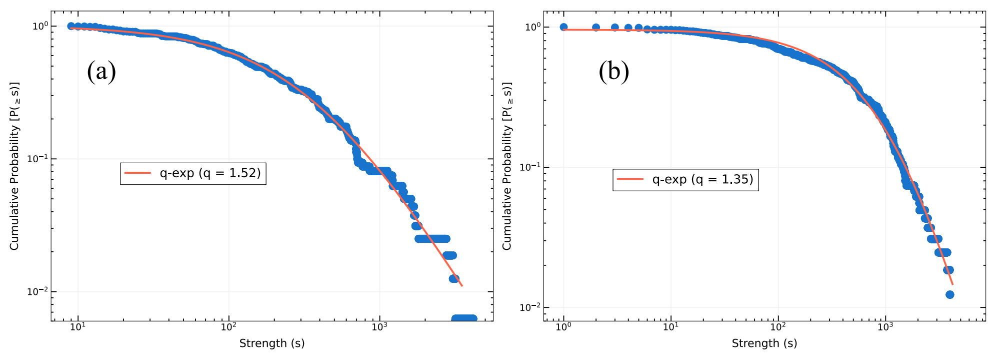

Fig.2- Distributions of strengths for vehicle (a) theft and (b) robbery networks. The solid lines correspond to adjustments according to equation (1) of the text.

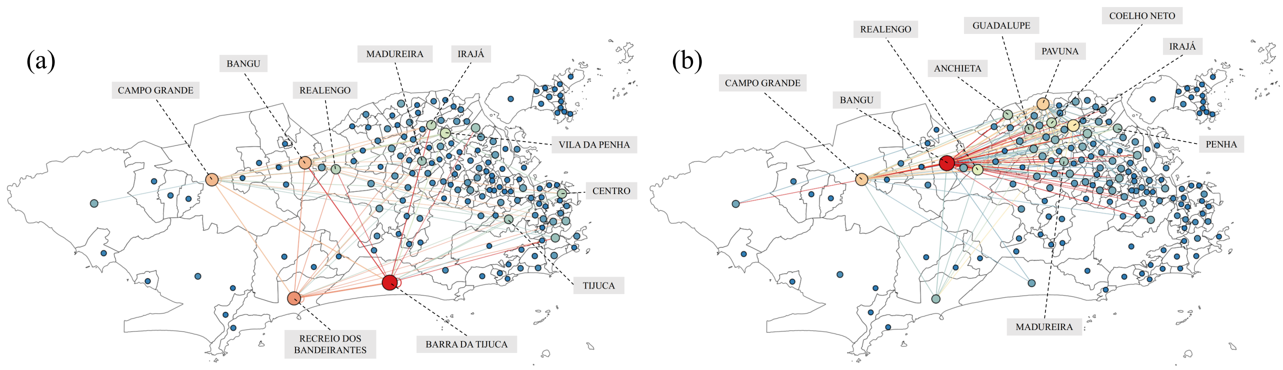

Fig.3- Network map for vehicle (a) theft and (b) robbery, from 2010 to 2015, where each edge has $s \geq 50$. The figure highlights the 10 neighborhoods with the highest *strength* value.

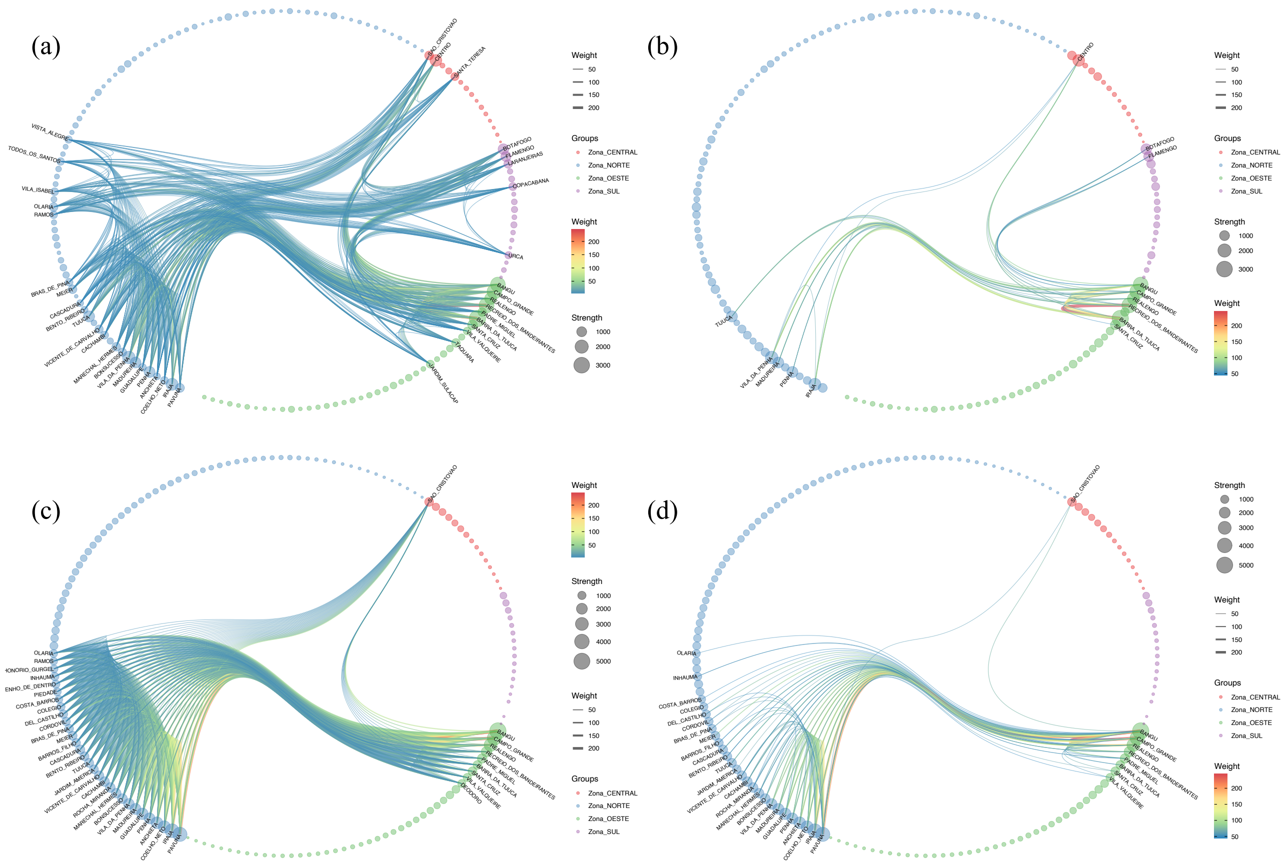

Fig.4- Networks divided by zones. The minimum weight values and vehicle type of crimes considered were: (a) 0, theft; (b) 50, theft; (c) 0, robbery; (d) 50, robbery.

References

[1] G. Farrell. *Crime Prevention & Community Safety*, vol.17, n.4, (2015) 233–248.
[2] C. Castellano, S. Fortunato, V. Loreto, Rev. *Modern Phys*. 81 (2009) 591.
[3] R. Pastor-Satorras *et al.*, *Rev. Modern Phys*. 87 (2015) 925.
[4] M. Perc *et al., Phys. Rep*. 687 (2017) 1–51.
[5] G. Spadon *et al.*, *Inf. Technol. Gener. - Springer*, (2018) 493–500.
[7] F. Calderoni, D. Brunetto, C. Piccardi, *Soc. Networks*. 48 (2017) 116–125.
[8] D. A. Bright *et al., J. Contemp. Crim. Justice*. 31 (2015) 262–278.
[9] C. Tsallis, *Journal of statistical physics*. 52.1 (1988) 479-487.