INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

Cohesion index for investigate criminal organizations in criminal big databases

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OPEN ACCESS

Received: 10-11-2020

Accepted: 23-03-2022

Published: 02.05.2022

Citation: Fredy HTE (2022) Cohesion index for investigate criminal organizations in criminal big databases. Indian Journal of Science and Technology 15(16): 750-759. https://doi.org/10.17485/IJST/v15i16.2042

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Funding: financial support of the FONDEF project ID20I10230ANID, Universidad del Bío-Bío by the Initiation Research Project 2060204 IF/I and Macro Facultad de Ingeniería Project ING 2030 I+D 20-34

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Abstract

Background: The disarticulation of criminal organizations reduces the rates of victimization and insecurity in the population. One of the main characteristics of a criminal organization is the cohesion among its members. This investigation proposes a cohesion index that allows identifying quickly in Big databases individuals suspect to belong to criminal organizations and focus investigation resources on them. **Methods:** To obtain the index, we analyze the information provided by the Criminal Analysis and Investigative Focus System from the Regional Public Prosecutor's Office in Biobío and the Investigation Police of Chile. **Findings:** The results show that the suspects with a higher cohesion index and a higher number of criminal cases commit crimes associated with criminal organizations.

Keywords: Criminal Cohesion; Crimes Against Property; Criminal Organization; Criminal Databases

1 Introduction

In 2004, the United Nations Office for Drug Control and Crime Prevention [1], defined an Organized Crime Group as a structured group of three or more people that exists for a certain time and that acts in concert to commit one or more serious crimes or offenses established by the present Convention to obtain, directly or indirectly, an economic or other material benefits.

The definitions of criminal organization, organized crime, and criminal gangs have been debated in different countries [2–4]. In general, it is possible to characterize a criminal organization using the following characteristics [5]:

- Group of subjects of two or more people
- Permanent criminal activity over time
- Serious crimes (social order, good customs, property or people)
- It has a hierarchical structure
- Strong internal cohesion
- It is articulated hierarchically and specializes

Within these characteristics, the level of cohesion and hierarchical articulation are elements hard to identify. Cohesion gives a sense of union, solidarity, and solidity within the organization. For example, an objective of gangs is to maintain a sense of camaraderie, belonging, and family [6]. Cohesion is increased by the frequency, intensity, and duration of the inter-activities in the criminal organization [7]. However, a low

cohesion does not imply that an individual is not part of a criminal organization [8].

In general, a group is cohesive if, on average, its members have stronger relationships with members of the same group than with individuals outside the group. Under a network approach, the cohesion of a criminal group is the average bond strength within the group divided by the average bond strength with the external ones [9].

The aim of this research is to propose an index to measure the cohesion of a suspect to a criminal group. This index lead to agilely identifying suspected of belonging to a cohesive criminal organization within criminal big databases.

The following section shows a review corresponding to criminal organizations to characterize them in terms of crime preference, specialization, and organization size. Then the structure of the criminal database and the methodology for obtaining the crime cohesion index is described. Finally, it is concluded and discussed the result of applying the proposed cohesion index in two criminal databases.

2 Use of data in the investigation of Criminal Organizations

The constant increase in crimes committed by criminal organizations and their evolution have encouraged their investigation for years [10,11]. The current availability of criminal datasets has allowed its investigation through statistical and data mining techniques [12,13]. Using data mining techniques has been possible to identify members of criminal organizations and take a criminal investigation on them [14–16].

In this context, a social network approach is a technique that allows identifying associations between individuals, key individuals, or individuals with important roles within criminal organizations [17,18]. In the same line, Sarvari et al. [19] built graph structures from criminals' e-mails to analyze criminal organizations' structure. Other techniques such as text mining have allowed them to investigate the use of words to help identify gang members on Twitter and then use machine learning to determine an individual's membership in a gang [20]. The phone calls logs have been used to identify the internal structure of criminal organizations, allowing to obtain the hierarchies, links, activities, and members with a key role within the criminal organization [21–23].

Salinero [24] determined the membership of associative entities in drug crimes to characterize the profiles of these types of criminals by a survey. The results show that of the total surveyed, 35% belong to a criminal organization, and of this percentage, 87% indicated only dedicating themselves to the drug business. Benson & Decker [25] also focused their research on prisoner surveys to study the organizational structure of international drug trafficking. Subjects described a general lack of formal structure and described drug trafficking operations as composed of isolated working groups without connections with others.

Giménez et al. [26] studied Spanish members of criminal organizations. This study identifies the distribution of illicit markets developed by criminal organizations, where in the first place were robberies with force with 25%, drug trafficking with 18%, and receiving stolen goods with 8%. Drug offenses, property crimes, and violent crimes are related to criminal organizations [27–29]. Regarding the specialization of crimes, criminal organizations develop more than one illicit activity [30] necessary to carry out the main activity [31]. Using criminal databases [28] found that 76.5% of crimes committed involve two criminals, 16.2% involve three criminals, and approximately 7.3% involve four or more criminals.

This description of criminal organizations in terms of crime preferences and specialization and the size of the criminal organization will serve to validate the results of the criminal cohesion index application.

3 Database description and proposed a Criminal Cohesion Index

Criminal database always contains the following relevant information:

- The crime describing the type of crime, the date of occurrence, and place.
- The individuals that describe victims, suspects, and witnesses.
- The activities that describe the actions associated with the crime investigation.

The criminal investigation process uses the information registered in a criminal database. In a criminal database, the relationship among crimes and individuals represents a Criminal Cause shown in Figure 1.

In a criminal database, a Criminal Cause is represented an identified by means a cause code and is unique. The victims and suspects are also identified by a unique identifier. In this investigation, criminal analysis is carried out with a focus on suspects and the form of the database used is shown in Table 1.

As mentioned previously, measuring the criminal cohesion of a suspect to a group implies obtaining one of the key characteristics for the analysis of criminal organizations. The proposed Criminal Cohesion Index, that called CCIndex, measures the degree of union or relationship that an individual has with the other individuals with whom he participates in the commission of crimes.

Fig 1. Relationship among crimes and individuals in a criminal database

Table 1. Attributes of the original database

Attribute	Description
Suspect Code	Corresponds to the unique identifier for each offender that has committed a crime.
Offence	Corresponds to the name of the crime committed by the offender.
Cause Code	The unique criminal case code assigned to Criminal Cause
Date	The date on which the crime was committed.

The CCIndex is defined by Equation 1:

$$CCIndex\ i = \frac{\sum_j N_{ij}/N_i}{Nd_i} \quad (1)$$

Where:

i represents a suspect within a criminal database with n suspects

j represents a cause within a criminal database with m causes

N_{ij} represents the number of suspects involved with suspect i in the cause j.

N_i represents the number of causes associated with suspect i.

Nd_i represents the total number of different suspects with whom the suspect i has participated in the causes associated with him. This value allows estimating the minimum size of the criminal organization to which the individual i belongs.

In CCIndex, the expression $\sum_j N_{ij}/N_i$ represents the average number of suspects with whom suspect i participates in the different causes in which he is involved. If this value is equal to Nd_i, it implies that i has participated in all the crimes registered in the database with the same individuals. Thus:

- If CCIndex i = 0, Suspect i acts alone.
- If CCIndex i = 1, Suspects i always act with the same individuals.
- If 0 < CCIndex i <1, Degree of cohesion of the Suspect i to the same group of suspects.

Table 2 showed a toy Criminal Database.Table 3 shown to obtain the CCIndex to the toy Criminal Database.

Table 2. Toy criminal database

Suspect Code	Cause Code
A	1
A	2
A	4
B	1
B	2
C	1
D	4
E	3

Table 3. Obtaining the CC Index

Suspect Code	N_i	$\sum_j N_{ij}$	$\sum_j N_{ij}/N_i$	Nd_i	$CCIndex$
A	3	2+1+1=4	4/3= 1,33	3	1,33/3=0,443
B	2	2+1=3	3/2= 1,5	2	1,5/2=0,75
C	1	2=2	2/1= 2	2	2/2=1
D	1	1=1	1/1= 1	1	1/1=1
E	1	0=0	0/1= 0	0	Undefined

Table 3 shows that the suspect E has a CCIndex undefined. This individual has only one Cause Code and commits the crimes alone. All individuals with only one Cause Code and commits the crimes associates with this Cause Code alone must be dropped from the analysis reducing this form the number of suspects to analyze. Criminal organizations consider a set of two or more individuals.

Table 2 shows the suspect C and D with only one Cause Code. For this reason, presents CCIndex equal to 1 in Table 3. The number of Cause Code within the database (N_i) represents the level of activity of a suspect over time. Active members of a criminal organization must show a permanent level of activity. Individuals with only one Cause Code do not show a permanent level and can be excluded from the analysis.

The joint analysis of the CCIndex and the number of causes associated with a suspect allows identifying the suspects with the most probability of belonging to a criminal organization. These suspects are those with a higher CCIndex and a higher number of associated causes in the database. In Table 3 these are individuals A and B.

Two additional measures to support the analysis of criminal groups in the databases are proposed. The first measure is the average number of suspects in the criminal cause associated with a crime of type k call $N_{prom\,k}$ and is obtained by Equation 2.

$$N_{prom\,k} = 1 + (\sum_{ij} N_{ijk}/N_{ik})/N_k \tag{2}$$

Where N_{ijk} represents the number of suspects involved with suspect i in the cause j for a crime of type k. N_{ik} represents the number of causes associated with suspect i for a crime of type k. N_k represents the total number of individuals who commit crime k and value 1 represents individual i.

This measure gives us an idea of how many suspects are participating on average in a crime of type k. If this value is greater or equal than 2, the crime type k must be analyzed as a type of crime commit by a Criminal Organization.

The second measure is the average number of different individuals with which a suspect commits crimes of type k called $N_{dif\,k}$ and is obtained by Equation 3.

$$N_{dif\,k} = 1 + \sum_i Nd_{ik}/N_k \tag{3}$$

N_{dik} represents the total number of different suspects with whom the suspect i has participated in the causes associated with him for a crime of type k. N_k represents the total number of individuals who commit crime k and value 1 represents individual i.

This measure allows establishing an estimate of the average size of an organization that commits a crime of type k within the database.

Assuming that the values obtained in Table 3 are for a type of crime k, the value of $N_{prom\,k}$ is 1+ (1.33 + 1.5 + 2 + 1 + 0) / 5 = 2.16 individuals and the value of $N_{dif\,k}$ is 1+ (3 + 2 + 2 + 1 + 0) / 5 = 2.6 individuals.

4 Application of the criminal cohesion index

Two databases are considered to demonstrate the applicability of the CCIndex. The first database was provided by the Criminal Analysis and Investigative Focus System (CAIFS) from The Public Prosecutor's Office of Región del Biobío, Chile. This database corresponds to 12.223 crimes and includes crimes against property and other violent crimes. The second database was provided by the Investigative Police of Chile. This database contains all crimes registered in Santiago of Chile between 2009 and 2011, corresponding to 273,000 crimes. To process the databases and obtain the $N_{prom\,k}$, $N_{dif\,k}$, an algorithm programmed in Python 3 was used. Table 4 shows the CC Index and the number of causes for some suspects of the database.

4.1 Case: The Public Prosecutor's Office of Región del Biobío – Chile Database

In this case, the types of crimes analyzed are crimes against property such as robbery, burglary, and theft. These types of crimes are most affect the tranquility and integrity of society in Chile. After processing the database, are obtained 351 suspects and

their respective CCIndex. Table 4 shows the CC Index and the number of causes for a sample of suspects of the database.

Table 4. Obtaining the CC Index

Suspect Code	CCIndex	N_i (Number of causes)
62	1	2
229	0.667	3
19220	0.667	2
299	0.5	2
359	0.5	10
402	0.5	4

In Table 4, the suspects 299 and 359 have the same CCIndex. However, suspect 299 has two causes and suspect 359 has 10 causes. Suspect 359 is more suspect of belonging to a criminal organization than suspect 359. It is necessary to consider that a high CCIndex could be due to a low number of causes associates. For this reason, is necessary to use the CCIndex together with the number of causes associated. To consider the CCIndex together with the number of cases is used the Jack-Knife diagram. The Jack-Knife diagram is a prioritization technique based on logarithmic dispersion methods. This diagram is made up of quadrants and is mainly used for the analysis of equipment failure[32,33]. In this case, the Jack-Knife diagram allows to identifying in graphic form, the suspects with a high CCIndex and a high number of causes (N_i). For this diagram, the CCIndex and N_i were transformed by applying the natural logarithm (Ln). Then, the quadrants of the diagram were established by the average Ln(CCIndex) and the average Ln(N_i). The average Ln (CCIndex) was 2.123 and the average Ln(N_i) was 1.067. The results are shown in Figure 2.

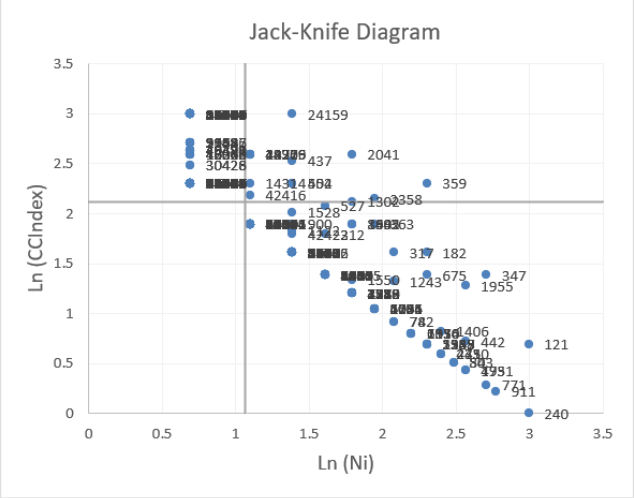

Fig 2. Jack-Knife Diagram of Public Prosecutor's Office Case

In Figure 2, the lower right rectangle indicates that suspects have grate number of causes but usually act with different suspects. The lower left rectangle shows the suspects with a low number of causes and a low CCIndex. The upper left rectangle shows the suspects with a low number of causes and those who act frequently with the same suspects. In this rectangle, a high CCIndex can be influenced by a low number of associated causes. The upper right rectangle shows the 15 suspects with the highest number of associated causes and the highest CCIndex. These suspects have the most probability of belonging to a criminal organization.

4.1.1 Crime preference and specialization

Figure 3 shows that the suspects analyzed prefer robbery with 42.3% of the crimes committed. Then burglary with 30.7 % and the remainder theft with 27%.

Regarding the specialization, Figure 4 shows 13 suspects specialized in one type of crime. Five suspects commit robbery, six commit burglary, and two commit theft. The type of crime more committed by the 15 suspects are robbery.

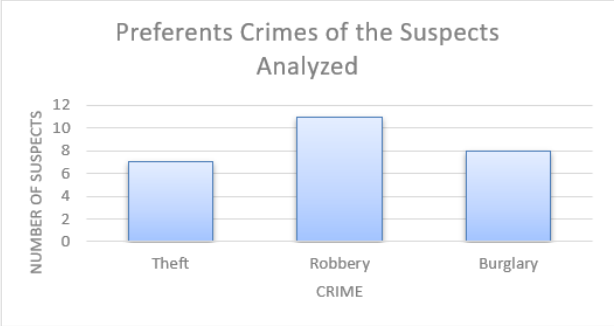

Fig 3. Preferential crimes in Public Prosecutor's Office case

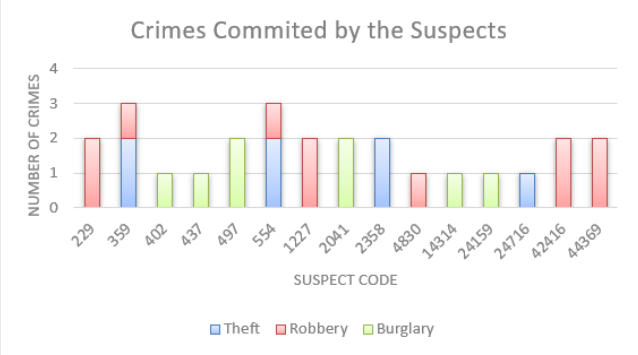

Fig 4. Number of crimes committed by suspects in Public Prosecutor's Office case

4.1.2 Criminal organization size

To estimate the minimal number of members of the criminal organizations that each suspect belongs to, Equation 2 and Equation 3 are used. Table 5 shows the results.

Table 5. Minimal number of members of the criminal organizations.

Number of members	2	3	4
Average number of members by crime	80%	20%	0%
Total number of members	67%	20%	13%

Table 5 shows that 80% of organizations carry out their crimes with a minimum of two members on average. The remaining 20% carry out the crimes with a minimum of three members on average. Concerning the total members, 67% of the criminal organizations have two members, 20% have three members, and 13% have four members. The difference between the aaverage number of members by crime, and the total number of members, reveals that not all members of a criminal organization participate in all crimes.

4.2 Case: Investigation Police of Chile Database

Figure 5 shows the results obtained to apply the CCIndex to the Investigation Police database. The highest suspect in the upper right rectangle is analyzed. The number of these suspects is 24 and shown in the circle.

4.2.1 Crime preference and specialization

The preferred crimes by the 24 suspects identified are burglary which corresponds to 34%. Then robbery with 14.4% and theft with 14.4%. All these crimes are crimes against property.

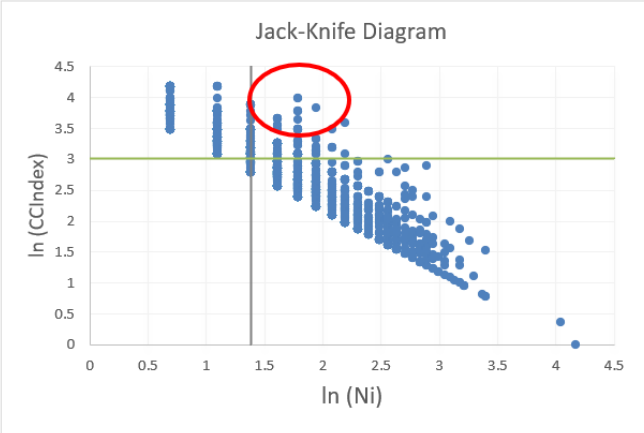

Fig 5. Jack- Knife Diagram of Investigation Police of Chile case

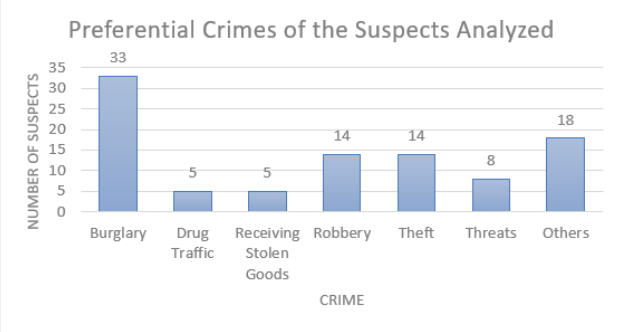

Fig 6. Preferential crimes in Investigation Police of Chile case

Figure 6 shows burglary, theft, and robbery are preference crimes by the suspects. The preference crimes are crimes against property.

Figure 7 shows the crimes committed by the 24 suspects selected. Two suspects with a specialization in theft and one in burglary. 58.8% (14) of the suspects commit burglary as a main criminal activity. 35.5% of the suspects commit burglary and robbery, and 58.3% of the suspect commit burglary and more than one other illicit activity.

4.2.2 Criminal organization size

As in the case of the Public Prosecutor's Office, to estimate the minimal number of members of the criminal organizations that each suspect belongs to, use Equation 2 and Equation 3. Table 6 shows the results. Table 6 shows the results.

Table 6. Minimal number of members of the criminalorganizations

Number of members	**2**	**3**	**4**
Average number of members by crime	87,5%	12,5%	0%
Total number of members	75%	17%	8%

Table 6 shows that 87.5% of organizations carry out their crimes with an average of two members. The remaining 12.5% carry out the crimes with a minimum of three members on average. These results are similar to those obtained in the case of The Public Prosecutor's Office. With respect to the total members, in general, 75% of the criminal organizations have two members, 17% have three members and 8% have four members. The difference between the average number of members by crime and the total number of members reveals that not all members of a criminal organization participate in all crimes.

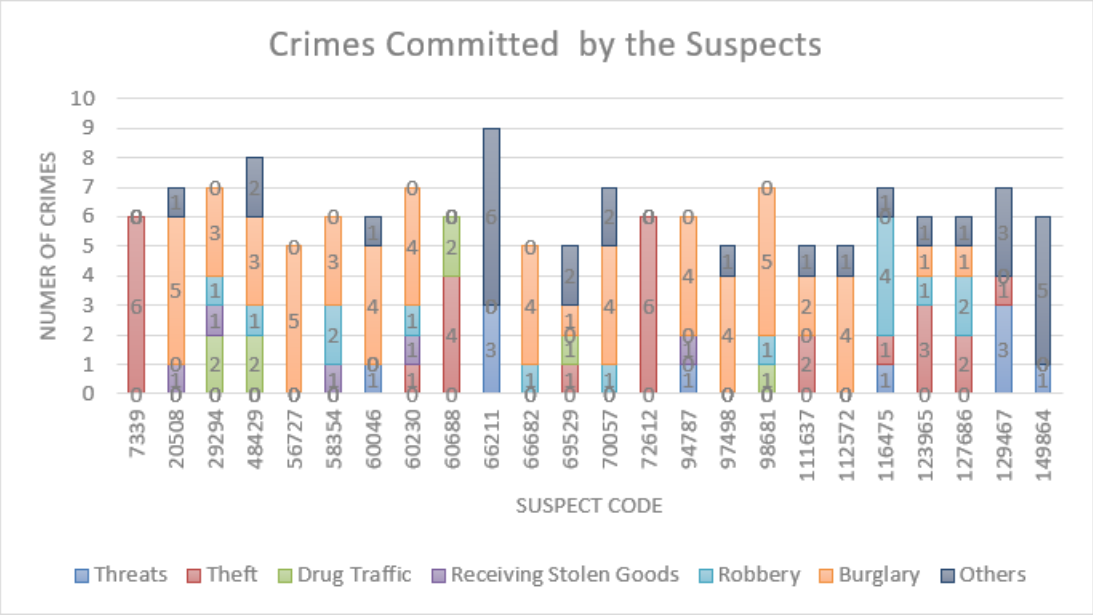

Fig 7. Number of crimes committed by suspects in Investigation Police of Chile case

5 Discussion

The Criminal Cohesion Index proposed, CCIndex, together with the number of causes associated with the suspects, allowed to identify members of criminal organizations, attending two of the main characteristics of a criminal organization: the strong cohesion and the permanent illicit activity over time.

The application of CCIndex shows that the crimes against property are strongly related to suspects with more probability to belong to criminal organizations. That is consistent with other investigations that rise that the crime against property is a kind of crime carried out by criminal organizations [27–29].

The suspects analyzed have a main criminal activity and secondary or instrumental activities necessary for the operation of a criminal organization [30,31]. An example is the crime of threats that appears in several suspects as a preferential crime and not as a principal crime due to the low number of associated causes. The crime of threats is instrumental because it has a defensive or offensive effect [34].

The use of the CCIndex allowed identifying possible criminal organizations small in size, of two or three members, but with strong cohesion. These results are consistent with the results of [28] that point out that 75% of the preferred crimes by criminal organizations involve two criminals.

Among the typologies of criminal organization structure established by the United Nations [1] is that of the central group. This structure is a reduced number of cohesive members and a high number of associated individuals who collaborate according to the needs of each crime. For this reason, a low cohesion does not rule out the membership of a suspect in a criminal organization. However, a high cohesion index and a high number of associated causes are strong evidence of a suspect's membership in a criminal organization.

Regarding the crime of drug trafficking, he did not find any suspects belonging to a criminal organization. Some organizations associated with this type of crime have an isolated work structure without formal connections between their members to prevent them from being detained [25].

6 Conclusion

This study proposes a Criminal Cohesion Index called CCIndex, to analyze the existence of possible members of criminal organizations using. The use of this index, together with the number of cases associated with a suspect, allows identifying which of them could belong to a criminal organization. A high level of CCIndex and a high number of associated causes are evidence of a high probability of belonging to a criminal organization.

In two real databases were identifying the suspects with a high CCIndex and a high number of causes associated. The crimes committed by these suspects were related to crimes committed by criminal organizations, agree with the literature. One of these databases was provided by The Public Prosecutor's Office of Región del Biobío – Chile and the other by the Investigation Police of Chile.The crimes identified in both databases were similar, being the preferred by the suspect burglary and robbery.

The structure of the proposed CCIndex together with the number of associated cases allows easily the identification of suspects belonging to criminal organizations within big databases. Through the application of the CCIndex, the Police and the Public Prosecutor Office can reduce the resources to the searching for suspects and to the investigation of criminal organizations focusing the investigation in the suspects with a high CCIndex and a high number of cases.

As future work, it is proposed to complement the results obtained through the CCIndex with Social Network Analysis tools, SNA, to determine the network associated with existing criminal organizations and their hierarchical relationships.

7 Acknowledgement

The author acknowledges the financial support of the FONDEF project ID20I10230ANID, Universidad del Bío-Bío by the Initiation Research Project 2060204 IF/I and Macro Facultad de Ingeniería Project ING 2030 I+D 20-34. The also author acknowledges the Criminal Analysis Unit of the Public Prosecutor's Office of Región del Biobío-Chile for the technical support and providing the dataset under a collaboration and internship agreement and acknowledges the Investigation Police of Chile for providing the database.

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