Crime Linkage: a Fuzzy MCDM Approach

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***Abstract*—Grouping crimes having similarities has always been interesting for analysts. Actually, when a set of crimes share common properties, the capability to conduct reasoning and the automation with this set drastically increase. Conjunction, interpretation and explanation based on similarities can be key success factors to apprehend criminals. In this paper, we present a computerized method for high-volume crime linkage, based on a fuzzy MCDM approach in order to combine situational, behavioral, and forensic information. Experiments are conducted with series in burglaries from real data and compared to expert results.**

Keywords—Crime analysis, crime linkage, fuzzy MCDM.

I. Introduction

Crime linkage is quite a particular challenge. As stated by Grubin et al., crime linkage consists in determining if a set of crimes has been committed by the same offender [1]. Basically, two tracks provide an answer to this problem: behavioral and situational similarities. The first aspect relies on the behavior of the offender, described by particular methods of crime (aka *modus operandi*). The second is based on spatio-temporal similarities: analyses are conducted in accordance with crime mapping theories. A third aspect can be considered: forensic case data (such as DNA, shoemarks or earmarks), which is much more reliable and always more integrated into intelligence databases [2].

As several studies mainly focus on behavioral linkage analysis (BLA) and on situational analysis, this current study attempts to combine behavioral, situational, and forensic information. Considering this objective, the proposed approach is a crime linkage method based on fuzzy multi-criteria decision making (MCDM) techniques, focused on high-volume crimes.

Section 2 introduces the key concepts in both fuzzy MCDM and crime linkage. A review of similar research is also presented. In Section 3, the proposed method is described. Experiments are conducted with real data about serial burglaries in Section 4. To sum up, Section 5 concludes on the perspectives of the artefact.

II. Literature Review

In this section, multi-criteria decision making theory is introduced and a comparison of the available techniques is undertaken. Fuzzy sets are then presented with the focus on translating experts' informal reasoning knowledge into membership functions. Finally, crime linkage studies are presented.

A. Multi-criteria Decision Making and Fuzziness

In the literature, two different approaches in multi-criteria decision making (MCDM) are frequently used: multiple objective decision making and multiple attribute decision making (MADM). Our interest lies in this latter: MADM.

Considering an MADM problem, the *decision maker* wants to select from a set of *alternatives* a particular subset. These alternatives are described by *criteria*, and each criterion can have a different importance (the *weight*) in regard to the other criteria (these weights usually reflect the subjectivity of the decision maker). From that point of view, three challenges can be thought of: (a) finding the best alternative (*choice* problem); (b) ranking all the alternatives in decreasing order (*ranking* problem); or (c), assigning the alternatives to predefined ordered categories (*sorting* problem).

Fuzzy sets are useful when the user's preferences among alternatives need to be translated into functions. Introduced by Zadeh [3], fuzzy sets form the basis of multi-valued membership functions. Traditional crisp logic represents the truthfulness of a statement with a dichotomy, i.e. a statement can only be *true* or *false*. On the other hand, with fuzzy sets, the real unit interval $[0, 1]$ can be used to assign the degree of truth of a statement. The smallest value of the interval denotes a total lack of membership of a class and the highest value denotes a full membership.

The most interesting characteristics of fuzzy sets, for an MADM problem, lie in the intrinsic flexibility of ad hoc membership functions and aggregation techniques.

B. Computational Forensics and Crime Analysis

Computational forensics (CF) is about applying computational methods from several disciplines in the forensic domain. Franke and Srihari [4] define three axes in which these methods support forensic sciences: (a) they provide a set of tools to overcome limitations of human cognitive abilities; (b) very large sets of data are potentially usable for analyses and are not anymore constrained by the human capacities; and (c) human expert knowledge can be modeled and made explicit to be used in inference mechanisms.

Crime analysis, supported by CF, becomes an interesting research field with the goal to overcome traditional limitations.

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In the case of crime linkage, detecting similarities with computational methods between crimes has not particularly been an active research area over the past years. Nevertheless, a few researchers have provided some answers: a primary emphasis has been given to analyzing spatial and temporal similarities (such as for predicting serial killers' home [5], or for finding a pattern of offenses of serial rapists [6]); another focus has been directed towards behavioral crime linkage (e.g., [7] or [8]) relying mainly on the crime method (modus operandi) inferred from crime scene investigation. More generally, a recent study [9] confirms a certain amount of predictability in certain crimes, but a practical gap still exists.

III. The Proposed Fuzzy MCDM Method

The objective of the proposed method is to link crimes by computing similarity coefficients. To compare crimes in regard to their properties, many techniques may be applied. In our situation, we chose to handle the problem by using the multi-attribute utility theory technique (MAUT). MAUT relies on the functions we devise to assign a *utility* to each crime against each criterion. The idea behind this choice is to give a chance to the experts to express their preferences with the help of fuzzy sets and membership functions. A utility function is therefore chosen by the expert according to his experience, which may be subjective. However, in the case of crime analysis, experts conduct such kind of reasoning on a daily basis and have a wide knowledge of exogenous factors. Many decision criteria often lie beyond the system, because of their intrinsic difficulty to be explicitly defined. This method is therefore an appropriate way to integrate uncertainty and subjectivity into the system. Then, an aggregation function will combine the utilities of each criterion to represent the overall *similarity* coefficient between two crimes.

Let us formalize the latter reasoning with some definitions. The finite list of crimes $C = \{c_1, ..., c_m\}$ is the set of m elements for which we are interested in finding similarities. Each crime $c_i, \forall i \in [1, m]$ is described by n properties, defining the set $P = \{p_1, ..., p_n\}$ (which can also be seen as a set of functions over C: the property p_j of the crime c_i is the function value $p_j(c_i)$). Moreover, a degree of importance, denoted as the *weight*, is attached to these properties. Subjective to the decision maker and his experience, weights can be represented by the vector $W = \{w_1, ..., w_n\}$. For each pair (c_i, p_j) compared to the crime c_{ref}, a fuzzy set membership function $\phi_j^{ref}(p_j(c_i)) : P \rightarrow [0, 1]$ is defined, which takes its maximum value in $c_i = c_{ref}$. Based on these definitions, we can enumerate the required steps to compute a similarity coefficient between two crimes.

In a first step, a crime c_{ref} is chosen as reference crime in order to be compared to all other crimes c_i $(c_{ref}, c_i \in C)$. In the second step, for a given crime c_i, the utility of each property p_j is respectively computed against each property p_j of c_{ref}. The utility of the property p_j of the crime c_i against the reference crime c_{ref} is defined as:

$$u_{i,j}^{ref} := \phi_j^{ref}(p_j(c_i)). \tag{1}$$

During the third step, these utilities are aggregated in order to get a similarity coefficient. In the specific case we are facing nominal non-ordinal properties (such as a multi-valued category or a crisp category), we suggest to use a pre-defined aggregation function. For that, the Jaccard's index [10] (a coefficient that has been used in many BLA, especially with modi operandi [7]) seems appropriate. Otherwise, more broadly, the aggregation function η ($\eta : [0, 1]^{2n} \rightarrow [0, 1)$) defines the similarity coefficient of the crime c_i with the reference crime c_{ref}:

$$s_{ref,i} := \eta(c_i) = \eta(u_{i,1}^{ref}, u_{i,2}^{ref}, ..., u_{i,n}^{ref}, w_1, w_2, ..., w_n). \tag{2}$$

Finally, we have to *repeat the same three steps of an MADM ranking, but by changing for each iteration the reference crime* c_{ref}. This means we will compute m times the ranking (i.e. the ordered sequence $s_{ref,i}$), with c_{ref} varying from c_1 to c_m.

At the end of these procedures an adjacency matrix can be defined, representing the coefficients of similarity for each pair of crimes. This matrix is symmetric with diagonal values equals to 1 (a crime is fully similar to itself). Depending on a minimum similarity coefficient (the threshold) and on series size, crimes are eventually merged into series according to the inference structure described in [11].

IV. Crime Linkage of Residential Burglaries

The goal of this section is to illustrate the proposed method with real data.

A. Description of the Data

Thanks to the Police de sûreté du Canton de Vaud (a canton police in Switzerland), we were able to access to a data set about serial and itinerant crime (high-volume crime). Stemming from police log reports, the data set was structured in accordance with the methodology given in [12]. From about $55,000$ events related to residential burglary involved in 6 cantons for a 4 year period, we focused on a particular subset for this experiment (basically, events where both behavioral and contextual information was available). This subset contains 2320 crimes conducted by 1141 distinct offenders (all along the study, we will assume that each crime has exactly one offender, even if sometimes crimes are committed by several offenders). The distribution of crimes is of 2 per offender on average (with a minimum of 1, a maximum of 52, and a standard deviation of 3.14).

B. Applying the Proposed Method

In order to apply the proposed method to the data set ($N = 2320$), we need to distinguish utility function types according to the nature of the variables, namely numeric (date and coordinates), categorical (modus operandi, entrance, phenomenon and the type of the place), and unique identifiers (forensic case data). For example, the fuzzy set $\langle d, \mu^{ref}(d) \rangle$ represents the utility of the *date* property. The date was first normalized to the unit interval, denoted by d, and its membership value was evaluated using a bell-shaped function centered on the reference date ($\phi_{ref}(d_{ref}) = 1$).

Then, to compute the score of each pair of events, a weighted sum (the SAW technique) was used as an aggregation

TABLE I. RESULTS FOR THE IMPLEMENTED SOLUTION ($N = 2320$ CRIMES). THE STATISTICS DESCRIBE THE NUMBER OF OFFENDERS PER SERIES (*#o per series*), AND THE NUMBER OF SERIES PER OFFENDER (*# s per offender*). THE PARAMETERS ARE THE FOLLOWING: t IS THE SIMILARITY THRESHOLD, s_{max} IS THE MAXIMUM SIZE OF A SERIES. ON AVERAGE, 927 CRIMES WERE LINKED IN SERIES.

	t=0.8, $s_{max} = 10$		t=0.9, $s_{max} = 7$	
	#total linked crimes: 960		#total linked crimes: 894	
Statistics	#o per series ($s_{tot} = 96$)	#s per offender ($o_{tot} = 533$)	#o per series ($s_{tot} = 128$)	#s per offender ($o_{tot} = 452$)
Min	2	1	1	1
Max	10	11	7	11
Mean	7.47	1.35	5.04	1.43
Median	8.00	1.00	5.00	1.00
Std Dev.	2.27	0.94	1.68	1.10

function for the sake of simplicity. For the values of the weights, a slightly higher importance was given to the date and the location of the crime compared to the other attributes. Concerning forensic case data (present in 11% of cases in N), we decided to add the weighted utility only when the field was not null (meaning that a similarity of 1 can be found even when forensic case data is missing). The implementation of this model was done using Octave, a language for numeric computations (a free alternative of Matlab).

The results of our implementation can be evaluated in many ways. Our choice was to analyze how series were detected by the system (i.e. how crimes were linked together as series when a particular threshold of similarity was reached). Results were obtained with two different settings (see Table I): the minimum similarity coefficient value for linking 2 crimes (the threshold *t*), and the maximum number of crimes per series (s_{max}). Then, in order to interpret these results, we defined two metrics for each of these setting: (a) the number of distinct offenders per series, describing the diversity of criminals in a series; and (b), the number of distinct series per offender, counting in how many series crimes of the same offenders are linked.

The most interesting metric is the number of series in which a unique offender has been linked. On average, all crimes of the same offender are split into only one or two series (the best findings occur for the first configuration, i.e. with a number of 10 crimes per series, for a total of 96 series). These results are encouraging, in the sense that one main objective of a computerized linkage system is to give to crime analysts a way to reduce linkage blindness. On the other hand, even when crimes of different offenders are linked, it is not a significant issue when considering the concept of false negatives to be more important than the concept of false positives (still with the purpose of decreasing linkage blindness).

To sum up, the results of such systems are to be used in a context of pure investigation. The main purpose is to enhance the cognitive capacities of analysts, but the conclusions still have to be drawn with extreme care.

V. CONCLUSIONS

Computerized crime linkage is an emerging research area and many challenges still need to be confronted. In this paper, we proposed a fuzzy MCDM method for combining behavioral, situational, and forensic information.

The impacts for crime analysts may be numerous: forming a basis for implementing their own crime linkage system, providing a flexible framework with the objective to combine several distinct information types, adapting or comparing existing crime linkage systems, etc.

With the potential to benefit to all police organizations, the proposed method lays the ground for conducting new experiments and sharing results in the area of crime linkage.

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