

# Can Fuzzy Decision Support Link Serial Serious Crime?

Don Casey and Phillip Burrell

London South Bank University, Borough Rd, London, SE1 0AA, U.K.

Keywords: Crime Linkage, Decision Support, Fuzzy Clustering.

Abstract: The problem addressed is one of great practical significance in the investigation of stranger rape. The linkage of these crimes at an early stage is of the greatest importance in a successful prosecution and also in the prevention of further crimes that may be even more serious. One of the most important considerations when investigating a serious sexual offence is to find if it can be linked to other offences; if this can be done then there is a considerable dividend in terms additional evidence and new lines of enquiry. In spite of a great deal of research into this area and the expenditure of considerable resources by law enforcement agencies across the world there is no computer-based decision support system that assist crime analysts in this important task. A number of different crime typologies have been presented but their utility in decision support is unproven. It is the authors' contention that difficulties arise from the inadequacy of the adoption of the classical or 'crisp set' paradigm. Complex events like crimes cannot be described satisfactorily in this way and it proposed that fuzzy set theory offers a powerful framework within which crime can be portrayed in a sensitive manner and that this can integrate psychological knowledge in order to enhance crime linkage.

## 1 INTRODUCTION

The need for computerised systems to support the work of crime analysts and investigators has been recognised for some time. The authors of an influential study into linking serious sexual assaults remarked that:

*The ultimate goal is to create a computer-based screening system that will allow routine and systematic comparison of serious offences on a national basis, selecting cases on the basis of their behavioural similarity that are appropriate for more detailed attention by detectives or crime analysts (Grubin et al., 2000)*

And this view has been reinforced by an eminent criminal psychologist:

*The development and test of theories and implementation of findings into computer-based, decision-support systems ... has to be the proper basis for any professional derivation of inferences about offenders. (Canter, 2000)*

The problem at the heart of crime linkage resides in the need for an adequate typology of offences but the search for an effective system has proved elusive.

The most influential crime classification system has been that proposed in the Crime Classification Manual (Douglas et al., 1992) which is the work of senior Federal Bureau of Investigation agents. It advances the notion of an organised-disorganised dichotomy and was developed from interviews with offenders (Ressler and Douglas, 1985). The basis of this approach is that crimes can be differentiated by the level of planning and organization associated with them and the authors extend this to assert that the dichotomy can be applied to the offender so that organised and disorganised crimes are committed by individuals who can be differentiated in discrete groups with distinct characteristics. Very serious objections have been made to the methodology employed by the FBI. Only 36 offenders were interviewed, no attempt was made to ensure this group was representative and the interviews conducted were not structured or consistent. An evaluation of this typology (Canter et al., 2004) applied to 100 serial murderers provided no support for it.

In the most comprehensive research programme into the linkage of serious sexual offences (Grubin et al., 2000) the authors propose

*Our starting premise is that rape attacks can be organized into distinct types*

It is certainly the aim of investigation of any field to initially classify the objects contained within it but it is the hypothesis of this paper that although rapes can be organized into types that these will be far from 'distinct'. And that the attempt to discriminate between crimes in this way is likely not only to be barren but actively misleading in that they will be forced into mutually exclusive types that will misrepresent their complexity; a perspective arrived at after many years of research by one of the area's foremost investigators

*... assigning criminals or crimes to one of a limited number of 'types' will always be a gross oversimplification. (Canter, 2000)*

Canter and his associates who are identified with Investigative Psychology have published numerous studies (Hakkanen et al., 2004); (Santilla et al., 2003) on sexual assault, homicide and other serious crimes but have been unable in any of them to construct a satisfactory typology with even the most relaxed rules of assignment (Salfati and Canter, 1999). Grubin is obliged to propose a 256 element taxonomy in which many of the elements are redundant, a classification system in which many if not most of the elements will never occur cannot be satisfactory. The assumption of the crisp set paradigm in this research appears to be the cause of the problems relating to these difficulties. This can be illustrated by a simple description of a crime such as 'a very violent assault on a middle-aged woman by a young man' which cannot be properly expressed in terms of crisp sets. It can lead to either the misallocation of fundamentally different offences to the same place or to crimes that bear strong resemblances to each other being regarded as entirely unconnected, a phenomenon referred to as linkage blindness (Egger, 1990) of which researchers are fully aware but have been unable to address.

In the analysis of serious crime, particularly sexual offences, there are two computer databases that dominate: the Violent Criminal Apprehension Program (ViCAP) introduced by the F.B.I and the Violent Crime Linkage System (ViCLAS) first developed by the Royal Canadian Mounted Police (RCMP). ViCAP is used predominantly in the USA while ViCLAS is employed throughout most of Europe. Both systems are essentially repositories of criminal records that analysts search using their training and expertise in order to link offences. This is achieved employing straightforward Boolean searches on groups of variables deemed to be significant. There has been no decision support system devised to assist in this task and no attempt

has been made to incorporate the results from psychological research into crime linkage.

## 2 DATA

We have been fortunate in being successful in obtaining data on 574 serious sexual offences from the Serious Crimes Analysis Section of the U.K National Policing Improvement Agency. We have excluded those offences that do not relate to serial stranger rapes, by which we mean a set of rapes committed by a single individual unknown to the victim. This results in a much narrower dataset ( $n = 112$ ), development set  $n = 83$ , test = 29). The development set consisted of 28 series, mean length 2.96, while the test set comprised 11 series with a mean length of 2.64.

The dataset made available contained 22 single or 'one off' stranger rapes which allowed variants on the set to be constructed that could be regarded as more realistic in that they contained a mixture of both serial and individual offences. In the first instance these were added to the 29 offences in Test Set 1 to produce Test Set 2 ( $n = 51$ ). By using this set of crimes the effect of a substantial group (> 40%) of unlinked offences in tests could be observed. Both Test Set 1 and 2 used the value of variables derived from Development Set 1. In order to replicate the development of a crime database over time the entire set of 112 linked crimes was used as Development Set 2. As with the other development set this pool of offences generated its own value for variables; they were found to be somewhat different but in line with the first set. Finally as before and for the same reasons this set was combined with the 22 single offences to produce a composite set of 134 linked and unlinked offences.

Table 1: Development and test datasets.

	n=	
Development 1	83	83 linked crimes
Test 1	29	29 linked crimes
Test 2	51	29 linked, 22 unlinked
Development 2	112	112 linked crimes
Test 3	134	112 linked crimes, 22 unlinked

### 3 CRIME AND FUZZY SETS

Fuzzy set theory (Zadeh, 1965) allows us to represent crimes and criminals as highly descriptive objects in the concept space and to undertake experimental procedures to discover what are the most significant differentiating features using mathematically and logically sound methods

The Grubin study was taken as a starting point for modelling stranger rape linkage because it was focussed on this crime, had used the most similar data and was the most lucidly expounded. The basis of this approach was to identify four ‘dimensions’ of criminal behaviour: Control, Sex, Escape and Style. The last of these was a late addition by the authors and was found to be of very limited use. It was therefore discarded and the first three employed. A total 44 variables were found to directly or indirectly correspond to those employed in the earlier research. On inspection the Control and Sex dimensions both appeared to have a natural division in their variables in that Control consisted of overtly violent actions such as assault and use of weapons and other more enabling actions such as engaging the victim in conversation. The Sex dimension similarly divided into those actions that constituted rape and others such as kissing. Consequently, in testing, offences were characterised by the original dimensions (3D); Control, Sex1, Sex2, Escape (4D2S); Control1, Control2, Sex, Escape (4D2C); and all five dimensions (5D). By extending the number of dimensions it was hoped that an optimum configuration would emerge

The number of variables in each dimension was distributed as: Control (19), Sex (14), Escape (11), Control1 (12), Control2 (7), Sex1 (6) and Sex2 (8).

#### 3.1 Membership Functions

We can define the universe of crimes as a data set (X) of n elements

$$X = \{ x_1, x_2, x_3, \dots, x_n \} \tag{1}$$

Where each crime ( $x_i$ ) is defined by j features or variables

$$x_i = \{ x_{i1}, x_{i2}, x_{i3}, \dots, x_{ij} \} \tag{2}$$

The variables constitute behavioural dimensions as above. A problem arises with these dimensional concepts because they cannot be incrementally or hierarchically scaled. This makes the use of a conventional membership function difficult. In order to overcome this we have proposed that the *amount* of these activities can be measured, i.e. the number

of separate sexual, controlling or escape-centred actions within each crime,  $x_i$ . These variables have dichotomous values that do not reflect their value in contributing to the distinctiveness of the crime in which they occur. However it can be posited that each variable,  $v_j$  be associated with a value  $w_j$  that represents a weighting based upon its prevalence in the dataset of n crimes. In order to assign a value to each variable that reflects this frequency the reciprocal of the sum of its occurrences is taken. As a result if the variable were to occur in every crime it would have a value of 1/n while if it were to occur only once its value would be equal to 1 with all intermediate frequencies being assigned corresponding values. This simple calculation assigns an appropriate value to each variable; thus the variable  $v_j$  is assigned a value or weight  $w_j$  by

$$w_j = \frac{1}{\sum_{i=1}^n x_{ij}} \tag{3}$$

Once each variable has a value it is a simple matter to sum the values of all the variables found in each crime to give it a score,  $S_i$ , n that dimension

$$S_i = \sum_{k=1}^j w_k \cdot x_{ik} \tag{4}$$

The degree of membership can then be calculated by normalising this score by dividing it by the highest score encountered in the dimension

$$\mu_A(x_i) = \frac{S_i}{\max \{ S_k : k = 1, \dots, n \}} \tag{5}$$

The result is intuitively satisfying in that the score attained is related directly to the most controlling or sexually demeaning, etc., crime encountered up to that point. It also means that a rudimentary form of learning can take place in that as more crimes are added the scores across dimensions for each crime will be liable to change and its position in the sample space will move. This could be taken to replicate the manner in which experience affects the performance of skilled users.

The membership function also derives closely from the techniques used in Investigative Psychology (Canter et al., 2003) which emphasizes the frequency of variables and their co-occurrence within crimes. An example of degrees of membership for two series in three dimensions is given at table 2.

#### 3.2 Fuzzy C-means Clustering

Having established the degrees of membership from the development dataset for each crime in all four of

the dimensional structures it was possible to investigate the relationship between them and how they were distributed in the concept space through clustering.

Table 2: Three Dimensional (3D) memberships.

Crime	series	Control	Sex	Escape
1	1	0,38	0,17	0,15
2	1	0,38	0,22	0,08
3	1	0,32	0,24	0,07
4	1	0,34	0,34	0,37
5	1	0,34	0,10	0,14
6	2	0,32	0,06	0,00
7	2	0,27	0,14	0,16
8	2	0,38	0,03	0,09

Fuzzy c-means clustering (Bezdek, 1981) is the most widely used fuzzy clustering strategy and effectively addresses the difficulties raised by Canter of exclusive types of crime. It does this by defining a set of fuzzy sets on the universe  $X$  so that the sum of degrees of membership of all the classes of any datapoint is unity, there will be no empty classes and no class that contains all the datapoints. This is an iterative optimisation technique of the objective function below where a degree of fuzziness  $1 \leq m < \infty$  is specified and elements are assigned degrees of membership of the clusters until some termination criterion has been reached.

$$J_m = \sum_{i=1}^N \sum_{j=1}^C u_{ij}^m |x_i - c_j|^2 \quad (6)$$

$u_{ij}^m$  is the degree of membership of  $x_i$  in cluster  $j$  and  $c_j$  is the cluster centre

Cluster centres are initially distributed randomly and are guaranteed to converge however there is no technique to determine the optimum number for any application. Therefore the number of clusters ( $j$ ) was specified from 2 to 5, 6 clusters produced inconsistent results. It was also possible to vary the degree of fuzziness ( $m$ ) from 1.25 to 3 in increments of 0.25. A value of  $m = 1$  equates to a crisp partition of the data which becomes correspondingly fuzzier as it increases. There is no agreed best value for  $m$  although around 2 is often cited (Ross, 2004).

### 3.3 Fuzzy Similarity

Clustering returned the membership of  $j$  fuzzy clusters for each offence. Two similarity methods were used to evaluate the strength of the relationship,  $r_{ij}$ , between the objects  $x_i$  and  $x_j$ .

Cosine amplitude reflects the size of the angle between them; where they are colinear the value is unity and when they are most dissimilar, i.e., at right angles the relationship has a value of 0.

Here there are  $n$  objects (crimes) represented in  $m$ -dimensional space

$$r_{ij} = \frac{|\sum_{k=1}^m x_{ik} x_{jk}|}{\sqrt{(\sum_{k=1}^m x_{ik}^2)(\sum_{k=1}^m x_{jk}^2)}} \quad (7)$$

where  $i, j = 1, 2 \dots n$

The max-min method is simpler than cosine amplitude and uses max, min operations on pairs of datapoints to establish similarity in a straightforward manner.

$$r_{ij} = \frac{\sum_{k=1}^m \min(x_{ik}, x_{jk})}{\sum_{k=1}^m \max(x_{ik}, x_{jk})} \quad (8)$$

where  $i, j = 1, 2 \dots n$

As a result an  $n \times n$  similarity matrix was generated for all values of fuzziness ( $m$ ) and number of clusters ( $j$ ) for both methods. The values in each row ( $n$ ) were then rank-ordered to show the relative closeness of all the other crimes to the  $n^{th}$  offence. For the development set of 83 crimes these values range from 1 (closest) or most similar to 82 for the most dissimilar.

## 4 RESULTS

The rank-ordered similarity distance for each dataset was computed to produce an  $n \times n$  matrix and the mean and median for the total of those comparisons between serial offences recorded. It should be noted that these distances were not symmetrical: if  $x_i$  and  $x_j$  have a similarity of 0.8 it does not follow that they are equally distant from each other.

These results should show distances of  $\approx n/2$  between linked crimes if they are randomly distributed. However it was found that for virtually all combinations of dimensions, clusters and fuzziness values that distances were consistently below this level and often considerably so. Table 3 shows the best results for each set; medians are shown as they would best represent the search strategy of analysts in searching for matches. In addition in nearly all results and particularly the more successful ones there was an evident positive skew indicating that successful matching was concentrated towards the low distance.

The exceptional performance obtained with Test

Set 2 suggests that the environment of this dataset in which serial offences are a bare majority may substantially enhance the outcome. This is an interesting result in that although there are no figures to indicate the ‘mix’ between serial and individual offences because of partial detection rates; it is likely to replicate ‘real life’ in which a set of stranger rapes is composed of both serial and single offences.

Results show that although there is a marked advantage in using the methodology and techniques outlined here there is no convincing combination of number of clusters or levels of fuzziness that consistently returns optimum distances.

Table 3: Median distances between linked crimes.

	n=	lowest median % n/2	dimensions	clusters	m =
Dev Set 1	83	< 50%	3D	2	low to medium
Test Set 1	29	<35%	3D	3	all vals
			4D2C	4,5	low to medium
			4D2S	4	all vals
Test Set 2	51	<25%	3D	4,5	low to medium
			4D2S	4,5	all vals
Dev Set 2	112	<55 %	3D	2	all vals
				5	med to high
Test Set 3	134	≈ 50%	4D2C	4	low to medium
				5	low
			4D2S	5	medium

## 5 CONCLUSIONS

A recent report into rape investigation in the U.K. (HMIC/HMCPSI, 2012) detailed the problems of productivity in terms of analysis in that only around 25% of suitable crimes submitted were analysed and that a backlog was building up that might never be cleared. These are some of the most serious crimes that occur in society and the need for more advanced techniques to assist investigators is clear.

This research has demonstrated that fuzzy methodology can be used successfully in representing serious crimes in a sensitive manner

that reflects their complexity and builds on insights from criminal psychology.

Although attempts have been made to associate stranger rapes in order to enable linkage there has been no input from Artificial Intelligence or Decision Support and they have been purely psychology-based. This is surprising in view of the clearly stated views of leading researchers. The research presented here has for the first time endeavoured to find the strength of similarity between offences in the way that crime analysis requires.

The problem of rigid typology that has hampered this area of research is precisely the one that fuzzy sets avoid. Because of the nature of the area under investigation any crisp classification method is bound to fail. Either a large number of crimes elude classification as in Investigative Psychology or a highly redundant typology of stranger rape, which is itself a small subset of rape has to be proposed.

Reference has been made to the possibility of increasing the productivity of analysts but it is also possible and perhaps probable that given assistive technology that the quality of analysis would improve. Given new, and better, ways of achieving their goals expert users are highly likely to adapt and improve their expertise.

The results obtained here strongly suggest that the methods used can be of considerable value in crime linkage and that further research may well refine dimensionality and clustering to produce even more useful inferences.

If this can be done then the consequences may feed back into criminal psychology in that cluster centres can be regarded as prototypes of criminal action and be interpreted as a usable typology. And a circle of effective advance and cross-fertilisation result.

It may be this approach can yield the *psychologically valid and meaningful set of numbers* (Canter, 1985) called for in the earliest days of research into this area .

## REFERENCES

Bezdek, J., (1981). *Pattern Recognition with Fuzzy Objective Function Algorithms*. New York: Plenum.  
 Canter, D., (1985). *Facet theory: approaches to social research*. New York: Springer-Verlag.  
 Canter, D., (2000). Offender profiling and criminal differentiation. *Legal and Criminological Psychology*, 5, 23-46.  
 Canter, D., Alison, L., Alison, E., & Wentink, N., (2004). The Organized/Disorganized Typology of Serial

- Murder. Myth or Model ? *Psychology, Public Policy and Law*, 10(3), 293-320.
- Canter, D., Bennell, C., Alison, L., & Reddy, S., (2003). Differentiating Sex Offences. *Behavioural Sciences and Law* 21.
- Douglas, J. E., Burgess, A. W., Burgess, A. G., & Ressler, R. K., (1992). *Crime classification manual: A standard system for investigating and classifying violent crime*. New York: Simon and Schuster.
- Egger, S. A., (1990). *Serial murder: an elusive phenomenon*. New York: Praeger.
- Grubin, D., Kelly, P., & Brunson, C., (2000). *Linking Serious Sexual Assault through Behaviour Home Office Research Study 215*. London.
- Hakkanen, H., Lindof, P., & Santilla, P., (2004). Crime Scene Actions and offender characteristics in a sample of Finnish stranger rapes. *Journal of Investigative Psychology and Offender Profiling*, 1(2), 153-167.
- HMIC/HMCPSP, (2012). *Forging the links: Rape investigation and prosecution. A joint Review by HMIC and HMCPSP*: H.M. Inspectorate of Constabularies / H.M. Crown Prosecution Service Inspectorate.
- Ressler R. K., & Douglas, J. E., (1985). Crime Scene and Profile characteristics of organized and disorganized murderers *FBI Law Enforcement Bulletin*, 54(8), 18-25.
- Ross, T., (2004). *Fuzzy logic with engineering applications*. Chichester: Wiley.
- Salfati, C., & Canter, D., (1999). Differentiating Stranger Murders: profiling offender characteristics. *Behavioural Sciences and Law*, 17(3).
- Santilla, A., Hakkanen, H., & Fritzon, K., (2003). Inferring the Crime Scene Characteristics of an Arsonist. *International Journal of Police Science and Management*, 5(1).
- Zadeh, L., (1965). Fuzzy Sets. *Information and Control*(8), 228-353.

WILEY PRESS  
TECHNOLOGY PUBLICATIONS