Fuzzy Methods for Forensic Data Analysis

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***Abstract*—In this paper we describe a methodology and an automatic procedure for inferring accurate and easily understandable expert-system-like rules from forensic data. This methodology is based on the fuzzy set theory. The algorithms we used are described in detail, and were tested on forensic data sets. We also present in detail some examples, which are representative for the obtained results.**

***Index Terms*—fuzzy inference system, fuzzy clustering, forensic data, computational intelligence**

I. Introduction

The evolution of the insecurity problematics, the arrival of new threats (terrorism, cybercrime, etc.) and the development of new technologies are factors which dramatically increased the importance of intelligence in the process of management, analysis, and utilization of the growing volumes of available crime data. Therefore, enhancing intelligence-based approaches for law-enforcement and intelligence-gathering organizations became a necessity, particularly supported by the emergence of a new interdisciplinary research domain, the computational forensics [1].

The design of specific intelligence processes and computational systems for crime analysis is related to the "type" of intelligence that is considered. Forensic Intelligence [2], [3], defined as *"the accurate, timely and useful product of logically processing forensic case data"*, can be viewed as the general frame. Traditionally, the results produced by forensic intelligence have been confined to discipline-specific activities. If information technology is used to produce information sets and digital evidence, then methods and techniques from Artificial Intelligence, defined as *"the science and engineering of making intelligent machines"* [4], can be used for digital forensic analysis and investigations. As an alternative to classical Artificial Intelligence, Computational Intelligence, defined as *"the study of adaptive mechanisms to enable or facilitate intelligent behavior in complex and changing environments"* [5] (one of the many definitions! [6]), may be used to support some of the phases of the crime investigation process [7], [8].

Computational Intelligence includes a number of computational methods as artificial neural networks, rough sets, evolutionary computing, swarm intelligence and fuzzy systems. This paper will concentrate on the last approach, the fuzzy set theory, by discussing the applicability of different fuzzy methods to improve the effectiveness and the quality of the data analysis phase for crime investigation. Besides the practical aspects/gain of using these methods - exemplified by the information/knowledge inferred from forensic case data representing robberies and residential burglaries in the region of Lausanne - the paper proposes a framework for applying fuzzy tools in digital investigation. The main goal is the extraction of expert-system-like rule sets based on fuzzy sets that can be presented to the experts in order to support them in their daily activities. This framework is conceived to be a potential starting point to a future standard framework for guiding the use of computational intelligence techniques in gathering digital evidence admissible in a court of law.

The paper is structured in the following way. First we will review how computational intelligence methods, with a particular attention to fuzzy tools, were already applied in the context of forensic service. Then we will describe the foundations of the fuzzy tools needed in our approach, followed by a description of the methodology we used. Then the experimental setup and the obtained results are presented, before we conclude.

A. Literature review

The importance of computational methods for forensic investigation service was revealed by the research community in the late nineties (especially in the domain of fingerprint identification [9] and DNA analysis [10]), but the growing number of articles related to this domain in the last years is especially due to the emergence of the concept of computational forensic. According to [11], the computational methods enable the forensic practitioner to analyze and identify traces in an objective and reproducible manner, to standardize investigative procedures, to search large volumes of data efficiently, to assist in the interpretation of results and their argumentation, to reveal previously unknown patterns, to derive new rules, and to contribute to the generation of new knowledge.

Computational Intelligence methods and techniques were considered for assisting analysis and discovery of leads in building digital evidence for forensic analysis. Evolutionary algorithms and genetic algorithms were adapted to solve the problem of identifying a missing person from a photograph and a skull found [12], writer identification by handwriting analysis [13], incomplete or partial fingerprints verification [14], [15] or detecting malicious intrusions into critical information infrastructures [16]. Fuzzy methods (including fuzzy sets, fuzzy logic, fuzzy inference systems, fuzzy clustering) and hybrid fuzzy methods (genetic fuzzy clustering, fuzzy neural networks, etc..) play an important role in learning complex data structures and patterns, and classifying them to make intelligent decisions. Fuzzy clustering is used in [17] to detect the explanation of criminal activities for crime hot-spot areas and their spatial trends. Compared with two hard-clustering approaches (median and k-means clustering problem), the empirical results suggest that a fuzzy clustering approach is better equipped to handle crime spatial outliers. An approach based on fuzzy logic and expert system for network forensics that can analyze computer crimes in network environment and make digital evidences automatically is proposed in [18]. Experimental results show that the system can classify most kinds of attack types (91.5% correct classification rate on average) and provide analyzable and comprehensible information for forensic experts. A pseudo outer-product based fuzzy neural network (POPFNN) is trained to detect similarity between two fingerprints and decide whether they belong to the same person [19]. The characteristics of POPFNN, such as the learning, generalization, and high computational abilities, make fingerprint verification particularly powerful when verifying authentic fingerprints subjected to external conditions and recognizing spurious ones. A two stage fuzzy decision classifier, using reference fuzzy set information, is used in [20] to create a text-independent Automatic Speaker Identification. Finally, a framework of intelligent decision-support model based on a fuzzy self-organizing map (FSOM) network to detect and analyze crime trend patterns from temporal crime activity data is proposed in [21]. The resultant model can support police managers in assessing more appropriate law enforcement strategies, as well as improving the use of police duty deployment for crime prevention.

II. Fuzzy sets theory

As outlined in the previous section the key component of the approach presented in this paper are Fuzzy sets, introduced by Lotfi A. Zadeh [22]. They differ from the classical notion of set by allowing the gradual assessment of the membership of elements. This is described with the aid of a membership function valued in the real unit interval $[0, 1]$. Emerged from the development of the theory of fuzzy sets, the fuzzy logic is an extension of the case of multi-valued logic, assigning to each proposition a degree of truth - a value varying between 1 (*absolutely true*) and 0 (*absolutely false*).

Fuzzy logic (together with neurocomputing and genetic algorithms) is one of the techniques of *soft computing*, i.e. computational methods tolerant to suboptimality, impreciseness (vagueness) and partial truth and giving quick, simple and sufficiently good solutions. The guiding principle of these methods is perfectly adapted to the way in which reasoning and deduction have to be performed in forensic science (for searching hidden traces in a mostly chaotic environment, traces never identical with known specimens in a reference base), i.e. on the basis of partial knowledge, approximations, uncertainties and conjectures [1].

Among the general statements about fuzzy logic, we may enumerate [23] the flexibility, the tolerance of imprecise data, the capacity to model nonlinear functions of arbitrary complexity (matching any set of input-output data), the capacity to be built on the top of the experience of experts, and the facility of use (due to its basis built on natural language).

A. Fuzzy Inference Systems

Describing generally vague concepts (as tall people, hot weather, morning hours, etc.), fuzzy sets have associated a membership function (denoted $\mu(x)$) which maps an input value to its appropriate membership value. A membership function may be any arbitrary function with values in $[0, 1]$, but in practice basic functions are used, as piece-wise linear functions, Gaussian distribution function, the sigmoid curve, quadratic and cubic polynomial curves. In a mathematical notation, a fuzzy set is the set of pairs $A = \{(x, \mu(x)\}$. The set of elements that have a non-zero membership is called the *support* of the fuzzy set.

The fuzzy logical reasoning is a superset of standard Boolean logic, i.e. the truth functions of connectives have to behave classically on the extremal values $0, 1$. For conjunction, a family of functions satisfying this condition is the set of binary T-norm operators [24] (*min* is a classical exemple), whereas for disjunction is the set of binary T-conorm operators (*max* is a classical exemple). Several parameterized T-norms and dual T-conorms have been proposed in the literature, such as those of Yager [25], Dubois and Prade [26] and Sugeno [27].

A fuzzy rule *if-then* has the form *If x is A Then y is B*, where A and B are fuzzy sets. Interpreting an *if-then* rule involves two distinct parts. Firstly, the premise of the rule is evaluated, which involves *fuzzifying* the input (i.e. calculate the membership value) and - if the premise have multiple parts - applying any necessary fuzzy operators. Secondly, the result is applied to the consequent (operation known as implication) using an *implication* function, which modifies the output fuzzy set to the degree specified by the antecedent. The modification is usually realized by truncation, using the *min* function, or by scaling, using the *prod* function, but other theoretical approaches have been proposed [28], [29].

The fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The systems using fuzzy inference have been applied in different domains, as automatic control, data classification, decision analysis, expert systems or computer vision. In the literature two types of fuzzy inference systems (FIS), differing by the way the output is determined, are the most known: Mamdani-type and Sugeno-type. The Mamdani's fuzzy inference method [30] expects the output membership functions to be fuzzy sets. For Sugeno-type systems [31], the output membership function is a singleton, which simplifies the defuzzification process. In general, Sugeno-type systems can be used to model any inference system in which the output membership functions are either linear or constant.

In the context of an universe comprising fuzzy sets and a number of weighted fuzzy rules *if-then*, a fuzzy inference process comprises five phases: (i) fuzzification of the input variables (those appearing in the antecedent part of the rules), (ii) application of the fuzzy operator (AND or OR) in the antecedent (if necessary), (iii) implication from the antecedent to the consequent, (iv) aggregation of the consequents across the rules, and (v) defuzzification.

If the system starts with more than one rule, the fuzzy sets representing the output of rules implying the same variable are combined (aggregated) into a single fuzzy set. This operation is applied during the fourth phase of the inference process. The output of the aggregation phase is one fuzzy set for each output variable. The fifth phase allows to obtain a single numerical value, by applying the defuzzification process on the output fuzzy sets. Among the most popular defuzzification methods we may enumerate the centroid calculation (for Mamdani-type systems) and the the weighted average (for Sugeno-type systems).

The basic model for a fuzzy inference system considers that membership functions, representing the characteristics input, are predetermined by the user. In the situation where these characteristics can't be "guessed" only by looking at the data, a neuro-adaptive learning technique may be used to *learn* information about a data set, by choosing the parameters so as to tailor the membership functions to the input/output data. The final system is called an *adaptive neuro-fuzzy inference system* because it uses a network-type structure similar to that of a neural network for the learning purpose. The fuzzy modeling approach comprises the classical system identification steps: hypothesizing a parameterized model structure, collecting input/output data in an appropriate form, training the FIS model according to a chosen error criterion and validating the model.

B. Fuzzy Clustering

Another essential element in our approach is Fuzzy Clustering. The aim of a cluster analysis is to partition a given set of data or objects into clusters (subsets, groups, classes), such that the data that belong to the same cluster should be as similar as possible, and the data that belong to different clusters should be as different as possible. The Fuzzy C-Means Clustering (FCM) is an unsupervised goal oriented clustering algorithm, introduced by Dunn [32] and generalized by Bezdek [33].

The term fuzzy is used here to refer to the way how the analysis of clusters is done: an item x_k can be assigned to several clusters c_i, through the membership functions μ_i. The goal function of the FCM is defined by

$$J(U,C) = \sum_{i=1}^{c}\sum_{k=1}^{n} \mu_{ik}^m d_{ik}^2 \tag{1}$$

where $\mu_{ik} = \mu_i(x_k)$, $m \in (1,\infty)$ defines the degree of fuzziness and $d_{ik}^2 = (x_k - c_i)^T(x_k - c_i)$ is the squared distance (usually the euclidian distance) between the item x_k and the center of the cluster c_i. The clusters' centers are stored in the matrix C whereas the matrix U contains the corresponding values of u_{ik}.

The optimization problem can be described as *minimize* $J(U,C)$ under the constraints (i) $\forall k \sum_{i=1}^{c} u_{ik} = 1$ and (ii) $\forall i \sum_{k=1}^{n} u_{ik} > 0$. In order to solve this optimization problem the Lagarange method can be used.

$$J(U,C,\lambda) = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^m d_{ik}^2 - \sum_{k=1}^{n}\left(\lambda_k\left(\sum_{i=1}^{c} u_{ik} - 1\right)\right) \tag{2}$$

The derivative for u, c and λ have to be calculated. This leads to the following solution

$$c_i = \frac{\sum_{k=1}^{n} u_{ik}^m x_i}{\sum_{k=1}^{n} u_{ik}^m}; u_{ik} = 1/\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{m-1}} \tag{3}$$

The FCM algorithm consists of the following steps:

1) initialize the matrix U^0
2) calculate the matrix $C^s = [c_i]$
3) calculate the matrix $U^s = [u_{ik}]$
4) if $||U^s - U^{s-1}|| < \epsilon$ then stop, else goto step2

The FCM algorithm is efficient, straightforward, and easy to implement, but it is sensitive to initialization (due to random selection of initial center points) and so is easily trapped in local optima. Moreover, the number of clusters to be generated for the given data set needs to be specified *a priori*. To overcome these problems, different solutions were proposed, such as a PSO-based fuzzy clustering algorithm [34], a genetic fuzzy k-Modes algorithm [35] or a hybrid fuzzy clustering algorithm based on FCM and rough sets theory [36].

III. Methodology and Tests

As mentioned in the introduction our overall goal of this paper is to devise a methodology for automatically constructing, starting from forensic data, expert-system-like if-then rules. These rules should fulfill two main constraints. On one hand they should be as accurate as possible and on the other hand they should be easily understandable by a human domain expert (not necessarily a specialist in expert systems). In order to achieve these goals we decided to base our approach essentially on the methods presented in the previous section i.e. on the fuzzy inference systems and on the fuzzy clustering.

A. Methodology

The methodology we are proposing is one of the many used for inferring membership functions for fuzzy variables from raw data. The overall procedure consists of three main steps:

1) clustering the raw data
2) extract the membership functions from the data
3) create the fuzzy inference system

We will give now a short description of each step.

1) Clustering the Raw Data: In this first step we have to find meaningful membership functions that will be part of the fuzzy variable that represents the dimensions we are interested in. In respect to the forensic data these fuzzy variables will correspond to the attributes of the database (see next section). To conduct this clustering we decided to use the Fuzzy C-Mean clustering. This algorithm has, in respect to our needs, one very important advantage. Namely, that it produces a membership value for each data point, defining its degree of membership to each cluster. Otherwise it has some negative points in the sense that it is not invariant to linear to linear transformations and it is also sensible to the initialization of the cluster centers. The important outcome for our purposes of the FCM algorithm is the U matrix (see description above). The element u_{ik} defines the degree of membership of the element k to the cluster i. In order to get this output from the algorithm, we have to provide the list of data points that have to be clustered with their corresponding values for each dimension as well as the number of cluster we would like to generate. For these experiments, the number of clusters was provided by the user, but it would also be possible to use automatic techniques, e.g. differential clustering to generate the number of clusters. In the following step we will describe how, starting from U, the membership functions can be generated.

2) Extraction of Membership functions: Obviously, the construction of the membership function depends on the type of membership function that will be used to construct the fuzzy inference system. For illustration purposes we will focus on the symmetric Gauss membership functions. However, the same general procedure as outlined here can be applied to all kinds of membership functions. The main idea consists of inferring the parameters of the membership function from the output values obtained in the previous step. The Gauss membership function has the following form: $mf(x, \sigma, c) = e^{\frac{-(x-c)^2}{2\sigma^2}}$. This function depends on two parameters c and σ. c corresponds to the centers of the clusters found during the FCM clustering. The only value that has to be calculated is σ. This can be done using the forensic raw data and the U matrix obtained from the FCM algorithm. For each cluster i and each fuzzy variable j (attribute of the database) the following formula can be applied.

$$\sigma(i,j) = \frac{1}{N} \sum_{k=1}^{N} (\sqrt{\frac{-(x_{kj} - c_i)^2}{2\log(u_{ik})}} \tag{4}$$

where N is the number of data points, x_{kj} is the value of data point k for the attribute j, c_i is the center of cluster i and u_{ik} is the degree of membership of point k in cluster i. However this function would go to infinity if one data point corresponds exactly to the center of the cluster. But these points are not adding or removing anything to the spread of the Gaussian curve and can therefore be removed, for our purposes. This concludes the second step; now the $\#cluster \times \#dimension$ membership functions are defined and we can start to construct the rules.

3) Creating the Fuzzy Inference System: The rules we like to create for the fuzzy inference system should fulfill the constraint of being easily understandable by a domain expert, e.g. a member of the police corps. Therefore, we are looking for rules of the form *if* x_1 *in* mf_1 *and* x_2 *in* mf_2 *then* y_1 *in* mf_3. An example of such a rule could be *if time=”late evining” and place=”rural” then value=”high”*. For each cluster we found in the second step the corresponding membership function for each attribute. Therefore, all elements for constructing rules are available.

The first decision we have to make is to choose which attributes of the forensic database will be used as antecedent and which will be used for the consequent. We will limit ourselves to rules with only one element for the consequent but our approach allows for multiple attributes. Once the list is created we can define, for each cluster, fuzzy rules of the given form. The set of all rules will then constitute the fuzzy inference system. Before we can finalize the fuzzy inference system we have to select the type of system that will be used. This choice depends on the further usage of the fuzzy inference system. For illustration purposes, we selected a Mamdani-type system for this paper, however, in the practical application we prefer the Sugeno-type system, especially for further automatic improvements of the system.

After finishing these steps a complete system is available. It can be used in the process of investigation to perform tasks such as: predication, characterization, or validation. All of the steps needed in our methodology are very easily implemented in most of the data analysis environments, some of them have even comparable procedures predefined.

B. Data

The forensic database we are working with in our study contains all the collected data about events representing robberies and residential burglaries in the canton of Vaud. This high-dimensional database contains information about events, persons, vehicles, tests, etc., characterized by about 70 attributes. We conducted tests an a wide range of attributes, for space constraints we decide in this paper to focus on the ”event” part of the database. This part is small enough to present our main results and does not need long presentations. Each event is identified as a point having three dimensions:

- Temporal dimension: characterized by starting/ending date and time of occurrence.
- Spatial dimension: characterized by the geographical x and y coordinates, based on the Swiss reference system CH1903.
- Typology dimension: characterized by the event type, address type (apartment, residential house, commercial store, etc..) and operating type.

As the goal of this paper is to present a methodology and the quality of the results one may expect by applying it to forensic data, testing it on real data might not permit to test all aspects necessary to judge the quality. Therefore we decided to create an artificial dataset strictly respecting the structure of the original forensic database however containing some

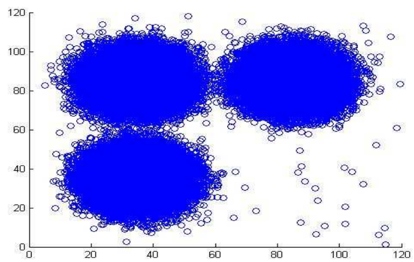

Fig. 1. Spatial distribution of the events.

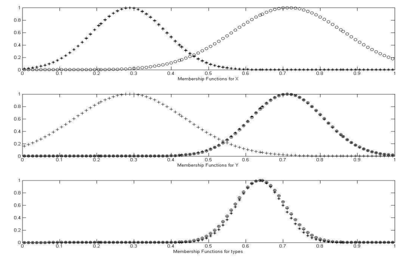

Fig. 2. Three cities with events of similar typology of events.

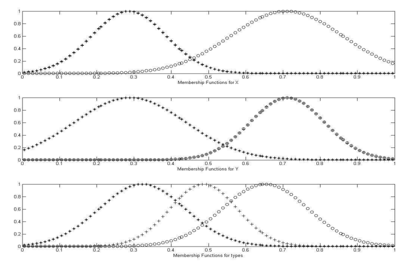

Fig. 3. Three cities with different typologies of events.

hidden internal structures. We would like to test if we are able to unveil these structures and at the same time guaranteeing that the system is not discovering non-existing structures. As explained above we simulated en event database containing temporal, spatial, and typological information.

- *Temporal:* five years worth of data, divided in year, month, day (including weekday).
- *Spacial:* x-y-coordinates of the region under investigation. Uniformly distributed events, cities and rural regions, and highways were simulated. The cities were simulated as independent, aligned in respect to the x-coordinate and in respect to the y-coordinate.
- *Typological:* simplified numerical value.

In this basic structure of the database we integrated hidden rules, e.g. the typological value is probabilistically higher for rural regions, the probability of having events occurring on a weekday are higher than on weekends, etc. The goal was to test if the system is able to unveil them. Some of this examples are presented in the next section.

C. Experiments

As outlined in the "Data" section we were able to create databases that allow us to verify a wide range of capabilities of the methodology we proposed. It would not be possible to present all the results in this context, but we selected some typical tests to present the overall results. Globally, we are very satisfied with the results obtained. Following the methodology we proposed, we were able to unveil all the hidden structures integrated into the generated datasets. Also, while being more difficult to asses, the accuracy of the results were very positive. The datasets are generated using probabilistic algorithms which introduce errors. The errors produced by the proposed methodology had also comparable statistical distribution as the errors introduced by the generation procedure. This is the bases on which we concluded that the accuracy of the approach is satisfactory. Furthermore it has to be underlined that the fuzzy inference system constructed in the three steps outlined above is not intended to be in its final shape. These systems can further be improved using methods not presented here. We will present the following two examples as an illustration of the kind of results obtained in general.

In both examples we used the same spatial distribution of events. It simulates three cities, two of them are aligned in respect to the x-axis and two in respect to the y-axis (see Figure 1). The goal of these examples is to predict the typology from the x and y values.

In the first example we simulated a situation where the typology attribute is the same for all the events in the three cities. It is higher in the center and then degrades as we move away from the center. In Figure 2 we can see in the first graph that the two left membership functions are overlapping, as the two cities on the left share similar x-values. In the second graph one can see the same phenomenon in respect to the y-values for the upper cities. For the output variable (typology) we even have all three membership functions that are overlapping, which is correct as the three cities have similar values.

In the second example (see Figure 3) we simulated a situation where the typology (output variable) for the events in the three cities has different values. Now we can see that the three membership functions of the output variable illustrate this fact.

It can be observed that in the first example two membership functions for x, two for y and one for the typology would have been sufficient, and in the second example the same for x and y, but three for the topology. The current approach does not automatically adapt the number of membership functions, however they can be manually adapted. The reasons are given in the next section.

D. Drawbacks

Even though the results are very encouraging, there is one important drawback to mention. Following the procedure outlined at the beginning of this section, the number of membership functions per fuzzy variable (i.e. database attribute) is always equal to the number of clusters created. Although this approach allows to fix the number of clusters by the user, only one value is possible. For the dimensions used in our examples it is very difficult to fix the number of clusters that would produce meaningful membership functions for the temporal and the spatial dimensions. This does not reduce the quality of the numerical results of the fuzzy inference system, however, it might be very difficult to assign a clear semantics to these membership functions, which is important in systems designed for domain experts. We are currently working on some solutions for this problem by merging and splitting membership functions.

IV. Conclusion and Future Work

In this paper we described a methodology to automatically extract expert-system-like if-then rules from forensic databases. The methodology and the algorithms used were proven to be easily implementable in most data analysis environments. The conducted tests have shown very satisfactory results. They were able to unveil all the hidden structures we were testing them on. The accuracy of the rules inferred was very high and clearly better then the minimum level required to make them usable in a practical setting. However, the tests have also shown a drawback that should not be neglected. Namely, the fact that it was very difficult to find an intuitive semantics for some of the membership functions (even though they are producing high quality rules), which complicates the communication with domain experts. We are currently working on this issue and got promising results using heuristics for splitting an merging fuzzy sets.

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