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An application of case-based reasoning with machine learning for forensic autopsy

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ABSTRACT

Case-based reasoning (CBR) is one of the matured paradigms of artificial intelligence for problem solving. CBR has been applied in many areas in the commercial sector to assist daily operations. However, CBR is relatively new in the field of forensic science. Even though forensic personnel have consciously used past experiences in solving new cases, the idea of applying machine intelligence to support decision-making in forensics is still in its infancy and poses a great challenge. This paper highlights the limitation of the methods used in forensics compared with a CBR method in the analysis of forensic evidences. The design and development of an Intelligent Forensic Autopsy Report System (I-AuReSys) basing on a CBR method along with the experimental results are presented. Our system is able to extract features by using an information extraction (IE) technique from the existing autopsy reports; then the system analyzes the case similarities by coupling the CBR technique with a Naïve Bayes learner for feature-weights learning; and finally it produces an outcome recommendation. Our experimental results reveal that the CBR method with the implementation of a learner is indeed a viable alternative method to the forensic methods with practical advantages.

1. Introduction

The database or perhaps more aptly the knowledge repository is the most important asset in the domain of forensic science as a whole, regardless of whether the information is computerized or otherwise. The database records the past forensic cases and assists personnel when they perform analysis as part of their current investigations. However, many systems, which store data, require some degree of intelligence to reduce turnaround time of an investigation process and mitigate errors such as those arising from human negligence or mistakes. For instance, currently, data of past case evidences are retrieved from the database to perform "eyeball" comparison. A positive result (based on human judgment) of the comparison suggests the two cases are similar. If the result is negative, the forensic personnel will need to retrieve evidence from the database and perform another comparison. A system capable of handling comparison with some degree of automation coupled with intelligence will definitely increase the productivity. In forensics, the relevant experts need to analyze the collection of evidences and interpret the results of analysis by using his or her theory (Srihari, 2010). Furthermore, the shortage of human resource and time are the main hurdles faced by these experts (Hoelz, Ralha, & Geeverghese, 2009). This is where machine intelligence comes in useful, which can assist these experts in their decision-making.

The use of computerized techniques in forensic science should not be mistaken for digital forensics, which is a field in forensic science that focuses primarily on investigations and recovery of data from digital devices. Digital forensics has developed rapidly due to the need to process huge volumes of data extracted from digital devices. Information retrieval (IR), a data extraction technique (Beebe, Clark, Dietrich, Ko, & Ko, 2011) is often used in the forensic investigation process, and this is where computer intelligence is essential to expedite the process. The extracted data are usually filtered and synthesized using a certain degree of machine intelligence. Compared with the use of machine intelligence in digital forensics, the use of machine intelligence in forensic science is minimal. Most of the analyses of evidence in forensic science are still based mainly on traditional methods, even though computational forensics can address some of the limitations in traditional methods (Srihari, 2010). Computational forensics is a relatively new field that aims to improve the analysis of evidence using computational methods. The forensic personnel can use many state-of-the-art automated tools to assist them in daily operations in forensic investigations. For example, ImaQuest (2013) and ASTIS (2012) are tools that provide a platform to facilitate the investigation process. These tools are visualization and screening devices that can assist the forensic personnel in their investigation process

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and double up as digital data stores. However, even with some degree of automation, narrowing down matches still requires human experts with specific knowledge to assess the evidence based on their professional opinion. Similarly, INFODADS (2013) is another integrated software application that not only acts as a visualization and screening tool, but assists the forensic personnel in post-mortem reporting. The Federal Bureau of Investigation (FBI) of the United States of America uses the CODIS (2005) as a DNA database to match DNA evidence from criminal cases. These state-of-the-art tools are only a few examples of the capability of machine intelligence. There are tremendous opportunities available to the members of the forensic fraternity to embark on future plans to tap the full potential of machine intelligence in investigative forensics.

In this research, our objective is to initiate a support system that can handle decision-making and reasoning of a decision, based on the available forensic data. The method incorporated in the decision support system must be capable of providing a conclusion with minimum participation of human experts throughout the entire system reasoning process. This is our main rationale to incorporate the Case Based Reasoning (CBR) method as the backbone of the decision support system in the field of forensic science. This work is originally motivated by a research work presented by Ribaux and Margot (1999), which adopted the CBR methodology as an inference structure using the forensic case data. The methodology was then generalized and modeled with better detail in his subsequent publication (Ribaux & Margot, 2003). Both the research works of Ribaux and Margot (1999), Ribaux and Margot (2003) proved the viability of using past cases to solve new cases. The underlying method and model proposed is technically underestimated compared with an actual problem-solving technique based on artificial intelligence. The methods of other researchers that are based on this similar approach are compared as well.

This paper is organized in the following manner. In Section 2, the state-of-the-art CBR method is reviewed. The related forensic methods and their advances that are used for decision support are also reviewed and compared with the CBR method. In Section 3, the methodology of this research work is described. This also includes the design and development of the system, which is based on our proposed method. In Section 4, the details of our experiment setup as well as data are described, and the experimental results are reported. This paper concludes with Section 5.

2. Artificial intelligence in forensic science

In this section, the literature is reviewed based on two questions regarding the application of artificial intelligence techniques in forensic science. The first question pertains to justification of the use of CBR method over other available methods as a forensic decision support system. The second question addresses the underlying challenges and would-be limitations of a forensic scientist in using the existing forensic methods, which includes the underestimation of the CBR method as merely another form of computerized systems. The deliberations on the two questions give rise to a proposal of a new CBR method which incorporates a full-fledge artificial intelligence approach; the new CBR method is deemed capable of meeting the need of more efficient investigative processes in the forensic domain.

CBR is an artificial intelligence paradigm of problem solving and learning by experience (Aamodt & Plaza, 1994; Leake, 2003). One of the goals of a CBR system is to solve new problems by retrieving solutions of old cases stored in a case base; these old solutions are adapted to solve new problems (Leake, 2003). With the maturity and the flexibility of a CBR method, it is often coupled with various other methods to solve a specific problem. Generally, the coupling of a CBR method with other methods is used to solve specific problems in various domains. These coupling methods include: the artificial neural networks (Henriet, Leni, Laurent, & Salomon, 2013), preference functions (Vukovic, Delibasic, Uzelac, & Suknovic, 2012), classification (Begum, Barua, Filla, & Ahmed, 2013), optimization algorithm (Teodorović, Šelmić, & Mijatović-Teodorović, 2012), genetic algorithm (Lam, Choy, Ho, & Chung, 2012; Liao, Mao, Hannam, & Zhao, 2012), fuzzy logic (Lao et al., 2012), and ontology (Yang, 2012). There are also works that implement the CBR method as a core learning mechanism, with minimal modification to the original CBR method. For example, the CBR method is applied in medical diagnosis (Guessoum, Laskri, & Lieber, 2013) and business management (Carmona, Barbancho, & Larios, 2012). Based on these examples, it is proven that the CBR method is indeed very flexible and viable for application in various forms of knowledge and domains. The potential of CBR method is limitless in providing a learning platform based on past cases to reduce the involvement of human experts.

There is evidence that the forensic investigators' experience and knowledge are directly proportional to the quantity of their previously investigated cases; they are able to retrieve the information of past cases and use the old situations or solutions as a means to deal with new problems. Furthermore, when an investigator mentors a newcomer, or when there is an attempt to tackle a new situation, he or she will systematically refer to his or her experience. This kind of reasoning process practiced by the investigators resembles the concept of CBR in artificial intelligence. This is the basis of Ribaux and Margot (1999), Ribaux and Margot (2003) in initiating the implementation of a CBR methodology in forensics, as part of the forensic intelligence. There is no report of result accuracy or extent of success pertaining to these works. The effort to develop the CBR methodology was not continued by the researcher, as the attention was later diverted to the area of forensic intelligence (Ribaux, Walsh, & Margot, 2006; Ribaux et al., 2010a; Ribaux et al., 2010b). Forensic intelligence is not related to artificial intelligence, even though "intelligence" is the common subject in both areas. Forensic intelligence is generally considered as an intelligence-led condition to gather traces from a crime scene, to process the traces and to interpret the results of the analysis (Ribaux et al., 2010b). We have reviewed some of the more recent related works that are based on this approach.

The subject of intelligence, within the forensic community, is seen to be advancing into a probabilistic approach such as the Bayesian networks and likelihood ratio. Biedermann, Bozza, Garbolino, and Taroni (2012) and Biedermann and Taroni (2012) reviewed the use of Bayesian networks in evaluating forensic evidence. The Bayesian network is one of the most frequently encountered approaches in that area; it is highly accepted by the community due to its bidirectional probabilistic inferences. The probabilistically driven inference allows forensic prediction to be done more naturally. For example, the Bayesian approach is used to analyze genetic evidence (Wolańska-Nowak, Branicki, Parys-Proszek, & Kupiec, 2008), DNA profiling (Dawid, Mortera, & Vicard, 2007), facial identification (Allen, 2008), gunshot particle evidence (Biedermann, Bozza, & Taroni, 2011), etc. In addition, the Bayesian network is often coupled with the likelihood ratio to analyze the relatedness and the relationship between evidences. An example that has adopted this approach is the interpretation of the shoemark evidence (Skerrett, Neumann, & Mateos-Garcia, 2011). With the Bayesian inference structure, the evidence is analyzed with likelihood ratio to measure the relationship vs. other possible evidences. On the other hand, Zadora and Neocleous (2009) proposed a model for forensic evidence classification that only used a likelihood ratio model to analyze glass fragments.

If we compare the methods used by the forensic researchers vs. the CBR method in the artificial intelligence field, we can observe that the main difference between both schools of thought is the