A Survey on the Profiles of Drug-related Cases and their Depiction

Chengling Huang[1a], Mingzhi Huang[2b], Fu Liao[3c], Huang Liang[4d], Zhen Zhang[5e], Xiaojian Li[*6f], Jinw Nong[7g]

[a]chengling89@stu.gxnu.edu.cn, [b] huangsanchuang@gmail.com, [c] liaof@stu.gxnu.edu.cn, [d] imliangh@foxmail.com, [e] zhangzh_2020@163.com,[f] xiaojian@mailbox.gxnu.edu.cn, [g] ari_nongjinwen@163.com

[1~7]School of Computer Science & Engineering, Guangxi Normal University, Guilin, China

Abstract. An important direction in the field of computer science research is computer application technology research. For example, how to use advanced deep learning technology to process crime big data to quickly assist in the detection of drug-related cases. Profile of criminal case is important intelligence for investigation. It should be a whole that constitutes a set of distinctive features such as the features of things, the characteristics of people, and the relations between them. This paper surveys on the profiles and their depiction methods in recent research. Those studies focus on spatio-temporal features of incidents such as personal security for travel, invasion of property, and fraud. However, other features, such as motives, processes, suspects and results, are also important for the investigation to drug-related complex cases. A taxonomy of the profiles and their depiction methods is given. We point out the problems: the studies didn't integrally focus on understanding and representing these features and their investigative experiences, and mostly characterize case features with their non-fully connected neural network-oriented data types. Meanwhile, the suggestions are proposed for the profiles of drug-related cases and their description.

Keywords: incident profile, incident depiction, neural network, machine learning

1 INTRODUCTION

As the first step of the research to computer application technology, this paper surveys the current research status to apply computing technology to assist the detection of drug-related cases, including the empirical study to the big data and the literature review, gives a taxonomy of the computing technology used in them, points out the recognition and presentation of the profiles of the cases as well as the computational difficulties to be solved in the depiction. A computational logic model is proposed to depict the case profiles as a technical approach.

Crime case features, including their intuitive and implicit features, need to have representational integrity and sufficient differentiation, then the case features must be optimized. In addition, there are important relations of certain between the case features. If the case dataset can form a feature system, it is a completely and systematically reflects the pattern and contour of the case (collectively referred to as the "profile"). Therefore, based on experiences of investigative, depicting the profile of the case will play an important role in supporting the detection of complex case.

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According to the integrity and the differentiation of the case feature, the profile and its depiction will involve the spatio-temporal, people, motives, processes, results and incident of the case, as well as the method of depiction and verify of the profiles.

The remainder of this paper is organized as follows. Review the recent research of incident profiles and incident depiction and the taxonomy are given in section 2; Section 3 gives challenges and suggestions. Finally, in Section 4, we present our conclusion.

2 RESEARCH REVIEW

It is included the research status of incident profile and its depiction currently in our review. Among them, the review of the research status of incident profile includes space contour, time pattern, suspect profile, process pattern, motive pattern and result pattern. The review of the research status of its depiction includes space depiction, time depiction, suspect depiction, process depiction, motive depiction and result depiction.

2.1 Incident Profile

2.1.1 Contour in Space and Pattern in Time.

The paper [1] study's the features of crime data such as geographic location, time and postal code in which a crime occurs, and correlates them to then discover the time and location patterns of crime. The spatio-temporal profile given in that paper is composed of characteristics such as location of crime occurrence, time, and postal code. The paper [2] explores the features of crime patterns, including date ("day", "month", "year", "hour", "minute", "second"), location (longitude, dimension), location description, and major crime types to predict where future crimes will occur. The paper gives a spatio-temporal profile consisting of date, moment, location, location description and type of crime. The paper [3] focuses on the type of crime, time (year, month, day, hour), location (district, address, latitude, longitude), precinct, age, gender, race and other characteristics of victims and suspects to derive a contour (tangible contour) of where the crime primarily occurred. The paper [4] examines the crime pattern, which is a whole consisting of the type of crime, the type of target, the time of occurrence, and the place of occurrence. The paper only deals with the "crime profile" of time and place.

The paper [5] describes a method to predict crime incidents using spatio-temporal generalized additive models that gives a spatio-temporal profile consisting of time and space. The paper [6] extracts the time and place of crime from mixed-structured crime data to give a plain Bayesian classification method to portray the time contours and place contours of crime events. The paper [7] studies the similarity between cases based on space and time. The paper does not specify the concept of "temporal crime patterns". The paper [8] proposes a computational method for determining crime boundaries using street contours and discrete calculus. The paper studies the range of boundaries where crime occurs in a more concentrated location and carves out the location contours. The paper gives the crime location pattern consisting of the range of locations where crime incidents are more concentrated.

The paper [9] proposes a system for crime trajectory prediction and visualization. This paper gives the crime spatio-temporal pattern as a path consisting of latitude, longitude, time, and the main types of crime. The paper [10] uses the GP-SMART to map the suspect's place of crime with the suspect's home address and the location of previous criminal incidents, thereby determining the suspect's suspected ranking of involvement based on the suspect's geographic profile in this suspect case. The location profile given in this article is composed of the suspect's crime place, home address, and location of previous criminal incidents, among other ternary activity locations.

It can be seen that the current study only considers time and location contours, and pays less attention to the characteristics of suspects' characteristics, motivation profiles, outcome profiles, process patterns and incident profiles. In summary, the time pattern that current studies focus on the range of dates and moments where crime incidents are concentrated. The space patterns are the names of places where crime events occur, and the spatio-temporal patterns that a few studies focus on include the dates, moments, and names of places where crime incidents occur, and also include the type of crime, longitude, and latitude. As shown in table 1.

Table 1. Features of time and space

Pattern in time	Date("day", "month", "year")
Pattern in time	Time("hour", "minute", "second")
Contour in space	longitude, dimension
Contour in space	district, address, precinct

2.1.2 Suspect Profile.

The offender profile given in the paper [11] is an incomplete exception to the person profile, consisting only of the offender type of the individual or entity and lacking more comprehensive information on the attributes of the person. The paper [12] proposes a method of correlating interpersonal interactions of offenders that gives interaction links between persons (i.e., interaction events between offenders). However, this was not used to give a profile of interaction events for offenders. The paper [13] calculates suspect similarity based on attributes such as the suspect's age, skin color, height, body type, hair style and accent. The paper [14] uses a crime dataset from Korea to analyze offender profiles using characteristics such as gender, age, education level, occupation, standard of living, marital status, religion and their relationship with the victim of their offenders, whose suspect profiles consist of characteristics such as gender, age, education level, occupation, standard of living, marital status, religion and their relationship with the victim of their offenders.

In summary, the current study focuses on people profiles that are too homogeneous and less comprehensive in their profile characteristics.

2.1.3 Process Pattern.

A single criminal act constitutes a criminal incident. A case is a whole of incidents consisting of several criminal incidents with their interconnections. Among them, the interconnections of the criminal incidents are the incident structure of the case. The criminal process is the sequence within the incident structure of the crime. Therefore, the study of process pattern also involves behavioral pattern (single incident contour), and structural pattern.

The paper [15] states that a behavioral pattern is a process used when a series of crimes are committed by an offender. The time and space of the crime, and a number of criminal acts and their connection to each other form the outline of the criminal process, which consists of the time, place, acts and their connection to each other of the crime, lacking the subject and object of the action information. The paper [16] examines the similarity of criminal behavior based on the time, place, and action of crimes within a criminal group. However, the study does not address the subject that initiates the action (the suspect) and the object that endures the action (the victim or the object), making it difficult for the method to paint a complete picture of the process pattern of the case.

The papers [17][18] calculate the triadic similarity of "attribute actions" such as number of criminals, tools, and modus operandi for a number of processes to arrive at a crime process pattern. However, it lacks information such as the time and place of the crime incident. The paper [19] investigates the similarity of criminal behavior of multiple events to form a criminal connection. The paper [13] inputs temporal, spatial, and behavioral features of robberies to give a neural network-based similarity method so as to calculate the similarity of criminal acts.

The paper [20] studies the links and effects between criminal acts, indicating the incident to which a particular criminal act co-occurred with other criminal acts in the same case through the co-occurrence index of criminal acts, thus constituting a structural profile, which consists of the acts of a crime and the extent to which they co-occur with each other, lacking information on the time and space of the crime.

The literature [21] states that the crime behavior pattern consists of six meta-groups such as NCIC crime code, suspect's gender, age, race, time of crime, and type of crime. However, it lacks information such as the behavioral action and location of the crime. The literature [22] states that the crime behavior pattern is a triad consisting of the time sequence of the crime, the crime connection, and the crime path. However, it lacks information such as the location of the crime and the attributes of the suspect.

The paper [11] constitutes a cybercrime case profile based on the basic incident description, the type of offender involved, the measures used, the target of the attack, the victim， and other attributes. It lacks information on the motivation for the crime, the gender, age, home address, and other attributes of the perpetrator.

In summary, on the one hand, the process pattern of the recent research consists of the time, space, act and their interconnection of the crime. On the other hand, the process pattern consists of information such as the similarity of the links between criminal acts and criminal incidents. The patterns of the act do not involve the subject who initiates the action (the suspect) and the object who suffers the action (the victim or the object).

2.1.4 Motive Pattern and Result Pattern.

The paper [23] examined the propensity of people to commit crimes and incorporated interactive links between offenders, such as remittances, phone calls and other contacts. In this way, a social network analysis (SNA) model was developed.

No studies focusing on outcome profiles have been seen.

In summary, current research on crime incident profiles involves time pattern, space contour and motivational pattern, single-attribute profiles of people, and less attention to result pattern, process pattern and features of incident profiles.

2.2 Incident Profile Depiction

2.2.1 Depiction Methods of Spatial and Temporal.

The multiple linear regression method used in the paper [3] must ensure that there is a linear relationship between the independent and dependent variables. However, for discrete events, such as crime incidents, it is difficult to ensure the existence of realistic data with a linear relationship. The paper also uses a supervised learning kNN approach for multi-class classification and regression problems. The supervised learning kNN method used in this paper is also applicable to multi-class classification and regression problems. However, if the training set contains noisy points, it will affect the classification effectiveness of the method. For drug-related incidents with noise in the data, the portrayal is less effective.

The multinomial logistic regression method used in the paper [4] is more effective for small and linearly correlated data. It also is suitable for solving binary classification problems. However, the method is not suitable for criminal incidents where the suspect is involved in multiple crime types at the same time, i.e., the method is not suitable for resolving cases where the suspect has multiple criminal manifestations.

The paper [5] uses an iteratively re-weighted least squares method to propose a generalized additive model. The method is a statistical approach and the GAM relies on the manual inclusion of interactive features. It is poorly portrayed for drug-related incidents.

The regression method is suitable for profiling data that have a linear relationship, while it is less effective in profiling crime incidents such as those that have a non-linear relationship.

The paper [2][3] uses a supervised Decision Tree method, which can handle data containing incident values and is suitable for multi-class classification and regression, but can produce over fitting situations and cannot self-correct for labels. The Random Forest and Extra Tree approach used in the paper [2] selects a random feature value to divide the decision tree, which can then be relied on supervised to classify the spatio-temporal pattern of the incident. For drug-related incidents, which are featured by a wide range of variables, the decision tree method is difficult to characterize incidents such as drug-related incidents that contain multiple things and each thing contains multiple features at the same time, relying on the experience of a single feature for a single multi-category single classification.

The paper [6] uses plain Bayesian classification of crime locations, which relies on a priori models, for a supervised multi-class classification learning approach. The method works well when classifying independent features such as "crime location". However, it is less effective than graphical neural networks when dealing with crime events where several features are associated with each other.

The paper [1] uses a statistical approach of spatial association rules to predict the spatio-temporal patterns of crime, identifying spatial targets that are characterized by spatial patterns such as adjacency, connectivity, co-occurrence, and inclusion. This statistical carving method built on rules is not suitable for carving the spatio-temporal pattern of drug-related incidents that have no rule-based operational efficiency to speak of.

The paper [24] uses spatial clustering methods and kernel density estimation methods to analyze the spatial distribution of crime. However, for the contouring of suspects, processes and structures in drug-related incidents, this unsupervised clustering method suffers from insufficient accuracy in contouring and multi-label clustering. It is not suitable for the identification of clusters with multiple characteristics such as drug-related incidents.

The GP-SMART used in the paper [10] is highly accurate when there is a close association between the crime location and the activity nodes of the offender. However, it is less effective when the correlation of the activity nodes of the crime event is low. It is more relevant for spatio-temporal data on drug-related incidents. However, in terms of suspect, process, and structural profiling of drug-related incidents, the literature lacks descriptions of attributes such as gender, ethnicity, occupation, education level, and type of involvement of suspects, so this profiling approach is currently unable to reflect the impact of these attributes on the spatio-temporal profile of drug-related cases, among other shortcomings.

Current spatio-temporal pattern methods mainly use non-neural network-type machine learning methods, such as regression linear methods that excel in statistics, non-fully connected decision tree methods, plain Bayesian methods, statistical methods with spatial association rules, spatial clustering methods, and geographic feature analysis methods. These methods are mostly used for multi-class classification and do not address multi-label classification. In addition, current approaches to spatio-temporal profiling are unable to deal with some of the important attributes embedded in drug-related cases. However, for the "spatio-temporal profile" of drug-related cases, where the location of drug trafficking changes frequently, it is better suited to neural network algorithms that deal with uncertain discrete data. Examples include neural network-based regression methods and neural network-based decision tree methods.

In summary, the current research findings on portraying the spatio-temporal contours of cases are not yet suitable for portraying the spatio-temporal contours of drug-related incidents that involve multiple things, multiple crime types and multiple characteristics at the same time. In particular, when the data contains noise, the spatio-temporal patterns are poorly portrayed and far less effective than the classification of graphical neural networks. The current approach is not yet self-correcting in terms of labeling and does not yet fully reflect the impact of suspect attributes on the spatio-temporal pattern of drug-related cases.

2.2.2 Depiction Methods of Suspect.

The literature [17] uses Jaccard's coefficient method to calculate the similarity of feature attributes. The method lacks information about the time and space of the crime. The method is not as accurate as it could be for profiling suspects in drug-related incidents. The paper does not involve multi-label clustering and self-correction and is not suitable for the clustering and classification of suspects suspected of multiple offenses at the same time.

In summary, the current method of suspect profiling mainly uses the Jaccard factor method. However， the accuracy of this is not high. Moreover, it is not suitable for clustering and classification of suspects suspected of multiple offenses at the same time.

2.2.3 Depiction Methods of Process.

The paper [17] states that the crime process is an ordered sequence consisting of action features and object features. This paper uses the dynamic time warping (DTW) method to calculate the similarity of the crime process based on the key features of the crime process. However, the recognition performance of this method is dependent on endpoint detection. For the process profile of drug-related incidents, the method only depicts the process as a similarity pattern in time. It does not fully account for the similarity profile of the features of the process such as space, suspects, actions, and objects.

The paper [19][25] uses a binary logistic regression method to analyze similarities in criminal behaviors. However, statistical methods are more suitable for regular data and not for irregular data on drug-related crime. Among them, because of the relatively large number and categories of drug-related crime features, the binary logistic regression is not suitable for portraying the various profiles of drug-related incidents, including the profile of drug-related behavior, because it does not take into account feature correlation. The iterative classification trees used in the paper [19][25] make it difficult to profile incidents such as drug-related incidents where there are multiple things and each thing contains multiple features at the same time. The Bayesian approach used in the paper [19] requires the features to be discrete and dependent on each other. The prerequisite is relatively close to the data on drug-related incidents. However, it needs to be adapted, for example by combining it with graph theory and thus building a graphical probabilistic inference model, to make it insensitive to missing data.

The paper [18] proposes a supervised information granular-based IGRF method to correlate crimes to identify serial crime incidents. The method relies on the experience of a single feature for a single multi-category single classification for the process pattern, behavioral pattern, and structural pattern of a crime incident. The IGRF makes it difficult to depict multiple things such as drug-related incidents, where each thing contains multiple features at the same time.

The paper [13] uses a similarity classification method of neural networks to give the similarity of criminal behavior. However, this paper does not quantify the category-based features numerically. Allowing police officers to subjectively specify and construct category-based feature similarity mapping tables, which results in the constructed similarity neural networks forgoing the ability to learn coefficients on category-based feature similarity. In addition, the paper goes overboard with the interpretability of the operations and abandons the fully connected construction approach. This deprives the neural network of the ability to learn deeply about certain similarities between different meaningful features that are not yet aware of or explainable to police officers. Ultimately, these deficiencies are due to an inadequate quantification of category-based features and are constrained by an over-reliance on pre-existing human cognitive awareness.

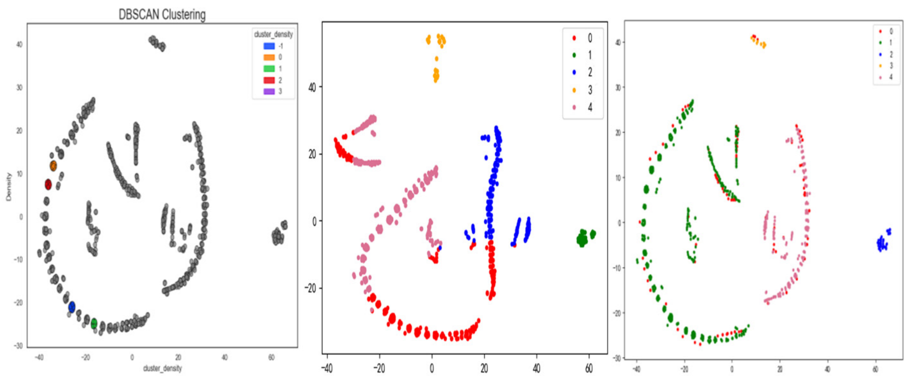
The paper [21] builds an unsupervised multi-class, multi-label classification model based on deep neural networks (DNNs) to portray criminal behavior. It does not yet have the ability to self-correct for result labels. The paper [22] uses the Path Similarity Metric (PSM) method to determine the consistency of criminal behavior. It is suitable for smaller numbers of cases. However, a good result from the PSM method depends both on good input coding and on human intervention in the potential connection of the case.

In summary, there are two main types of similarity-oriented carving methods for the current process pattern. These include statistical-based similarity classification methods such as logistic regression methods, iterative classification tree methods, Bayesian methods, random forest methods, and path similarity methods; and a neural network-based similarity classification method. However, statistical-based similarity classification methods are not suitable for portraying the profile of drug-related cases with weak statistical patterns. On the other hand, most of the current similarity classification methods are based on unsupervised neural networks, none of which are yet capable of self-correction of labels.

2.3 A big data study: the suspects profiles

This paper examines the dataset used for CAIL-2022 competition task technology, which includes legal instruments from 2011 to 2021. Our empirical study shows that certain similar properties do exist in the characteristics of personnel, which we refer to as suspect profiles.

The original data were first clustered using the density-based clustering method named DBSCAN to produce Figure 1a. The original data were then still clustered using the clustering method named k-means to produce a 5-attribute profile of the suspect (Fig. 1b), which differed significantly before and after. However, we standardized the suspect's data and still clustered it using the k-means method, allowing us to unexpectedly find that the profile presented by the new results (Fig. 1c) was nevertheless highly similar to that presented by the previous density method (Fig. 1a). This phenomenon allowed us to develop a new understanding that there is some relatively clear profile in the composition of the attributes of drug-involved persons.



a b c

Fig. 1. Some profiles of suspects depicted by DBSCAN and k-means.

There is therefore a need for further work on suspect profiles and its depicting algorithm to be able to provide investigators with guidelines for identifying the attribute categories of drug-related persons.

3 A TAXONOMY OF THE PROFILE AND ITS DEPICTION

This section summarizes and gives the relevant taxonomy of incident contours and incident portrayals from the current situation.

Exploring the features of the incident profile is a prerequisite for studying incident profile and incident depiction. Among them, based on the features of incident profiles covered in the papers [1-18][20-23] and combined with the features of incidents, the incident profiles are summarized as time pattern, space pattern, suspect profile, process pattern, and result, as shown in Figure 2.

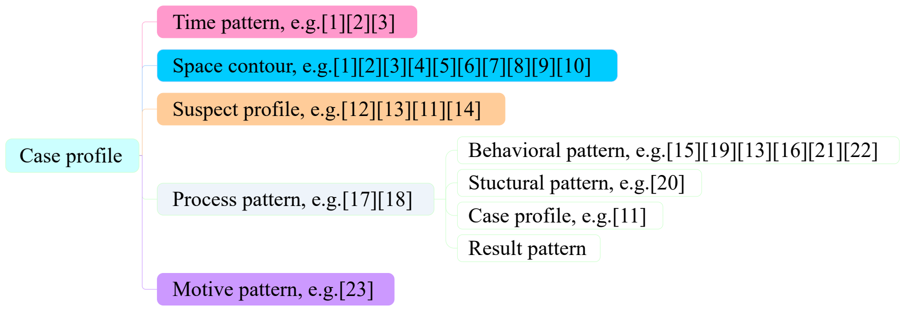


Fig. 2. A taxonomy of profiles of case.

Based on the papers [1-6,13,17-19,21-22,24-25], a taxonomy of incident depiction methods is summarized as depiction methods of spatial and temporal, depiction methods of suspect, depiction methods of process and depiction methods of motive and result. Among which, depiction methods of spatial and temporal have depiction methods of regression-based, depiction methods based on decision tree classification, and depiction methods based on neural network classification. Depiction methods of motive and result have statistically based similarity classification methods, and classification method of neural networks, as shown in Figure 3.

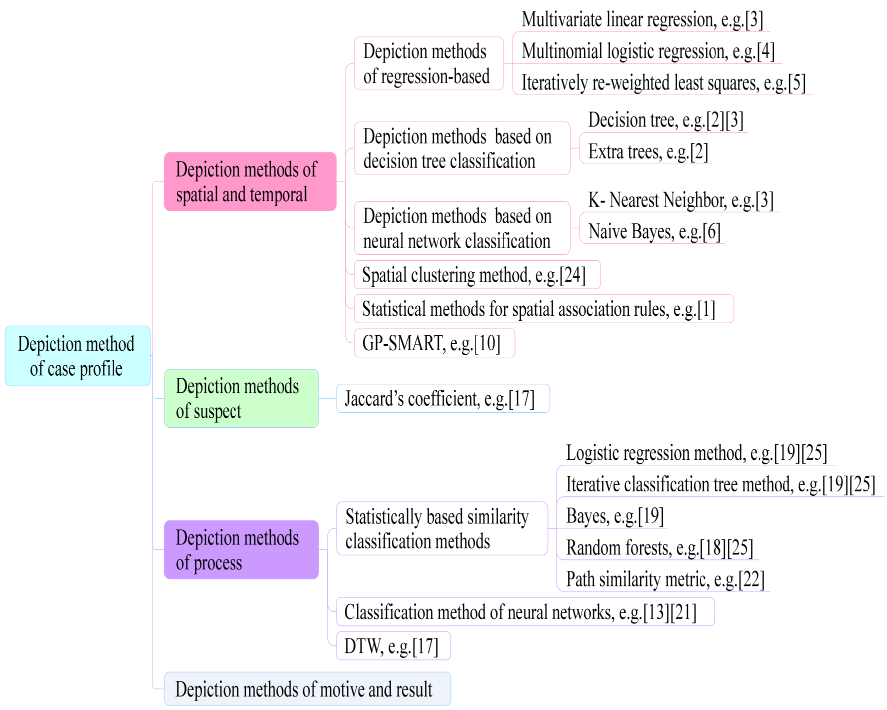


Fig. 3. A taxonomy of depiction of incident.

4 RECENT CHALLENGES AND SUGGESTION

This question addresses 3 scientific questions, including recognition of incident features, representation of successful investigative experience, and extraction and selection of incident features. Research suggestions are given to address the above three problems.

4.1 Recent Challenges

There are two types of math equations: the numbered display math equation and the unnumbered display math equation. Below are examples of both.

4.1.1 Problem 1: Recognition on Incident Features.

Problem one is the controversial recognition challenge between the general features of recent research such as the time and space of the case and the integral features of the case. Among the integral features are the time and place of the case, as well as the incident feature of the suspect, motive, process, and result. The more profound ones are the case characteristics that comprehensively cover the shape of incident profiles. If we focus only on the time and place of the case or the suspect, we can only recognize the general characteristics of the case in isolation, which will lead to a one-sided and superficial understanding of the case by the investigator.

4.1.2 Problem 2: Representation to Case Features with Their Fully Connected Neural Network-oriented Data Types.

The problem of challenging representation is case features with their fully connected neural network-oriented data types, e.g. the challenge of numerical features of category-based features. There is also the challenge of representation between investigative experience and machine learning-oriented labels. Investigative experiences include suspects who have lived in the same apartment building or neighborhood, their usual mode of transportation, their usual modus operandi, etc. Moreover, if one marks a characteristic based on these experiences, but the machine marks another, the inconsistency indicates that the representation will be challenging.

4.1.3 Problem 3: Extraction and Selection to Incident Features.

The problem of feature selection is the representational challenge between the selection failure of characteristics and their precision. Among them, the typical characteristics of cases that can be used for selection, they include the profile of the whole incident, the pattern of wrongdoing and process, suspects' the habits and characteristics. If the selection of case characteristics is expanded, more characteristics may even introduce fallacies, which in turn interfere with the accuracy of the classification. If the selection of case characteristics is narrowed, fewer characteristics will result in incomplete and inaccurate classification.

4.2 Suggestions

In response to the problems in the profile depiction of crime cases, we give suggestions for research approaches.

In order to fully understand the case characteristics, it is necessary to recognize not only the time and place characteristics of the case, but also the incident characteristics such as people, motives, processes and results. Most of the recent studies, however, consider only time patterns and space contours, and a few study person contours. In future studies, we can explore the suspects' characteristics, motive patterns, process patterns, and result patterns.

The profile of incidents also requires comprehensive features of the case and experience of success. Recent research methods of depicting incident profiles, such as statistical-based similarity classification methods, are not suitable for portraying the profiles of drug-related cases that do not have strong statistical patterns. On the other hand, most of the current similarity classification methods are based on unsupervised neural networks, none of which are yet capable of self-correction of labels. A multi-label fully connected neural network approach for machine learning could be explored in the future.

Based on the above urgent problems, the prospective model shown in Figure 3 is proposed.

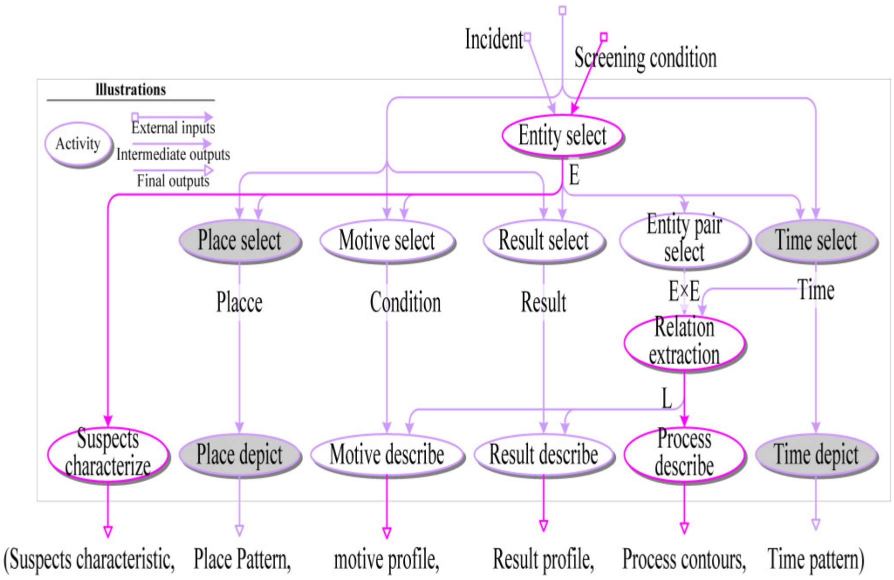


Fig. 4. A prospective model.

The ellipse in Figure 4 represents the computing activity and the directed solid line represents the entity. The directed line with a hollow rectangle at the starting point indicates the original income, the directed line with a solid arrow at the end point indicates the intermediate outcome, and the directed line with a hollow arrow at the end point indicates the final outcome. The drug-related case profile carving includes 13 activities such as time select, place select, entity select, motive select, result select, entity pair generation, connection extract, time depict, place depict, suspects characterize, motive describe, and result describe.

Based on the expected system shown in Figure 4, a research proposal is given: first, the case characteristics involved in suspects, motives, processes and outcomes, as well as incident contours are studied, and the concept of case characteristic contours is analyzed and formally defined. Second, using deep learning theory, the characteristics of entity connections including entities such as suspects and objects are studied, and connection extraction methods are given. Third, analyze the detection experience to categorize the suspects, motives, processes and the inscribed labels of results. Fourth, deep learning theory is used to give screening conditions based on the expression form of big data. Fifth, based on steps three and four, the neural network and machine learning theories are studied to construct deep learning inscription methods and framework models for incident profiles of suspects, motives, processes, and results. Finally, the machine inscription effect of the research results is analyzed and discussed.

5 CONCLUSIONS

This paper surveys the current research status to apply computing technology to assist the detection of drug-related cases, including the empirical study to the big data and the literature review, gives a taxonomy of the computing technology used in them, points out the recognition and presentation of the profiles of the cases as well as the computational difficulties to be solved in the depiction. This paper reviews the recent research of research on drug-related case profiles and their portrayal, which leads to the identification of the following three common problems. Problem one is controversial perceptions of case characteristics. Problem two is the representation to case features with their fully connected neural network-oriented data types. What's more, problem three is the challenging selection problem of case characteristics.

We address this challenge by giving the expected system and research ideas of drug-related case profiles and their portrayal, which meet the needs of drug-related case profiles and their portrayal.

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