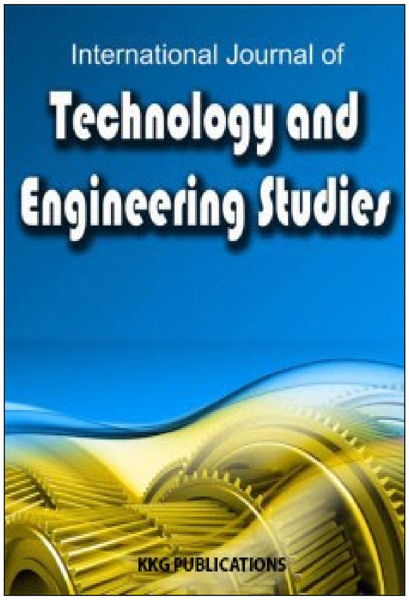

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PAKAMAJ WONGSAI [1], WICHAI PAWGASAME [2]

[1, 2] Defence Technology Institute Pakkred, Nonthaburi, Thailand

Published online: 24 October 2016

To cite this article: P. Wongsai and W. Pawgasame, "Analysis of a crime scene getaway vehicle's escaping path," *International Journal of Technology and Engineering Studies,* vol. 2, no. 5, pp. 134-139, 2016.
DOI: https://dx.doi.org/10.20469/ijtes.2.40002-5

To link to this article: http://kkgpublications.com/wp-content/uploads/2016/2/Volume2/IJTES-40002-5.pdf

International Journal of Technology and Engineering Studies
vol, 2, no. 5, pp. 134-139, 2016

IJTES

ANALYSIS OF A CRIME SCENE GETAWAY VEHICLE'S ESCAPING PATH

PAKAMAJ WONGSAI [1*], WICHAI PAWGASAME [2]

[1, 2] Defence Technology Institute Pakkred, Nonthaburi, Thailand

Keywords:
Bayesian Decision
Path Prediction
Artificial Intelligence

Received: 02 August 2016
Accepted: 08 September 2016
Published: 24 October 2016

Abstract. This paper explores the analysis method for predicting criminal's escape paths, which predicts the possible escape routes of the criminals or terrorists from the crime scene. Better prediction should be obtained as we explore the decision of criminals on selecting an escape path based on the path's condition and distance from the crime scene. In addition, real-time information collected by sensors along the paths (i.e., camera sensors) can help improve the accuracy of escape path prediction. The analysis is based on the Bayesian Network, in which the path from a node to node is chosen based on the Bayes Inference theory. In particular, the criminal's decision on the path selection is modeled by the Bayesian Network. The analysis involves finding the selection probability on each path conditional on path conditions, spotted suspected vehicles, and assumed criminal preference (i.e., distance from the crime scene). Hence, the predicted path is likely the path with the highest probability. The analysis presented in this paper would contribute to the domain of artificial intelligence, such that it can be used as the analysis tool to model and predict criminal behaviors in selecting escape paths.

INTRODUCTION

Crime scene getaway is an act of a perpetrator to flee from the crime scene in order to avoid being apprehended by the law enforcement. Fleeing by vehicle is the most common method [1].

By knowing the escape path of the fleeing vehicle, the law enforcement can track down the perpetrator or cut off the escape path. This requires analysis and prediction of intensive information on road traffic and criminal's behavior, in which human investigator cannot handle this workload single-handedly.

Thus, an automated system capable of analysis and prediction on escape route would be of great benefit. However, the system must rely on intensive amount of information.

Some information may not be available i.e., no witness has spotted any getaway vehicle. Sometimes, information has changed over time i.e., a perpetrator changes vehicle or license plate during escape.

Criminal may have a preference in selecting a path. Hence, the possible escape paths are dynamic based on available information at the time. The automated system must be able to cope with adaptive information and uncertainty of criminal's behavior.

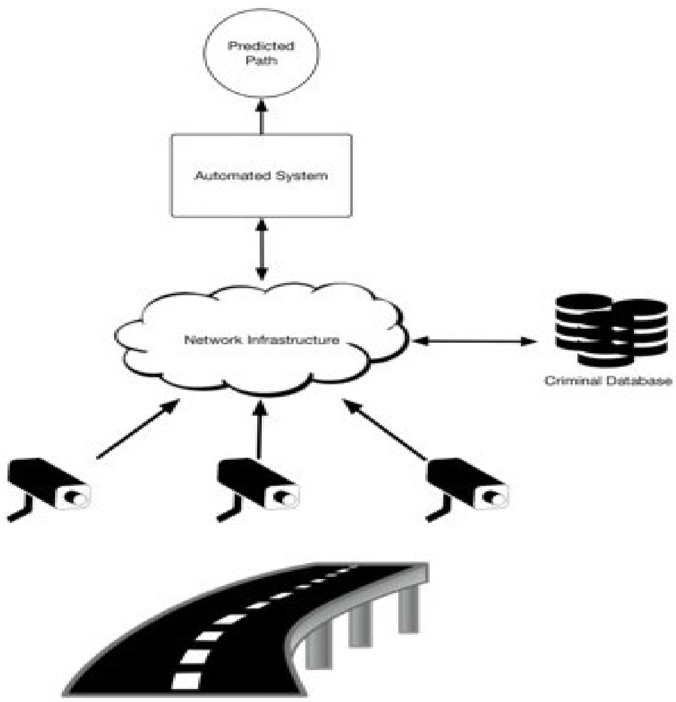

Fig. 1 . Smart camera system for predicting criminal's escape path

*Corresponding author: Pakamaj Wongsai
†Email: pakamaj.w@dti.or.th

A Smart Camera System with the recognizing capability ranging from license plate number to vehicle's appearance can be deployed along the roads as part of an intelligent transport system [2]. A Smart Camera System can be connected to the criminal database and able to identify suspected vehicles. A Smart Camera System acts as a sensing layer for an automated system for escape route prediction as illustrated in Figure 1. A Smart Camera System contains camera sensors interconnected with recording database and criminal database. The system can provide the information about suspected vehicles and irregular behaviors of vehicle movements by comparing the record with the criminal database and vehicle database. This information can be constituted to the automated system through network infrastructure in order for the automated system to conduct the prediction mechanism in the real-time [3].

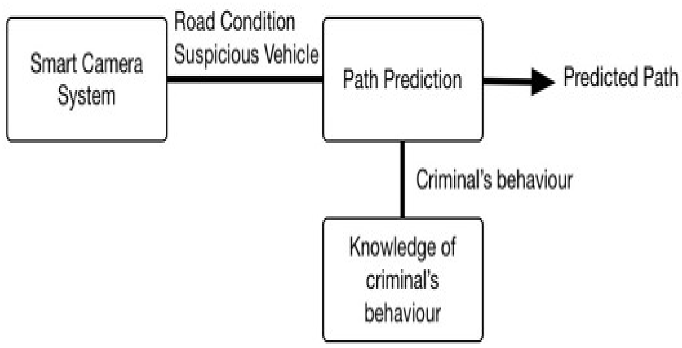

Fig. 2 . Path prediction process

According to the system illustrated in Figure 1, there will be a huge amount of captured images of vehicles including road condition and traffic reports. Hence, we will need a data mining and machine learning method to recognize, classify, analyze and predict the possible escape path. When data are collected, a machine learning method is required to recognize identities of a vehicle. These identities can be license plate, color, brand, or type of a vehicle. Once the identity of a vehicle is identified, the captured image of a vehicle along with its identity and location are recorded in the database. To classify whether the recorded vehicle is suspicious or not, the identity of the record is compared with the criminal and vehicle database. Sometimes the vehicle's identity may not exist in the criminal and vehicle database. The pattern recognition, which is a branch of machine learning method, can be applied to discover abnormal patterns in a vehicle's movement. Both classification and pattern recognition are incorporated to discover suspicious vehicles on the roads. Once the suspicious vehicle is found, it constitutes to escape path prediction. However, as a crime scene takes place, we may not have information about criminal's vehicle. Thus, we have to rely on criminal's predicted decision in order to guess on a possible path. The criminal's predicted decision and suspicious vehicles information extracted from a smart camera system constitute to a path estimation as illustrated in Figure 2. In this figure, the smart camera system serves as the sensing layer for collecting information about road condition, traffic, and trespassing vehicles. Then, the collected information is forwarded to the automated system for further processing. The automated system compares collected vehicle information with the criminal record in the database. If the collected vehicle information matches with the criminal record, it is defined as suspicious vehicle. The suspicious vehicle information then constitutes to the path prediction process along with information of road and traffic conditions. In addition, the practical criminal's behaviors are also included as the input parameter in the path prediction process. The practical criminal's behaviors help predict the escape path when there is no information about suspicious vehicle, and increase the accuracy of path prediction.

This paper will concentrate on path estimation using extracted information from a smart camera system and criminal's predicted decision. The problem is illustrated in Figure 3, where a path from node to node is estimated based on current road information, spotted suspected vehicle and criminal's predicted behaviors. The path is updated when there is new information available to the system. We will ignore the process of classification and pattern recognition in discovering suspicious vehicles, and will only focus on path estimation method. In Figure 3, the criminal would try to avoid the road with high traffic or having a blockade. The paths with spotted suspected vehicle are likely used by the criminal as the escape path. We will investigate how this information constitutes to escape path prediction and presents the framework for escape path prediction. This paper is organized as follows: Section 2 discusses about the related works on path finding and path prediction, Section 3 describes the problem as a mathematical model, Section 4 presents path prediction algorithm, Section 5 discusses the presented algorithm, and Section 6 concludes the work.

RELATED WORKS

The topic of path finding has been explored for decades. The very popular methods are Dijkstra's algorithm and A* algorithm, which are graph-based path finding. Dijkstra's algorithm is the shortest path finding algorithm between two nodes on the graph [3]. Given known source and destination on the graph, the Dijkstra's algorithm can be used to find the path from source to destination with the least cost.

The cost of path can be distance from the source to the destination. In the escape path finding, the cost can be distance and road conditions. Although the Dijkstra's algorithm is very popular in path finding, the algorithm is used for shortest path finding of known source and destination. The escape path prediction is dealing with unknown destination, in which the Dijkstra's algorithm may not be suitable.

A* algorithm is an improved version of the Dijkstra's algorithm for complex path finding [4]. A* algorithm uses the heuristic that selects the next nodes that are likely to have the least remaining cost to the destination. A* algorithm is very popular in robot's path planning and game programming. However, the constraint of A* algorithm is the same as the Dijkstra's algorithm, in which both source and destination must be known. For solving the escape path prediction, the A* algorithm may not be suitable.

Our paper discusses the escape path prediction by using criminal's behaviors, road condition, and suspected vehicles as the constraints. The smart camera system serves as the sensing layer for collecting information about road condition and suspected vehicles. Information is gathered in one place for further processing. The work by [5] and [8] presents another aspect of path prediction in Vehicular Ad Hoc Network (VANET). In this work, each vehicle is equipped with sensors that measure position, velocity, acceleration, and heading. Measured data are collected and distributed among connected vehicles via VANET. Each individual vehicle uses these distributed information to predict the safe path in order to avoid collision with other vehicles. This work presents the method that uses the information from sensing devices to help predict the path.

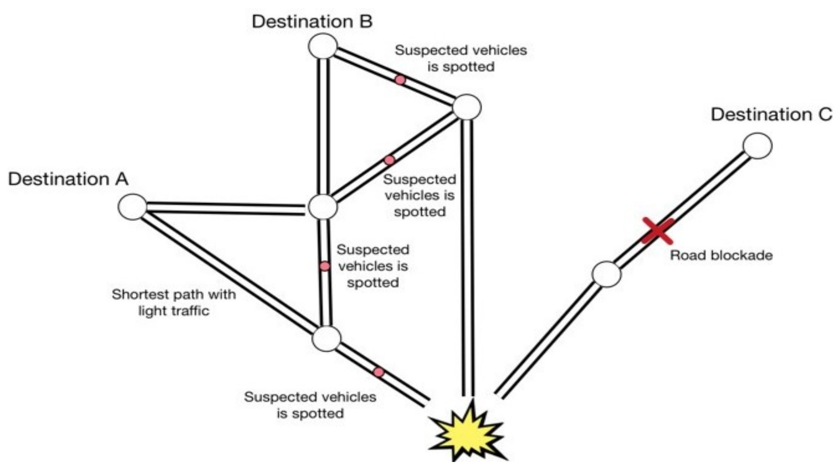

Fig. 3 . Path prediction problem

Our work presented in this paper has the same concept, but we apply the sensed data to predict escape path instead of predict the collision-free path. The work by [10] presents the prediction of driver's intention on the path selection using vehicle's movement and predetermined road geometry. The author relies the prediction on the current measurement from the vehicle and road geometry. Unlike our work, we cannot rely our prediction on the sensor equipped on the vehicle.

PROBLEM MODEL

The problem can be modelled as a decision tree problem [6], where possible paths from the crime scene can be represented as a tree-like graph. The following sections describe the decision tree model of an escape path and the criminal decision rules.

Path Model

A path from one location to another location can be modelled as a tree-like graph [7] as illustrated in Figure 4. The root of the tree is the location of crime scene. Vertices that are connected to the root, are the next possible locations of the criminal getaway path. Each vertex vehicle that can travel from the current location. An edge that connects two vertices, represents a path. Each path has the score that indicates the difficulty of the path (r,v,b). To predict the escape path, we also need to determine where the path will end. In this problem, we do not know when the getaway vehicle would stop. We will assume that the getaway vehicle is moving at constant speed (v). For specific time instance (t), we will predict the location of the perpetrator on the path (x). The path is defined as the sequence of tuple (xi, ti), where xi is the possible vertex that the perpetrator would be found at step i and ti is the time that the perpetrator would be at this vertex. Hence, the escape path can be represented as the sequence of tuple,

$$s = (x_0, t_0), (x_1, t_1), (x_2, t_2), ... \quad (1)$$

where x0 is the starting point and t0 is the starting time. The perpetrator moves to x1 and x2 at the time t1 and t2 respectively as illustrated in Figure 4. contains the child vertices, which are possible location that the getaway vehicle can travel from the current location. An edge that connects two vertices, represents a path. Each path has the score that indicates the

Criminal Path Selection Model

The problem scenario in this paper is to predict the escape path from the crime scene. We make the assumption that criminals would choose the fastest or most obscure path in order to escape from the crime scene. We will consider a node in the tree graph, where there are more than one edge leading to other nodes as illustrated in Figure 4. Each edge represents a path from the source node to another node in the tree. Each path has the weight, which is the probability that the criminal would select the path (Pi). It implies that the more weight of the path, the more likelihood that the criminal would select the path. The probability that the criminal would select the path is dependent on the criminal's decision on the path. We will model the criminal's decision by Bayes Decision Theory [9], [11]. In Bayes Decision Theory, the posterior probability that an event (A) would occur with conditions is dependent on the prior probability of conditional event (B) and the likelihood of the conditional event (B) given that an event A would occur [12,13]. According to Bayes's theorem, the posterior probability of an event A is

$$P[A|B] = \frac{P[B|A]P[A]}{P[B]} \tag{2}$$

where P [A|B] is the posterior probability, P [B|A] is the likelihood, P [A] is the prior probability of event A, and P [B] is the prior probability of event B. When applying the Bayes's theorem to our problem, we would like to find the posterior probability that the criminal would select the specific path from one node to another node with constraints on road condition (R), spotted suspicious vehicle (V), and practical criminal's behavior (B). We define X as the random process for the path selection, R as the random process for the event with specific road condition, V as the random process for the event with spotted suspicious vehicle, and B as the random process for the event with specific criminal's behavior.

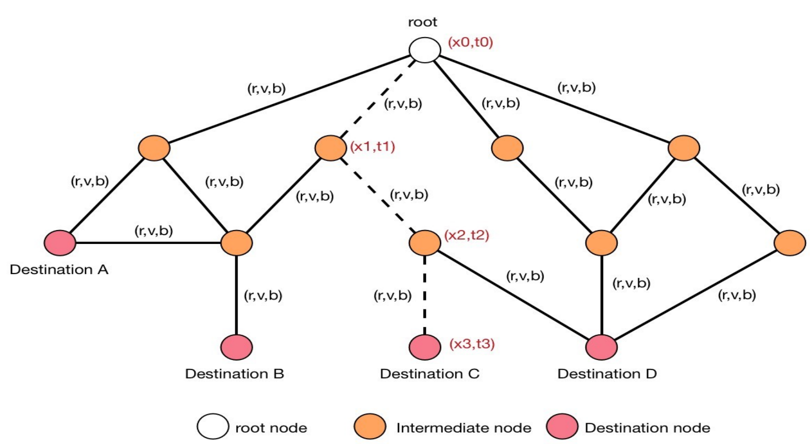

Fig. 4 . Path model as a tree graph

According to Bayes's theorem, the posterior probability that the criminal would select the path s among other paths is

$$P[X = s_i R \cap V \cap B] = \frac{P[R \cap V \cap B|X = s_i P[X = s_i]}{P[R \cap V \cap B]}$$
(3)

where P [R ∩ V ∩ B|X = si] is the likelihood that event R, V , and B occur given that the path si would be selected. P [R ∩ V ∩ B] is the probability that event R, V and B would occur, which can be determined by the statistical probability of captured information from the smart camera system.

For simplicity, we define 3 conditions of road condition by vehicle speed: normal movement, slow movement, and no movement (i.e., heavy traffic or road blocked). We assign numerical value to each condition: r, r, and r respectively, where $\alpha r > \beta r > \gamma r$. Spotted suspicious vehicle is defined as spotted and not spotted. αv and βv are assigned as numerical value for spotted vehicle condition respectively, where $\alpha v > \beta v$. We define criminal behavior as the preference on the path. Hence, each path from each node has the value that indicates the level of preference. We define the range of path preference as integer value from 0 to cmax. The higher level of preference implies that it is more preferred.

Next, we derive the likelihood probability P [R $\cap V \cap B|X = si]$. Assuming that there are n paths, that are $s_0, ..., s_{\{}n1\}$. If path si is selected, where i ε0, ..., n 1. The values of road condition and spotted vehicle as collected by the smart camera system are ri and vi respectively, where ri $\varepsilon\{\alpha r, \beta r, \gamma r\}$ and vi ε $\{\alpha v, \beta v\}$. The criminal path preference on the path si is bi, where bi ε $\{$0, ..., cmax$\}$. Then, we define the likelihood probability as

$$\frac{r_i.w_r + v_i.w_v + b_i.w_b}{w_r.\sum_{i=0}^{n-1} r_i + w_i.\sum_{i=0}^{n-1} v_i + w_b.\sum_{i=0}^{n-1} b_i} \quad (4)$$

where w_r, w_v, and w_b are significant weights on the path for road condition, spotted vehicle, and criminal behavior respectively. The numerical value for wr, wv , and wb are based on how much we are concerned on each condition. For example, if a spotted vehicle is the most concerned, we would assign wv as the highest weight.

The probability of joint event P [R $\cap$ V $\cap$ B] can be determined by using frequentist statistic method. By counting the number of specific joint event occurrence and divided by total number of event occurrences, we obtain the statistic probability of the joint event R $\cap$ V $\cap$ B.

From equation (3), we use it to determine the probability of criminal's path selection. We assume that the criminal would select the path with the highest posterior probability

PATH PREDICTION ALGORITHM

The process of path prediction algorithm is summarized in Figure 5. Starting from arbitrary node at the location xi and the time ti with the tuple (xi, ti), we determine the available paths connected to the node i.e., $\{_s0, ..., s_{n1}\}$. For each available path sj , we collect values rj , vj , and bj where j ε 0, ..., n 1. We calculate P[R= $r_j \cap V = v_j \cap B = b_j|x = s_j]$ for each path s_j. Then, find the path s_{max} with max $\{P[R = r_j \cap V = v_j \cap B = b_j x = s_j]\}$. This path smax is our predicted path from the location xi at time ti to the location xi+1 at time ti+1. To find the next consecutive path, we increment i by 1 and repeat the process. The prediction process stops when I reaches the predetermined number.

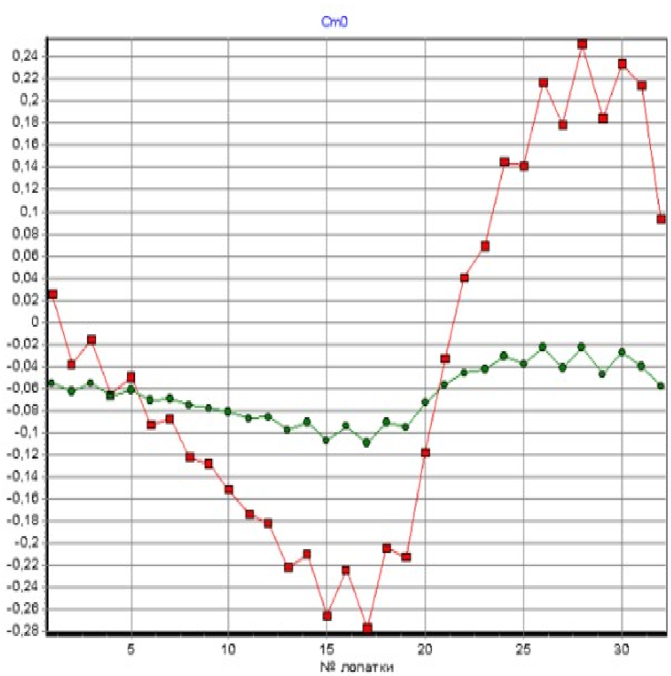

Fig. 5 . Path prediction algorithm

CONCLUSION AND RECOMMENDATIONS

In this paper, the prediction system of escape path from the crime scene is introduced. The prediction system contains the smart camera system as the sensing layer, which collects information about road condition and suspicious vehicles. The method of machine learning for extracting information from the sensors is not mentioned in this paper. We assume that the smart camera system can provide the information about road condition and suspicious vehicles. The prediction process takes the information from the smart camera system along with the knowledge about criminal's behavior into account, when determining path decision probability. The path decision probability is determined based on Bayes theorem. Hence, the path decision probability is the posterior probability of the path selection under certain events of road condition, spotted suspicious vehicles, and criminal's behavior. The path prediction algorithm follows the path with maximum posterior probability until it reaches destination.

Declaration of Conflicting Interests

This work has no conflicts if interests. Authors confirm that no financial/non-financial conflicts are present in this study.

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— This article does not have any appendix. —