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Driver Behavior Prediction Based on Environmental Observation Using Fuzzy Hidden Markov Model

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Abstract

The development of autonomous vehicle systems has progressed rapidly in recent years. One challenge that persists is the capability of the autonomous system to respond to human drivers. Human behavior is an integral part of driving; thus, driver behavior determines changing lanes and speed adjustments. However, human behavior is unpredictable and immeasurable. Some traffic accidents are caused due to the erratic behavior of the driver. Although, traffic laws, such as in Indonesia, regulate the use of lanes concerning the vehicle's speed. The drivers' behavior in the lane is more likely to be influenced by the regulation. This paper proposes a novel method of predicting drivers' behavior by utilizing the concept of fuzzy Hidden Markov Model (fuzzy HMM). HMM has been proven reliable in predicting human behavior by observing measurable states to determine unmeasurable hidden states. The use of fuzzy logic is to mimic the way that humans perceive the speeds of other vehicles. The fuzzy logic determines the relative observed state of other vehicles according to the measured velocity of an ego vehicle and the observed state of observed vehicles. Observation data is obtained by equipping an ego vehicle with an action camera. The observed data, in the form of a video, is then discretized every 2 seconds. The resulting sequence of images is processed to determine several variables: speed and state of the observed vehicles (lane position and speed) and the time instance of the observation. The fuzzy HMM is generated based on observational data. A predictor created using fuzzy HMM equipped with a training and prediction algorithm successfully predicts the behavior of other drivers on the road.

Keywords

Driving behavior; Autonomous vehicle; Fuzzy logic; Fuzzy HMM; Behavior prediction

1 Introduction

Autonomous vehicle systems have progressed rapidly in recent years. Several autonomous systems have been deployed in traffic, either commercially or for research purposes. However, there are limitations when autonomous systems have to respond to maneuvers done by human drivers. Human drivers are unpredictable due to the unique behavior that each driver possesses. According to [1], there are four categories of on-road driving behavior, which are aggressive, conservative, professional, and experienced. The classifications are made based on several factors such as acceleration, driving experience, and number of accidents. Therefore, it can be inferred that human drivers tend to follow certain behavior while driving. Another factor that heavily influences driver behavior is the regulation that applies on the road. In Indonesia, one of the regulations that apply in the use of lanes is stated in [2]. The regulation states that all drivers on a multi-lane road must use the left lane in normal conditions. Moreover, using the right lane can only be for vehicles with higher speeds or intending to overtake other vehicles. Therefore, the regulation is taken as a reference for modeling the driver's behavior.

Driving behavior has been modeled in [3][4] by utilizing Hidden Markov Model (HMM) approach. According to a recent survey [5], modeling driver behavior with HMM has proven to generate accurate behavior predictions. However, previous research only generates predictions for the person driving that is driving the vehicle. This paper proposes modeling driver behavior with HMM is also applicable in predicting the behavior of other drivers surrounding an autonomous system or human driver while driving an ego vehicle. The behavioral model is generated using a fuzzy HMM approach based on real-time environmental observations. Based on [5], fuzzy HMM has better accuracy than other HMM-based modeling methods. Experiments are carried out by observing real-time driving data by equipping an ego vehicle with an action camera.

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2 Fuzzy HMM

2.1 Hidden Markov Model

HMM is a model that is derived from the concept of Markov chain. Markov chain defines the changes of states from a certain system based on a probability distribution [6]. HMM or other Markov models are developed based on the assumption that for each random variable $(X_1, X_2, \dots, X_n)$ in a time series, the newest variable at a time t depends only on the previous variable at time $t-1$. Equation (1) defines the probability of the random variables occurring sequentially. $\mathbb{P}(X_n|X_{n-1})$ is the probability of the variable X_n occurring due to the previous variable X_{n-1}.

$$\begin{aligned}&\mathbb{P}(X_1, X_2, \dots, X_n)\\ &= \mathbb{P}(X_1)\mathbb{P}(X_2|X_1)\dots\mathbb{P}(X_n|X_{n-1})\end{aligned} \tag{1}$$

These random variables are also known as states on a Markov model. Most systems have states that are measurable and observable. HMM plays a key role in representing systems with an unobservable state, such as human driving behavior. Several researchers, such as [3][4], have used HMM to define human driving behavior. According to [7], there are 5 main components of an HMM:

1. Set of N-hidden states

$$\boldsymbol{S} = [S_1, S_2, \dots, S_N] \tag{2}$$

2. Set of M-observed states

$$\boldsymbol{O} = [O_1, O_2, \dots, O_M] \tag{3}$$

3. Transition Probability Matrix (TM)

   TM ($\boldsymbol{A} \in \mathbb{R}^{N\times N}$) represents the probability of transition from one hidden state s_i to another hidden state s_j. The elements of TM are defined by

$$\begin{gathered}a_{i,j} = \mathbb{P}\left(s_j(t+1)\middle|s_i(t)\right)\\ \sum_{j=1}^{N} a_{i,j} = 1\end{gathered} \tag{4}$$

4. Emission Probability Matrix (EM)

   EM ($\boldsymbol{B} \in \mathbb{R}^{N\times M}$) represents the probability of the hidden state s_i occurring due to the observed state o_j. The elements of EM are defined by

$$\begin{gathered}b_{i,j} = \mathbb{P}\left(o_j(t)\middle|s_i(t)\right)\\ \sum_{j=1}^{N} b_{i,j} = 1\end{gathered} \tag{5}$$

5. Initial Probability Distribution

   The vector $\boldsymbol{\Pi} = [\pi_1, \pi_2, \dots, \pi_N] \in \mathbb{R}^N$ is used to define the initial probability distribution of each possible hidden state in the system. The elements of $\boldsymbol{\pi}$ are defined by

$$\pi_i = \mathbb{P}\big(s_i(1)\big) \tag{6}$$

Based on the components mentioned, an HMM model, therefore, is a tuple $\lambda = (\boldsymbol{\pi}, \boldsymbol{A}, \boldsymbol{B})$. This paper proposes to model the human driving behavior based on HMM with the velocity of an observed vehicle as the observed state and the chosen lane of an observed vehicle as the hidden state. Information from observed vehicles is obtained by an ego vehicle equipped with a camera. Figure 1 illustrates the difference between an ego and an observed vehicle.

2.2 Fuzzy HMM

Fuzzy HMM is an improved version of HMM that combines fuzzy logic and HMM to model a system. There are several applications of fuzzy HMM, such as for driving behavior [8], speaker and speech recognition [9], and multiple sequence alignment [10]. Based on [5] and [8], driving behavior is best modeled with fuzzy HMM. Fuzzy HMM is applied to model an ego vehicle driver behavior. However, an alternative form of the fuzzy HMM is introduced in this paper to model the behavior of other drivers surrounding the ego vehicle.

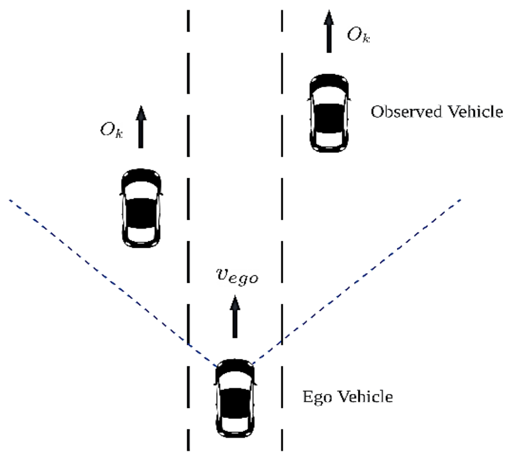

Figure 1 Illustration of ego and observed vehicle

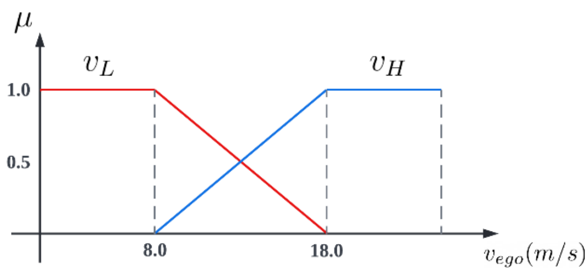

Figure 2 Fuzzy set for HMM

The decision-making of human drivers is unpredictable and imprecise; hence, fuzzy logic is an appropriate solution to assist HMM in modeling human behavior. In this paper, fuzzy logic is utilized to mimic how humans determine other vehicles' velocities by comparing the measured velocity of the ego vehicle (v_{ego}) and the observed state of observed vehicles (O_k). The proposed fuzzy logic to fulfill the requirements is represented by Figure 2 and (7).

$$\begin{cases} O_k = SL; \ \mu_{v_L} + 0.5 \\ O_k = EQ; \begin{cases} \mu_{v_L} + 0.25 \\ \mu_{v_H} + 0.25 \end{cases} \\ O_k = FT; \ \mu_{v_H} + 0.5 \end{cases} \tag{7}$$

Figure 2 represents the fuzzy set for determining the relative observed vehicle state based on the velocity of the ego vehicle. The output from the fuzzy set is a degree of membership for both low-speed μ_{v_L} and high-speed μ_{v_H}. The values for each μ_{v_L} and μ_{v_H} are processed further according to the observation state (O_k) of the observed vehicles. There are three states for observed vehicles, namely slower than (SL), equal to (EQ), or faster than (FT) the ego vehicle. Each state will be processed further with the following relations:

$$\begin{cases} \mu_{v_L} \geq \mu_{v_H}; \ V_k = v_L \\ \mu_{v_L} < \mu_{v_H}; \ V_k = v_H \end{cases} \tag{8}$$

From (7), the value of μ_{v_L} and μ_{v_H} will be updated based on O_k. Most of the time, drivers tend to stay in their current lane at lower speeds. For example, in the case of driving in Indonesia, vehicles are forced to move at lower speeds because, most of the time, the traffic surrounding the vehicle is densely packed. Therefore, the HMMs must be divided according to the observed vehicle speed. Equation (8) determines V_k, also known as the relative observed states. There are only two types of V_k, which are low-speed state (v_L) and high-speed state (v_H). If μ_{v_L} is higher than μ_{v_H}, the relative observed state is a low-speed state (v_L) and vice versa. Every value of V_k, for each time instance k, is accumulated into the vector $\boldsymbol{V} = [V_1, V_2, \ldots, V_k]$. The vector $\boldsymbol{V}$ will be utilized for the HMM to predict the highest possible hidden state for the observed vehicles.

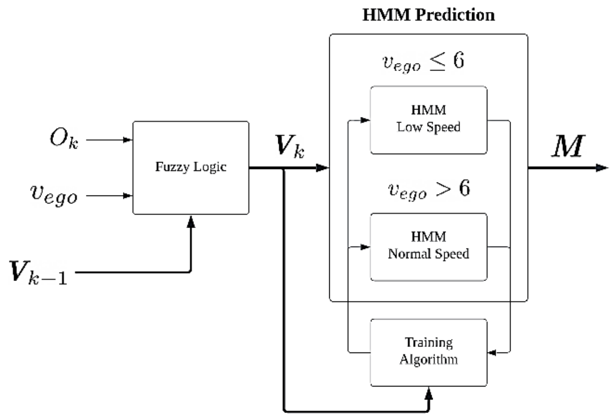

Figure 3 Block diagram for the prediction with the fuzzy HMM

Figure 3 shows the block diagram that represents the prediction process with the fuzzy HMM, as proposed in this work. The fuzzy logic receives two observation data, which are O_k and v_{ego}. Moreover, the vector $\boldsymbol{V}$ at time instance $k-1$ is utilized to accept the fuzzy logic output. After the fuzzy logic determines the relative observed state at k, the HMM prediction block uses the vector $\boldsymbol{V}$ at time instance k to generate the predicted hidden state vector of observed vehicle $\boldsymbol{M}$. The prediction is carried out by utilizing a prediction algorithm. Furthermore, vector $\boldsymbol{V}$ is used by a training algorithm to update the low and high-speed HMM. Both algorithms are discussed in the next sub-section.

2.3 Algorithms

The HMM can only function as far as modeling or representing a system. As stated in the previous sub-section, the HMM must be provided with a training and prediction algorithm. In this investigation, the Baum-Welch algorithm [11] and the Viterbi algorithm [12] are applied to train HMM and generate the predictions, respectively. The algorithms are commonly used with HMM to generate the prediction based on a trained model. Both algorithms were adjusted to match the parameters used in this paper. The algorithm receives the relative observed state $\boldsymbol{V}$ rather than the observed state $\boldsymbol{O}$. Moreover, the algorithm iterates for every time instance k is further discussed in the next section.

The Baum-Welch algorithm is a form of Expectation-Maximization (EM) algorithm that searches for the best maximum estimated parameters from a statistical model. According to [11], the Baum-Welch algorithm optimizes parameters to a local optimum point. The algorithm has several phases, which are the forward phase, the backward phase, and the update phase. The α-table is generated in the forward phase, and the β-table is generated in the backward phase. Afterward, in the update phase, the algorithm calculates the values of γ and ξ based on the values of α and β to update the values of $\boldsymbol{\Pi}$, $\boldsymbol{A}$, and $\boldsymbol{B}$. Each matrix is updated by changing the elements from π, a, and b to π^*, a^*, and b^* consecutively. In this paper, the Baum-Welch algorithm is used to update the HMM every time the system receives observation data.

Next, the Viterbi algorithm is an algorithm that searches for the best sequence of states from an HMM. According to [12], the Viterbi algorithm finds the most likely hidden state sequence based on a sequence of observations. The steps of the Viterbi algorithm are written in Table I. The algorithm finds the best possible hidden state sequence based on the values of δ and ψ. The variable δ represents the possibility of the highest possible hidden state to happen (S^*), whereas ψ represents the index of the highest possible hidden state. The sequence of the hidden states is appended to the vector $\boldsymbol{M}$, which represents the estimated movement prediction of the observed vehicles.

Table 1 Pseudocode for The Viterbi Algorithm

Viterbi Algorithm
Input: $\lambda = (\Pi, A, B), V, M$
for $i = 1,2,\dots,I$ do
// Initialization
$\quad\delta_i(1) = \pi_i b_i(V_1)$
$\quad\psi_i(1) = 0$
// Recursion
for $j = 1,2,\dots,N$ do
$\quad$for $k = 1,2,\dots,\tau$ do
$\qquad\delta_j(k) = \max\limits_{1\le i\le I}[\delta_i(t-1)a_{i,j}]b_j(V_k)$
$\qquad\psi_j(k) = arg\max\limits_{1\le i\le I}[\delta_i(t-1)a_{i,j}]$
// Termination
$p^* = \max\limits_{1\le i\le I}\delta_i(\tau)$
$S^*(\tau) = arg\max\limits_{1\le i\le I}\delta_i(\tau)$
// Backtracking
for $k = \tau-1,\dots,1$ do
$\quad S^*(k) = \psi_{S^*(k+1)}(k+1)$
$\quad M \leftarrow S^*(k = 1,2,\dots,\tau)$
return M

3 Results and Discussion

3.1 Behavior model

The following configuration shows the HMM states which are created in this work:

1. Hidden state: $\boldsymbol{S} = [L, T, R]$
2. Observed state: $\boldsymbol{O} = [SL, EQ, FT]$
3. Relative observed state: $\boldsymbol{V} = [v_L, v_H]$

$$\boldsymbol{\Pi} = \begin{bmatrix}\mathbb{P}(L(1)) & \mathbb{P}(T(1)) & \mathbb{P}(R(1))\end{bmatrix}$$

$$\boldsymbol{A} = \begin{bmatrix}\mathbb{P}(L|L) & \mathbb{P}(L|T) & \mathbb{P}(L|R)\\ \mathbb{P}(T|L) & \mathbb{P}(T|T) & \mathbb{P}(T|R)\\ \mathbb{P}(R|L) & \mathbb{P}(R|T) & \mathbb{P}(R|R)\end{bmatrix} \tag{9}$$

$$\boldsymbol{B} = \begin{bmatrix}\mathbb{P}(v_L|L) & \mathbb{P}(v_H|L)\\ \mathbb{P}(v_L|T) & \mathbb{P}(v_H|T)\\ \mathbb{P}(v_L|R) & \mathbb{P}(v_H|R)\end{bmatrix}$$

The possible hidden states are left lane (L), transition lane (T), and right lane (R), whereas the possible observed and relative observed states are as mentioned in the previous section. The 'transition lane' acts as a buffer state before any observed vehicle changes lanes. While the ego vehicle observes the environment, any vehicle in the 'transition lane' is expected to be cruising normally following its current lane. Experimental data are obtained to determine the values of the HMM, which are divided into HMM for low speed and high speed. The probabilities defined for the initial probability, TM, and EM are stated in (9).

$k = 73$

$k = 74$

$k = 75$

Figure 4 Example of discretized observation images

The data for the HMM are obtained by equipping an ego vehicle with a GoPro HERO7 action camera. The camera is mounted in the vehicle's middle section to record other vehicles surrounding the ego vehicle. Only vehicles in front of the ego vehicle will be considered observed vehicles. Afterward, the videos are discretized to generate images every 2 seconds. The discretization time is chosen based on (cite green) that states drivers have a 1.5 second response time for unexpected events. The predictions are generated for 2 seconds ahead of the current time. Therefore, human drivers or autonomous vehicle systems have a response window from the observation to the prediction. An example of the observation data, in the form of images, is shown in Figure 4.

$$\boldsymbol{\Pi_H} = [0.22\ 0.60\ 0.18] \tag{10}$$

$$\boldsymbol{A_H} = \begin{bmatrix} 0.49 & 0.52 & 0.0 \\ 0.34 & 0.36 & 0.30 \\ 0.0 & 0.52 & 0.49 \end{bmatrix}$$

$$\boldsymbol{B_H} = \begin{bmatrix} 0.59 & 0.41 \\ 0.53 & 0.47 \\ 0.42 & 0.58 \end{bmatrix}$$

$$\boldsymbol{\Pi_L} = [0.22\ 0.60\ 0.18]$$

$$\boldsymbol{A_L} = \begin{bmatrix} 0.35 & 0.65 & 0.0 \\ 0.11 & 0.79 & 0.10 \\ 0.0 & 0.68 & 0.32 \end{bmatrix} \tag{11}$$

$$\boldsymbol{B_H} = \begin{bmatrix} 0.59 & 0.41 \\ 0.71 & 0.29 \\ 0.40 & 0.60 \end{bmatrix}$$

Figure 4 shows examples of the discretized images, each number of k representing 2 seconds in real-time. The HMM for low and high speeds is generated according to the observation data. Moreover, Indonesian lane usage regulation [2] is chosen as a reference for the model. According to the regulation, the leftmost lane is more likely to be used by slower vehicles, whereas the rightmost lane is more likely to be used by faster vehicles. Based on the observations and the regulation information, the HMM for low and high speed is stated in (10) and (11) consecutively.

3.2 Prediction Result

The fuzzy HMM based on Figure 3 is utilized as the predictor to find the best possible hidden states from several observation data. There are 1781 data obtained from the environment. The predictor will generate the best possible hidden states after receiving observation data. An example of hidden state prediction and ground truth is illustrated in Figures 5 and 6. The data in Figure 5 is an observation at an average v_{ego} of 6 meters per second, whereas Figure 6 shows data observed at an average v_{ego} of 16 meters per second. In both figures, the blue lines represent the ground truth hidden state, and the orange lines represent the predicted hidden state. The ground truth hidden states are determined based on observation images, such as in Figure 4.

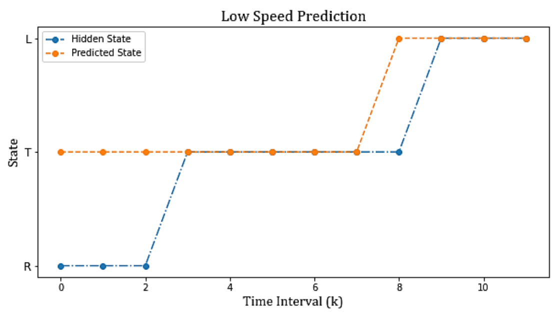

Figure 5 Low speed prediction example

Based on Figure 5, at low speeds, the predictor can predict the movement of the observed vehicle before it changes to the left lane at $k = 8$. However, the predictor misses the right lane change at $k < 3$. Furthermore, in Figure 6, the predictor can predict the left lane change of the observed vehicle at $k = 2$. There are some mispredictions where the predictor believes the observed vehicle did a right lane change and left lane change consecutively.

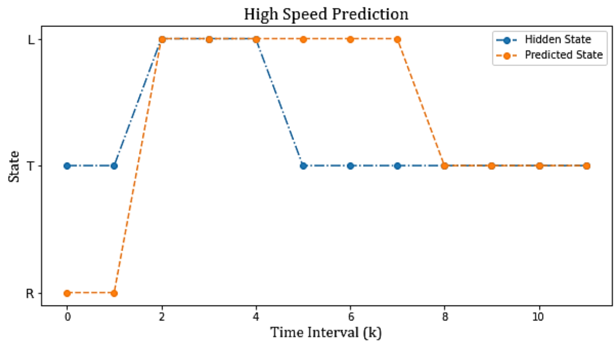

Figure 6 High speed prediction example

According to the prediction results, the predictor manages to give movement predictions for the observed vehicles. From all the observation data, the predictor has a successful prediction rate of 59.15%. The percentage is divided into 95.44% successful prediction at low speed and 51.59% at high speed. The difference in successful prediction percentage shows that driver behavior at low and high speeds differ significantly. Based on the model data, drivers tend to stay in their own lane in lower speed conditions rather than change to other lanes. The HMM is successful in representing low-speed behavior. Moreover, the low successful percentage in high-speed prediction indicates that the HMM model must be improved further to generate better predictions.

The predictor is given a score of 1 if the prediction is the same as the ground truth. Moreover, a score of 0.5 is given if the prediction is the right or left lane and the ground truth is the transition lane. This is done because the predictor's purpose is to warn human drivers or autonomous systems. Some mispredictions, therefore, are tolerable because if the prediction is a lane change, any human drivers or autonomous systems can prepare themselves before deciding on any maneuvers. The condition only applies if the prediction is a lane change and the observed vehicle still cruises at its current lane. Therefore, a prediction percentage near 50% implies that the predictions are more preemptive rather than accurate.

The mispredictions are mostly caused because the fuzzy HMM must be further tuned according to the real-time data. There are some ways to increase the accuracy of the fuzzy HMM predictor. First, the number of fuzzy HMM can be increased to three, and another model can be added for an exceedingly higher speed. Like lower speeds, drivers at higher speeds tend to follow their current lane. Based on the 1781 data used in this work, the trend shows that the drivers rarely change lanes at speeds over 20 meters per second. Another way to increase the predictor's accuracy is to improve the fuzzy HMM. The current predictor is limited because the model relies on statistical values only.

4 Conclusion

This paper delivers a novel approach to predicting driver behavior based on an environmental observation approach. The purpose of predicting driver behavior is to help human drivers or autonomous systems in responding to other drivers in their environment. Driving behavior is unpredictable and immeasurable; however, this investigation proves that driver behavior can be modeled and predicted using fuzzy HMM based on the perspective of an ego driver. The prediction is generated with lane changes as hidden states, which have three possible states, namely the left lane, transition lane, and right lane. Furthermore, ego vehicle speed and observed vehicle speed estimation are utilized as the observed state. The fuzzy HMM parameters are determined based on the observation data and regulation that applies to Indonesian roadways.

According to the experimental results, the predictor successfully predicted driving behavior for 59.15% over 1781 data. Specifically, the predictor has a higher success rate in predicting at low speed than at high speed. The difference in success rate shows that the predictions at low and high speeds are distinct from one another. Improvements must be made for the high-speed HMM to generate better prediction results. Moreover, the predictor has a successful prediction percentage near 50%, indicating that the predictor generates preemptive predictions rather than accurate predictions. This conclusion is based on the scoring conditions stated in the previous section for evaluating the predictor.

Future work includes improving the fuzzy HMM predictor. Higher prediction accuracy can be obtained by enhancing the predictor through ways mentioned in the previous paragraph. This investigation proves that predictions can be made for vehicles cruising in front of an ego vehicle. Further improvements can be made to predict the movements of every vehicle surrounding the ego vehicle, not only vehicles in front of it. Therefore, implementing multiple cameras and object detection algorithms can help to improve the predictor in predicting multiple vehicles at once. Implementing other sensors can increase the number of observed physical information, henceforth increasing the predictor's accuracy.

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