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# Pedestrian's Intention Prediction Based on Fuzzy Finite Automata and Spatial-temporal Features

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## Abstract

*In this research, we present a novel Fuzzy Finite Automat (FFA) for predicting pedestrian's intention for advanced driver assistant system. Because dangerous pedestrians generally have a higher moving velocity and lateral moving direction than the 'standing' pedestrian as well as tracking trajectory in the time domain, we estimate the state probability of pedestrian by considering spatial domain such as pedestrian's face (looking back or not). To consider the above characteristics over temporal and spatial domain, 'distance between a pedestrian and curb', 'distance between a pedestrian and vehicle', and 'head orientation and orientation variation', and 'speed of a pedestrian' are used to generate probability density functions for the state transition value. In this paper, the four states connected with transitions of FFA are defined as Walking-SW, Standing, W-Crossing, and R-Crossing, and these states correspond to "walking sidewalk," "standing sidewalk," "walking crossing," and "running crossing," respectively. The state changes are controlled by various transition probabilities. There is no standard dataset for evaluating prediction performance using a stereo thermal camera, and we therefore created a KMU prediction dataset. The proposed algorithm was successfully applied to various pedestrian video sequences of the dataset, and showed an accurate prediction performance.*

## Introduction

Among a few researches related to advanced driver assistant system (ADAS), pedestrian's intention prediction is one of important works to avoid collision between a pedestrian and a vehicle in advance. In particular, most pedestrian-vehicle accidents are highest between 4 a.m. and 6 a.m., far infrared (FIR) camera based pedestrian detection has been receiving attention in recent years. However, many researches have been focusing on only pedestrian detection in the field of driver's view. Therefore another solution is necessary to decrease accidents; a driver can get alert about the pedestrian who is entering the road without noticing a vehicle.

Recent studies on pedestrian's intention prediction using video camera install in a vehicle are as follows. Gandhi and Trivedi [1] predicted pedestrian's path using pedestrian's body direction. Pedestrian's body direction is firstly estimated using histogram of gradient (HOG) and support vector machine and final pedestrian's path is predicted using Bayesian framework based on combination of pedestrian detection and previous state information. Keller et al. [2] proposed a system for pedestrian path prediction and action classification within short time intervals using stereo vision data obtained from the vehicle. Xu et al. [18] proposed sudden pedestrian crossing (SPC) detection using a potential reference line and pedestrian detection. In this study, SPC is detected when the ratio of overlap between the pedestrian and reference line, along with the movement magnitude, is over a predefined threshold. Huang et al. [4] investigated prediction of pedestrian's intention based on head pose and pose change features using a discrete dynamic Bayesian network (DBN). This study used a hierarchical clustering method to process the histogram of head pose and the change of head pose under the assumption that different head pose patterns reflect different intentions. The clustering results are used as features feeding into a dynamic Bayesian network. Kooij et al. [5] also used a DBN for pedestrian path prediction in the intelligent vehicle domain. The model incorporates the pedestrian situational awareness such as head orientation, situation criticality such as the distance between vehicle and pedestrian, and spatial layout such as the distance of the pedestrian to the curbside.

This research presents novel fuzzy finite automata (FFA) for pedestrian's intention prediction for intelligent ADAS instead of DBN using a stereo FIR camera mounted on the front-roof of a car. For pedestrian detection and tracking, we use the low-level feature with boosted type random forest classifier. To consider the characteristics of pedestrian over temporal and spatial domain, the variations in trajectory, a pedestrian distance derived from dense stereo, the speed of a pedestrian, and direction of head are used to generate probability density functions (PDFs) for the state transition value of FFA. In contrast to the existing DBN related methods [4][5], the novel pedestrian's intention prediction proposed herein uses FFA with four probability density functions based on spatial-temporal feature variations. Moreover, it can handle continuous spaces by combining the capabilities of automata with fuzzy logic. The moving direction and velocity of pedestrian continuously changes over time; hence, the states of previous pedestrian influence the state of the current frame. Therefore, for pedestrian's intention prediction as shown in Fig. 1, fuzzy finite automata are the most appropriate tools because the variables are time-dependent and continuous.

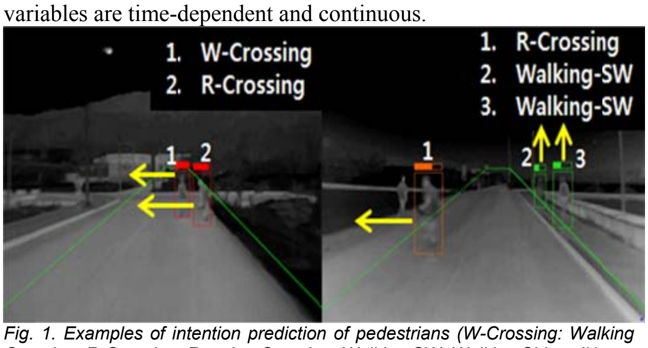


*Fig. 1. Examples of intention prediction of pedestrians (W-Crossing: Walking Crossing, R-Crossing: Running Crossing, Walking-SW: Walking Sidewalk)*

## Pedestrian Detection and Tracking

For pedestrian's intention prediction, pedestrian detection and tracking is essential work. In this study, we use a cascade random forest (CaRF) with low dimensional Haar-like features and

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oriented center symmetric-local binary patterns (OCS-LBP), based on the previous work in [6], to verify a pedestrian region. For pedestrian tracking, we perform real-time online learning for trackers using boosted random ferns (BRFs) and update trackers in each frame by using of [7], unlike the previous online learning-based tracking algorithm. In addition, a feed-forward data association is used to link detection responses to trajectories using short-term optimization based on similarities in position, size, and appearance. Pedestrian detection and tracking information is used for the velocity and direction estimation of pedestrian.

## Fuzzy Finite Automata

For pedestrian's intention recognition, recognition method should take into account robust against the variability of appearance of shape, moving speed, and direction of pedestrian together. One approach to recognize the temporal pattern is the hidden Markov models (HMMs) [8]. HMMs have been showed good performance in speech recognition, these models are difficult to understand because the obtained states usually do not coincide with the ones that human experts [9]. In addition, HMMs require an exponential number of parameters (exponential in the number of objects) to specify the transition and observation models and HMMs also require exponential time for inference [10]. DBN is a way to extend Bayes nets to model probability distributions over semi-infinite collections of random variables $Z_1, Z_2, ..., Z_n$, and these random variables can be partition into $Z_t = (U_t, X_t, Y_t)$ to represent the input, hidden and output variables of a state-space model [10]. However, it has the similar problem with HMMs such as exponential time for parameter estimation and inference when the number of states is increased

In contrast to previous methods based on HMMs and DBN, this study use fuzzy finite automata (FFA) [11] to predict pedestrian's behavior intention. For FFA, the state is represented graphically by nodes, while the transition is represented by arcs between the nodes. The states have corresponding membership values, and these states are interpreted as the probability of a pedestrian's event at a particular time.

In this paper, the four states connected with transitions of FFA are defined as **Walking-SW**, **Standing**, **W-Crossing**, and **R-Crossing**, and these states correspond to "walking sidewalk," "standing sidewalk," "walking crossing," and "running crossing," respectively. Each state is associated with probability distributions of five features. The state changes are controlled by various transition probabilities. For finite automata, the state is represented graphically by nodes, while the transition is represented by arcs between the nodes as shown in Fig. 2.

FFA with final states are considered as a special case of fuzzy Moore finite-state automata [12], and a finite set of output symbols **Z** is defined as $\mathbf{Z} = \{Danger, Safe\}$, which only has two output symbols (labels). A finite set of output symbols **Z** is defined as $\mathbf{Z} = \{\mathbf{accept}(Danger), \mathbf{reject}(Safe)\}$, which only has two output symbols (labels). As the set of final states $\mathbf{Q_{fin}} = \{W-Crossing, R-Crossing\}$ ($Q_{fin} \in Q$) only has two states, the final decision of the system is determined by using the following output assignment by modifying [13].

$$\begin{aligned} \omega(q_j) &= accept(Danger) \Rightarrow f_{q_j} \in Q_{fin} \\ \omega(q_j) &= reject(Safe) \Rightarrow f_{q_j} \notin Q_{fin} \end{aligned} \quad (1)$$

In equation (1), if the activate state $q_j$ is an element of $Q_{fin}$, it is declared a '*danger of pedestrian*'.

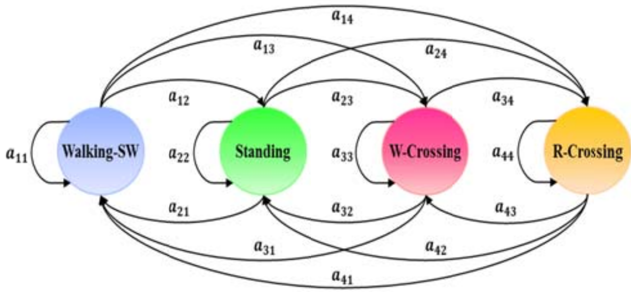


*Fig. 2. Proposed FFA for predicting of pedestrian's intention. The circular nodes represent a state, while the transition from the current state to the next state is shown by an arrow with an input symbol (event). The start state is represented by the purple color.*

In Figure 2, membership value **(mv)** of each state at time $t_0$ is denoted as $\mu^{t_0}(Walking-SW)$ and it is allowed to have a value between 0 and 1 as opposed to only 0 or 1; this is called a fuzzy state as opposed to a crisp state and permits partial membership according to [12]. In this study, the most appropriate **mv** of each state at time t+1 is estimated on product between mv of time t and transition values (tvs) which are presented in equation (5).

The fuzzy augmented transition function $\tilde{\delta}$ maps the active state to the fuzzy interval [0,1]. The membership assignment of state $q_i$ at t+1 times takes place upon the tvs from state $q_i$ to $q_j$ on input $a_k$ is represented as

$$\mu^{t+1}(q_i) = \tilde{\delta}((q_i, u^t(q_i)), a_k, q_j) = F_1(u^t(q_i), \delta(q_i, a_k, q_j)) \quad (2)$$

which means that the mv of the state $q_i$ at time t+1($\mu^{t+1}(q_i)$) is computed by function $F_1$ using the mv of $q_i$ at time t ($\mu^t(q_i)$) and the weight of the transition $\delta(q_i, a_k, q_j)$. Here, $\alpha_k$ is an input symbol (event) is represented by a vector [0,1]. In this study, we assume that all the states are activated simultaneously.

A single output **mv** can be assigned as the **mv** ($\mu^{t+1}(q_j)$) for a particular state at time t + 1 by using the following maximum multi-membership resolution [11][12].

$$u^{t+1}(q_j) = \underset{i=1\ to\ n}{\mathbf{Max}}[\mathbf{F}(\mu^t(q_i), \delta(q_i, a_k, q_j))] \quad (3)$$

where $n$ is the number of simultaneous transitions from states $q_i$'s to state $q_j$ prior to time t+1.

Hence, an event in fuzzy automata can take the system to more than one state with different degrees. The **tv**s connected to a state are estimated from the probability values of the PDFs for state Walking-SW, Standing, W-Crossing, and R-Crossing, respectively, and estimated using equation (4) with the input feature value.

$$\begin{bmatrix} a_{11} & a_{12} = a_{11} - a_{11}/4 & a_{13} = a_{12} - a_{11}/4 & a_{14} = a_{13} - a_{11}/4 \\ a_{21} = a_{22} - a_{22}/4 & a_{22} & a_{23} = a_{22} - a_{22}/4 & a_{24} = a_{23} - a_{22}/4 \\ a_{31} = a_{32} - a_{33}/4 & a_{32} = a_{33} - a_{33}/4 & a_{33} & a_{34} = a_{33} - a_{33}/4 \\ a_{41} = a_{42} - a_{44}/4 & a_{42} = a_{43} - a_{44}/4 & a_{43} = a_{44} - a_{44}/4 & a_{44} \end{bmatrix} \quad (4)$$

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where, four self-transition values ( $a_{11}, a_{22,} a_{33}, a_{44}$ )are estimated for each state at time $t$ by using a linear combination of the PDFs for **Walking-SW**, **Standing**, **W-Crossing**, and **R-Crossing**.

FFA permit partial membership and all events can occur simultaneously; hence, using these conditions, the next state candidate mv vector $\tilde{q} = [\tilde{q}_1 \cdots \tilde{q}_n]$ can be estimated by using the dot product between mvs of current states and tv matrix as follows,

$$\tilde{\mathbf{q}} = [mv_1 \cdots mv_n] \cdot \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \vdots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \quad (5)$$

After calculating the next state candidate vector $\tilde{\mathbf{q}}$, the next activate state and its **mv** at time t+1 are estimated by using the **Max** operation [12] based on equation (5) and (6).

$$\mu^{t+1}(q_j) = \mathbf{Max}[\tilde{q}_1 \cdots \tilde{q}_n] \quad (6)$$

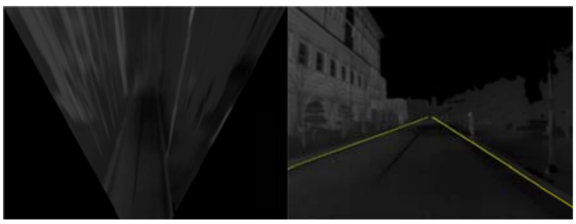
## Spatial-temporal Features Extraction

Because this study uses the spatial-temporal features as the tv of each state, we make the four PDFs for individual feature using the training data. As the spatial feature, 'distance between a pedestrian and curb', 'distance between a pedestrian and vehicle', and 'head orientation and orientation variation' are used. Moreover, as the temporal feature, 'speed of a pedestrian' is used.

### *Distance between a pedestrian and curb (DPC)*

Many pedestrians are usually stay nears the curb before crossing the street and if suddenly approaching pedestrians on the curb means that the probability of crossing road is high.

First, to remove the perspective effect in the image and distortion occurred by top view camera location and detect road curb, we use the inverse perspective mapping (IPM) [14] to generate a top view of road image as shown in Fig. 3. By applying IPM, we can focus our attention on only a sub-region of the input image and compute the exact distance from a pedestrian to road curb.



(a) (b)

*Fig. 3. IPM example, (a) the IPM view, (b) detected road curb*

After IPM processing, we estimate the distance from left and right curb to a pedestrian. DPC vector at time t consists of two values, $\mathbf{DPC}^t = [dist\_LC, dist\_RC]$. Here, $dist\_LC$ means that the distance from left curb to a pedestrian and $dist\_RC$ means that the distance from right curb to a pedestrian. From the estimated DPC data using annotated training data, we generated the PDFs for four states $\mathbf{p}_{d\_car}(\mathrm{x}|Walking-SW)$ , $\mathbf{p}_{d\_car}(\mathrm{x}|Standing)$ , $\mathbf{p}_{d\_car}(\mathrm{x}|W-Crossing)$, and $\mathbf{p}_{d_car}(\mathrm{x}|R-Crossing)$as shown in Fig. *. Thus, $\mathbf{p}_{d\_car}(\mathrm{x}|Walking-SW)$ and $\mathbf{p}_{d_car}(\mathrm{x}|Standing)$are used to compute the transition values for events $a_{11}$ and $a_{22}$, respectively, according to input vector **x,** while $\mathbf{p}_{d\_car}(\mathrm{x}|W-Crossing)$ and $\mathbf{p}_{d\_car}(\mathrm{x}|Walking-SW)$ are used to compute the transition values for event $a_{33}$ and $a_{44}$, respectively. In Fig. 4, for Walking-SW and Standing has the longer distance between the pedestrian and the curb than other two states. In contrast, W-Crossing and R-Crossing has the shorter distance between the pedestrian and the curb than other two states.

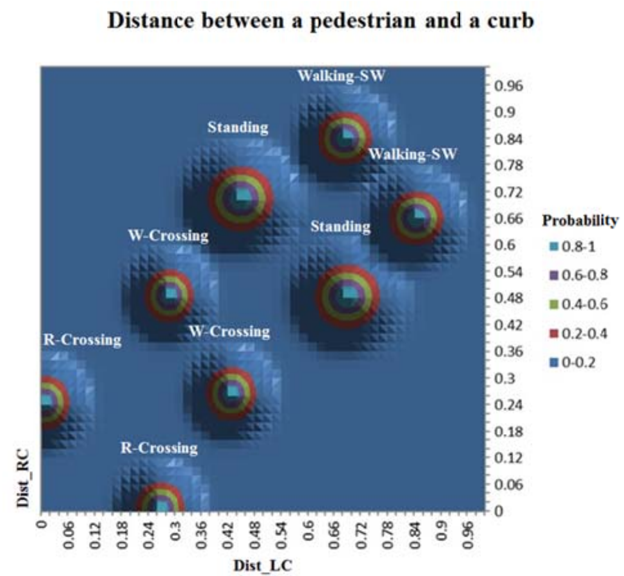



*Fig. 4. Two-dimensional PDF of Dist_LC and Dist_RC. X-axis represents Dist_LC feature, and Y-axis represents Dist_RC feature.*

### *Distance between a pedestrian and a vehicle (DPV)*

Distance between the pedestrian and a car (DPV) is an important clue in accidents between pedestrians and cars because the probability of an accident is higher as the DPC is closer. In this paper, to measure the DPV, two thermal cameras were configured for stereo as shown in Figure 5 (a).

From the thermal stereo camera, we make the disparity map to estimate the depth map as shown in Figure 5 (b). Depth map is used to measure the distance between the pedestrian being tracked and the car in the current frame.

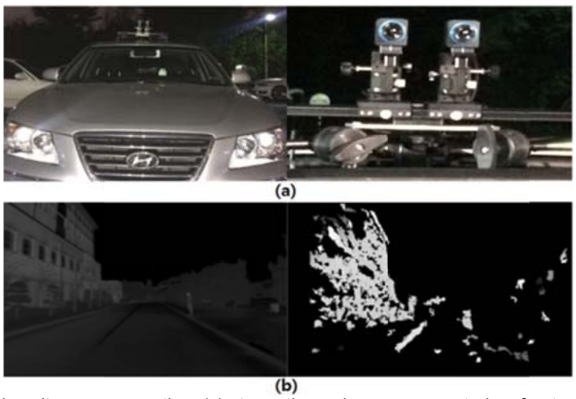



*Fig. 5. Disparity map generation, (a) stereo thermal camera mounted on front-roof of a car, (b) disparity map*

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DPV vector at time t consists of two values, $\mathbf{DP}V^t = [depth, dist_x]$. Here $dist_x$ means the relative distance of the pedestrian from the center x-axis of the car after IPM is performed. This value has the positive when a pedestrian is right side against a car and has negative value when a pedestrian is left side against a car. From the estimated DPV data using annotated training data, we generated the PDFs for four states.

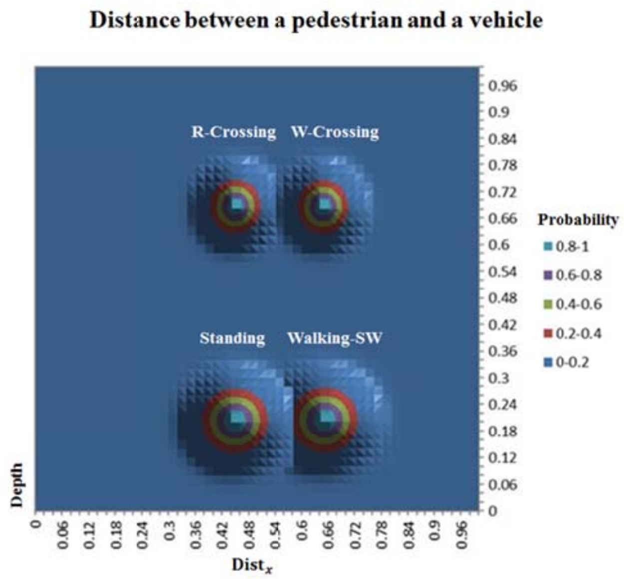


*Fig. 6. Two-dimensional PDF of depth and Distx. X-axis represents the distance feature, and Y-axis represents the depth feature.*

### *Head orientation and orientation variation (HOV)*

In general, a pedestrian tends to decide the next move position while moving through the eye. Therefore, we use head orientation and orientation variation (HOV) as one of cue to predict the intentions.

First head of the pedestrian is detected using the OCS-LBP and the four classes Boosted Random Forest classifier based on the [6] within the current location of a pedestrian being tracked. After head detection, we find the orientation of the pedestrian by recognizing the detection of a head that is facing in any direction out of four orientation classes ( $315^\circ \sim 45^\circ$ , $45^\circ \sim 135^\circ$ , $135^\circ \sim 225^\circ$, $225^\circ \sim 315$) as shown in Fig. 7.

Head orientation variation means a difference between the head orientation in current frame from the previous frame.

HOV vector at time t consists of two values, $\mathbf{HOV}^t = [HO, OV]$. Here, $HO$ means that the head orientation of a pedestrian and $OV$ means that head orientation variation of a pedestrian. From the estimated HOV data using annotated training data, we generated the PDFs for four states.

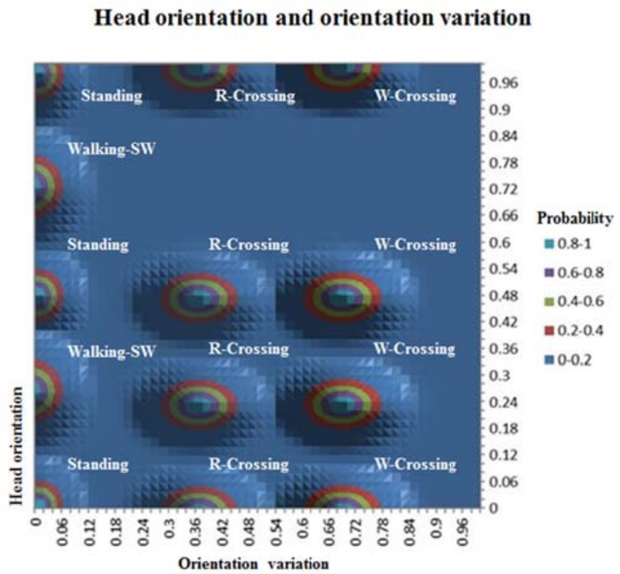


*Fig. 7. Two-dimensional PDF of head orientation and orientation variation. X-axis represents orientation variation feature, and Y-axis represents head orientation feature.*

### *Pedestrian's moving speed (PMS)*

Pedestrian's moving speed (PMS) of the pedestrian is valuable information to predict the next location of the pedestrian because pedestrians tend to keep the moving speed or suddenly increase speeds when they try to cross the road. To measure the moving speed of a pedestrian, we use the optical flow algorithms. PMS vector at time t consists of two values, $\mathbf{PMS}^t = [Mag\ of\ X-axis, Mag\ of\ Y-axis]$ . Here, $Mag\ of\ X-axis$ and $Mag\ of\ Y-axis$ means that magnitude of optical flow in orientation of X and Y axis, respectively. From the estimated PMS data using annotated training data, we generated the PDFs for four states.

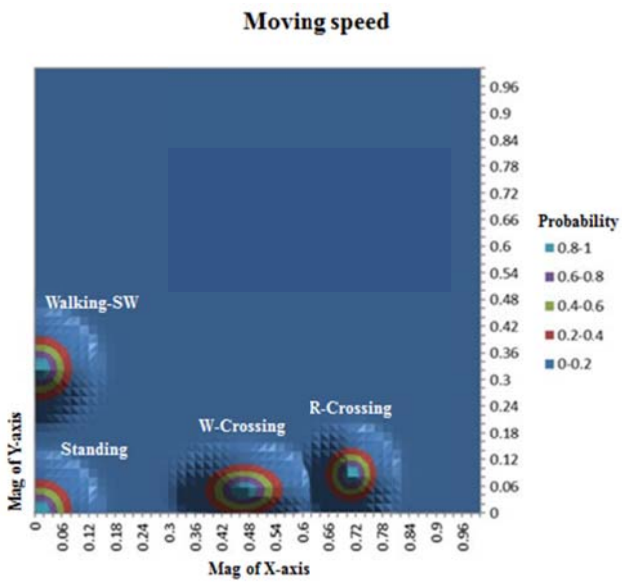


*Fig. 8. Two-dimensional PDF of moving speed. X-axis represents moving speed of X-direction, and Y-axis represents moving speed of Y-direction.*

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## Intention Prediction using FFA

After pedestrian detection and tracking algorithm is performed, the pedestrian's intention is predicted using the extracted feature. The intention of the pedestrian as defined in this paper is about whether a pedestrian in sidewalk wants to cross the road or not. We define the two output symbols of FFA $\mathbf{Z} = \{Danger, Safe\}$ . The output symbol 'Danger' includes two states {W-Crossing, R-Crossing} and 'Safe' includes two states { Walking-SW, Standing}.

First, to estimate the intention of the pedestrian using the FFA, we estimate new mv of four states $\tilde{q}$ at t+1 by dot product between mv of at time t and transition matrix using Equation (5).

After calculating the next state vector $\tilde{\mathbf{q}}$ , the next activate state and its **mv** at time t+1 are estimated by using the **Max** operation using Equation (6).

Finally, after n times later, if the final sate is a member of a finite set of $\mathbf{Q}_{\mathbf{fin}} = \{W-Crossing, R-Crossing\}$, it is determined as the 'Danger and if the final sate is not a member of a finite set of $\mathbf{Q}_{\mathbf{fin}}$ , it is determined as the 'Safe' ' using Equation (1)

## Experimental Results

Current dataset for pedestrian detection or tracking are unsuitable because it was captured from a visible camera and only considers normal walking pedestrians without a sudden crossing scenario. Therefore, we proposed a dataset for an evaluation of the prediction of pedestrian intention. Our proposed KMU dataset was captured from moving vehicles for prediction of pedestrian intention using a moving stereo camera. Therefore, to evaluate the performance of the proposed algorithm, we captured three types of FIR stereo video sequences, 5 for training and 5 for testing, while varying the speed and activities of the pedestrians. Table 1 shows the number of sequences and frames for each class.

Table 1. Number sequences and frames for each class

| Classes | Sequences / Total Frames |
|---|---|
| Walking-SW | 864 / 1097 |
| Standing | 453 / 1097 |
| W-Crossing | 198 / 1097 |
| R-Crossing | 279 / 1097 |

Sequences are labeled with event tags and time-to-event (TTE in frames) values as the same method of [5]. Figure 9 shows the performance evaluation graph on 5 testing data in terms of average precision.

The overall average error rate is 24.5% and "Standing" class shows the highest performance because it had the characteristic that distinguished it from the other classes. In contrast, "W-Crossing" class has the lowest performance because it includes a few ambiguous pedestrian's actions.


*Fig. 9. Average error rate using the proposed method on five test data.*

Figure 10 shows the intention prediction results for the seven test videos, respectively, when the proposed method was used.

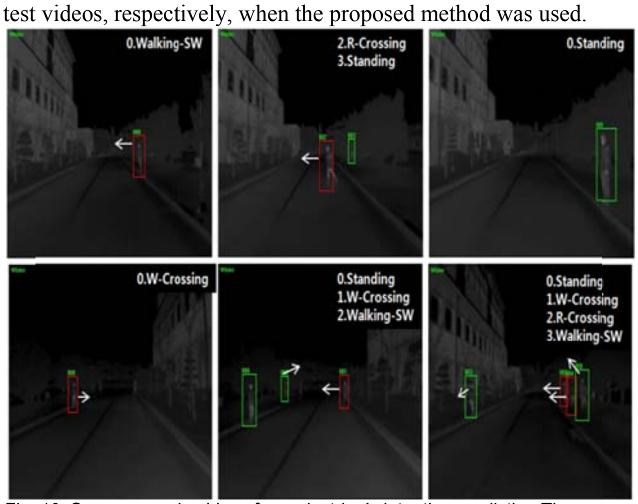


*Fig. 10. Some example videos for pedestrian's intention prediction.The green box represents "Safe" and the red box represents "Danger".*

## Conclusion and future works

The main contributions and overall procedures of our study can be summarized as follows; This research presents novel FFA instead of previous heuristic methods for pedestrian's intention prediction for intelligent ADAS using a stereo thermal camera mounted on the front-roof of a car.

To consider the above characteristics over temporal and spatial domain, 'distance between a pedestrian and curb', 'distance between a pedestrian and vehicle', 'head orientation and orientation variation', and 'speed of a pedestrian' used to generate probability density functions (PDFs) for the state transition value of FFA. The four states connected with transitions of FFA are defined as Walking-SW, Standing, W-Crossing, and R-Crossing, and these states correspond to "walking sidewalk," "standing sidewalk," "walking crossing," and "running crossing," respectively.

Finally, we proposed a dataset for an evaluation of the prediction of pedestrian intention as shown Table 1. Our proposed KMU dataset was captured from moving vehicles for prediction of pedestrian intention using a stereo thermal camera.

Experimental results showed that the proposed approach is robust prediction results about pedestrian intention although

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vehicle and pedestrian are moving. However, there still exist a few limitations on ambiguous pedestrian's action.

In the future, we plan to solve some problems related to ambiguous pedestrian's actions by designing advanced finite state automata and PDFs for pedestrian's intention.

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