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Motion Cue-Based Sudden Pedestrian Behavior Prediction Using Fuzzy Inference

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ABSTRACT As the motion of pedestrians is largely unpredictable, situational awareness presents a challenge for safe autonomous driving in urban areas. In particular, conventional sensor information about the dynamic states involved in determining and predicting pedestrian motion, including the walking speed, is significantly affected by latency when pedestrians suddenly increase their pace. In this paper, we propose a framework for predicting the steady-state walking speed of sudden pedestrian movement at the early stage of walking after heel-off. Based on the analysis that some motion cues during gait initiation are related to the steady-state walking speed, a fuzzy inference framework for predicting the steady-state walking speed, where the related motion cues are input to the inference model, is developed. The proposed framework can accurately predict the steady-state walking speed, even at the end of the first gait cycle. Moreover, the future trajectory of the pedestrian can be predicted using the piecewise linear speed model. Using the proposed framework, installed on the edge server of the cooperative-intelligent transportation system (C-ITS), this study aims to ensure the safety of autonomous vehicles by enabling them to successfully navigate the danger caused by sudden pedestrian movement. Experimental results obtained from testing the system at a real urban intersection verify the value offered by the proposed framework.

INDEX TERMS Autonomous vehicle, C-ITS, fuzzy inference, pedestrian, sudden pedestrian, walking speed prediction.

I. INTRODUCTION

Autonomous vehicles must inevitably navigate traffic involving non-autonomous vehicles and vulnerable road users, including pedestrians, whose unpredictable actions pose the biggest challenge to safe vehicle autonomy. Urban areas such as intersections are particularly problematic. In such areas, the line of sight of autonomous vehicle sensors is often blocked or interrupted by a variety of obstacles. Moreover, the behavior of pedestrians is much more unpredictable than that of massive objects such as vehicles. Consequently, it is very difficult for autonomous vehicles to achieve appropriate situational awareness in terms of possible threats to pedestrians. The cooperative-intelligent transportation system (C-ITS) is a promising solution for supporting

autonomous driving, as contemporary C-ITS technology incorporates multiple sensors, installed in fixed locations to provide an unobstructed view. Studies [1], [2] provide examples of C-ITS using sensor networks. These sensor networks were composed of multiple cameras, LIDAR, and RADAR sensors that monitored the mixed traffic in urban intersections. In particular, these networks facilitated the measurement of the position of pedestrians with a margin of error of only a couple of centimeters by virtue of the sophisticated sensor configuration and sensor fusion [2]. Although such technology addresses the challenge of sensor obstruction, sudden pedestrian motion, specifically abrupt rushing or dashing, remains an area of great uncertainty that is inadequately addressed in behavior prediction systems used by autonomous vehicles. For example, although a sensor system may detect a pedestrian in a sudden motion (referred to as a “sudden pedestrian”) behind a stationary vehicle,

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such detection would come too late to facilitate collision avoidance; sudden pedestrian motion is highly dynamic and there is significant latency in recognizing the dynamic states, including the walking speed. What is really required is a preemptive approach that enables the prediction of steady- and dynamic-state data at an early stage of walking (after heel-off) with reduced latency.

A possible solution is to use motion cues during the initial stage of sudden pedestrian motion. In contrast to the on-board sensors of autonomous vehicles, where the pedestrians' bodies are partially recognized by the noises induced by the vehicle motion, the sensor network used in C-ITS is advantageous for measuring the motion cues of the pedestrians by virtue of the aforementioned characteristics of the technology.

In [4]–[7], the relationships between motion cues and dynamic pedestrian states were studied. In [4], [5] the authors demonstrated that two motion cues of stride length and walking cadence are related with the walking speed from the regression based and statistical analysis, respectively. Moreover, it was demonstrated that these relationships were maintained regardless of gender and age in [5], [6]. In [7], the authors verified that the movement of the vertical head and the inclination of the upper body were also related to the walking speed, an important insight when classifying high speed walking, as will be explained later in this study. In [8], it was found using the Bland-Altman analysis that the stride frequency was related to the walk-to-run transition. A walking speed prediction system in which the stride frequency was set as an input was proposed. In [9], the authors proposed a simple walking prediction model in which the human body was modeled as an inverted pendulum, with the leg-to-leg angle and stride length used as model inputs. In addition, motion cues were used to classify the motion status of pedestrians [10]–[15]. In [10], a motion contour histogram of oriented gradients (MCHOG)-based framework was proposed for the early recognition of gait initiation. In this method, a histogram of oriented gradient features of multiple body parts was extracted, and the motion status was classified using a support vector machine (SVM). This enabled earlier decision-making, before the end of the first gait cycle. In [11]–[13], the motion of pedestrian's heads turning toward approaching vehicles was used to evaluate whether a pedestrian was likely to start walking. Similarly, the approach in [14] classified the motion status of pedestrians, such as stopping or walking, based on the situational awareness of whether the pedestrian recognized nearby vehicles. In [14], the orientation of the head was utilized for situational awareness. A latent-dynamic conditional random field (LDCRF) method was developed to classify the motion status using motion cues, including the position, speed, and head-orientation in [15]. However, in the studies considered up to this point, only present motion states could be classified; the prediction of future states was not considered.

In [16]–[19], prediction methods for dynamic states, including walking speed, were developed. In [16], the authors proposed a framework for the short-term prediction of

walking speed at the early stage after heel-off. Here, piecewise linear and sigmoid models were utilized to make the predictions before the walking pace reached a steady state. However, as the prediction in [16] was optimized for average walking, compromising the accuracy for lower or higher walking speeds. The authors in [17], [18] utilized a probabilistic framework based on the use of a dynamic Bayesian network (DBN) to predict the motion status and dynamic states, including the walking speed and position. By incorporating contextual information, including the traffic-light state and the current dynamic states obtained from sensors, the framework proposed in [17], [18] could make situationally-aware predictions. Similarly, in [19], contextual information, including the traffic-light state, was considered for the intent-aware long-term predictions in a Markov decision-process framework, where the intent of the pedestrian was modeled as a policy. However, it should be noted that conflicts or sudden motions of pedestrians often occur in an unusual context. In [20], a random walk model was utilized to predict the future trajectory of a pedestrian, while [21] predicted the trajectory by matching the obtained motion cues from the vision sensor with previously learned trajectories. It is noteworthy that these previous studies into the prediction of future motion states usually relied on currently recognized sensor information, and did not use motion cues for prediction. Indeed, there is a distinct paucity of literature addressing the use of motion cues for predicting the dynamic states of pedestrians. Consequently, the prediction approaches in the literature are prone to latency, as discussed in [11], especially for sudden pedestrians.

The objective of this study is to facilitate, within the service area of C-ITS and thus with the proposed framework running on a C-ITS edge server, the autonomous vehicle's preemptive awareness of the sudden motion of surrounding pedestrians, supporting safe path planning. More specifically, the scope of this study focuses on predicting the future motion of pedestrians suddenly running out of the roadside into the corridor of approaching vehicle, which is one of typical pedestrian accident types, rather than to predict for arbitrary situations. As such, in this paper, a framework is proposed for predicting the steady-state walking speed of a pedestrian at the early stage after gait initiation, using the relationship between motion cues and dynamic states. The motion cues considered by the framework include stride length, walking cadence, and upper-body inclination. Motion cues and the steady-state walking speed were found to be correlated, and a fuzzy inference model is designed for the predictions, in which the motion cues are used as inputs to the inference model. The future trajectory is also predicted at the aforementioned early stage using a piecewise linear speed model. The main contributions are summarized as follows:

- The proposed framework with motion cues facilitates the prediction of the steady-state walking speed as early as the end of the first gait cycle after gait initiation, enabling reduced latency in recognizing sudden motions.

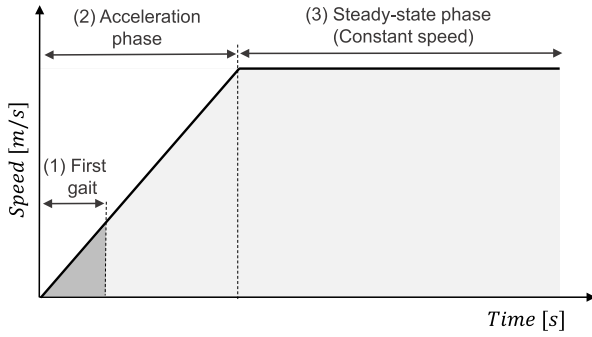


FIGURE 1. Illustrative example of gait procedure.

- The proposed framework can make early predictions of steady-state walking speed for overall speed ranges including the high speed of main concern for detecting the sudden pedestrians, unlike the previous work that predicts only for normal walking speed. The provided experiment results of early prediction for sudden pedestrians of high speed range are unique throughout the literatures.
- Moreover, the proposed model is not reliant on particular pedestrian characteristics such as gender, age, or height, which is advantageous in reducing the burden on the sensors and simplifying the prediction architecture.

II. PROPOSED FRAMEWORK

A. CONCEPT

The gait procedure for a pedestrian after heel-off is shown in Fig. 1. It can be observed that the walking pace accelerates within a couple of gait cycles, and the walking speed saturates at the steady-state value. The main goal of our study is to predict the steady-state speed at the end of the first gait cycle, well before the walking speed reaches the steady-state value, offering an improvement on what is possible using conventional sensor information that only becomes valid after the walking pace reaches the steady state. Although the distance traveled during the first gait cycle is negligibly small, measuring at most half of the stride length, the gait parameters during this period provide significant clues for the prediction of the steady-state speed. Furthermore, the higher the steady-state speed, the longer the acceleration phase; as such, prediction of the steady-state speed by the end of the first gait cycle becomes increasingly advantageous for reducing the latency in recognizing sudden motion for higher final steady-state values. In addition, with the assumption that a pedestrian tends to maintain their walking speed after reaching the steady state, the future trajectory of a pedestrian can be also predicted from the steady-state walking speed predicted at the early state of the gait cycle using the proposed framework.

B. ARCHITECTURE OF FRAMEWORK

The architecture of the speed prediction method is shown in Fig. 2. First, the roadside sensors in the ITS environment

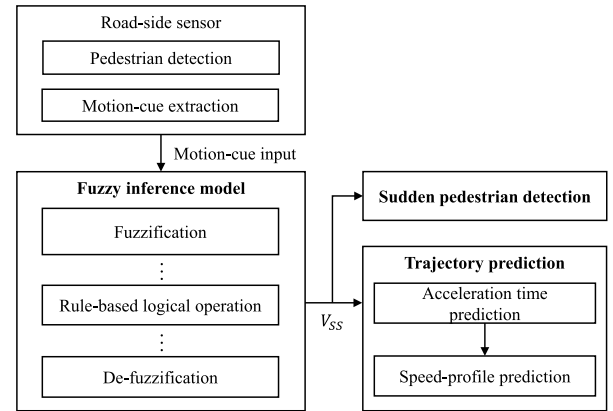


FIGURE 2. Architecture of prediction framework.

measure the motion cues of nearby pedestrians standing at a cross-walk. The acquired motion cues are input to the fuzzy inference model, and the physical values of these motion cues are fuzzified with the input membership functions that are defined from the statistics of the motions for different speed groups. The fuzzification process is based on the relationship between the motion cues and steady-state walking speed. Throughout the de-fuzzification process, the predictions for the steady-state walking speed V_{ss} are inferred as numerical values, with which the sudden motion of the pedestrians can be predicted in a preemptive manner. Subsequently, the future trajectory of pedestrians is predicted by estimating the acceleration time, which is a function of the predicted steady-state walking speed. The predictions of the trajectory are based on the piecewise linear speed model, which is the implementation of the gait procedure depicted in Fig. 1.

III. PEDESTRIAN MOTION ANALYSIS

A. RELATIONSHIP OF MOTION CUES WITH STEADY-STATE SPEED

The motion that occurs in the body during locomotion can be largely distinguished into lower- and upper-body characteristics. The lower-body motion cues, the stride length and walking cadence, are strongly linked to the steady-state speed and proportional to walking speed. Increased walking speed is caused by either extended stride length or increased walking cadence (or a combination of both), as proven by experiments in [4]–[6]. With respect to the upper-body, head movement is regarded as the critical motion cue related to walking speed [7]. A pedestrian tends to tilt the center of gravity of their body in the direction in which they are heading to stabilize the walking motion when they walk with high acceleration [22]. Based on the findings in the literature, it is assumed that these three motion cues - stride length, walking cadence, and upper-body inclination - are related to the steady-state walking speed, such that the values of each motion cue may be represented as follows:

$$x_g = [x_{SL} \ x_{LV} \ x_{BI}]^T. \quad (1)$$

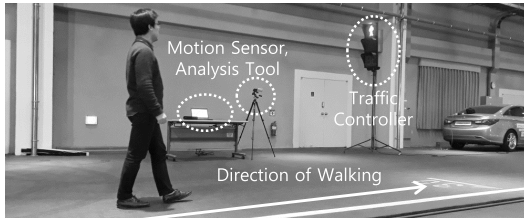
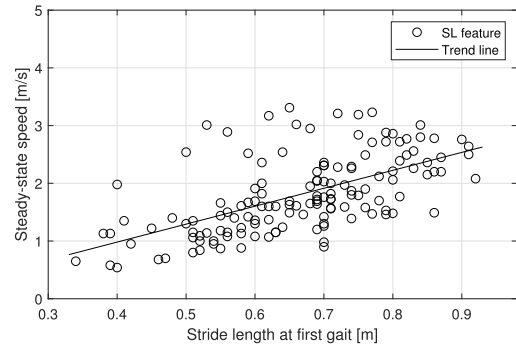


FIGURE 3. Set-up for the indoor experiments for the motion analysis.

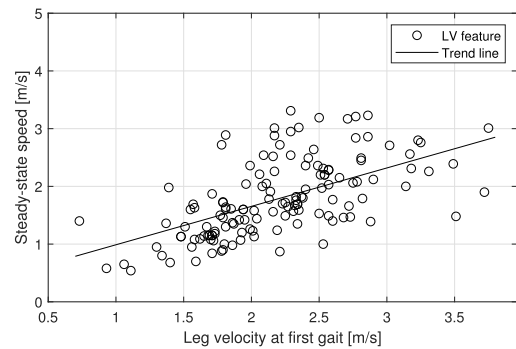
where x_{SL} , x_{LV} , and x_{BI} denote the physical values of the stride length, walking cadence, and upper-body inclination, respectively. The physical value of the walking cadence was represented by the leg velocity. To verify the relationship between these gait parameters and steady-state speed, we analyzed the physical values of the first gait cycle with the indoor experiment results.

For the dataset construction in the experiments, the MS Kinect V2 was used to record the motion data across 24 joints of the whole body, as shown in Fig. 3. A total of 134 pedestrian samples were collected in the ages of 20 s to 40 s for both females and males. Physical properties such as gender, height, and age were not considered in the experiments. The subject pedestrians were instructed to initiate walking from a standstill, assuming a traffic-rich road environment. The steady-state speed of the pedestrians was distributed within a range of 0.5 m/s to 3.4 m/s. For the analysis, the steady-state speed levels were grouped into the categories low, mid, and high, which were defined as the ranges [0.5, 1.3], [1.3, 2.3], and [2.3, 3.4] in m/s, respectively. The dataset obtained in these experiments becomes a training data set for the proposed prediction model, which will be discussed subsequently.

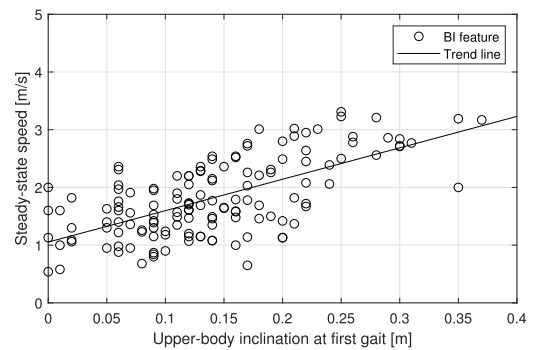
Furthermore, for the acquisition of motion cues, three physical measuring points were defined. First, the stride length was determined by the difference in distance between the initial position of the foot and the ending position of the foot after the first stride. Second, the leg velocity was measured as the maximum velocity of the knee joint during the first gait cycle, because the position of the knee showed the most change in motion relative to the other joints in the lower body. Finally, the upper-body inclination was measured as the displacement between the center of the body and the center of the head position at the end of the first gait cycle. As shown in the experimental data in Fig. 4, the three motion cues were proven to be relevant to the steady-state speed, and the values of the three motion cues were proportional across the overall steady-state speed ranges. Moreover, with reference to the result of upper-body inclination in Fig. 4(d), a pedestrian walking fast shows a distinctive difference compared with pedestrians moving at normal walking speed. In this study, a walking speed of above 2.4 m/s was categorized as fast walking based on the fact that a motion transition from walking to running occurs at around this speed [8]. The motion cue of upper-body inclination occurs around this transition point, in which a pedestrian abruptly accelerates



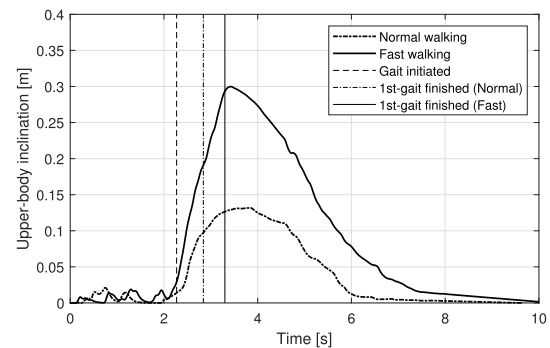
(a) Stride length



(b) Leg velocity



(c) Upper-body inclination



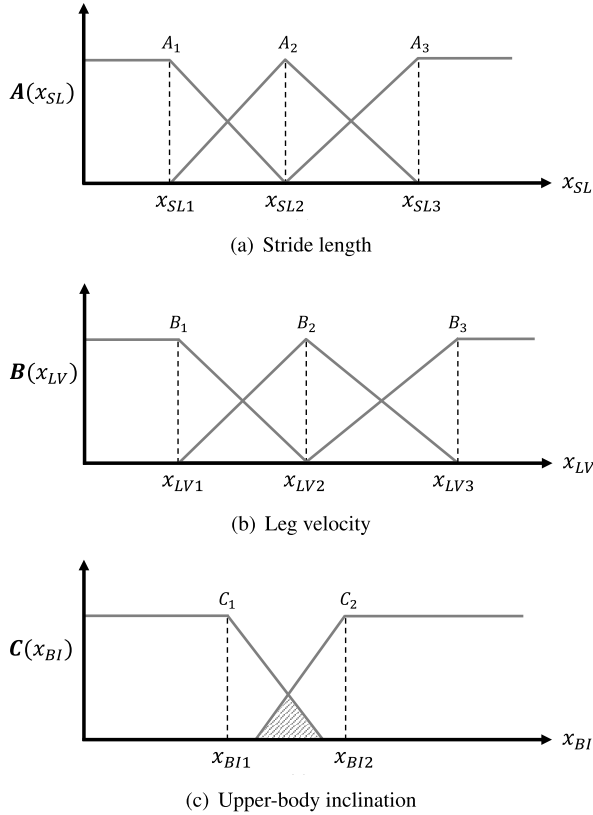
(d) A sample of upper-body inclination at the end of first gait (Comparison between normal and fast walking)

FIGURE 4. Correlation of motion cues with steady-state speed.

to reach a high walking speed. This upper-body inclination motion property provides a crucial hint for identifying sudden pedestrians.

TABLE 1. PCC analysis of motion cues with steady-state speed.

Motion Cue	Result
ρ_{SL}	0.597
ρ_{LV}	0.616
ρ_{BI}	0.659

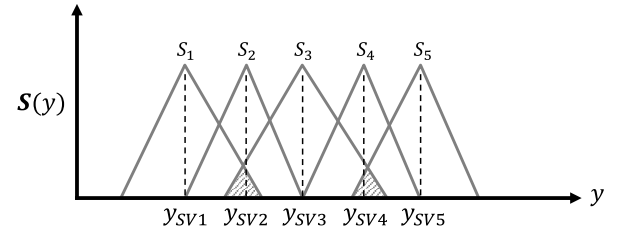
**FIGURE 5.** Input membership functions.

The relationship between steady-state speed and motion cues was verified by Pearson correlation coefficient (PCC) analysis, a statistical method used to measure linear correlation. As presented in the PCC results in Table 1, all motion cues are apparently correlated with steady-state speed. The upper-body inclination level shows a particularly strong relationship, which is crucial for the classification of sudden pedestrians. Even if the motion cues of stride length and leg velocity are correlated each other, both of motion cues are informative as the system inputs because the stride length reveals non-linearity at the extreme speed ranges. For example, the stride length is limited in the high speed range.

IV. PEDESTRIAN MODEL

A. STEADY-STATE SPEED PREDICTION

Based on the discussion in the previous section, we propose a prediction model to infer the steady-state walking speed using the motion cues obtained during the first gait cycle after heel-off. In the prediction model, stride length, leg

**FIGURE 6.** Output membership function (Steady-state speed).

velocity, and upper-body inclination were used as the inputs. The prediction result output from the model is a steady-state speed, which a pedestrian is predicted to reach in two to three gait cycles' time. A fuzzy inference-based approach is applied to predict the steady-state walking speed. In this study, the Mamdani fuzzy model [23] is utilized for fuzzy inference, based on the interpretable rule based on the causal relationship in the motion patterns observed empirically. First, the input fuzzy sets map the physical values of the three motion cues $x_g \in X$ into the input fuzzy values.

$$A, B, C : X \rightarrow [0, 1] \quad (2)$$

where A, B , and $C \in F(X)$ denote the input fuzzy sets for the stride length, leg velocity, and upper-body inclination, respectively, and are associated with the linguistic terms as follows:

$$\begin{aligned} A &= \{A_1 : \text{low}, A_2 : \text{mid}, A_3 : \text{high}\} \\ B &= \{B_1 : \text{low}, B_2 : \text{mid}, B_3 : \text{high}\} \\ C &= \{C_1 : \text{low}, C_2 : \text{high}\}. \end{aligned} \quad (3)$$

In (3), each linguistic term represents the level of the physical values of each motion cue. Note that the upper-body inclination features only low and high values. It reflects the property of sudden pedestrians that distinctively show features at high speed induced by abrupt acceleration. Fig. 5 shows the input fuzzy sets with notations in (3). Here, the properties of fuzzy sets, such as the *core* and the *support*, for x_{SL} and x_{LV} , are learned statistically from the dataset explained in the previous section, whereas those for x_{BI} are empirically tuned. All of these input fuzzy sets are combined into the following Mamdani fuzzy relation:

$$D(x_g) = A(x_{SL}) \wedge B(x_{LV}) \wedge C(x_{BI}). \quad (4)$$

In addition, the output fuzzy sets $S \in F(Y)$ are defined as depicted in Fig. 6, and are associated with the following linguistic terms:

$$S = \left\{ \begin{array}{l} S_1 : \text{low} \\ S_2 : \text{mid} \\ S_3 : \text{mid-high} \\ S_4 : \text{high} \\ S_5 : \text{very-high} \end{array} \right\} \quad (5)$$

where each term represents steady-state speed. Among the five levels, pedestrians walking fast or running are considered

TABLE 2. Fuzzy rule base.

n	SL	LV	BI	SSVel
1	Low	Low	Low	Low
2	Mid	Low	Low	Low
3	High	Low	Low	Mid
4	Low	Mid	Low	Low
5	Mid	Mid	Low	Mid
6	High	Mid	Low	Mid-high
7	Low	High	Low	Mid-high
8	Mid	High	Low	High
9	High	High	Low	Very-high
10	Low	Low	High	Low
11	Mid	Low	High	Mid
12	High	Low	High	Mid
13	Low	Mid	High	Mid-high
14	Mid	Mid	High	High
15	High	Mid	High	High
16	Low	High	High	Very-high
17	Mid	High	High	Very-high
18	High	High	High	Very-high

to be operating at high or very high speeds. The reason for the subdivision of the high-speed group into these two categories is to increase the resolution of inferences in high-speed ranges and thus improve the classification quality for sudden pedestrians. The input and output fuzzy values are associated with each other throughout the fuzzy rule base, which is based on the Mamdani relation as follows:

$$R_M(x_g, y) = D(x_g) \wedge S(y) \quad (6)$$

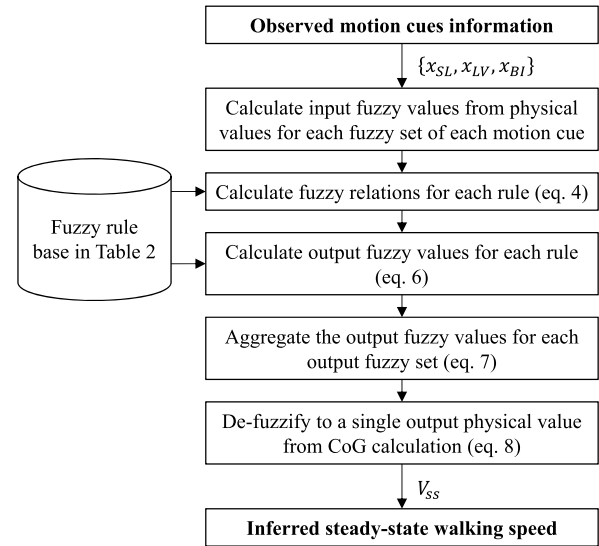
where $y \in Y$. The fuzzy rule base is proposed as given in Table 2, based on observations from the training data set. As presented in Table 2, multiple combinations of input motion cues exist for the same linguistic level of output. Based on the discussion in Section III, the rules with the higher upper-body inclination value are associated with a higher level of steady-state speed. Moreover, the multiple rules will buffer the predictions from the effects of uncertainty related to any observed motion cue. With the fuzzy rule base discussed above, the steady-state walking speed is inferred by following the Mamdani fuzzy inference:

$$S'(y) = \bigvee_{x_g \in X} D'(x_g) \wedge R_M(x_g, y) \quad (7)$$

where $S'(y)$ denotes the conclusion inferred from the observations $D'(x_g)$. In the last step, the center of gravity (CoG) in (8) is calculated for defuzzification as follows:

$$V_{ss} = \frac{\int_W y \cdot S'(y) dy}{\int_W S'(y) dy}. \quad (8)$$

The defuzzification process translates the fuzzy output values into the physical value of the steady-state speed (V_{ss}), where V_{ss} denotes the predicted steady-state walking speed from the fuzzy inference, $W = \text{supp}(S)$, which is defined in

**FIGURE 7.** Flow-chart of fuzzy inference in the proposed framework.

the experiments. The Fig. 7 represents the flow-chart of fuzzy inference in the proposed framework.

B. TRAJECTORY PREDICTION

The trajectory of a pedestrian is predicted based on the steady-state walking speed predicted by (8). For trajectory prediction, we use a piecewise linear speed model [16] as follows:

$$\hat{v}_p(t) = \begin{cases} v_p(t_c) + a_g(t_a(V_{ss}) - t_c), & t_c \leq t < t_a \\ V_{ss}, & t \geq t_a \end{cases} \quad (9)$$

The predictions are performed at t_c , the point at which the first gait cycle was completed. Here, v_p and $\hat{v}_p$ are the measured and predicted velocities at t_c , respectively. As represented in (9), it is assumed that the walking speed increases with a constant acceleration level of a_g , but that it saturates to the inferred steady-state speed after the acceleration is finished at t_a . Note that t_a is a function of the steady-state walking speed. That is, the duration of the acceleration phase depends on how fast the pedestrian will walk. In (9), the speed profile after the gait initiation is divided into two phases: accelerating and steady state, as shown in Fig. 8. Fig. 9 shows the regression results of the acceleration time t_a according to the steady-state walking speed from the indoor experiments explained in Section III. It can be observed that the acceleration time t_a is proportional to the steady-state speed for normal walking, but that it saturates to a constant value for fast walking. Thus, t_a is calculated using the inferred steady-state walking speed, as follows:

$$t_a = \begin{cases} \alpha V_{ss} + \delta, & V_{ss} < 2.4 \text{ m/s} \\ \beta, & V_{ss} \geq 2.4 \text{ m/s} \end{cases} \quad (10)$$

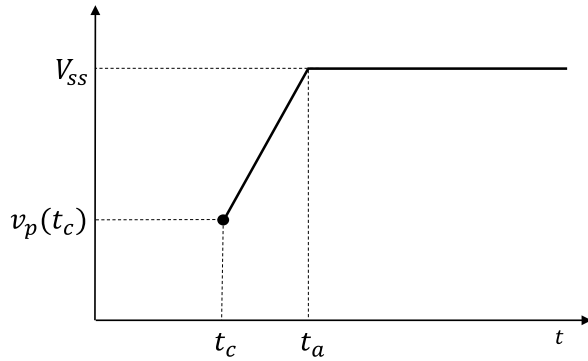


FIGURE 8. Piecewise linear speed prediction model.

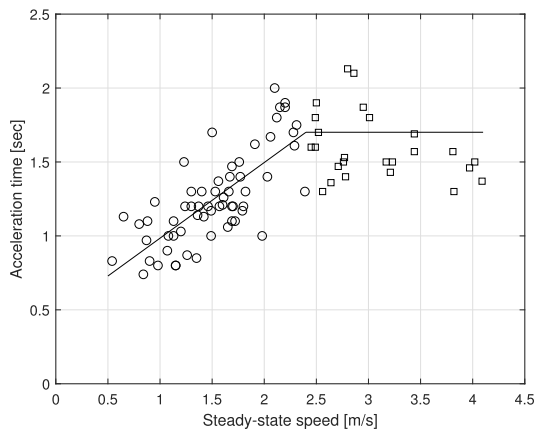


FIGURE 9. Regression of acceleration time.

TABLE 3. Road-side sensors system specification.

No. of sensors	(Total 8 pcs.) 2pcs. in each corner
Position	(Height) 5 m from ground, (Tilting angle) 73.5 degree
Field of view	(Horizontal) 60 degree, (Vertical) 33 degree
Size	(HD) 1280 x 720 pixels
Resolution	4 cm/pixel (From 40 m distance)
FPS	15 frame/s

From the regression shown in Fig. 9, the parameters in (10) are obtained as $\alpha = 0.52$, $\beta = 1.70$, and $\delta = 0.47$, respectively. With the predicted acceleration time t_a and steady-state walking speed V_{ss} , the acceleration levels a_g are decided automatically, as depicted in Fig. 8. This implies that the acceleration level is increased for fast walking because the predicted acceleration time is saturated, as depicted in Fig. 9, and this aspect corroborates the characteristic of the abrupt motion of sudden pedestrians.

V. EXPERIMENTS

A. TEST SITE

The proposed framework was verified with the dataset acquired at 'Biseul' 4-way intersection (Daegu-si, South Korea). The camera-based roadside sensors were set up on the C-ITS facilities at a height of 5 m, and the motion of the



FIGURE 10. Test site: Biseul intersection.



FIGURE 11. Samples of pedestrian motion detection; The box surrounding the pedestrian denotes the region of interest (ROI).

pedestrians was monitored by the roadside sensors, as shown in Fig. 10. The roadside sensors were configured to be perpendicular to the pedestrian's walking direction, an advantageous positioning for monitoring pedestrian motion cues as well as dynamic states such as the position and walking speed. The specifications of the sensor system are listed in Table 3.

B. ACQUISITION OF MOTION CUES

The motion cues of stride length and leg velocity were obtained from the region of interest (ROI), represented by a bounding box, and the horizontal width of the ROI varies with the pedestrian's gait progression, as shown in Fig. 11. The maximum width of the ROI during the gait cycle was recorded as the stride length of the pedestrian, and the leg velocity was calculated by the time difference of that stride length. Moreover, the sensor value of the upper-body inclination was discretized into three levels, considering the degree of body bending. Specifically, the upright posture, characteristic of pedestrians who are either stationary or walking normally as shown in the left sample of Fig. 11, was judged to be the first level of bending. As the walking speed increased, the inclination level of the body shifted to the second or third level. As the motion cues were obtained at the time of completion of the first gait cycle, it was necessary to detect the completion of the first gait cycle using the sensor

TABLE 4. Core of each fuzzy set.

Stride length [m]		Leg velocity [m/s]		Upper-body Inclination [-]	
x_{SL1}	0.52	x_{LV1}	0.5	x_{BI1}	1
x_{SL2}	0.69	x_{LV2}	1.0	x_{BI2}	3
x_{SL3}	0.87	x_{LV3}	1.7	-	-

TABLE 5. Support of each fuzzy set.

[a,b]=supp(Fuzzysset)								
-	a	b	-	a	b	-	a	b
A_1	0	0.69	B_1	0	1.0	C_1	0	2.4
A_2	0.52	0.87	B_2	0.5	1.7	C_2	1.5	3.5
A_3	0.69	1.4	B_1	1.0	4.0	-	-	-

TABLE 6. Core of output fuzzy set.

Steady-state speed [m/s]				
y_{sv1}	y_{sv2}	y_{sv3}	y_{sv4}	y_{sv5}
0.98	1.53	2.23	2.85	3.4

information. This was achieved by determining the point at which the ROI width was maximized.

C. PARAMETERS

The prediction model for predicting the steady-state walking speed was learned by training the dataset acquired from the indoor experiments with MS Kinect V2, as discussed in Section III. The 134 pedestrian samples were divided in half, one half for the training of the prediction model and the other half for the verification of the model. Based on the training dataset, the model parameters for the fuzzy sets presented in Section IV were obtained through the harmonization of statistical and empirical methods. The *core* of input fuzzy set for stride length and leg velocity was set to the mean value of each linguistic level as presented in Table 4, and the *support* of them was fixed to the *core* of adjacent fuzzy set as depicted in Fig. 5(a) and 5(b). Moreover, the *core* of two input fuzzy sets for upper-body inclination was set to the values of the first and third level, and the *support* of it was initially set to the *core* of adjacent fuzzy set and then tuned by incrementally decreasing the shaded area in Fig. 5(c). This is especially for the enhanced predictions in high speed range. The *support* values fixed or tuned for input fuzzy sets are presented in Table 5. Because the input fuzzy sets were overall constructed from the statistics, the tuning with data was mainly focused on the output fuzzy sets. The output walking speed was divided into 5 groups and the *core* of output fuzzy set was set to the mean value of each group as presented in Table 6. Initially, the *support* of each fuzzy set was set to the *core* of adjacent fuzzy set and then the *support* around the boundaries between the linguistic levels was tuned by incrementally increasing two shaded areas in Fig. 6. The *support* values for output fuzzy sets are presented in Table 7. The performance index for tuning was the prediction accuracy.

TABLE 7. Support of output fuzzy set.

[a,b]=supp(Fuzzysset)					
-	S_1	S_2	S_3	S_4	S_5
a	0.31	0.98	1.5	2.23	2.7
b	1.6	2.23	2.87	3.4	3.97

TABLE 8. Composition of dataset.

Dataset		Class 1	Class 2	Class 3	Total
Indoor	Training	13	37	17	67
	Validation	13	37	17	67
Outdoor	Validation	13	27	24	64

D. PREDICTION RESULT

Model verification was performed using two types of dataset. One was the dataset for the indoor experiments mentioned in Section V-C, and the other was the one acquired from the roadside sensors at the outdoor test site. The composition of dataset for each linguistic level is presented in Table 8. The classification level of *class 1*, *class 2*, and *class 3* correspond to the linguistic levels of *low*, *mid*, and *high*, respectively. The frame rate of the roadside sensors was 15 fps, as presented in Table 3, while that of MS Kinect V2 was 30 fps, resulting in an imprecise decision about the first gait cycle; moreover, the resolution of the motion recognition was low for the roadside sensors, as they monitored the scene from a relatively long distance. Thus, it was expected that the motion cues measured from the roadside sensors would be less accurate. In addition, the ground truth of the steady-state walking speed was obtained for verification by analyzing the screenshots of all the time steps for every sample data element. The proposed framework was validated with a total of 131 samples, which consisted of 67 indoor samples and 64 outdoor samples. Table 9 shows the experimental results of the steady-state walking speed prediction for the indoor samples with the framework proposed in Section IV-A. The overall average accuracy was 87.51 %, and the total MAE was calculated as 0.33 m/s. The MAE was calculated as follows:

$$MAE = \frac{\sum_{i=1}^N |v_{GT}(i) - V_{ss}(i)|}{N} \quad (11)$$

where $v_{GT}(i)$ and $V_{ss}(i)$ denote the ground truth and the predicted steady-state walking speed for the i -th sample, respectively, and N denotes the total number of samples. Each ground truth steady-state speed was calculated as the averaged value of the velocities over a duration of 2 s after the start of steady-state walking. The averaging was required for *class 3* because sudden pedestrian movement tends to be characterized by a swaying walking motion during the steady state. Table 10 gives the experimental results of the steady-state walking speed prediction for outdoor samples. The overall average accuracy was 81.13 %, which was slightly worse than the result for indoor samples; this may be attributed to the relatively low accuracy of motion cue measurement, as expected. In addition, the recall for *class 3* was considered

TABLE 9. Result of steady-state speed prediction (indoor 67 samples).

	Steady-state speed [m/s]	Averaged first gait cycle [s]	Averaged accuracy [%]	MAE [m/s]
Class 1	0.5 ~ 1.3	0.43	89.75	0.12
Class 2	1.3 ~ 2.3	0.50	86.63	0.23
Class 3	2.3 ~ 3.4	0.47	86.15	0.37

TABLE 10. Result of steady-state speed prediction (outdoor 64 samples).

	Steady-state speed [m/s]	Averaged first gait cycle [s]	Averaged accuracy [%]	MAE [m/s]
Class 1	0.5 ~ 1.3	0.46	82.12	0.22
Class 2	1.3 ~ 2.3	0.53	80.54	0.27
Class 3	2.3 ~ 3.4	0.46	83.12	0.42

TABLE 11. Result of position prediction (indoor 67 samples).

Prediction horizon [s]	MAE [m]		
	Class 1	Class 2	Class 3
1.0	0.08	0.11	0.10
1.53	0.14	0.25	0.26
2.0	0.18	0.22	0.52

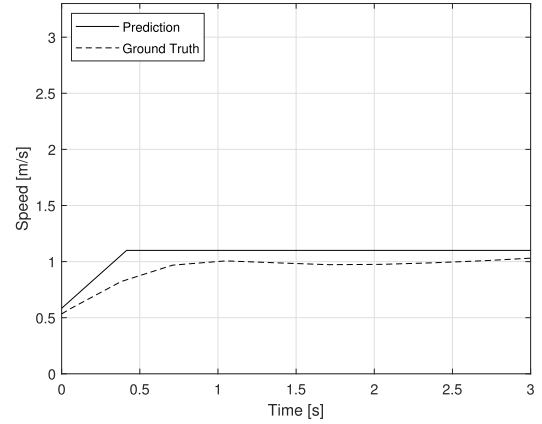
TABLE 12. Result of position prediction (outdoor 64 samples).

Prediction horizon [s]	MAE [m]		
	Class 1	Class 2	Class 3
1.0	0.15	0.19	0.17
1.53	0.22	0.25	0.47
2.0	0.19	0.30	0.72

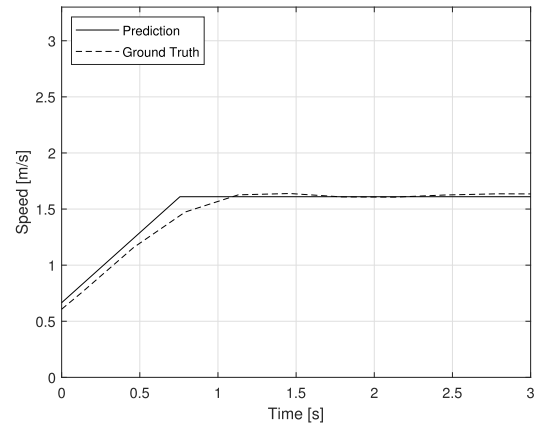
for evaluation of the quality of classification of the sudden pedestrians with the outdoor samples, and this value was calculated as 83.12 %.

It is noteworthy that the time for the completion of the first gait cycle was only about 0.5 seconds, following on quite rapidly from gait initiation. This means that it took approximately 0.5 seconds to make the predictions of the steady-state walking speed with noticeable accuracy, as presented in Tables 9 and 10. Fig. 12 presents the sample results of the speed profile prediction for each *class* based on the discussion in Section IV-B. The prediction was performed at the end of the first gait cycle. As seen in the sample of *class 3* in Fig. 12 (c), the steady-state walking speed was accurately predicted about 1.2 seconds in advance of the walking speed entering the steady state. This preemptive information will be beneficial in a possible conflict between autonomous vehicles and sudden pedestrians, as it increases the chance that the autonomous vehicles will have enough time to react.

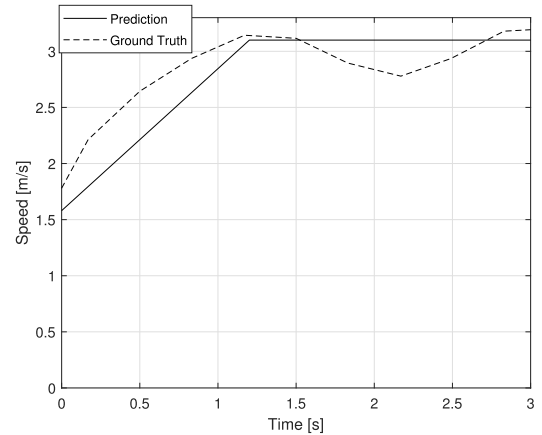
In addition, the experimental results of the position prediction with the predicted speed profile are presented in Tables 11 and 12. Even though the exact prediction of position is not the main concern of this study, position predictions, as represented by the MAE values in Tables 11 and 12, were verified to be relatively accurate. These MAE values are



(a) Case 1



(b) Case 2



(c) Case 3

FIGURE 12. Speed profile prediction results for outdoor samples.

calculated as follows:

$$MAE = \frac{\sum_{i=1}^N |e(p_{GT}(i), p_{ss}(i))|}{N} \quad (12)$$

where $p_{GT}(i)$ and $p_{ss}(i)$ denote the ground truth and the predicted position for the i -th sample, respectively, and $e(\cdot)$ denotes the Euclidean distance between two points.

As expected, the quality of predictions was worse for the longer prediction horizons and for the outdoor samples, as was the case for the speed predictions. The results in Table 11 and 12 for *class 2*, which corresponds to the cases of normal walking, are comparable to the results of previous work in [16]. Note that the proposed framework is able to predict the steady-state walking speed for overall speed ranges including the high speed of main concern of this study.

E. LIMITATIONS

If the suddenly rushing pedestrians recognize the approaching vehicle and change their behavior for the collision avoidance, the system integrated with the proposed framework might trigger a false positive response. However, a certain amount of false positive cases would be inevitable for the collision avoidance in the true positive cases. It would be similar for human drivers if the sudden pedestrians are visible to the drivers. The human drivers would react to such a fake behavior of pedestrians in the same way even if the collision might not actually happen. Moreover, because the predictions are made at the end of the first gait cycle for the early stage predictions, the direction of walking is not considered in the proposed framework. The prediction of complete trajectories including the direction would require several tracked samples after heel-off, which is beyond the scope of this study.

VI. CONCLUSION

Sudden pedestrians present a major navigation challenge for autonomous vehicles owing to vehicle latency in recognizing them and the unpredictability of their motion. To address this problem, this study developed a prediction framework, using C-ITS with camera-based roadside sensors, which is capable of predicting the dynamic states of pedestrians at an early stage of walking after heel-off. Indoor experiments with a high-precision sensor proved that the key motion cues were related to the steady-state walking speed of the pedestrians and that the proposed framework could predict the steady-state walking speed at the time of completion of the first gait cycle with motion cue information from the sensors. Further experiments, using roadside sensors at a real intersection, showed that the steady-state walking speed could be accurately predicted hundreds of milliseconds before the walking pace of sudden pedestrians reached the steady state. This time margin earned from the early prediction made possible by the proposed framework will contribute to the safety of pedestrians and autonomous driving. A representative application would be the collision avoidance by C-ITS in the typical pedestrian traffic accident scenarios where the pedestrians suddenly rush into carriageway to cross the road. A collision can be avoided by transmitting the predicted sudden motion information from the infrastructure to the autonomous vehicles via the wireless communication. In future work, the quality of the predictions will be improved with more advanced sensor technology and richer datasets. For example, higher framerates and precise motion cue information will be used to

enable more elaborate predictions. And the framework will be studied with the consideration of the direction of the velocity.

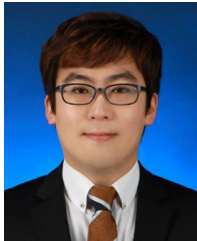
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