講演番号	

文献番号	

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Estimation of Driver s Behavior based on Pedestrian s Attributes when Passing by a Pedestrian

Fumito Shinmura Yasutomo Kawanishi Daisuke Deguchi Takatsugu Hirayama Ichiro Ide Hiroshi Murase Hironobu Fujiyoshi

n by observing his/her behavior and decides whether the vehicle can safely pass by or not. Estimation of t
method to estimate driver behavior when passing by a pedestrian based on his/her attributes. We consider that the process of a driver deciding his/her behaviors according to the pedestrian's state and behavior is similar to a conversation. Therefore, the proposed method makes use of the sequence to sequence model which is based on the recurrent neural networks and is usually used for a conversational model. We evaluate the performance of the proposed method using actual driving data collected by experienced drivers in control of the vehicle.

KEY WORDS: **Safety, Pedestrian detection/protection, Driving support/driver support,** imation (C1)

1

(3)

(1,2)

7

Sequence to Sequence Seq2Seq (4)

1 1

1

1 (464-8601)
2 (487-8501 1200)

2

Tao

[5] Flohr

[6]

Kohler

[7] Fang

SVM

[8]

Shimosaka

[9] Misawa

10 10

[10]

3

3.1.

7

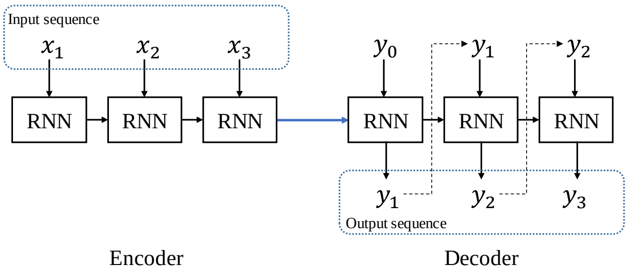

Fig.1 Outline of Seq2Seq model.

3

8

3. 2. Seq2Seq

Seq2Seq [4]

Seq2Seq

Recurrent Neural Networks:

RNN Encoder Decoder

Seq2Seq 1

Encoder RNN RNN

RNN

RNN

Decoder Encoder RNN

RNN

RNN 2

RNN 1 RNN

RNN

Encoder Decoder

3. 3.

Seq2Seq

2

RNN Long Short - Term Memory LSTM

3

Encoder

Full connect Full connect

LSTM Seq2Seq LSTM

LSTM

Decoder Seq2Seq Encoder

LSTM LSTM

LSTM

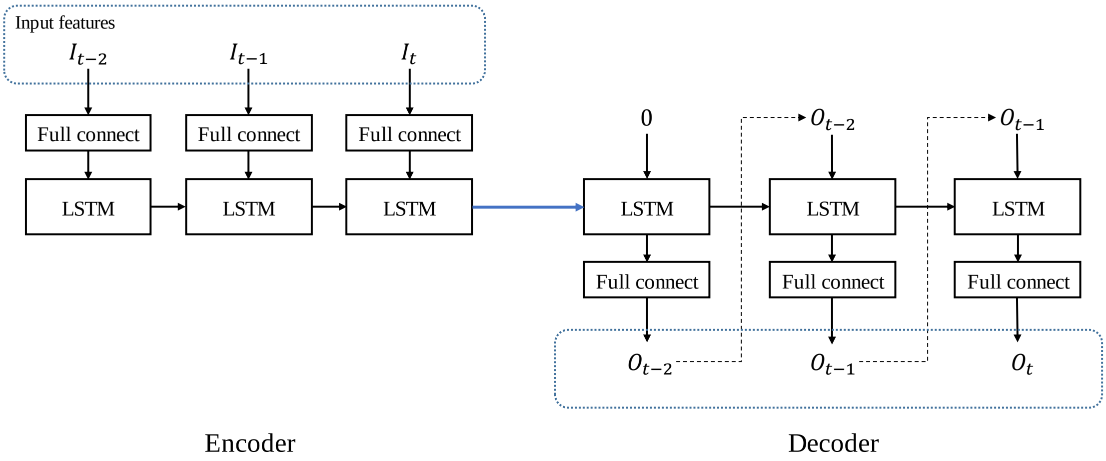

Fig.2 Outline of the proposed model for estim .

0 LSTM
LSTM 84 1
Full connect Full connect 4,837

2 LSTM Seq2Seq
1 LSTM LSTM 4.2 .
Full connect 10
9 1
10
10 10
4
4.1.

3 3
3
3
3 4
LiDAR CAN 2
CAN 3 3
3 3

4. 3.
1
SVM (3)
1 Seq2Seq

(3)

LiDAR
CAN

Table. 1

Seq2Seq	57. 2 %
SVM [3]	55.9 %

Encoder Decoder

4. 4.

(10)

5

1

JST

COI

(1) P. F. Felzenszwalb, R. B. Girshick, D. McAllester and D. Ramanan: Object Detection with Discriminatively Trained Part - Based Models, IEEE Transact ions on Pattern Analysis and Machine Intelligence, Vol.32, No.9, p.1627 - 1645 (2010)

(2) S. Ren, K. He, R. Girshick and Jian Sun: Faster R - CNN: Towards Real-Time Object Detection with Region Proposal Networks, Advances in Neural Information Processing Systems 28 (NIPS), p.91 - 99 (2015)

(3)

2017

p. 480-485 (2017)

(4) I . Sutskever, O. Vinyals and Q.V. Le: Sequence to Sequence Learning with Neural Networks, Advances in Neural Infor mation Processing Systems 27 (NIPS), p.3104 - 3112 (2014)

(5) J. Tao and R. Klette : Part - based RDF for Direction Classification of Pedestrians, and a Benchmark, In Proc. of Workshop on Intelligent Vehicles with Vision Technology in the 12th Asian Conference on Computer Vision, w11 - p2 (2014)

(6) F. Flohr, M. Dumitru - Guzu, J. F.P. Kooij and D . M. Gavrila : Joint Probabilistic Pedestrian Head and Body Orientation Estimation, In Proc. of 2014 IEEE Intelligent Vehicles Symposium, p.617 - 622 (2014)

(7) S. Kohler, M. Go ldhammer, S. Bauer, K. Doll , U. Brunsmann and K. Dietmayer: Early Detection of the Pedestrian ' s Intention to Cross the Street, In Proc . of 15th IEEE Intelligent Transport System Conference (ITSC), p.1759-1764 (2012)

(8) Z. Fang, D. V quez and A. M. L pez: On-Board Detection of Pedestrian Intentions, Journal of Sensors, 17(10) , 2193-1-14 (2018)

(9) M. Shimosaka, K. Nishi, J. Sato and H. Kataoka : Predicting Driving Behavior Using Inverse Reinforcement Learning with Multiple Reward Functions toward Environmental Diversity , In Proc. of 2015 IEEE Intelligent Vehicles Symposium, p.567 - 572 (2015)

(10) H. Misawa, K. Takenaka, T. Sugihara, H. Liu, T. Taniguchi and T. Bando: Prediction of Driving Behavior Based on Sequence to Sequence Model with Parametric Bias, In P roc. of 20th IEEE International Conference on Intelligent Transportation Systems, p. 1310-1315 (2017)