Identification des Situations de Conduite des Deux Roues Motorisés par les Réseaux de Neurones Récurrents

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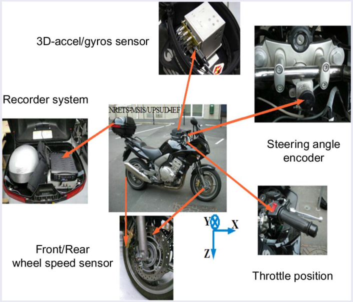
Introduction
Motivations and objectives

Motivations
- Motorcyclists are among the most vulnerable road users
- Less than 2% of traffic with 23% of fatalities and 28% of injuries
- Most common crashes occur during roundabouts and abrupt turns

Naturalistic riding study (NRS)
- Vehicles are equipped with several small cameras and sensors
- Analyzing riders' behavior
  - Interaction between rider and motorbike
  - Interaction between rider and infrastructure
- Collecting large heterogeneous data
  - Vehicle's dynamic
  - Localisation
  - Context (video footage)

Instrumented motorbike


Introduction

Motivations and objectives

Challenges

- Manual identification of riding situations using video footage data is fastidious
- Processing of the collected heterogeneous data is not straightforward

Objectives: Decision making tools

- Automatic segmentation of trajectories
- Identification of riding patterns
- Characterizing the rider's behavior during the risky events
- Providing contextual information for «intelligent transportation systems»
  - Improving their effectiveness
  - Increasing the rider's safety

State of the art on driving and riding behavioral analysis

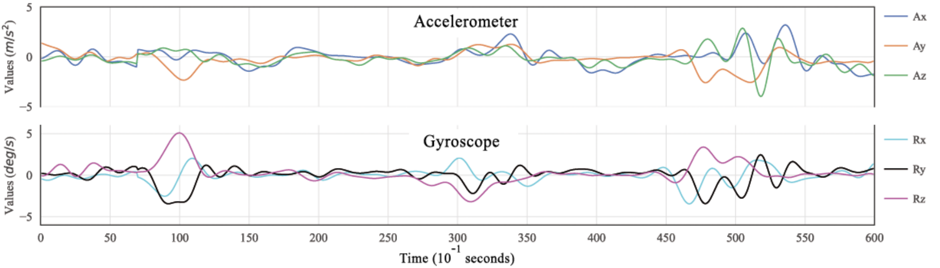
- Clustering
  - A model-based algorithm is proposed in (Hallac et al., 2017) to identify the turning patterns. Each cluster is defined by a Markov random field.
- Neural networks
  - Characterizing the different driving styles using CNNs and RNNs in (Dong et al., 2016)
- Machine learning methods
  - Comparison of different machine learning methods (SVM, RF and ANN) for the identification of riding patterns without considering the temporal dependency (Ahmed et al., 2019) and (Attal et al., 2014)

Contributions

- Few works devoted to the identification of **riding patterns**
- Analysis of riders' behavior when transitioning between riding patterns
- Recurrent neural networks for identification of riding patterns
  - Long short-term memory network
  - Modeling the temporal dependence among riding patterns
  - Does not require explicit feature engineering
  - Interpretation of network estimated weights

Data description

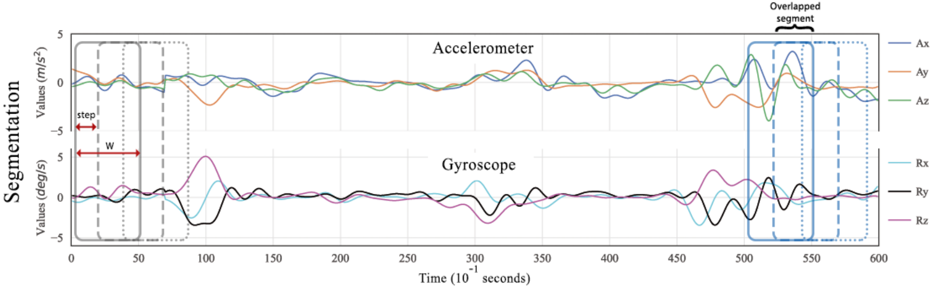
- Five riders (each with up to 3 riding experience)
- 11 sequences of riding patterns
- Data acquisition frequency of 1000 Hz downsampled to 10 Hz (10 measurements per second)
- Inertial Measurement Unit (IMU) comprises 6 sensors providing the data over time
    - 3-D accelerometer (longitudinal, lateral and vertical accelerations)
    - 3-D gyroscope (roll, pitch and yaw angular velocities)



Methodology

First step: Input data segmentation

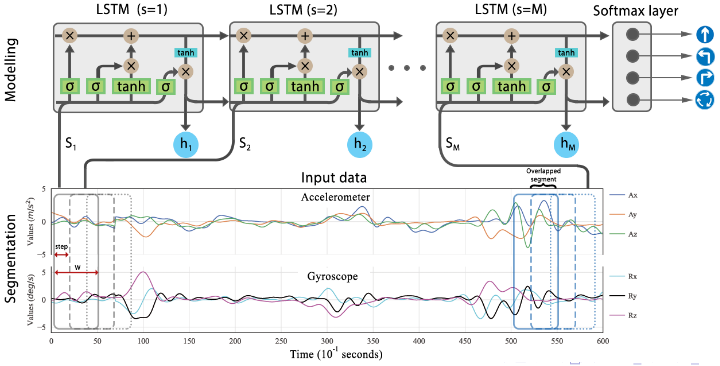
- Each riding pattern lasts a few seconds
- Segmentation of input signals using a sliding window of length W
- Overlapping between segments ($W - step$)
- Each sequence comprises M segments



Methodology (continue)

Second step: Modeling

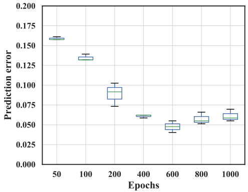
- Modeling the temporal dependency between the riding segments
- Find a mapping between the segments and four riding patterns
  - Straight line (SL)
  - Left turn (LT)
  - Right turn (RT)
  - Roundabout (RA)



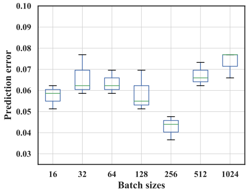
Experimental settings : LSTM network parameters fine-tuning

- Grid search over various parameter configurations
- Optimal values for each parameter is noted between parentheses

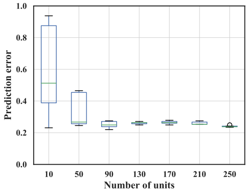
Epoch size (600)



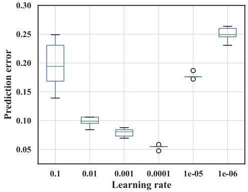
Batch size (256)



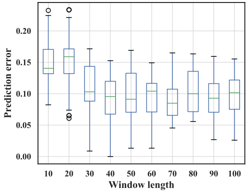
Number of units (90)



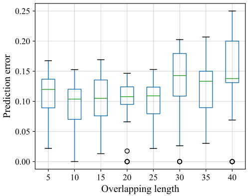
Learning rate (10^{-4})



Window length (50 Hz = 5 seconds)



Step size (10 Hz)



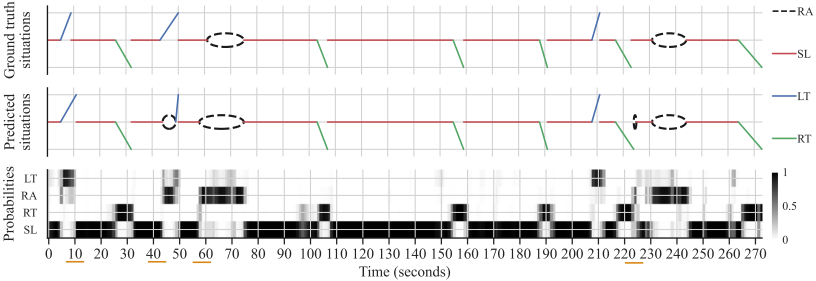
Results (LSTM)

Experimental setup

- Training using leave-one-out sequence approach
- Evaluation using the remaining sequence

An example of riding pattern classification for one sequence

(RA: roundabout, SL: straight line, LT: left turn, RT: right turn)



Evaluated methods and criteria

Evaluated methods

- Gaussian Mixture Model (GMM)
- K-nearest neighbors
- Support vector machine (SVM)
- Random forest (RF)
- Discrete hidden Markov model (DHMM)
- Continuous hidden Markov model (CHMM)
- Gradient Boosting (GB)
- Long short-term memory network (LSTM)

Evaluation criteria

- Accuracy: proportion of correctly classified observations
- F-measure: harmonic mean of precision and recall
- Cohen's kappa statistic: evaluate assessor agreement

Results (comparison table)

- Accuracy is used for evaluation of each individual sequence
- Best performances are highlighted in bold
- Methods highlighted with $\star$ are the same used in (Attal et al., 2018)

	Sequence										
Method	1	2	3	4	5	6	7	8	9	10	11
GMM*	80.7	95.8	80.9	82.7	78.9	62.8	74.3	70	84	86.3	88
k-NN*	84.6	95.8	76.1	86.2	78.9	60	61.5	76.6	84	77.2	92
SVM*	84.6	95.8	80.9	82.7	78.9	60	69.2	70	84	81.8	**96**
RF*	88.4	95.8	80.9	86.2	78.9	65.7	64.1	80	84	81.8	88
DHMM*	88.4	91.6	80.9	86.2	94.7	65.6	69.6	80	84	81.8	84
CHMM*	88.4	87.5	90.4	82.7	89.4	71.4	74.3	76.6	88	**90.9**	84
GB	88.6	92.9	86.9	86.2	92.9	74.5	80.2	85.4	91.1	85.1	88.1
LSTM	**94.5**	**97.8**	**95.1**	**92.9**	**95.5**	**76.3**	**83.4**	**88.4**	**94.9**	88.6	90.1

Results (evaluation per riding pattern)

Comparison is drawn using

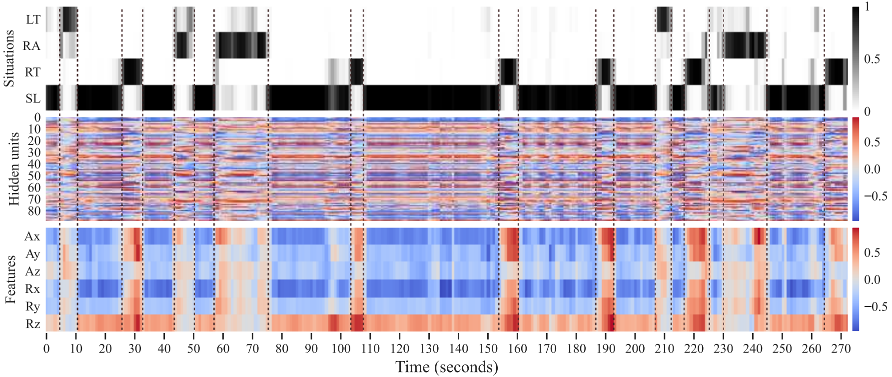
- F-measure per class
- Global F-measure computed over 11 sequences
- Cohen's kappa statistic (κc)
- Accuracy expressed by mean (R) and standard deviation (std)

	F-measure per class				F-measure	κc	Accuracy $(R) \pm (std)$
	SL	LT	RT	RA			
GMM	89.1	50	83.3	70.2	70.2	0.74	82.1 ± 7.8
k-NN	89.1	29.4	86.2	73.1	75.8	0.75	82.4 ± 7.4
SVM	89.2	47.3	85.9	75.6	78.4	0.75	83.9 ± 9.8
RF	90.1	45	88.2	78.9	78.3	0.76	84.7 ± 7.6
DHMM	91.2	65.3	87.9	68.4	79	0.78	85.7 ± 5.1
CHMM	90.8	**75**	**89.2**	68	82.6	0.81	86.4 ± 4.5
GB	92.2	56.3	80.7	73.8	86.2	0.74	88.6 ± 2.9
LSTM	**94.9**	67.8	87.5	**86.3**	**89.4**	**0.83**	**93.1** ± 3.1
FEATURE SELECTION							
ANN	95	75	87	**87**	92	NaN	90 ± 2
RF	**97**	75	90	80	**94**	NaN	**94** ± 1
SVM	95	43	**93**	38	87	NaN	91 ± 1

Network interpretation

Graphics from top to bottom show

- Softmax layer probabilities for each riding pattern
- LSTM hidden layer unit activation over time
- Feature-associated weights over time



Conclusion and insights for future works

Conclusion

- Proposing a recurrent neural network framework for identification of different riding patterns
- Analysis of network activations and weights allowed to describe the complex riding patterns
- Obtained analytic results may improve the effectiveness of existing intelligent transportation system and increase the rider's safety

Perspective

- Estimation of a risk index for each riding maneuver
- Taking into account context variables
    - Environmental variables
    - Inherent behavior of riders
    - Infrastructural conditions

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Thank you for your attention!

Questions ?