Towards Multimodal Understanding of Passenger-Vehicle Interactions in Autonomous Vehicles: Intent/Slot Recognition Utilizing Audio-Visual Data

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1 Introduction

Understanding passenger intents from spoken interactions and car's vision (both inside and outside the vehicle) are important building blocks towards developing contextual dialog systems for natural interactions in autonomous vehicles (AV). In this study, we continued exploring AMIE (Automated-vehicle Multimodal In-cabin Experience), the in-cabin agent responsible for handling certain multimodal passenger-vehicle interactions. When the passengers give instructions to AMIE, the agent should parse such commands properly considering available three modalities (language/text, audio, video) and trigger the appropriate functionality of the AV system. We had collected a multimodal in-cabin dataset with multi-turn dialogues between the passengers and AMIE using a Wizard-of-Oz scheme via realistic scavenger hunt game.

In our previous explorations (Okur et al., 2018, 2019), we experimented with various RNN-based models to detect utterance-level intents (set destination, change route, go faster, go slower, stop, park, pull over, drop off, open door, and others) along with intent keywords and relevant slots (location, position/direction, object, gesture/gaze, time-guidance, person) associated with the action to be performed in our AV scenarios.

In this recent work, we propose to discuss the benefits of multimodal understanding of in-cabin utterances by incorporating verbal/language input (text and speech embeddings) together with the non-verbal/acoustic and visual input from inside and outside the vehicle (i.e., passenger gestures and gaze from in-cabin video stream, referred objects outside of the vehicle from the road view camera stream). Our experimental results outperformed text-only baselines and with multimodality, we achieved improved performances for utterance-level intent detection and slot filling.

2 Methodology

We explored leveraging multimodality for the NLU module in the SDS pipeline. As our AMIE in-cabin dataset[1] has video and audio recordings, we investigated 3 modalities for the NLU: text, audio, and video. For text (language) modality, our previous work (Okur et al., 2019) presents the details of our best-performing Hierarchical & Joint Bi-LSTM models (Schuster and Paliwal, 1997; Hakkani-Tur et al., 2016; Zhang and Wang, 2016; Wen et al., 2018) (H-Joint-2, see A) and the results for utterance-level intent recognition and word-level slot filling via transcribed and recognized (ASR output) textual data, using word embeddings (GloVe (Pennington et al., 2014)) as features. This study explores the following multimodal features:

Speech Embeddings: We incorporated pre-trained speech embeddings (Speech2Vec (Chung and Glass, 2018)) as features, trained on a corpus of 500 hours of speech from LibriSpeech. Speech2Vec[2] is considered as a speech version of Word2Vec (Mikolov et al., 2013) which is compared with Word2Vec vectors trained on the transcript of the same speech corpus. We experimented with concatenating word and speech embeddings by using pre-trained GloVe embeddings (6B tokens, 400K vocab, dim=100), Speech2Vec embeddings (37.6K vocab, dim=100), and its Word2Vec counterpart (37.6K vocab, dim=100).

Audio Features: Using openSMILE (Eyben et al., 2013), 1582 audio features are extracted for each utterance using the segmented audio clips from in-cabin AMIE dataset. These are the INTERSPEECH 2010 Paralinguistic Challenge features (IS10) including PCM loudness, MFCC, log Mel Freq. Band, LSP, etc. (Schuller et al., 2010).

[1] Details of AMIE data collection setup in (Sherry et al., 2018; Okur et al., 2019); in-cabin dataset statistics in A.

[2] github.com/iamyuanchung/speech2vec-pretrained-vectors

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Modalities	Features (Embeddings)	Intent Recognition			Slot Filling		
		Prec	Rec	F1	Prec	Rec	F1
Text	GloVe (400K)	89.2	89.0	89.0	95.8	95.8	95.8
Text	Word2Vec (37.6K)	86.4	85.2	85.6	93.3	93.4	93.3
Audio	Speech2Vec (37.6K)	85.1	84.4	84.5	93.2	93.3	93.1
Text & Audio	Word2Vec + Speech2Vec	88.4	88.1	88.1	94.2	94.3	94.2
Text & Audio	GloVe + Speech2Vec	91.1	91.0	90.9	96.3	96.3	96.3
Text & Audio	GloVe + Word2Vec + Speech2Vec	91.5	91.2	91.3	96.6	96.6	96.6

Table 1: Speech Embeddings Experiments: Precision/Recall/F1-scores (%) of NLU Models

Modalities	Features	Prec	Rec	F1
Text	Embeddings (GloVe)	89.19	89.04	89.02
Text & Audio	Embeddings (GloVe) + Audio (openSMILE/IS10)	89.69	89.64	89.53
Text & Video	Embeddings (GloVe) + Video_cabin (CNN/Inception-ResNet-v2)	89.48	89.57	89.40
Text & Video	Embeddings (GloVe) + Video_road (CNN/Inception-ResNet-v2)	89.78	89.19	89.37
Text & Video	Embeddings (GloVe) + Video_cabin+road (CNN/Inception-ResNet-v2)	89.84	89.72	89.68
Text & Audio	Embeddings (GloVe+Word2Vec+Speech2Vec)	91.50	91.24	91.29
Text & Audio	Embeddings (GloVe+Word2Vec+Speech2Vec) + Audio (openSMILE)	91.83	91.62	91.68
Text & Audio & Video	Embeddings (GloVe+Word2Vec+Speech2Vec) + Video_cabin (CNN)	91.73	91.47	91.50
Text & Audio & Video	Embeddings (GloVe+Word2Vec+Speech2Vec) + Video_cabin+road (CNN)	91.73	91.54	91.55

Table 2: Multimodal (Audio & Video) Features Exploration: Precision/Recall/F1-scores (%) of Intent Recognition

Video Features: Using the feature extraction process described in (Kordopatis-Zilos et al., 2017), we extracted intermediate CNN features[3] for each segmented video clip from AMIE dataset. For any given input video clip (segmented for each utterance), one frame per second is sampled and its visual descriptor is extracted from the activations of the intermediate convolution layers of a pre-trained CNN. We used the pre-trained Inception-ResNet-v2 model[4] (Szegedy et al., 2016) and generated 4096-dim features for each sample. We experimented with adding 2 sources of visual information: (i) cabin/passenger view from the BackDriver RGB camera recordings, (ii) road/outside view from the DashCam RGB video streams.

3 Experimental Results

For incorporating speech embeddings experiments, performance results of NLU models on in-cabin data with various feature concatenations can be found in Table 1, using our previous hierarchical joint model (H-Joint-2). When used in isolation, Word2Vec and Speech2Vec achieves comparable performances, which cannot reach GloVe performance. This was expected as the pre-trained Speech2Vec vectors have lower vocabulary coverage than GloVe. Yet, we observed that concatenating GloVe + Speech2Vec, and further GloVe + Word2Vec + Speech2Vec yields better NLU results: F1-score increased from 0.89 to 0.91 for intent recognition, from 0.96 to 0.97 for slot filling.

For multimodal (audio & video) features exploration, performance results of the compared models with varying modality/feature concatenations can be found in Table 2. Since these audio/video features are extracted per utterance (on segmented audio & video clips), we experimented with the utterance-level intent recognition task only, using hierarchical joint learning (H-Joint-2). We investigated the audio-visual feature additions on top of text-only and text+speech embedding models. Adding openSMILE/IS10 features from audio, as well as incorporating intermediate CNN/Inception-ResNet-v2 features from video brought slight improvements to our intent models, reaching 0.92 F1-score. These initial results using feature concatenations may need further explorations, especially for certain intent-types such as stop (audio intensity) or relevant slots such as passenger gestures/gaze (from cabin video) and outside objects (from road video).

4 Conclusion

In this study, we present our initial explorations towards multimodal understanding of passenger utterances in autonomous vehicles. We briefly show that our experimental results outperformed certain baselines and with multimodality, we achieved improved overall F1-scores of 0.92 for utterance-level intent detection and 0.97 for word-level slot filling. This ongoing research has a potential impact of exploring real-world challenges with human-vehicle-scene interactions for autonomous driving support with spoken utterances.

[3] github.com/MKLab-ITI/intermediate-cnn-features

[4] github.com/tensorflow/models/tree/master/research/slim

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A Appendices

AMIE In-cabin Dataset: We obtained 1331 utterances having commands to AMIE agent from our in-cabin dataset. Annotation results for *utterance-level intent* types, *slots* and *intent keywords* can be found in Table 3 and Table 4.

AMIE Scenario	Intent Type	Utterance Count
Set/Change Destination/Route	SetDestination	311
	SetRoute	507
Finishing the Trip	Park	151
	PullOver	34
	Stop	27
Set/Change Driving Behavior/Speed	GoFaster	73
	GoSlower	41
Others (Door, Music, A/C, etc.)	OpenDoor	136
	Other	51
	Total	*1331*

Table 3: AMIE In-cabin Dataset Statistics: Intents

Slot/Keyword Type	Word Count
Intent Keyword	2007
Location	1969
Position/Direction	1131
Person	404
Time Guidance	246
Gesture/Gaze	167
Object	110
None	6512
Total	*12546*

Table 4: AMIE In-cabin Dataset Statistics: Slots

Hierarchical & Joint Model (H-Joint-2): 2-level hierarchical joint learning model that detects/extracts *intent keywords & slots* using seq2seq Bi-LSTMs first (Level-1), then only the words that are predicted as *intent keywords & valid slots* are fed into Joint-2 model (Level-2), which is another seq2seq Bi-LSTM network for *utterance-level intent* detection (jointly trained with *slots & intent keywords*) (Okur et al., 2019).