BERTtraffic: A ROBUST BERT-BASED APPROACH FOR SPEAKER CHANGE DETECTION AND ROLE IDENTIFICATION OF AIR-TRAFFIC COMMUNICATIONS

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ABSTRACT

Automatic Speech Recognition (ASR) is gaining special interest in Air Traffic Control (ATC). ASR allows transcribing the communications between air traffic controllers (ATCOs) and pilots. These transcriptions are used to extract ATC command types and named entities such as aircraft callsigns. One common problem is when the Speech Activity Detection (SAD) or diarization system fails and then two or more single speaker segments are in the same recording, jeopardizing the overall system’s performance. We developed a system that combines the segmentation of a SAD module with a BERT-based model that performs Speaker Change Detection (SCD) and Speaker Role Identification (SRI) based on ASR transcripts (i.e., diarization + SRI). This research demonstrates on a real-life ATC test set that performing diarization directly on textual data surpass acoustic level diarization. The proposed model reaches up to ~0.90/~0.95 F1-score on ATCO/pilot for SRI on several test sets. The text-based diarization system brings a 27% relative improvement on Diarization Error Rate (DER) compared to standard acoustic-based diarization. These results were on ASR transcripts of a challenging ATC test set with an estimated ~13% word error rate, validating the approach’s robustness even on noisy ASR transcripts.

Index Terms— Diarization, named entity recognition, air traffic control communications, speaker change detection, speaker role identification

1. INTRODUCTION

For the past decades, many studies have focused on applying ASR in the ATC domain. A general overview of ASR for ATC is lead by Lin [1]. They reviewed 10 different tasks for spoken instruction understanding on ATC data. In recent years, the ASR systems reached maturity to be applied as an assistant for air traffic controllers [2, 3]. E.g., AcListant project provides assistant based speech recognition (ABSR). Later, MALORCA project shows that novel data-driven machine learning approaches cause to reach good ABSR performance that reduces the workload [4] and increases the efficiency of ATCOs [5]. However, this project did not focus on transcribing voice commands issued by pilots. Ongoing HAAWII† and SOL-Cnt‡ projects focus on developing a reliable and adaptable solution to automatically transcribe voice commands issued by both ATCOs and pilots. Higher accent variability and noise level, cause pilot data to be more challenging for current ASR systems, sometimes as twice as ATCO data [6]. Similarly, closeness and overlap between speech segments of ATCO and pilots cause SAD systems to fail, thus splitting the segments correctly. Applying acoustic level speaker diarization on noisy data causes high Diarization Error Rate (DER). This paper explores fine-tuning a BERT-based Named Entity Recognition (NER) model that performs Speaker Change Detection (SCD) and Speaker Role Identification (SRI) on text level of automatically transcribed speech recordings. This model uses the same SAD module as in standard acoustic based diarization. We evaluated the proposed system on five single-speaker test sets (i.e., one speaker per sample) and on one multi-speaker test set (i.e., where SAD failed). We implemented a data augmentation technique in order to reduce the class imbalance (i.e., train sets distribution for ATCO, pilot, and mixed → 64/33/3%). The text-based diarization system yielded ~90%/~0.95 F1-scores on SRI for ATCO/pilot single-speaker test sets while an 0.89 F1-score in the multi-speaker one. Additionally, we compared text-based with standard acoustic-

Table 1. Conversation between two speakers with correct (rows 1 and 2), and segmentation and SCD fault (row 3), which occurs when SAD and SCD systems fail. Sample from SOL-Cnt test set (mixed subset). Blue — ATCO; magenta — pilot.

| Speaker Label | Detected segment |
|---------------|------------------|
| ATCO          | <s> November six two nine charlie tango report when established </s> |
| Pilot         | <s> Report when established November six two nine charlie tango </s> |
| Mixed (SAD and SCD failed) | <s> November six two nine charlie tango report when established </s> <s> November six two nine charlie tango </s> |

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‡https://www.haawaii.de
§https://cordis.europa.eu/programme/id/H2020_SESAR-IR-VLD-WAVE2-10-2019
based diarization on mixed subset of SOL-Cnt test set. This experiment is carried on ASR transcripts level rather than ground truth annotations. This assessment gives insights into how the system would behave in a real ATC scenario. For instance, the BERT-based NER system outperforms classical diarization by 27% relative improvement on DER for mixed subset of SOL-Cnt test set.

The rest of the paper is organized as follows: Section 2 reviews acoustic-based diarization and recent works on text-based SRI. Later, Section 3 presents the databases and the data augmentation technique for BERT fine-tuning (SCD and SRI system). The results are discussed in Section 4 and conclusions and future work are shown in Section 5.

2. RELATED WORK

Diarization systems answer the question “who spoke when?”. SAD, segmentation or SCD, embedding extraction, clustering, and labeling are the main parts of diarization systems. Many studies focused on diarization using acoustic features while some work has explored text-based techniques for SRI.

**Acoustic-based diarization:** Feature representations of speakers are one of the main factors in the accuracy of a speaker diarization system. Mel Frequency Cepstral Coefficients (MFCCs) are commonly used for the task of speaker diarization. In comparison to MFCC, Mel Filterbank Slope (MFS) and Linear Filterbank Slope (LFS) features have more speaker discriminability power caused by emphasis on higher-order formants. Agglomerative Information Bottleneck (aIB) based approach to speaker diarization has shown competitive performance [7]. Here, for clustering the fixed-length audio segments, a bottom-up clustering approach is performed on the posterior space of the Gaussian component. Speaker discriminative embeddings such as x-vectors are investigated in the speaker diarization systems [8]. For finding the speaker clusters in a sequence of x-vectors, the variational Bayesian hidden Markov model (VBx) was investigated in [9]. For continuously learning speaker discriminative information, “Remember-Learn-Transfer” was proposed in [10]. For retaining the previously learned parameters and adapting the parameters for the current conversation, this method uses transfer learning. Applying lexical and acoustic information for speaker diarization was investigated in [11].

**Text-based speaker role identification:** This work leverages NER for SRI. NER is the task of identifying entities such as locations, organizations, or names on text data. NER was initially reviewed by Grishman and Sundheim [12]. Early NER techniques were based on handcrafted lexicons, ontologies, dictionaries, and rules. These systems were prone to human errors and were not robust against noise (e.g., noisy labels). Collobert et al. [13] introduced machine learning-based methods for text processing in topics such as part-of-speech tagging, chunking, NER, and semantic role labeling. Further work on NER was carried by [14, 15]. Examples of named entities in ATC communications are callsigns, commands, units or values. These entities carry rich information such as i) flight number, ii) aircraft’s location and destination, iii) speed and altitude indications and, iv) clearances for aircraft arrival and departure. All this information gives key information about the speaker’s role i.e., ATCO or pilot. Additionally, ATC communications follow a well-defined grammar (e.g., dictionaries, lexicons, and ontologies) that could be leveraged to identify speaker roles. Previous research on a grammar-based SRI for ATC communications was carried by Prasad et al. [16]. This approach is useful on single-speaker samples, but it might fail on multi-speaker utterance/sentence (i.e., SAD and SCD failure), such as the example in Table 1.

3. DATASETS AND EXPERIMENTAL SETUP

ATC data is commonly seen as ‘scarce’, where few tens hours of speech data are available (public) for ASR train and test. The collection of ATC data poses challenges due to noisy conditions, speaker and language accent, and rate of speech. In most cases, the transcription process of this data requires skilled personal such as ATCOs.

3.1. Datasets

This research employs data from four different projects as listed below: i) EC-H2020 ATC2 project [17, 18], ii) HAAWAI [19, 16], iii) SOL-Cnt and, iv) SOL-Twr [20]. In these projects, six datasets in English language with various accents are provided.

**SOL-Cnt & SOL-Twr:** These two data sets have been recorded and collected in the course of three SESAR-2020 funded industrial research projects PJ.10-W2-96 (“SOL-Cnt”), PJ.16-W1-04^4, and PJ.05-W2-97^5 (both combined and called “SOL-Twr”). SOL-Cnt aims to reduce ATCOs’ workload with an ASR-supported aircraft radar label. Voice utterances of ATCOs and pilots have been recorded in the operations room from Vienna approach at the Air Navigation Service Provider (ANSP) site of Austrocontrol in Vienna, Austria. SOL-Twr aims to reduce ATCO’s workload in an ATC tower environment, including the speech of ATCOs from the Lithuanian ANSP. The SOL-Twr audio data is less noisy compared to SOL-Cnt due to the laboratory recording environment.

**MALORCA:** MALORCA was one of the first initiates to overcome the need for significant expert knowledge on ASR systems for ATC tasks [2, 21]. During the project, two main datasets (i.e., train and test sets available) were collected: Prague and Vienna (airports) approach. Both datasets are cataloged as good quality speech (i.e., SNR usually above 20dB) sampled at 8kHz, that only contains ATCO samples (more details in Table 2).

**HAAWAI:** The speech data is collected and annotated by ANSPs: i) London approach (NATS) and ii) Icelandic en-route (ISAVIA). For NATS, the amount of manually transcribed data available is around 10h (9h for train and 1h for test). For ISAVIA, a total of 13h of manually transcribed data is available (12h for train and 1h for test). ISAVIA recordings are of better quality than NATS.

3.2. Data Augmentation

In addition to word-level transcripts of the train and test speech recordings, the speaker labels and segmentation were also available i.e., each sample has a wav recording, transcripts, and speaker and time segmentation (e.g., ATCO/pilot/mixed, see example in

### Table 2. Amount of train and test data.

| Project    | Test set | Number of Samples (Train/Test) | ATCO | Pilot | Mixed |
|------------|----------|--------------------------------|------|-------|-------|
| SOL - SOL-Cnt | 662 / 138 | 945 / 204 | 535/205 |
| SOL - SOL-Twr | 1399 / 594 | - / - | - / - |
| MALORCA - VIENNA | 6335 / 1557 | - / - | - / - |
| MALORCA - PRAGUE | 1364 / 1419 | - / - | - / - |
| HAAWAI - NATS | 4228 / 631 | 4782 / 758 | - / - |
| HAAWAI - ISAVIA | 2625 / 493 | 3046 / 590 | - / - |

^4https://www.sesarju.eu/projects/cwpvhmi
^5https://www.remote-tower.eu/wp/project-pj05-w2/solution-97-2
The NER system follows the IOB format (Inside-Outside-Beginning), where each entity is composed of two tags: the Beginning tag ‘B-’ and the Inside tag ‘I-’. The train and test are formatted with either one of the following tags: atco class: B-atco or I-atco and; pilot class: B-pilot or I-pilot. We developed and implemented a data augmentation pipeline due to the large class imbalance between the train sets (i.e., 64%/33%/3% for ATCO/pilot/mixed recordings, see Table 2). We generated a 1M sample data set from 26k initial sentences. The train sets are split and appended in two Python dictionaries; each dictionary contains only ATCO or pilot sentences. New samples depend on the: i) the number of sentences and ii) speaker label for each new sentence. The new sample has between one to four sentences with a 50% chance that each one is ATCO or pilot class. The process is repeated until we gather 1M sentences (∼350MB of text data). Left column in Figure 1 depicts the proposed data augmentation pipeline. Finally, we trained two NER systems: i) only applying data augmentation on HAAWAI train set and, ii) employing a mix between SOL, MALORCA and HAAWAI systems: i) only applying data augmentation on HAAWAI train set and ii) employing a mix between SOL, MALORCA and HAAWAI systems; iii) only applying data augmentation on the pilot set. The tags follow the standard IOB format mentioned in Section 3.2.

Diarization system: Here we performed a B based approach for speaker diarization. For details of the algorithm, the reader is referred to [7]. We used the open-source IB toolkit⁶ in our experiment. 19 dimension MFCCs were extracted from 8kHz audio data to extract the Gaussian Mixture Model (GMM) components for the fixed duration segments. The values for Normalized Mutual Information (NMI), the maximum number of clusters, and β were set to 0.4, 2, and 10, respectively.

Automatic Speech Recognition: Our ASR system was trained with Kaldi toolkit [25]. The system follows the standard Kaldi recipe e.g., MFCC and i-vectors features with standard chain training based on Lattice-free MMI (LF-MMI). Further information about the ASR system for ATC is in [17, 26].

3.4. Evaluation protocol

Experiments are divided into three tasks. First, two use our BERT-based diarization system (SCD and SRI). The third task compares the first two with acoustic-based diarization.

Speaker role identification: we evaluate SRI with F1-scores on five test sets that are perfectly segmented (ground truth segments) and with only one speaker per segment. We use the ground truth transcripts in order to validate our approach. The F1-score is the harmonic mean of precision and recall, giving equal importance and thus reducing the impact of class imbalance. These results are shortlisted in Table 3.

Speaker change detection: In addition to speaker role identification, the BERT-based NER system is capable of detecting speaker changes e.g., SCD (see IOB format from Section 3.2). We evaluated this task also with F1-scores but only on SOL-Cnt test set, because it has a subset where SAD failed i.e., multi-segments recordings (see MIXED column in Table 4). We shortlisted these results in Table 4.

Acoustic-based diarization: In acoustic-based diarization we use DER and Jaccard Error Rate (JER). DER is a well-known metric in the literature, it measures the fraction of time that is not attributed correctly to a speaker or to non-speech. JER is a recent metric that avoids the bias towards the dominant speaker i.e., evaluating equally all speakers. Results shortlisted in Table 5.

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⁶https://github.com/idiap/IBDiarization
Table 3. F1-scores [0-1] in detecting the desired speaker (i.e., ATCO or Pilot). These test sets only contain single-speaker segments. (*ALL_DATA*: see Section 3.2).

| Project - Test set | Training Data | HAAWAII | ALL_DATA |
|-------------------|---------------|---------|----------|
|                   | ATCO / PILOT  | ATCO / PILOT |
| HAAWAI (NATS)     | 0.90 / 0.93  | 0.96 / 0.91 |
| HAAWAI (ISAVIA)   | 0.94 / 0.89  | 0.97 / 0.89 |
| SOL - SOL-Twr     | 0.82 / -     | 0.97 / -  |
| MALORCA - VIENNA  | 0.81 / -     | 0.95 / -  |
| MALORCA - PRAGUE  | 0.83 / -     | 0.95 / -  |

Table 4. F1-scores [0-1] in detecting the desired speaker on SOL-Cnt test set on both, ground truth and ASR transcripts. (*ALL_DATA*: see Section 3.2).

| Training Data | Subset | ATCO | PILOT | MIXED |
|---------------|--------|------|-------|-------|
| HAAWAII       | Ground Truth | 0.85 | 0.87 | 0.72  |
|               | ASR output  | 0.83 | 0.84 | 0.70  |
| ALL_DATA      | Ground Truth | 0.96 | 0.87 | 0.89  |
|               | ASR output  | 0.94 | 0.85 | 0.82  |

### 4. RESULTS AND DISCUSSION

#### 4.1. Text-based diarization

Experiments are on two BERT models: i) trained on HAAWAI train set, which evaluated the robustness of the system on out of domain data (SOL and MALORCA); and ii) trained on all available data (*ALL_DATA* in Table 3 and 4, see Section 3.2). We noted that using in-domain data (HAAWAI -> ALL_DATA) brought 15%, 14% and 12% relative improvement in F1-score for SRI on SOL-Twr, Vienna and Prague, respectively. F1-scores in SRI on HAAWAI test set did not increase significantly (around ~1%), because domain data was part of the initial training (see Table 3). These results are mainly directed to speaker role identification because the test sets only contain one segment per sample (i.e., single-speaker case).

#### 4.2. Robustness on ASR transcripts

We evaluated the speaker change detection task only on SOL-Cnt text set which has recordings with more than one speaker (mixed subset). The BERT-based NER system is fed with the 1-best transcript from an ASR system that was trained on in-domain data. Table 4 list the main results for the two proposed BERT models (trained on HAAWAI and ALL_DATA) with an additional line for ‘ASR output’. In the single-speaker case (ATCO/pilot) the degradation (ASR transcripts instead of ground truth text) in SCD from BERT-based diarization was no more than 3% absolute (worse, Pilot subset 0.87 -> 0.84), while in the MIXED case the degradation was from 0.89 -> 0.82. This behavior is mainly due to the noisy labels produced by the ASR system i.e., 13% word error rate on SOL-Cnt text set.

#### 4.3. Acoustic-based diarization

On challenging tasks such as ATC, where the rate of speech is high and time between speakers’ utterances is low, the standard SAD systems could fail and merge the segments. I.e., SOL-Cnt data set (see Table 2) where ~38% of the test set is ‘Mixed’. Comparison of acoustic level (aIB) and text level diarization result of SOL-Cnt test set is shown in Table 5. As both systems use the same SAD segments, the DER using oracle SAD which is Speaker Error Rate (SER) is reported. In diarization system, we are not evaluating the speaker role identification and in this experiment setup with considering a maximum of two clusters in aIB, we are evaluating the SCD and clustering. For computing the DER of text-based diarization systems, we align the text with audio data and prepared the labeled segments from it. In noisy conditions, acoustic-based diarization mistakenly oversplit the segments with one speaker (ATCO/pilot). However, the text-based diarization shows robust performance on these segments (3.0/3.7% DER for ATCO/pilot). Even in the Mixed segments, the BERT-based NER system (9.5% DER) with data augmentation outperforms the acoustic-based model (13.1% DER) by 27% relative.

#### 5. CONCLUSION

In this work, we demonstrated that acoustic-based tasks (such as diarization) can be aided or even replaced (in some cases) by natural language processing techniques (e.g., NER), even in challenging scenarios like ATC. Our results in SOL-Cnt test set (example where SAD failed) validated this hypotheses as shown in Table 4 and Table 5. Additionally, we developed a simple but useful data augmentation pipeline for ATC text, allowing us to generate a 1M-sample train set from 26k sentences. To the authors’ knowledge, this is the first time that a BERT-based NER system has been used for speaker change detection of ATC data. This approach is capable of recognizing ATCO segments with ~95% F1-score for SRI while pilot segments were more challenging, the performance is ~90% on SRI (see Table 3). In the case of segments with more than one speaker i.e., SOL-Cnt - mixed 89% F1-score was achieved on SOL-Cnt test set.
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