Automatic Callsign Detection: Matching Air Surveillance Data with Air Traffic Spoken Communications

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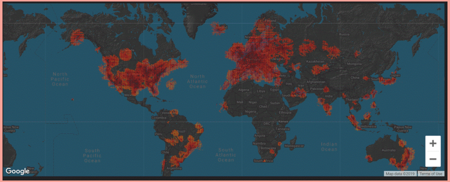
Highlights

- ATCO^2 EU project (Clean Sky 2 Joint Undertaking & European Union)
- Main challenges in speech recognition and callsign detection for ATC communications
- Standardization and data collection of ATC speech + radar data
- Deployment of first VHF receivers in different airports/countries
- ATCO^2 approach to use context-information such as radar (from OSN servers)
- Introduced state-of-the-art speech-to-text technologies for ATC communications
- First version of ATCO^2 text-to-callsign system

Outline

What is ATCO2[1]?

- EU project, with goal to collect, organize and pre-process air-traffic control audio data
- We collect voice communications between pilots and Air Traffic Controllers (ATCos)
- And generate meta-data useful for further processing



Funding Parties:

[1] https://www.atco2.org/.

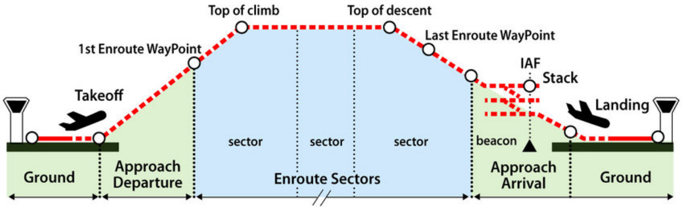
ATC speech is not an easy task!

Speech

- Speech variations (stress, fatigue)
- Inter-speaker variations
- Different accents/dialects
- Neither spontaneous, read nor pure command speech

ATC scenarios

- Clearances, arrivals, takeoffs
- Climb, cruise, descent, ground taxiing



Automatic Speech Recognition for ATC in previous projects

- Previous projects MALORCA[2] and AcListant[3], audio data limitations:
  - Focused on ATCo speech, not on pilot's speech
  - Limited amount of training data <100 hr
  - Data from few airports (Prague, Vienna), few speakers and English accents
  - Only clean data without noise
- ATC communications follow ICAO[4] regulations (constrained vocabulary/lexicon and grammar)
  - 1 message = one callsign (airplane name) and one command (in normal conditions)

[2] MAchine Learning Of speech Recognition models for Controller Assistance, http://www.malorca-project.de/wp

[3] Active Listening Assistant, www.AcListant.de

[4] International Civil Aviation Organization

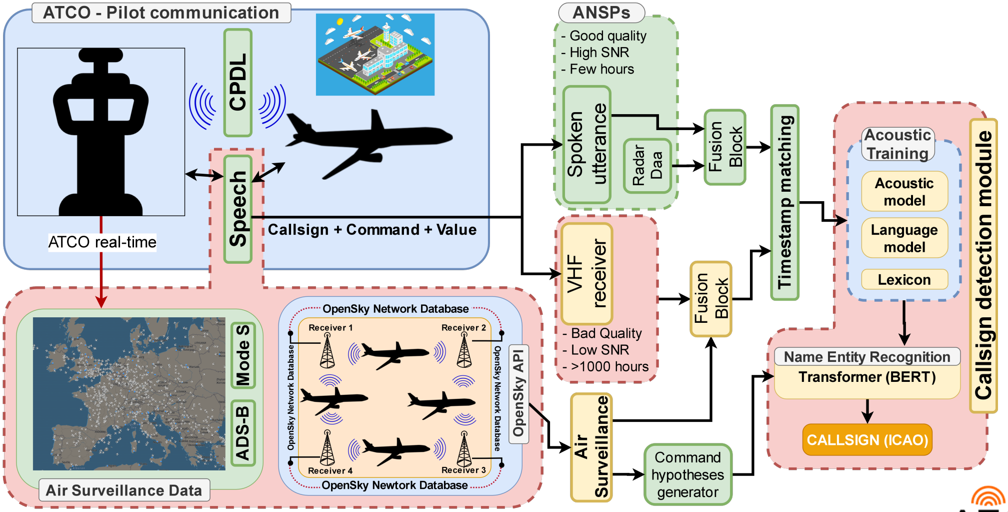
What we want to solve?

- Manually transcribed ATC data **EXPENSIVE** to produce (one man-week work = 1 hour speech[5,6])
- First phase: Collect public ATC data (LiveATC, some are quite noisy)
- Second phase: Design, build and deploy a system based on VHF receivers to record our own data (complying with legal regulations)
  - Data with different accents, protocols, speakers, quality. Also include pilot speech.
- Generate automatic transcripts by Automatic Speech Recognition (ASR)
  - Correct transcripts manually on a subset of data
  - Use surveillance data to assist the recognition
- Build ASR and **Callsign detection** system for ATC communications[7]
  - This non-trivial task is the current research goal of **ATCO2** project

[5] Ferreiros et al., "A speech interface for air traffic control terminals".

[6] Cordero, Dorado, and Pablo, "Automated speech recognition in ATC environment".

[7] Kleinert et al., "Semi-supervised adaptation of assistant based speech recognition models for different approach areas".



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Done so far:

1. Gathered around 195 hours of pre-existing annotated ATCo speech (different speakers, accents and quality)
2. We are recording data with VHF receivers in several pilot locations
3. We have a Speech-to-text recognition system, the sub-tasks were:
   - Data pre-processing, unification of transcripts across ATC databases
   - Voice Activity Detection and Diarization
   - Building the lexicon and language model (LM)
   - Training the acoustic model (AM) with two state-of-the-art approaches
   - Extraction of lists of call-signs from surveillance data, for given location and timestamp
4. We designed a test set to evaluate our **speech-to-text** and **text-to-callsign** systems

What we can do with surveillance data?

- Main target: extract the callsign from a given utterance
- Initial solution: use speech-to-text and text-to-callsign system
- Previous results: good performance BUT only with **good quality data**
- New target: improve the performance on good/**BAD quality data**
- New solution: use surveillance data from **OSN servers** either in:
  - The output of the speech-to-text system
  - The input and/or output of the text-to-callsign system, or,
  - Simultaneously in both systems, a hybrid approach
- Expected results: much better performance in data

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Air surveillance data and timestamp with spoken communications

1. Gather an ATC segment with a VHF receiver
2. Record the timestamp, add location (airport/receiver)
3. Send a query to OSN servers composed of:
   - Time range: input from timestamp
   - Location: area to search centered around the receiver/airport
4. OSN sends back the matching callsigns in ICAO format

Such as: LUF189AF (ICAO format)
LUFTHANSA ONE EIGHT NINE ALFA FOXTROT (verbalized format)

Nevertheles...

Non-standard abbreviations

- LUFTHANSA → HANSA
- SCANDINAVIAN → SCAN
- SCANWING → SCAN
- TRANSAVIA → AVIA
- RYANAIR → RYAN
- SPEEDBIRD → BIRD

Then what?

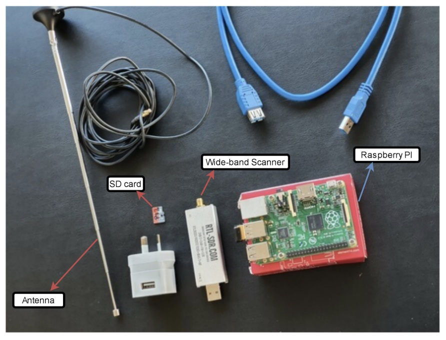
- Several "deviations" per callsign
- Initial contact: full callsign
- After: abbreviations are allowed

We work with many possible verbalizations of the ICAO callsign

How do we record our own data?

Very High Frequency Receivers

- Capture raw audio data from different airports/countries
- Recording software: RTL-SDR-Airband
- Output: complex I/Q format, converted by csdr to flac
- We evaluated SNR of 2 different hardware setups
  - RTL-SDR receiver, dipol antenna → RSP1A receiver, Watson WBA-20 antenna
  - More expensive setup, better SNR (less noise)
  - The WER was 8.3% smaller for more expensive setup (33.0% → 24.7%)



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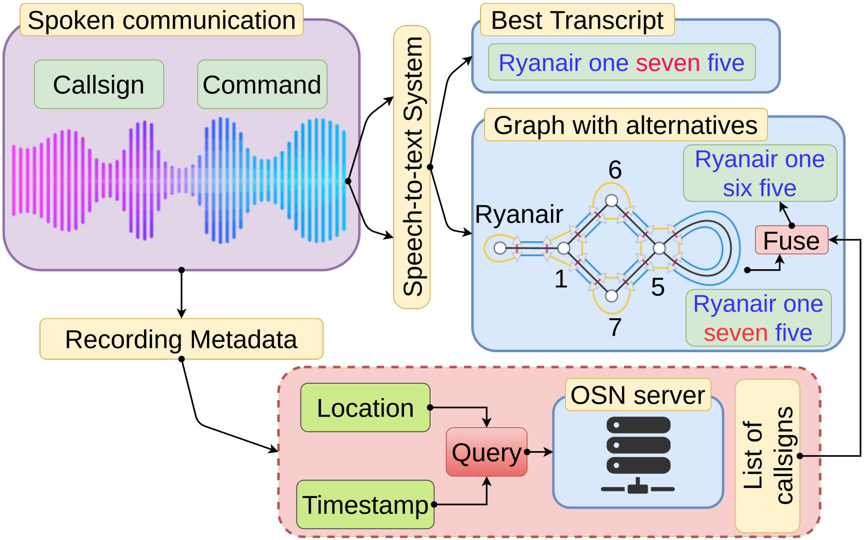
Speech-to-text system

(= ASR)

How we produce transcripts from speech?

Speech-to-text system

- One of the main components of the overall pipeline
- Speech-to-text system has as:
  - Input: audio signal with speech of ATCOs and pilots
  - Output: hypothesised transcript
- The output could be "best transcript" or a lattice (weighted graph of alternatives)
- Challenge: use context information (radar) to increase the performance


Spoken communication
Callsign
Command
Speech-to-text System
Best Transcript
Ryanair one seven five
Graph with alternatives
Ryanair
6
1
5
7
Ryanair one six five
Fuse
Ryanair one seven five
Recording Metadata
Location
Query
Timestamp
OSN server
List of callsigns

Proposed speech-to-text systems

Hybrid approach

- Pronunciation lexicon, acoustic and language model trained separately
- Based on HMM systems and Deep Neural Networks (DNN)
- More complex, but more freedom during training
- Requires less data to generalize and it is faster to train

End-to-End approach

- Pronunciation lexicon, acoustic model and implicit language model are trained jointly as one model
- Less complex, but less freedom
- Requires more data and more training time to generalize
- Word-piece output-symbols, difficult to generate lattices

Data, data and more data

Audio related

- Training on 7 databases, 195 hours (Table 1, manuscript)
- Doubled the data by adding noise corresponding to LiveATC audio channels (helps a lot!)
- The test sets:
  - Test set 1 Airbus database (see Airbus challenge[8])
  - Test set 2 from MALORCA (previous EU project)
  - Two test sets from LiveATC; low quality data → more challenging
  - Test set gathered from LKTB airport (Brno, Czechia) with better equipment

Delpech et al., "A Real-life, French-accented Corpus of Air Traffic Control Communications".

Text related pre-processing works

- Unify the transcripts from all databases
  - Use same ICAO alphabet and "number words"
  - Standardize the word-splitting such as: "take off" "take-off" or "takeoff" to single type
  - Ligature the multi-word airline designators: "air berlin" → "air_berlin"
- Create airline designator table for callsign verbalization: LUF → LUFTHANSA
- Preparing external data for language model training:
  - Verbalized callsigns from OSN flight-lists (2019/2020)
  - Adding all possible runaways numbers
  - Adding waypoints from Europe

Performance of current speech-to-text system

Table: Performance measured in Word Error Rates (WER).

Test set	WER%	
	Hybrid	End-to-End
AIRBUS	8.1	10.2
MALORCA	5.0	7.2
LiveATC set1	34.5	44.8
LiveATC set2	33.0	40.4
LKTB	24.7	32.6

Quick takeaways

Performance of speech-to-text system

- Test sets with better audio quality (AIRBUS, MALORCA & LKTB) → better performance
- Drop of performance for LiveATC test sets → due to worse audio quality
- Performance difference LKTB vs MALORCA (24.7 vs 5.0):
  - Lexical difference: callsigns, runways, local names. And accent.
- Solution: "boost" the system with "local words" (names and also verbalised callsigns from OSN)

What is boosting? And, how this can help?

A-priori boosting

1. Applied to "recognition grammar" prior to the time-taking recognition search
2. Give score-discounts to certain words/phrases (callsign)
3. Output: Increase chance that the speech-to-text system outputs the correct "phrase"

Ex-post boosting

1. Applied to "lattices" with alternative outputs generated by time-taking recognition search
2. Give score-discounts to certain words/phrases (callsign)
3. Output: Increase chance to get correct "phrase" as best hypothesis (faster, but less effective than "a-priori" boosting)

Boosting the speech-to-text system with retrieved callsigns from OSN

Table: A-priori boosting with list of callsigns from surveillance data retrieved from OSN (query: location/radius and timestamp), boosting done once per test-set, hybrid recognizer

Test set	WER%	
	non-boosted	boosted
LiveATC set1	34.5	33.6
LiveATC set2	33.0	30.8

A-priori boosting with phrases is slow (about 5min per run).
→ It cannot be used per-utterance.
→ **We are on a good way. More experiments as future work!**

Callsign identification system

Callsign identification system

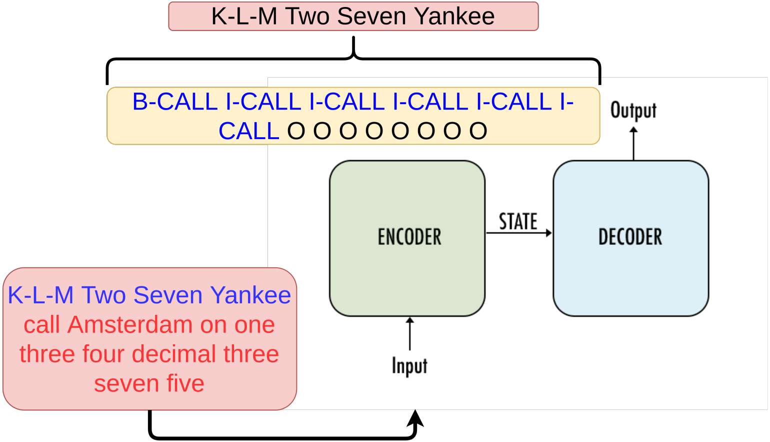
Detection Module - Transformer (BERT)

Sequence labeling task → Input seq. (transcripts) → Output seq. CALLSIGN
IOB format used; i) **I**: Inside; ii) **O**: Outside; iii) **B**: Beginning

Example

Input:
KLM Two Seven Yankee call Amsterdam on one three four decimal three seven five
Output:
B-CALL I-CALL I-CALL I-CALL I-CALL I-CALL O O O O O O O O

If you are wondering how the Callsign Detection Module works...



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Callsign Detection Module - Generalities

1. Named Entity Recogition system, fine-tuned BERT model (Transformer)
2. Only, AIRBUS data used (only training set with callsign per each utterance)
3. System tested on AIRBUS (dev set) and LiveATC set 1
4. Currently testing on the "ground truth transcripts" (not the output of the speech-to-text system)

Table: Current performance of the NER module (with ground truth labels). Note: F1 roughly corresponds to "accuracy", the value 1.0 would be a perfect detection.

Test set	**F1**	**Precision**	**Recall**
AIRBUS	0.953	0.978	0.934
LiveATC set1	0.738	0.897	0.638

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Recap

- Introduced ATCO^2 project and the main goals
- We are working on improving our callsign detection system
- Context information from OSN helps!
- Introduced each sub-system:
  - Data recording: VHF receivers
  - Speech-to-text: Hybrid and end-to-end systems
  - Text-to-callsign system: Based on BERT (Transformer neural network)

Thank you. Questions?

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