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Fearless Steps Challenge Phase-3 (FSC P3): Advancing SLT for Unseen Channel and Mission Data across NASA Apollo Audio

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Abstract

The Fearless Steps Challenge (FSC) initiative was designed to host a series of progressively complex tasks to promote advanced speech research across naturalistic "Big Data" corpora. The Center for Robust Speech Systems at UT-Dallas in collaboration with the National Institute of Standards and Technology (NIST) and Linguistic Data Consortium (LDC) conducted Phase-3 of the FSC series (FSC P3), with a focus on motivating speech and language technology (SLT) system generalizability across channel and mission diversity under the same training conditions as in Phase-2. The FSC P3 introduced 10 hours of previously unseen channel audio from Apollo-11 and 5 hours of novel audio from Apollo-13 to be evaluated over both previously established and newly introduced SLT tasks with streamlined tracks. This paper presents an overview of the newly introduced conversational analysis tracks, Apollo-13 data, and analysis of system performance for matched and mismatched challenge conditions. We also discuss the Phase-3 challenge results, evolution of system performance across the three Phases, and next steps in the Challenge Series.

Index Terms: NASA Apollo, speaker diarization, speaker identification, speech recognition, conversational analysis.

1. Introduction

The importance of naturalistic datasets in the advent of a technology revolution led by deep neural networks has become paramount. With deep learning system performance linearly scaling with the amount of data provided, naturalistic "Big Data" corpora serve as a benchmark for developing a competitive edge in artificial intelligence (AI) domain. Establishing good quality naturalistic datasets is challenging [1, 2, 3, 4]. There are additional challenges in developing a corpus with rich information content across multiple SLT domains [2, 5, 6]. The NASA Apollo missions data is a collection of 150,000+ hours of audio with unprompted multi-party conversations recorded over 30 channels. This data contains over 450 personnel in constant air-to-air, air-to-ground, and ground-to-ground communication working collaboratively to solve time-critical challenges. Speech and natural language systems can significantly benefit utilizing this data. The Fearless Steps Challenge (FSC) series has led the efforts in promoting such system development by annotating a small portion of this Apollo corpus (115 hours) and establishing challenge tasks to benchmark SLT systems [6, 7, 8].

The goal of FSC Phase-3 (FSC P3) is to assess the robustness of speech and language systems across channel, noise, speech, speaker, and semantic variabilities. The FSC P3 set provides such a test platform, sourcing its data from multiple channels from Apollo-11 and Apollo-13 missions [9, 10, 11].

FSC P3 was conducted in collaboration with the National Institute of Standards and Technology (NIST) and Linguistic Data Consortium (LDC) from February through March of 2021. Nine participating organizations, with 14 task-specific teams contributed 235 system submissions. Phase-3 evaluation reported state-of-the-art (SOTA) results on 3 of the 8 challenge tracks. The current edition of the FSC was run entirely online using the NIST OpenSAT evaluation platform [1]. The web platform supported a variety of services including evaluation registration, data distribution, system output submission, submission validation, scoring, and system description/presentation uploads [5, 12, 13].

2. Challenge Tasks

The NASA Apollo Missions audio data were recorded on 30-channel analog tapes ranging from 14 to 17 hours in duration. Large data streams of this nature are often a hindrance in effective development of SLT systems. In an effort to streamline such development, 30-minute audio chunks were annotated from the most high-impact events in Apollo 11 and Apollo 13 missions. These chunks have been presented in the FSC corpus as "audio streams". These streams of undiarized audio are supplemented by annotation files with diarized labels. Essentially, audio streams for Training (*Train*) and Development (*Dev*) sets provided to challenge participants contain a single markup-styled annotation file per stream. Each annotation file contains a ground-truth label or transcription per single-speaker utterance. Participants are expected to diarize the Evaluation (*Eval*) set audio streams in addition to the primary task. This requires using multiple systems to process downstream tasks, often propagating error at each functional block. FSC P2 established the necessity for developing separate speaker diarization (SD) and automatic speech recognition (ASR) tracks to streamline the development of effective clustering and acoustic models/language models respectively [3, 4, 14]. This format has been extended for FSC P3, which provides separate tracks for diarized "audio segments" in the speaker diarization (SD), automatic speech recognition (ASR), and conversational analysis (*CONV*) tasks. The entire list of tasks and tracks available for the FSC P3 are presented below. The five original channels (*FD*, *MOCR*, *EECOM*, *GNC*, *NTWK*) used in the FSC P1 and P2 have been preserved in Train and Dev sets, with no additions to the data-sets [6, 7, 8].

[1]https://sat.nist.gov/fsc3

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- *TASK 1*: Speech Activity Detection ***(SAD)***
- *TASK 2*: Speaker Identification ***(SID)***
- *TASK 3*: Speaker Diarization
  - (3.a.) *Track 1*: using system SAD ***(SD_track1)***
  - (3.b.) *Track 2*: using reference SAD ***(SD_track2)***
- *TASK 4*: Automatic Speech Recognition
  - (4.a.) Track 1: using system SAD ***(ASR_track1)***
  - (4.b.) Track 2: using diarized audio ***(ASR_track2)***
- *TASK 5*: **Conversational Analysis**
  - (5.a.) Track 1: using system SAD ***(CONV_track1)***
  - (5.b.) Track 2: using diarized audio ***(CONV_track2)***

Tasks established in previous challenges are still core speech tasks, and do not directly benefit spoken language understanding (SLU) of the multi-party conversations. With SOTA word error rates (WER) as high as 24%, SLU systems cannot be expected to effectively extract meaningful information regarding topic, sentiment, emotion, or semantic context. This effect was observed in the FSC P1 sentiment detection task. Accordingly, a new task with separate tracks was created with an aim to identify key conversational moments in the data [9, 15, 16, 17].

2.1. Conversational Analysis

Methodologies to identify salient conversations in continuous audio streams can significantly reduce the cost of information retrieval [18, 19]. These methodologies are valuable for analyzing Apollo Missions data, which can have important conversations during intermittent time-critical events, followed by large periods of inactivity or normal conversations. Identification of such conversational "Hotspots" can help both STEM and non-STEM researchers parse through 150,000 hours of data and retrieve segments with high value semantic content. In the context of the Apollo Missions data, these conversational cues can be characterized as an intersection of the conventional tasks; 'topic detection' and 'extractive summarization'[20, 21]. A total of 25 hotspots critical to successful deployment of the Apollo Missions were identified as conversational "Hotspots" and presented as diarized segments for a classification task (*CONV_track2*). The task of diarizing and identifying hotspots in continuous audio streams was also presented as a separate track for FSC P3 (*CONV_track1*).

2.2. Challenge Deployment

The NIST OpenSAT web platform[2] was used to conduct FSC P3. Participants were allowed to download Train, Dev, and Eval sets after agreeing to the terms and conditions of the Challenge. The scoring toolkit developed for the FSC P2 was used for validation and back-end scoring in the platform. Participants were provided with basic analytics for each submission to assist their system development efforts. Every team was allocated a single submission slot per task/track with multiple submissions (up to 3 per day) allowed to update the system performance.

2.3. Performance Metrics

The performance metrics and conditions for FSC P3 remained largely consistent with conditions for FSC P2. A NIST defined detection cost function (DCF) measure was used for scoring the speech activity detection (SAD) task, with a forgiveness collar of *0.25* seconds, which was reduced from the collar duration of *0.5* seconds for FSC P2. Both tracks for SD and ASR were evaluated using diarization error rate (DER) and word error rate (WER) respectively for the same testing conditions as FSC P2. The Speaker Identification (SID) task performance metric was updated from Top-5 % Accuracy (Top-5 Acc.) to Top-3 % Accuracy (Top-3 Acc.). The newly introduced *CONV* tracks were evaluated using separate metrics. Track-2 using diarized segments was evaluated using Top-3 % Accuracy, and Track-1 using audio streams was tested using the measure Jaccard error rate (JER) [22, 23, 24]. The Jaccard index has been traditionally used in image segmentation and more recently in speaker diarization in the DIHARD Challenge series [22, 25]. JER as an initial measure provides a good representation for a task involving diarizing and identifying hotspot labels. For each reference speaker *ref* the speaker-specific JER_{ref} is computed as:

$$\text{JER}_{\text{ref}}(\%) = \left(\frac{FA + Miss}{Total}\right) \times 100, \quad (1)$$

where

- *Total* is the total reference speaker time; that is, the sum of the durations of all reference speaker turns,
- *FA* is the total system speaker time not attributed to a reference speaker,
- *Miss* is the total reference speaker time not attributed to a system speaker.

The JER metric for CONV_track1 could be replaced with a different metric for future Phases depending on the evolution of the data and labels developed for this task.

3. Data

Robustness and efficacy of SLT systems can be measured by their ability to adapt to real-world data with varying and often previously unseen acoustic characteristics. In this section we describe the training and testing conditions used in FSC P3 to evaluate system adaptability and robustness.

3.1. Unseen Channel & Mission

Every channel in the Apollo Missions is associated with different task. Speech density, conversational content, and speakers can vary drastically with each channel. The operations and propulsion (OPS&PRO) channel from Apollo-11 was annotated to test system performance over such unseen channel characteristics. A total of 5 hours were selected from three Apollo-13 channels to form the unseen mission data, providing additional variability in channel noise, air-to-ground communication noise, different speakers, and speech conversations markedly different to conversations in the Apollo-11 Mission.

3.2. General Statistics

Table 3 summarizes the overall statistics for the audio streams data, and highlights the variability within the Eval set. Tables 1 and 2 present statistics on the diarized segments for the SID and CONV_track2 tasks, while Table 4 provides insight into the distribution of segments in the Train, Dev and Eval sets.

3.3. Evaluation Set Variability

The unseen channel and mission data present in the *Eval* set are set up in a blind format. Participants were not provided with mission or channel labels during the evaluation phase, thereby making it possible to evaluate systems for their generalizability to unseen data conditions.

[2] https://sat.nist.gov

Table 1: *General statistics for the SID task. The mean, median, minimum, and maximum values for cumulative speaker durations, and individual speaker utterances are all expressed in seconds [7]*

Data set	# Speakers	Speaker Duration (s)			Speaker Utterances (s)		
		mean	median	(min , max)	mean	(min , max)	total
Train	218	505.5	106.7	(6.89 , 11254.36)	4.03	(1.84 , 16.95)	27336
Dev	218	118.1	24.2	(3.13 , 2596.18)	4.04	(1.78 , 16.95)	6373
Eval	218	264.3	38.2	(3.19 , 5834.46)	4.09	(1.8 , 16.22)	14077

Table 2: *General statistics for the CONV_track2 task. The mean, median, minimum, and maximum values for cumulative label durations, and individual labels are all expressed in seconds.*

Data set	# Hotspots	Hotspot Duration (s)			Hotspot Utterances (s)		
		mean	median	(min , max)	mean	(min , max)	total
Train	25	1546.8	796.4	(193.26 , 6274.85)	2.4	(0.5 , 30.4)	16059
Dev	25	464.8	233.7	(45.11 , 2626.05)	2.5	(0.5 , 33.2)	4662
Eval	25	976.3	435.9	(59.05 , 8036.36)	2.6	(0.5 , 29.96)	9360

Table 3: *Overall Statistics of audio streams for the FSC P3. The mean, min, and max values are expressed in seconds.*

	Train	Dev	Eval			
			A-11	A-13	Unseen	Total
# Streams	125	30	40	10	18	68
Dur. (hrs)	63.5	15.3	20.1	5	9.1	34.4
% Speech	29.4	32.5	34.4	33.4	37.3	35
#Spkrs/Stream	19	24	20	13	25	20

Table 4: *Duration Statistics of audio segments for ASR_track2. The mean, min, and max values are expressed in seconds [7]*

Data set	Segments	Utterance Duration (s)		
		mean	min	max
Train	35,473	2.85	0.10	70.37
Dev	9,203	2.97	0.12	67.39
Eval	21,846	2.98	0.10	162.75

Table 5: *Baseline Results for all tasks/tracks in FSC P3 [7]*

Fearless Steps Phase-3 Baseline Results			
Task	**Metric**	**Dev (%)**	**Eval (%)**
SAD	DCF	12.84	15.16
SD_track1	DER	79.72	88.27
SD_track2	DER	68.68	77.91
SID	Top-3 Acc.	75.20	72.46
ASR_track1	WER	83.80	92.3
ASR_track2	WER	80.50	86.4
CONV_track1	JER	58.6	71.5
CONV_track2	Top-3 Acc	67.1	54.2

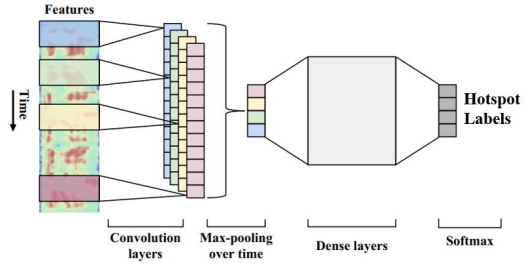

Figure 1: *CNN-Saliency network illustration, used as baseline system for CONV_track1 and CONV_track2 [26]*

4. Results

In this section, we analyze baseline performance for all tasks, and assess system generalizability factor for all FSC3 submissions.

4.1. Baseline Results

All the original FS2 baseline systems were used without modifications for evaluating the FSC P3 Eval set [27, 28, 29] with the exception of the extractive summarization tracks 'CONV_track1' and 'CONV_track2'. The baseline results for all tasks are reported in Table 5. We notice a degradation in performance on the FSC3 Eval sets for all tasks/tracks, caused by the addition of the unseen channel and mission data. Since most of the baseline systems are unsupervised and rely on core acoustic features [30, 31], their degraded performance indicates added acoustic complexity in the Eval set due to the unseen mission and channel inclusion. The baseline system used for both tracks of the conversational analysis task was originally developed for emotion detection [26]. The convolutional network illustrated in Figure 1 is designed to aggregate high level context over time (log-Mel-Filterbank feature frames) to generate a single hotspot label.

4.2. Best Systems Comparison

Table 6 provides a comparative illustration of the improvements in SOTA for Phase-2 and Phase-3 [32, 33, 34, 35]. We report significant improvements in FSC3 Top system performance over FSC2 for SID task, ASR_track2 and both SD tracks. However, the SOTA for SAD and ASR_track1 tasks are maintained from FSC2. Comparisons to the FSC2 systems have been conducted over the same data evaluated by participants in FSC2. We also observe that the top systems for every task/track were able to adapt efficiently to the unseen channel data.

4.3. System Generalizability

Figure 2 illustrates six comparative performance distribution plots, one for each task/track. Scores from all FSC P3 system submissions were used to fit four distributions per task/track. System results for audio from Apollo-11 were used to form the green outlined distribution. Likewise, red outlined distribution represents Unseen Mission, and blue represents Unseen Channel. Cumulative FSC P3 Eval set results form the yellow outlined distribution. We use these distributions to visually represent the disparity of system outputs between seen and unseen channel/mission. While the top 2 systems were able to generalize well to the unseen mission and channel data, a majority of the systems had degraded performance. The unseen channel performance for all tasks was seen to be closely related to the seen channel data, and in some cases even showed improved performance. ASR_track2 and SD_track1 saw significantly de-

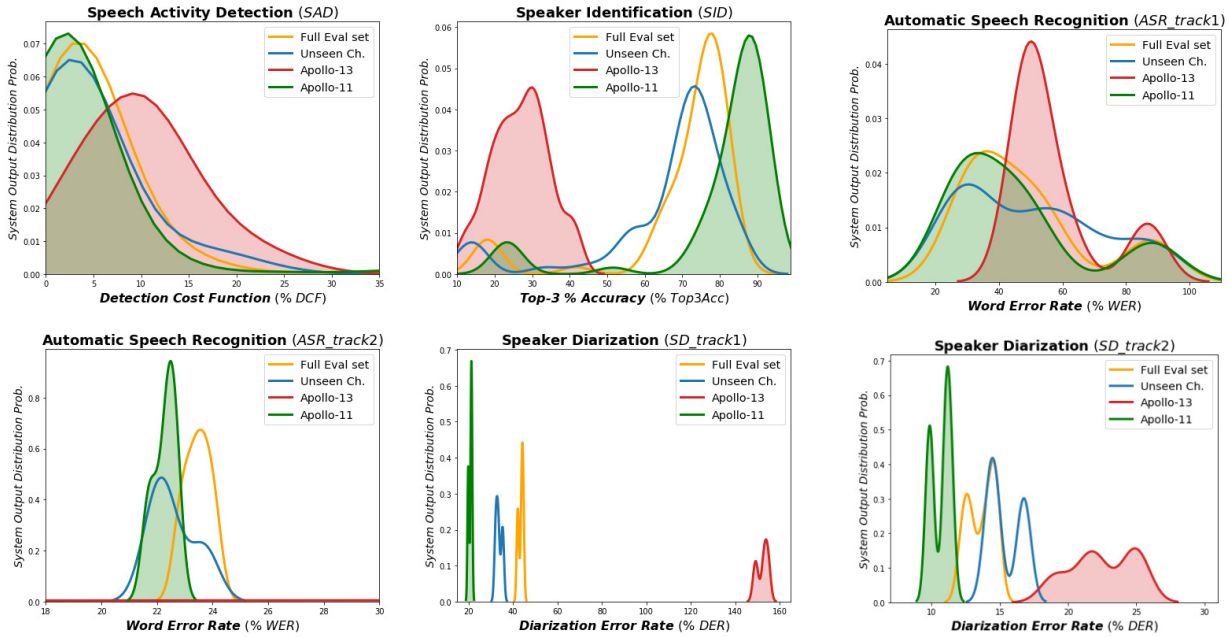

Figure 2: *Distribution of system submission results between the Apollo-11 (green), Unseen Channel (blue), and Apollo-13 (red) segments/streams of the Eval set. Distribution over the entire FSC P3 Eval set is outlined (yellow) for reference.*

Table 6: *Comparison of the best systems developed for all FSC P2 and P3 challenge tasks.* FSC3 *(in bold) represents system performance over the entire blind set provided for participants. Relative improvement of top-ranked system per task in the FSC P3 seen channel data* (FSC3-A11) *(underlined) over FSC P2 evaluation set is illustrated.* FSC3-A13 *and* FSC3-UnkCh *represent the top system performance for the Unseen Mission and Unseen channel data respectively.*

Comparison of Best System Submissions on FSC3 Eval set (and sub-sets)						
Task	**FSC2 (%)**	**FSC3 (%)**	**FSC3-A11 (%)**	**FSC3-A13 (%)**	**FSC3-UnkCh (%)**	**Rel. Imp. (%)**
SAD	1.07	**1.47**	1.16	2.37	1.67	*-7.57 %*
SID	92.39	**83.27**	93.26	23.77	85.16	**12.9 %**
SD_track1	28.85	**42.20**	19.92	149.1	32.33	**30.95 %**
SD_track2	26.55	**12.32**	9.82	19.05	14.15	**53.59 %**
ASR_track1	24.01	**29.96**	26.87	47.94	26.82	*-11.9 %*
ASR_track2	24.26	**22.85**	21.69	100	21.82	**10.59 %**

graded performance for Unseen Mission (flat distribution for ASR_track2 indicating no transcriptions generated by competing systems for Apollo-13 audio segments). Based on this analysis, we hypothesize that system generalizability is a key component in developing systems for the remaining Apollo Missions.

5. Discussion

We notice that system generalizability was positively correlated with better overall performance. We report that the systems competing in the FSC P3 showed marginal degradation performance for channel variabilities, but significantly lacked the ability to generalize to unseen mission data. The availability of 9 hours of Unseen Channel data to only 5 hours of the Unseen Mission data may be a factor in improved relative performance between the two sub-sets.The imbalance in these Eval sub-sets could have caused some bias in the overall submission results. Notwithstanding the biases, developing robust systems for the remaining 9 Apollo Missions would require algorithms that could adapt to the variabilities introduced with each unseen Mission. We also report no participation for the conversational analysis tracks. This may have resulted from insufficient documentation on the task and hotspot label development. We aim to promote this task in the upcoming challenges by providing detailed descriptions of each hotspot event label in addition to an open-sourced baseline system made available ahead of the next challenge.

6. Conclusions

Through FSC Phase-3, we introduced a new challenge task that aims to extract high level context from conversations. We tested system capability to generalize for previously unseen channel and mission variability. In the next Phase of the Challenge we plan to extend the Training and Development datasets to include audio from Apollo missions '8' and '10'. In conclusion, we assert the need for further development in SLT systems for naturalistic data. Future efforts in the Fearless Steps Challenge series will increasingly involve SLT development of highly adaptable systems that are robust to out-of-domain data.

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