CrossASR++: A Modular Differential Testing Framework for Automatic Speech Recognition

Muhammad Hilmi Asyrofi, Zhou Yang and David Lo
School of Computing and Information Systems
Singapore Management University
{mhilmia,zyang,davidlo}@smu.edu.sg

ABSTRACT
Developers need to perform adequate testing to ensure the quality of Automatic Speech Recognition (ASR) systems. However, manually collecting required test cases is tedious and time-consuming. Our recent work proposes CrossASR, a differential testing method for ASR systems. This method first utilizes Text-to-Speech (TTS) to generate audios from texts automatically and then feed these audios into different ASR systems for cross-referencing to uncover failed test cases. It also leverages a failure estimator to find failing test cases more efficiently. Such a method is inherently self-improvable: the performance can increase by leveraging more advanced TTS and ASR systems. So in this accompanying tool demo paper, we devote more engineering and propose CrossASR++, an easy-to-use ASR testing tool that can be conveniently extended to incorporate different TTS and ASR systems, and failure estimators. We also make CrossASR++ chunk texts from a given corpus dynamically and enable the estimator to work in a more effective and flexible way. We demonstrate that the new features can help CrossASR++ discover more failed test cases. Using the same TTS and ASR systems, CrossASR++ can uncover 26.2% more failed test cases for 4 ASRs than the original tool. Moreover, by simply adding one more ASR for cross-referencing, we can increase the number of failed test cases uncovered for each of the 4 ASR systems by 25.67%, 39.63%, 20.95% and 8.17% respectively. We also extend CrossASR++ with 5 additional failure estimators. Compared to worst estimator, the best one can discover 10.41% more failed test cases within the same amount of time.

Demo: https://youtu.be/ddRk-f0QV-g
Tool: https://github.com/soarsmu/CrossASRplus

KEYWORDS
Automatic Speech Recognition, Text-to-Speech, Test Case Generation, Cross-referencing

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1 INTRODUCTION
Automatic Speech Recognition (ASR), an essential technique supporting human-computer interaction, has been widely applied in modern life. Due to its ubiquity and importance, ensuring the quality of ASR systems is important. In software engineering, testing is a common practice to reveal defects, which can then be fixed to improve the quality of software products. Intuitively, a test case for an ASR system is straightforward: one piece of audio (input) and the corresponding transcription (oracle). However, manually curating these test cases requires significant human effort and time [17]. As a result, researchers have developed automated test generation techniques to reduce the expense for testing ASR systems and helping uncover failures at an early stage.

Such works can be divided into two branches: metamorphic testing and differential testing. The former is built on a basic assumption that adding a subtle disturbance to a piece of audio should not change the recognized transcript produced by an ASR system [1, 5, 6, 15, 20–22]. Work from the other branch, CrossASR [3] that we recently introduce, employs Text-to-Speech (TTS) engines to synthesize test inputs from a text corpus. Then, it performs black-box differential testing on ASR systems by cross-referencing multiple ASRs to detect different transcriptions produced by the ASRs. If the transcribed text recognized by the ASR system under test does not match the text input to TTS while another ASR’s transcribed text does, this input audio is viewed as a failed test case. To increase its efficiency, CrossASR also employs a failure estimator to select tests from the input corpus that are more likely to become failed test cases.

Although these research works and prototypes demonstrate great potential to test ASR systems automatically, the community still lacks an easy-to-use tool that leverages state-of-the-art techniques. Besides, new TTS and ASR systems are continuously emerging and evolving. For example, wav2letter++ [18], an ASR system used in the CrossASR experiments, is no longer maintained (migrated to another platform) [19] and additional ASR systems, e.g., Wav2Vec2 [4], are newly proposed. CrossASR can inherently improve its ability to uncover failed test cases for a system under test by utilizing more TTS and ASR systems for cross-referencing. These facts motivate us to devote more engineering effort and propose CrossASR++ in this paper. We modularize the original tool so it can be easily extended to support additional TTS and ASR systems to achieve better performance. Besides, the original CrossASR adopts a static chunking strategy: splitting an input corpus into a fixed number of batches. It analyzes only one batch in each iteration.
We devote more engineering effort to enhancing the extensibility of CrossASR++. We believe such extensibility can make CrossASR++ self-improvable: the performance can increase by leveraging more advanced TTS and ASR systems. Theoretically, if no timeout is set for each iteration, adding CrossASR++ with more ASR systems for cross-referencing never decreases the number of failed test cases uncovered. The intuition is that newly added ASR systems may turn indeterminable test cases into failed test cases while the original successful and failed test cases remain. As reported in our prior paper [3], TTS systems also differ in their ability to help in finding failed test cases. The main reason is that more advanced TTSes generate fewer invalid audios that are more likely to be indeterminable test cases. As a result, using better TTSes can improve CrossASR++. The failure estimator can estimate the probability that a text leads to a failed test case. Intuitively, a better failure estimator can help CrossASR++ find more texts that result in failed test cases. The analysis above motivates us to enhance the extensibility of the original CrossASR by introducing a modular design to CrossASR++.

We discard the implementation of the original CrossASR as it serves more as a prototype to demonstrate the viability of the research idea rather than a tool that others can easily use and expand. So we implement all necessary processes presented in Algorithm 1 and pay attention to its extensibility. Extensibility is mainly enabled by modeling a TTS, ASR, and failure estimator with interfaces, i.e., abstract base classes. Users can add a new TTS, a new ASR, or a new failure estimator by simply inheriting the base class and implementing necessary methods.

We have 3 base classes, i.e., ASR, TTS, and Estimator. When inheriting from each class, users need to specify a name in the constructor. This name will be associated with a folder for saving the audio files and transcriptions. Thus, we require that each derived class has a unique name. When inheriting ASR base class, users must override the recognizeAudio() method which takes an audio as input and returns recognized transcription. TTS and failure estimator can be added similarly. In TTS base class, the method generateAudio() must be overridden by derived classes. This method converts a piece of text into audio. In Estimator base class, methods fit() and

Algorithm 1: CrossASR++ Workflow

```
Input: corpus: a list of texts
Output: failed_tests: generated failed test cases
1. failed_tests, other_tests = None, None;
2. texts = getFirstBatch(corpus);
3. while not exceed maximal iteration do
   4.   /** new text selection; 
      5.   if failed_tests not None then
         6.     estimator.train(failed_tests, other_tests);
         7.     texts = estimator.select(getNextBatch(corpus));
      8.   end
      9.   audios = tts.generateAudio(texts);
     10.   /** cross-referencing process: 
        11.   transcriptions = asrs.recognizeAudio(audios);
        12.   f_tests, o_tests = crossReferencing(transcriptions, texts);
        13.   failed_tests.append(f_tests);
        14.   other_tests.append(o_tests);
    15. end
    16. return failed_tests
```
predict() must be overridden by derived classes. These methods are used for training and predicting, respectively.

As default setting of CrossASR++, we have incorporated some latest components. The supported TTSes are Google Translate’s TTS [8], ResponsiveVoice [16], Festival [9], and Espeak [7]. The supported ASRs are DeepSpeech [12], DeepSpeech2 [2], Wit [14], and wav2letter++ [18]. CrossASR++ supports any transformed-based classifier available at HuggingFace [13]. CrossASR++ can be easily extended to leverage more advanced tools in the future.

2.3 Dynamic Chunking and Visibility

The original CrossASR adopts a static chunking strategy. Before processing the corpus, it splits the corpus into a fixed number of batches and assigns each batch to one iteration. When processing texts in each iteration, CrossASR can only access a limited number of texts assigned in the text batch. If it reaches the time limit, it will discard all the unprocessed texts in the text batch. Also, the estimator can only predict the failure probability of texts in that batch as well. There are two main drawbacks of this static chunking strategy. First, the unprocessed texts can also be failed test cases. Thus discarding them will decrease the number of failed test cases.

Second, the visibility of the estimator is limited. The limited visibility means that the estimator can only access a small number of texts to prioritize. No matter how effective the estimator is, it can only give a higher rank to a few texts that are likely to be failed test cases.

We design CrossASR++ with dynamic chunking and more flexible visibility. We allow users to adjust the visibility of the failure estimator, and the text batches are no longer split statically before processing. After ranking texts according to their failure probabilities, CrossASR++ processes the texts starting from the one with the highest failure probability estimate. There is still a timeout (or time budget) for each iteration, but when the timeout is reached, CrossASR++ appends unprocessed texts to the next iteration rather than simply discards them. In other words, CrossASR++ chunks texts in each iteration dynamically.

2.4 Tool Usage

2.4.1 Installation. CrossASR++ can be installed via a simple command: `pip install crossasr`. The components that CrossASR++ relies on, e.g. TTS, ASR systems and estimators, can also be easily install and incorporated into CrossASR++ as described in Section 2.2. Please refer to the Github repository for more information.

2.4.2 Configuration and Execution. After adding ASRs, TTSes and estimators, we can run CrossASR++ with some configuration parameters. Users need to set tts, asrs, target_asr and estimator parameters to let CrossASR++ know the TTS to generate audios, ASRs for cross-reference, the ASR under test and the failure estimator to use. Each of these parameters takes a string or a list of strings.

Other important parameters are num_iteration, time_budget, text_batch_size, and recompute. CrossASR++ runs in multiple iterations as specified by num_iteration. The timeout for each iteration is limited to time_budget measured in second. The number of texts can be processed in each iteration, i.e. the visibility, can be set by specifying text_batch_size. Users can adjust these parameters according to their situation. For example, users with a sufficient time can increase the time_budget and num_iteration to generate more failed test cases. In the Github repository, we also provide all the TTS-generated audios we use. Users can set recompute as false to use them directly.

All of the configuration parameters are saved at config.json. We provide an example script `test_asr.py`. Users can execute ASR testing with command `python test_asr.py config.json`.

3 EXPERIMENTS

In this section, we evaluate CrossASR++ using the Europarl dataset – the same corpus was used to evaluate CrossASR as reported in [3]. After removing duplicates and dropping empty texts, we randomly pick 20,000 texts for our evaluation. To measure how CrossASR++ performs in finding failed test cases, we answer the following two research questions. For both RQs, we use ResponsiveVoice as TTS, set timeout as 1 hour and run for 5 iterations (with a time budget of 1 hour for each iteration).

**RQ1. How many failed test cases can CrossASR++ find?**

To answer RQ1, we run CrossASR++ with four ASR systems under two configurations. The first configuration uses static chunking and the albert t-base-v2 estimator (the setting used by CrossASR), while the second configuration uses dynamic chunking, sets visibility to 1,200, and uses a more advanced estimator (facebook-bart-t-base). These two configurations are helpful for comparing the superiority of CrossASR++ over CrossASR. Table 1 illustrates the results of running the tool using the two configurations. Each column represents the number of failed test cases uncovered for the system under test (SUT) when we use one ASR as the SUT and the remaining 3 ASRs for cross-referencing. The result shows that for each SUT, CrossASR++ can help find more failed test cases. In total, CrossASR++ can find 26.2% more failed test cases than the original tool, which demonstrates significant improvements to the original tool.

**RQ2. To what extent do enhanced features help find more failed test cases?**

We enhance CrossASR++ with three main features: (1) extensibility to use more ASR, (2) dynamic chunking and flexible visibility of estimator, and (3) extensibility to use advanced estimators. In this RQ, we select the second configuration from RQ1 as the base configuration. By means of an ablation study, we explore how these three features contribute to the performance of CrossASR++; specifically, we modify only one parameter related to one of the features each time and keeping the other parameters untouched.

First, we analyze the effect of extensibility to use more ASRs. Table 2 illustrates the changes in number of failed test cases when adding one more ASR (Wav2vec2) into the system. We can observe that by simply adding one more ASR for cross-referencing can increase the number of failed test cases uncovered for 4 SUTs by
We fix other parameters and only replace failure estimators used.

CrossASR++ we incorporate into this section briefly introduces works related to testing ASR systems. We divide current methods to test ASR into two branches:

4 RELATED WORK

This section briefly introduces works related to testing ASR systems. We divide current methods to test ASR into two branches: metamorphic testing and differential testing. Most of works fall into the first branch. Researchers from SE communities [6, 11], follow the conventional software testing principles: define some coverage criteria in ASR systems and generate metamorphic transformations guided by these coverage criteria. Then, they apply transformations to original audios to derive mutants that are expected to have the same recognized transcripts as the original ones. In the AI community, researchers often generate such transformations adversarially by using optimization-based methods [1, 5, 15, 20–22].

The other branch, differential testing [10], provides the same input to different softwares with the same function and to see whether they produce different outputs. CrossASR [3], which is our prior work, is the first to apply differential testing to ASR systems. CrossASR employs Text-to-Speech (TTS) engines to synthesize test inputs from texts. Then it performs black-box differential testing on ASR systems by cross-referencing multiple ASRs to detect different transcriptions recognized by ASRs. If the transcribed text recognized by the ASR system under test does not match the text input to a TTS, while another ASR’s transcribed text does, this input audio is viewed as a failed test case. To increase its effectiveness to find failed test cases, CrossASR utilizes a failure estimator that selects texts that are more likely to lead to failed test cases.

5 CONCLUSION AND FUTURE WORK

This paper presents CrossASR++, an extensible tool that performs black-box differential testing on ASR systems. CrossASR++ can be conveniently extended to incorporate different TTS and ASR systems, and failure estimators. The extensibility allows CrossASR++ to flexibly utilize more tools to boost its performance on uncovering failed test cases. In the default package of CrossASR++, we incorporate 4 TTS and 5 ASR systems, as well as 6 failure estimators. Our evaluation results show that CrossASR++ outperform CrossASR by revealing 26.2% more failed test cases. In addition, we find that the new features introduced by CrossASR++ help discover more failed test cases. For example, by simply adding one more ASR system for cross-referencing, the number of failed test cases for each of the 4 ASRs under test increases by 25.07%, 39.63%, 20.95% and 8.17% respectively. The number of failed test cases also increases by increasing the visibility until some point. We also find that leveraging a more advanced failure estimator can help CrossASR++ achieve better performance. We encourage practitioners and researchers to augment CrossASR++ with more TTS and ASR systems and failure estimators.

Table 2: Adding one more ASR to the system.

| ASR       | Visibility | # Failed Test Case |
|-----------|------------|--------------------|
|           | DS         | DS2                | W2L    | Wit    | W2V    | Total   |
| 4         | 1,200      | 319                | 217    | 420    | 978    | -       | 1,934   |
| 5         | 1,200      | 399                | 303    | 508    | 1,058  | 309     | 2,577   |

Table 3: Results when using different estimators.

| Estimator                  | # Failed Test Cases |
|----------------------------|---------------------|
| No estimator               | 1,574               |
| bert-base-uncased          | 2,334               |
| albert-base-v2             | 2,419               |
| distilbert-base-uncased    | 2,446               |
| xlnet-base-cased           | 2,495               |
| roberta-base               | 2,559               |
| facebook-bart-base         | 2,577               |
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