Adjust-free adversarial example generation in speech recognition using evolutionary multi-objective optimization under black-box condition

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Abstract This paper proposes a black-box adversarial attack method to automatic speech recognition systems. Some studies have attempted to attack neural networks for speech recognition; however, these methods did not consider the robustness of generated adversarial examples against timing lag with a target speech. The proposed method in this paper adopts Evolutionary Multi-objective Optimization (EMO) that allows it generating robust adversarial examples under black-box scenario. Experimental results showed that the proposed method successfully generated adjust-free adversarial examples, which are sufficiently robust against timing lag so that an attacker does not need to take the timing of playing it against the target speech.

Keywords Deep neural network, Speech recognition, Black-box adversarial attack, Robust optimization

1 INTRODUCTION

In recent years, Automatic Speech Recognition (ASR) systems are widely used in many products such as personal assistants of smartphones, voice command technologies in cars, and so on. On the other hand, deep learning methods are known to be vulnerable to adversarial examples, small perturbations added to target samples [1]. It is essential that ASR systems have high security because ASR systems perform various tasks which may require user personal data.

Therefore, studies have been conducted to generate adversarial examples to improve the robustness of ASR systems. Early studies of adversarial attack to ASR systems [2,3] were based on white-box conditions, where internal information of a target Deep Neural Network (DNN) classifier such as gradients of a loss function is available; however, most consumer ASR systems and services prohibit the access to their internal structure and parameters. Therefore, the white-box conditions are not realistic in terms of analyzing the safety of the consumer systems. Recently, a few studies attempted to attack the ASR systems under black-box condition where classification result (class labels) and its confidence are available but internal information is not [4,5]. The black-box attack can be applicable consumer ASR services and it is expected to find their vulnerabilities. On the other hand, to discover more serious vulnerabilities in the real world, it is indispensable to design robust perturbations against environmental changes, time gap between the target speech and perturbation, and so on.

Therefore, this paper proposes a method for generating adversarial examples to ASR systems that are robust against time difference. In the actual environment, it is difficult for an attacker to play the perturbation noise accurately in time with the target speech, and a time difference significantly reduces the effect of the attack. In other words, robust adversarial perturbations, which cause misrecognition even when the timing is slightly off, are more threatening. Creating such robust adversarial noises makes it easier for the attacker to determine when to start the noise. Moreover, an adversarial example that leads the classifier to misrecognize it even with the arbitrary length of the time difference makes it unnecessary for the attacker to pull the trigger; the attacker only needs to repeat the adversarial noise sound like an environmental sound. We term such a highly threatening example an adjust-free adversarial example. In the proposed method, adjust-free adversarial example design is formu-
lated as a multi-objective optimization problem, and an evo-
luational multi-objective optimization algorithm solves the
problem. Experiments using speech commands classification
model [6] showed that the proposed method successfully generated robust adversarial examples against the time
difference and also adjust-free adversarial examples.

2 RELATED WORK

Yakura has proposed a method for generating robust adver-
sarial examples for ASR systems in physical environments,
which considers the reverberation and noise from the regen-
erative environment [2]. This method generates adversarial
examples by simulating a transformation process of play-
back or recording in the physical environments. However, it
assumes the white box setting and therefore it is difficult to
apply this method to commercial ASR systems.

Recently, a few studies proposed adversarial attack meth-
ods under black-box setting where internal information of a
target classifier cannot be available and only class labels and
their confidence scores can be referred. For instance, Su et
al. proposed a method to generate adversarial perturbations
using evolutionary computation, which does not require gra-
dients of an objective function [7]. Khare et al. proposed a
method to generate adversarial perturbations using Evolu-
tionary Multi-objective Optimization (EMO) that controls
the balance between conflicting objectives such as the text
dissimilarity and acoustic similarity [8].

In the field of image recognition, studies on adversarial
examples robust to image translations caused by changes of
viewpoints and lighting conditions have been conducted [9].
Suzuki et al. proposed a method of generating adversarial
perturbations using EMO [10], which optimizes the expecta-
tion and variance of classification accuracy to design robust
adversarial examples against image transformation.

On the other hand, in the real environment of speech
recognition, it is expected that a timing gap may occur be-
tween a target voice sound and a designed adversarial pertur-
bation. Then, generating robust adversarial examples against
the timing difference is necessary to find vulnerabilities that
could be a threat in the real situation. Although there are few
studies that attempt to design different kinds of robust adver-
sarial examples for speech recognition [11], further studies
that design robust adversarial examples are necessary to en-

tance the safety of ASR systems based on DNN.

3 THE PROPOSED METHOD

3.1 Key ideas

This paper proposes a black-box adversarial attack method
to speech recognition using DNN. Followings are the key
ideas:

1. Formulating as a Multi-Objective Optimization (MOO)
   problem: Problems of generating adversarial examples
   against DNN essentially involves multiple objective func-
tions that have a trade-off relationship, e.g., perturba-
tion amount and classification performance — it is dif-
ficult to design imperceptive perturbations that mislead
DNN while ones involving large perturbation can be eas-
ily created. Generally, such competing criteria are com-
bined with a weighted linear sum; however, it is natu-
ral to solve the problem without integrating them into
one single objective function. The proposed method for-
mulates the adversarial example generation problem as
an MOO problem. Therefore, the proposed method does
not need a parameter to integrate objective functions.

2. Applying EMO algorithm: Because the proposed method
   solves the MOO problem using an EMO algorithm, ob-
   jective functions can be flexibly designed; non-differentiable,
   non-convex and noisy functions are available.

3. Finding more serious vulnerabilities via robust op-
timization: In the case of speech recognition, finding
   robust adversarial examples against timing lag is impor-
tant because it is quite difficult to add perturbation to
   a target speech with accurate timing in actual environ-
   ments. Therefore, taking advantages of EMO, the pro-
   posed method performs robust optimization by simul-
taneously minimizing the expected value of classifica-
tion accuracy and its variance [10]. In particular, this
   study aims to generate an adjust-free adversarial exam-
   ple, which fools the classifier even with the arbitrary
   length of time difference against a target speech.

3.2 Formulation

The proposed method designs an adversarial noise by opti-
mizing perturbation amount to a sound wave amplitude of a
target speech. For instance, if the a target speech length is
one second and sampling rate is 16 kHz, the number of de-
sign variables, or the number of dimensions, gets into 16,000.

The proposed method utilizes EMO-based approach, which
allows designing objective functions and constraints flexibly
and eliminating the need to combine objective functions into
one function. To design adversarial examples robust against
3.3 Process flow

This paper adopts Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) [13] to solve the MOO problem shown in eq. (1). Here, an original MOO problem is described as follows:

$$\text{minimize } \vec{f}(\vec{x}) = (f_1(\vec{x}), f_2(\vec{x}), f_3(\vec{x}))$$

subject to $\vec{x} \in \mathcal{F}$  \hspace{1cm} (2)

In this paper, the above problem can be decomposed into many single objective optimization problems using the Tchebycheff method as follows:

$$\text{minimize } g(\vec{x}, \lambda^j, z^*) = \max_{1 \leq i \leq N_f} \left\{ \lambda_i^j | f_i(\vec{x}) - z_i^* \right\}$$

subject to $\vec{x} \in \mathcal{F}$  \hspace{1cm} (3)

where $\lambda^j = (\lambda_1^j, \ldots, \lambda_{N_f}^j)$ are weight vectors ($\lambda_i^j \geq 0$) and $\sum_{i=1}^{N_f} \lambda_i^j = 1$, and $z^*$ is a reference point calculated as follows:

$$z_i^* = \min \{ f_i(\vec{x}) | \vec{x} \in \mathcal{F} \}$$  \hspace{1cm} (4)

By preparing $N_D$ weight vectors and optimizing $N_D$ scalar objective functions, MOEA/D finds various non-dominated solutions at one optimization.

Figure 2 shows the detailed algorithm of the proposed method based on MOEA/D. The initial solution candidates $\vec{x}_1, \ldots, \vec{x}_{N_{\text{pop}}}$ are generated by sampling them at uniformly random from the entire search space. Then, $N_f$ ($= 3$) best individuals are selected for $N_f$ objective functions respectively, and the indexes of the subproblems $\mathcal{I}$ are selected. To reproduce new solution candidates, crossover operator in Differential Evolution (DE) [14] and polynomial mutation are applied to each $i \in \mathcal{I}$. The generated new solution candidates are evaluated by applying a target speech recognition model and by calculating objective function values from the classification result $\mathcal{C}(\vec{S} + \vec{\rho})$ with confidence scores. Then, the reference point and the population are updated according to the amount of constraint violations and values of $g$. After iterating $N_G$ generations, the algorithm stops.

4 EVALUATION

4.1 Experimental setup

In order to verify the effectiveness of the proposed method, we tried to generate adversarial examples for the speech command classification [6]. As a target model, we adopt the trained model based on a convolutional neural network that achieved classification accuracy of 90% in the speech command dataset [6], which contains 65,000 samples of 10 classes such as "off", "on", "right" and "stop."

In the experiment, the proposed method is compared with the previous method for generating adversarial examples for
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(a) 1st generation (b) 250th generation (c) 500th generation (d) 1,000th generation (d) 2,000th generation

Fig. 3 Trasition on distributions of the non-dominated solutions for "down" sample.

(a) previous method (b) proposed method

Fig. 4 Generated adversarial examples for class "down".

ASR systems using genetic algorithm [4]. To design adjust-free perturbation, when evaluating solution candidates, the proposed method evaluates 9 perturbed sounds with lags within \( T_{\text{max}} = 0.5 \) [s] lags for each candidate. Population size \( N_{\text{pop}} \) and generation limit \( N_{\text{g}} \) were set to 100 and 2,000, respectively.

4.2 Experimental results

Figure 3 shows the transition of the solution candidate distribution in the objective function space during the optimization by the proposed method. In the early step of the optimization, perturbations were large and did not cause misrecognition of the target model; however, after 250 generations, the confidence of the correct class to the input began to fall below 0.5 while their perturbation amount decreased. Figure 4 shows the obtained adversarial examples for class “down”, which reveals that the one generated by the proposed method includes the smoother pattern than that by the previous method.

Figure 5 shows the obtained non-dominated solution distributions projected to \( f_1 - f_2 \) plane. Solutions located at the bottom left of the graphs are more robust i.e., more stable in causing misrecognition. A representative robust solution for each class is selected from the bottom-left part of the distribution and compared with ones generated by the previous method in terms of the robustness against time difference to the target speech as shown in Figure 6. The horizontal axis of each graph shows the time difference between adversarial perturbation and the input speech to be attacked, and the vertical axis shows the confidence of the correct class of the input. Although the confidence score of the adversarial examples generated by the previous method were sufficiently low when the lag was almost zero, the effect of the attack rapidly deteriorates when there is even a small time difference. On the other hand, the proposed method succeeded in reducing the confidence over the whole range in the tested time difference in almost all classes except “left” class where the generated examples failed to fool the classifier in some ranges such as from -0.25 to -0.15 [s] and 0.25 to 0.35 [s].

Because the target sound length is 1.0 seconds, the generated adversarial examples that could lead the misclassification from -0.5 to 0.5 [s] time lag can be recognized as adjust-free. That is, for instance, by repeatedly playing the perturbation sound, the 0.7 [s] time difference can be regarded as -0.3 [s] lag. Therefore, the proposed method succeeded in generating the adjust-free adversarial examples in six over 10 classes when assuming the confidence threshold of 0.49 that was the average of the maximum confidence except the correct class.

4.3 Effect of Minimize standard deviation

Because the proposed method minimizes the standard deviation of the confidence of the correct class in addition to the expected value, this section describes the effects of minimizing the standard deviation. Figure 7 shows the non-dominated solutions designed for an input speech belonging to class “down.” The robustness against the time difference of the two individuals \( x_L \) and \( x_H \) that have the same expected value \( f_1 \) but different values of standard deviation \( f_2 \). \( x_H \) sometimes failed to make the classifier fool when there was a time lag of about +0.2 to +0.4 seconds, whereas \( x_L \) successfully mislead the classifier throughout the time lag from -0.5 to +0.5, achieving generating the adjust-free adversarial perturbation. Therefore, it is effective to use the standard deviation of confidence as one of objective functions to create robust adversarial examples against the time lag.

5 CONCLUSION

This paper proposes a method to generate robust adversarial examples using evolutionary multi-objective optimization for ASR systems. The proposed EMO-based black-box attack method generates robust adversarial examples against
the time difference to target speech by minimizing the standard deviation of the confidence score in addition to the expectation of it. Experimental results showed that the proposed method could generate adjust-free adversarial examples, which are sufficiently robust against the time difference so that attackers do not need to determine the timing of playing the adversarial noise sound. In future, we plan to design a problem dimension reduction method and verify the effectiveness of our method for other ASR models.

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