# Selective Acoustic Feature Enhancement for Speech Emotion Recognition with Noisy Speech



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# Introduction

### **Background:**

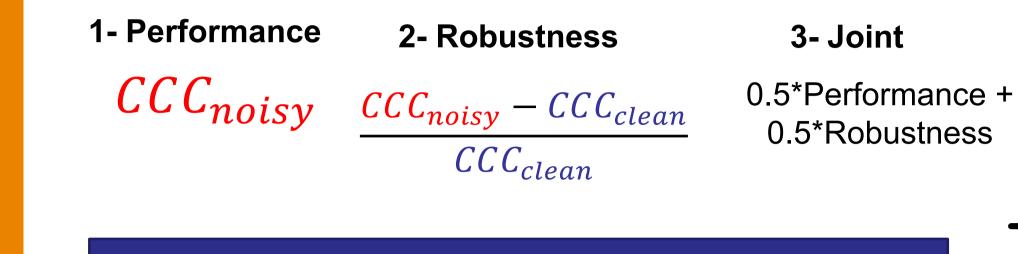
- SER model requires multiple types of acoustic features
- Each feature has a difference in noise robustness
- Only using noise-robust features improves an SER performance under noisy conditions [Leem et al., 2022]

### **Our work:**

Keep the noise-robust features

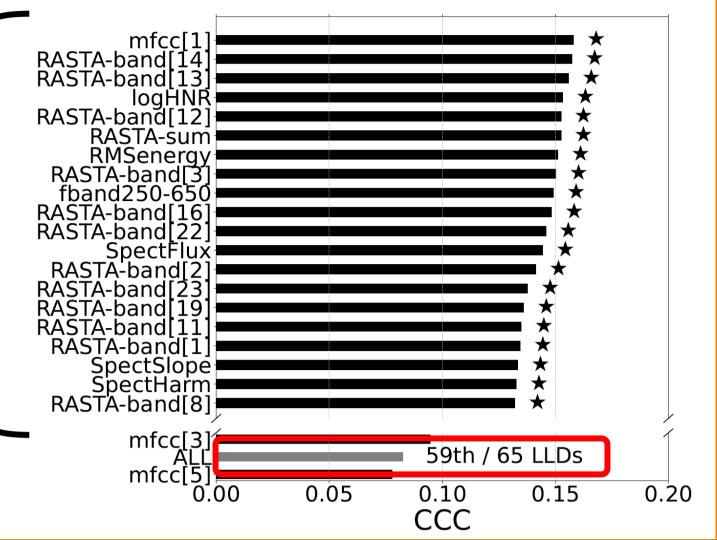
# Single feature assessment

- Train each probe model by using a **single clean LLD**
- Evaluate performance with a single clean/noisy LLD
- Rank features based on the following criteria:



Some features perform better than

#### (e.g.) Valence, 10dB condition



**Enhance the noise-sensitive features** 

using all features in noisy condition!

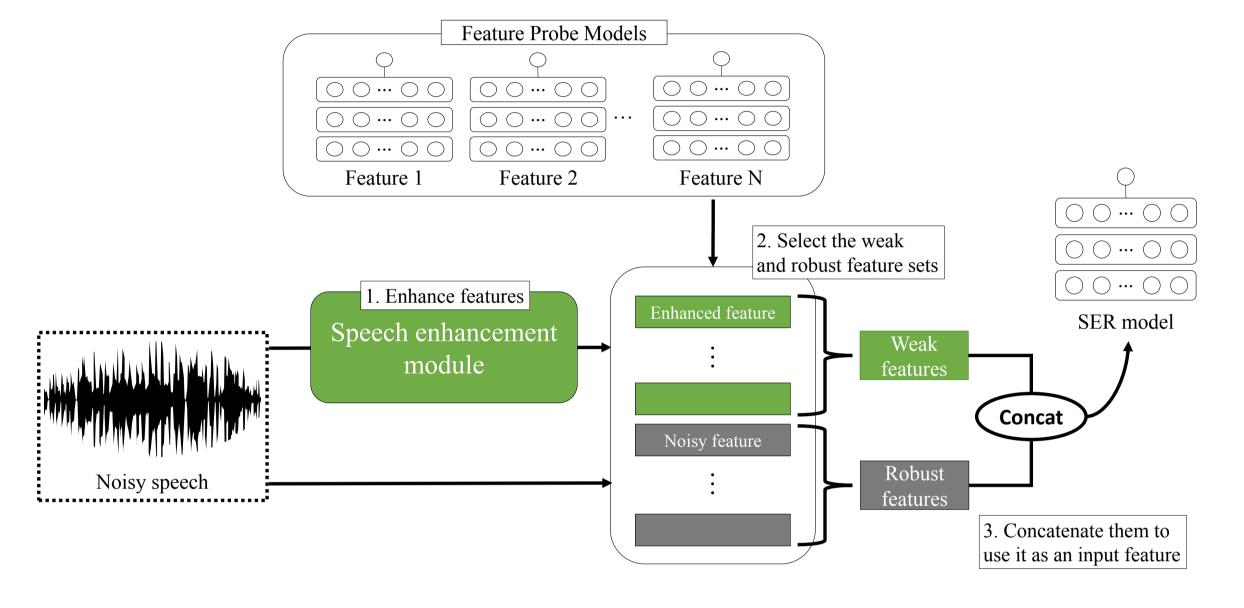
# Proposed Method

0.5

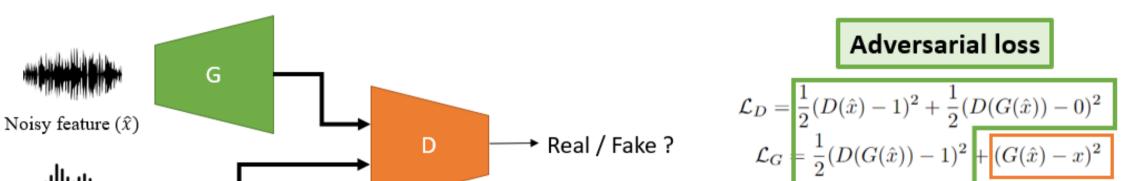
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0.3

### Selective feature enhancement



#### **GAN-based feature enhancement**



# **Robust feature set selection**

- Rank each feature based on the proposed metric
- Add LLDs in increments of 10% from the bottom to the top to define a weak feature set
  - Consider the rest of the features as robust features
- 3. Check SER performance with original robust features + enhanced weak features
  - (e.g.) 80% coverage = 80% features are enhanced + 20% features are kept

Robustness: 80%

- Select the best feature set based on the development set analysis
  - (e.g.) 10dB condition

Robustness: 90%

ပ <sup>0.4</sup> | ပ

0.3



Perforamance: 90% ပ္ပ 0.2 ပ္ပ 0.1



- Generator: 4 layers of 512 bidirectional gated recurrent unit (GRU) + linear output layer
- Discriminator: 3 layers of 32 bidirectional GRU + sigmoid output layer

# Experiment Settings

### Data preparation

- Use the MSP-Podcast corpus (v1.8) as a clean speech set
- Noisy version of the corpus by directly recording the emotional speech with non-stational radio noise
  - We collect 10dB, 5dB, and 0dB conditions

#### **Acoustic features**

- Interspeech 2013 Computational Paralinguistic Challenge feature set
- 65 LLDs in the set

## **Emotion Recognition Framework**

- Predict the emotional attribute scores
- Use multitask learning approach during training [Parthasarathy, 2017]

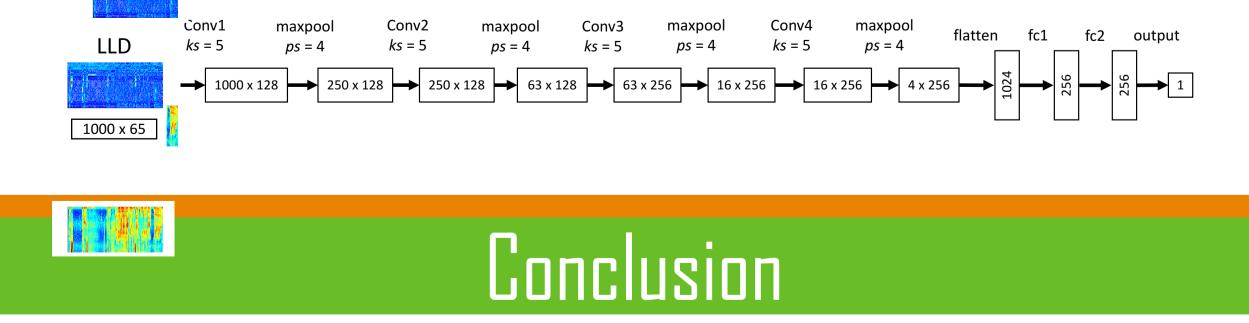
Arousal	Dominance	Valence
0% 20% 40% 60% 80% 100%	0% 20% 40% 60% 80% 100%	0% 20% 40% 60% 80% 100%
Coverage	Coverage	Coverage

SER performance in noisy condition: enhancing weak features ≥ enhancing all the features

# **KESUITS**

### **Emotion Recognition Performance (CCC)**

	10dB			5dB			0dB		
	Aro.	Dom.	Val.	Aro.	Dom.	Val.	Aro.	Dom.	Val.
Model w/o	0.278	0.288	0.097	0.228	0.262	0.076	0.194	0.214	0.058
enhancement									
DCCRN	0.151	0.138	0.140	0.111	0.087	0.081	0.083	0.068	0.081
MetricGAN	0.342	0.297	0.110	0.227	0.247	0.111	0.168	0.135	0.073
Only using	0.364	0.385	0.159	0.302	0.370	0.139	0.268	0.321	0.117
robust features									
Enhancing all	0.450	0.400	0.179	0.412	0.403	0.177	0.393	0.376	0.147
features									
Selective	0.530	0.485	0.185	0.467	0.457	0.178	0.397	0.392	0.151
feature									
enhancement									



- Our selective feature enhancement approach can improve the prediction of emotional attribute scores under noisy conditions
- Feature-based enhancement approach leads to clear improvements for the top-performing features, which compensate for other features when all the LLDs are combined.
- Some features lead to lower SER performance after they are enhanced by the feature-based enhancement model
  - Not all the features need to be enhanced

#### 

- Feature enhancement > signal-based enhancement
- Feature enhancement > feature selection
- Enhancing all features > Selective feature enhancement 3.

### Individual feature analysis (Aro. 10dB)

