OpenVNA: A Framework for Analyzing the Behavior of Multimodal Language Understanding System under Noisy Scenarios

Ziqi Yuan[1, 2], **Baozheng Zhang**[1, 3, 5], **Hua Xu**[1, 5]*, **Zhiyun Liang**[1, 4], and **Kai Gao**[3]

[1] State Key Laboratory of Intelligent Technology and Systems, Department of Computer Science and Technology, Tsinghua University

[2] Beijing National Research Center for Information Science and Technology (BNRist)

[3] School of Information Science and Engineering, Hebei University of Science and Technology

[4] College of Information and Electrical Engineering, China Agricultural University

[5] Samton (Jiangxi) Technology Development Co., Ltd

xuhua@tsinghua.edu.cn

Abstract

We present OpenVNA, an open-source framework designed for analyzing the behavior of multimodal language understanding systems under noisy conditions. OpenVNA serves as an intuitive toolkit tailored for researchers, facilitating convenience batch-level robustness evaluation and on-the-fly instance-level demonstration. It primarily features a benchmark Python library for assessing global model robustness, offering high flexibility and extensibility, thereby enabling customization with user-defined noise types and models. Additionally, a GUI-based interface has been developed to intuitively analyze local model behavior. In this paper, we delineate the design principles and utilization of the created library and GUI-based web platform. Currently, OpenVNA is publicly accessible at `https://github.com/thuiar/OpenVNA`, with a demonstration video available at `https://youtu.be/0Z9cW7RGct4`.

1 Introduction

The Multimodal Language Understanding (MLU) task aims to empower artificial intelligence agents with the capability to comprehensively understand human communication, discerning the speaker's affective states (Baltrušaitis et al., 2018; Soleymani et al., 2017) and intentions (Zhang et al., 2022). Despite the proliferation of multimodal large language models has yielded remarkable achievements (Li et al., 2023; Maaz et al., 2023; Zhang et al., 2023), their application in real-world scenarios is still under development.

Analyzing the behaviors of MLU systems under carefully constructed noise offers a potential avenue for researchers to gain deeper insights into the possible limitations and underlying mechanisms of current MLU systems (Liang et al., 2021, 2022). Specifically, by evaluating the global behavior of MLU system under homologous manually constructed noise, researchers can ensure their model operate effectively in practical usage scenarios. Moreover, analyzing the local behavior of the MLU system under customized perturbed instances provides an understanding of how the model makes decisions, pinpointing which aspects of multimodal signals are pivotal for prediction. In recent years, researchers in this field have faced obstacles in imitating real-world noise in multimodal systems and quantitatively assessing the global robustness of MLU methods (Ma et al., 2022; Hazarika et al., 2022). Due to the lack of open-source noise injection toolkits and evaluation benchmarks, researchers frequently provide the model performance under specific simulated noise, leading to inequitable comparisons and susceptibility to overfitting on such noise patterns (Yuan et al., 2023).

To bridge the gap between simulated scenario and real world multimodal noise, benchmark current approaches, and provide intuitive local behavior analysis, we introduce OpenVNA, an open-source framework dedicated to analyze MLU system behavior under noisy scenario. The composition of the OpenVNA and the interconnections among its components are illustrated in Figure 1. Firstly, OpenVNA serves as a Python Library providing easy-to-use Application Programming Interfaces (APIs) for noise simulation, model reproduction, and global robustness evaluation. Presently, it incorporates fifteen noise injection techniques, eight integrated baseline models pertaining to two video understanding tasks, and can be easily extend to user defined tasks, noise configurations and models. Moreover, OpenVNA provide researchers a GUI-based interface to interactively analyze the local model behavior under user specific noisy scenario. The contributions of this work can be succinctly summarized as follows,

1. The OpenVNA contains one of the most com-

[*] Hua Xu is the corresponding author. Email: xuhua@tsinghua.edu.cn

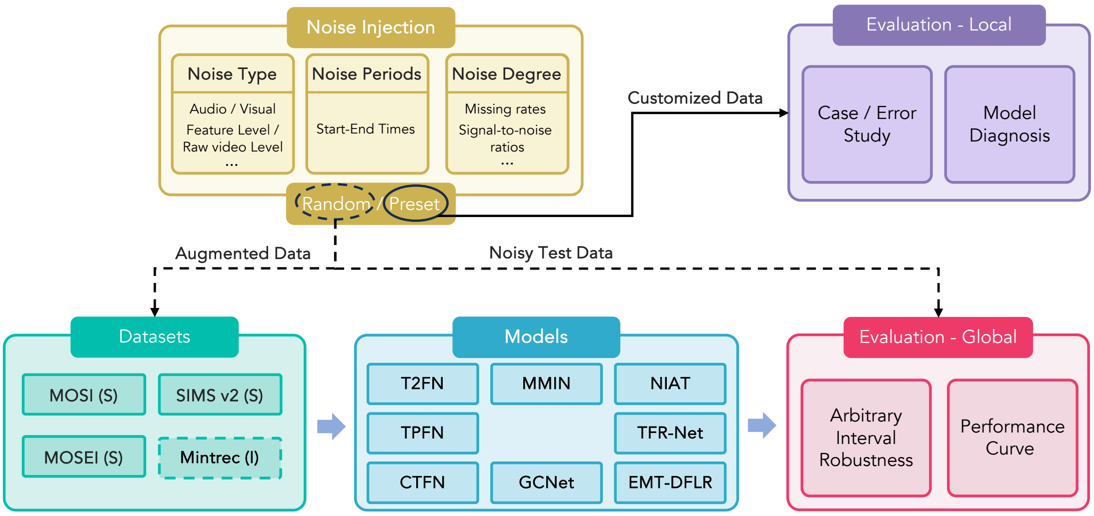


Figure 1: OpenVNA is an comprehensive Python library for analyzing MLU system behavior under noise, which consists of noise injection module, datasets module, models module, instance-level (local) and batch-level (global) evaluation module. For instance level model behavior evaluation, an online platform is also available.

prehensive video noise injection toolkits, covering the most cases in real world applications.

2. The OpenVNA framework serves as a robust MLU benchmark, which providing unified noisy dataset construction, benchmark model reproducing and global robustness evaluation. The modular pipeline makes it very easy to integrate new models for a reliable comparison with existing baselines.

3. The OpenVNA framework offers a GUI-based interface, facilitating users to effortlessly apply user-defined noise to a given video and compare extracted features and model predictions, thus enabling the analysis of local model behavior and even model diagnostics.

2 Related Works

MultiBench. MultiBench (Liang et al., 2021) is a comprehensive benchmark that presents three fundamental challenges in multimodal representation learning, including generalization, complexity, and robustness. Concerning robustness, MultiBench initially outlines potential perturbations across diverse heterogeneous sources and introduces several criteria for measuring robustness. However, MultiBench primarily treats video resources as time-series and restricts the discussion to feature-level imperfections, overlooking general raw video-level perturbations. In this study, we concentrate on perturbations in video applications and further extend the previous quantitative robustness criteria to encompass all types of video noise.

Robust-MSA. The Robust-MSA (Mao et al., 2022b) is developed primarily as a demonstration platform to showcase the impact of raw video-level perturbations on MSA models. The instance level evaluation platform integrated in OpenVNA is carefully enhanced, derives partially from the Robust-MSA system. It now provides support for a broader spectrum of perturbation types, allows for custom noise injection in JSON format, and includes other notable advancements to enhance its capabilities. Furthermore, the OpenVNA framework presented in this paper strives for a more comprehensive scope by establishing a standardized evaluation process, facilitating seamless integration of newly developed models, and providing noise generation APIs to enable large-scale data generation with real-world imperfections, specifically tailored for human-centered video understanding applications.

3 System Design

In this section, we present the functionality of the noise injection toolkit, the global robustness evaluation benchmark, and the GUI-based interface for local behavior analysis. We commence with the noise injection toolkit, as it occupies a central position within the OpenVNA.

3.1 Noise Injection Toolkit

The noise injection module is designed to processes raw video input in accordance with the provided configuration. For raw data level noise, we implement a *real_noise* function to generate user-specific

	Noise Type	Fine-grained Noise Category
Text	Erasing	Word Erasing Attack.
	Replacement	Word Replacement Attack.
	ASR Error	Automatic translation error using wav2vec2-large (Grosman, 2021).
Audio	Mute and Insulation	Low-pass Filter and Volume Attenuation.
	Reverberation	Hall Equalization and Room Equalization.
	Color Noise	White, Pink, Brown, Blue, Violet and Velvet Noise.
	Scenarios Noise	Sudden Noise and Background Noise (traffic and music, etc.)
Video	Visual Occlusion	Partial Black Draw-box and Entire Black Screen.
	Visual Blurriness	Gaussian Blur and Average Blur.
	Noises in Digital Images	Gaussian Additive Noise.
	Visual Noise on Color Space	Contrast, Brightness, Saturation Adjustment, Color Inversion, Channel Switching.

Table 1: Types of raw data level noise supported in the OpenVNA framework. In general, eight categories of raw video level noise with more than twenty fine-grained noise is covered in the OpenVNA.

	Categories	Integrated Dataset and Methods
Datasets	Intention	MIntrec (Zhang et al., 2022)
	Sentiment	MOSI (Zadeh et al., 2016), MOSEI (Zadeh et al., 2018), SIMS v2 (Liu et al., 2022)
Methods	Tensor Regularization	T2FN (Liang et al., 2019), TPFN (Li et al., 2020)
	Reconstruction	TFR-Net (Yuan et al., 2021), NIAT (Yuan et al., 2023), EMT-DFLR (Sun et al., 2023)
	Translation	CTFN(Tang et al., 2021), MMIN (Zhao et al., 2021), GCNet (Lian et al., 2023)

Table 2: Integrated Datasets and Methods in OpenVNA.

noise according to the list of noise items indicating the type of noise, start time, end time, and degree of noise. Based on the above function, a class named *RealNoiseConfig* is implemented to generate random noise configurations given alternative noise types and intensity levels. This class serves the purpose of generating noisy test data or facilitating noise-based augmentation. OpenVNA is capable of adapting to different video formats for input, and processing different video resolutions and duration, efficiently completing original video processing. For implementation, FFmpeg[1] library is utilized for video format conversion and video editing.

Supported Noise. Human-centered video applications naturally contains three distinct modalities: audio, visual, and textual modalities. At feature level, all three modality can be regraded as extracted feature sequence, therefore existing perturbations on time series data are considered, including random feature drop (random erasure of feature sequences with zero-padding vectors) and structural feature drop (erasing of feature sequences with zero-padding vectors in succession) (Yuan et al., 2023; Liang et al., 2021). While at raw data level, audio, visual, and text are heterogeneous, different structure of noise should be considered separately. For textual modality, as the spoken words are commonly obtained from the audio modality using the Automatic Speech Recognition (ASR) technique, ASR error[2] becomes the most common noise, and supported in OpenVNA system. Besides, attacks on text including word erasing or word replacement are also supported in OpenVNA APIs. For the audio modality, four types of noise, simulating various noise sources, are considered, including mute and insulation, reverberation, color noise in laboratory environment, and additive real-world scenarios noise. For visual modality, occlusion, blurriness, noises in digital images, and noise on color space are supported. Table 1 summarizes the supported raw data level noise and provides brief description for each type of noise, while detailed introduction can be found in Appendix A.

3.2 Global Robustness Benchmark

OpenVNA offers researchers a unified pipeline for robust MLU model training, comprising the dataset module, method module, and evaluation module. Here, we will introduce each module individually.

Dataset Module. The dataset module furnishes a unified data loader interface for each supported dataset with high extensibility. Users can specific the used dataset for model reproduction using the

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

[2] ASR errors resulting from the injected audio modality noise are also taken into account.

-dataset command line argument. As shown in Table 2, OpenVNA now encompasses two specific downstream tasks, namely multimodal sentiment analysis (MSA) and multimodal intention recognition (MIR). For the MSA task, it offers support for CMU-MOSI (Zadeh et al., 2016), CMU-MOSEI (Zadeh et al., 2018) in English, as well as CH-SIMS v2 (Liu et al., 2022) in Chinese. As for the MIR task, it also integrates the Mintrec dataset (Zhang et al., 2022). Detailed description of the above integrated databases can be found in Appendix B. Additionally, it is noteworthy that the constructed noisy instances are retained within the overall databases to facilitate noise-based data augmentation.

Method Module. The method module offers a unified interface for model construction. Users can specific the used approach using the --model command line argument. Besides performing model training on original MLU datasets, OpenVNA provides optional robust training technique with generated noisy training data. By utilizing the --augmentation argument, the framework will additionally load the constructed noisy training instances and treat them as augmented data during the training process. Currently, as summarized in Table 2, OpenVNA contains eight robust MLU methods and can be roughly segmented into the tensor regularization based methods (Liang et al., 2019; Li et al., 2020), the reconstruction based methods (Yuan et al., 2021; Sun et al., 2023; Yuan et al., 2023) and the translation based method (Zhao et al., 2021; Tang et al., 2021; Lian et al., 2023). Detailed description of all above baselines are presented in Appendix D.

Evaluation Module. The batch-level evaluation module of OpenVNA is devised with the aim of offering a thorough quantitative performance comparison between various methods under certain type of noise. For quantitative comparison, OpenVNA amalgamates the model performance across varying degrees of noise, offering a holistic evaluation of the robustness pertaining to the given type of noise. Specifically, OpenVNA utilizes Arbitrary Interval Robustness (AIR) as evaluation metrics,

$$\gamma_{\mathtt{abs}}(f) = \int_{\sigma_{\min}}^{\sigma_{\max}} acc_{\sigma}(f) d\sigma, \qquad (1)$$

where $[\sigma_{\min}, \sigma_{\max}]$ denotes the range of considered imperfection levels, which may vary for different types of video perturbation. This criteria geometrically evaluates the area under the accuracy-imperfection curve. In default evaluation process in OpenVNA, the integral is approximately calculated by uniformly taking the function values of 10 interior points on the interval. Besides quantitative results, performance curve are also provided for intuitive demonstration.

3.3 Local Robustness Interface

The instance-level evaluation module is an GUI-based web platform designed to provide a user-friendly interface for intuitive noise injection, error case studies, and even model diagnosis. It facilitates an intuitive comparison of the extracted modality features and model predictions between the original and noisy video clips. In terms of implementation, the frontend of the platform is constructed using Vue 3.0, while the backend is crafted using the Flask library in Python. Detailed installation instructions for the platform are provided on GitHub to enhance user accessibility.

4 Framework Evaluation

4.1 Noise Injection Toolkit

We present an example of injecting raw data level noise with the provided APIs below. In this example, for the visual modality, noise is randomly chosen from ‘Gaussian blur’ and ‘blank’, covering 80% of the video clip with a noise intensity of 0.5. Meanwhile, for the acoustic modality, ‘reverberation’ noise with a noise intensity of 0.3 is injected into the entire (100%) audio waveform.

```python
from noise_api.real_noise import
    real_noise, real_noise_config

cfg = real_noise_config(
    "test.mp4",
    mode = "random_full",
    v_noise_list = ["gblur", "blank"],
    v_noise_num = 2,
    v_noise_ratio = 0.8,
    v_noise_intensity = 0.5,
    a_noise_list = ["reverb"],
    a_noise_num = 1,
    a_noise_ratio = 1.0,
    a_noise_intensity = 0.3,
)._asdict()

# Noise Injection with cfg.
real_noise(
    "examples/test.mp4",
    "examples/test_out.mp4", **cfg
)
```

Listing 1: An example of injecting raw data level noise using OpenVNA framework.

Model	R-Drop		S-Drop		G-Blur		Impulse		Color-W		BG-Park	
	Acc-2	F1	Acc-2	F1	Acc-2	F1	Acc-2	F1	Acc-2	F1	Acc-2	F1
TPFN	64.06	62.96	64.76	64.04	76.91	76.81	76.77	76.63	61.95	59.61	62.19	59.57
T2FN	64.97	63.70	66.56	65.88	77.61	77.58	77.33	77.14	62.63	60.88	62.07	60.21
MMIN	63.33	62.23	65.90	65.45	76.47	76.53	76.34	76.42	60.31	59.90	59.32	58.87
CTFN	62.35	60.09	63.48	61.86	76.87	76.88	76.98	76.98	63.13	61.50	62.04	60.61
GCNET	63.84	63.01	64.78	62.80	76.44	76.10	76.35	76.30	59.10	58.58	59.76	58.92
TPFN*	66.89	63.06	67.54	65.56	76.34	76.35	77.30	77.22	63.39	61.90	62.74	60.05
T2FN*	65.70	64.21	66.15	62.11	76.34	76.35	76.23	76.24	63.02	59.26	62.16	59.29
MMIN*	66.76	64.74	68.19	66.09	76.31	76.29	76.84	76.78	62.62	61.54	61.72	61.55
CTFN*	66.54	65.05	66.73	66.04	77.14	77.09	76.82	76.79	63.32	61.27	62.94	61.23
GCNET*	66.32	63.70	67.44	63.80	76.26	76.17	75.47	75.23	62.05	59.72	61.34	60.27
TFR-Net*	67.47	65.93	67.55	66.84	76.06	76.03	76.36	76.31	63.07	61.81	61.80	61.95
NIAT*	66.32	66.19	64.94	63.66	76.51	76.54	76.11	76.02	63.29	62.64	63.04	62.50
EMT-DLFR*	67.93	67.22	68.85	68.37	77.41	77.45	76.69	76.80	63.36	63.34	63.81	63.85

Table 3: The performance of baselines on SIMS v2 dataset under random drop (denote as R-Drop), strutural drop (denote as S-Drop), Gaussian blur (denote as G-Blur), impulse value noise (denote as Impulse), white color noise (denote as Color-W) and background noise in park (denote as BG-Park). Models marked with a * indicate the utilization of noise-based data augmentation techniques for robust training.

Type	Indicator	Interval
R-Drop	Missing Rate	[0.0, 1.0, 0.1]
S-Drop	Missing Rate	[0.0, 1.0, 0.1]
G-Blur	Sigma of Gaussian blur	[0, 10, 1]
Impulse	Strength for specific pixel	[0, 100, 10]
Color-W	Amplitude of the Noise	[0, 0.10, 0.01]
BG-Park	Amplitude of the Noise	[0.0, 1.0, 0.1]

Table 4: Considered noise interval and brief description, where intervals are recorded in format [min, max, step].

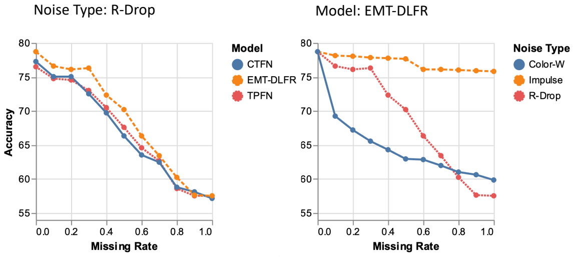


Figure 2: Fine-grained performance curve provided in OpenVNA for global robustness evaluation.

4.2 Global Robustness Benchmark

The global robustness benchmark contains both quantitative model comparison as well as the qualitative performance curve analysis.

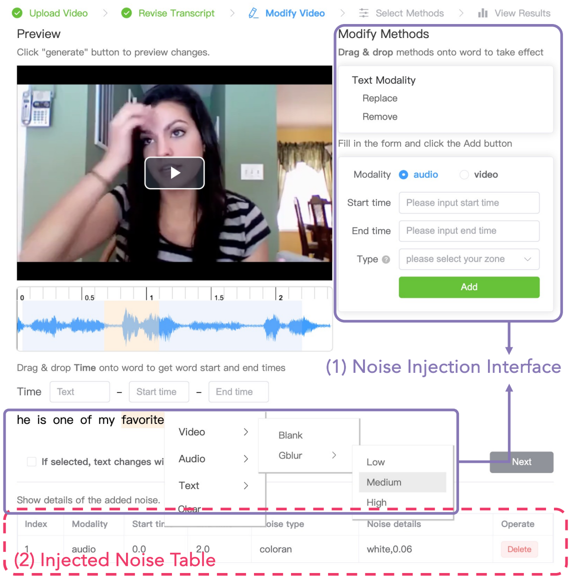
Quantitative Model Comparison. In Table 3, we recorded the AIR metrics for typical type of noise on SIMS v2 dataset. Specifically, six types of noise are considered. For feature level noise, performance under random drop (denote as **R-Drop**) and structural drop (denote as **S-Drop**) are recorded. While for raw video level noise, Gaussian blur (denote as **G-Blur**) and impulse value noise (denote as **Impulse**) are evaluated for visual, white color noise (denote as **Color-W**) and background noise in park (denote as **BG-Park**) are utilized for audio modality. The noise level intervals being considered are documented in Table 4. Models marked with * indicate the utilization of noise-based data augmentation techniques, where the augmented data are generated by random drop. It can be observed that model robustness can be enhanced through noise-based augmentation even for unseen type of noise. More experimental results for other datasets are provided on Github[3].

Qualitative Performance Curve. OpenVNA also offers fine-grained performance curve comparison. As depicted in Figure 2, it allows researchers to analyze global performance from two perspectives. Firstly, comparisons can be made on the same type of noise with different models (the left sub-graph in Figure 2), providing an intuitive demonstration of how different models perform as the noise intensity increases, and aiding in model selection for various applications. Secondly, comparisons can be made on the same model with different types of noise (the right sub-graph in Figure 2), illustrating the model's sensitivity to each type of noise further enables model diagnosis and refinement.

4.3 GUI-based Interface for Local Analysis

The overall workflow of analyzing MLU model behavior through the provided GUI-based interface contains four main steps. Firstly, the user should upload their original video file. The Auto-

[3] https://github.com/thuiar/OpenVNA



Preview

Click "generate" button to preview changes.

Drag & drop methods onto word to take effect

Fill in the form and click the Add button

Modality ● audio ○ video

Start time: Please input start time

End time: Please input end time

Type: please select your zone

Drag & drop **Time** onto word to get word start and end times

Time: Text – Start time – End time

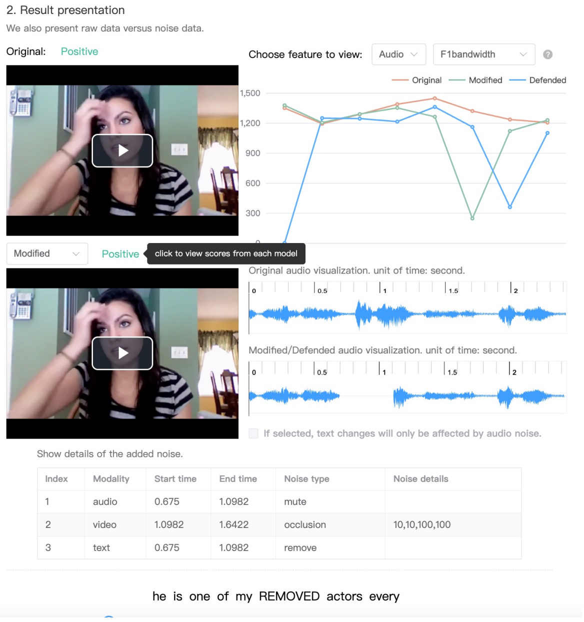
he is one of my favorite

□ If selected, text changes wi

Show details of the added noise.

Index	Modality	Start tir		oise type	Noise details	Operate
1	audio	0.0	2.0	coloran	white,0.06	Delete

Figure 3: The GUI-based Interface of Noise Injection.



2. Result presentation

We also present raw data versus noise data.

Original: Positive

Choose feature to view: Audio F1bandwidth

Modified: Positive

Original audio visualization. unit of time: second.

Modified/Defended audio visualization. unit of time: second.

□ If selected, text changes will only be affected by audio noise.

Show details of the added noise.

Index	Modality	Start time	End time	Noise type	Noise details
1	audio	0.675	1.0982	mute	
2	video	1.0982	1.6422	occlusion	10,10,100,100
3	text	0.675	1.0982	remove	

he is one of my REMOVED actors every

Figure 4: The GUI-based Interface of the Local model behavior analysis.

matic Speech Recognition (ASR) technique with wav2vec-large (Grosman, 2021) is employed to generate spoken words. Following generation process, users can manually edit and correct the ASR outputs. Based on the revised transcript, CTC segmentation (Kürzinger et al., 2020) is used to find utterance alignments within the audio files. Secondly, users can perform customized noise injection either by completing noise configuration forms or by directly applying specific noise onto the video. We provide the GUI-based interface of the noise injection step in Figure 3. The provided interface provides the boundaries of each recognized words and thus supports injecting aligned modality noise. After editing the noise configuration, the selected noise item will be found below in the injected noise table. The noise injection is processed after clicking the generate button. User can preview the generated noisy instance before performing local analysis. The third step becomes the selection of the evaluation model and optional denoising technique. Finally, the comparison of extracted feature sequences as well as the model prediction is demonstrated for error cases analysis and causality analysis. An example of the demonstration is shown in Figure 4.

5 Conclusion

In this work, we introduce OpenVNA, an open-source framework tailored for analyzing the behavior of multimodal language understanding systems under noisy conditions. This developed framework facilitates future researchers in two key ways. Firstly, OpenVNA serves as a highly extensible global robustness evaluation benchmark, integrating two video understanding tasks, four databases, and eight robust baselines. With a unified evaluation pipeline, convenient baseline reproduction is achievable, which enables a fair performance comparison. Moreover, with flexible noise injection toolkits, the provided pipeline further empowers researchers to assess designed models under analogous noise, which can be regarded as a superior simulation for real-world application scenarios. Secondly, OpenVNA provides a GUI-based interface for local model behavior analysis. Through detailed comparisons of extracted feature sequences and model predictions, ad-hoc model behavior explanations can be formulated, facilitating error case analysis and model diagnostics. The authors firmly believe that OpenVNA will make a significant contribution to the advancement of robust multimodal applications and foster future research endeavors.

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A Details of Supported Noise

Detailed description of raw data level audio noise is provided as follows,

Emulation of Mute and Insulation. Due to the occurrence of insulation or translation errors, some voice components might be lost in the recorded audio wave form. A low-pass filter is employed to replicate the insulation effect, as high-frequency components are more susceptible to insulation. Additionally, a mute mode is incorporated to simulate the translation error and severe volume attenuation.

Emulation of Reverberation. Reverberation is a common speech phenomenon that arises within enclosed spaces, resulting from the superposition of direct and reflected sounds. This study involves simulating two archetypal forms of reverberation, namely hall and room equalization, by employing finite impulse response filters with pre-established reverberation hyperparameters.

Color Noise in Laboratory Environment. Color noise is a series of meticulously crafted laboratory-generated noise, stemming from the domain of psychological acoustics. It provides researchers with an ideal and controllable emulation of various environmental noises. Within this study, we have amalgamated six common types of color noise - white, pink, brown, blue, violet, and velvet noise - and blended them with the original speech to assess the overall robustness of the model. For an elaborate elucidation and depiction of each variant of color noise, comprehensive information can be found on the demo website, and Github.

Real-world Scenarios Noise. In addition to the ideal simulations, this study also presents nine distinct real-world recordings of acoustic noise from various environments, such as noise captured in parks, restaurants, and others. A comprehensive description and instances can be accessed on the public website. The real-world noise scenarios offered are properly combined with the original speech to effectively demonstrate the potential impacts on downstream video understanding tasks when exposed to such types of noise.

Detailed description for raw data level visual noise is provided as follows,

Visual Occlusion. Video clips in real-world applications may encounter occlusion in certain parts of the video region. The OpenVNA framework introduces occlusion by overlaying a black draw-box to cover the designated region.

Visual Blurriness. The most common types of blur include Gaussian blur, box blur, variable blur and radial blur. The developed OpenVNA implements Gaussian blur, which emulates a "frosted glass" effect, and the box blur, which imitates the Bokeh effect of a single-lens reflex camera.

Noises in Digital Images. This type of noise is naturally prevalent in digital images during image acquisition, coding, transmission, and processing stages. The OpenVNA framework incorporates Gaussian additive noise that normalizes the histogram concerning the gray values.

Visual Noise on Color Space. To introduce noise in the color space, the OpenVNA framework offers

Model	R-Drop		S-Drop		G-Blur		Impulse		Color-W		BG-Park	
	Acc-2	F1	Acc-2	F1	Acc-2	F1	Acc-2	F1	Acc-2	F1	Acc-2	F1
TPFN	64.26	56.22	65.69	61.48	78.81	78.92	79.85	79.90	62.17	61.82	63.12	62.94
T2FN	64.07	59.19	63.87	59.92	79.14	79.19	79.43	79.40	64.72	64.64	65.23	65.24
MMIN	64.89	56.64	66.66	63.05	79.42	79.49	80.58	80.53	62.94	62.65	63.57	63.41
CTFN	65.52	57.76	67.61	63.92	80.02	80.05	79.44	79.51	66.34	66.19	66.39	66.19
GCNET	64.23	60.40	64.12	56.11	78.86	78.90	78.33	78.26	64.18	64.29	65.11	65.25
TPFN*	63.61	61.18	66.70	65.72	79.83	79.88	78.98	78.95	62.62	62.46	63.17	62.90
T2FN*	63.69	62.46	64.22	63.74	78.96	79.02	79.32	79.32	62.48	62.64	64.75	64.63
MMIN*	65.53	64.39	67.05	65.31	80.56	80.49	81.05	80.99	65.57	65.00	67.62	66.99
CTFN*	65.60	63.63	64.93	64.53	78.43	78.54	79.21	79.28	64.89	64.92	66.01	65.85
GCNET*	62.98	61.51	64.76	63.75	76.46	76.59	78.48	78.38	65.58	65.59	65.07	64.89
TFR-Net*	67.39	66.48	66.60	64.90	81.88	81.92	82.20	82.30	64.98	64.93	67.47	67.35
NIAT*	67.92	67.19	70.65	70.23	83.66	83.67	84.27	84.15	66.29	65.98	66.87	67.01
EMT-DLFR*	68.67	67.51	71.00	70.79	84.16	84.17	84.79	84.73	66.48	66.55	65.10	64.85

Table 5: The performance of selected baselines on MOSI dataset. * indicates that data augmentation is applied, and the augmentation type is consistent with the validation type.

strategies for contrast, brightness, saturation, and gamma adjustments, effectively simulating diverse illumination environments using color filters. Besides, color inversion and channel switching (e.g., from 'RGB' to 'BGR') are also integrated.

B Details of Integrated Databases

The framework offers support for three distinguished benchmark datasets, namely MOSI, MOSEI, and CH-SIMS v2, meticulously curated for Multimodal Sentiment Analysis (MSA) endeavors. Furthermore, it encompasses the MIntRec dataset, designed to cater to the domain of Multimodal Information Retrieval (MIR) tasks.

CMU-MOSI (Zadeh et al., 2016) is a widely used MSA dataset containing 2199 video clips from 93 YouTube movie review videos. Labels range from -3 (strongly negative) to 3 (strongly positive).

CMU-MOSEI (Zadeh et al., 2018) is an extended version of the MOSI dataset, designed to include a larger number of utterances, a wider range of samples, speakers, and topics. It consists of 23,453 annotated video segments extracted from 5,000 videos. The dataset includes utterances from 1,000 distinct speakers and covers 250 different topics.

CH-SIMS v2 (Liu et al., 2022) is a popular Chinese MSA benchmark dataset. It has doubled the size of the original CH-SIMS dataset, making it more comprehensive and diverse. Notably, this dataset has been verified to demonstrate the significance of nonverbal behaviors in predicting emotions.

MIntRec (Zhang et al., 2022) formulates intent classification based on data collected from the TV series Supermarkets. The dataset consists of 2,224 high-quality samples with text, video, and audio patterns, and includes 20 intent categories.

C Feature Extraction

For all experiments in this paper, the MMSA-FET toolkit (Mao et al., 2022a) is employed to extract unaligned features. For visual modality, we extract 35 dimensions of Action Units (AUs) as described in OpenFace (Baltrušaitis et al., 2016) and 136 dimensions of 68 facial landmarks, at a sample rate of 10 frames per second. For audio modality, we use the eGeMAPSv02 feature set (Eyben et al., 2015), which is of 25 dimensions. For the text modality, we use BERT (Kenton and Toutanova, 2019) which consists of 768 dimensions.

D Details of Integrated Baselines

Tensor regularization based methods: T2FN (Liang et al., 2019) uses tensor rank minimization to regularize the high rank caused by partial missing modalities. TPFN (Li et al., 2020) takes high-order statistics over both modalities and temporal dynamics into account, and calculate outer products along time-steps.

Reconstruction based methods: TFR-Net (Yuan et al., 2021) exploits intra-modal and inter-modal attention-based extractors to learn robust representations for each element in modality sequences and then use a reconstruction module to generate the missing modality features. EMT-DLFR (Sun et al., 2023) improve former low-level feature reconstruction with high-level feature attraction to achieve robust performance. NIAT (Yuan et al., 2023) integrates noise-aware adversarial training and utterance-level semantics reconstruction to narrow the representation gap between original and noisy data pairs.

Translation based methods: cTFN (Tang et al., 2021) models bi-directional cross-modality intercorrelation in parallel via couple learning, and establishes a hierarchical architecture to exploit multiple bi-directional translations. MMIN (Zhao et al., 2021) learns robust joint multimodal representations via the Cascade Residual Auto-encoder and Cycle Consistency Learning. GCNET Lian et al. (2023) leverages graph neural networks to capture temporal and speaker information in conversations, aiming to learn discriminative representations from modality-incomplete conversational data.

E Supplementary Experiments

To gain a deeper understanding of the model's performance across various noise conditions, we have carefully chosen six distinct types of noise. For feature level noise, performance under random drop (denote as **R-Drop**) and structural drop (denote as **S-Drop**) are recorded. While for raw video level noise, Gaussian blur (denote as **G-Blur**) and impulse value noise (denote as **Impulse**) are evaluated for visual, white color noise (denote as **Color-W**) and background noise in park (denote as **BG-Park**) are utilized for audio. By introducing these noise types, our objective is to evaluate how the model behaves and performs in different noisy environments. This analysis will enable us to assess the model's robustness and adaptability to various noise sources, potentially identifying areas that require improvement. Table 3 presents the results on the SIMS v2 dataset, while Table 5 showcases the results on the MOSI dataset.