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DEVELOPMENT OF HYBRID EXEMPLAR BASED DLSRGAN MODEL FOR RESTORATION OF THE DISTORTED SIGNALS

Tammineni Shanmukha Prasanthi[1], Swaraiya Madhuri Rayavarapu[2], Gottapu Sasibhushana Rao[3] and Rajkumar Goswami[4]

[1,2] Department of Electronics and Communication Engineering, Research Scholar, Andhra University college of engineering, Visakhapatnam, India.
[3]Department of Electronics and Communication Engineering, Professor, Andhra University college of engineering, Visakhapatnam, India.
[4]Gayatri vidya parishad college of engineering for women, Visakhapatnam, India

[1]http://orcid.org/0009-0000-5352-2265, [2]http://orcid.org/0000-0001-6346-8274
[3]http://orcid.org/0000-0001-6346-8274, [4]http://orcid.org/0000-0002-0651-6783

E-mail: prashanthitammineni.rs@andhrauniversity.edu.in, madhutirayavarapu.rs@andhrauniversity.edu.in
sasigps@gmail.com, rajkumargoswami@gmail.com

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ABSTRACT

This research focuses on the Development of a Hybrid Exemplar-based Deep Learning SRGAN Model for the restoration of distorted signals. Traditional signal restoration techniques often struggle with noise and distortion, leading to loss of critical information. The proposed model integrates Super-Resolution Generative Adversarial Networks (SRGAN) with exemplar-based method to enhance the quality and fidelity of degraded signals. By leveraging the adversarial training framework, the generator learns to produce high-resolution outputs while the discriminator ensures perceptual realism. Initial results indicate significant improvements in signal clarity and detail recovery, outperforming conventional methods in metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM) and Mean Squared Error (MSE). This hybrid approach not only restores signals more effectively but also preserves essential features, making it a valuable tool for applications in telecommunications and audio processing. Future work will focus on optimizing the model for real-time applications and expanding its use across various types of signal degradation scenarios.

I. INTRODUCTION

Signal inpainting is an essential modern technique used for restoring and enhancing visual data. It plays a critical role in data recovery, maintaining the integrity of information affected by loss or corruption. By filling in missing areas, inpainting [1] improves the visual quality of images, making them more coherent and aesthetically pleasing. This technique is particularly valuable in areas such as signal processing and digital content creation. In addition to visual enhancement, inpainting facilitates the recovery of lost or obscured information, which aids in better analysis and decision-making. It also contributes to data compression by reconstructing missing parts of signals, thereby reducing overall data size without compromising quality. In medical imaging, for instance, it can restore corrupted scans, leading to more accurate diagnoses and improved patient care. Overall, signal inpainting is vital across various fields, providing solutions for data restoration and information recovery. This paper introduces a Hybrid Exemplar-based Deep Learning Super Resolution Generative Adversarial Network (DLSRGAN) specifically designed for recovering deteriorated signals. The proposed method demonstrates superior performance across key metrics higher Peak Signal-to-Noise Ratio (PSNR), lower Mean Squared Error (MSE) and higher Structural Similarity Index Measure (SSIM) compared to the exemplar method.

Recovering deteriorated signals is equally important in domains such as audio restoration, seismic data processing and communication systems. In audio restoration, eliminating noise and artifacts enhances the quality of historical recordings. For seismic data processing, addressing noise and interference is crucial for accurately interpreting subsurface structures and identifying hydrocarbon reservoirs. Advanced techniques like deconvolution and filtering can help recover original signals and improve interpretation accuracy. In communication systems, effective signal recovery ensures reliable data transmission through methods like error-correction codes and adaptive filtering. Overall, investing in advanced signal processing techniques enhances the quality, accuracy and reliability of processed data.

II. DEVELOPMENT OF HYBRID EXEMPLAR BASED DLSRGAN INPAINTING TECHNIQUE

This section offers an in-depth look at the proposed Hybrid Exemplar based DLSRGAN Inpainting method, which combines the advantages of exemplar-based techniques with Deep Learning Super Resolution Generative Adversarial Networks (DLSRGAN) [2] to achieve high-quality image inpainting. The hybrid approach starts with exemplar-based inpainting, which effectively fills in missing areas with coherent textures and structures. Subsequently, DLSRGAN enhances the resolution of the inpainted image, particularly targeting regions that lack detail.

Exemplar-based inpainting is a technique that fills missing regions of an image by propagating similar patches from known areas [3]. The process involves patch matching through data propagation and confidence propagation [4]. In this method, the confidence propagation ascertains the presence of known information. This process is repeated iteratively until the entire patch or hole is filled. However, exemplar-based inpainting has limitations such as the inability to synthesize novel content and blending artifacts. It is highly sensitive to patch size. This method will give inaccurate results if the patch size is large. Further this method lacks the semantic understanding.

The Super-Resolution Generative Adversarial Network (SRGAN), introduced by Ledig et al. in 2017, aims to improve the resolution of images. SRGANs employ adversarial training to produce high-resolution images from low-resolution inputs, resulting in a substantial enhancement in image quality and the level of detail. Later studies have expanded upon SRGAN to further improve its effectiveness [5]. The perceptual loss function of SRGAN enables the production of high-fidelity, aesthetically attractive and lifelike images. The model also utilizes residual blocks to extract features, capturing complex details and textures, hence improving the authenticity of the image. The discriminator in SRGAN distinguishes between super-resolved photos and genuine high-resolution images, guaranteeing their close resemblance to real-world data [6-9]. Furthermore, SRGAN integrates a content loss that relies on perceptual similarity, resulting in high-resolution images that preserve the visual attributes and intricacies of the original material.

The integration of these two techniques provides several benefits over traditional inpainting methods, including enhanced resolution and better texture and structure propagation. Initially, the input image is processed using exemplar-based inpainting to enhance texture coherence. This is then followed by the application of DLSRGAN to improve overall resolution and recover finer details in low-resolution areas. This hybrid method has a wide range of applications in video processing, including image video inpainting and video outpainting.

Key features of the hybrid Exemplar-based DLSRGAN technique include its capacity to combine the strengths of both methods for improved image reconstruction and quality. It employs a tensor-based data term for more effective pixel selection when filling in missing regions, surpassing conventional techniques.

]Additionally, a fast patch lookup strategy is utilized to ensure improved geometric coherence in the results. The hybrid approach also addresses common issues faced by traditional methods, such as blurriness in large damaged areas, by leveraging both exemplar-based and deep learning advantages. The limitations of conventional inpainting methods are well-recognized and include problems like blurriness in large damaged regions, high computational complexity, insufficient perceptual similarity between inpainted areas and their surroundings, and challenges in handling complex structures and textures. While traditional methods often yield blurry results for extensive missing areas, the hybrid technique alleviates this issue through a tensor-based data term for better pixel selection and a fast patch lookup strategy to enhance coherence. Moreover, although traditional methods can be resource-intensive, literature suggests modifications that can reduce processing time without significantly affecting quality. The hybrid method demonstrates potential for producing more realistic results by utilizing deep neural networks to replicate complex textures. By merging exemplar techniques with DLSRGAN, this new approach referred to as Hybrid Exemplar-based DLSRGAN aims to effectively address these limitations.

III. RESULTS AND DISCUSSIONS

In this work, the proposed Hybrid Exemplar based DLSRGAN technique is applied to recover the deteriorated signals. To analyze the performance of Hybrid technique for signal inpainting, Received Signal Strength Indicator (RSSI) signal is wantedly distorted in three ways; large, medium and small. This RSSI signal is taken as input from RSSI dataset for Indoor Positioning Fingerprinting [10].

Dataset:

The RSSI Dataset for Indoor Localization Fingerprinting is a comprehensive dataset created by Petros Spachos to support research in indoor localization using fingerprinting techniques. The dataset aims to improve the accuracy and robustness of localization systems relying on Received Signal Strength Indicator (RSSI) values. The dataset includes RSSI readings from three different wireless technologies such as Zigbee, Bluetooth Low Energy (BLE) and Wireless Fidelity (Wi-Fi). The dataset was collected in diverse indoor environments to provide a realistic testing environment for algorithms that need to operate under different conditions and interferences typical of indoor spaces.

The dataset is suitable for research and development, testing and validation and machine learning, as it enhances indoor localization algorithms and techniques, provides a benchmark for evaluating the performance of different localization methods, and trains models to predict locations based on RSSI values. The dataset is available on Institute of Electrical and Electronics Engineers (IEEE) Data port and can be accessed via the provided DOI (Digital Object Identifier) link. By making this dataset available, Petros Spachos has contributed a valuable resource to the research community, enabling advancements in indoor localization technologies.

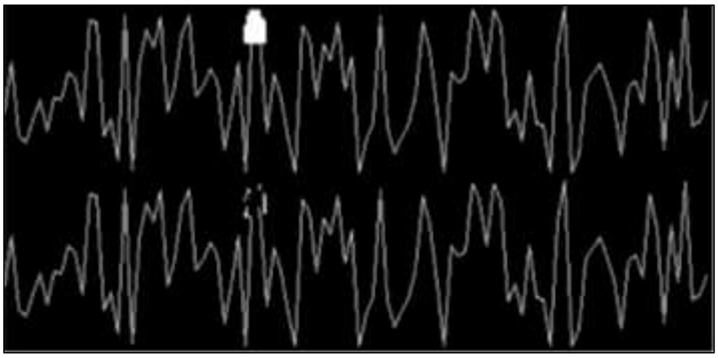

Figure 1: Output of Exemplar based signal inpainting for less distorted signal.
Source: Authors, (2025).

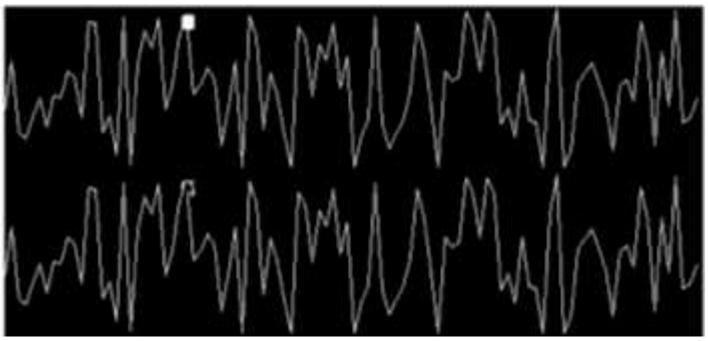

Figure 2: Output of Exemplar based signal inpainting for medium distorted signal.
Source: Authors, (2025).

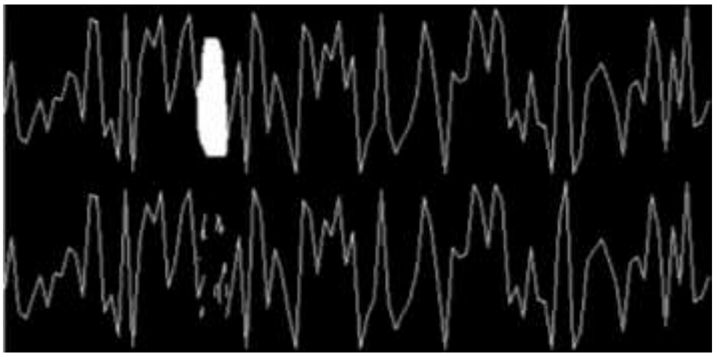

Figure 3: Output of Exemplar based signal inpainting for more distorted signal.
Source: Authors, (2025).

The resultant processed signals through Exemplar technique for corresponding input signals are shown in upper part of the Figure 1, Figure 2 and Figure 3 are respectively presented in lower part of Figgure 1, Figure 2 and Figure 3.

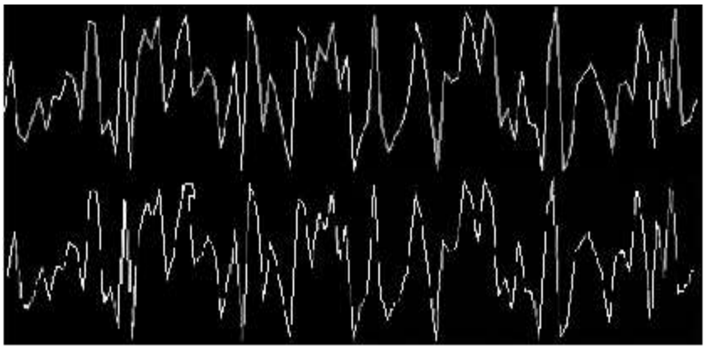

Figure 4: Output of Hybrid DLSRGAN based signal inpainting for less distorted signal.
Source: Authors, (2025).

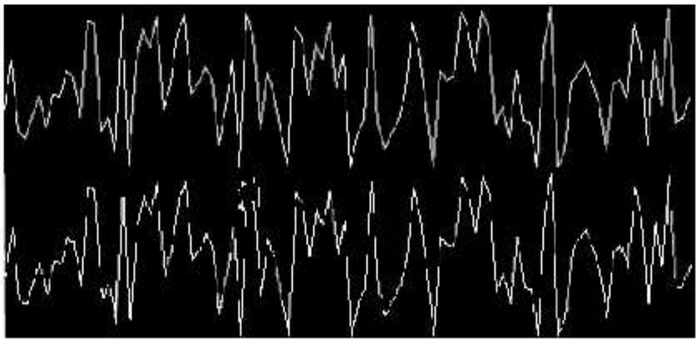

Figure 5: Output of Hybrid DLSRGAN based signal inpainting for medium distorted signal.
Source: Authors, (2025).

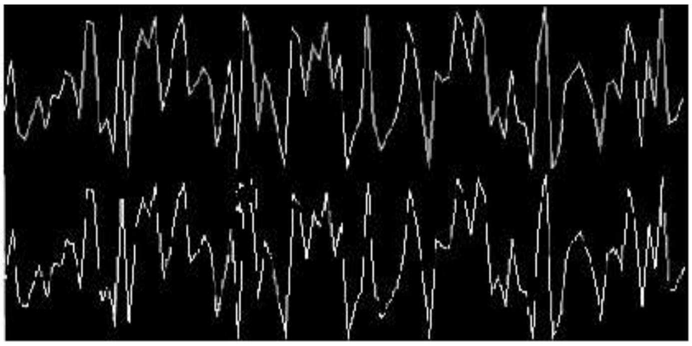

Figure 6: Output of Hybrid DLSRGAN based signal inpainting for more distorted signal.
Source: Authors, (2025).

The upper signals shown in the Fig. 4, Fig. 5 and Fig. 6 correspond to the distorted signal and the lower signals corresponds to their respected super resolution signals. The resultant processed signals through hybrid technique are shown in Fig. 4, Fig. 5 and Figure 6.

Table 1: Comparison of various metrics of Exemplar technique and Hybrid method for inpainted signals.

Sl. No	**Metrics**	**Inpainting Method**					
		Exemplar Method			**Hybrid GAN**		
		More distortion	**Medium distortion**	**Less distortion**	**More distortion**	**Medium distortion**	**Less distortion**
1.	**PSNR**	10.67	11.7	12.0	13.7	14.5	15.2
2.	**MSE**	5565	4118	4088	2805	2465	1958
3.	**SSIM**	0.46	0.57	0.59	0.71	0.75	0.785

Source: Authors, (2025).

The metrics MSE, PSNR and SSIM are used to evaluate the performances of the hybrid and exemplar techniques [11]. Results are tabulated for all these distorted signals in Table 1.

From Table 1, it is very clear that signal with less distortion has high PSNR, high SSIM and low MSE. To explore this for more distorted signals deeper studies should be carried on by assessing more number of variants.

IV. CONCLUSIONS

Signal inpainting is an essential process for accurately repairing images in Signal Processing and Biomedical applications. The hybrid method effectively improves the resolution, quality, and visual coherence of images by integrating exemplar-based inpainting which fills in missing areas by replicating similar patches from known regions with the super-resolution capabilities of Generative Adversarial Networks (GANs). This combined approach seeks to address the challenges of signal enhancement and restoration by leveraging the strengths of both inpainting and super-resolution techniques, leading to better inpainting results.

The proposed hybrid exemplar-based DLSRGAN Signal Inpainting method for less distortion demonstrates significant improvements, achieving a 26.6% increase in Peak Signal-to-Noise

Ratio (PSNR), a 52.1% reduction in Mean Squared Error (MSE) and a 33% enhancement in Structural Similarity Index Measure (SSIM) compared to traditional exemplar method. Further research in signal inpainting using GANs is anticipated to bring advancements in signal processing, data recovery and information extraction in diverse fields.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Tammineni Shanmukha Prasanthi, Swaraiya Madhuri Rayavarapu, Gottapu Sasibhushana Rao and Rajkumar Goswami.
Methodology: Tammineni Shanmukha Prasanthi, Swaraiya Madhuri Rayavarapu, Gottapu Sasibhushana Rao and Rajkumar Goswami.
Investigation: Tammineni Shanmukha Prasanthi, Swaraiya Madhuri Rayavarapu, Gottapu Sasibhushana Rao and Rajkumar Goswami.
Discussion of results: Tammineni Shanmukha Prasanthi, Swaraiya Madhuri Rayavarapu, Gottapu Sasibhushana Rao and Rajkumar Goswami.
Writing – Original Draft: Tammineni Shanmukha Prasanthi, Swaraiya Madhuri Rayavarapu, Gottapu Sasibhushana Rao and Rajkumar Goswami.
Writing – Review and Editing: Tammineni Shanmukha Prasanthi, Swaraiya Madhuri Rayavarapu, Gottapu Sasibhushana Rao and Rajkumar Goswami.
Resources: Tammineni Shanmukha Prasanthi, Swaraiya Madhuri Rayavarapu, Gottapu Sasibhushana Rao and Rajkumar Goswami.
Supervision: Tammineni Shanmukha Prasanthi, Swaraiya Madhuri Rayavarapu, Gottapu Sasibhushana Rao and Rajkumar Goswami.
Approval of the final text: Tammineni Shanmukha Prasanthi, Swaraiya Madhuri Rayavarapu, Gottapu Sasibhushana Rao and Rajkumar Goswami.

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