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A Comprehensive Survey of Channel Attention Mechanisms in Single Image Super-Resolution

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Abstract: This paper explores the significant role of channel attention mechanisms in advancing single-image super-resolution (SISR) methods. By strategically emphasizing key channels within neural networks, channel attention enhances feature representation. This targeted approach enables models to better capture significant details and structures in images, leading to improved fidelity and perceptual quality in reconstructed images. The effectiveness of these mechanisms is evaluated using key performance metrics, including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Learned Perceptual Image Patch Similarity (LPIPS), collectively demonstrating the enhanced capabilities of SISR models that incorporate channel attention.

While these mechanisms offer advantages, challenges such as increased computational complexity and generalization concerns persist, necessitating further exploration. The paper highlights channel attention's importance in streamlining feature representation and emphasizes the potential for future SISR advancements through ongoing research and innovation.

Keywords: Single-Image Super-Resolution, Channel Attention Mechanisms, Image Reconstruction, Parallel Attention

1- Introduction

Single Image Super-Resolution (SISR) has emerged as an essential domain within image processing and computer vision, focusing on the generation of high-resolution images from their low-resolution counterparts, as illustrated in Fig.1. This task poses a significant challenge because it necessitates the creation of additional pixel data that is not available in the original low-resolution image. Recently, the demand for effective SISR solutions has surged across various fields, including satellite imaging, video enhancement, medical imaging, and personal photography[1, 2].

Conventional SISR techniques often face challenges due to inherent ambiguities during reconstruction. The fact that various high-resolution images can result from one low-resolution input makes it difficult to develop a general solution. With the rise of deep learning, numerous architectures have been developed to address SISR, using advanced techniques to improve image quality. A key innovation is the integration of channel attention mechanisms, which have shown considerable promise in boosting the performance of SISR models. Single image super-resolution is particularly valuable in various applications such as medical imaging, satellite imagery, and surveillance, where capturing fine details is crucial. By leveraging advanced algorithms, including deep learning models like convolutional neural networks (CNNs), SISR can reconstruct lost information and improve image quality significantly, thus enabling more accurate analysis and interpretation. Furthermore, the integration of SISR with other technologies, such as augmented reality and computer graphics, opens up new avenues for innovation, enhancing user experiences and providing more detailed visual content across different industries[3-7].

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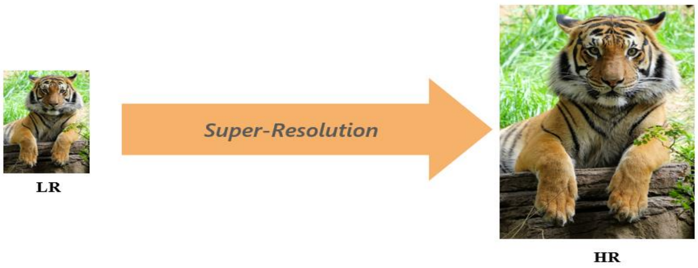


Figure 1: Super Resolution Task

The channel attention mechanism enables neural networks to selectively prioritize different feature map channels, optimizing information flow and enhancing the quality of reconstructed images. By adjusting each channel's influence based on its importance, these mechanisms allow for a more refined representation of the input data, leading to improved high-resolution image synthesis [6, 8].

This paper reviews various channel attention-based methods employed in SISR architectures, considering their implementations, evaluating performance metrics, discussing current limitations, and identifying possible directions for future research. As the field progresses, understanding and enhancing channel attention mechanisms will be essential in improving SISR methods, ultimately leading to more reliable and adaptable image enhancement solutions[9].

The advent of Convolutional Neural Networks (CNNs) has fundamentally transformed SISR, dramatically enhancing the ability to extract intricate features from low-resolution images. CNNs utilize hierarchical structures to learn and represent patterns at various scales, significantly improving the network's understanding of spatial contexts, textures, and complex image characteristics. This capability allows CNNs to move beyond simple interpolation methods, enabling the reconstruction of finer details and more realistic textures. However, the common approach of merely adding more layers or increasing model depth does not automatically ensure better performance. As the architectural complexity increases, challenges such as overfitting and the vanishing gradient problem can emerge, hindering effective training and limiting the model's ability to generalize to new, unseen images.

To mitigate these issues and optimize network performance, advanced techniques like attention mechanisms have become increasingly prominent. These mechanisms strategically focus on the most important and discriminative features within feature maps, enabling the model to allocate its computational resources more efficiently and effectively by adaptively emphasizing the most relevant channels or spatial regions, attention mechanisms suppress noise and facilitate improved information flow throughout the network, which ultimately leads to enhanced image recovery and reconstruction in SISR tasks. This strategic emphasis allows networks to achieve superior performance by selectively amplifying the most informative and salient aspects of the input data while suppressing less relevant or distracting elements.

The incorporation of channel attention mechanisms into SISR architectures has demonstrated significant improvements in the overall quality and perceptual realism of reconstructed images. By dynamically adjusting the weights or scaling factors assigned to different channels within the feature maps, these mechanisms provide a means to selectively hone in on features that are most critical for accurate and visually compelling high-resolution image synthesis. As a result, channel attention has emerged as an essential and powerful strategy for advancing the performance of SISR models, paving the way for more sophisticated, robust, and effective image enhancement techniques.

Channel attention mechanisms are based on the principle that not all feature channels contribute equally to a given task by calculating an attention score for each channel, the network can amplify or reduce the importance of specific features during the forward pass. This recalibration process typically involves global feature aggregation techniques, where statistical measures, such as average pooling or max pooling, are applied across the spatial dimensions of the feature maps. The resulting channel descriptors are then processed by a gating mechanism, often implemented as a feed-forward neural network, to generate attention weights. Fig. 2 illustrates nine SISR methods that incorporate the attention mechanism into their design.

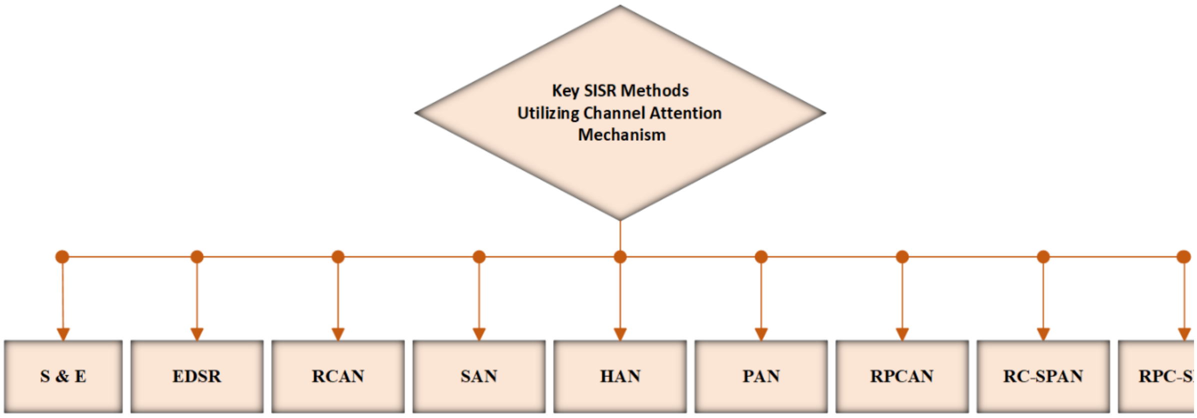


Figure 2: Key SISR Methods Utilizing Channel Attention Mechanism

The rest of the paper is organized as follows: Section 2 begins with an introduction to the fundamentals of the channel attention mechanism, followed by the presentation of nine SISR methods that incorporate this mechanism into their designs. In Section 3, we discuss various metrics for evaluating SISR tasks. Section 4 addresses the limitations and challenges associated with SISR methods. Finally, Section 5 concludes the paper and highlights potential future work.

2: Attention Mechanism Fundamentals

Attention mechanisms are based on the principle of assigning varying weights to different features, allowing models to concentrate on the most pertinent aspects of input data, which enhances decision-making. This flexible focus adjustment aids networks in capturing essential patterns while reducing the impact of less significant features. By highlighting key information, attention mechanisms greatly improve performance across various tasks, particularly in SISR [10].

One notable advancement in attention mechanisms is the Squeeze-and-Excitation (SE) block, which functions through a two-step process. In the Squeeze stage, feature information is aggregated across spatial dimensions, typically using global average pooling (GAP). This process generates a channel descriptor that synthesizes essential features from all spatial locations for each channel, effectively capturing global contextual information crucial for accurate image reconstruction. The subsequent Excitation phase processes this descriptor through two fully connected layers with a non-linear activation function, usually ReLU. The first layer reduces the descriptor's dimensionality, while the second restores it to the original channel count.

After applying a sigmoid activation function, a set of attention weights is produced, indicating the relative importance of each channel. These weights allow for the recalibration of the original feature map by element-wise multiplication with the weights, thereby enhancing the impact of important channels and diminishing that of less useful ones. Integrating SE blocks into neural networks enables models to adjust their focus dynamically during training and inference, significantly improving performance in SISR tasks by effectively identifying and leveraging the most relevant features for reconstructing high-resolution images from low-resolution inputs.

2.1 Squeeze-and-Excitation Blocks (S & E)

Squeeze-and-Excitation blocks (S & E) [10] are important in modern attention mechanisms and consist of two main steps: Squeeze and Excitation. In the Squeeze step, global average pooling is used to gather feature information across different areas of an image. This process converts the feature maps into a smaller form known as a channel descriptor, which helps capture the overall context of each channel and highlights important features. In the next step, Excitation, two fully connected neural networks create weights for each channel based on the gathered information. This process helps the network figure out which channels to focus on more and which to downplay. By adjusting these weights, the network can enhance its focus on the most important features. This approach not only improves the quality of image reconstruction but also increases the strength and accuracy of models used for SISR tasks. This structured method is shown in Fig. 3.

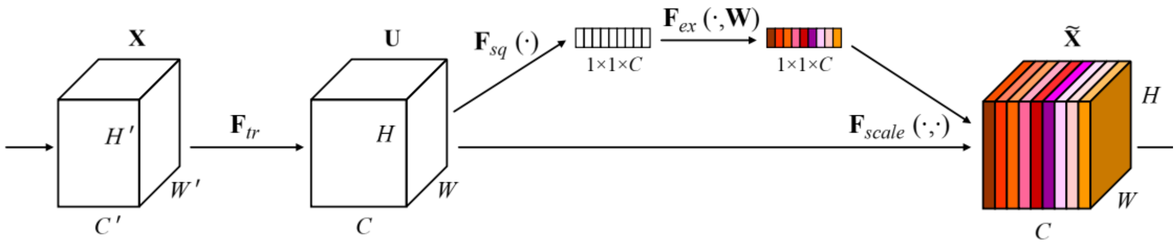
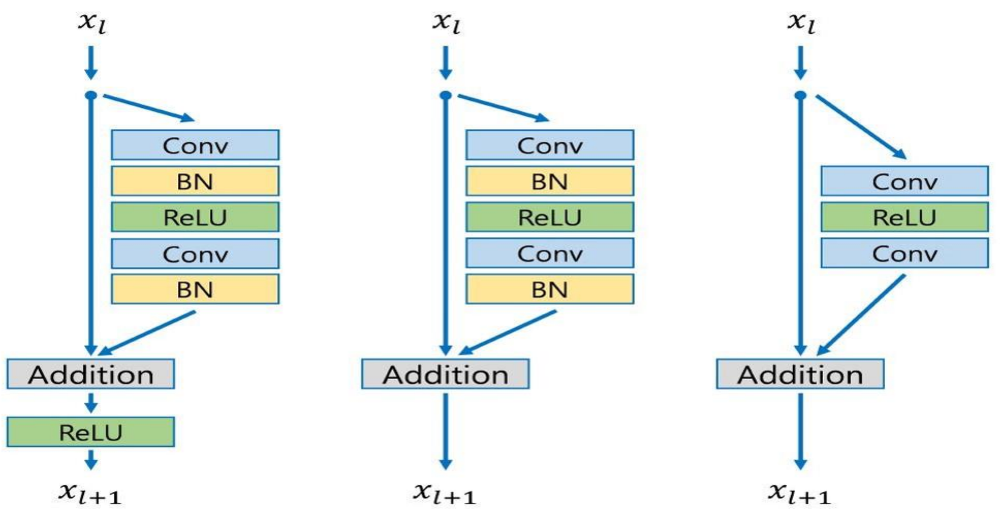


Figure 3: Squeeze-and-Excitation Networks (S & E) Structure) [10]

2.2 Enhanced Deep Residual Network (EDSR)

The Enhanced Deep Residual Network (EDSR)[11] is a refined version of the standard residual network architecture, ResNet [12], and SRResNet[13], prioritizing simplification to improve efficiency and performance in image super-resolution tasks. A key modification in EDSR is the removal of unnecessary batch normalization layers, which can introduce noise and impede performance in certain scenarios. This simplification allows the network to better capture features and improve generalization. Fig.4 illustrates a comparison of the residual blocks in the original ResNet, SRResNet, and EDSR architectures.

To further enhance performance, EDSR can be augmented by incorporating channel attention mechanisms. By integrating channel attention into the residual blocks, the architecture can dynamically emphasize the most significant features during the reconstruction process. This enhancement leads to a considerable improvement in performance on SISR benchmarks, allowing EDSR to set new standards in image fidelity and quality.



a) Original ResNet b) SRResNet C) EDSR

Figure 4 : Comparison of residual blocks in original ResNet[12] , SRResNet [13] and EDSR [11]

2.3: Residual Channel Attention Network (RCAN)

The Residual Channel Attention Network (RCAN) [14] effectively integrates the advantages of residual learning with channel attention mechanisms to enhance feature extraction in deep neural networks. This architecture features residual blocks that facilitate the training of very deep networks by promoting more efficient gradient flow, which helps overcome the vanishing gradient problem. Each residual block incorporates channel attention mechanisms that refine the extracted features, enabling the model to prioritize and focus on the most relevant channels during the reconstruction process. By capturing complex dependencies across both spatial and channel dimensions, RCAN significantly boosts the quality of reconstructed images.

The channel attention module dynamically modifies the weights for each channel by performing global average pooling to assess their significance for the reconstruction task. This flexibility improves the model's ability to capture complex patterns within the data. As a result, RCAN delivers exceptional performance across several SISR benchmarks, achieving high scores in Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). Figures 5 and 6 provide visual representations of the RCAN architecture, the residual channel attention block, and the channel attention mechanism.

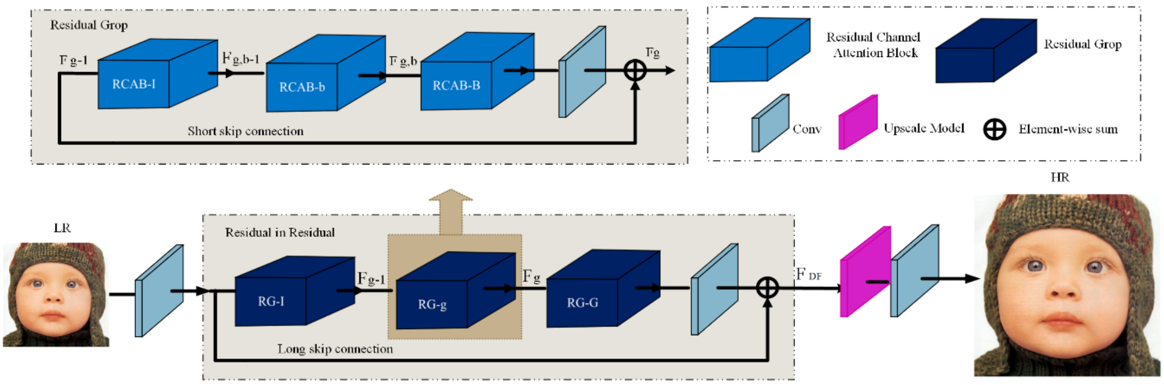
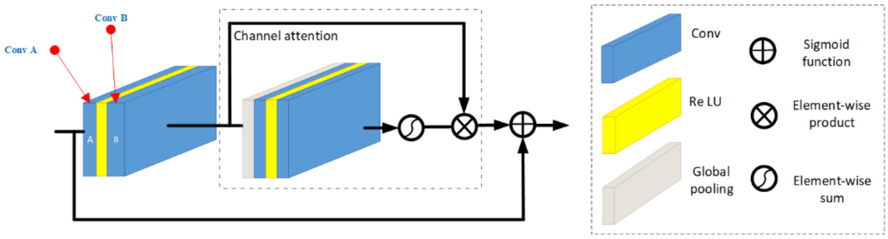
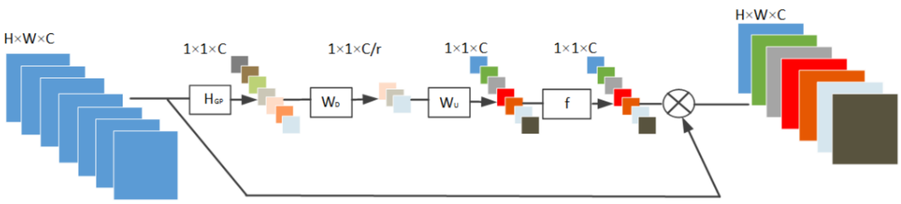


Figure 5: RCAN [14] Architecture



a) Residual Channel Attention Block



b) Channel Attention Mechanism

Figure 6: a) Residual Channel Attention Block b) Channel Attention Mechanism in RCAN [14] architecture

2.4: Second Order Channel Attention Network (SAN)

The Second Order Channel Attention (SAN) Network [15] introduces a sophisticated method aimed at enhancing the performance of deep learning models in SISR tasks through an advanced channel attention mechanism. This approach sets itself apart by utilizing second-order statistics of features, as opposed to relying solely on first-order features. By leveraging these second-order statistics, SAN can achieve a more nuanced and effective attention mechanism, thereby improving its ability to focus on important features while reconstructing images.

A key feature of the SAN Network is its emphasis on second-order statistics, which captures the relationships between different feature channels rather than just their individual contributions. Traditional attention mechanisms typically focus on first-order statistics, such as the mean or sum of features, which may overlook important interactions between channels. By incorporating second-order statistics like covariance, the SAN Network enables a deeper understanding of channel interactions, allowing it to identify which channels are most critical for reconstruction based on their dependencies. This enhanced channel relationship analysis ensures that channels are assigned more meaningful weights, significantly improving the retrieval of rich information from the input data.

Moreover, the SAN Network demonstrates improved reconstruction performance by enhancing critical image details and overall fidelity in reconstructed outputs. Preserving fine textures is particularly vital for SISR, and the implementation of second-order statistics effectively addresses this need. Additionally, SAN can be integrated with spatial attention mechanisms, allowing it to focus on both "where" and "what" aspects of feature maps, thereby further enhancing model performance. Despite the complexity introduced by second-order attention, SAN maintains computational efficiency, making it a practical choice for deep learning applications. Research indicates notable improvements in performance on various benchmark datasets, reinforcing SAN's value as a robust technique for image super-resolution and other computer vision tasks. Fig.7 presents the structure of the SAN Network.

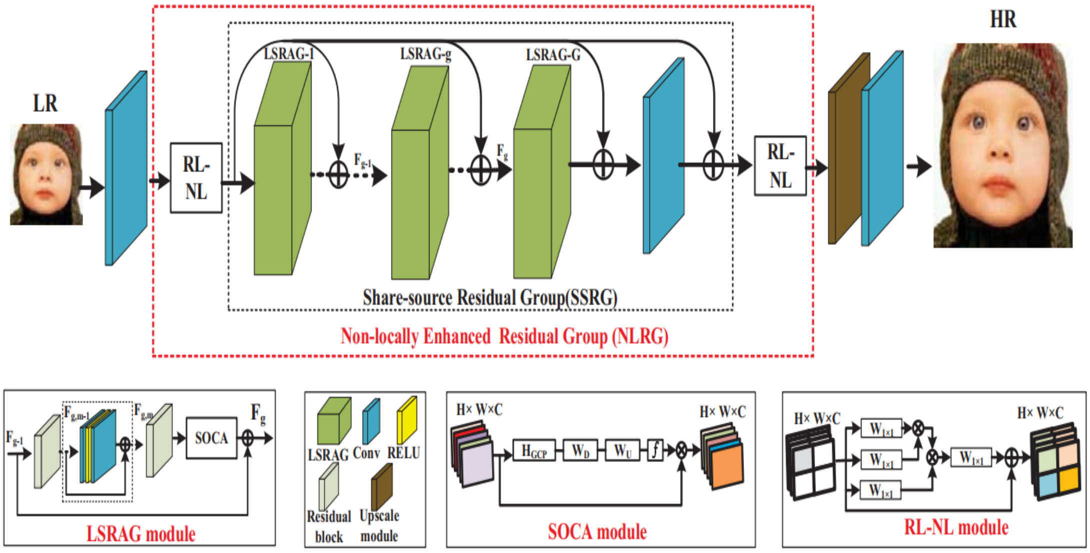


Figure 7: SAN Architecture [15]

2.5 Holistic Channel Attention Network (HAN)

The Holistic Channel Attention Network (HAN) [16] is engineered to enhance performance in Single Image Super Resolution (SISR) by employing holistic attention mechanisms that effectively capture both channel-wise and spatial correlations. This innovative approach provides a more comprehensive understanding of feature significance, ultimately resulting in higher-quality image reconstruction. By integrating both spatial and channel attention into a unified framework, HAN allows the network to weigh features based on their relevance in both domains, leading to a more nuanced interpretation of the entire feature map.

A key feature of the Holistic Channel Attention Network is its adaptive feature representation, which allows the network to dynamically adjust its focus on different features within the input data. This capability is crucial as it enables the model to prioritize regions of the image that are most important for reconstruction while reducing the impact of less significant information. By emphasizing these critical areas, HAN can effectively capture fine details that are vital for generating high-resolution images. This adaptability leads to substantial improvements in SISR tasks compared to traditional models, as the network can better understand and utilize the intricate relationships between features.

Furthermore, HAN excels at capturing correlations across both channel and spatial dimensions, which enables it to leverage richer feature representations. This comprehensive understanding of the input data not only enhances the fidelity of the reconstructed images but also improves their perceptual quality, resulting in outputs that are more visually appealing and accurate. Despite the complexity of its attention mechanisms, HAN is designed with computational efficiency in mind, facilitating faster training and inference times. This efficiency makes HAN a practical option for real-world applications where quick processing is essential.

Evaluations conducted on various benchmark datasets have consistently demonstrated HAN's superiority over several state-of-the-art methods, particularly in terms of Peak Signal-to-Noise Ratio and Structural Similarity Index. Its holistic approach to integrating channel and spatial attention mechanisms significantly advances SISR techniques, establishing HAN as a valuable asset in the field of image processing. Fig. 8 illustrates the structure of the HAN architecture, providing a visual representation of its innovative design.

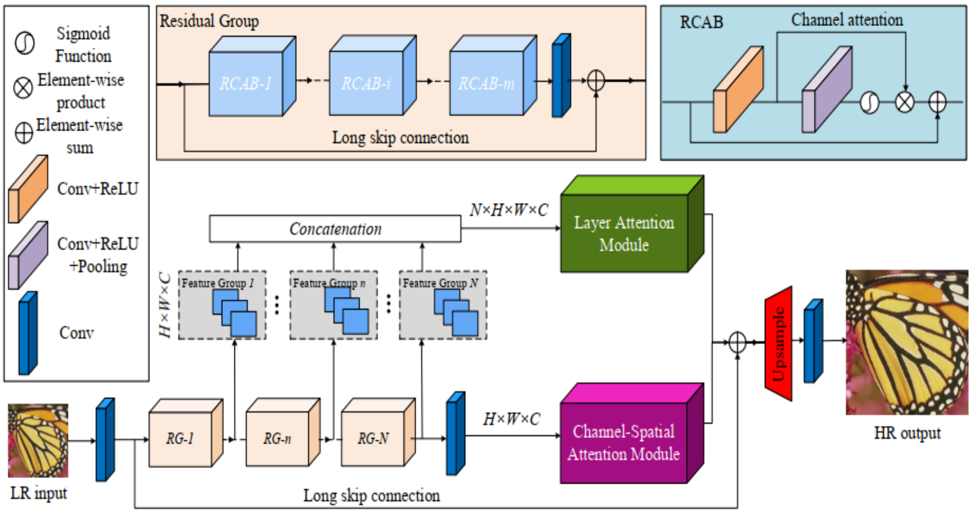


Figure 8: HAN [16] Architecture

2.6: Pyramid Attention Network (PAN)

The Pyramid Attention Network (PAN)[16] is an advanced architecture specifically designed to improve performance in various vision tasks, with a strong emphasis on image super-resolution. One of its key innovations is the incorporation of a multi-scale attention mechanism that allows the model to effectively capture and leverage contextual information from images at multiple resolutions. By utilizing a pyramid structure, PAN is able to concentrate on crucial features across different scales, leading to a more holistic understanding of the input images. This multi-layered approach not only enriches the feature extraction process but also aids in recognizing patterns that may be too subtle to discern at a single scale.

A notable aspect of PAN's functionality is its adaptive emphasis on relevant features, which is achieved through an effective channel attention mechanism. This mechanism dynamically assigns different importance levels to various feature channels based on their relevance to the specific task of image reconstruction. In doing so, PAN ensures that critical information is highlighted while suppressing less important features. This targeted attention significantly enhances the network's capability to reconstruct high-resolution images from their low-resolution versions, resulting in outputs that are more precise and detailed.

Building on the strengths of PAN, the Pyramid Attention EDSR (PA-EDSR) further integrates pyramid attention within the EDSR architecture, enhancing the original design’s ability to manage features at multiple levels of detail. This combination allows PA-EDSR to harness the benefits of pyramid attention while maintaining the powerful residual learning framework of EDSR. As a result, PA-EDSR achieves even greater improvements in image fidelity and perceptual quality during the super-resolution process. Fig. 9 illustrates the structure of the PA-EDSR model, showcasing how pyramid attention is effectively integrated into the EDSR framework for enhanced performance in image super-resolution tasks.

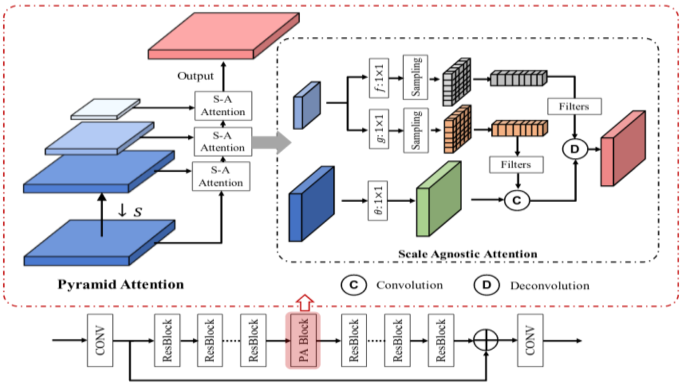


Figure 9: PAN [16] Structure for EDSR (PA-EDSR)

2.7: Residual Parallel Channel Attention Network (RPCAN)

Residual Parallel Channel Attention Network (RPCAN) [17], is a novel approach to SISR that enhances the traditional channel attention mechanism. Unlike conventional methods that rely solely on global average pooling to determine channel importance, RPCAN introduces a dual criterion by incorporating both the average and contrast of each channel. This innovative design allows the model to effectively focus on channels that contain significant textural information, which is crucial for reconstructing high-resolution images. The architecture features a parallel channel attention mechanism, enabling the network to weigh channels adaptively based on their contribution to image quality.

This research underscores the crucial role of channel attention in achieving better results in SISR and stresses the importance of computationally efficient methods. By incorporating a contrast measurement in addition to the average, RPCAN effectively improves the depiction of subtle details in super-resolution applications, all while keeping the increase in model parameters at a reasonable level. Findings reveal that RPCAN not only boosts quantitative performance indicators but also improves the visual quality of the images. Fig. 10 illustrates the structure of the Residual Parallel Channel Attention Block that was used in RPCAN architecture.

This method has shown significant advancements compared to the RCAN method, leading to improved outcomes in addressing functional defects in images. In particular, it enhances visual quality by rendering edges more distinctly and preserving intricate textures more effectively. By focusing on the details and nuances present in the images, the method not only rectifies flaws but also contributes to a more refined and lifelike representation of visual content. The enhancements in edges ensure that boundaries are sharper, which is crucial for maintaining the integrity of objects within the image. Additionally, the method's ability to accurately depict textured areas means that surfaces appear more realistic and engaging, which is particularly important in applications where visual fidelity is critical, such as medical imaging, satellite imagery, and photography. Overall, this approach results in images that are not only functionally improved but also visually appealing, making it a valuable tool in various image processing tasks.

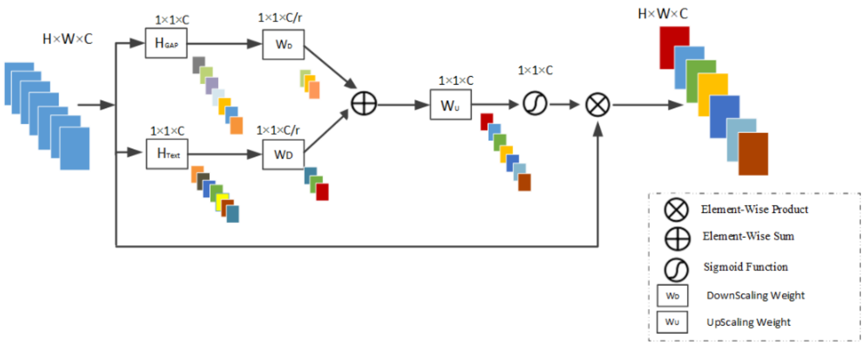


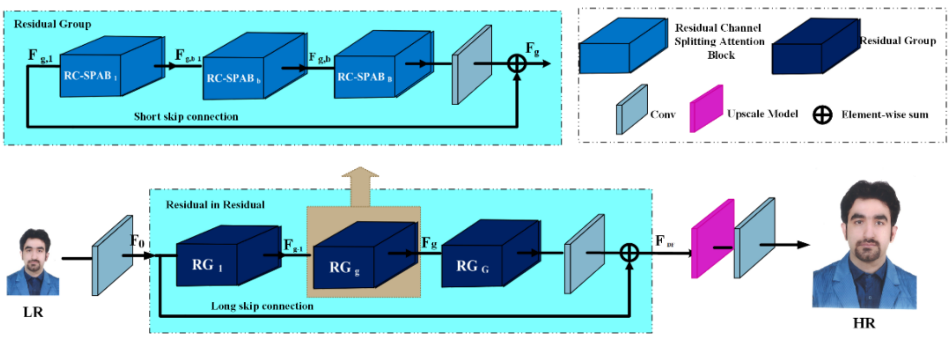
Figure 10: Parallel Channel Attention Block in RPCAN [17]

2.8: Residual Channel Splitting Attention Network (RC-SPAN)

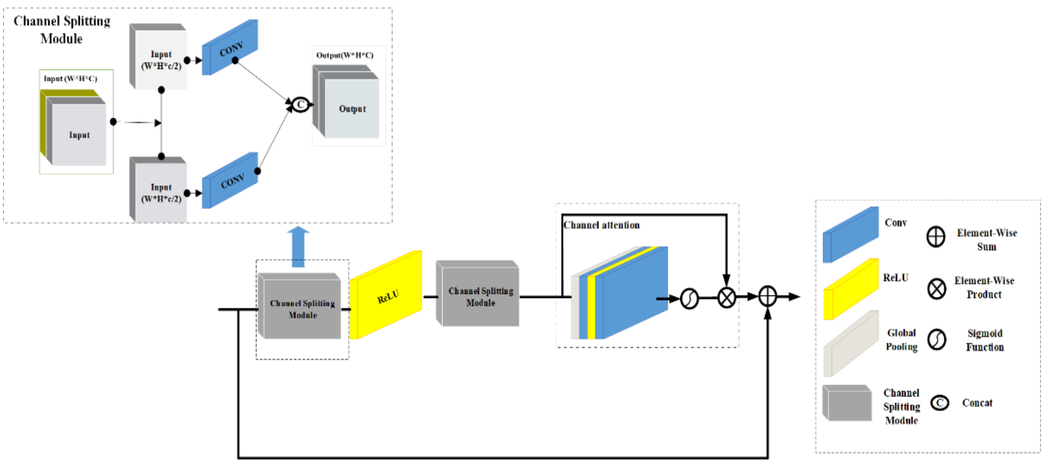
Recent developments in deep learning for SISR have concentrated on minimizing computational complexity while ensuring high-quality results. A variety of strategies have been introduced to decrease the number of network parameters, resulting in faster inference times and improved memory efficiency, as well as enhanced generalization capabilities. One effective approach involves channel splitting, which enables independent processing of input segments before they are recombined. The RC-SPAN model [18] significantly reduces parameter counts while maintaining the original input dimensionality, thereby fostering the creation of more resource-efficient SISR architectures.

Although there are existing methods to optimize SISR frameworks, the specific application of channel splitting for parallel processing within super-resolution tasks remains relatively underexplored, as illustrated in Fig. 11. Most current research primarily focuses on other aspects of model efficiency, such as pruning and quantization. Therefore, further investigation into channel segmentation techniques is necessary to effectively balance model complexity with output quality. This area presents exciting opportunities not only for super-resolution but also for related image enhancement tasks like denoising and deblurring.

The proposed method modifies the traditional structure of the channel attention module by dividing it into multiple branches while simultaneously reducing the overall parameter count. This approach achieves satisfactory results without a significant decline in performance or visual quality metrics. It effectively maintains robust attention mechanisms while enhancing efficiency, demonstrating that a streamlined design can still deliver strong image processing performance. Fig.11 illustrates the various components of the RC-SPAN architecture, showcasing both the standard design and a modified structure that includes the RC-SPAB and the Channel Splitting Module. This alternative design improves information flow management within the network and reduces the number of network parameters by approximately 47.5 percent.



a) RC-SPAN Model



b) Residual Channel Splitting Attention Block (RC-SPAB) and Channel Splitting Module

Figure 11: Structure of RC-SPAN [18] a) RC-SPAN Model b) RC-SPAB and Channel Splitting Module

2.2.9 Residual Parallel Channel Splitting Attention Network (RPC-SPAN)

The Residual Parallel Channel Splitting Attention Network (RPC-SPAN)[19] presents an innovative method for image super-resolution by incorporating the Parallel Channel Attention (PCA) mechanism into the existing Residual Channel Split Attention Network (RC-SPAN) framework. This integration significantly enhances the network's capability to prioritize crucial features while effectively balancing the contributions from various channels. As a result, this leads to improved image quality and better preservation of details during the reconstruction process.

As illustrated in Fig. 12, the RPC-SPAB architecture features two attention mechanisms that evaluate the importance of each channel based on both contrast and average values, which facilitates superior texture representation in the reconstructed images. Additionally, the incorporation of the channel attention mechanism in this network helps to reduce the overall number of parameters. RPC-SPAN has shown substantial performance improvements compared to existing methods, achieving elevated metrics such as PSNR, SSIM, and PI.

These results underscore the model's effectiveness in enhancing image fidelity while maintaining a smaller parameter footprint, showcasing RPC-SPAN as a proficient solution for image super-resolution tasks that balances performance with computational efficiency. Performance analysis based on PSNR and the number of parameters for the Urban 100 database at scale 4 is presented in Fig 13.

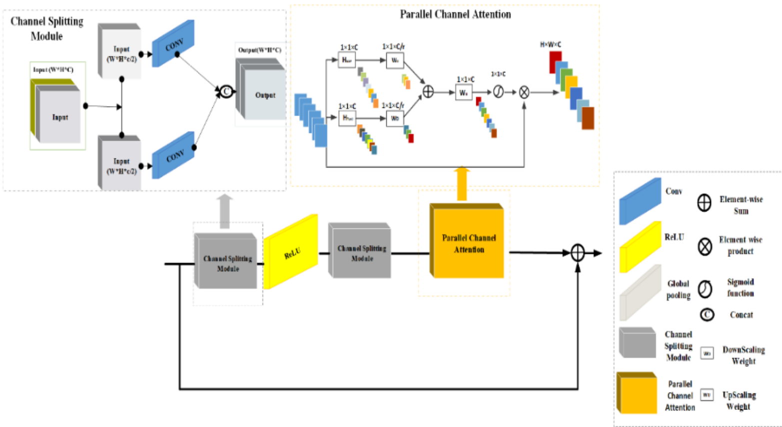


Figure 12: Residual Parallel Channel Splitting Attention Block [19]

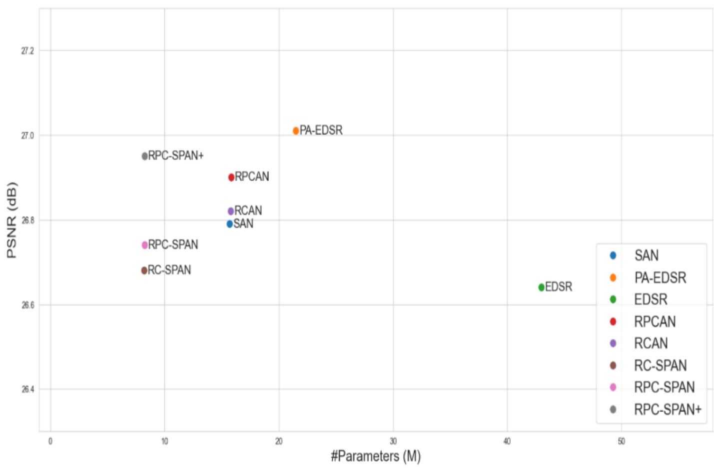


Figure 13: Performance analysis of different SISR methods

3. Performance Metrics

Performance evaluation is essential for determining the effectiveness of various single-image super-resolution models [20-23]. Key metrics collectively assess both fidelity and visual quality, with the most important ones highlighted in Fig. 14. More details are provided below:

- **PSNR (Peak Signal-to-Noise Ratio)**: This metric measures the maximum error between the original and reconstructed images, expressed in decibels (dB). Higher PSNR values indicate better quality, signifying reduced distortion.

- **SSIM (Structural Similarity Index Measure)**: SSIM assesses images by analyzing perceived changes in luminance, contrast, and structure, providing a metric that aligns closely with human visual perception and sheds light on image degradation.

- **LPIPS (Learned Perceptual Image Patch Similarity)**: This perceptual metric evaluates the similarity between images using features derived from deep learning. It employs neural networks trained on human evaluations of image similarity, offering a finer understanding of visual quality that corresponds better to human perception than traditional pixel-based metrics.

- **PI (Perception Index)**: This index helps evaluate how well super-resolved images resonate with human viewers by analyzing perceptual differences.

- **MSE (Mean Squared Error)**: A conventional metric that calculates the average squared difference between predicted and actual pixel values, where lower values indicate a closer alignment.

- **L2 Norm**: This metric quantifies the Euclidean distance between the pixel values of the original and generated images, providing a numerical representation of distortion.

- **Cross-Correlation**: This metric assesses the correlation between the original and super-resolved images, allowing for an understanding of how well image structures are maintained.

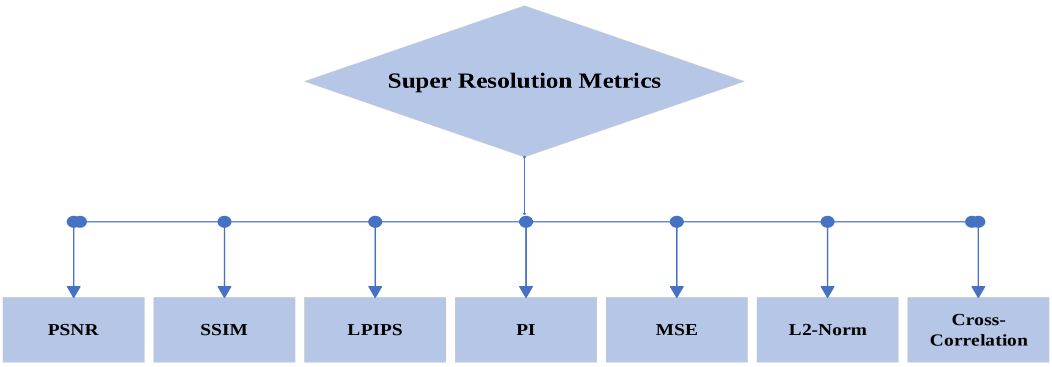


Figure 14: Super Resolution Metrics

4. Limitations and Challenges

While channel attention mechanisms have significantly improved the quality of SISR, they present several limitations and challenges. One major issue is increased computational complexity, which can result in longer inference times and higher energy consumption, particularly in real-time applications. Additionally, the incorporation of attention layers complicates the model architecture, making training and tuning more difficult and potentially leading to overfitting. Moreover, the performance gains achieved through these mechanisms may exhibit diminishing returns, raising concerns about resource utilization [24].

Sensitivity to parameter initialization can hinder convergence and optimal performance, while limited generalization capabilities may arise if models are overfitted to specific datasets, restricting their adaptability to diverse image types. Furthermore, the interpretability of models utilizing attention can be compromised, making it challenging to understand their decision-making processes. The need for high-quality, diverse training data is essential to fully leverage attention mechanisms, and practical implementation can pose challenges for practitioners without deep expertise in the intricacies of these advanced techniques. Addressing these issues through ongoing research is critical for enhancing the efficacy and applicability of channel attention mechanisms in SISR [25, 26].

5-Conclusion and Future Work

The incorporation of channel attention mechanisms has spurred a notable advancement in single-image super-resolution, marking a significant improvement in image processing capabilities. Architectures such as RPCAN, RC-SPAN, and RPC-SPAN showcase considerable progress in tackling the inherent difficulties of SISR. RPCAN stands out by refining the conventional channel attention approach, utilizing both the average and contrast metrics of each channel to more effectively emphasize channels containing vital textural details for high-resolution image reconstruction. RC-SPAN, conversely, addresses computational demands by segmenting input channels and processing them in isolation, thereby decreasing the number of network parameters and boosting efficiency without sacrificing overall performance. RPC-SPAN further expands upon these improvements by merging the Parallel Channel Attention (PCA) mechanism into the RC-SPAN structure, enhancing the network's aptitude to prioritize key features while balancing the contributions from various channels. Despite the achievements of these models, ongoing challenges related to computational efficiency, interpretability, and generalization underscore the necessity for continuous innovation. The progression of SISR depends on resolving these constraints and investigating fresh paths for advancement.

Promising future research directions include combining attention mechanisms to integrate channel and spatial awareness for a more holistic understanding of features, creating efficient, lightweight designs to facilitate real-time applications on devices with limited resources, and employing unsupervised and self-supervised learning techniques to lessen the reliance on extensive labeled datasets. Moreover, drawing inspiration from other domains like natural language processing especially the adaptation of Transformer-based self-attention, and utilizing neural architecture search to discover optimized attention architectures offer the potential for significant breakthroughs.

By actively engaging in these research avenues, the domain of channel attention in SISR is well-positioned to expand its influence across a wide range of practical applications, encompassing fields like medical imaging, surveillance systems, and digital photography. Adopting these forward-thinking strategies will be crucial in unlocking the full capabilities of SISR, satisfying the evolving requirements of emerging technologies, and ultimately producing more visually appealing and practically valuable high-resolution imagery. [27-29]

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CONFLICT OF INTEREST STATEMENT

The authors declare no competing interests.

Ethical approval It is approved

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