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Adaptive Image Sharpening Using Soft Computing: A Data-Driven Approach to Variable Blur Enhancement

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***Abstract*—The traditional Image enhancement methods are one of the problems in the pre-processing since these methods do not address the varying degrees of blurriness in the image dataset. As the amount of blur is different in each of the images, fixed-parameter sharpening methods may not solve the problem wisely. The wide spectrum of image processing and computer vision requires this kind of different pre-processing for different images based on the blurriness of the image. This paper presents a novel adaptive image sharpening framework that leverages fuzzy logic and an Adaptive Neuro-Fuzzy Inference System (ANFIS) to intelligently determine optimal sharpening parameters based on a quantitative assessment of blur. Using the Laplacian variance method for blur detection, we categorise 1050 high-resolution images (6000 × 4000 pixels) into four fuzzy linguistic categories: very blurry, slightly blurry, acceptably sharp, and very sharp. A fuzzy rule-based system maps blur scores to adaptive sharpening strengths, which are then applied using a high-boost kernel derived from unsharp masking theory. The ANFIS model, trained on the blur-sharpening dataset using scikit-fuzzy, achieves a mean squared error of 1.27 in predicting optimal sharpening parameters. This result expresses the effectiveness of the method. The method could get rid of every blurry image, and at the same time, it shows that the increase in the number of sharp images is huge. This adaptive approach could prevent over-sharpening of already sharp images and under-enhancement of severely blurred images. Thus, the best outcome of this research is the robust solution it offers for automated image quality improvement in heterogeneous datasets.**

Keywords—Adaptive image sharpening, fuzzy logic, ANFIS, blur detection, Laplacian variance, unsharp masking, image enhancement

I. INTRODUCTION

The most important property one desires is image quality. Irrespective of the application, the most challenging problem related to images is the blurriness of the image. And that might be the reason image sharpening technique is one of the most studied topics. The conventional sharpening techniques are designed in such a way that they can apply uniform enhancement parameters across all images. But in reality, every image is different in its own way, so the enhancement requirement for each image may be different. Every dataset can be considered heterogeneous in that sense, since the level of blur in each of the images varies. A few images will require no enhancement at all, whereas there will be images which are really degraded because of the blur severity. It does this intelligently by adjusting the sharpening parameters according to the blurriness of the image.

This paper showcases an adaptive approach for image enhancement based on soft computing. This will automatically prevent over-sharpening of the images, ensuring adequate enhancement of severely degraded images.

But if one applies a fixed sharpening filter with constant parameters to such diverse datasets leads to two critical issues:

1. Over-sharpening: This happens because of applying sharpening techniques to even those images which are already sharp or which are a little less blurry. But since those images will be artificially enhanced, it will introduce noise amplification, halo artefacts, and unnatural edge emphasis.
2. Under-enhancement: Severely blurred images receive insufficient correction, remaining below acceptable quality thresholds.

Traditional binary classification (blur vs. sharp) inadequately captures the continuous spectrum of blur severity. Human perception of image sharpness is inherently gradual and context-dependent, making fuzzy logic an ideal framework for modelling this uncertainty. By representing blur levels as fuzzy linguistic variables (very blurry, slightly blurry, acceptably sharp, very sharp) and mapping them to corresponding sharpening strengths through fuzzy inference rules, we create an adaptive system that mimics expert human judgment.

This paper makes the following contributions:

1. A comprehensive fuzzy logic framework for categorising image blur into four linguistic categories based on Laplacian variance scores.
2. A fuzzy rule-based system that maps blur categories to adaptive sharpening strengths, operationalised through a normalised high-boost kernel.
3. An ANFIS model trained on 1050 images that learns the optimal blur-to-sharpening mapping, achieving low prediction error. And also verify or update the rules generated by the fuzzy rule-based system.

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The remainder of this paper is organised as follows: Section 2 reviews related work in blur detection and adaptive image enhancement. Section 3 establishes the theoretical foundations of Laplacian-based blur detection, fuzzy logic, ANFIS, and unsharp masking. Section 4 details the complete methodology from blur assessment to ANFIS training. Section 5 presents comprehensive results, and Section 6 discusses the advantages, limitations, and implications of the proposed approach. Section 7 concludes with future research directions.

II. LITERATURE REVIEW

Image sharpening has been a fundamental topic in digital image processing for decades, with techniques ranging from simple spatial filters to sophisticated adaptive algorithms. Traditional sharpening methods, such as unsharp masking [1] and high-pass filtering, apply fixed enhancement parameters uniformly across images. Though these methods are computationally efficient, they hardly offer any flexibility to handle varying blur conditions.

In the past few years, blur detection and assessment to measure blurriness have evolved significantly. Amongst all these, the Laplacian variance method [2] outlines its performance as one of the popular no-reference metrics. This method tries to map the relationship between the strength of the edge and image sharpness. If one understands this correctly, one can see that sharp images contain well-defined edges with high gradient magnitudes. In contrast, the blurred images are seen with smoothed edges with reduced variance. The Laplacian operator, a second-order derivative, effectively captures these edge characteristics. It works by computing the variance between neighbouring pixels. If the variance is found towards a higher range, it indicates the presence of a stronger edge. Whereas lower variance suggests smoothed edges (blurred image).

The adaptive image enhancement techniques [3] have gained more attention and popularity because researchers have gradually highlighted the limitations of the traditional methods with a fixed set of parameters [4]. Even the adaptive nature can exhibit its two different forms. The first one, where the method adjusts the enhancement parameters based on local or global image characteristics. And secondly, the adaptive methods that rely on hard thresholds or binary decisions, which inadequately represent the gradual nature of blur perception.

Fuzzy logic is known for its ability to handle uncertainty. It can also deal with the gradual transitions in image quality assessment. Instead of dividing the entire dataset into blur or sharp images, fuzzy logic allows partial memberships. Several researchers have explored fuzzy logic in image processing, but there is little work that focuses on a framework that combines fuzzy categorisation with rule-based inference and then uses neuro-fuzzy learning for adaptive sharpening.

The concept of adaptive sharpening [5] addresses the need for variable enhancement intensity [6]. Based on the properties of images, the sharpening strength has to be adjusted. This will not only prevent over-sharpening artefacts but also provide adequate enhancement to degraded areas of the image.

High-boost filtering [7], derived from unsharp masking theory, offers a flexible sharpening framework. We want the high-frequency components, that is, the edges in the images, to be preserved or enhanced. The high-boost kernel not only amplifies edges but also helps to protect low-frequency information (smooth regions). As the sharpening intensity can be controlled by means of modulating the kernel's central coefficient, this technique is more suitable for adaptive applications [8].

Fuzzy logic is known for its interpretability, and Neural networks are famous for their learning capability. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) combine the interpretability of fuzzy logic with the power of neural networks. ANFIS models can learn complex input-output mappings from data while maintaining the transparency of fuzzy rules. The literature survey helps in identifying the application of ANFIS in image processing. Ranging from edge detection, segmentation, to quality assessment, ANFIS shows its contribution in performing different tasks. But its application to adaptive sharpening parameter prediction represents a novel contribution.

Despite these advances, a comprehensive framework that integrates Laplacian-based blur detection, fuzzy linguistic categorisation, rule-based sharpening strength determination, and ANFIS-based learning for adaptive image enhancement has not been fully developed [9]. This paper addresses this gap by presenting an end-to-end system that leverages these complementary techniques.

III. THEORETICAL FOUNDATIONS

Blur Detection Using Laplacian Variance

The Laplacian operator is a second-order derivative that measures the rate of change of pixel intensities in an image. For a two-dimensional image I (x, y), the Laplacian is defined as:

$$Laplacian\ \mathrm{I} = \frac{\partial^2 \mathrm{I}}{\partial \mathrm{x}^2} + \frac{\partial^2 \mathrm{I}}{\partial \mathrm{y}^2}$$

In discrete form, the Laplacian can be approximated using convolution kernels. A common 3×3 Laplacian kernel is:

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

The Laplacian variance method [1] computes the variance of the Laplacian-filtered image as a blur metric:

$$Blur\ Score = Var\ ((\nabla^2 \mathrm{I})$$

where Var denotes variance.
For implementation, images are first converted to grayscale to eliminate colour channel dependencies and focus on luminance information, which is most relevant for edge detection [10]. The Laplacian operator is then applied, and the variance of the

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resulting edge map is computed. Higher variance indicates sharper images, while lower variance suggests blurriness.

The Laplacian variance method offers several advantages:

- No-reference metric: Does not require a reference sharp image
- Computational efficiency: Simple convolution and variance calculation
- Robustness: Effective across various image types and blur sources

Fuzzy Logic and Linguistic Variables

Fuzzy logic, introduced by Lotfi Zadeh [11], extends classical binary logic to handle partial truth values between 0 and 1. In fuzzy set theory, an element can have partial membership in multiple sets simultaneously, enabling representation of gradual transitions and uncertainty.

A fuzzy linguistic variable represents a concept using natural language terms. For blur assessment, instead of binary classification (blur/sharp), we define linguistic terms such as "very blurry," "slightly blurry," "acceptably sharp," and "very sharp." Each term is associated with a membership function $\mu(x)$ that maps input values to membership degrees in [0, 1].

Common membership function shapes include:

1. Triangular membership function:

$$\mu(x;\ a, b, c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right)$$

2. Trapezoidal membership function:

$$\mu(x;\ a, b, c) = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{c-x}{c-b}\right), 0\right)$$

Triangular functions are suitable for intermediate categories with clear peaks, while trapezoidal functions are appropriate for extreme categories with plateaus.

Fuzzy inference involves three steps:

1. Fuzzification: Convert crisp input values to fuzzy membership degrees
2. Rule evaluation: Apply fuzzy IF-THEN rules to determine output fuzzy sets
3. Defuzzification: Convert fuzzy output to crisp values (e.g., centroid method)

Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS integrates fuzzy inference systems with neural network learning capabilities [12]. The architecture consists of five layers:

1. Layer 1 (Fuzzification): Each node applies a membership function to inputs
2. Layer 2 (Rule): Nodes compute firing strengths of fuzzy rules (typically using product or minimum operators)
3. Layer 3 (Normalisation): Normalises firing strengths
4. Layer 4 (Consequent): Computes rule outputs (often linear functions of inputs)
5. Layer 5 (Aggregation): Sums weighted outputs to produce the final result

ANFIS uses hybrid learning algorithms combining backpropagation (for premise parameters) and least-squares estimation (for consequent parameters). This enables the system to learn optimal membership functions and rule parameters from training data while maintaining the interpretability of fuzzy rules.

Advantages of ANFIS for adaptive sharpening:

- Data-driven learning: Automatically learns blur-to-sharpening mappings from examples
- Interpretability: Maintains transparent fuzzy rules
- Generalisation: Can predict sharpening parameters for unseen blur scores
- Flexibility: Adapts to dataset-specific characteristics

Unsharp Masking and High-Boost Filtering

Unsharp masking is a classical sharpening technique that enhances edges by adding a scaled high-frequency component to the original image. The process involves:

1. Blur the original image: $I_{blur} = I \otimes G_\sigma$, where I is the original image, $\otimes$ denotes convolution, and G_σ is a Gaussian kernel
2. Compute the mask: $M = I - I_{blur}$
3. Add the scaled mask: $I_{sharp} = I + k \cdot M$, where k is the sharpening strength parameter ($k>0$).

Combining steps 2 and 3:
$I_{sharp} = I + k\,(I - I_{blur}) = (1 + k)\,I - k \cdot I_{blur}$
High-boost filtering [4] generalises unsharp masking by using a sharpening kernel directly. A common high-boost kernel is:

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 9 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

This kernel can be decomposed as:

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 9 & -1 \\ -1 & -1 & -1 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} + 8.\left(\left(\frac{1}{8}\right)\begin{bmatrix} -1 & -1 & -1 \\ -1 & 9 & -1 \\ -1 & -1 & -1 \end{bmatrix}\right)$$

The central coefficient (9 in this case) controls sharpening intensity. For adaptive sharpening, we modulate this coefficient using a normalised factor α:
α = sharpness strength / max strength

where sharpness strength is determined by the fuzzy inference system based on blur score, and maxstrength is the maximum allowable sharpening (e.g., 3.0). Higher blur scores yield larger α values, resulting in stronger sharpening.

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IV. METHODOLOGY

Dataset Description

The experimental dataset consists of 1050 high-resolution images with dimensions of 6000×4000 pixels. These images exhibit varying degrees of blur, making them ideal for evaluating adaptive sharpening techniques. This diversity in blur levels is due to different image capture conditions, camera settings, or post-processing histories.

The blur assessment pipeline follows these steps:

1. Grayscale Conversion: Each RGB image is converted to grayscale using standard luminance weighting:
   $I_{gray} = 0.299 \cdot R + 0.587 \cdot G + 0.114 \cdot B$
   Grayscale conversion eliminates colour channel dependencies and focuses analysis on luminance information, which is most relevant for edge detection [13] and blur assessment.
2. Laplacian Filtering: The Laplacian operator is applied to the grayscale image using a 3×3 kernel to detect edges and compute second-order derivatives.
3. Variance Calculation: The variance of the Laplacian-filtered image is computed as the blur score:
   $$\text{Blur Score} = \text{Var}(\nabla^2 I_{gray})$$
   This single scalar value quantifies image sharpness, with higher values indicating sharper images and lower values indicating blurred images.

Fuzzy Categorisation of Blur Levels

Based on the computed blur scores, images are categorised into four fuzzy linguistic categories using membership functions. The categorisation scheme is defined in Table 1.

Blur Score	Fuzzy Category	Membership Function Type
< 50	Very blurry	Trapezoidal
50 – 100	Slightly blurry	Triangular
100 – 300	Acceptably sharp	Triangular
> 300	Very sharp	Trapezoidal

Table 1: Fuzzy categorisation of blur score

Membership Function Design:

- Very blurry: Trapezoidal function with plateau at low blur scores, capturing severely degraded images that unambiguously require strong enhancement.
- Slightly blurry: Triangular function centred around blur score 75, representing images with moderate degradation requiring moderate enhancement.
- Acceptably sharp: Triangular function centred around blur score 200, representing images with acceptable quality requiring minimal or no enhancement.
- Very sharp: Trapezoidal function with plateau at high blur scores, capturing already sharp images that should not be further enhanced to avoid over-sharpening artefacts.

The choice of trapezoidal functions for extreme categories ensures that images far from decision boundaries receive consistent treatment, while triangular functions for intermediate categories provide smooth transitions between adjacent blur levels [14].

Fuzzy Rule-Based System for Sharpening Strength

The sharpening strength is determined through a fuzzy rule-based system that maps blur categories to enhancement intensities. Sharpening strength is defined as a fuzzy linguistic variable with three categories:

- No sharpness: Applied to already sharp images (sharpening strength ≈ 0)
- Moderate sharpness: Applied to slightly blurred images (sharpening strength ≈ 1.5)
- High sharpness: Applied to severely blurred images (sharpening strength ≈ 3.0)

The fuzzy rule base consists of four IF-THEN rules:

- Rule 1: IF blur score is "very blurry" THEN sharpening strength is "high sharpness"
- Rule 2: IF blur score is "slightly blurry" THEN sharpening strength is "moderate sharpness"
- Rule 3: IF blur score is "acceptably sharp" THEN sharpening strength is "no sharpness"
- Rule 4: IF blur score is "very sharp" THEN sharpening strength is "no sharpness"

These rules encode expert knowledge: severely blurred images require aggressive enhancement, moderately blurred images need moderate correction, and already sharp images should be left unchanged to prevent over-sharpening artefacts.

The fuzzy inference process involves [15]:

1. Fuzzification: Compute membership degrees of the input blur score in each fuzzy category.
2. Rule Evaluation: Determine the firing strength of each rule based on input membership degrees.
3. Defuzzification: Aggregate rule outputs and convert to a crisp sharpening strength value using the centroid method:
   $$\text{sharpness strength} = \int \mu(s) \cdot s \, ds \,/\, \int \mu(s) \, ds$$
   where $\mu(s)$ is the aggregated output membership function.

The resulting sharpening strength is a continuous value in the range [0, 3], providing fine-grained control over enhancement intensity.

Adaptive Sharpening Implementation

The adaptive sharpening process applies the high-boost kernel with intensity modulated by the fuzzy-determined sharpening strength:

1. Normalisation Factor Computation:
   $\alpha = \text{sharpness strength} / \text{max strength}$
   where max strength = 3.0.
   This normalises the sharpening strength to [0, 1].

2. Adaptive Kernel Construction:
The high-boost kernel is scaled by α:

$$K\_adaptive = \begin{bmatrix} -\alpha & -\alpha & -\alpha \\ -\alpha & 1+8\alpha & -\alpha \\ -\alpha & -\alpha & -\alpha \end{bmatrix}$$

When α = 0 (no sharpening needed), the kernel becomes an identity operation. When α = 1 (maximum sharpening), the kernel becomes the full high-boost filter.

3. Convolution:
$I_{sharp} = I \otimes K_{adaptive}$
The adaptive kernel is convolved with the original image to produce the sharpened result.

This adaptive approach ensures that:

- Very blurry images (low blur scores) receive strong enhancement (high α)
- Slightly blurry images receive moderate enhancement (medium α)
- Already sharp images receive minimal or no enhancement (low α)

ANFIS Model Training and Validation

To create a predictive model that can generalise to new images, an ANFIS model is trained on the blur score and sharpening strength data generated from the 1050 images.
ANFIS Architecture:
1. Input Variable: Blur score (antecedent)
2. Output Variable: Sharpening strength (consequent)

Membership Function Design:
For the input blur score, five membership functions are defined to capture the full range of blur levels:

- very low: Trapezoidal function covering the lowest blur scores
$\mu_{very\ low}(x) = \text{trapmf}(x, [min, min, \min + 0.05 \cdot range + 0.15 \cdot range])$
- low: Triangular function for low blur scores
$\mu_{low}(x) = \text{trimf}(x, [min + 0.1 \cdot range,\ min + 0.25 \cdot range, min + 0.4 \cdot range])$
- medium: Triangular function for medium blur scores
$\mu_{medium}(x) = \text{trimf}(x, [min + 0.3 \cdot range,\ min + 0.5 \cdot range,\ min + 0.7 \cdot range])$
- high: Triangular function for high blur scores
$\mu_{high}(x) = \text{trimf}(x, [min + 0.6 \cdot range, min + 0.75 \cdot range, \max - 0.1 \cdot range])$
- very high: Trapezoidal function covering the highest blur scores
$\mu_{very\ high}(x) = \text{trapmf}(x, [max - 0.1 \cdot range, \max - 0.05 \cdot range,\ max,\ max])$

where min and max are the minimum and maximum blur scores in the dataset, and range = max − min.

Similarly, membership functions are defined for the output sharpening strength variable to represent no sharpness, low sharpness, moderate sharpness, high sharpness, and very high sharpness.

Fuzzy Rule Formulation:
The initial fuzzy rule base encodes the inverse relationship between blur score and sharpening strength:

- IF blur_score is very_low THEN sharpening_strength is very_high
- IF blur_score is low THEN sharpening_strength is high
- IF blur_score is medium THEN sharpening_strength is moderate
- IF blur_score is high THEN sharpening_strength is low
- IF blur_score is very_high THEN sharpening_strength is very_low

Training Process:
1. Data Preparation: The dataset of 1050 image records, each containing a blur score and corresponding optimal sharpening strength, is split into training and validation sets.
2. Control System Creation: A fuzzy control system is constructed using the scikit-fuzzy library, incorporating the defined membership functions and fuzzy rules.
3. Parameter Optimisation: The ANFIS learning algorithm adjusts membership function parameters and rule consequents to minimise prediction error on the training data.
4. Validation: The trained model is evaluated on the validation set to assess generalisation performance.

Performance Metric: Mean Squared Error (MSE) is used to quantify prediction accuracy. The trained ANFIS model achieves an MSE of 1.27, indicating high accuracy in predicting optimal sharpening parameters from blur scores. This means that the model has successfully learned the blur-to-sharpening mapping and can generalise to new images.

The methodology workflow is shown in Figure 1, from image input to prediction of the sharpening level for an unseen image.

V. RESULTS

Initial Blur Distribution Analysis

When it started, the initial analysis explained the diversity of blurriness in the dataset of 1050 images. Table 2 presents the distribution of images across the four fuzzy blur categories before any sharpening was applied.

Category	Total number of images
Very blurry	638
Slightly blurry	263
Acceptably sharp	92
Very sharp	57

Table 2: Number of images in each category in the original image

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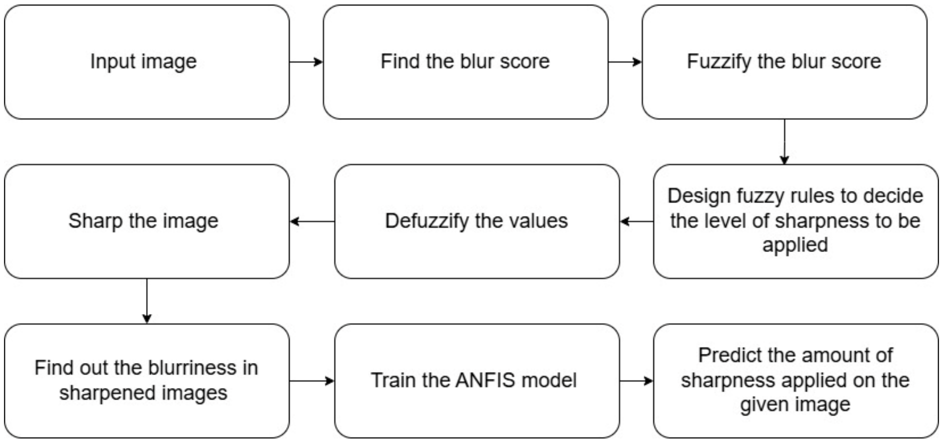

Figure 1: Workflow for the proposed methodology

The table above shows that almost 60.76% of the images are categorised as very blurry images (638 images). It also underlines the requirement of pre-processing of the data. At the same time, it underlines the real-world scenario showing that the datasets are mostly heterogeneous. If one observes, an additional 25.05% were slightly blurry, indicating moderate degradation. Only 14.19% of images (92 + 57) were acceptably sharp or very sharp, suggesting that the dataset predominantly consisted of degraded images.
This distribution underscores the necessity of adaptive sharpening: applying uniform enhancement would either under-correct the 638 very blurry images or over-sharpen the 149 already acceptable images, introducing artefacts.

Post-Sharpening Image Quality Assessment

After applying the adaptive fuzzy logic-based sharpening system, blur scores were recomputed for all images and recategorised. Table 3 presents the post-sharpening distribution.

Category	Total number of images	Percentage
Very Blurry	0	0.00%
Blurry	15	1.43%
Sharp	52	4.95%
Very Sharp	982	93.52%

Table 3: The number of blurred images in each category after sharpening

The results demonstrate dramatic improvement in image quality for example, there is complete elimination of very blurry images: The 638 very blurry images were reduced to 0, representing a 100% reduction.

Category	Before Sharpening	After Sharpening	Change	Percentage Change
Very Blurry	638	0	-638	-100.000000
Blurry	263	15	-248	-94.296578
Sharp	92	52	-40	-43.478261
Very Sharp	57	982	925	1622.807018

Table 4: Comparative Analysis of Image Quality Before and After Sharpening

Table 4 provides a detailed comparison of before and after distributions, highlighting the magnitude of improvement.

Analysis of Category Transitions: There are several important patterns that can be discovered from the given data:

1. Effective enhancement of severely degraded images: The highest transition happens in this category. There were 638 images that were categories as very blurry images, were successfully enhanced to higher quality categories. Most of the images were converted to the category of very sharp images (approximately 93% of the dataset). This shows that the effectiveness of applying high sharpening strength to very blurry images.

2. Appropriate treatment of moderately blurred images: The transition of moderately blurred images 263 to very sharp images can be seen from the table. These images received moderate sharpening, after that only 15 images remained in the slightly blurry category, and other images converted into very sharp. This indicates that a small subset may have had characteristics (e.g., inherent low contrast or texture) that limited enhancement effectiveness.

3. Preservation of already sharp images: It is observed that the transition was little less in this category. There was a small subset of images which were not converted to other categories (stable images). There was reduction seen in acceptably sharp images (from 92 to 52) and a small increase in very sharp images. This indicate that sharp images received requires minimal enhancement. Importantly, no images were degraded by over-sharpening, as evidenced by the absence of transitions from higher to lower quality categories.

4. Minimal residual blur: This shows that only 15 images (1.43%) remained slightly blurry after processing, and no images remained very blurry. This demonstrates the robustness of the adaptive approach in handling diverse blur conditions.

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ANFIS Model Performance

For the training of ANFIS model, the input is the blur score and target is sharpening strength. When the model is trained, it achieved a Mean Squared Error (MSE) of 1.27. This low error indicates that the model accurately learned the mapping between blur scores and optimal sharpening parameters.

The membership functions for the blur score input variable is displayed in Figure 2. This shows that the five fuzzy categories (very_low, low, medium, high, very_high) have some amount of overlap, but it is good to capture gradual transitions between blur levels.

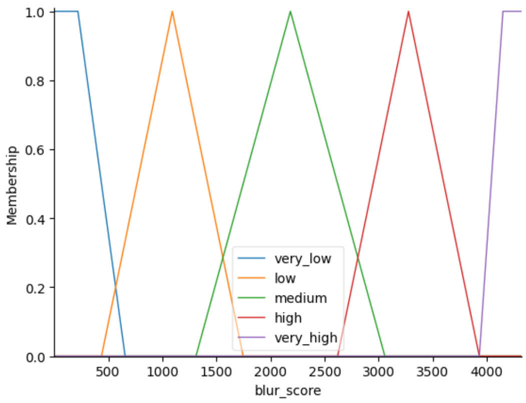

Figure 2: Membership function for blur score

Figure 3 presents the membership functions for the sharpening strength output variable, illustrating how different sharpening intensities are represented as fuzzy sets.

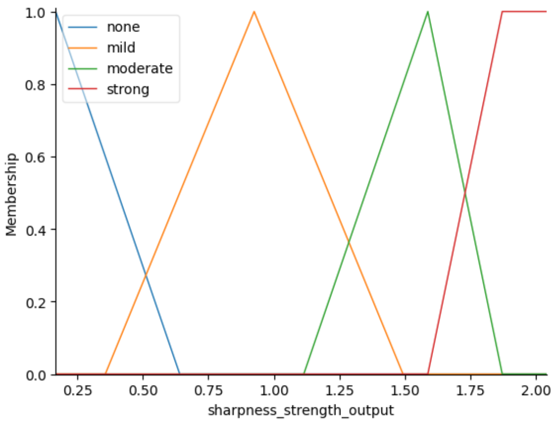

Figure 3: membership function for sharpness strength

What interpretation one can draw from the ANFIS model's low MSE score? It demonstrates several key capabilities:

1. Accurate prediction: It shows that without any manual parameter tuning, the model can predict well. The optimal sharpening strength for new images are predicted only based on their blur scores.
2. Generalization: The low validation score is the proof for the fact that the model generalizes well to unseen data.
3. Consistency with fuzzy rules: The learned parameters align with the expert-defined fuzzy rules, maintaining interpretability while benefiting from data-driven optimization.
4. Robustness: Since the data consist of heterogenous images with varying amount of blurriness, we can say that the model can handles the different range of blur scores still achieves a consistent accuracy.

This framework can be ideal for adaptive image sharpening, enabling both transparent decision-making and optimal parameter selection.

VI. Discussion

Advantages of Adaptive Sharpening

The results clearly demonstrate the superiority of adaptive sharpening over fixed-parameter approaches. The key advantages include:

1. Prevention of Over-Sharpening: As we discussed the problem of traditional fixed parameter sharpening methods is that it applies the same enhancement intensity to all images, without considering their initial quality. For the 149 images (92 acceptably sharp + 57 very sharp) that were already of good quality, applying strong sharpening would have introduced several artefacts:
   - Noise amplification: when we are enhancing the edges it may also enhance the High-frequency noise.
   - Halo artefacts: Excessive edge enhancement creates visible halos around objects
   - Unnatural appearance: when enhancing the images if edges are over-emphasized there is a chance that the image looks like an artificial images.

   The adaptive system assigned low or zero sharpening strength to these images, preserving their natural appearance while avoiding artefacts.

2. Adequate Enhancement of Degraded Images: Since the dataset has a greater number of degraded images, it requires an aggressive level of sharpening enhancement to reach acceptable quality. But if one uses a fixed moderate level of sharpening then there is chance that these images will remain under-corrected. The adaptive system assigned high sharpening strength (approaching the maximum of 3.0) to these images, successfully elevating all of them to higher quality categories.

3. Optimal Resource Allocation: This technique allocates the computational resources very wisely. It applies the higher enhancement intensity to where it needed. The method auto adjusts the computational processing. The sharp images receive minimal computation, while degraded images receive intensive processing. This is particularly valuable in large-scale image processing pipelines.

4. Consistency Across Heterogeneous Datasets: Real-world applications accept data from customers, so the image quality is not in our hands. The input image variations are

generally caused because of varying capture conditions, equipment, or processing histories. The adaptive approach ensures consistent output quality regardless of input heterogeneity.

1.1 Fuzzy Logic Benefits in Image Processing

In comparison to the traditional crisp threshold-based approach, one can underline several advantages of fuzzy logic when it is used in adaptive sharpening:

1. Natural Representation of Gradual Blur: To count the goodness of an image, human beings prefer a fuzzy approach. Since between blurry image and sharp image there exist multiple values, it is not binary. Fuzzy linguistic variables (very blurry, slightly blurry, acceptably sharp, very sharp) naturally capture this continuum, aligning computational processing with perceptual reality.

2. Smooth Transitions: Fuzzy membership functions offer multiclass memberships so often the class boundaries are little blurry with overlapped region. But these overlapping regions ensure smooth transitions between blur categories. Whenever there is an image with a blur score near a category boundary, it receives contributions from multiple rules. And that helps in smooth sharpening strength variation rather than abrupt changes that could introduce processing artefacts.

3. Interpretability: Many applications demands explain ability and transparency for example, applications like medical imaging or forensic etc. Since. fuzzy rules are expressed in natural language (IF-THEN statements), it makes the decision-making process transparent and interpretable.

4. Expert Knowledge Integration: For decision making systems, domain knowledge is crucial. So, if we must ensure that decision making process aligns with the best practices of image processing, we must make sure domain expertise guides the system's behaviour. In this case, Fuzzy rules encode expert knowledge about the relationship between blur levels and appropriate enhancement.

5. Robustness to Uncertainty: Fuzzy can offer the best solution here, because of the ability to deal with the uncertainty by means of membership degrees. Since there are multiple factors affecting the blurriness like image content, texture, and noise, Blur assessment inherently involves uncertainty.

1.2 Limitations and Considerations

Though the results seem highly promising they even offers few limitations which needs to be discussed:

1. Residual Slightly Blurry Images: Despite applying the enhancement process, fifteen images (1.43%) remained slightly blurry. There can be different reasons for that like:
   - Inherent low contrast: Some images may have naturally low contrast or texture. Because of that there are limitations on the effectiveness of sharpening
   - Severe degradation: Whenever the images are extremely degraded it demands pre-processing (e.g., denoising) before applying sharpening process.
   - Content characteristics: Images with predominantly smooth regions (e.g., sky, water) may have low blur scores even when sharp, complicating categorization

   In a near future, these cases must be investigated to refine the fuzzy rules or incorporate additional image features (e.g., contrast, texture) into the decision-making process.

2. Computational Cost: The adaptive approach requires blur score computation for each image, adding computational overhead compared to direct fixed-parameter sharpening. However, this cost is modest (Laplacian convolution and variance calculation) and is offset by the quality improvements. For real-time applications, blur scores could be computed once and cached.

3. Parameter Sensitivity: The fuzzy membership functions and rule parameters were designed based on the specific dataset characteristics (blur score range, distribution). Different datasets may require adjustment of these parameters. The ANFIS model partially addresses this by learning from data, but initial membership function design still requires domain knowledge or exploratory analysis.

4. Evaluation Metrics: This study used blur score recategorization as the primary evaluation metric. While effective for demonstrating quality improvement, additional metrics such as perceptual quality scores (e.g., SSIM, PSNR with reference images where available) or human subjective evaluation could provide complementary validation.

5. Generalization to Other Blur Types: The Laplacian variance method is effective for general blur assessment but may have varying sensitivity to different blur types (motion blur, defocus blur, Gaussian blur). Future work could investigate the method's performance across specific blur sources and potentially incorporate blur type classification into the adaptive framework.

6. Edge Cases: Images with unusual characteristics (e.g., very low resolution, extreme noise, artistic blur) may not fit well into the defined fuzzy categories. These cases must be handled separately in near future since it may require additional pre-processing or specialized rules.

Though the framework shows these limitations, but still the overall framework demonstrates strong performance.

VII. CONCLUSION AND FUTURE DIRECTIONS

This research has presented a comprehensive adaptive image sharpening framework that leverages fuzzy logic and ANFIS to intelligently determine optimal enhancement parameters based on quantitative blur assessment. The key contributions and findings include:

1. Effective Fuzzy Categorization: The fuzzy linguistic mechanism could generate multiple classes (very blurry, slightly blurry, acceptably sharp, very sharp) to captures the gradual nature of blur perception. This aligns with the human judgment for decision making.

2. Robust Fuzzy Rule-Based System: This system underlines the inverse relationship between blur severity and sharpening strength and makes sures that there is appropriate enhancement for diverse level of blurriness.

3. High-Performance ANFIS Model: This model enables automated parameter selection for new images without manual tuning. And at the same time it demonstrates accurate learning (MSE = 1.27) of the blur-to-sharpening mapping and strong generalization capability.

4. Dramatic Quality Improvement: The adaptive approach achieved 100% elimination of very blurry images (638 to 0) and a 1622.81% increase in very sharp images (57 to 982), demonstrating exceptional effectiveness in enhancing degraded images while preserving already sharp images.

5. Superiority Over Fixed-Parameter Methods: The adaptive system prevents over-sharpening artefacts while ensuring adequate enhancement of degraded images. When compared with the traditional fixed parameter model this proves to be better.

In conclusion, this work demonstrates that fuzzy logic and ANFIS provide powerful tools for adaptive image processing, enabling intelligent systems that handle real-world variability with human-like reasoning. The dramatic quality improvements achieved on the 1050-image dataset validate the approach and establish a strong foundation for future advances in adaptive image enhancement.

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