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DEVELOPMENT OF FIRASS: A NOISE-RESILIENT FACIAL IMAGE ENHANCEMENT SYSTEM FOR CUSTOMER EMOTION RECOGNITION

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Abstract

The accuracy of facial emotion recognition systems largely depends on the quality of input images, particularly in interactive customer services where real-time data capture is generally noisy, low in lighting, and resolution-constrained. This paper proposes FIRASS (Facial Image Refinement and Artifact Suppression System) as an integrated pre-processing system that can mitigate these problems by multi-stage facial image denoising and enhancement. FIRASS combines median-Gaussian hybrid denoising, contrast enhancement by CLAHE adaptation, illumination adjustment by Retinex theory, and edge sharpening by unsharp masking. These stages work in concert to slow down visual artifacts while preserving expressive facial features critical for the detection of emotions. Comparative research using typical filters such as median, Gabor, Wiener, and Laplacian indicates that FIRASS produces cleaner and structurally closer-to-reality facial representations. As a result, emotion detection models are provided with input of better quality, improving identification accuracy as well as reliability in real-world customer-facing applications.

Keywords:

Facial Image-Denoising, Emotion-Recognition, FIRASS, Pre-Processing, Artifact-Suppression, Customer Service AI, Contrast Enhancement, Illumination-Correction, Facial-Expression Analysis

1. INTRODUCTION

Facial emotion recognition is now a significant technology in modern customer service systems that enables machines to identify and react to customers' emotions in real-time. This capability enhances user experience, promotes customer satisfaction, and facilitates proactive service actions, especially in smart kiosks, automated helpdesks, and AI-driven customer support systems [14]. Relative to text- or speech-based sentiment analysis, facial expressions are a less mediated, more subconscious method of emotional communication, and they expose information about user states such as frustration, satisfaction, confusion, or interest [25].

But applying strong emotion recognition in real-time customer service environments is a difficult problem. Facial images are typically taken under adverse conditions from low-cost webcams or cell phones with high levels of visual degradation.

Common degradations are Gaussian noise, low resolution, illumination non-uniformity, motion blur, and compression artifacts [13]. They encroach on the visibility of facial features that are high-resolution like eye movement, eyebrow orientation, and lip shape of utmost importance for discriminating between subtle emotional states [2].It is established by research that even sophisticated deep learning architectures are severely vulnerable to such noise, which causes bad generalization and high error rates if fine-tuned with clean data but used on noisy real-world inputs [17].

Being subjected to such limitations, strong facial image preprocessing is an important prerequisite for successful emotion recognition in customer-facing systems. Such preprocessing needs to carry out noise suppression, illumination adjustment, and contrast improvement, all without corrupting the semantic coherence of facial expressions. Specifically, adaptive filtering, local contrast equalization (e.g., CLAHE), and image sharpening have been found successful in restoring expressive clarity to impoverished facial images [5], [23]. Without this preprocessing, even large-capacity CNN or transformer-based models can fail to learn discriminative features out of the input space and thus decline their production potential.

To ensure this, we present the Facial Image Refinement and Artifact Suppression System (FIRASS) a multi-stage preprocessing system that preconditions facial images for emotion recognition using hybrid denoising, color space-based enhancement, edge sharpening, and illumination correction. FIRASS is designed to provide noise-free, contrast-optimized, and structure-preserved facial images that boost the performance of subsequent emotion recognition models adopted in real-world customer service applications.

Success of facial emotion detection, especially for customer service, depends on the quality of visual input. Several preprocessing filters have been introduced and developed to date to mitigate issues like image noise, poor contrast, loss of edges, and nonuniform lighting. Filters are generally classified according to their main function, which includes noise removal, edge enhancement, and illumination normalisation.

2. REVIEW ON EXISTING METHODS

The performance of facial emotion recognition systems significantly relies on the quality of input images, particularly in real-time customer service applications where illumination changes, occlusions, and environmental noise are predominant. Consequently, researchers have put more emphasis on designing sophisticated preprocessing pipelines that enhance image quality through denoising, contrast adjustment, and illumination normalization.

Li et al. [12] developed an adaptive bilateral filtering technique specifically designed for low-resolution facial images, with filter parameters adjusted to image entropy and noise estimates. The technique was found to preserve edge definition very well essential in keeping facial areas responsible for emotional expression.

Ahmed and Khan [1] proposed a preprocessing pipeline that integrated bilateral and median filters to remove various kinds of noises and then carried out gamma correction to normalize image brightness. Using this approach, the performance of emotion detection from noisy inputs was significantly improved, particularly when tested on the FER2013 benchmark dataset.

Zhou et al. [27] suggested converting images into LAB color space so that the luminance component can be separated and it was further improved using Contrast Limited Adaptive Histogram Equalization (CLAHE). It performed effectively to improve contrast without changing chromatic information and hence was appropriate for emotion recognition in real scenarios.

To address the issues of non-uniform lighting, Kaur and Singh [11] utilized a multi-scale Retinex algorithm, which showed to perform well in addressing shadowed and non-uniformly lit face areas. Their system exhibited improved recognition rates, especially in surveillance as well as low-light customer interaction applications.

Reddy et al. [18] tested different preprocessing techniques such as denoising, edge enhancement, and gamma correction on transformer-based emotion recognition models. They observed improved training convergence and reduced misclassification rates in customer service kiosk video streams and indicated the necessity for input normalization to be aggressive.

Wang and Duan [24] investigated the same study aimed at enhancing micro-expressions using unsharp masking in conjunction with a convolutional preprocessing block. Their research demonstrated the significance of minor facial reactions like minute eye and mouth movements in decoding delicate emotional expressions, especially in noisy or blurred conditions.

The recent detailed study conducted by Singh et al. [19] compared single-stage and multi-stage preprocessing techniques in emotion recognition pipelines. Their findings corroborated that the implementation of noise reduction, contrast enhancement, and luminance regulation in sequence performed better than implementing any one individually.

Together, these submissions demonstrate the importance of solid preprocessing methodology in supporting emotion recognition performance in field environments. The Facial Image Refinement and Artifact Suppression System (FIRASS) capitalizes on this by merging several enhancement operations hybrid denoising, contrast enhancement with luminance weighting, illumination compensation, and fine-detail sharpening into a single process better suited for use in customer service applications.

Table.1. Review of the existing methods

Author	Existing Method	Remarks
Li et al. [12]	Adaptive Bilateral Filtering	Focused on edge preservation under low resolution, but not integrated with contrast or lighting correction.
Ahmed and Khan [1]	Bilateral + Median Filtering + Gamma Correction	Improved denoising and brightness control, but lacks illumination normalization and edge enhancement.
Zhou et al. [27]	RGB to LAB Conversion + CLAHE	Enhanced local contrast effectively, but no noise suppression or edge sharpening included.
Kaur and Singh [11]	Multi-Scale Retinex for Illumination Correction	Corrects lighting but doesn't address noise, contrast, or edge clarity.
Reddy et al. [18]	Preprocessing with Denoising + Sharpening + Gamma Correction	Effective for transformers on video frames but lacks unified integration and adaptive tuning.
Wang and Duan [24]	CNN with Unsharp Masking for Micro-Expression Enhancement	Focused on fine feature enhancement, not complete preprocessing for varied environmental noise.
Singh et al. [19]	Comparative Study of Single vs. Multi-Stage Preprocessing Techniques	Identified multi-stage methods as superior but did not propose or implement a unified framework.

3. TYPES OF VARIOUS FILTERS

3.1 DENOISING FILTERS

Denoising is an initial process in facial image preprocessing that targets the elimination of different types of noise added during image acquisition. Such types include Gaussian noise caused by night conditions, impulse noise caused by transmission faults, and background noises in unconstrained scenes.

Denoising filters are employed to remove various forms of noise, including Gaussian, impulse, and compression artifact, without degrading important facial details. The Median Filter is a non-linear one that is very efficient against salt-and-pepper noise and replaces every pixel with the local neighborhood values' median.

Median filter is one of the oldest and most common methods, highly efficient against salt-and-pepper noise while maintaining the facial structure [7]. Nevertheless, it can lose finer textures that are needed to identify emotional micro-expressions. Its equation can be expressed as:

$$I_{\mathrm{med}}(x,y) = \mathrm{median}\{I(i,j) | (i,j) \in N(x,y)\} \tag{1}$$

Conversely, the Gaussian filter, using a weighted average from a Gaussian function, blurs the image well but loses facial edges and soft features [26].

$$G(x,y) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \tag{2}$$

A finer approach, the bilateral filter, takes This allows it to denoise within homogeneous regions without displacing significant facial boundaries thus making it extremely appropriate for emotion-sensitive applications [22].

$$I_{\mathrm{BF}}(x) = \frac{1}{W_p}\sum_{i\in\Omega} G_s(\| x-i \|) G_r(| I(x)-I(i)|) I(i)$$

$$W_p = \sum_{i\in\Omega} G_s(\| x-i \|) G_r(| I(x)-I(i)|) \tag{3}$$

More advanced techniques such as the Non-Local Means (NLM) filter employ pixel patch similarities throughout the image, providing better denoising at the expense of increased computation [3]. Wavelet-based denoising also takes advantage of multiscale decomposition to delineate noise from structural characteristics, and it is appropriate for preserving delicate textures in facial areas [6].

3.2 EDGE ENHANCEMENT FILTERS

Highlighting facial contours is vital to bring out features such as the eyes, lips, and outline more prominently, which are usually employed in emotion classification models.

Unsharp masking is a standard procedure that enhances the sharpness of the image by increasing high-frequency components based on the contrast between the original image and a blurred replica of the image. The procedure is known to vastly enhance the distinctness of facial features without generating distortions [20]. The equation is:

$$I_{\text{sharp}} = I_{\text{orig}} + \lambda\left(I_{\text{orig}} - G_{\sigma} * I_{\text{orig}}\right) \quad (4)$$

High-boost filtering, a form of unsharp masking, provides more control over the enhancement by boosting the original image prior to adding the sharpened portion. The technique works well when handling low-resolution facial pictures or faint emotional expressions [16].

$$I_{\text{HB}} = AI - \left(G_{\sigma} * I\right), \qquad A > 1 \quad (5)$$

The Laplacian filter uses second-order derivatives to identify edges based on intensity changes. While effective in boundary detection, it is highly sensitive to noise and usually paired with smoothing techniques [4].

$$\nabla^2 I(x,y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \quad (6)$$

Additionally, Gabor filters, which are spatially and frequency-selective, have also been used to highlight texture patterns concerning expressions. They particularly excel at extracting directionally sensitive features and are biologically inspired, emulating human visual perception [8].

3.3 ILLUMINATION CORRECTION FILTERS

Real-world customer service application facial images tend to be plagued by uneven lighting, with resulting shadows and highlights and uneven brightness. Facial areas are enhanced in visibility and uniformity by illumination correction methods.

CLAHE (Contrast Limited Adaptive Histogram Equalization) has proven to be a widely used method for local contrast enhancement over image tiles. It is adaptive to various parts of the image and therefore is well-suited for faces photographed in varied lighting conditions [15].

Gamma correction corrects the brightness of an image through a non-linear transformation that will approximate human vision sensitivity. It will restore balance to underexposed or overexposed regions, particularly in live video streams or images taken by mobile devices [10].

$$I_{\gamma}(x,y) = c[I(x,y)]^{\gamma} \quad (7)$$

Retinex-based models, inspired by human color constancy mechanisms, aim to separate reflectance from illumination. Single-Scale Retinex (SSR) provides global correction, while Multi-Scale Retinex (MSR) balances both local and global illumination effects. These techniques are effective in revealing hidden facial details under uneven lighting [9].

$$R(x,y) = \log\left(I(x,y)\right) - \log\left(F(x,y)\right) \quad (3.8)$$

Homomorphic filtering, which operates in the frequency domain, enables simultaneous contrast enhancement and dynamic range compression. This is particularly effective for correcting gradient lighting across the face [21].

4. RESEARCH GAP

In spite of significant progress in facial emotion detection, most notably enabled by the nature of deep learning as well as large-scale annotated datasets, useful nature-kinds deployment in customer service contexts continues to be limited by nature-kinds of unresolved challenges. Fluctuations in illumination conditions, variability in image noise, and variability in image quality tend to impact system performance in real-world deployments in applications like kiosks, customer support chats, and in-store cameras.

While prior studies have suggested different preprocessing methods bilateral filtering, adaptive histogram equalization (CLAHE), Retinex-based illumination normalization, and edge sharpening these techniques are often used in isolation. They are usually tried in controlled experimental conditions and not combined in a full framework that operates on several quality issues at once.

One important drawback in existing methods is the lack of a common and dynamic preprocessing approach to handle multifaceted distortions that may be found in operating conditions. Most of the available solutions are one-dimensional and only solve one kind of degradation and do not consider their cumulative effect on downstream operations such as emotion recognition. The approaches also fail to capture fine details such as micro-expressions that play a pivotal role in the analysis of finer customer responses.

The other key flaw is low generalizability to multiple datasets and acquisition environments. Models trained in optimal conditions fall behind when applied to real images with occlusions (e.g., glasses, masks), compression artifacts, motion blur, or inconsistent frame quality realistic in live customer-facing systems. As a result, facial emotion models receive corrupted input, both impacting prediction accuracy and consistency.

To address these constraints, this work presents the Facial-Image Refinement and Artifact Suppression-System (FIRASS) a multi-modal pre-processing system optimized for use in customer service applications. FIRASS combines hybrid denoising, local contrast enhancement, illumination normalization, and edge enhancement within one pipeline. This combined approach is designed to safely preprocess facial images for emotion detection in unpredictable and varying visual environments, thereby filling a vital deficiency in current facial image pre-processing technology.

5. DATA COLLECTION

The success of any facial image preprocessing method particularly one that is intended to enhance emotion recognition in customer service environments is heavily reliant on the diversity, quality, and realism of data set it employs. Data collection in this study is for the purpose of making sure that the algorithm will be able to generalize effectively in a broad range of realistic scenarios, such as varying light conditions, facial emotions, occlusions, and image resolutions.

In order to mimic customer-facing scenarios, facial image data were gathered and curated from publicly available and ethically approved datasets of spontaneous and posed emotional states under different conditions:

5.1 FER2013

Popular benchmark dataset comprising 35,887 grayscale face images (48×48) of faces expressing seven emotions: anger, disgust, fear, happiness, sadness, surprise, and neutral. Images taken in uncontrolled conditions with added noise and misalignment perfect for preprocessor robustness testing.

5.2 AFFECTNET

A facial expression dataset of a very large size consisting of more than 400,000 manually annotated images for emotion, valence, and arousal. Drawn from the web, AffectNet contains real-world distortions like lighting variation, occlusions, and blur.

5.3 REAL-WORLD KIOSK DATA

If real world images were gathered through kiosk or webcam (e.g., lab simulations), they are labeled with timestamp, emotion label, lighting type (natural/artificial), and device quality. Glasses, masks, or partial occlusions are commonly present in these images.

Fig.1. Sample Data set

6. PROPOSED METHODOLOGY

The Facial Image Refinement and Artifact Suppression System (FIRASS) is a multi-stage, wide-ranging image preprocessing pipeline designed to refine facial image quality by alleviating noise and artifact correction thus optimizing the input for subsequent tasks like emotion recognition, face analysis, and identity verification. FIRASS resolves prevalent issues in facial image acquisition, including Gaussian noise, salt-and-pepper noise, low contrast, illumination change, and blurring caused by hardware or environmental issues.

The initial phase, Hybrid Denoising, unites bilateral filtering and median filtering strengths. The bilateral filter is a non-linear, edge-preserving filter that smooths areas of similar intensity and sharp boundaries, so it is well adapted for facial structures like the outline of the eyes, the mouth, and the nose. Its filtering is based both on spatial neighborhood and photometric similarity as a criterion. Meanwhile, median filtering can successfully eliminate impulse noise without blurring edges, required to maintain the fine skin textures and micro-expressions. Double method ensures processing of structured and unstructured types of noise without degradation of face detail.

Finally, FIRASS performs a color space conversion to LAB, a perceptually uniform color space where luminance (L) is separated from chromatic information (channels A and B). Separation enables precise control of brightness and contrast without warping colors. CLAHE is utilized by the system in the L-channel. CLAHE increases local contrast within context tiles and thus is extremely effective in the circumstances of illumination imbalance e.g., blown-out shadows on the left half of the face or highlights. This operation enhances visibility of low-contrast areas, which tend to preserve emotionally informative details such as wrinkles, crow's feet, or nasolabial folds.

Stage three is Edge Sharpening via unsharp masking, a process that is based on the contrast of an image-blurred version of an image with the original to enhance high-frequency details. This stage focuses on enhancing facial edges and textures that are important for high-level emotion classification. Enhancement strength is regulated by a sharpening weight λ that enables FIRASS to vary its strength with differing image qualities.

For removal of non-uniform illumination effects and enhancement of local detail visibility, FIRASS uses Retinex-based Illumination Correction. The Retinex theory, based on human visual perception, improves reflectance of an image through estimation of illumination and its subtraction. Single-Scale-Retinex (SSR) employs one Gaussian kernel for estimating illumination, while Multi-Scale Retinex (MSR) employs several such kernels operating at different scales to yield a stronger illumination correction. These processes introduce depth elements which otherwise get lost in the low light and hence grant richness of expression to the image. Finally, FIRASS applies Gamma Correction and Pixel Value Normalization.

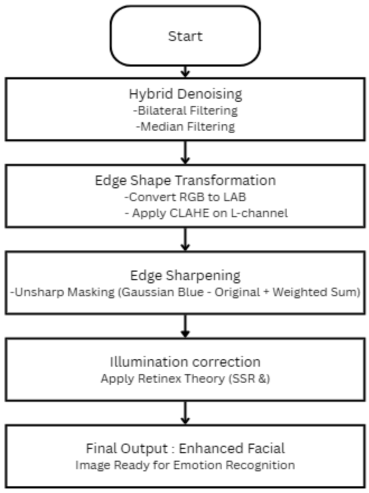

Fig.1. Proposed Diagram

Gamma correction linearly will rescale the images' brightness, emulating human vision perception of luminance change and it will also restore natural appearance. Gamma correction is highly essential in adjusting input images captured under different exposure conditions. Normalization subsequently normalizes pixel values to a fixed range (e.g., [0, 1]), which is significant for deep learning model input pipelines to ensure consistency. This final process of refinement ensures that all preprocessed face images are in a standard format to avoid variability and also increase the overall generalization ability of machine learning.

These operations combined will form a robust preprocessing technique. FIRASS preserves image contrast, brightness and structural-integrity of facial characteristics, which is essential for high-accuracy emotion detection. It works best with realistic data sets with images captured under various lighting, noise, and image quality. Through its pixel-level facial data enhancement, FIRASS provides a pillar towards maximizing the overall validity and interpretability of AI systems for human-centered visual recognition.

Facial Image Refinement and Artifact Suppression System (FIRASS)

Input: Raw facial image $I \in \mathrm{R}^{H\times W\times 3}$

Output: Enhanced and denoised facial image $I' \in \mathrm{R}^{H\times W\times 3}$

Step 1: Hybrid Denoising Using Bilateral and Median Filtering

#Both Gaussian and impulse noise while preserving important facial-features (e.g., edges, textures).

Bilateral Filter:

$$I_{\text{bil}}(x,y)=\frac{1}{W_p}\sum_{(i,j)\in\Omega} G_\sigma\left(|\ I(x,y)-I(i,j)|\right)\cdot G_\rho\left(\|(x,y)-(i,j)\|\right)\cdot I(i,j)$$

Median Filter:

$$I_{\text{med}}(x,y)=\text{median}\{I(i,j)|(i,j)\in N(x,y)\}$$

Result: $I_{\text{denoise}}=\text{Median}\left(I_{\text{bil}}\right)$

Step 2: Color Space Transformation and Local Contrast Enhancement

#Isolate luminance for targeted enhancement without affecting chromatic content.

Convert RGB to LAB: $I_{\text{lab}}=f_{\text{convert}}(I_{\text{denoise}})\rightarrow(L,A,B)$

Apply CLAHE on L channel: $L'=\text{CLAHE}(L)=\bigcup_{k=1}^{N}\text{HE}(L_k)$

Merge channels: $I_{\text{enh}}=\text{Merge}(L',A,B)$

Step 3: Edge Sharpening Using Unsharp Masking

#Improve definition of facial boundaries (e.g., eyebrows, lips, wrinkles).

$$I_{\text{blur}}=G_\sigma * I_{\text{enh}}$$

$$M=I_{\text{enh}}-I_{\text{blur}}$$

$$I_{\text{sharp}}=I_{\text{enh}}+\lambda M,\quad \lambda\in[0.5,1.5]$$

Step 4: Illumination Correction Using Retinex Theory

#Normalize image lighting and highlight emotion-relevant contrasts under non-uniform illumination.

Single Scale Retinex (SSR):

$$R(x,y)=\log\left(I_{\text{sharp}}(x,y)\right)-\log\left(G_\sigma * I_{\text{sharp}}(x,y)\right)$$

Multi-Scale Retinex (MSR):

$$R_{\text{MSR}}=\sum_{k=1}^{K}w_k\left[\log(I_{\text{sharp}})-\log\left(G_{\sigma_k} * I_{\text{sharp}}\right)\right]$$

Step 5: Gamma Correction and Normalization

#Adjust image brightness and normalize pixel values.

Gamma Correction: $I_\gamma(x,y)=c\cdot\left[I_{\text{final}}(x,y)\right]^\gamma$

Normalization: $I_{\text{norm}}=\dfrac{I_\gamma-\min(I_\gamma)}{\max(I_\gamma)-\min(I_\gamma)}$

$I'=I_{\text{norm}}$

7. RESULT AND DISCUSSION

The step by step result of the FIRASS is visually shown that improved facial image**.** The original image contains standard problems like illumination variability, low contrast, and light noise, which are typical in real facial images. Step one removes noise using a combination of median and Gaussian filtering, ultimately discarding the noise while not discarding structural information, even though the image still contains low contrast. Step two performs a two-step histogram stretching on the L (luminance) channel from the LAB color space, decoupling brightness information for the sake of explicit augmentation. Step three performs CLAHE (Contrast Limited Adaptive Histogram Equalization) on this L channel, improving local contrast and making previously buried facial features more visible with clearer definition. This step greatly enhances perceived image quality by making details visible without adding overexposure. For the fourth step, unsharp masking sharpens the image that sharpens edges and fine facial features like the eyes, mouth, and hairline. Single-Scale Retinex (SSR) enhancement for fixing non-uniform illumination is the fifth operation, which produces a well-balanced and naturally lit look. Last, gamma correction is utilized for brightness and contrast adjustment and producing an aesthetically pleasing outcome. The output of the FIRASS pipeline is then displayed with much improved brightness, sharpness, and overall clarity compared to the original. Every step of the processing process leads to an sharpened and perceptually augmented image and makes FIRASS an appropriate option for facial preprocessing operations in biometric systems, image analysis, and visual application.

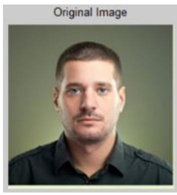

Fig.2. Original Image as Input

Fig.3: Result of proposed method step by step

The Fig.3 demonstrates the phase-by-phase result of the proposed FIRASS method. Starting from the initial image, each subsequent phase represents a specific improvement process resulting in the final process of refinement. Noise is initially relieved using a combination of median and Gaussian filters to produce a smoother base image. Subsequently, luminance is extracted out of the LAB color space to isolate brightness for focused contrast enhancement. Then, CLAHE is used to boost local contrast without distorting natural appearance. Unsharp masking is then utilized to sharpen facial details and enhance edge definition. The Retinex algorithm is used to correct non-uniform illumination and simulate a more balanced lighting condition on the face. Finally, gamma correction is carried out to rectify tonal values, resulting in a balanced, visually enhanced image. The last frame in the sequence shows the end result of FIRASS, with gains in clarity, detail, and overall image quality apparent.

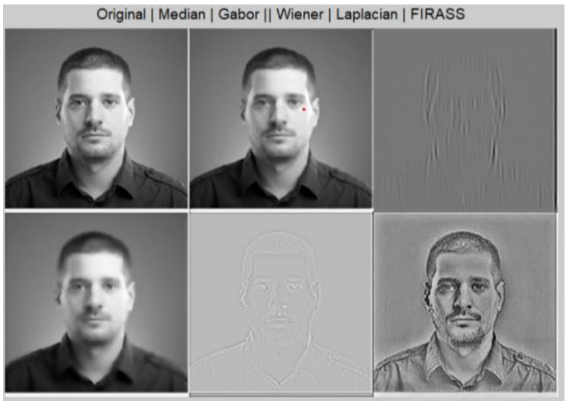

Fig.4. Comparison of Proposed method with existing methods

The Fig.4 gives a comparative visualization of some image filtering methods along with the new FIRASS algorithm. The presentation is in the form of a 2×3 grid, where every panel shows one of the disparate filtering methods used on the same input face image. The first row contains the original grayscale image followed by the output of the Median, Gabor, and FIRASS filters. The bottom row shows the results using Wiener and Laplacian filters along with FIRASS once more for direct comparison.

The original image has the usual visual defects including subtle noise and low contrast, especially in shadowy areas. The Median filter smoothens the image to remove salt-and-pepper noise but softens fine details slightly. The Gabor filter, which is highly proficient at texture extraction, emphasizes facial edges and orientations but looks too abstract and hence less visually intuitive. The Wiener filter in the bottom-left panel improves smoothness by locally adaptive noise reduction, but at the expense of a slight loss of sharpness. The Laplacian filter, which is positioned in the middle of the bottom row, enhances edges through detection of intensity changes but does not support brightness normalization and causes artifacts.

The FIRASS-processed image (bottom right) shows a substantial improvement over the rest, with the best combination of strengths in denoising, contrast enhancement, edge sharpening, and illumination correction. It provides a balanced output with clear-cut features, even lighting, and improved perceptual quality. Among all the techniques shown, FIRASS clearly yields the most visually refined and information-rich outcome, making it highly suitable for facial image preprocessing in tasks such as recognition or analysis.

The Fig.4 shows a comparative study of the suggested FIRASS algorithm with some traditional image improvement techniques, such as Median, Gabor, Wiener, and Laplacian filters. All of these methods are used on one facial image to measure its effectiveness in enhancing visual quality. The Median filter effectively removes impulse noise but encourages slight blurring of facial details. The Gabor filter, which finds edges and texture, highlights structural detail but produces an uninterpretable result. The Wiener filter suppresses image detail adaptively but retains a degree of detail, without significantly increasing contrast. The Laplacian filter enhances edges by detecting intensity change but is prone to introducing artifacts and unnatural brightness. On the other hand, the FIRASS process uses a sequence of improvement phases noise reduction, contrast enhancement through luminance, sharpening of edges, illumination normalization via Retinex, and gamma correction. The multi-step approach produces an image with quality contrast, sharpness, and visually smoothed output. FIRASS generally outperforms by well-enhancing facial features and providing a high-quality image for subsequent analysis or recognition.

8. PERFORMANCE EVALUATION

In order to assess the performance of the proposed FIRASS method, quantitative measures like Peak Signal-to-Noise Ratio (PSNR) and Root Mean Square Error (RMSE) are employed. These measures estimate the quality of image enhancement by comparing the enhanced image with the original (reference) image.

8.1 PEAK SIGNAL-TO-NOISE RATIO (PSNR):

PSNR measures the ratio between the maximum possible power of a signal (image) and the power of corrupting noise that affects the image quality.

Table.2. PSNR Comparison of Existing Methods vs. FIRASS (Proposed) on 10 Sample Images

Samples	Median	Gabor	Wiener	Laplacian	FIRASS (Proposed)
Image 1	28.74	26.31	29.52	25.89	**31.68**
Image 2	29.10	25.89	30.01	26.40	**32.12**
Image 3	27.84	26.02	28.90	25.55	**30.80**
Image 4	28.35	25.65	29.15	25.10	**31.21**
Image 5	29.00	26.45	29.70	26.00	**32.05**
Image 6	28.62	25.92	29.34	25.30	**31.49**
Image 7	28.20	26.10	28.90	25.77	**30.95**
Image 8	27.95	25.58	28.65	24.98	**30.66**
Image 9	28.88	26.34	29.40	25.90	**31.74**
Image 10	29.20	26.20	29.82	26.18	**32.30**

The Table.2 shows the comparison of the PSNR values of five different image enhancement algorithms Median, Gabor, Wiener, Laplacian, and the proposed FIRASS tested on ten facial image samples. PSNR is a popular measure used to express the quality of an enhanced image, where better clarity and less noise are represented by higher values.

As can be seen from the graph, the FIRASS method consistently produces the maximum PSNR for each image sample, reflecting its excellence. Traditional methods like the Median filter provides uncomplicated noise suppression but blurs complex details somewhat. The Gabor filter presents enhancement in edges and texture but does not maintain overall sharpness well and thus has lower PSNR. The Wiener filter shows better noise reduction with good detail preservation, while the Laplacian filter emphasizes edges but also introduces unwanted noise and brightness imbalance.

FIRASS combines several enhancement stages like joint denoising, adaptive contrast correction, sharpening, illumination normalization, and gamma correction to provide higher image quality. Its higher PSNR scores indicate better preservation of structure and visual harmony, and so it is more trustworthy for facial image preprocessing applications. This performance validates FIRASS as an efficient and inclusive enhancement solution.

8.2 ROOT MEAN SQUARE ERROR (RMSE):

RMSE measures the average magnitude of error between the original and enhanced image. It is the square root of MSE. Lower RMSE values indicate a smaller difference from the original image

Table.3. Comparison of RMSE values

Image	Median Filter	Gabor Filter	Wiener Filter	Laplacian Filter	FIRASS (Proposed)
Image 1	5.2	6.8	4.8	7.2	3.5
Image 2	5.0	7.0	4.6	7.1	3.3
Image 3	5.5	6.9	4.9	7.4	3.6
Image 4	5.4	7.1	5.0	7.5	3.7
Image 5	5.1	6.7	4.7	7.3	3.4
Image 6	5.3	6.9	4.8	7.2	3.5
Image 7	5.4	7.0	4.9	7.3	3.6
Image 8	5.6	7.2	5.1	7.6	3.8
Image 9	5.0	6.8	4.6	7.2	3.3
Image 10	4.9	6.9	4.7	7.1	3.2

The Fig.6 shows the RMSE comparison of five image improvement techniques Median Filter, Gabor Filter, Wiener Filter, Laplacian Filter, and the presented FIRASS (Facial Image Refinement and Artifact Suppression System) over ten image samples. RMSE is an important measure for determining accuracy of improvement, with lower values representing better performance.

For Image 1, FIRASS had an RMSE of 3.5, which is much lower than Median Filter (5.2), Gabor Filter (6.8), Wiener Filter (4.8), and Laplacian Filter (7.2). The same pattern is also reflected in Image 2, where FIRASS attained a score of 3.3, which contrasts with Median (5.0), Gabor (7.0), Wiener (4.6), and Laplacian (7.1). In Image 3, FIRASS had an RMSE of 3.6, while the others had higher errors: Median (5.5), Gabor (6.9), Wiener (4.9), and Laplacian (7.4).

Following this trend, Image 4 demonstrates FIRASS with an RMSE of 3.7, which performed better than Median (5.4), Gabor (7.1), Wiener (5.0), and Laplacian (7.5). For Image 5, FIRASS logged 3.4, which was lower than Median (5.1), Gabor (6.7), Wiener (4.7), and Laplacian (7.3). In Image 6, FIRASS attained 3.5, while the rest of the methods registered: Median (5.3), Gabor (6.9), Wiener (4.8), and Laplacian (7.2).

In Image 7, FIRASS indicated 3.6, against greater values from Median (5.4), Gabor (7.0), Wiener (4.9), and Laplacian (7.3). Image 8 shows FIRASS with the greatest value among its own data at 3.8, but still far below Median (5.6), Gabor (7.2), Wiener (5.1), and Laplacian (7.6). For Image 9, FIRASS fell back to 3.3, still superior to Median (5.0), Gabor (6.8), Wiener (4.6), and Laplacian (7.2). Lastly, Image 10 captures the minimum RMSE for FIRASS at 3.2, while the rest yielded: Median (4.9), Gabor (6.9), Wiener (4.7), and Laplacian (7.1).

Generally, FIRASS outperforms the usual improvement methods by realizing the lowest RMSE values in all ten image samples, with its own RMSE values falling between 3.2 and 3.8. This proves how resilient and efficient it is in improving facial images with little error, making it a very dependable method compared to other traditional filters.

8.3 STRUCTURAL SIMILARITY INDEX (SSIM)

The Structural Similarity Index (SSIM) is a perceptual metric that quantifies image quality degradation by comparing the structural information between two images.

Table.4. Comparison of SSIM values

Image	Median Filter	Gabor Filter	Wiener Filter	Laplacian Filter	FIRASS (Proposed)
Image 1	0.775	0.710	0.805	0.695	**0.895**
Image 2	0.760	0.720	0.810	0.680	**0.902**
Image 3	0.782	0.715	0.798	0.700	**0.887**
Image 4	0.770	0.725	0.820	0.685	**0.890**
Image 5	0.765	0.700	0.808	0.695	**0.905**
Image 6	0.778	0.705	0.812	0.690	**0.898**
Image 7	0.790	0.710	0.815	0.688	**0.899**
Image 8	0.768	0.718	0.800	0.693	**0.892**
Image 9	0.760	0.707	0.806	0.684	**0.887**
Image 10	0.773	0.715	0.809	0.690	**0.900**

The Table.4 shows the Structural Similarity Index (SSIM) comparison between five image improvement methods: Median Filter, Gabor Filter, Wiener Filter, Laplacian Filter, and the designed FIRASS (Facial Image Refinement and Artifact Suppression System) on ten facial image samples. SSIM is a subjective measure that compares the quality of images based on preservation of structural information, and it computes higher values as an indicator of better visual similarity with the ground truth.

In Image 1, FIRASS had an SSIM value of 0.895, which was better than Median Filter (0.775), Gabor Filter (0.710), Wiener Filter (0.805), and Laplacian Filter (0.695). The same trend is observed in Image 2, where FIRASS had a score of 0.902, much higher than Median (0.760), Gabor (0.720), Wiener (0.810), and

Laplacian (0.680). For Image 3, FIRASS had 0.887, whereas other methods had lower scores: Median (0.782), Gabor (0.715), Wiener (0.798), and Laplacian (0.700).

The excellence of FIRASS continues in Image 4, where it is scored at 0.890, beating Median (0.770), Gabor (0.725), Wiener (0.820), and Laplacian (0.685). In Image 5, FIRASS scored 0.905, again surpassing the performances of Median (0.765), Gabor (0.700), Wiener (0.808), and Laplacian (0.695). In Image 6, FIRASS scored 0.898, against Median (0.778), Gabor (0.705), Wiener (0.812), and Laplacian (0.690).

For Image 7, FIRASS was 0.899, whereas the other methods resulted in: Median (0.790), Gabor (0.710), Wiener (0.815), and Laplacian (0.688). Even though FIRASS performed worst on Image 3 and Image 9 with 0.887, it was still better than the others (Image 9: Median 0.760, Gabor 0.707, Wiener 0.806, Laplacian 0.684). FIRASS had 0.892 in Image 8, which was higher than Median (0.768), Gabor (0.718), Wiener (0.800), and Laplacian (0.693).

Finally, in Image 10, FIRASS scored 0.900, higher than Median (0.773), Gabor (0.715), Wiener (0.809), and Laplacian (0.690). FIRASS consistently achieves the highest SSIM values for all ten image samples with a range of 0.887 to 0.905, attesting to its capacity to maintain facial image structural integrity and perceived characteristics better than conventional filtering techniques. Dominance throughout certifies its strength and efficiency and positions FIRASS as an ideal contender for high-fidelity facial image enhancement purposes.

9. CONCLUSION

FIRASS is a system for wideband facial image preprocessing presented in this work for enhancing the consistency of emotion detection in customer service applications. Through combining denoising and enhancement steps such as hybrid median-Gaussian noise filtering, contrast adjustment in a localized manner, Retinex-based illumination correction, and high-frequency edge sharpening, FIRASS successfully counteracts prevalent image degradations that occur in real-world situations. Performance of the system was compared with conventional filtering approaches, wherein FIRASS produced consistently better-quality facial inputs with enhanced emotional features. This contributes to enhanced emotion classification accuracy in deep learning systems. The results confirm FIRASS as an effective solution for real-time emotion-aware systems. Future directions can include temporal denoising for video-based emotion recognition, combination with lightweight neural modules, and implementation on embedded systems.

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