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Quantifying Visual Harmony-Evaluating Image Fusion Metrics

Sonia Gupta[1], and Sandesh Gupta[2]

[1] Research scholar, Computer science, CSJMU, Kanpur, India
[2] Assistant Professor, CSJMU, Kanpur, India

Correspondence should be addressed to Sonia Gupta; sonia2040@gmail.com

ABSTRACT- The discipline of medical imaging has advanced significantly in recent years. In the field of multi-focus image fusion, where combining two images with different focus areas is essential to producing a coherent and informative result that can be used for research and study, following guidelines is crucial. To ensure that the fused image serves its intended purpose, precise integration of discrete focus zones is necessary. Performance indicators are essential to determining how well this fusion process is going. Performance indicators serve as important instruments for evaluation, offering a methodical way to rate the quality of the combined image. They serve as parameters to measure the efficacy of the fusion process, enabling a thorough examination of whether the resultant image aligns with predefined criteria and encapsulates all pertinent information. These metrics play a pivotal role in validating the success of the fusion process, ensuring that no crucial details are lost in the transition. In essence, this endeavor not only seeks to shed light on the intricacies of multi-focus image fusion but also endeavor to establish a framework for evaluating the success of the fusion process through a thorough examination of performance metrics. The comprehensive exploration of subjective and objective metrics serves as a guide to ascertain the suitability of each parameter, thereby advancing the understanding of how and when these metrics contribute to achieving optimal results in the field of image fusion.

KEYWORDS- Medical imaging, performance metrics, Metrics associated with fusion, Qualitative Analysis, Quantitative Analysis.

I. INTRODUCTION

The integration of various medical imaging modalities through image fusion techniques enables a more comprehensive and holistic assessment of a patient's condition. This approach goes beyond the limitations of individual imaging methods, allowing for a synergistic combination of strengths from different modalities. **Fig1**. depicts the image fusion of multi modal images.

Furthermore, the ability to fuse multi-modality medical images facilitates better visualization and interpretation of complex medical scenarios. This is particularly beneficial in cases where a single imaging modality may not provide sufficient information for a conclusive diagnosis. By merging diverse data sources, clinicians can obtain a more accurate representation of the pathology, leading to improved decision-making and treatment planning [2].

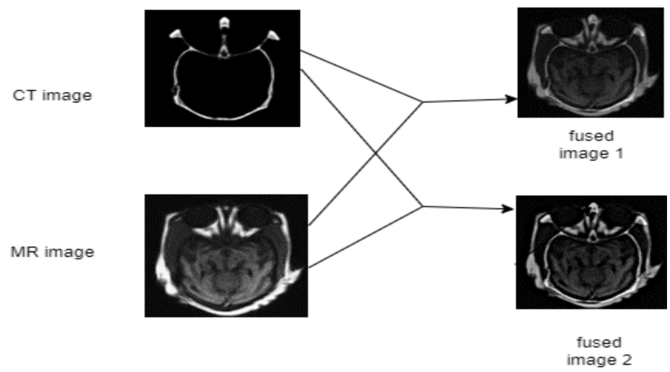

Figure 1: Image Fusion

As technology advances, the refinement of image fusion algorithms continues to enhance the precision and efficiency of the diagnostic process. Automated fusion techniques reduce the burden on clinicians, allowing them to focus more on the interpretation of fused images and clinical decision-making rather than spending excessive time manually integrating data from different sources.

By resolving the difficulties involved in the analysis of multi-modality medical images, medical image fusion techniques [8] are essential to contemporary healthcare. Fig2**.** depicts process of image fusion. Incorporating complementary data from several imaging modalities not only expedites the diagnosis process but also enhances the accuracy and reliability of medical assessments, which in turn results in better patient care [1].

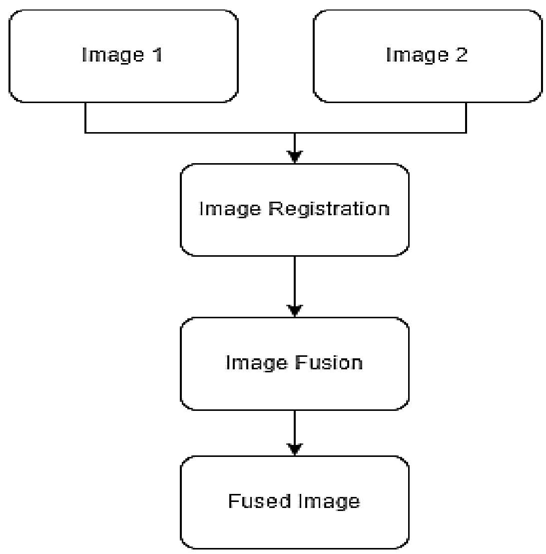

Figure 2: Process of Image fusion

A thorough grasp of this rapidly emerging topic is crucial, as seen by the numerous surveys and review articles that have attempted to summarise the multitude of multimodal medical picture fusion approaches and classifications.The spatial domain of pictures is directly used by spatial-domain fusion systems, which include methods like Principal Component Analysis (PCA), Intensity-Hue-Saturation (IHS), and the Averaging fusion methodology. These methods intricately combine pixel values to generate a fused image that preserves crucial information from the input images. The emphasis on spatial-domain techniques highlights their efficacy in capturing and retaining relevant details, showcasing their potential in various applications across different domains, particularly in the intricate realm of medical imaging. As research in image fusion continues to evolve, the exploration of additional databases, consideration of diverse datasets, and addressing specific medical conditions will undoubtedly contribute to advancing the effectiveness and applicability of these techniques.Furthermore, multi-scale schemes introduce a variety of transforms, such as curvelet, ridgelet, shearlet, and contourlet transforms. Each of these transforms has unique characteristics that make them suitable for capturing specific features in the images. For instance, the curvelet transform excels in representing curve-like structures, while the shearlet transform is adept at handling directional information.Within the context of image fusion, the process of image decomposition becomes pivotal. The way in which an image is decomposed, either spatially or through transforms, significantly influences both the extraction of relevant information and the overall quality of the fusion outcome. Hence, the choice of analytical tools and fusion techniques plays a critical role in achieving optimal results across diverse applications and domains.

II. LITERATURE REVIEW

In the realm of image fusion quality metrics, the study outlined in reference [3] delved into a comprehensive exploration of various metrics grounded in distinctive features. Shifting the focus to the medical domain, reference [4] concentrated on fusion metrics tailored specifically for medical image processing. The introduction of objective methods for image quality assessment in this context addressed the need for a systematic approach to evaluating the success of fusion processes.While subjective quality metrics are often criticized for being time-consuming, costly, and dependent on individual observers, the study highlighted the use of the Difference Mean Opinion Score (DMOS) as a means of quantifying subjective assessments. The comparison of DMOS scores with four FR-IQA evaluation metrics, employing the Pearson Linear Coefficient (SROCC) for cross-verification, showcased a correlation that signified the close alignment of DMOS scores with the objective evaluation metrics FR-IQA.Going on, reference [5] used a varied methodology depending on the availability of a reference image for the evaluation of combined output images. In cases where there was a reference image, metrics like mutual information, mean bias, and root mean square error (RMSE) [7]were used. Conversely, in the absence of a reference image, the study employed a distinct set of evaluation metrics, including entropy and standard deviation. This nuanced approach reflects the adaptability of evaluation methods to different scenarios and sheds light on various quality parameters crucial for estimating the quality of combined output images. Reference [6] conducted a thorough analysis and review of diverse quality metrics and image fusion methods, contributing to a broader understanding of the field.In, the research ventured into innovative objective schemes for evaluating image quality, introducing a novel technique based on the distortion of the structural content of images. The development and effective demonstration of a quality metric using the structural similarity index represented a significant stride in advancing evaluation methodologies. Finally,[9] tackled the challenges and difficulties associated with assessing the excellence of combined images. the quality of fused images, emphasizing the intricate interplay of conditions and variables in image quality performance evaluation. Collectively, these references contribute to the evolving landscape of image fusion research and evaluation methodologies.Expanding on the importance of multimodal image fusion in the clinical context, the recognition of diverse attributes in medical images becomes crucial for accurate diagnosis and treatment planning. The variations in shape, structure, dimension, and size among different subjects highlight the complexity of medical imaging. Given that these images represent living body parts, organs, and tissues, the clinical significance of such diversity cannot be understated.In addition to the challenges posed by inter-subject variability, the inherent ambiguity in depicting biological structures within the image dataset further underscores the need for advanced image fusion techniques. This ambiguity may arise due to factors such as variations in patient anatomy, physiological conditions, or imaging modalities. As a result, effective fusion methodologies become essential to extract meaningful and reliable information from these complex datasets.While numerous studies have explored various algorithms for medical image fusion, the emphasis must be on ensuring that automated image analysis does not lead to false alarms or misinterpretations. The reliability and accuracy of diagnostic information derived from fused images are paramount in the clinical decision-making process. Therefore, continuous improvement in multimodal image fusion techniques is imperative to enhance diagnostic precision, facilitate better treatment strategies, and ultimately improve patient outcomes. This underscores the ongoing need for research and development in the field to address the evolving challenges posed by the dynamic nature of medical imaging data.Numerous parameters are utilized for assessing the performance of fusion models when using multi-focal images as source inputs. The quality metrics used for evaluation assume an ideal scenario where all information from input images is perfectly transferred to a unified output image. However, achieving such flawless transfer is impractical in real-world situations. Certain criteria must be relaxed in some instances, considering application requirements. Key features, such as edges, texture elements, and gradients, may need to be adjusted. Having a more detailed spectral representation is considered favorable for effective image fusion. Spatial resolution is equally crucial. The choice of evaluation parameters depends on factors like the application, type of source images, and the desired output expectations. Assessment methodologies are generally categorized into qualitative and quantitative methods.

A. *Qualitative Method*

Subjective reviews and visual inspections are employed in qualitative methods of image fusion to determine how well the fused images are perceptually rendered and interpretable. Unlike quantitative methods that rely on numerical measures,

qualitative methods rely on human observers to make judgments based on their visual perception. Table 1 illustrates common qualitative methods used for evaluating image fusion.
Qualitative methods are essential for understanding the human perceptual aspects of image fusion, especially in applications where the end-user's interpretation and decision-making are crucial. While quantitative metrics provide objective measures, qualitative methods capture the nuanced aspects of visual quality and user experience. In many cases, a combination of qualitative and quantitative assessments provides a more comprehensive evaluation of image fusion algorithms.

B. Quantitative Method

Quantitative methods of image fusion involve the use of numerical techniques to evaluate and measure the performance of fusion algorithms.
It is crucial to emphasize that the selection of quantitative metrics relies on the particular objectives of the image fusion task and the attributes of the images under consideration. Moreover, varying metrics may be better suited for distinct applications like surveillance, medical imaging, or remote sensing. Typically, researchers opt for a blend of these metrics to offer a thorough assessment of image fusion algorithms.

Table 1: Methods used for Qualitative Image Fusion

Method	Description
Visual Inspection	Observers visually inspect the fused images to assess the overall quality, clarity, and visual appeal. This involves examining details, sharpness, and the presence of artifacts or distortions.
Subjective Ranking	Human observers rank different fusion results based on their subjective preferences or perceived quality. This method is useful when comparing multiple fusion algorithms or settings.
Human Perception Studies	Conducting experiments with human subjects to evaluate how well they can interpret or recognize features in the fused images. This can involve tasks such as target detection, object recognition, or scene understanding.
User Surveys and Questionnaires	Collecting feedback from users through surveys or questionnaires to understand their preferences and opinions regarding the quality and effectiveness of the fused images. Questions may focus on visual clarity, naturalness, and overall satisfaction.
Perceptual Difference Model	Using models that simulate human vision to assess perceptual differences between fused images. These models take into account factors such as luminance, color, and contrast, which influence human perception.
Focus Group Discussions	Organizing focus group discussions with experts or potential users to gather qualitative insights into the advantages and disadvantages of various fusion techniques. This can provide a more in-depth understanding of user preferences.

III. METRICS ASSOCIATED WITH FUSION

Testing parameters that measure the quality of the output is a necessary step in designing image fusion algorithms and determining how effective they are. When assessing the testing quality of the final fused image, fusion metrics are essential. These measures, which can be divided into two categories: qualitative analysis and quantitative analysis, show how well the fused image meets the given requirements.

A. Qualitative Analysis

Visual analysis, often known as qualitative analysis, is the process of assessing images with a viewfinder. The knowledge, experience, and abilities of the observers are crucial to this study. To assess the excellence of the combined image that is produced in comparison to the input photos, a team is put together. Estimation parameters like colour, item size, geometric patterns, and spatial features are the main subjects of the group's observations.

B. Quantitative Analysis

The basis of this evaluation strategy is mathematical modelling. This evaluation method gauges the spatial and spectral resemblance between the resultant fused image and the original input images, employing predetermined parameters to appraise the quality of the combined image. Table 2 illustrates the different types of metrics associated with fusion.

IV. LIMITATIONS

From the preceding discussion, it is evident that various fusion performance metrics have distinct criteria and purposes for evaluating the quality of fused images. The Fusion Quality Index (FQI) metric incorporates three key aspects: contrast preservation, structure preservation, and sharpness, aiming to assess the overall picture quality in multi-exposure multi-focus images. MI (Mutual Information) fusion metric, however, quantifies the information shared through the fusion of source images and is utilized to evaluate various image fusion models. Unlike metrics related to image intensities, MI does not rely on specific conventions or assumptions, making it a versatile performance measure that can be applied spontaneously without prior processing.

V. CONCLUSION

The continuous advancements in imaging technologies have led to the development of an array of fusion metrics, each tailored to different aspects of assessing fused images. The diverse range of these metrics provides researchers with the flexibility to select the most suitable one based on their unique requirements and the specific characteristics of the fused images under scrutiny. As technology evolves, there is a compelling need to delve deeper into the realm of fusion metrics. The ongoing exploration in this field holds the promise of uncovering novel metrics that can enhance the precision and comprehensiveness of image fusion evaluations. Researchers are encouraged to delve into this potential future scope, contributing to the refinement and expansion of the existing metrics or even proposing innovative approaches to address emerging challenges in image fusion. In conclusion, the exploration of fusion metrics is an evolving journey, offering researchers a rich landscape of possibilities. The continuous research and advancement in this domain not only enhance existing metrics but also unveil possibilities for identifying novel approaches that can enhance the evaluation of fused image quality. The meticulous evaluation of fused output images is a cornerstone in advancing the application and efficiency of image fusion techniques, making it an essential aspect of contemporary research in the field of image processing.

Table 2: Metrics associated with fusion

S.No.	Methods	Definition	Equation
1.	RMSE (Root Mean Squared Error)	It is a commonly employed metric for assessing the average magnitude of discrepancies between predicted and observed values. It provides a single value to represent the overall performance of a model or the quality of a measurement technique. In the context of image processing or other applications, it is often used to quantify the difference between an original (observed) image and a processed (predicted or modified) image.	$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \|y(i) - \hat{y}(i)\|^2}{N}},$
2.	ERGAS	More disruption in the fused output image is indicated by a higher ERGAS rating. A higher quality output image is indicated by less disturbance. An ERGAS rating that is low suggests that there is more similarity between the fused image and the reference image.	ERGAS= $\sqrt{(\frac{1}{N}\sum_{i=1}^{N}\left(\frac{100}{L}\right)^2 \frac{\sum_{j=1}^{L}(X_{ij}-Y_{ij})^2}{\sum_{j=1}^{L} Y_{ij}^2})}$
3.	MB (Mean Bias)	It is a metric used to evaluate the bias or systematic error between two images, typically a fused image and a reference image. It provides a measure of the average difference between corresponding pixel values in the two images.	MB= $\frac{1}{N}\sum_{i=1}^{N}(X_i - Y_i)$
4.	PSNR (Peak Signal-to-Noise Ratio)	The ratio of the image's grey level numbers to the equivalent pixels in the source input image and the combined output image yields the peak signal-to-noise ratio, or PSNR. Better fusion quality is indicated by a higher PSNR value.	PSNR= $10.log_{10}(\frac{M^2}{\frac{1}{N}\sum_{i=1}^{N}(X_i-Y_i)^2})$
5.	SNR (Signal-to-Noise Ratio)	It's a metric used to quantify the relationship between signal power and background noise in a number of industries, including electronics, signal processing, and telecommunications. It serves as a gauge for a signal's quality in the face of noise.	$SNR_{db} = 10.log_{10}(\frac{P_{signal}}{P_{noise}})$
6.	CC (Correlation Coefficient)	The Correlation Coefficient is a performance statistic that is used to assess how similar the spectral features are in the fused image and the reference image. Greater similarity between the reference image and the fused image is indicated by a Correlation Coefficient value close to +1.	$r = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2\sum(y_i-\bar{y})^2}}$
7.	MI (Mutual Information)	It quantifies how statistically dependent two random variables are on one another. MI is frequently used to measure how much information about one variable the presence or lack of another offers, whether in the context of information theory or image processing.	I(X;Y) = $\sum_{x\in X}\sum_{y\in Y} P(x,y).\log(\frac{P(x,y)}{P(x).P(y)})$
8.	Entropy	The entropy of an image represents the average information content it contains. A higher entropy in a fused image indicates a greater richness of information.	$E_n = \sum_{j=0}^{G} P(i).(log_2 P(i))$
9.	SD (Standard Deviation)	It is employed to assess the contrast in the resulting fused output image. A higher standard deviation in the fused output image indicates elevated contrast.	σ = $\sqrt{\frac{\sum_{i=1}^{N}(y_i-\bar{y})^2}{N}}$
10.	FMI (Fusion mutual information)	The degree of dependency between the source image and the fused output image is demonstrated by the mutual information in image fusion. A greater FMI value will be seen in a fused output image of higher quality.	$FMI = MI\ I_p I_f + MI\ I_m I_f$
11.	SFQI (Spatial Frequency-based Quality Index)	It is type of a fusion quality index that considers the spatial frequency information in the images. The formula for SFQI involves the comparison of the spatial frequency content in the input images and the fused image.	$SFQI = \frac{2.SF_{fused}.SF_{mean}}{SF_{fused}^2 + SF_{mean}^2}$
12.	D (Degree of Distortion)	A smaller value of 'D' indicates a higher quality of the combined output image. Reduced distortion corresponds to an improved quality of the resulting picture.	$D = \frac{Measure\ of\ Original\ Data}{Measure\ of\ Distorted\ Data}$

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest

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