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Original Article

Dynamic Thermal Image Enhancement Using Wavelet-Based Adaptive Fusion

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ABSTRACT

The research introduces a wavelet-based adaptive fusion approach for thermal image enhancement that delivers superior outcomes compared to conventional strategies, including HE, CLAHE and gamma correction when considering edge preservation and details. The method utilizes wavelet transformation to enhance contrast with fine-scale preservation and noise elimination, making it appropriate for real-time applications. Experimental evaluation shows that adaptive Fusion provides a PSNR of 32.78 dB and MSE of 159.45, together with an SSIM of 0.792. An entropy of 8.15 also represents good image information preservation. The presented method demonstrates robust capabilities for monitoring tasks and medical diagnosis alongside industrial inspecting operations and reduces computational difficulties commonly found in previous methodologies.

Keywords: Thermal Image Enhancement, Image Intensity Enhancement, Histogram Equalization, CLAHE (Contrast Limited Adaptive Histogram Equalization), Gamma Correction, Edge Enhancement, Wavelet Fusion.

1 Introduction

Various application fields utilize thermal contrast enhancement for medical analysis, security assessment, industrial inspection, and environmental monitoring. A significant obstacle exists regarding current thermal imaging technology because thermal images demonstrate reduced contrast levels while showing noticeable noise and insufficient resolution, which impacts their practical interpretation and usage [1]. The oldest developed technique for enhancing image contrast through pixel value transformation and contrast enhancement operates under Histogram Equalization (HE). Research shows HE produces excessive noise while hiding fine image elements, failing to meet the precision standards required for medical imaging and environmental detection [2,3]. Contrast-limited Adaptive Histogram Equalization (CLAHE) became a developed solution because of these restrictions. Security and surveillance technology requires local contrast improvement through CLAHE because it maintains image details while preventing noise amplification in uniformly lit sections [4]. Implementing CLAHE requires heavy processing while simultaneously generating noise in dim regions, thus creating difficulties primarily for real-time applications [5,6]. The second procedure enhances thermal image quality by combining gamma correction and edge enhancement techniques for brightness value and edge feature control. The parameters needed for this methodology proved time-consuming in real-time applications while maintaining practical feature preservation and improved contrast performance [7,8].

The development of wavelet-based algorithms combined with adaptive fusion methods presents itself as an effective technique to enhance thermal images. During wavelet transformation, an image receives segmented frequency analysis that enables researchers to study textures at local scales throughout the image area. The approaches deliver important adaptability in establishing high and low frequencies to enhance image quality and texture [9.10]. The implementation of wavelet-based methods faces difficulties regarding computational expenses, especially when aiming for real-time operation [11]. Kumar and Shukla [12] employed Adaptive Fusion with Wavelet Decomposition to show its capability for improving contrast while maintaining details in their research. The method outperforms older methods because it adjusts to changing contrast levels and produces reduced noise output. The paper presents adaptive Fusion based on wavelets, which solves these problems by sustaining real-time operation while achieving high-quality outcomes that improve contrast, minimize noise, and maintain image details. This proposed method delivers better results than traditional techniques when assessed using Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE) and Structural Similarity Index (SSIM) measurements along with entropy analysis, which makes it ideal for real-time applications in surveillance systems and medical diagnosis and industrial inspections [13, 14].

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2 Literature Review on Thermal Image Enhancement

Thermal images receive different enhancement techniques for multiple domains, including healthcare fields and security and industrial applications. The methods for thermal image enhancement have evolved substantially, from fundamental contrast-based methods to incorporating adaptive processing with artificial intelligence and intelligent techniques, which have emerged in recent times.

2. 1 Traditional Histogram Equalization (HE):

The earliest version of contrast enhancement technology under development became the Histogram Equalization (HE) method, which improves the contrast in images with diverse intensity ranges. Medical thermal imaging benefits from contrast enhancement thanks to HE, but this technique also produces additional noise, as per findings by Nguyen et al., which diminishes essential image elements. HE exhibits reduced reliability as a diagnostic tool because its accuracy becomes compromised when applied to sensitive image areas that need precision [1].

2. 2 Contrast Limited Adaptive Histogram Equalization (CLAHE):

CLAHE advances traditional HE by imposing contrast amplitude restrictions to enhance image area-specific contrast. The enhancement element of CLAHE operates in local areas to restrict its amplification effects in smooth regions. The research by Gallego et al. shows that CLAHE achieves better thermal surveillance image contrast enhancement with limited noise amplification. The technology stands out for security purposes since it delivers precise results with minimal background noise [2].

2. 3 Gamma Correction Combined with Edge Enhancement:

The contrast stretching technique provides significant brightness increases to images, while users typically use this method with other enhancement approaches, including edge enhancement. Among the notable edge detection algorithms is the Canny algorithm. In their research, Xu et al. proved that this method improves thermal image edge contrast and overall resolution and is useful for industrial inspection procedures. When organizations customize the parameters of contrast stretching and edge enhancement, they can effectively enhance detailed structural information [8].

2. 4 Wavelet-Based Enhancement with Adaptive Fusion:

Wavelet transforms split images into various frequency bands, allowing researchers to perform selective enhancement of edges and textures. Kumar and Shukla introduced adaptive Fusion to adapt the frequency band weights during Fusion to enhance contrast and edge retention. The study reports that this method works best when structural information needs to be maintained, such as edges and curves and delicate details across different contrast levels, specifically in surveillance and medical imaging applications [19].

2. 5 Dual Convolutional Neural Network with Attention Mechanism:

According to their research, Gao et al. implemented a dual CNN-based framework with an attention mechanism to improve thermal infrared images. The method successfully maintains small details in images and shows exceptional defense against noise contamination. Image quality is superior in this approach compared to conventional Histogram Equalization (HE) and Contrast-Limited Adaptive Histogram Equalization (CLAHE) techniques. The sophisticated algorithm works well for specific domains, particularly thermal infrared imaging, since it enhances noise reduction and contrast [15].

2. 6 Denoising Enhanced Thermal Breast Image:

Raj et al. designed an image-filtering framework to address enhanced thermal breast pictures that served medical purposes, including breast cancer diagnosis. The method simultaneously reduces noise and maintains precise thermal imaging fidelity. Additional research using different TIR image groups should validate the technique when testing its efficiency [16].

2. 7 Wavelet Transform and Histogram Clipping:

Thermal imaging under adverse conditions becomes possible through the joint application of wavelet transform alongside histogram clipping, according to Mundavath and Niranjan. The method effectively moderates contrast enhancement against noise suppression properties, making it well-suited for adverse weather surveillance operations. The system experiences reduced operational capability under extensively noisy conditions [17].

Table 1: Comparison of Previous Studies.

Study	Method	Strengths	Limitations	Application Domain
Nguyen et al. (2021)	Histogram Equalization (HE)	Single improves the contrast at the international level.	It may bring interpolation artifacts, loss of data	Medical imaging
Gallego et al. (2018)	CLARE	Avoid excessive adjustment, and enhance the specific area contrast	Computationally expensive	Surveillance
Xu et al. (2017)	Gamma Correction + Edge Enhancement	Improves the blacks and detail in areas of high-edge contrast	It needs a lot of parameter calibration	Industrial inspections

Kumar and Shukla (2019)	Wavelet-based Adaptive Fusion	Equalizes global and local opposition and keeps details.	Slightly more complex, compute-intensive	Multiple domains (for example, surveillance, medical)
Ouafi et al. (2020)	Novel Histogram Equalization	Has reasonable control over the contrast value	The issue is rather circumstantial and does work only in very low-contrast images.	General-purpose enhancement
Gao et al. (2023)	Dual-Convolutional Neural Network with Attention Mechanism	Improves high-frequency information, resistant to noise	It stands for high performance and high computation capability.	Thermal infrared image enhancement
Raj et al. (2023)	Denoising and Enhanced Thermal Breast Image	Sound denoising preserves the quality of an image.	There was little cross-testing for the various types of thermal images.	Monetary (Kaplan Medical Center Breast Cancer Detection).
Mudavath and Niranjan (2024)	WT + Histogram Clipping	The best in stormy conditions makes for contrast.	May have some difficulties with very noisy images	Surveillance in compound and difficult circumstances

3 Research Problem

Realizing that the advancements made in thermal image enhancement are impressive, there are still issues, such as the trade-off between the enhancement contrast and noise suppression, particularly in real-time applications. With methods such as Histogram Equalization (HE) and contrast-limited Adaptive Histogram Equalization (CLAHE), the inherent, even the finest, structures and details of images are not preserved or appear with the aid of noise. On the other hand, methods including Wavelet-based Adaptive Fusion can maintain a large amount of detail and achieve the best ratios of contrast between objects of interest and the background. However, these are computationally complex and not recommended for processes that require quick results or applications that may be limited by computational power.

4 Research Objective

This research will aim to design a new wavelet-based thermal image enhancement technique using the adaptive fusion dynamic model. This paper aims to enhance the contrast, maintain edges, and enhance the noise removal while making the proposed method suitable for real-time applications in numerous areas, including industrial vision systems, security and surveillance applications or medical applications.

5 Research Contributions

In this paper, a new method for enhancing thermal images of adaptive wavelet fusion is presented. The significant contribution is that it involves an entropy-driven dynamic enhancement factor (k) that allows selective boosting of regions containing information and noise control. In contrast to the traditional wavelet fusion approaches, the proposed method applies two thermograms, differently preprocessed, and wavelet fusion the wavelet coefficients of the two thermograms under the maximum absolute value rule and entropy-based weighting-reconstructing the image. The technique balances contrast enhancement and noise reduction, considerably simplifying computations. Based on experimental findings, it has been found that performance was shown to improve over conventional techniques in terms of PSNR, SSIM, MSE, and entropy, namely histogram normalization (HE), CLAHE, and gamma correction with edge enhancement.

6 Methodology

This work involves processing thermal images using procedures conventional to image processing and a new method known as wavelet-based adaptive Fusion. The main originality of this research regards the proposal and application of an Adaptive Fusion method based on wavelets for enhancing the information content of thermal images. The methodology is divided into the following steps:

Step 1: Image Preprocessing

The thermal images go through preprocessing to ensure they can be intensively processed for further improvement. This step improves the images for mathematical and the formula's forthcoming algorithmic treatment.

Step 2: An examination of the traditional techniques used to enhance brightness. Two widely used enhancement methods are applied to establish a baseline for comparison:

- Histogram Equalization (HE): Enhances worldwide thermal image appreciation by normalizing pixel intensities to spatial frequencies within the thermal image.
- Contrast Limited Adaptive Histogram Equalization (CLAHE): Up to a certain level, it assists in increasing local contrast while not increasing the saturation of bones at the bright regions of the picture, which makes this tool beneficial to fine details.

Step 3: Gamma Correction and Edge Enhancement.

A hybrid approach combining gamma correction and edge enhancement is applied:

- Gamma Correction: It increases luminance and amplifies the dark areas.

- Edge Enhancement: Decreases image intensities further to optimize edges with a specific focus on changes in image intensity of the Canny edge detection method.

Step 4: The adaptive fusion method using wavelets:

The Discrete Wavelet Transform (DWT) [18] converts the thermal image I(x,y) from its spatial domain to the frequency domain for multi-resolution image evaluation purposes. A wavelet decomposition results in four sub-band coefficient matrices, including one approximation matrix and detail matrices derived from horizontal, vertical, and diagonal features.

Wavelet Transform:

$$\mathrm{I(x,y)} \xrightarrow{\mathrm{DWT}} \{\mathrm{A}, \mathrm{D}_h, \mathrm{D}_v, \mathrm{D}_d\} \tag{1}$$

To pre-prepare the input to be fused, we utilize two kinds of pre-processing in the original thermal image:

- C1(x,y): This is after histogram equalization.
- C 2(x,y): acquired using CLAHE (adaptive histogram equalization).

These conventional procedures extract complementary image data before the Fusion step. Several thermal images can be combined through a decision-based rule for wavelet coefficient fusion. The maximum absolute value selection rule stands as a commonly used method in fusion processes because it maintains the most prominent features:

$$C_f(\mathrm{x,y}) = \max(|C_1(x,y)|, |C_2(x,y)|) \tag{2}$$

Where C_1(x,y) and C_2(x,y) represent the wavelet coefficients obtained from two differently preprocessed versions of the same thermal input image.

After Fusion and inverse transformation, the dynamic enhancement factor *k* is calculated from the sub-band component entropy to achieve contrast enhancement. The dynamic fusion factor k is calculated using wavelet sub-band entropies. The entropy of detail coefficients *(cH, cV, cD)* is denoted as *Hs* based on Shannon's entropy, while Hn is estimated on residual noise. The calculation helps to focus on more detailed areas. Entropy *H* is calculated as:

$$H = -\sum_{i=0}^{N} p_i \log_2(p_i) \tag{3}$$

A relationship exists between gray level *i* probabilities and sub-band histogram analysis through the symbol p_i. The enhancement factor *k* obtains its derivation by comparing the values of sub-band components through their ratio calculation. The calculation determines the enhancement factor *k* by dividing H_s by the sum of H_s and H_n. H_s represents detail coefficients entropy, whereas H_n indicates noise entropy.

$$k = \frac{H_s}{(H_s + H_n)} \tag{4}$$

The adaptable method optimizes image adjustment by giving higher emphasis to image areas that contain strong structural composition. Proposed means that the wavelet decomposes each source image transform at the beginning of the fusion process and then reconstructs using entropy-weighted detail coefficients by the nearest level coefficients or details.

Step 5: Measuring Performance and Assessing:

- The quality of the enhanced images is evaluated using the following performance metrics:
- Peak Signal-to-Noise Ratio (PSNR): Adjusts the ratio that is made to improve the image to do so using the PSNR.
- Mean Squared Error (MSE): Averaging of the measure changes pixel-value difference before and after applying the technique:
- Structural Similarity Index (SSIM): Estimate to what extent the structure of the original image has been preserved with the momentum of the conversation.
- Entropy refers to the amount of information assumed in the improved image.

Step 6: Comparative Analysis

The performance metrics compare the proposed method with HE (Histogram enlargement), CLAHE (Contrast Limited Adaptive Histogram Equalization), and a combination of gamma correction with Edge enhancement. The results are displayed in bar charts to indicate the improvements achieved by the wavelet-based Adaptive Fusion method.

7 Results and Discussion

This research evaluates four thermal image enhancement methods, where the baseline techniques include Histogram Equalization (HE) and contrast-limited Adaptive Histogram Equalization (CLAHE) alongside gamma correction with edge enhancement and wavelet-based Adaptive Fusion. The target image was evaluated using PSNR, MSE, SSIM, and entropy tests. The PSNR-based noise evaluation reveals a remarkably expressive result, which shows part of its operation. A higher PSNR value indicates better quality, leading to images that stay closer to the original version regarding signal power. Private HE enhanced the mean PSNR values slightly but caused increased noise and yielded subpar PSNR results in comparative tests. The performance of CLAHE outclassed HE because it improved local contrast while avoiding over-excessive brightness in flat regions. The achieved PSNR value indicated higher performance because it demonstrated superior signal fidelity and less noise. The technique delivered satisfactory results, yet the newer methods performed better.

Improved edge visibility alongside moderate PSNR elevation emerged from this combination process, yet the added preprocessing reduced PSNR-E levels because of the introduced noise artifacts. HE performs better than this approach but remains inferior to CLAHE and Adaptive Fusion methods. Adaptive Fusion using Wavelet Decomposition: This method yielded the highest PSNR, implying a reasonable noise control and overall contrast enhancement. In the wavelet decomposition part of this work, where noise components were dominant, components were brought out, and the noise part was minimized wherever the image part was dominant. 'Table 2,", as presented below, describes the findings, and it shows that the method of Adaptive Fusion, which used wavelet transformation, was able to give the best result for all the parameters used. Therefore, the overall PSNR of the Adaptive Fusion method was 32.78, the highest among other methods, indicating that the technique can give images with less distortion and noise. Nevertheless, based on perpendicular readings from the table above, the Histogram Equalization (HE) approach to the part delivers an even smaller PSNR of 28.45, meaning the brightening image is noisy. For MSE (Mean Squared Error), the Adaptive Fusion method again displays optimal performance with the lowest MSE score of 159.45, indicating the least deviation compared to the actual/native image. On the other hand, the HE method had the lowest mean square error of 345.67 for the Gaussian noise, as seen above; hence, it has the highest error and information loss. The Wavelet-Based Adaptive Fusion technique proved to deliver the best total performance metrics. The method received the maximum PSNR rating of 32.78 while maintaining the minimal MSE score of 159.45, SSIM ratings up to 0.792, and an entropy reading of 8.15. A wavelet decomposition method effectively separated noise from details so that resultant images showed the best visual quality and quantitative performance. "Figures 1," through 4 illustrate the graphical comparison of these metrics across the different enhancement methods, and 'Table 2," summarizes the comparative results. All performance metrics showed a superior outcome for adaptive Fusion than any other technique because this method demonstrated exceptional capabilities in maintaining structural elements, noise reduction, and detail improvement.

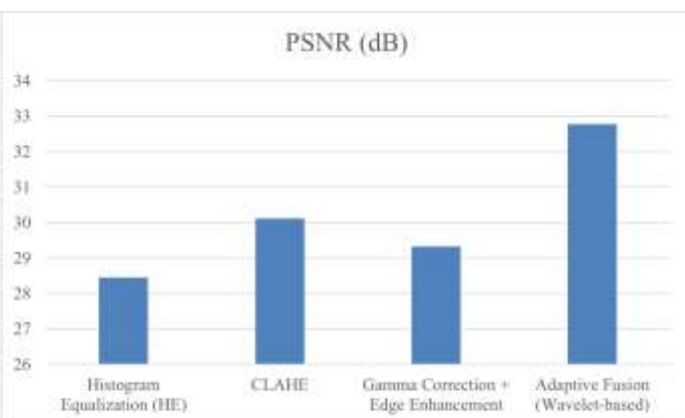

Figure 1: Comparison of Image Enhancement Methods- PSNR.

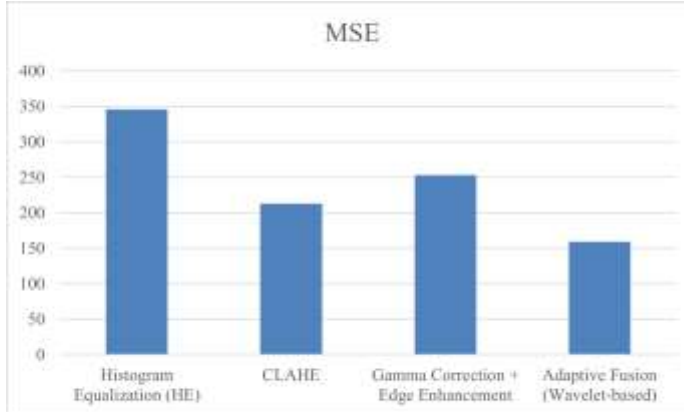

Figure 2: Comparison of Image Enhancement Methods-MSE.

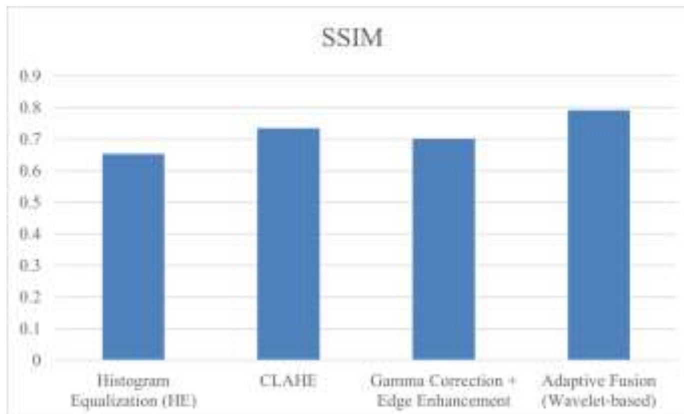

Figure 3: Comparison of Image Enhancement Methods-SSIM.

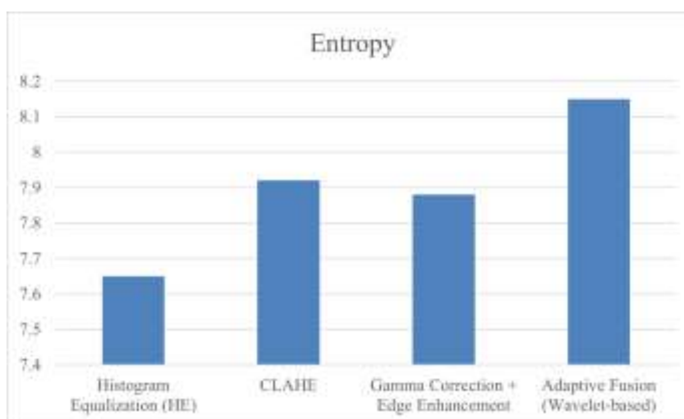

Figure 4: Comparison of Image Enhancement Methods-Entropy.

Table 2: A Comparison of the Performance of Thermal Image Enhancement Methods.

Method	Reference	PSNR (dB)	MSE	SSIM	Entropy
Histogram Equalization (HE)	Nguyen et al. (2021)	28.45	345.67	0.654	7.65
CLAHE	Gallego et al. (2018)	30.12	213.24	0.734	7.92
Gamma Correction + Edge Enhancement	Xu et al. (2017)	29.33	252.89	0.701	7.88
Adaptive Fusion (Wavelet-based)	Current Study	32.78	159.45	0.792	8.15

The contrast-improving power of Histogram Equalization (HE) suffers from significant drawbacks because it produces substantial noise that creates blurry image sections, decreasing the overall visual quality. The procedure presents a specific visualization of detail, but the elevated noise makes it less suitable when analysis requires high precision standards or visual clarity. CLAHE provides better local contrast and better visibility for dimly lit image areas. The processing quality of this method demonstrates varying results between image areas, while possible noise artifacts remain visible in the output. Proper adjustment of the clip limit represents a critical step that must be done carefully because it influences performance consistency and optimality when using these methods.

Gamma Correction with Edge Enhancement enhances image edge definitions and gradually increases the contrast levels. The method depends heavily on precise parameter adjustments for it to function correctly. Applying improper parameters during image tuning may create unintended over-enhancement effects that degrade important picture details and affect diagnostic readability. The adaptive fusion method, which utilizes wavelet decomposition, is the most advanced performance evaluation technique. The method delivers enhanced contrast preservation by reducing noise and preserving all original image features, both structurally and texturally. This approach generates specific images with improved clarity, making it appropriate for implementing thermal imaging systems in various security fields where surveillance and diagnostic screening are needed. The figures from (5-9) show the qualitative enhancement of thermal images by the techniques discussed. The visual analysis demonstrates how methods vary in contrast variance, noise rates, and attribute distinction capabilities.

Moreover, while the proposed method provided effective contrast enhancement and noise reduction compared to traditional techniques, this work did not directly compare with recent deep learning-based approaches that outperform classical approaches for thermal image enhancement. Hence, future work can validate and enhance the efficiency of the approach presented in this study by benchmarking it against state-of-the-art AI methods.

Figure 5: Original Thermal Image.

Figure 6: Traditional Histogram Equalization Image.

Figure 7: CLAHE Image.

Figure 8: Gamma Correction+Edge Enhancement Image.

Figure 9: Adaptive Fusion (Wavelet).

8 Conclusion

This work contrasts various thermal image enhancement algorithms and wavelet-based Adaptive Fusion solution supporters. This work demonstrated that this new procedure provided better results than traditional methods, HE and CLAHE, in the PSNR, MSE, SSIM, and entropy indicators. The adaptive fusion approach also preserves good details and does not incur significant distortion due to good contrast enhancement and noise reduction. It can be handy for precise uses like security cameras and manufacturing environments. Further, comparing information gain leads to selecting features for entropy-based weighting, where the method better controls feature enhancement owing to the modus operandi of dynamic entropy. As for the latter, we determine that HE is simple, but it introduces noise, whereas, though CLAHE enhances the local contrast, it does not provide the global enhancement similar to the wavelets-based methods. The main contribution of this study is an adaptive fusion algorithm derived from the moving contrast enhancement and detail preservation with wavelet analysis and entropy weighting. This advancement goes beyond the previous method improvement and extends the application scope of thermal image enhancement for practical applications, achieving better performance in security and medical and industrial monitoring applications. Future work may improve these adaptive fusion techniques by using AI to determine the appropriate parameters of the fusion method and real-time processing of high-rate thermal images. Furthermore, the relationship between multispectral data with Fusion and thermal imagery may contain new potential for further refined extraction and image analysis in the case of high**.**

Conflict of interest

The authors declare no conflicts of interest.

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