Journal of Information Hiding and Multimedia Signal Processing ©2021 ISSN 2073-4212
Ubiquitous International Volume **12**, Number **4**, December **2021**

A novel method based on parameter optimization for medical image fusion

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Received June 2021; revised September 2021

Abstract. *Medical image synthesis is a very significant topic in medical image processing, through fusing information from the multimodality images for increasing the clinical diagnosis accuracy. This paper introduces a new algorithm about fusing multimodal images. This is based on parameter optimization. This algorithm is called the particle swarm optimization (PSO) and wavelet transform (WT) based on Image Fusion (WPSOIF). First, we use wavelet transform for splitting the input images into components over the high and low frequency domains. We then use the composition association rule to obtain the composite image. Next, from this composite image, the algorithm creates 3 intermediate images using basic transformations: histogram equalization, candy edge detection and median filtering. Next, we use the PSO optimization algorithm to find the optimal coefficients for each image based on the contrast index function. The final enhancement image combines three intermediate images with optimized coefficients with the following advantages: enhanced brightness, edge enhancement, image sharpening and noise reduction. The experimental results of the paper show that the proposed algorithm outperforms than some recent methods.*
Keywords: Medical image, image fusion, wavelet, parameter optimization, particle swarm optimization.

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1. **Introduction.** Medical image fusion is combining the information of multimodality images to acquire accurate information [1]. Purposing of this fusion is used to improve image quality and preserve the specific features. These are for increasing the clinical applicability to assist assessment and diagnosis of medical problems [2]. The methods of medical image fusion generally use knowledge of fields as clinical medicine, computer vision, digital imaging, machine learning, pattern recognition to fuse different medical images [3]. The methods of fusing image include two main approaches. These are the spatial-domain approach and the transform-domain approach [4]. With the spatial domain approach, the fused image is chosen from the regions/pixels of the input images without transformation [5]. This approach includes the region based [4] and pixel based on [6] methods. The techniques of transform domain do fusing the corresponding transforming coefficients and then the inverse transformation is applied for producing the fused image. One of the popular fusion techniques is transform of multi scales. There are multi transform techniques such as contour transform based [9][10][11], dual tree complex wavelet transform based [8] techniques, the discrete wavelet transform based [7], sparse representing based [12]. Recently, there are many new techniques. Hari et al. [13] presents a method of fusing CT-MRI images that based on discrete wavelet transform. In [14] and [15], the authors presented a method of fusing images using the Principal Component

Analysis. Sarmad et al. [16] proposed a method of fusing multimodal medical images that is based on representing sparse and two-scale decomposition of images. Lina et al. [17] proposed a method of fusing medical images using hybrid wavelet-homomorphic filter and a algorithm of modified shark smell optimization. Srinivasu et al. [18] proposed a method of fusing the information of the various image modalities such as SPEC, PET and MRI using fusion rule of local energy maxima and empirical wavelet transform representation. Qiu Hu et al. [19] proposed a fusing method of combining dictionary optimization with the filter Gabor in non-subsampled contourlet transform domain. Jingyue et al. [20] proposed a medical image fusion method that is based on Rolling Guidance Filtering. Maruturi et al. [21], proposed statical measurements of medical image fusion for MRI-PET images using 2D Herley transform with HSV color space. Meenu Manchanda et al. [22] proposed an improved algorithm of medical image fusion that based on fuzzy transformation (FTR). Om Prakash et al. [23] proposed a new algorithm for fusing medical images that uses lifting scheme-based bioorthogonal wavelet transform. Hikmat Ullah et al. proposed a method of fusing multimodality medical images that this method is based on fuzzy sets with local-features and new sum-modified-Laplacian in domain of the non-subsampled shearlet transform [24]. In [33], YU Liu and coauthors proposed a new method of medical image fusing that is Convolutional Sparsity-based by Analysis of Morphological Component. The image enhancement methods are divided into 3 categories including histogram, fuzzy logic and optimal methods [25]. Histogram based contrast enhancing methods focus on modifying histogram of images. Histogram specification and histogram equalization are commonly used as conventional contrast enhancement methods. Optimal methods are based on optimizing parameters. The fuzzy logic based on image enhancement methods make image whose quality is clearer than the traditional methods. In order the image enhancement, there are many optimization techniques such as bacterial foraging, genetic, ant colony and greedy system. In [28], a Guassian membership function is introduced for bluring the images which consists of the crossover point, intensifying parameter and fuzzier for image enhancement. A new algorithm is introduced that is based on Histogram Equalization with Adaptively Increasing Value, [26]. In [29], Prakash and coauthors used Artificial Ant Colony System to propose a enhancement method of High dynamic range optimal fuzzy color image. In [30], Malikaet al. proposed a method of image enhancement in Discrete Wavelet Domain using Artificial Bee Colony. In [36], the authors presented a new algorithm of swarm intelligence that named Cat Swarm Optimization. While Shu-Chuan and et al. presented a method of Migration Optimization for Traveling Salesman Problem [37]. Song and et al. proposed a population evolution algorithm for optimization. And in [38], the authors presented an enhanced structure for differential evolution. The contributions in our article are: we propose a new image fusion algorithm based on parametric optimization for improving the quality of medical images. This algorithm is called the wavelet transform and PSO based on Image Fusion (WPSOIF). First, the article uses wavelet transform to split the input images into components over the high and low frequency domains. We then use the composition association rule to obtain the composite image. Next, from this composite image, the algorithm creates 3 intermediate images using basic transformations: histogram equalization, candy edge detection and median filtering. Next, the PSO algorithm is used for finding the optimal coefficients for each image based on the contrast index function. The final enhancement image combines three intermediate images with optimized coefficients with the following advantages: enhanced brightness, edge enhancement, image sharpening and noise reduction.Many meta-heuristic-based image synthesis methods have been proposed in recent years, such as MPA [40], GOA [41], and EOA [42].

The remaining of this article is structured as follows. In section 2, some related works presented. in section 3, the proposed algorithm about image fusion is presented. In section 4 presents some experiments. We present conclusions and plan of future reseach in Section 5.

2. **Related Work.**

2.1. **Wavelet transformation.**

Wavelet Transformation (WT) is a mathematic tool [31]. This tool is used for presenting images with multi-resolution. After transforming, Wavelet coefficients is obtained. With digital signals like remote sensing images, Wavelet coefficients can be got by Discrete Wavelet Transform (DWT). In which, the most important content is low frequency. This content keeps most of the features of input image and its size is decreased by four times. By using low pass filter with two directions, the approximate image (LL) is got. When DWT performed, the size of image LL is decreased four times smaller than the image LL of the previous. Therefore, if the input image is disaggregate 3 levels, size of the final approximate image is decreased 64 times smaller than the input image. Wavelet transformation of image is illustrated in figure 1.

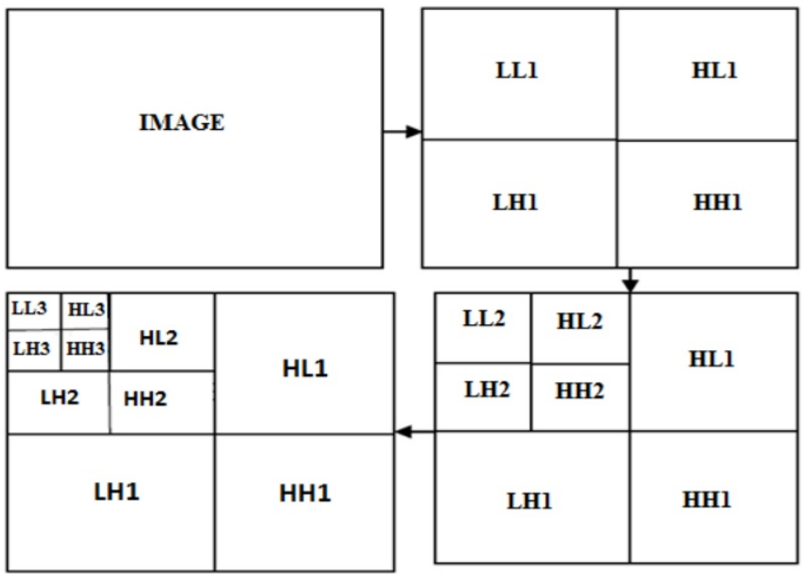

FIGURE 1. Image Decomposition using 2D DWT.

2.2. **Particle swarm optimization (PSO).**

PSO is a algorithm about finding solutions to optimization problems [32]. Kennedy and Eberhart introduced PSO in 1995. PSO is the result of modeling bird flocks that fly to find foods. This algorithm has been applied in many fields successfully. First, PSO initialized a group of individuals randomly. Then, the algorithm updates generations to find the optimal solution. With each generation, two best positions of each individual is updated: P_{best} and G_{best}. Wherein the first value, P_{best} is best the position that has ever reached. Another optimal solution is the global optimal solution G_{best}. G_{best} is the best position in the whole search process of the population up to the present time. Specifically, after each generation updating, with each individual, its position and velocity are updated by the formula as follows:

$$PX_i^{k+1} = X_i^k + V_i^{k+1} \tag{1}$$

$$V_i^{k+1} = \omega * X_i^k + c_1 * r_1 \left(P_{best\_i}^k - X_i^k\right) + c_2 * r_2 \left(G_{best}^k - X_i^k\right) \tag{2}$$

Where:

- X_i^k: Position of the individual i^{th} in generation k^{th}.
- V_i^k: Velocity of the individual i^{th} in generation k^{th}.
- X_i^{k+1}: Position of the individual i^{th} in generation $k+1^{th}$.
- V_i^{k+1}: Velocity of the individual i^{th} in generation $k+1^{th}$.
- $P_{best\_i}^k$: Best position of the individual i^{th} in generation k^{th}.
- $G_{best\_i}^k$: Best position of in population in generation k^{th}.
- $\omega = 0.729$ is the inertia coefficient.
- c_1, c_2: The acceleration coefficients, getting values from 1.5 to 2.5.
- r_1, r_2: Random numbers get values in the range [0, 1].

2.3. **Image fusion based on wavelet transformation.** Hari et al. [13] presented a method of fusing CT-MRI images that based on the discrete wavelet transform (WIF), as shown on figure 2.

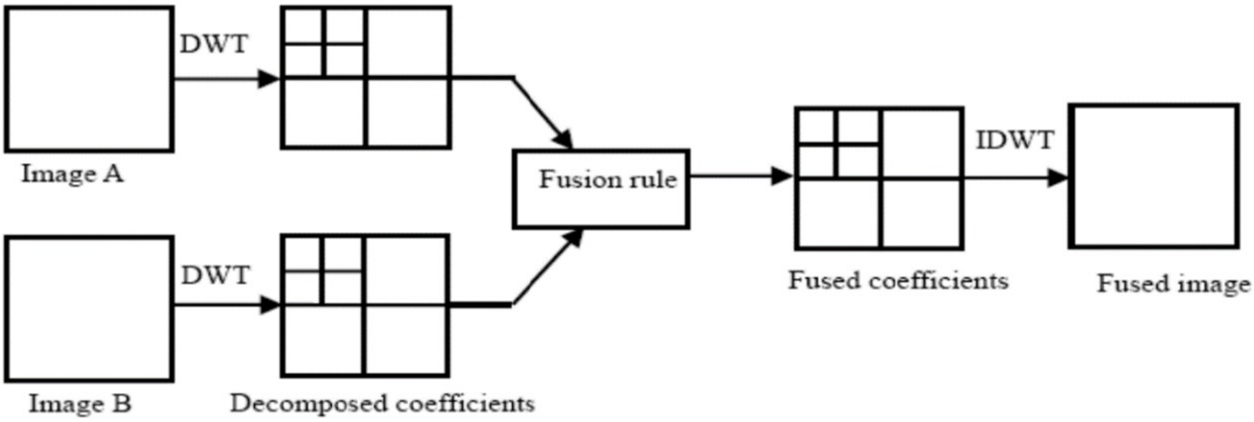

FIGURE 2. The scheme of image fusing using the wavelet transform.

With $I_A(x_i, y_i)$, $I_B(x_i, y_i)$ are two input images and $I_F(x_i, y_i)$ is fused image, fusion rule includes:

- Average method:
$$I_F(x_i, y_i) = \frac{I_A(x_i, y_i) + I_B(x_i, y_i)}{2} \tag{3}$$
- Select Maximum:
$$I_F(x_i, y_i) = Max\left(I_A(x_i, y_i), I_B(x_i, y_i)\right) \tag{4}$$
- Select Minimum:
$$I_F(x_i, y_i) = Min\left(I_A(x_i, y_i), I_B(x_i, y_i)\right) \tag{5}$$

3. **Proposed Method.** In this section, a new algorithm for fusing of medical image is proposed. This algorithm is named Wavelet transform and PSO based Image Fusion (WPSOIF). The scheme of the algorithm WPSOIF is shown in figure 3.

Where, Img_1 is PET or SPEC image (color images), Img_2 is CT or MRI image (grey images). According to the above diagram, the algorithm includes the steps as follows:

- Step 1: Convert image img_1 from RGB color space to HIS color space to get I_{Img_1}, H_{Img_1},
- Step 2: Transform I_{Img_1} and I_{Img_2} (Img_2 is grey image) to get HL_1, LL_1, HH_1, LH_1 and HL_2, LL_2, HH_2, LH_2 using DWT transformation.

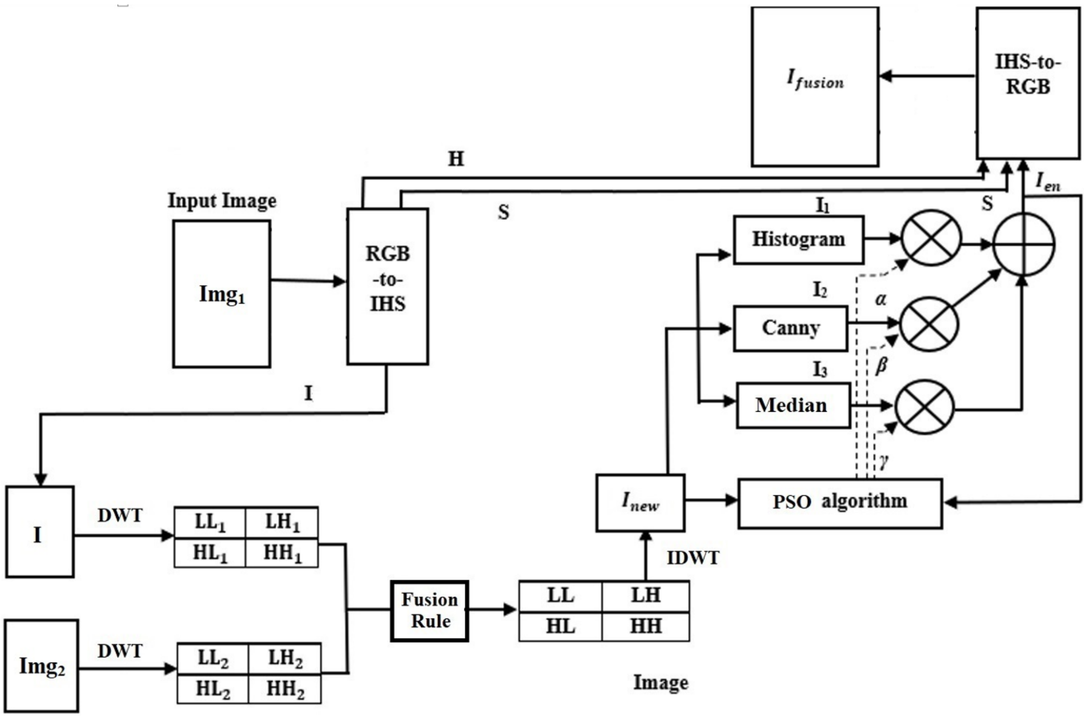

FIGURE 3. The scheme of the algorithm of medical image fusion WPSOIF.

- Step 3: Fuse the components (HL_1, LL_1, HH_1, LH_1) and (HL_2, LL_2, HH_2, LH_2) to get HL, LL, HH, LH using fusion rules Select Average and Select Max as follows:

$$LL = \frac{LL_1 + LL2}{2} \tag{6}$$

$$LH = max\,(LH_1, LH_2) \tag{7}$$

$$HL = max\,(HL_1, HL_2) \tag{8}$$

$$HH = max\,(HH_1, HH_2) \tag{9}$$

- Step 4: Transform the components (LL, LH, HL, HH) to get I_{new} using IDWT transformation.
- Step 5: Generate images I_{hist} (histogram equalization image) I_{can} (candy edge image) and I_{median} (median image) of I_{new}, using histogram equalization, candy edge detection and median filtering:

$$I_{hist} = histEq\,(I_{new}) \tag{10}$$

$$I_{can} = candy\,(I_{new}) \tag{11}$$

$$I_{median} = median\,(I_{new}) \tag{12}$$

- Step 6: Generate Ien by following formula:

$$I_{en} = \alpha * I_{hist} + \beta * I_{can} + \gamma * I_{median} \tag{13}$$

The parameters α, β, γ are found, using an algorithm PSO with the optimization of objective function as follows:

$$J = \left(\frac{\sigma^2}{\mu}\right)(H_2 - H_1) \tag{14}$$

Where, σ^2 and μ are variance and mean intensity value for the enhanced intensity channel. H_1 is entropy of I_{new} and H_2 is entropy of I_{en}.

- Step 7: Convert the components I_{en}, H_{Img_1}, S_{Img_1} from color space HIS to color space RGB to get the output fused image.

In this algorithm, we proposed some improvements:

- A schema of image fusion with combining of DWT and parameter optimization based on PSO.
- Combining some image transformations: histogram equalization, edge detection candy and median filter for creating enhanced image.
- The parameters α, β, γ are found by optimizing function J using the PSO algorithm.

4. **Experiments.**

4.1. **Experimental setting.** Input data is download from link: *http://www.med.harvard.edu/AANLIB*. Methods that used for comparing with proposed methods includes: Wavelet based image fusion (WIF) [13], image fusion based on PCA (PCAIF) [14] and the CSMCA [33]. To assess image quality, we use the measures: μ, σ^2, E, G [34] and VIFF [35].

4.2. **Experimental results.** Due to the limitation of the paper, in this subsection, we illustrate the experiment with 6 slices: image combination PET-MRI with 2 slices 060 and 085, image combination SPEC-CT with 2 slices 009 and 012, image combination SPEC-MEI with 2 slices 002 and 005.

Figures 4, 5, 6 The table illustrates input images and output images of the fused methods.

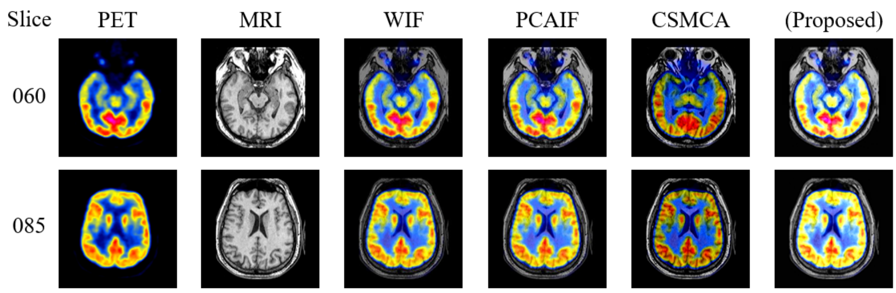

FIGURE 4. Input images PET, MRI and output images of the fused methods.

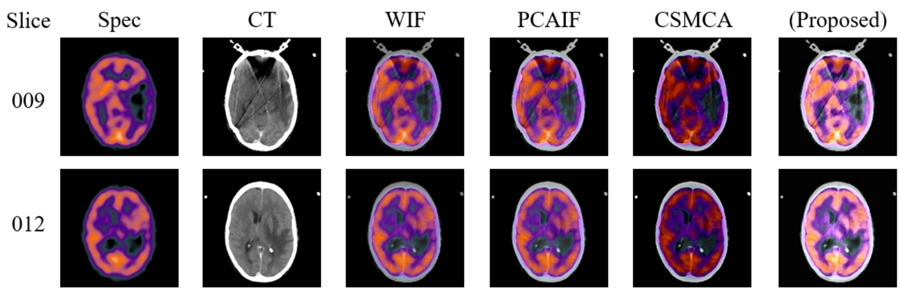

FIGURE 5. Input images Spec, CT and output images of the fused methods.

Figures 4, 5 and 6 show that the fused image generated by the proposed method has better contrast than fused images using the compared methods. The CSMCA method (2019) even generates very dark fused image compared to the two WIF and PCAIF methods. This makes it difficult to distinguish objects in the image. Meanwhile, the

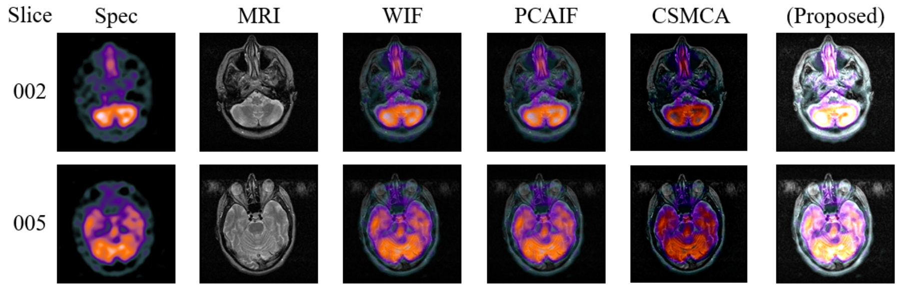

FIGURE 6. Input images Spec, MRI and output images of the fused methods.

proposed method for the composite image is very bright, clearly distinguishing the objects in the image, which greatly aids in diagnosis. In addition, the WIF and PCAIF methods do not highlight the boundary of the objects in the resulting image. The WPSOIF method clearly demonstrates this feature due to the incorporation of a candy filter method with enhancement.

The table in figure 7 shows the μ, σ^2, E, G, and VIFF indexes of the output image of the fusing method. From this table, the evaluation indexes show that the quality of output images of our proposed method is much better than some compared recent methods.

Fusion	Slice	Index	Other methods			WPSOIF
			WIF	WPCAIF	CSMCA	(Proposed)
PET_MRI	060	μ	0.2238	0.2486	0.1695	**0.3083**
		σ^2	0.0650	0.0765	0.0498	**0.1115**
		E	5.2135	5.1538	4.6118	**5.8465**
		G	0.0472	0.0459	0.0565	**0.0653**
		VIFF	0.3718	0.4552	0.7021	**0.7508**
	085	μ	0.2236	0.2332	0.1535	**0.2938**
		σ^2	0.0700	0.0737	0.0409	**0.1117**
		E	4.8818	4.8328	4.2999	**5.3853**
		G	0.0416	0.0373	0.0499	**0.0574**
		VIFF	0.4203	0.4430	0.6925	**0.8043**
Spec-CT	009	μ	0.1871	0.1995	0.1298	**0.2811**
		σ^2	0.0533	0.0652	0.0462	**0.1135**
		E	4.2502	4.2636	3.8472	**4.8258**
		G	0.0262	0.0240	0.0286	**0.0380**
		VIFF	0.3495	0.5081	0.7367	**0.7629**
	012	μ	0.1846	0.1976	0.1271	**0.2827**
		σ^2	0.0521	0.0620	0.0412	**0.1175**
		E	3.9509	3.9139	3.7335	**4.6063**
		G	0.0207	0.0188	0.0232	**0.0323**
		VIFF	0.3331	0.4757	0.7441	**0.7770**
Spec-MRI	002	μ	0.1235	0.1239	0.0750	**0.3417**
		σ^2	0.0248	0.0246	0.0133	**0.1433**
		E	5.8924	5.6465	4.7454	**6.8805**
		G	0.0317	0.0251	0.0359	**0.0836**
		VIFF	0.3865	0.3973	0.6929	**2.6589**
	005	μ	0.1528	0.1538	0.0931	**0.3335**
		σ^2	0.0318	0.0316	0.0150	**0.1194**
		E	6.1192	5.9112	5.0778	**7.1380**
		G	0.0340	0.0272	0.0395	**0.0695**
		VIFF	0.4037	0.4174	0.6776	**1.8852**

FIGURE 7. The assessment indexes the quality of the results image of the fused methods.

5. **Conclusions.** This paper introduces the new algorithm of fusing multimodal images which is based on parameter optimization. This algorithm is WPSOIF with purpose is

enhancing the quality of the output fused images. The results getted by the experiments show that the ouput images of the proposed algorithm are better than some others recent methods about brightness, edge enhancement, image sharpening and noise reduction. In future works, we intend to continue applying the parameter optimization to other problems of image processing.

Acknowledgment. This work is partially supported by Department of Information Technology, Thuyloi university and Institute of Information Technology, Vietnamese Academy of Science and Technology. The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

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