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MRI and PET Image Fusion by Using Curvelet Transform

Nasrin Amini[1]✉, Emad Fatemizadeh[2], Hamid Behnam[3]

1) Biomedical engineering department, Science and Research branch, Islamic Azad University, Tehran, Iran

2)Biomedical Signal and Image Processing Lab (BiSIPL), Dept. Electrical EngineeringSharif University of TechnologyTehran, Iran

3)Bio-Medical Engineering group, Department of Electrical Engineering, Iran University of Science and Technology, Tehran, Iran

nasrin.amini67@gmail.com; fatemizadeh@sharif.edu; behnam@iust.ac.ir

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Abstract

The fusion of medical images is very useful for clinical application. Generally, the PET image indicates the function of tissue and the MRI image shows the anatomy of tissue. In this article we fused MRI and PET images and the purpose is adding structural information from MRI to PET image. The images decomposed with Curvelet Transform, and then two images fused with applying fusion rules. We used MATLAB software for fused images and evaluated the result. The data set consists 34 images of color PET images and high resolution MRI images. The brain images are classified into two groups, normal (Coronal, Sagittal and Transaxial) and Alzeimer's disease dataset images. Finally we used visual and quantitative criteria to evaluate the fusion result. In quantitative evaluation we used entropy, discrepancy and overall performance. Results show the amount of entropy, achieved by the proposed method, was the highest and amount of discrepancy and overall performance was the lowest. The small amount of discrepancy, overall performance and high amount of entropy means high quality.

Keywords: *Image Fusion, Multiscale Geometric Analysis, Curvelet Transform, Fusion Rules*

1. Introduction

Image fusion is the process that combines information from two or more images into a single image. The result is a new image that retains the most desirable information of each source image [1]. Medical imaging is divided into structural systems such as MRI and CT (computed tomography) images and functional systems such as PET (positron emission tomography) and SPECT (single-photon emission computed tomography) images [2]. A single image isn't enough for clinical needs, so combining anatomical and functional images provide much more useful information.

Image fusion techniques can also be classified on the three main levels include pixel level, feature level and decision level pixel level fusion methods are the most mature ones. The algorithm in this paper is a pixel level fusion method [3], [4], [5], [6]. Pixel level algorithms work either in the spatial domain such as averaging, HIS [7], [8] or in the transform domain such as Multiscale decomposition and Multi geometric analysis

[2], [9]. Spatial domain method usually leads to undesirable effect such as reduced contrast and spectral distortion. Transform domain methods don't have spatial domain problems. Typical Multiscale decomposition included the Laplacian Pyramid, 2-D Wavelet Transform. Laplacian Pyramid generates only one subband image in each level [9]. Wavelet transform can provide better spatial and spectral localization of image information as compared to other multiresolution representations. But 2-D wavelet transform decompose images into only three directional vertical, horizontal and diagonal, capturing only limited directional information [1], [10]. Multiscale Geometric Analysis (MGA) tool have been developed, which include in ridgelets and curvelets, and these are very different from wavelet-like systems [11], [12]. Curvelets and ridgelets exhibit very high directional sensitivity and are highly anisotropic. Therefore, the curvelet transform represents edges better than wavelets, and is well suited for multiscale edge enhancement and provide more information for image processing [11], [13]. In this paper, we introduce a new image fusion method based on the Curvelet Transform. Experimental results show that the proposed fusion method provides an effective way to the analysis of MRI and PET images. The rest of this paper is organized as follows. In Materials and Methods, we briefly introduce the Curvelet Transform, image fusion based on Curvelet Transform and fusion rules. The experimental results, visual and quantitative evaluation are presented in Results. Discussion concludes the paper.

2. Materials and Methods

The first step is finding a transformation capable of representing straight edges with different slopes and orientations. The solution is the ridgelet transform, which may be regarded as the 1D wavelet transform of the Radon transform. However, an inconvenience with the ridgelet transform is that it is not capable of representing curve lines. To overcome this drawback, the input image is partitioned into square blocks and the ridgelet transform is applied to each block. Figure1 outlines the block ridgelet transform and highlights that the discrete Radon transform is obtained with a recto-polar resampling of the 2D FFT of the image block [11]. Candès and Donoho proposed the curvelet transform (CVT) with the idea of representing a curve as a superposition of bases of various lengths [8].The curvelet transform, unlike wavelet transform, is a multiscaletransformand contains directional elements. Curvelets are based on multiscaleridgelet combined with a spatial bandpass filtering operation to isolate different scales [12].The algorithm is outlined in the following:

• This transform decomposes an image f in its coarse version, c_J, and in the details $\{d_j\}_{J=1,\dots,J}$, at scale 2^{-j}.

$$f(m,n) = c_j(m,n) + \sum_{j=1}^{J} d_j(m,n) \qquad (1)$$

•Select the minimum dimension of window, Q_{min} to apply to the finest scale d_1;
• For a fixed scale j, make a partition of d_j in disjoint blocks having size.

$$Qj=\begin{cases} 2^{\frac{j}{2}}Qmin & if\ j\ is\ even \\ 2^{\frac{j-1}{2}}Qmin & if\ j\ is\ odd \end{cases} \qquad (2)$$

•Apply the ridgelet transform to each block.

According to the original definition of curvelet transform, the base-band approximation $c_j(m,n)$ is not further analysed by the block ridgelet transform shown in fig1. However, this has been done in the present work, in order to derive the injection model in the directional domain [11].

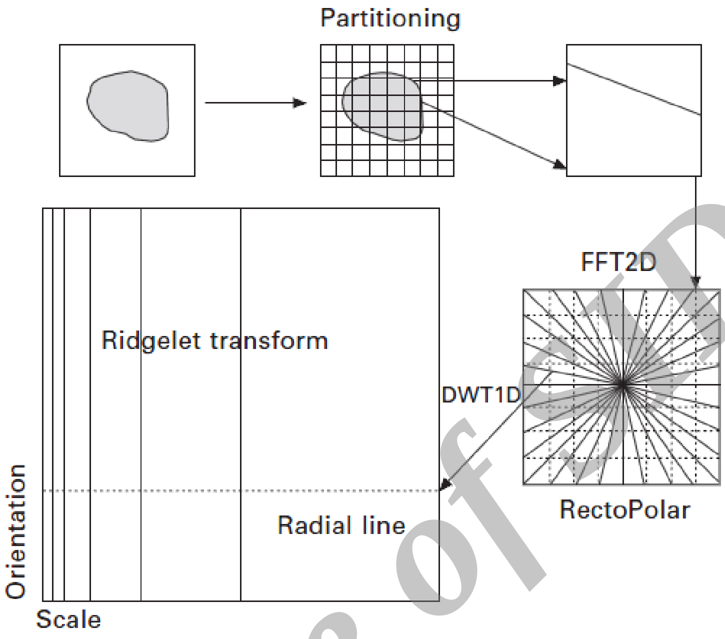

Figure1. Flowchart of ridgelet transform applied to square image blocks [11]

The HSI transform converts a multispectral image with red, green and blue channels (RGB) to intensity, hue and saturation (IHS) independent components. The intensity displays the brightness in a spectrum, the hue is the property of the spectral wavelength, and the saturation is the purity of the spectrum [2].Before applying curvelet transform, source images convert from RGB space to HSI space because we can separate the intensity and color information (hue and saturation) [1].The I component is an image without color information so we can work on this component and be sure that color information don't change. In the end of fusion we retuned color information (H and S components) to fusion result.

Therefore, The fundamentals of MRI and PET images based on Curvelet Transform are: (1) Two images to be fused must be registered to assure the corresponding pixels are aligned; (2) PET image to be converted from RGB space to HSI space; (3) Two image are decomposed with Curvelet transform and images include one low frequency band and sets ofhigh frequency bands; (4) The transform coefficients of different bands are combined with the fusion rules. The fusion rules were averaging in the low frequency band and maximum selection in the high frequency bands; (5) Performing the inverse Curvelet on result of step4; (6) The fused image is constructed by converting the result back to RGB space. Fig2 shows the flowchart of MRI and PET image fusion based Curvelet transform.

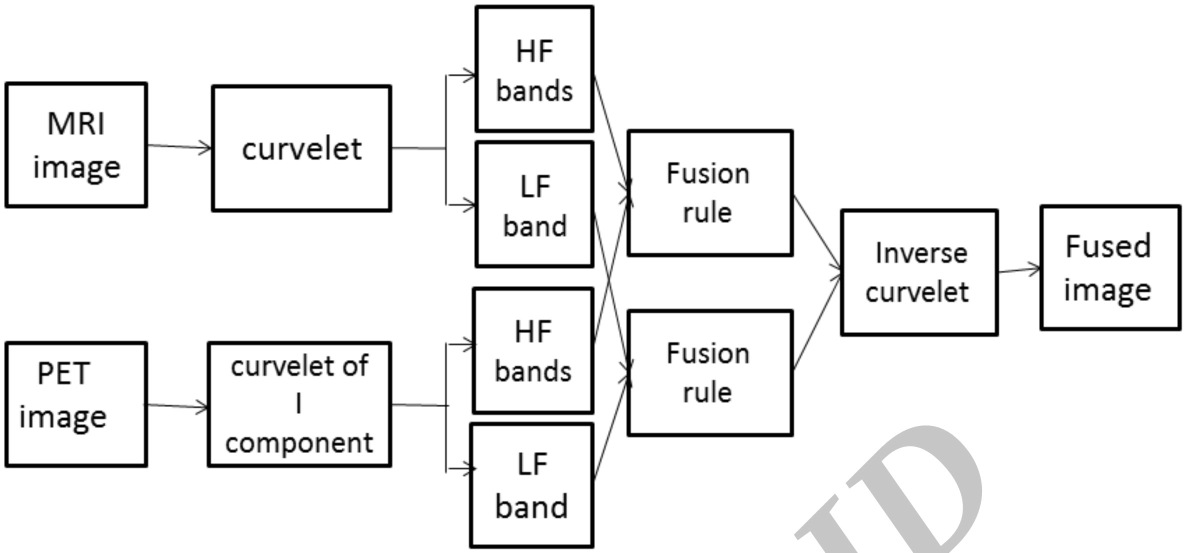

Figure2. Schematic diagram of MRI and PET image fusion based curvelet transform.

When image decomposed with Curvelet transform, images include one low frequency band and sets ofhigh frequency bands that they have different physical meanings. As a result, the coefficients in low frequency and high frequency portions should be performed with different fusion rules [9].Fusion rules and the way they are applied directly affect the final fusion performance. Selection and averaging are probably the most popular coefficient combining methods.

Most information of their source images is kept in the low frequency band, such as the mean intensity and texture information [14], [15]. Based on this analysis, we used averaging for combined coefficients in the low frequency. Averaging method is employed while the curvelet coefficients between two images are both important. Therefore, averaging method is suitable for combing the low-frequency bands because the approximation images of the images to be fused usually look similar [1].

The HF bands contain the detail coefficients of an image and preserve salient information in the image. Maximum selection method can collect the largest curveletcoefficients between two images. Therefore, it is suitable for collecting the edges or corners, i.e. detailed information. In the high-frequency bands, the larger curveletcoefficients correspond to sharper brightness changes and thus to the salient features in the image such as edges, lines, and region boundaries. Therefore, the maximum selection method is useful in the collection of the detailed information [1].

3. Results

In this section, we indicate the effectiveness of the proposed method on desired dataset. The dataset consist 34 of color PET images and high resolution MRI images. The MRI images and PET images are 256×256 and 128×128 pixels. All images resized to 256×256. The color PET images were registered to the corresponding MRI images. All images have been downloaded from the Harvard university site (http://www. med.harvard.edu/AANLIB/home.html). The brain images are divided into two groups normal (Coronal, Sagittal and Transaxial) and Alzeimer's disease images. The

Averaging, HSI transform, Wavelet transform, Laplasian Pyramid, and the proposed method (Curvelet Transform) were employed to fuse the images. The samples of original images and fusion results are displayed in fig3 and fig4.

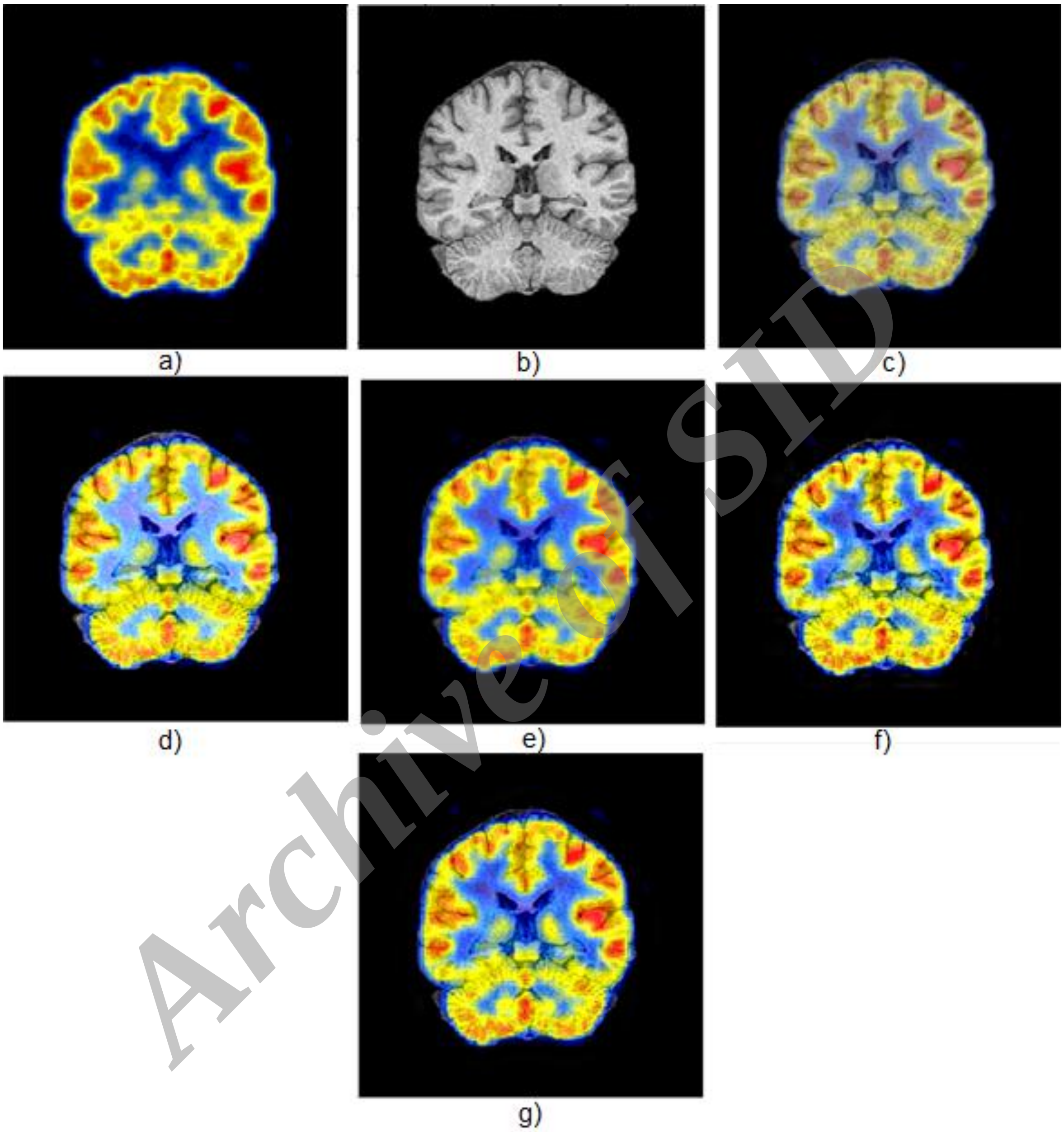

Figure3. Normal coronal PET and MRI images (a and b), Averaging (c), HSI model (d), Laplacian Pyramid (e), Wavelet transform (f), proposed method (Curvelet transform) (g)

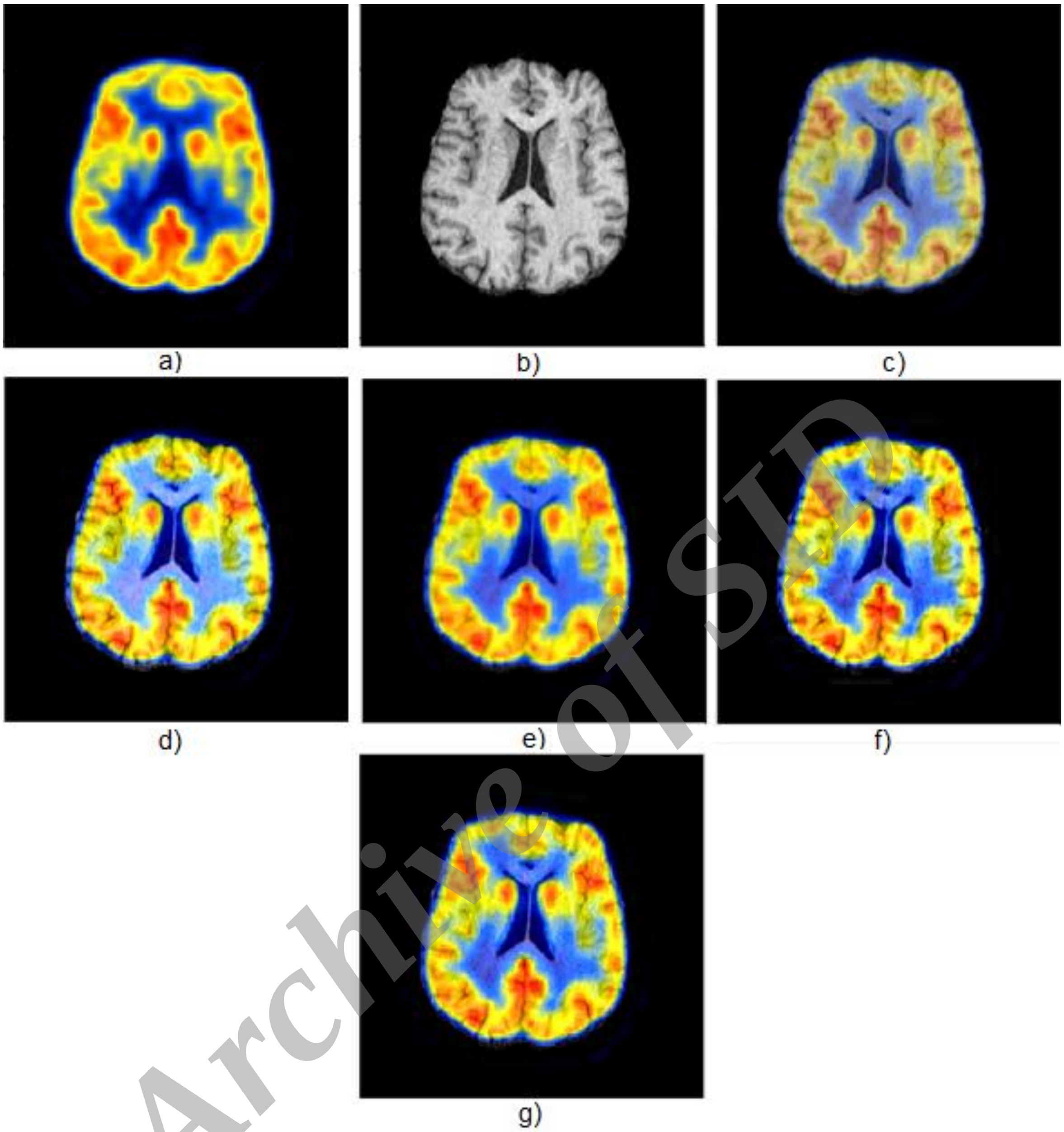

Figure4. Normal axial PET and MRI images (a and b), Averaging (c), HSI model (d), Laplacian Pyramid (e), Wavelet transform (f), proposed method (Curvelet transform) (g)

As we said, the source images are firstly decomposed into one low frequency subband and a sequence of high frequency subbands in different scales and orientations. Then at each position in the transformed subbands, the value of averaging in low frequency subband and Maximum coefficients in high frequency subbands is selected to construct the fused subbands. Finally, the fused image is obtained by applying inverse transform on the fused subbands. Apparently, the results from the proposed method appear the best among all the results visually.

The widespread use of images of different sensors and multiscale images in medical diagnosis has increased the importance of fusion techniques quality assessment. A good fusion of multi-spectral image should preserve source spectral characteristics and also

keep panchromatic image spatial attributes. In this paper, we evaluate three criteria for quantitative evaluating offusion method. Entropy, discrepancy and overall performance are selected as the quantitative measurements [2], [7].Entropy is defined as amount of information contained in a signal. Shannon was the first person to introduce entropy to quantify the information. Entropy can directly reflect the average information content of an image. The maximum value of entropy can be produced when each gray level of the whole range has the same frequency. If entropy of fused image is higher than parent image then it indicates that the fused image contains more information [16]. Discrepancy is difference between fusion result and PET image. Small discrepancy of the result is acceptable. Overall performance is different between average gradient and discrepancy. Small amount of overall performance (O.P) means a higher overall fusion quality [2].
Average and standard deviation of the above mentioned parameters for 34 images are calculated and listed in table 1. Table 1 shows that the amount of entropy of the fused images, achieved by the proposed method, was the highest. Amount of discrepancy and overall performance of the fused images, achieved by the proposed method, were the lowest. In visual comparison you can see proposed method have more details of PET than other methods.

Table1. Quantitative comparison of the 5 fusion methods.

Method	Entropy	Discrepency	OP
Pixel averaging	3.1141$\pm$0.6050	6.1358$\pm$ 3.1009	3.2292$\pm$2.6033
HSI based	2.7465$\pm$0.5273	7.8387$\pm$2.9109	3.3772$\pm$2.2280
Laplacian Pyramid	2.8755 $\pm$ 0.5634	7.7678$\pm$2.8812	0.9461 $\pm$2.2068
Wavelet	3.0815$\pm$0.5789	5.5806$\pm$1.7392	1.1012$\pm$ 0.7471
Curvelet	3.1371$\pm$0.5607	5.5333$\pm$1.7438	1.0148$\pm$0.8064

4. Discussion

In this paper, we proposed a method based Multiscale Geometric Analysis for fusion of MRI and PET images. Multiscale Geometric Analysis such as curvelet transform exhibit very high directional sensitivity and are highly anisotropic. Therefore, the curvelet transform represents edges better than Multiscale decomposition such as wavelet transform, and therefore more information from the source images can be transferred into the fused images. The PET produces images with suitable color and low spatial resolution, while MRI provides appropriate spatial resolution with no color information. In this study, we firstly decomposed images with curvelet transform into low frequency band and high frequency band. Then each band combined with different fusion rules. Results show that the performance of the proposed fusion method is better than that of other methods including pixel averaging method, HSI transform method, gradient pyramid method and wavelet transform method.It is clear that the proposed method is the best in both human visualization and objective evaluation criterion. We will work on other Multiscale Geometric Analysis methods for further work in this domain.

Conflict of Interests

Authors have no conflict of interests.

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