PIBB 生物化学与生物物理进展
Progress in Biochemistry and Biophysics
2017, 44(11): 1026~1036
www.pibb.ac.cn

基于 Renyi 熵滤波的光声图像重建算法设计与实现 *

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摘要 针对光声图像重建过程中存在的原始光声信号信噪比差、重建图像对比度低、分辨率不足等问题，提出了基于 Renyi 熵的光声图像重建滤波算法．该算法首先根据原始光声信号的 Renyi 熵分布情况，确定分割阈值，并滤除杂波信号；再利用滤波后的光声数据进行延时叠加光声图像重建．利用该滤波算法分别处理铅笔芯横截面(零维)、头发丝(一维)以及小鼠大脑皮层血管(二维)等不同维度样本的光声信号，实验结果表明：相比 Renyi 熵处理之前，重建图像对比度平均增强了 32.45%，分辨率平均提高了 30.78%，信噪比提高了 47.66%，均方误差降低了 35.01%；相比典型的滤波处理算法(模极大值法和阈值去噪法)，本研究中图像的对比度、分辨率和信噪比分别提高了 25.94%/10.60%、27.90%/19.48%、35.21%/10.60%，均方误差减小了 28.57%/16.66%．因此，选择利用 Renyi 熵滤波算法处理光声信号，从而使光声图像重建质量得到大幅改善．

关键词 光声图像重建，滤波处理算法，Renyi 熵，阈值分割
学科分类号 Q8，R4，TP751 **DOI**: 10.16476/j.pibb.2017.0248

光声成像[1-6]是一种通过获取物体内的光声信号，进而对物体进行三维或者二维纵向切面成像的方法．在光声效应中，光子首先被物体吸收转化为热，随着物体局域温度快速提升而导致热膨胀效应，从而产生宽频带的超声波．该超声波迅速向组织边界传播并可被一个或多个超声换能器接收，因接收器接收到的光声信号携带有组织的位置、吸收强度等信息，因此可以用来定性或定量地重建光声图像．光声成像结合了光学成像的高对比度和超声成像高穿透深度的技术优点[7-8]，同时，还可提供诸如血红蛋白、氧饱和度、代谢速率等功能参数，在外源光声探针辅助下具有分子影像及靶向识别能力．因此，在生物成像[9-14]、乳腺癌[15-17]、关节炎[18]等的早期诊断、针刺治疗[19]方面具有广阔的应用前景．

在光声图像重建的过程中，影响最终成像质量的因素有很多，其中最重要的两点为图像重建算法的选择和原始光声信号的信噪比．在光声图像重建算法方面，目前的研究主要分为两大类：一类是变换重建方法，另一类是级数展开重建法．其中变换重建方法又可分为傅里叶变换重建法和滤波反投影重建法．Yang 等[20]提出了用于压缩感知 - 磁共振成像(compressed sensing magnetic resonance imaging，CS MRI)应用的径向样伪极坐标(pseudo-polar，PP)轨迹．PP 轨迹保留径向轨迹的所有基本特征，并允许使用 PP 快速傅里叶变换代替内插进行图像重建，该方法为 MR 图像(其峰值信噪比超过 2dB 增益)高质量重建提供支持的同时，保持了结构的相似性(≥0.88)．Yu 等[21]使用滤波反投影算法比较曝光参数对图像质量的影响．Ke 等[22]提出了一种改进的滤波反投影图像重建算法，将该算法应用于磁感应层析成像，提高了重建图像定位精度，改进的磁感应层析成像(magnetic induction tomography，MIT)反投影算法具有重构速度快、定位准确的特

* 国家自然科学基金(61474079，11602159)，山西省优秀人才科技创新项目(201605D211020)和山西省高等学校科技创新项目(2016136)资助.
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收稿日期：2017-08-04，接受日期：2017-08-31

点．Wang 等[23]提出将小波阈值去噪的方法用于滤波反投影算法，基于改进小波阈值函数的滤波反投影重建算法具有更好的重建效果，因为更具弹性．级数展开重建法，其特点是从开始就对数据进行离散化分析，直接得到数值解．如迭代变换法、迭代重建投影．Rajashree 等[24]提出了基于迭代反投影来提高超分辨率性能的改进算法，该算法收敛速度快并提供了适当的初步猜测、增强了重建图像的性能，优化了整体重建系统的误差．Hashemi 等[25]开发了一种改进空间分辨率的新型迭代重建算法，该算法表示为在模糊的同时进行迭代重建，通过明确计算重构公式中不同因素引起的图像不清晰度，提高了空间分辨率．Jia 等[26]比较了滤波反投影重建算法、混合迭代重建算法、迭代模型重建算法三种重建算法在计算机断层扫描血管造影的成像质量．上述两类光声图像重建方法中，变换重建方法可以很好地保留图像细节 / 边缘信息并能够抑制伪像，从而实现更精确的重建，另一方面，级数展开重建法能够降低噪声，得到较高的信噪比和边缘清晰度，能够提升整体图像质量．

综上所述，经过近十几年的不断探索和研究，光声图像重建在算法方面得到了长足的发展，但基于原始光声信号处理的研究却略显滞后．目前，光声信号滤波处理的基本方法包括模极大值法与阈值去噪法．Qin 等[27]提出了一种新型的多分量信号分解方法．通过优化的复小波变换来计算多组分信号的小波模最大值，所提出的信号分解方法具有更高的精度、分辨率以及更好的鲁棒性．为了解决特征尺寸过大和冗余信息存在的问题，Chen 等[28]提出了基于双树复小波变换(double-tree complex wavelet transform，DT-CWT)阈值去噪，原始信号的降噪处理通过 DT-CWT 阈值去噪方法实现，既充分利用了 DT-CWT，又结合了鲁棒原理的小波阈值．综合国内外研究现状发现，通过滤波算法提高光声信号的信噪比从而来优化光声图像重建质量的研究已得到部分发展，但在具体实现方面，模极大值算法的运算过程较复杂，输出信噪比受算法分解尺度的影响较大．传统的小波阈值去噪方法受阈值函数的选取影响较大，在信号的去噪过程中容易出现噪声残留．

基于此，本文提出了一种基于 Renyi 熵的滤波处理算法，该算法阈值(Renyi 熵频数直方图中出现频次最小的熵值)由信号自身的性质决定，不会由于阈值选取的不同而对去噪效果产生影响；另外该算法运算过程简单，计算量小．利用该算法对原始光声信号进行滤波处理，提高光声信号质量，从而提高光声信号的信噪比，提高光声图像重建质量．

1 理论基础

1.1 光声信号处理流程

光声信号处理流程如图 1 所示，其处理过程具体分为以下几个步骤：

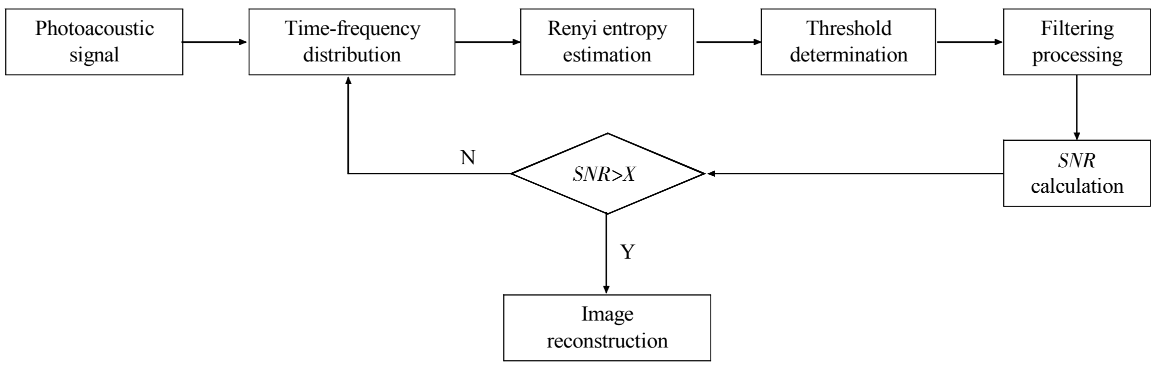

Fig. 1 Photoacoustic signal processing flow chart

a．首先利用短时傅里叶变换方法求出光声信号的时频分布；

b．根据时频分布情况求取光声信号各个点所对应的 Renyi 熵值；

c．根据前一步所得各光声信号点的 Renyi 熵，勾画熵值直方图，并选取直方图中在低熵范围内出现频次最小的熵值作为分割阈值；

d．利用得到的分割阈值对光声信号进行滤除杂波处理；

e．计算去除杂波之后光声信号的信噪比，与设定的值 X 进行对比，只有当信噪比大于 X 时，才可以利用时域延迟叠加算法[29]将处理之后的光声信号用于图像重建．

1.2　光声信号的时频分布

光声信号从信号学上讲是一种典型的非平稳信号．为了描述该类信号在不同的时间和频率范围内的能量密度和强度，主要利用短时傅里叶变换取窗的概念，定义局部相关函数，对这个局部函数进行 Fourier 变换，并最终得到该信号的时频分布函数(公式 1)．

$$S(t, f)=\int x(\theta)h(t-\theta)e^{-j2\pi f\theta}d\theta \qquad (1)$$

其中 $x(\theta)$表示待处理的光声信号，$h(t)$为选取的窗函数．

1.3　Renyi 熵求解

利用光声信号的时频分布计算其所对应的 Renyi 熵[30]，

$$R_\alpha=\frac{1}{1-\alpha}\log_2\iint S(t, f)dtdf \qquad (2)$$

其中 $S(t, f)$表示的是光声信号的时频分布，$\alpha(\alpha\geqslant 2)$[31]为 Renyi 熵的阶数．

图 2 为 Renyi 熵阶数、窗函数等参量对原始光声信号熵值的影响分析结果．其中，图 2a 为一列头发丝样本的原始光声信号．图 2b 为选取不同 Renyi 熵阶数(α)对应原始光声信号的 Renyi 熵值，由图可知，随着阶数的增大，原始光声信号中噪声部分的 Renyi 熵值与有用信号部分的 Renyi 熵值之间的差距逐渐缩小，信噪比变差，为使阈值分割的结果更为准确，选取信噪比最大的 Renyi 熵阶数(α=2)作为后续处理参数．图 2c 为选取不同窗函数对应的原始光声信号 Renyi 熵值，结果表明，不同窗函数对应的原始光声信号 Renyi 熵值无明显差异，本文在后续处理中选用汉宁窗．图 2d 为选取不同窗长(L)时计算出的原始光声信号 Renyi 熵值，由图可得，当选取的窗长分别为 L=80、L=320 时，有用信号部分的 Renyi 熵值收敛性较差；相比之下，当窗长为 L=160 时，其原始光声信号有用部分对应的 Renyi 熵具有较好的收敛性，因此，本文选取 L=160 作为窗长进行后续研究．

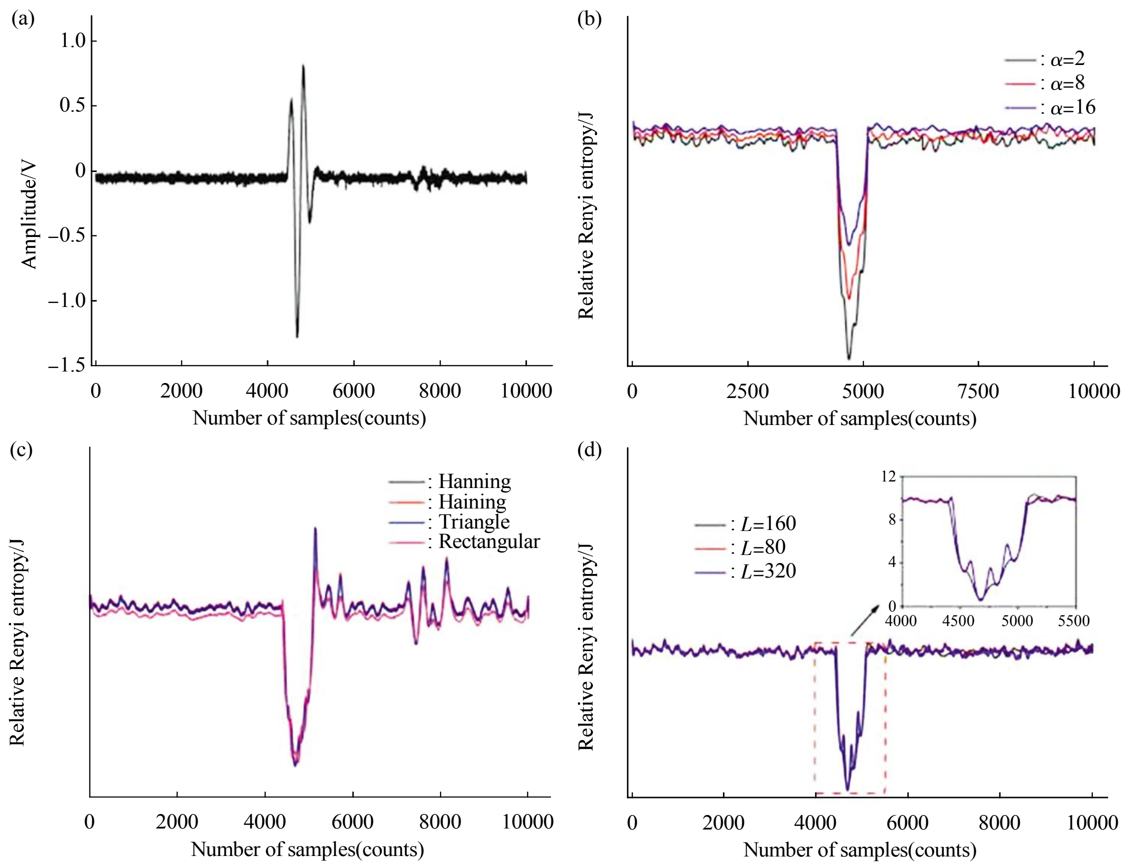

Fig. 2　The influence of Renyi entropy order, window function and window length on the entropy of original photoacoustic signal

(a) Original photoacoustic signal. (b) Select the different order, the original photo sound signal corresponding to the Renyi entropy. (c) Select the different window function, the original photoacoustic signal corresponding to the Renyi entropy. (d) Select the different window length, the original photo sound signal corresponding to the Renyi entropy.

1.4 光声图像重建的质量评估参数

以图像对比度、分辨率[32]、信噪比、均方误差[33]和作为图像质量的评估参数，计算公式如下：

$$C=\sum_{\delta}\delta(i,j)^2P_\delta(i,j) \tag{3}$$

$$SNR=10.1\text{g}\left(\frac{255^2}{\sum_i (A(i)-O(i))^2/N}\right) \tag{4}$$

$$MSE=\frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}I(i,j)-K(i,j)^2 \tag{5}$$

利用公式(3)来表征重建图像的对比度，其中，$\delta(i,j)=|i-j|$，即相邻像素间的灰度差，$P_\delta(i,j)$表示相邻像素间的灰度差为δ的像素分布概率．公式(4)表示图像的信噪比，其中，N表示图像像素数目，O表示原始图像，A表示重建图像．公式(5)表示图像的均方误差，其中m，n表示图像的宽和高．I表示图像某一点的像素值，K表示整幅图像的平均像素值．系统分辨率近似等于点吸收体光声信号脉冲的半高宽，其表征的是光声重建图像是否能够反映吸收体真实尺寸特征的能力．

2 实验部分

2.1 光声实验平台及实验参数设置

光声成像实验平台所采用的是单元旋转扫描光声探测系统(图 3)．该系统由激光器(Surelite I-20, Continuum, 美国)、PCI4732 数据采集卡(中科动态仪器公司)、步进旋转台及其电机控制箱(M600, 北京卓立汉光仪器有限公司)、前置放大器(5077PR, Olympus, 美国)、非聚焦超声探头(V310-SU, Olympus, 美国)、计算机等组成．实验过程中，选用 532 nm 波长脉冲激光作为激发光源，脉冲宽度 4～6 ns，重复频率 20 Hz；选用中心频率为 5 MHz 的非聚焦超声换能器作为探测装置，完成光声信号的采集；光声信号采集过程中，超声换能器由步进旋转电机驱动，步长为 2 度进行环形扫描，扫描半径 4.5 cm；超声换能器在每一个位置采集 5 000 个点后旋转至下一个位置，进行全角度的圆周扫描．

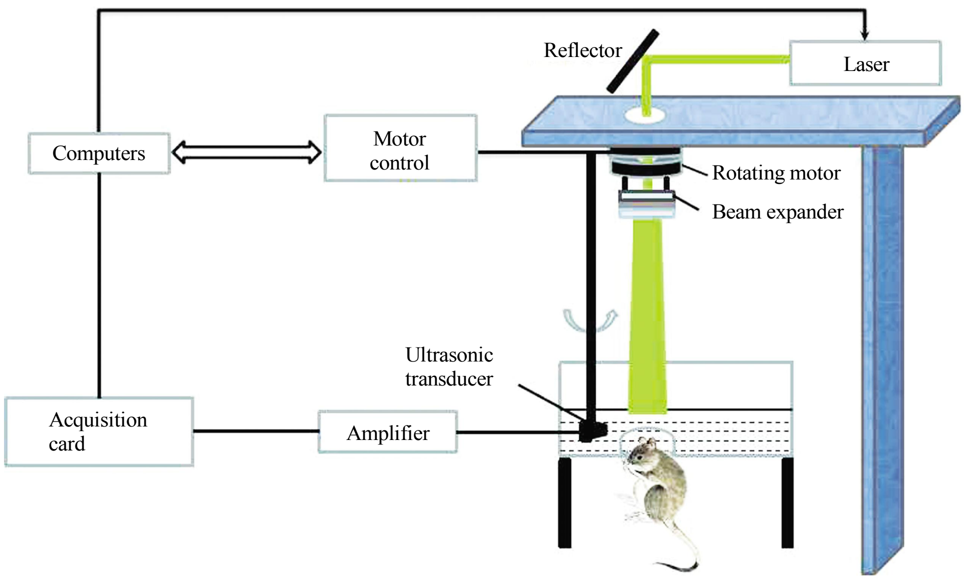

Fig. 3 Photoelectric system imaging equipment schematic diagram

2.2 铅笔芯横截面 (零维) 光声成像

铅笔芯横截面(样品 *1*，零维)的光声成像，是将 1 根直径为 0.7 mm 的铅笔芯垂直插入到仿体内部，将激光器产生的光斑照射到铅笔芯横截面的中心处进行光声成像实验．

2.3 头发丝 (一维) 光声成像

头发丝(样品 2，一维)的光声成像，是将 2 根头发丝交叉内嵌到仿体内部，2 根头发丝长度分别为 2 cm，直径为 0.06 mm，将激光器产生的光斑照射到 2 根头发丝的交叉处，进而进行光声成像

实验.

2.4　小鼠大脑皮层血管 (二维) 光声成像

小鼠大脑皮层血管(样品 3，二维)的光声成像中，需对小鼠进行短暂的气体麻醉，随后向其腹腔内注射水合氯醛(10%)，剂量为 0.04 ml/10 g．待其彻底麻醉后，剔除小鼠头部毛发，使得小鼠大脑皮层裸露出来，然后将其固定在一个光声系统自制的容器中，调整位置确保小鼠头部与超声探头的中心相平，调整光斑大小与位置使其照射在小鼠大脑皮层中心位置，进而进行光声成像实验.

3　结果与讨论

3.1　铅笔芯成像结果分析

图 4 为利用 Renyi 熵处理前后的铅笔芯横截面(零维)的光声信号进行光声图像重建的实验结果．其中，图 4a 为铅笔芯实物图，光声重建图像与其在结构上基本吻合．图 4b 为一段铅笔芯光声信号利用 Renyi 熵滤波处理前后的对比结果，由图可知，经 Renyi 熵滤波处理后铅笔芯横截面的光声信号只保留了有用信号部分，背景噪声及杂波被有效滤除．图 4c, d 分别对应铅笔芯光声信号在 Renyi 熵处理前后的光声图像重建结果．在两幅图中，分别选取重建前后任意相同位置的一个像素点，以图中(X=1.3, Y=6.5)为例进行对比，该像素点对应的成像对比度分别为 2.292 和 3.182，经滤波处理后，重建图像的对比度提高了 38.80%．图 4e, f 分别为滤波处理前后对应的铅笔芯光声信号的相对幅值变化情况，由图可知铅笔芯的直径分别约 1 450 μm、800 μm[32]，经滤波处理后，重建图像的分辨率提高约 44.80%．另外，在重建图像中任意选取多个位置进行统计分析计算(详见附件表 S1)，结果表明，经 Renyi 熵处理后重建图像的对比度平均提高 36.75%，分辨率平均提高 43.74%．同时，经过信噪比和均方误差计算，Renyi 熵处理后重建图像的信噪比提高了 43.20%，均方误差减少了 7.10% (表 1).

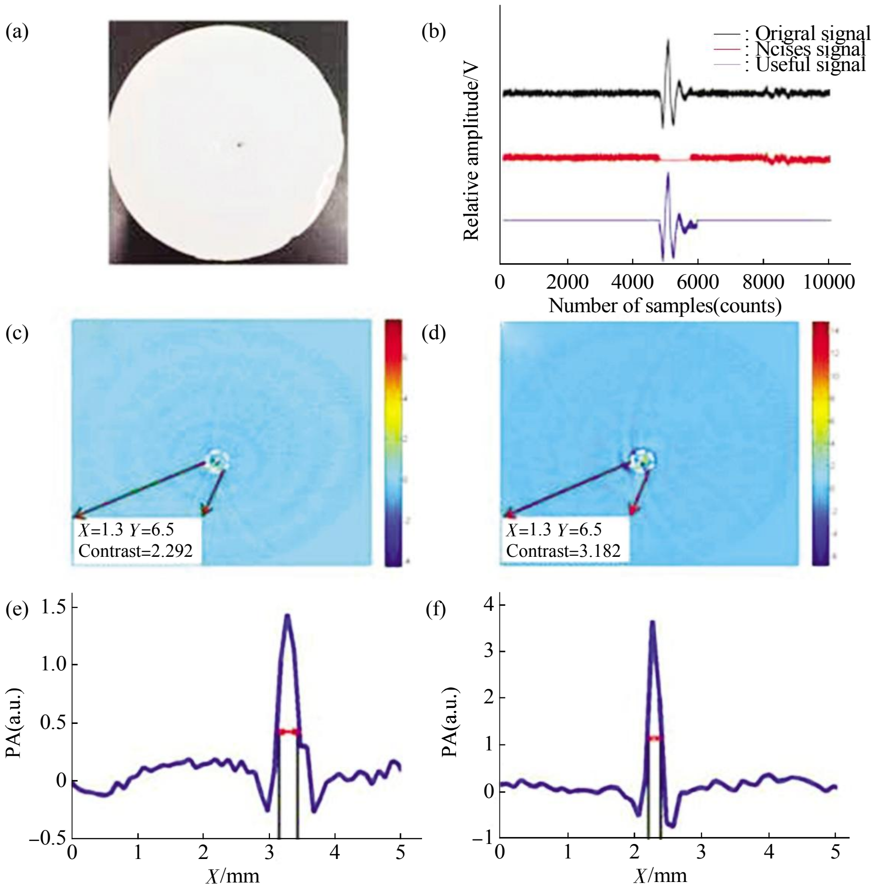

Fig. 4　The photoacoustic image reconstruction of the cross-section　(zero dimension) of the pencil core before and after Renyi entropy

(a) The pencil core in the imitation. (b) Filtering the photoacoustic signal of pencil core. (c) The photoacoustic image reconstruction of pencil core before the Renyi entropy algorithm processing. (d) After Renyi entropy algorithm processing, photoacoustic image reconstruction of the pencil core. (e) The relative amplitude of the photoacoustic signal of pencil core before the Renyi entropy algorithm processing. (f) The relative amplitude of photoacoustic signal of pencil core after Renyi entropy algorithm.

Table 1 Filter processing situation of three different samples

Sample number	Sample name	Sample characteristics	Filtering processing situation	Contrast	Resolution	SNR	MSE
1	Cross-section of the pencil core	Zero-dimension Diameter: 0.7 mm	Before processing	2.292	1 450 μm	3.000	0.056
			After processing	3.182	800 μm	4.296	0.052
			Filter optimization percentage	38.80%	44.80%	43.20%	7.10%
2	Hair imitation	One-dimension Length: 2 cm Diameter: 0.06 mm	Before processing	3.262	300 μm	2.297	0.007
			After processing	4.318	170 μm	3.483	0.005
			Filter optimization percentage	32.30%	43.30%	51.60%	28.57%
3	Mouse cortical Blood vessels	Two-dimensional Imaging range: 15 mm×15 mm	Before processing	3.092	420 μm	3.039	0.049
			After processing	4.057	350 μm	4.506	0.015
			Filter optimization percentage	31.20%	16.60%	48.20%	69.38%

3.2 头发丝仿体成像结果分析

图 5 为头发丝(一维)光声信号在利用 Renyi 熵处理前后所对应的光声重建图像结果．图 5a 为头发丝仿体实物效果图．图 5b 为利用 Renyi 熵频数直方图确定的分割阈值对头发丝光声信号进行分割前后的对比结果，插图为头发丝光声信号所对应的

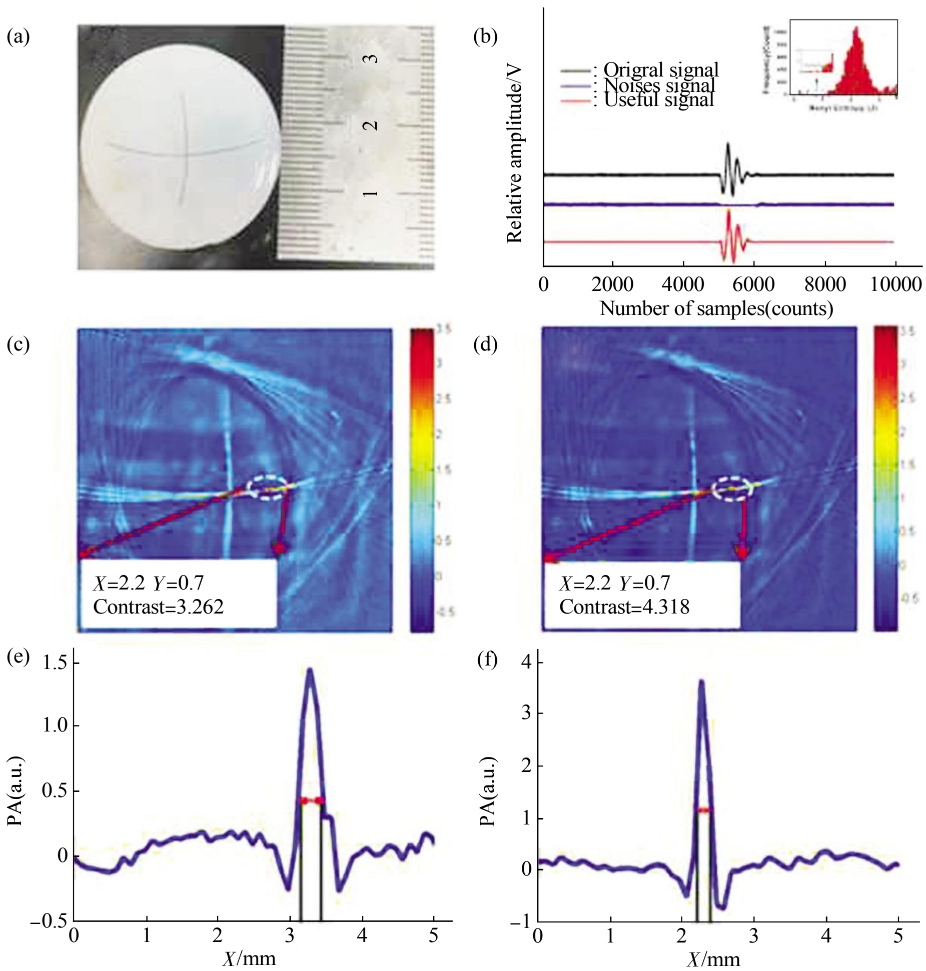

Fig. 5 The hair (one-dimensional) photoacoustic signal reconstructs the image results with the corresponding photoacoustic sound before and after the Renyi entropy

(a) Embedded in the imitation of two crossed hair; (b) Filtering of the hair photoacoustic signal; (c) The photoacoustic image reconstruction of the hair before the Renyi entropy algorithm processing; (d) After Renyi entropy algorithm processe, the photoacoustic image reconstruction of hair; (e) The relative amplitude of the photoacoustic signal of hair before the Renyi entropy algorithm processing; (f) Relative amplitude of photoacoustic signal of hair after Renyi entropy algorithm.

Renyi 熵频数直方图，对比发现，经 Renyi 熵滤波处理后头发丝光声信号只保留了有用光声信号部分．头发丝光声信号在经过 Renyi 熵处理前后所对应的光声重建图像如图 5c, d 所示，任意选取同一个像素点，以图中(X=2.2, Y=0.7)像素点为例，两幅图像在该点的成像对比度分别为 3.262、4.318，经过 Renyi 熵处理后的重建图像中该点的对比度提高了 32.30%．头发丝光声信号在 Renyi 滤波处理前后相对幅值的变化如图 5e, f 所示，头发丝的直径分别对应 300 μm、170 μm，成像分辨率较 Renyi 熵处理之前提高 43.30%．同时，在样本(图 5c, d)中进行多点统计分析计算(详见附件表 S2)可知，经 Renyi 熵处理后重建图像的对比度平均提高 30.22%，分辨率平均提高 30.96%．另外，重建图像的信噪比较未处理之前提高了 51.60%，均方误差减少了 28.57%(表 1)．

3.3　小鼠大脑皮层血管成像结果分析

图 6 为小鼠大脑皮层血管(二维)光声信号经过 Renyi 熵算法处理前后的光声成像结果．图 6a 为小鼠大脑皮层解剖实物图．选取一段小鼠大脑皮层血管的光声信号为样本，比较 Renyi 熵处理前后的信号波形图(图 6b)，结果发现，经 Renyi 熵处理后小鼠大脑皮层血管光声信号的杂波被有效抑制．图 6c, d 分别对应小鼠大脑皮层血管光声信号在 Renyi 熵处理前后的光声图像重建结果．重建图像的血管成像轮廓与图 6a 结构上基本吻合．在两幅图像中任意选取相同位置上一个像素点，图中以(X=–3.2, Y=–0.5)点为例，该像素点对应的光声图像重建的对比度分别为 3.092，4.057，经 Renyi 熵处理后重建图像在该点的对比度提高 31.20%．小鼠大脑皮层血管光声信号的相对幅值在滤波处理前后的变化情况如图 6e, f，由图可知小鼠大脑皮层血

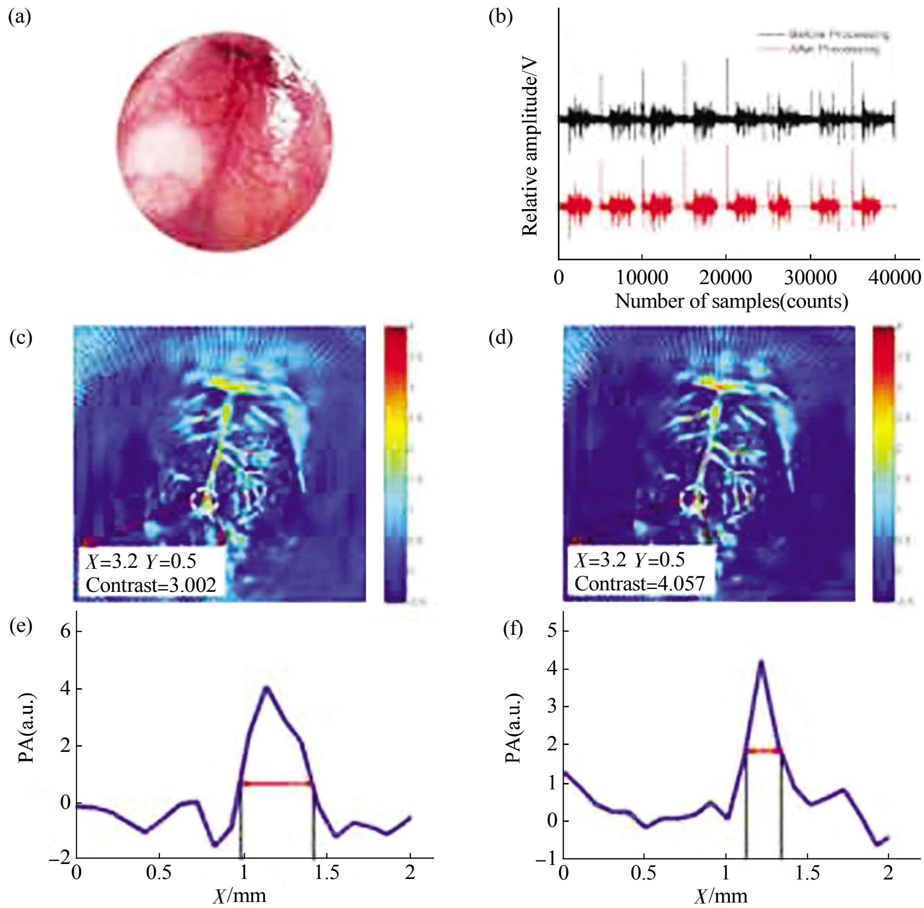

Fig. 6　The photoacoustic image reconstruction of the mouse cortical blood vessels (two-dimensional) before and after the Renyi entropy algorithm processing

(a) The mouse cortical blood vessels. (b) Filtering photoacoustic signal of the mouse cortical blood vessels. (c) The photoacoustic image reconstruction of the mouse cortical blood vessels before the Renyi entropy algorithm is processed. (d) Renyi entropy algorithm was used to reconstruct the image of mouse cortical blood vessels photoacoustic signal. (e) The relative amplitude of the photoacoustic signal of the mouse cortical blood vessels before the Renyi entropy algorithm processing. (f) Relative amplitude of photoacoustic signal of the mouse cortical blood vessels after Renyi Entropy Algorithm.

管直径分别约 420 μm，350 μm，其表征的光声图像的分辨率提高 16.60%．选取滤波处理前后对应的重建图像上多个位置进行统计分析计算(详见附件表 S3)，经 Renyi 熵处理后，重建图像的对比度平均提高 30.38%，分辨率平均提高 17.65%．另外经计算，重建图像的信噪比较未处理之前提高了 48.20%，均方误差减少了 69.38%(表 1)．

综合比较上述三个不同维度的实验样本，我们发现，经过 Renyi 熵滤波处理之后，光声重建图像的对比度均有较大幅度提高(表 S1, S2, S3)，分别为：36.75%(铅笔芯横截面，零维)，30.22%(头发丝，一维)和 30.38%(小鼠大脑皮层血管，二维)．其次，重建图像的分辨率同样均有较大幅度的提高(表 S1, S2, S3)，但相较于零维和一维样本，小鼠大脑皮层血管光声重建图像的分辨率提高有限(17.65%)，我们推测这与生物样本的选择有关(前 2 个样本为仿体，该样本为实物，小鼠大脑皮层血管和周围生物组织的光声信号差异性较仿体弱)．再次，重建图像的信噪比得以大幅提高(表 1)，分别为：43.20%(铅笔芯横截面，零维)，51.60%(头发丝，一维)和 48.20%(小鼠大脑皮层血管，二维)．最后，重建图像的均方误差(表 1)分别减少 7.10%(铅笔芯横截面，零维)，28.57%(头发丝，一维)和 69.38%(小鼠大脑皮层血管，二维)，随样本维度的增加图像均方误差大幅减小，我们推测这是由于随样本维度的增加，被滤除杂波的有用光声信号的比重增加，进而减小了整幅图像的平均误差，从而使得重建图像对应的均方误差随之减小[33]．

3.4 Renyi 熵与典型算法的对比

本文分别利用 Renyi 熵、小波阈值、模极大值算法对头发丝(二维)光声信号进行滤波处理(图 S1)，处理后光声信号所对应的重建图像的对比度、分辨率、信噪比、均方误差的结果对比如图 S2 所示．以图中(X=2.2，Y=0.7)像素点为例，4 幅图像(分别为原始信号、Renyi 熵处理、小波阈值处理以及模极大值处理后的光声重建图像)在该点的成像对比度分别为 3.262、4.318、3.325 和 3.675，经 Renyi 熵滤波处理后，光声重建图像的对比度最优．另外，在 4 幅图中分别选取若干个点进行对比(表 S4)，可以发现，经 Renyi 熵、小波阈值、模极大值处理后的图像对比度平均值分别为 1.835、1.457 和 1.659；图像分辨率平均值分别为 248 μm、344 μm 和 308 μm；重建图像的信噪比分别为 3.483、2.576 和 3.149；均方误差分别为 0.005、0.007 和 0.006(表 2)．相比小波阈值和模极大值处理方法，利用 Renyi 熵方法滤波处理后，光声重建图像的对比度、分辨率和信噪比分别提高 25.94%/ 10.60%、27.90%/19.48%、35.21%/10.60%，均方误差减小 28.57%/16.66%．在光声信号的滤波处理中，Renyi 熵相比传统滤波处理方法更为有效．

Table 2 Comparison of Renyi entropy with various typical algorithms

Characteristic parameters	Original signal	Renyi entropy		Wavelet threshold		Modulus maxima	
		Average	Optimization percentage	Average	Optimization percentage	Average	Optimization percentage
Contrast	1.406	1.835	30.51%	1.457	3.62%	1.659	17.99%
Resolution	360 μm	248 μm	31.11%	344 μm	4.44%	308 μm	14.43%
SNR	2.297	3.483	51.63%	2.576	12.15%	3.149	37.09%
MSE	0.007	0.005	28.57%	0.007	0%	0.006	14.28%

4 结　论

本文以提高光声图像重建质量为目的，从优化光声成像系统采集到的光声信号质量出发，在利用延迟叠加算法进行图像重建之前，利用 Renyi熵滤波算法对原始光声信号进行滤波处理．实验结果表明，与原始光声信号得到的重建图像相比，经 Renyi 熵处理后的光声重建图像对比度平均增强了 32.45%，分辨率提高了 30.78%，信噪比提高了 47.66%，均方误差降低了 35.01%．与现有的经典滤波算法(模极大值法和阈值去噪法)相比，该算法的对比度平均提高 18.27%，分辨率平均提高 23.69%，信噪比平均提高 2.90%，均方误差平均减少 2.61%．Renyi 熵滤波处理算法对光声图像重建质量的大幅改善，将有助于推动光声成像在生物医学诊疗方面的临床应用，如关节炎、乳腺癌以及癫痫等病灶的早期诊断．

附件 表 S1～S4，图 S1, S2 见本文网络版附录(http://www.pibb.ac.cn)

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Design and Implementation of Photoacoustic Image Reconstruction Algorithm Based on Renyi Entropy Filter*

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Abstract In order to improve the quality of photoacoustic image reconstruction, aiming at the problems that the signal-to-noise ratio of the original photoacoustic signal is poor, the reconstructed image contrast is low and the resolution is insufficient in the process of photoacoustic image reconstruction, based on the quality of photoacoustic signal which collected from the optimized photoacoustic imaging system, a reconstructed filtering algorithm in view of Renyi entropy is proposed(before using the delay superposition algorithm to reconstruct the image, the original photoacoustic signal is filtered by Renyi entropy filter). Compared with the existing classical filtering algorithm (modulus maxima method and threshold denoising method), the contrast ratio of the algorithm is improved by 18.27% on average, the resolution is increased by 23.69% on average, the *SNR* is increased by 2.90% on average, and the mean square error is reduced by 2.61% on average by using Renyi algorithm. The photoacoustic signal of the pencil (zero-dimension), hair (one dimension) and mouse cortical blood vessels (two-dimensional) was filtered by the Renyi entropy filter before performing the photoacoustic image reconstruction. After Renyi entropy filtering, the contrast of the photoacoustic reconstructed images was greatly improved by 36.75% (pencil cross section, zero dimension), 30.22% (hairline, one dimension) and 30.38% (mouse cortical blood vessels, two-dimensional). The resolution of reconstructed images also increased significantly, but the resolution of mouse cortical blood vessels was limited (17.65%) compared with zero-dimensional and one-dimensional samples. We speculate that this is related to the selection of biological samples (the first two samples were imitation, the samples of mouse cortical blood vessels were *in vivo*, and the differences in the photoacoustic signals between the mouse cortical blood vessels and the surrounding biological tissues were weaker than those). The signal-to-noise ratio of reconstructed images was significantly increased by 43.20% (pencil cross section, zero dimension), 51.60% (hairline, one dimension) and 48.20% (mouse cortical blood vessels, two dimensions). Finally, the mean square error of reconstructed images decreased by 7.10% (pencil core cross section, zero dimension), 28.57% (hairline, one dimension) and 69.38% (mouse cortical blood vessels, two dimensions), with the increase of the sample dimension, the mean square error of the image is greatly reduced. We assume that this is due to the increase in the size of the sample with the increase of the sample, and the average error of the whole image is reduced, so that the mean square error corresponding to the reconstructed image is reduced.

The experimental results show that the reconstructed images of the photoacoustic reconstructed by Renyi entropy compared with the reconstructed images obtained from the original photoacoustic signal, the contrast ratio of the photoacoustic reconstructed image is enhanced by 32.45%, the resolution is increased by 30.78% and the signal-to-noise ratio is increased by 47.66%, and the mean square error is reduced by 35.01%. The Renyi entropy filter processing algorithm improves the quality of photoacoustic image reconstruction which will help to promote the clinical application of photoacoustic imaging in biomedical diagnosis and treatment, for example, the early diagnosis about the arthritis, breast cancer and epilepsy and other lesions.

Key words photoacoustic image reconstruction, filter processing algorithm, Renyi entropy, threshold segmentation

DOI: 10.16476/j.pibb.2017.0248

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*This work was supported by grants from The National Natural Science Foundation of China(61474079，11602159)，The Outstanding Talent Science and Technology Innovation Project of Shanxi Province(201605D211020) and Science and Technology Innovation Project of Higher Education of Shanxi Province(2016136).

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Received: August 4, 2017 Accepted: August 31, 2017

附　　录

Table S1　The corresponding contrast and resolution of the pencil core photoacoustic signal before and after filtering

Pixel coordinate point	Contrast			Resolution		
Coordinate	Before processing	After processing	Filter optimization percentage/%	Before processing/μm	After processing/μm	Filter optimization percentage/%
a(-1.7,6.5)	5.428	7.344	35.29	750	422	43.73
b(-2.3,5.6)	5.502	7.488	36.09	790	440	44.30
c(-3.5,7.1)	1.776	2.410	35.69	900	510	43.33
d(-2.9,7.4)	8.217	11.331	37.89	1100	625	43.18
e(-2.6,8.0)	2.968	4.081	37.50	810	445	45.06
f(-1.4,6.8)	2.626	3.608	37.39	835	470	43.71
g(-2.0,5.0)	8.246	11.346	37.59	780	440	43.58
h(-2.3,5.9)	4.486	6.078	35.48	910	520	42.85
i(-4.1,7.1)	4.398	5.998	36.37	930	530	43.01
j(-2.6,7.7)	8.553	11.820	38.20	850	470	44.70
Statistical average			36.75	Statistical average		43.74

Table S2　The corresponding contrast and resolution of the hair photoacoustic signal before and after filtering

Pixel coordinate point	Contrast			Resolution		
Coordinate	Before processing	After processing	Filter optimization percentage/%	Before processing/μm	After processing/μm	Filter optimization percentage/%
a(0.3,0.8)	1.394	1.786	28.12	375	245	34.66
b(-2.3,0.9)	1.910	2.489	30.31	354	252	28.81
c(2.4,0.6)	2.610	3.468	32.87	343	240	30.02
d(1.8,0.6)	0.242	0.317	30.99	363	233	35.81
e(3.9,0.3)	1.236	1.582	27.99	372	263	29.30
f(-2.9,1.1)	0.914	1.199	31.18	359	237	33.98
g(2.2,0.8)	0.582	0.766	31.61	365	265	27.33
h(3.2,0.5)	2.389	3.163	32.39	370	250	32.43
i(1.9,0.9)	1.266	1.616	27.64	357	256	28.29
j(-2.6,1.0)	1.521	1.965	29.19	345	245	28.98
Statistical average			30.22	Statistical average		30.96

Table S3　The corresponding contrast and resolution of the mouse cortical blood vessels photoacoustic signal before and after filtering

Pixel coordinate point	Contrast			Resolution		
Coordinate	Before processing	After processing	Filter optimization percentage/%	Before processing/μm	After processing/μm	Filter optimization percentage/%
a(-0.2,-3.6)	2.095	2.716	29.64	310	260	16.12
b(-1.3,-0.5)	2.226	2.836	27.40	410	340	17.07
c(-3.2,5.1)	2.781	3.742	34.55	265	220	16.98
d(-2.8,-2.3)	2.557	3.419	33.71	274	224	18.24
e(-3.1,-0.4)	2.048	2.636	28.71	380	310	18.42
f(-2.6,2.5)	1.735	2.214	27.60	340	284	16.47
g(-2.6,-3.9)	1.029	1.318	28.08	370	295	20.27
h(-1.5,-3.1)	2.348	3.012	28.27	330	270	18.18
i(-2.1,-5.5)	2.827	3.782	33.78	235	195	17.02
j(-1.0,-2.0)	2.631	3.475	32.07	365	300	17.80
Statistical average			30.38	Statistical average		17.65

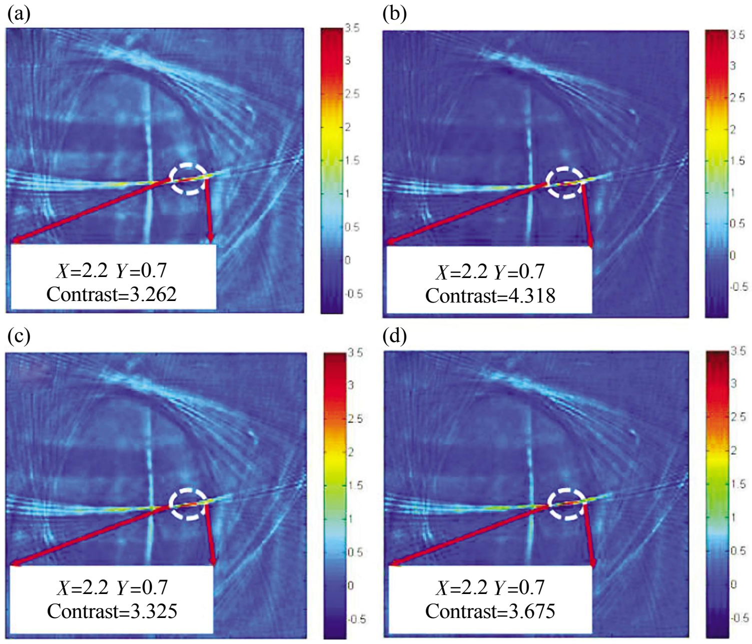

Fig. S1　The hair (one-dimensional) photoacoustic signals were reconstructed using the different algorithms

(a) The original hair photoacoustic signal corresponds to the photoacoustic reconstruction of the image. (b) Processed by Renyi entropy, the photoacoustic image reconstruction of hair. (c) After processe with Wavelet threshold algorithm, the photoacoustic image reconstruction of hair. (d) The photoacoustic image reconstruction of hair using the Modulus maxima algorithm.

Table S4　The corresponding contrast and resolution of the hair photoacoustic signal after the algorithms are processed

Pixel coordinate point	Contrast			Resolution		
Coordinate	Before processing	After processing	Filter optimization percentage	Before processing/μm	After processing/μm	Filter optimization percentage/μm
a(0.3,0.8)	1.786	1.417	1.571	245	364	323
b(-2.3,0.9)	2.489	1.932	2.246	252	340	307
c(2.4,0.6)	3.468	2.643	3.153	240	335	297
d(1.8,0.6)	0.317	0.253	0.275	233	350	315
e(3.9,0.3)	1.582	1.301	1.426	263	354	308
f(-2.9,1.1)	1.199	0.943	1.175	237	331	289
g(2.2,0.8)	0.766	0.607	0.654	265	345	326
h(3.2,0.5)	3.163	2.579	2.879	250	357	305
i(1.9,0.9)	1.616	1.324	1.453	256	346	301
j(-2.6,1.0)	1.965	1.579	1.763	245	325	314
Average	1.835	1.457	1.659	248	344	308

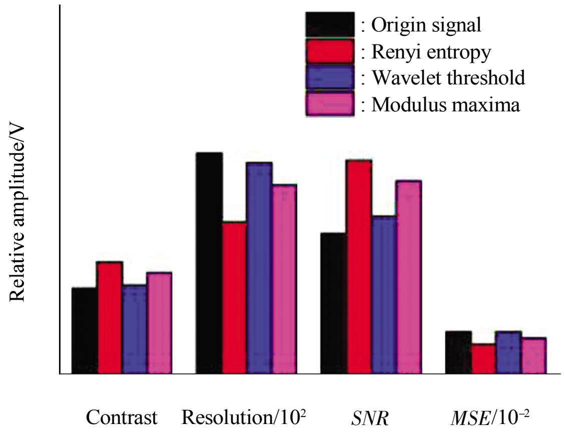

Fig. S2　Comparison of Renyi entropy with various typical algorithms