基于影像融合诊断前列腺癌的研究进展

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附件 1　融合图像质量评价指标

Supplement 1　Evaluation indexes of fusion image quality

指标	公式	说明	参考文献
MI	$MI_F^{AB}=MI_{FA}+MI_{FB}$	A、B 为输入图像，F 为融合图像。	[1]
SSIM	$SSIM(A,B/F)=\frac{(2F_AF_B+c_1)(2\sigma F_AF_B+c_2)}{(F_A^2+F_B^2+c_1)(\sigma^2F_A+\sigma^2F_B+c_2)}$	σ^2为源图像方差，σ为输入图像 A 和 B 的平均值。	[2]
FMI	$FMI=\sum_{f,m}P_{FM}(i,j,k,l)\ell og_2\frac{P_{FM}(i,j,k,l)}{P_F(i,j)P_M(k,l)}+\sum_{f,n}P_{FN}(i,j,k,l)\ell og_2\frac{P_{FN}(i,j,k,l)}{P_F(i,j)P_N(k,l)}$	P_{FM}和P_{FN}代表源图像与融合图像之间的联合分布，FMI 值越大，表明融合图像包含源图像信息量越大。	[3]
UIQI	$UIQI=\frac{\sigma XY}{\sigma X\sigma Y}\frac{2X^*Y^*}{X^{*2}+Y^{*2}}\frac{2\sigma X\sigma Y}{\sigma X^2+\sigma Y^2}$ $\sigma XY=\sum_{i=1}^{N}\frac{(X_i-X^*)(Y_i-Y^*)}{N-1}$	X^*和Y^*为平均值，方差用σX和σY表示。	[4]
PSNR	$PSNR=20X\ell og_{10}\frac{I_{\max}}{\sqrt{MSE}}$ $MSE=\frac{1}{QR}\sum_{n-1}^{Q}\sum_{n=1}^{R}(I(m,n)-J(m,n))$	式中 I 代表源图像，J 是源图像，I_{max}表示 I 的最大像素灰度，MSE 表示均方误差。	[5]
EN	$EN=-\sum_{m=0}^{M-1}P(m)\ell og_2P(m)$	m 表示该点处的像素灰度值，P(m)指	[6]

		该点处为该灰度值的概率。	
SD	$SD=\frac{\sqrt{\sum_{i=1}^{Q}\sum_{j=1}^{R}(f(i,j)-u^*)^2}}{QR}$	其中u^*是合成图像的均值。	[7]
SF	$SF=\sqrt{RF^2+CF^2}$ $RF=\sqrt{\frac{\sum_{i=1}^{M}\sum_{j=2}^{N}(F(i,j)-F(i,j-1))^2}{M\times N}}$ $CF=\sqrt{\frac{\sum_{i=1}^{N}\sum_{j=2}^{M}(F(i,j)-F(i-1,j))^2}{M\times N}}$	RF 和 CF 分别对应上述二三式。	[8]
AG	$AG=\frac{1}{(M-1)(N-1)}\times$ $\sum_{i=1}^{M-1}\sum_{i=1}^{N-1}\sqrt{0.5(\Delta xF(i,j)^2+\Delta yF(i,j)^2)}$ $\Delta xF(i,j)=F(i+1,j)-F(i,j)$ $\Delta yF(i,j)=F(i,j)-F(i,j+1)$	AG 越大，融合图像中的信息保留越好，融合质量越高	[9]

参考文献

1 Meng Changhan, Huang Mengxing, Li Yunchun, et al. Multi-modal MRI image fusion of the brain based on joint bilateral filter and non-subsampled shearlet transform. J Bio-inspir Com, 2023, 21(1): 26-35.

2 Padmavathi K, Asha C, Maya K V. A novel medical image fusion by combining TV-L1 decomposed textures based on adaptive weighting scheme. JESTECH, 2020, 23(1): 225-239.

3 Hammad M, Chelloug A S, Alayed W, et al. Optimizing multimodal scene recognition through mutual information-based feature selection in deep learning models. Appl Sci, 2023, 13(21): 11829-11847.

4 Ehar N, Shrivastava M. Pixel-level feature extraction model for breast cancer detection. CMC, 2022, 74(2): 3371-3389.

5 Subbiah V P, Sivakumar P. Multi-modality medical image fusion using hybridization of binary crow search optimization. HCMS, 2019, 23(4): 1-9.

6 Maqsood S, Javed U. Multi-modal medical image fusion based on two-scale image

decomposition and sparse representation. Biomed Signal Proces, 2020, 57(3): 101810-101817.

7 Goyal S, Singh V, Rani A, et al. FPRSGF denoised non-subsampled shearlet transform-based image fusion using sparse representation. Signal Image Video P, 2020, 14(6): 719-726.

8 Duan Junwei, Mao Shuqi, Jin Junwei, et al. A novel GA-based optimized approach for regional multimodal medical image fusion with superpixel segmentation. Access, 2021, 9(3): 96353-96366.

9 Fu Qiang, Ma Ninglan, Liu Xuanwei, et al. Analysis of multispectral polarization imaging image information based on micro-polarizer array. PloS, 2024, 19(1): e0296397.