Supplemental Document

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Automated assessment of breast margins in deep ultraviolet fluorescence images using texture analysis: supplement

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Automated assessment of breast margins in deep ultraviolet fluorescence images using texture analysis: supplemental document

This supplemental document provides a brief summary of the texture features and texture analysis methods used in this study.

1. FIRST-ORDER METHODS

First-order methods extract features based on first-order statistics of pixel intensities. Assume a given image of $m \times n$ pixels and the i-th pixel intensity is denoted as x_i ($1 \le i \le m \times n$), common first-order texture features, including mean (Eq. (S1)), variance (Eq. (S2)), skewness (Eq. (S3)), and kurtosis (Eq. (S4)) can be obtained.[1] Additionally, the entropy (Eq. (S5)) can be extracted from the image histogram, where N is the total level of gray-levels (e.g., 256 for 8-bit image) and $p_j = \frac{1}{mn}\sum_{i=1}^{mn} \#(x_i = j)$ is the probability of gray level j. The skewness measures the level of symmetry of the gray-level histogram. The kurtosis is a measure of heaviness of distribution tails from a normal distribution. And the entropy reflects the degree of randomness within an image.

$$Mean : \mu = \frac{1}{mn}\sum_{i=1}^{mn} x_i \tag{S1}$$

$$Variance : \sigma^2 = \frac{1}{mn}\sum_{i=1}^{mn}(x_i - \mu)^2 \tag{S2}$$

$$Skewness : g = \frac{1}{\sigma^3}\sum_{i=1}^{mn}(x_i - \mu)^3 \tag{S3}$$

$$Kurtosis : k = \frac{1}{\sigma^4}\sum_{i=1}^{mn}(x_i - \mu)^4 \tag{S4}$$

$$Entropy : H = -\sum_{j=1}^{N} p_j \cdot \log_2 p_j \tag{S5}$$

In this study, all five features were used.

2. GRAY-LEVEL RUN LENGTH MATRIX(GLRLM) METHOD

GLRLM is a representative second-order statistical texture analysis method. Let $p(i,j)$ ($1 \le i \le M, 1 \le j \le N$) be an element in a GLRLM matrix that has a size of $M \times N$ elements. The $p(i,j)$ is defined as the number of runs of gray level i and run length j.[2] Denote n_r as the total number of runs and n_p as the total number of pixels within the given image. To represent texture information from the run-length distribution, several metrics have been proposed for feature extraction from a GLRLM matrix based on reasoning. Traditional features includes short run emphasis (SRE) (Eq. (S6)), long run emphasis (LRE) (Eq. (S7)), gray-level nonuniformity (GLN) (Eq. (S8)), run length nonuniformity (RLN) (Eq. (S9)), and run percentage (RP) (Eq. (S10)).[2]

$$SRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p(i,j)}{j^2} \tag{S6}$$

$$LRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N} p(i,j) \cdot j^2 \tag{S7}$$

$$GLN = \frac{1}{n_r}\sum_{i=1}^{M}\left(\sum_{j=1}^{N} p(i,j)\right)^2 \tag{S8}$$

$$RLN = \frac{1}{n_r} \sum_{j=1}^{N} \left(\sum_{i=1}^{M} p(i,j) \right)^2 \tag{S9}$$

$$RP = \frac{n_r}{n_p} \tag{S10}$$

The other two features proposed by Chu et al. regarding feature extraction are the low gray-level run emphasis (LGRE) (Eq. (S11)) and high gray-level run emphasis (HGRE) (Eq. (S12)).[3]

$$LGRE = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{p(i,j)}{i^2} \tag{S11}$$

$$HGRE = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} p(i,j) \cdot i^2 \tag{S12}$$

Dasarathy et al. proposed four additional metrics based on joint statistical measures.[4] They are the short run low gray-level emphasis (SRLGE) (Eq. (S13)), short run high gray-level emphasis (SRHGE) (Eq. (S14)), long run low gray-level emphasis (LRLGE) (Eq. (S15)) and long run high gray-level emphasis (LRHGE) (Eq. (S16)).

$$SRLGE = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{p(i,j)}{i^2 \cdot j^2} \tag{S13}$$

$$SRHGE = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{p(i,j) \cdot i^2}{j^2} \tag{S14}$$

$$LRLGE = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{p(i,j) \cdot j^2}{i^2} \tag{S15}$$

$$LRHGE = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} p(i,j) \cdot i^2 \cdot j^2 \tag{S16}$$

In this study, the eleven metrics were used as GLRLM features.

3. GRAY-LEVEL CO-OCCURRENCE MATRIX (GLCM) METHOD

GLCM is another widely-used second-order statistical texture analysis method. For a given image of N gray levels, a calculated GLCM matrix has a size of $N \times N$ elements. Each element $p(i,j)$ in a GLCM matrix refers to the number of times when a pair of pixels with gray levels of i and j are of a specified distance in a given direction.[5] For convenience, define two types of means and variances as $\mu_i = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} i \cdot p(i,j)$, $\mu_j = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} j \cdot p(i,j)$, $\sigma_i^2 = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i - \mu_i)^2 p(i,j)$, and $\sigma_j^2 = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (j - \mu_j)^2 p(i,j)$, respectively. Haralick features including contrast (Eq. (S17)), correlation (Eq. (S18)), energy (Eq. (S19)), and homogeneity (Eq. (S20)) can be extracted from a GLCM matrix.[6] Contrast measures the local variations, correlation quantifies the joint probability occurrence of specified pairs of pixel intensities, energy provides the summation of squared GLCM matrix elements, and homogeneity represents the smoothness of gray level distributions. GLCMs from multiple directions (0°, 45°, 90°, and 135°) are usually calculated and the Haralick features are averaged over all directions to achieve rotational invariance.

$$Contrast = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} p(i,j) \cdot (i-j)^2 \tag{S17}$$

$$Correlation = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} p(i,j) \frac{(i-\mu_i)(j-\mu_j)}{\sqrt{\sigma_i^2 \sigma_j^2}} \tag{S18}$$

$$Energy = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} p(i,j)^2 \tag{S19}$$

$$Homogeneity = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{p(i,j)}{1+(i-j)^2} \tag{S20}$$

The four directions and a pixel distance of 3 were used for the extractions of the four GLCM features in this study.

4. GABOR FILTERING METHOD

A Gabor function describes a 2-dimensional area in the complex space with a sine or cosine function modulated by a Gaussian window:[7]

$$G(x,y;k_x,k_y) = exp\left[-\frac{(x-X)^2+(y-Y)^2}{2\sigma^2}\right] e^{j(k_x x + k_y y)} \tag{S21}$$

The role of a Gabor filter can be regarded as a bandpass filter for feature extraction. For a given image $I(x,y)$, the filtered result is the convolution with the Gabor filter:

$$R(x,y) = I(x,y) \circledast G(x,y) = \iint_{\Omega} I(u,v) \cdot G(x-u, y-v)\, du\, dv \tag{S22}$$

In this study, four wavelengths of 2, 3, 4, 5 pixels/cycle and four orientations (0°, 45°, 90°, 135°) were used to construct the Gaobor filter bank with sixteen filters. And the mean intensity of the filtered image $R(x,y)$ was used as a feature. The results were averaged over the four orientations to achieve rotational invariance.

5. LOCAL BINARY PATTERN (LBP) METHOD

LBP is an efficient visual descriptor of local textures. Let $s(x)$ be a signing function: $s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}, x \in \mathbb{R}$. Consider a center pixel of intensity g_c, and with a local area having P number of circularly symmetric neighborhood pixels $(g_0, g_1, g_2, ..., g_{P-1})$ with a radius of R pixels from the center pixel, the original LBP code is defined as:[8]

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c) \cdot 2^p. \tag{S23}$$

Rotational invariance LBP is achieved by rotating the binary code bit-wisely until the minimum value is achieved. The rotation-invariant LBP is therefore expressed as ($ROR(X,y)$, which means rotating X binary code of y bit(s)):[9]

$$LBP_{P,R}^{ri} = min\{ROR(LBP_{P,R}, i) | i = 0, 1, 2, ..., P-1\}. \tag{S24}$$

Let $U(LBP_{P,R})$ be the number of bit-wise 0/1 transitions within an LBP binary code, and patterns with more than 2 bitwise 0/1 spatial transitions are considered to be "nonuniform". The uniform rotation invariant LBP is obtained by encoding uniform patterns only:[9]

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c) & \text{if } U(LBP_{P,R}) \leq 2 \\ \text{P+1} & \text{otherwise} \end{cases} \tag{S25}$$

Regions with a distance less than R pixels from the image boundary are excluded, and a LBP histogram can be formed by LBP values for all remaining pixels in the image. The LBP histogram can be used as features. The uniform rotation invariant LBP method was used in this study. $R = 3$ and $P = 12$ were selected. Thus, a total of $P + 2 = 14$ features (histogram bins) were extracted. L_2 normalization was applied to reduce numerical value of features.[10]

6. FRACTAL MEASURES METHOD

Fractal dimension and lacunarity were estimated as fractal measures. Fractal dimension is a measure of structural complexity and self-similarity over a range of scales. Differential box-counting (DBC) method was applied for fractal dimension computation.[11] In this method, given a 2-dimensional image is treated as a 3-dimensional array by extending gray-level intensities to the third dimension (along z-axis). For a given square image with $M \times M$ pixels, the image is divided into cells by a non-overlapping grid with a cell size of $s \times s$ pixels where $\frac{M}{2} \geq s > 1$ and s is an integer. The height (z-axis) of the cubic box s' can be obtained by the constraint $\lfloor \frac{G}{s'} \rfloor = \lfloor \frac{M}{s} \rfloor$ where G is the number of gray levels. After that, a $s \times s \times s'$ size cubic box is used to fill the 3-dimensional image array, and the number of "piles" at both image axis is defined as N_s. Record k and l fulfilling that the minimum and maximum gray levels of the image surface within a specific "pile" are in the box k and l, respectively. Then, assign the value $n_r(i,j) = l - k + 1$ to this "pile". The summation of n_r from all "piles" is calculated by:

$$N_r = \sum_{i=1}^{N_s} \sum_{j=1}^{N_s} n_r(i,j). \tag{S26}$$

Repeat the process with different s values and let $r = \frac{s}{M}$, the fractal dimension can be estimated as

$$FD = \lim_{r \to 0} \frac{ln(N_r)}{ln(1/r)}. \tag{S27}$$

In this study, s values of 4, 8, 16, 32, 64, and 128 were used for the estimation of fractal dimensions.

Lacunarity measures the deviation of a geometric subject from translational invariance and it is a representation of the distribution of gaps. At a given scale, homogeneous objects with more translational invariance exhibit high lacunarity while heterogeneous objects with less translational invariance yield low lacunarity. Lacunarity is usually used to provide supplementary textural descriptions to fractal dimension. In this study, the binary gliding-box method was used for lacunarity estimation.[12] Cell nuclei segmentation was conducted by a combination of Otsu's algorithm and intensity thresholding. The gliding-box method estimates lacunarity by analyzing the fluctuations of the mass distribution function in a manner of gliding a fixed-size box on the image lattice with all possibilities. Define the box mass as the number of occupied pixels with a value of 1 (a binary image consists of 0 and 1) in a box and let $n(M,r)$ be the distribution of mass M in the gliding box of the size r, then the probability function for a given mass and box size can be obtained by dividing $n(M,r)$ by the total number of boxes of the size r:

$$Q(M,r) = \frac{n(M,r)}{N(r)}. \tag{S28}$$

The q-th statistical moment of the probability function $Q(M,r)$ is

$$Z_Q^{(q)}(r) = \sum_M M^q \cdot Q(M.r). \tag{S29}$$

A binary image satisfies $Z_Q^{(1)}(r) = \mu[M(r)]$ and $Z_Q^{(2)}(r) = \sigma^2[M(r)] + [\mu[M(r)]]^2$. The first moment and the second moment of $Q(M,r)$ are used to estimate the lacunarity. Therefore, lacunarity is estimated as

$$\Lambda(r) = \frac{Z_Q^{(2)}(r)}{[Z_Q^{(1)}(r)]^2} = \frac{\sigma^2[M(r)]}{[\mu[M(r)]]^2} + 1. \tag{S30}$$

A gliding box size of 3 was used in this study.

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