Robust texture analysis of multi-modal images using Local Structure Preserving Ranklet and multi-task learning for breast tumor diagnosis

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\textbf{A B S T R A C T}

Robust texture analysis of multi-modal images is important for practical breast tumor diagnosis applications. Texture features based on ranklet transform were proposed for breast tumor classification of multi-modal images and improved diagnostic performance. However, two limitations still exist in these features. Ranklet transform ignores local characteristics of images which are important for texture feature extraction. In addition, due to application of multi-resolution analysis of ranklet transform, some noises or redundant information may be introduced. These issues may result in performance degradation. To solve these problems, this paper proposes a robust texture feature based on Local Structure Preserving Ranklet (LSP-Ranklet) transform and multi-task learning. First of all, multiple LSP-Ranklet images are generated via LSP-Ranklet transform. In this procedure, the distance-based weighting method is proposed to preserve local structure of images by learning local relevance between pixels. Based on LSP-Ranklet images, texture features based on Gray-Level Co-occurrence Matrix (GLCM) are extracted. To eliminate noises of extracted features, multi-task feature learning is employed to select common feature subsets which are robust for tumor classification of multi-modal images. At last, SVM model is used for tumor classification. Experimental results on our multi-modal breast ultrasound images database demonstrate the effectiveness and robustness of the proposed feature.

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1. Introduction

Early diagnosis and treatment of breast cancer play an important role in improving survival rates [1,2]. Mammography and ultrasound imaging are commonly used tools for early detection of breast cancer. Compared with mammography, ultrasound imaging has following advantages [3]: (1) it is more sensitive to detect abnormalities in dense breasts. (2) It is cheaper and safer.

Radiologists can discriminate benign and malignant masses according to tumors’ characteristics such as shapes, internal echo, and posterior acoustic behavior in breast ultrasound (BUS) images [4]. However, interpretation of images is dependent on radiologists’ expertise, resulting in subjective diagnosis. To overcome problem of inter-/intra-observer variation, computer-aided diagnosis (CAD) is developed [5–8]. An ultrasound CAD system for breast cancer mainly involves three phases: tumor segmentation [9–15], feature extraction [16–32] and tumor classification. Feature extraction is crucial for accurate tumor classification. Therefore, this paper mainly focuses on this stage.

Texture features can be employed for depicting the scattering properties of breast tissue [16], which were useful for distinguishing benign lesions from malignant [17]. Rotation-invariant textural patterns were extracted via Local Binary Patterns (LBP) for tumor classification in BUS images [18]. Fractal dimensions [19] were employed to improve diagnostic performance because it can measure roughness of texture. In addition, some gray-level co-occurrence matrix (GLCM)-based texture features [20–24] were also demonstrated to be discriminative for breast tumor classification. To make texture features more effective, some studies had focused on the texture features extracted from the transformed images. Considering advantages of wavelet transform, texture features were extracted via wavelet transform [26,27]. Oriented local texture descriptor was introduced for breast tumor classification by

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combining phase congruency (PC) approach with local binary pattern (LBP) [28]. Contourlet-based texture feature which can capture the tumor’s elastic heterogeneity was proposed for breast tumor classification [29]. Considering advantages of shearlet, such as directional sensitivity and localization property at various scales, texture feature based on shearlet transform was developed [30]. Most proposed texture features were demonstrated to be effective for breast tumor classification. However, performance of these features was evaluated on images from single device. In this paper, images captured from different devices are referred to as multi-modal images while images from single device are referred to as single-modality images. For example, breast images from different ultrasound devices whose types are SIEMENS Sequoia 512 and GE LOGIQ E7 can be seen as multi-modal images.

Robust texture analysis of multi-modal images is important for practical tumor diagnosis applications because a large number of multi-modal images are generated for breast tumor diagnosis in the real world. However, challenge arises for robust texture analysis of multi-modal images because different imaging principle of ultrasonic devices may lead to incoherent texture features extraction from multi-modal images [31,32]. Fig. 1 shows multi-modal images from four devices. Tumors in images belong to the same class i.e., benign ones. However, texture representation of these tumors is different. For example, texture of the tumor in the second image (Fig. 1(b)) is relatively smooth, and others are coarse. To extract robust texture features of multi-modal images, multi-resolution gray-scale invariant features based on ranklet transform were proposed, and experimental results suggested the effectiveness of the proposed feature [32]. However, there were two limitations in ranklet transform-based texture features: (1) ranklet transform ignored the local structure of images. (2) Some noises or redundant information may be introduced into the feature due to application of multi-resolution analysis. These problems may lead to performance degradation.

To address these two issues, this paper proposes a robust texture feature based on Local Structure Preserving Ranklet (LSP-Ranklet) and multi-task learning. In this study, LSP-Ranklet transform is firstly proposed for image transform. In LSP-Ranklet coefficients calculation step, distance-based weighting method is proposed to assign different weights to the pixels in a crop, which can preserve the local structure of images. And then, GLCM-based texture features [32] via LSP-Ranklet transform are extracted. To eliminate noises, feature selection is performed by employing multi-task feature learning [35,36] which can make use of inter-modality relationship. $l_{2,1}$-norm regularization is incorporated into feature learning model, which can select common features. The selected common features contain discriminative information, which are robust for tumor classification of multi-modal images. At last, SVM is adopted for tumor diagnosis. Experiments are conducted on our multi-modal breast ultrasound images database, and the experimental results demonstrate the effectiveness and robustness of the proposed feature.

The main contribution of this paper can be summarized as follows:

1. LSP-Ranklet is proposed for image transform. In the procedure of LSP-Ranklet coefficients calculation, distance-based weighting method is developed to preserve the local structure of images which plays important role in texture feature extraction.
2. Robust feature subsets are selected via multi-task feature learning which can employ inter-modality relationship.
3. Multi-modal breast ultrasound images database is constructed by collecting breast ultrasound images from four different ultrasound devices.

2. Proposed method

In this section, ranklet transform is firstly introduced briefly. To overcome the drawback of ranklet transform, LSP-Ranklet transformation is developed. After that, GLCM-based texture feature [32] is extracted via LSP-Ranklet transform. Finally, multi-task feature learning is employed for feature selection.

2.1. Ranklet

Ranklet transform was proposed for image transform by using the relative rank of pixels instead of their gray-scale value [41]. It mainly consisted of following three steps:

1. Multi-resolution analysis: The image is separated into some overlapping square crops at different resolutions as shown in Fig. 2.
2. Orientation-selective analysis: For each resolution, pixels of each crop are divided into two subsets. Different subsets are generated depending on the orientation considered. Fig. 3 shows three orientations such as horizontal, vertical, and diagonal.
3. Non-parametric analysis: Ranklet coefficient of each pixel is calculated using Eq. (1). In this equation, variables $d$ and $r$ denote different orientations and resolutions respectively. $R_{SA}^{d}(p,i)$ represents the rank value of pixel $i$ in the subset $A$ of the crop centered at point $p$. $N$ is the number of pixels in the crop centered at point $p$.

$$
R_{SA}^{d}(p) = \frac{\sum_{i=1}^{N/2} (R_{SA}^{d}(p,i) - R_{SA}^{d}(p,i))}{N/2}
$$

$$
d \in \{V, H, D\}, r \in \{2, 4, 6, \ldots \}.
$$

2.2. LSP-Ranklet

Despite encouraging performance of ranklet transform on multi-modal images, this method suffers from the issue that it
ignores local information of images in the procedure of calculating ranklet coefficient. Generally speaking, for a central pixel $p$ of a crop, neighbor pixels are more relevant to it than the pixels on the border of crop, the local relevance between pixels can reveal the local structure of the image, which is useful for texture feature extraction. However, the local relevant information is failed to be considered for ranklet coefficient calculation. Therefore, to preserve local structure of image, pixels in the crops should play different roles in image transform. Based on this idea, we propose LSP-Ranklet.

LSP-Ranklet can be calculated as the following three steps:

1. **Multi-resolution analysis:** The image is divided into overlapping square crops according to the selected resolution. The square crop can be achieved by giving an arbitrary point $p$ and even resolutions $r$ as shown in Fig. 2.

2. **Orientation-selective analysis:** Pixels of each square crop are split into two subsets (i.e., Subset A and B) with same size according to the orientations considered. The orientations of the two subsets can be defined as horizontal (H), vertical (V), and diagonal (D) directions, as drawn in Fig. 3.

3. **LSP-Ranklet coefficient calculation:** To calculate LSP-Ranklet coefficient, we firstly obtain the rank descriptive matrix $R$ by ranking the gray values of the pixels within the crop centered at point $p$. Meanwhile, we form two subsets SA and SB into two descriptive vectors $R_{SA}$ and $R_{SB}$, respectively according to spatial order of pixels in each subset. As mentioned above, local relevance between pixels can represent local characteristics of image. Therefore, we assign different weights to the pixels to preserve local structure of image. LSP-Ranklet Coefficient (LSPRC) can be calculated using Eq. (2):

$$d(V, H, D), r = \{2, 4, 6, \ldots\}$$

$$\text{LSPRC}_r^a(V, H, D) = \frac{\sum_{i=1}^{i=N/2} w^a_i \left( R_{SA}^d(p, i) - R_{SB}^d(p, i) \right)}{\sum_{i=1}^{i=N/2} w^a_i}$$

We propose distance-based weighting method to calculate different weights of pixels in the crops. For the pixels in the crop centered at arbitrary point $p$, windows with different sizes centered at point $p$ are used to measure the spatial distance between the pixels and point $p$. We separate the pixels into different groups according to the size of the windows, and the weight of the pixels on the $m \times m$ size of window can be assigned using Eqs. (3) and (4):

$$w^m_r(p) = \frac{r}{2} - \left( \frac{m-1}{2} - 1 \right) \frac{Z}{2}$$

$$\sum_{i=1}^{i=m^2} w^m_r(p) = 1$$

In Eq. (3), $Z$ is the normalization factor, and Eq. (4) guarantees that the sum of the weights is 1. Combining Eqs. (3) and (4), the value of variable $Z$ can be solved, as shown in Eq. (5). After that, the analytical solution of $w^m_r(p)$ can be obtained according to Eqs. (3) and (5), as shown in Eq. (6):

$$Z = \frac{4}{r + 2}$$

$$w^m_r(p) = \frac{4}{r + 2} \left( 1 - \left( \frac{m-1}{2} - 1 \right) \frac{Z}{2} \right)$$

An example to illustrate weight calculation of the pixels in a crop centered at point $p$ is shown in Fig. 4. The weights of pixels can be obtained by using proposed distance-based weighting method. For central pixel $p$, the weight of its neighbor pixels is larger, in contrast, the weight of pixels in the border of crops is smaller. For example, the weight of eight pixels on $3 \times 3$ windows is 0.4, higher than eighty pixels on $9 \times 9$ windows whose weight is 0.1. Therefore, proposed distance-based weighting method...
can make pixels in the crops play different roles in calculating LSP-Ranklet coefficients, which can make full use of local spatial relationship between pixels and preserve the local structure of the image transformed. Furthermore, local information of image plays important role in texture feature extraction. Therefore, the texture feature extracted via LSP-ranklet transform may be more effective.

After LSP-Ranklet transform, we extract GLCM-based texture features [32].

2.3. Feature selection with multi-task learning

Some noises or redundant information may exist in the extracted texture feature due to application of multi-resolution analysis. Therefore, feature selection is necessary for improving the effectiveness and efficiency of feature. Different from single-modal images, inter-modality relationship may exist in multi-modal images, which can be employed to improve the performance of selected features [33,34].

Multi-task learning [35-37] aims to learn the intrinsic relationship between related tasks and has achieved encouraging performance in many application areas such as Alzheimer’s Disease diagnosis [38-40]. In this paper, we regard the breast tumor diagnosis of single-modal images as single task and diagnosis using multi-modal images as multi tasks. Inter-modality relationship may make different tasks share discriminative information. Therefore, multi-task feature learning is employed to select common features due to its sparsity property of $L_{2,1}$-norm regularization [35,36]. The objective function of multi-task feature learning is listed in Eq. (7). $T$ is the number of tasks, $w_i$ is the weight vector of the $i$th task, $X_i$ is texture feature matrix extracted from the $i$th modal training images. $W$ is the weight matrix consisting of $T$ weight vectors. The first term of Eq. (7) is the data fitting term which aims to minimize the training error, and the second term is the $L_{2,1}$-norm regularization term, encouraging weight vectors of different tasks to share similar parameter sparsity patterns[35,36], which can be used for selecting common features. SLEP toolbox [37] is adopted for obtaining values of matrix $W$.

$$\text{Min} \sum_{t=1}^{T} ||w_t X_t - y_t||^2 + ||W||_{2,1}.$$  

(7)

An example for illustrating feature selection based on multi-task feature learning is shown in Fig. 5. In this figure, color elements denote discriminative information for tumor classification while white elements represent noises. We can see that discriminative information is different in the features extracted from different modal images. However, inter-modality relationship exists, i.e., the discriminative features share some common elements. For example, the first element is discriminative for B modal while noise for other modalities. If the first element is selected, the feature may be effective for B modal images while useless for A and C modal images. The second element is discriminative for all modals images. Therefore, the common discriminative information such as the second element should be selected for tumor classification of multi-modal images. In this figure, a sparse weight matrix $W$ is trained to select common feature subsets, value of white elements in the matrix is zero while color elements are used for feature selection.

2.4. The framework of texture feature based on LSP-Ranklet and multi-task learning for breast tumor diagnosis of multi-modal images

The proposed framework is shown in Fig. 6. In the training phase, tumor ROI is firstly selected manually. Based on the selected ROI, LSP-Ranklet transform is used for generating LSP-Ranklet transformed images with different orientation and resolution. After that, GLCM-based texture features [32] are extracted from LSP-Ranklet transformed images. And then, weight matrix for feature selection is trained via multi-task feature learning. Finally, based on the selected features, SVM is trained for distinguishing between benign and malignant lesions. In the testing phase, using same method to obtain GLCM-based texture features, and then, weight matrix trained in training phase is used for feature selection. Finally, diagnosis result can be obtained by inputting selected feature into SVM model.

3. Experiments and results

3.1. Data description

We construct the Multi-Modal Breast UltraSound (MMBUS) images database whose images were collected from Qianfushan Hospital of Shandong Province. Our database contains 186 cases (135 benign cases and 51 malignant cases) in total, and each case contributes one image. The images were captured from four ultrasonic devices whose types are ALOKA α 10, ApioXG, GE LOGIQ E7 and SIEMENS Sequoia 512 respectively. In our experiments, to test the robustness of different methods, we separate the MMBUS database into four sub-databases (i.e., database A, database B, database C and database D) according to the device type respectively. Detailed tumor distribution of the four databases is listed in Table 1. In addition, tumor boundaries were manually demarcated by experienced radiologists, and tumor ROI can be selected according to the tumor boundary labeled. Raw image examples from four devices are listed in Fig. 7.

3.2. Experiment setting

In our experiments, to avoid problem of class imbalance, thirty-five percent of the benign lesions and eighty percent of malignant lesions are selected as the training data, and remain images are regarded as the testing data. Diagnostic performance of the proposed features is evaluated with some diagnostic metrics used in [32], such as the area under the ROC curve (AUC), accuracy (ACC), sensitivity (SENS), specificity (SPEC), positive and negative predictive values (PPV and NPV). To extract GLCM-based texture feature, we adopt same parameters in [32], using 1-pixel displacement, averaged angular feature (i.e., averaged four canonical angles) and 256 quantization levels as texture descriptor parameters. For training SVM model, RBF kernel is adopted, and parameters C and g are selected via grid search [32]. We conduct three experiments to demonstrate the effectiveness and robustness of proposed feature.

3.3. Comparison with texture feature based on Ranklet

In this experiment, we compare the performance of texture feature based on LSP-Ranklet (LSP-Ranklet-TF) and texture feature...
Fig. 6. Framework of the proposed texture feature for tumor diagnosis of multi-modal images.

Table 1
Tumor distribution of collected database.

<table>
<thead>
<tr>
<th>Finding</th>
<th>Database A Number of cases</th>
<th>Database B Number of cases</th>
<th>Database C Number of cases</th>
<th>Database D Number of cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benign</td>
<td>47</td>
<td>38</td>
<td>47</td>
<td>3</td>
</tr>
<tr>
<td>Malignant</td>
<td>14</td>
<td>6</td>
<td>28</td>
<td>3</td>
</tr>
<tr>
<td>Total</td>
<td>61</td>
<td>44</td>
<td>75</td>
<td>6</td>
</tr>
</tbody>
</table>

Table 2
Performance of LSP-Ranklet-TF and Ranklet-TF on each database.

<table>
<thead>
<tr>
<th>Database</th>
<th>Method</th>
<th>AUC</th>
<th>ACC</th>
<th>Sen</th>
<th>Spec</th>
<th>PPV</th>
<th>NPV</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Ranklet-TF</td>
<td>0.8871</td>
<td>0.7879</td>
<td>1</td>
<td>0.7742</td>
<td>0.222</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>LSP-Ranklet-TF</td>
<td>0.9355</td>
<td>0.8788</td>
<td>1</td>
<td>0.871</td>
<td>0.333</td>
<td>1</td>
</tr>
<tr>
<td>B</td>
<td>Ranklet-TF</td>
<td>0.88</td>
<td>0.7692</td>
<td>1</td>
<td>0.76</td>
<td>0.1429</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>LSP-Ranklet-TF</td>
<td>0.96</td>
<td>0.9231</td>
<td>1</td>
<td>0.92</td>
<td>0.333</td>
<td>1</td>
</tr>
<tr>
<td>C</td>
<td>Ranklet-TF</td>
<td>0.7782</td>
<td>0.8</td>
<td>0.75</td>
<td>0.8065</td>
<td>0.333</td>
<td>0.9615</td>
</tr>
<tr>
<td></td>
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<td>1</td>
<td>0.7742</td>
<td>0.3636</td>
<td>1</td>
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<tr>
<td>D</td>
<td>Ranklet-TF</td>
<td>0.5</td>
<td>0.667</td>
<td>0</td>
<td>1</td>
<td>N/A</td>
<td>0.667</td>
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<td>0.333</td>
<td>1</td>
<td>0</td>
<td>0.333</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Based on Ranklet [32] (Ranklet-TF). The Experimental results are shown in Fig. 8 and Table 2.

Fig. 8 shows the performance of LSP-Ranklet-TF and Ranklet-TF. From this figure, we can see that LSP-Ranklet-TF achieves better performance, especially in AUC and Sen. The reason is that LSP-Ranklet can preserve the local information of the image transformed. Furthermore, local information of image play important role in effective texture feature extraction.

Table 2 shows performance of LSP-Ranklet-TF and Ranklet-TF on each sub-database. From this table, we can see that LSP-Ranklet-TF achieves better performance on the first three databases. The performances of LSP-Ranklet-TF and Ranklet-TF on database D are not satisfactory, we can infer that all tumors may be diagnosed as the same class (i.e., all benign tumors are classified as the malignant tumors or otherwise). Due to application of multi-resolution analysis, some noise or redundant information may be introduced into the features, resulting in dimension curse. Furthermore, the number of training data from database D is small. High dimension of feature and small training data may make diagnose model to overfit training data of other three sub-databases, and achieve the worse performance on database D.
Table 3
Performance of Ranklet-TF and Ranklet-TF-MTL on each database.

<table>
<thead>
<tr>
<th>Database</th>
<th>Method</th>
<th>AUC</th>
<th>ACC</th>
<th>Sen</th>
<th>Spec</th>
<th>PPV</th>
<th>NPV</th>
</tr>
</thead>
<tbody>
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<td>0.7879</td>
<td>1</td>
<td>0.7742</td>
<td>0.222</td>
<td>1</td>
</tr>
<tr>
<td></td>
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<td>0.9839</td>
<td>0.9697</td>
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<td>0.9677</td>
<td>0.6667</td>
<td>1</td>
</tr>
<tr>
<td>B</td>
<td>Ranklet-TF</td>
<td>0.88</td>
<td>0.7692</td>
<td>1</td>
<td>0.76</td>
<td>0.1429</td>
<td>1</td>
</tr>
<tr>
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<td>0.9231</td>
<td>1</td>
<td>0.92</td>
<td>0.33</td>
<td>1</td>
</tr>
<tr>
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<td>0.75</td>
<td>0.8065</td>
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</tr>
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<td>0.8</td>
<td>1</td>
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<tr>
<td>D</td>
<td>Ranklet-TF-MTL</td>
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<td>0.6677</td>
<td>0</td>
<td>N/A</td>
<td>0.667</td>
<td></td>
</tr>
</tbody>
</table>

3.4. Comparison with texture feature without feature selection

This experiment is carried out to demonstrate effectiveness and efficiency of feature selection based on multi-task feature learning. We evaluate performance of Ranklet-TF and LSP-Ranklet-TF with multi-task feature learning (Ranklet-TF-MTL and LSP-Ranklet-TF-MTL). Figs. 9 and 10 show the performance of the original feature and the selected feature. Tables 3 and 4 reveal the performance of two selected features on each database, respectively.

Fig. 9 shows the performance of Ranklet-TF and Ranklet-TF-MTL. From this figure, we can see that performance is improved on each metric after feature selection, especially on metric Sen, increasing more than ten percent. We can also infer that SVM model obtained based on Ranklet-TF only predicts about eighty percentages of malignant lesions correctly while Ranklet-TF-MTL can distinguish all malignant lesions from benign lesions. After feature selection, missed diagnosis of malignant tumors is reduced, which is important in clinical application.

Fig. 10 reveals performances of LSP-Ranklet-TF and LSP-Ranklet-TF-MTL. We can see that LSP-Ranklet-TF can achieve satisfactory results on some metrics such as Sen. However, LSP-Ranklet-TF-MTL can not only hold high Sen but also achieve better performance on benign lesions diagnosis, and further boost the performance.

From Figs. 9 and 10, we can see that performances of the selected features have been greatly improved. Because selected features not only abandon the noise and other redundant information, but also reduce the complexity of the features, avoiding model overfit. Furthermore, performance of LSP-Ranklet-TF-MTL is better than Ranklet-TF-MTL.
Table 4
Performance of LSP-Ranklet-TF and LSP-Ranklet-TF-MTL on each database.

<table>
<thead>
<tr>
<th>Database</th>
<th>Method</th>
<th>AUC</th>
<th>ACC</th>
<th>Sen</th>
<th>Spec</th>
<th>PPV</th>
<th>NPV</th>
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<tbody>
<tr>
<td>Database</td>
<td>LSP-Ranklet-TF</td>
<td>0.9355</td>
<td>0.8788</td>
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<td>1</td>
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<tr>
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<td>C</td>
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<td>1</td>
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<tr>
<td>Database</td>
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<td>LSP-Ranklet-TF-MTL</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 5
Computation time of LSP-Ranklet-TF and LSP-Ranklet-TF-MTL.

<table>
<thead>
<tr>
<th>Method</th>
<th>Time (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LSP-Ranklet-TF</td>
<td>0.047</td>
</tr>
<tr>
<td>LSP-Ranklet-TF-MTL</td>
<td>0.012</td>
</tr>
</tbody>
</table>

Table 6.
AUC of two features via cross-platform training/testing.

<table>
<thead>
<tr>
<th>Train database</th>
<th>Test database</th>
<th>Ranklet-TF-MTL</th>
<th>LSP-Ranklet-TF-MTL</th>
</tr>
</thead>
<tbody>
<tr>
<td>A + B + C</td>
<td>D</td>
<td>0.8333</td>
<td>1</td>
</tr>
<tr>
<td>B + C + D</td>
<td>A</td>
<td>0.922</td>
<td>0.9688</td>
</tr>
<tr>
<td>A + C + D</td>
<td>B</td>
<td>0.9605</td>
<td>0.9035</td>
</tr>
<tr>
<td>D + A = B</td>
<td>C</td>
<td>0.8603</td>
<td>0.9571</td>
</tr>
<tr>
<td>A + D</td>
<td>B</td>
<td>0.7412</td>
<td>0.9737</td>
</tr>
<tr>
<td>A + C</td>
<td>A</td>
<td>0.8449</td>
<td>0.8826</td>
</tr>
<tr>
<td>B + C</td>
<td>D</td>
<td>0.8333</td>
<td>1</td>
</tr>
</tbody>
</table>

Comparing Tables 4 and 3 with Table 6, we observe that most of diagnostic performance suffers from degradation. However, AUC of LSP-Ranklet-TF-MTL decreases more slowly than Ranklet-TF-MTL. We can infer that LSP-Ranklet-TF-MTL is more robust. The reason may be that LSP-Ranklet is able to preserve local structure of image, which makes texture feature more effective. Furthermore, common features selected via multi-task feature learning are more robust for tumor classification of multi-modal images.

4. Conclusion and future work

Texture patterns have been deemed as a useful feature for tumor classification. Ranklet transform-based texture features [32] were proposed for tumor diagnosis using multi-modal images and achieved good performance. However, ranklet transform ignores local information of images, which may degrade performance of extracted texture features. In addition, some noises may be introduced into the features due to application of multi-resolution analysis. To solve these two problems, this paper proposes a robust texture feature based on LSP-Ranklet and multi-task learning. Different weights are assigned to the pixels in a crop via proposed distance-based weighting approach for LSP-Ranklet coefficients calculation, which can preserve the local structure of the images. Local characteristics of images are useful for improving performance of texture feature. After texture feature extraction, $L_{2,1}$-norm regularization is incorporated into multi-task feature learning model to select common features which are robust for tumor classification of multi-modal images. The experimental results on MMBUS database demonstrate the effectiveness and robustness of the proposed feature.

In the future, we will focus on the investigation of breast tumor classification by combining ultrasound images and mammography images, expecting to employ more useful information to further improve diagnostic performance.

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