Feasibility of Using Radio-Frequency Ultrasound Signals for Breast Lesion Classification with Deep Learning

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Editors: Under Review for MIDL 2019

Abstract

Ultrasound (US) images, typically displayed by US scanners and used to develop computer-aided diagnosis systems, are reconstructed using radio-frequency (RF) backscattered echo signals recorded by US transducers. During the US image reconstruction process, however, information related to tissue structure carried by RF signals is partially lost due to irreversible compression, which is necessary to make US data readable to humans. In this work we propose a novel approach to breast lesion classification based on applying deep learning to RF data directly. We develop a classification model composed of 1D and 2D convolutional layers, which can process 2D patches of RF data extracted from breast lesions. Our method can also be used to generate parametric maps illustrating the level of lesion malignancy. The proposed model achieved good classification performance, with area under the receiver operating characteristic curve and balanced accuracy of 0.86 and 0.78, respectively. Our study presented the feasibility of applying deep learning methods for RF data analysis.

Keywords: breast lesion classification, convolutional neural networks, deep learning, radio-frequency signals, ultrasound imaging

1. Introduction

Ultrasound (US) imaging is a popular medical imaging modality used for breast lesion differentiation. Various computer-aided diagnosis systems have been proposed to help radiologists assess breast mass malignancy in US (Flores et al., 2015). Recently, we can observe a growing interest in applying deep learning (DL) methods for breast lesion classification based on B-mode US images (Byra et al., 2019; Qi et al., 2019; Yap et al., 2018). B-mode images are reconstructed using raw radio-frequency (RF) backscattered US signals recorded by scanner transducer, see Fig. 1. During the B-mode image reconstruction, however, information related to tissue structure carried by RF signals is partially lost due to irreversible compression.
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Figure 1: Acquired single RF signal (left, blue), its envelope (left, red) and an ultrasound B-mode image (right) produced from envelopes.

compression, which is necessary to reduce large volume of RF data and make them readable to humans. In this work we propose a DL based approach to RF data analysis. We develop convolutional neural networks (CNNs), which can differentiate malignant and benign breast lesions based on 2D patches of RF data.

2. Methods

2.1. Data Set

We performed experiments on the OASBUD data set (Piotrzkowska-Wróblewska et al., 2017), which includes 200 US RF signal matrices recorded from 52 malignant and 48 benign lesions of 78 patients. For each lesion two orthogonal scans were acquired. Regions of interest (ROIs) were outlined by a radiologist to indicate lesion areas. We applied the sliding window technique to generate $2 \times 2$ mm (104 x 27 samples) 2D patches of RF signals based on the provided ROIs. In total, we obtained 3344 and 6301 2D patches from benign and malignant breast lesions, respectively.

2.2. Model

Classification of 2D patches extracted from malignant and breast lesions is a binary classification problem. We approached this task using a neural network composed of 1D and 2D convolutional layers, which was inspired by a work on EEG signal processing (Schirrmeister et al., 2017). The model was defined as a composition $f = g(\phi_s(\phi_t(X)))$, where: $X$ is the input signal matrix (2D patch of RF data in our case), $\phi_t(X)$ computes signal features over time (1D convolutional and pooling layers), $\phi_s(Y)$ computes features over 2D region (2D convolutional and pooling layers) and $g$ is the output function. A detailed structure of the network is provided in Table 1. To evaluate the method we randomly divided the data into train/validation/test subsets 30 times. During training, we minimized loss comprised of
Table 1: Architecture of the proposed convolutional neural network for breast lesion radio-frequency data analysis.

<table>
<thead>
<tr>
<th>Layer</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>convolutional</td>
<td>32 filters $5 \times 1$, no padding, Batch Normalization, ReLU</td>
</tr>
<tr>
<td>max pooling</td>
<td>pool size and stride: $2 \times 1$, no padding</td>
</tr>
<tr>
<td>convolutional</td>
<td>64 filters $3 \times 1$, no padding, Batch Normalization, ReLU</td>
</tr>
<tr>
<td>max pooling</td>
<td>pool size and stride: $2 \times 1$, no padding</td>
</tr>
<tr>
<td>convolutional</td>
<td>128 filters $4 \times 4$, no padding, Batch Normalization, ReLU</td>
</tr>
<tr>
<td>max pooling</td>
<td>pool size and stride: $3 \times 3$, no padding</td>
</tr>
<tr>
<td>output</td>
<td>flatten, fully connected, sigmoid</td>
</tr>
</tbody>
</table>

Figure 2: Parametric maps indicating the level of malignancy obtained using the proposed approach for a benign (starting from the left: 1st, 2nd) and malignant (3rd, 4th) lesions.

negative log-likelihood of the training labels and $L_2$ regularization term using mini-batch stochastic gradient descent. The better performing hyper-parameters were determined on validation subset. Due to a disproportion between the number of benign and malignant 2D patches, we incorporated class weights into the loss function accordingly to the imbalance ratio. Next, for each 2D patch we calculated the a posteriori probability of malignancy and used those estimates to create parametric maps indicating the level of lesion malignancy within each ROI (Uniyal et al., 2015).

3. Results & Conclusion

The proposed method achieved good classification performance. We obtained the following results (average over test splits ± std. dev.): area under the receiver operating characteristic curve: 0.86 (± 0.02), balanced accuracy: 0.78 (± 0.02), precision: 0.89 (± 0.02), recall: 0.83 (± 0.05). Parametric maps indicating the level of malignancy are presented in Fig. 2.

In this work we showed the feasibility of developing deep learning models for breast lesion classification based on RF US data. We hope that our preliminary results encourage the researchers interested in medical image analysis to devote more interest to the analysis of raw medical data, like RF US signals.
References


