Application of machine learning in optimizing b-value acquisition strategy of diffusion Magnetic Resonance Imaging

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Abstract. The b-value acquisition strategy of diffusion Magnetic Resonance Imaging (dMRI) is very important for medical clinical application, especially the low b-value strategy. However, the choice of b-values is affected by several factors: for example, different tissue, different regions of tissue, the dependence of dMRI signals on b-values are different. Specifically, dMRI signals in areas with faster blood circulation may be more sensitive to low b-values (b<50 s/mm²); in addition, to obtain the diffusion or perfusion information from the diffusion-weighted (DW) signal, fitting methods are required, which also affected by low b-values. In this paper, Convolutional Neural Network (CNN), a machine learning based method is first used for learning the different characteristics of the DW signals in different regions of tissue and generated by different b-value acquisition strategy, and then analyse the dependence of DW signals on low b-values in different regions of the tissue. Finally, to study the dependence of the fitting methods on low b-values, which to determine the b-value acquisition strategy. The results show that the b-value acquisition strategy are different in different perfusion regions and using different fitting methods.

1. Introduction
Diffusion Magnetic Resonance Imaging (dMRI) is an MRI imaging technology, which adds diffusion gradient to the MR sequence in order to obtain the information of irregular movement of water molecules in the human body. In details, the water molecule movement information in the tissue is called diffusion information, and the water molecule movement information in the blood vessel is called pseudo-diffusion or perfusion. The diffusion and perfusion information is very useful in the clinical application, such as the diagnosis of liver cirrhosis [1–3] and brain tumour[4–7].

Once the acquisition sequence is determined, such as the b-value acquisition strategy, the multi b-values dMRI signals are obtained. To obtain the diffusion or perfusion information form the diffusion-weighted (DW) signals, the signal model should be first assumed, which is to descript the relations between the diffusion or perfusion parameter and DW signals. Then, using fitting methods to obtain the diffusion or perfusion parameter in the signal model. Normally, the DW signal model is assumed to be a fixed model, such as a monoexponential model or bi-exponential model (intravoxel incoherent motion (IVIM) model). Therefore, in the situation of fixed signal model, b-value acquisition strategy and fitting methods[8–10] are the key factors to determine whether the obtained model parameters (diffusion or perfusion parameters) are accurate.

About the b-value acquisition strategy, the choice of low b-values (b<50 s/mm²)[11] is the most important. The previous studies show that the number of low b-values will affect the estimation of pseudo-diffusion (or perfusion) parameters. Indeed, the most of DW signal model is exponential decay
model, the perfusion coefficient is much higher than the diffusion coefficient. If the number of low b-values is insufficient, the contribution of perfusion coefficient to DW decay signal is almost zero in some high perfusion regions. In this case, the DW decay signals only keep the character of diffusion component (similar as signals in low perfusion regions). Therefore, the low b-value acquisition strategy determines the difference between the generated DW signal in the high and low perfusion regions of tissue. The difference of the DW signal in the high and low perfusion regions is the guarantee for the accurate evaluation of the perfusion parameters. In addition, fitting methods based on different principles, so the dependence on low b-values in parameter estimation are different, which will also affect the acquisition strategy of low b-values.

Currently, the b-value acquisition strategy is based on empiricism. The analysis of the influence of low b-values on distinguishing the DW signals in different perfusion regions were not clear. In the diffusion or perfusion parameter estimation, the impact of low b-values on fitting methods was also unknown. To solve this problem, this paper proposed a CNN method to learn the characteristics of DW signals in different perfusion regions and generated by different low b-value acquisition strategy, and then using the learned CNN to analyze the influence of low b-values on distinguishing the DW signals in different perfusion regions. On this basis, initially determine the acquisition strategy of low b-values. Finally, to study the effect of low b-values on diffusion or perfusion parameter estimation when using different fitting methods. According to this, the optimized b-value acquisition strategy were determined.

2. Construct and train CNN network

2.1. DW signal simulation in different perfusion regions

To learn the characteristics of the DW signal in different perfusion regions and generated by different low b-value distribution, we should simulate the DW signals as the training data for the CNN training. To achieve this, we set IVIM bi-exponential model [12] as the DW signal decay model used for simulation.

\[ S_n = S_0 (F e^{-bD^*} + (1 - F) e^{-bD}) \]  

(1)

Where \( D^* \) is the pseudo-diffusion or perfusion coefficient, which presents the perfusion information. \( D \) is the diffusion coefficient indicates the diffusion information. \( F \) is the perfusion fraction, \( b \) is the diffusion sensitivity factor, which affects the DW signal strength. \( S_n \) is the DW signal measured at the b-value \( b_n \).

The experiments of this paper were based on human brain. To simulate the DW signal of the brain in different perfusion regions, the bi-exponential model parameter ranges for simulation were set as follows.

In the high perfusion regions of the brain, the perfusion coefficient \( D^* \) was sampled with a Gaussian distribution with mean value of \( 45.8 \times 10^{-3} \) mm\(^2\)/s and a standard deviation of \( 4.5 \times 10^{-3} \) mm\(^2\)/s. After 50 times sampling, the value range of \( D^* \) in brain high perfusion regions was obtained.

In the low perfusion regions of the brain, the perfusion coefficient \( D^* \) was sampled with a Gaussian distribution with mean value of \( 6.9 \times 10^{-3} \) mm\(^2\)/s and a standard deviation of \( 0.6 \times 10^{-3} \) mm\(^2\)/s. After 50 times sampling, the value range of \( D^* \) in brain high perfusion regions was obtained.

As for parameters \( D \) and \( F \), no distinction was made between high and low perfusion regions. \( D \) is uniformly sampled in 50 equal parts in the range of \( [0, 4] \times 10^{-3} \) mm\(^2\)/s, and \( F \) is similarly sampled in the range of \([0, 1]\).

In order to study the difference in sensitivity of different perfusion regions to the number of low b-values (b<50 s/mm\(^2\)), different number of low b-values was used for simulations: 4 low b-values, 3 low b-values, 2 low b-values, 1 low b-value and 0 low b-value. The low b-values was sampled in two ways: uniform sampling and random sampling. And then the DW signals of brain were generated according to Equation (1). For either way, uniform or random sampling, in total of 125000 samples for each b-value distribution were obtained (50\(^3\)=125000; there are three parameters in IVIM model, each
parameter has 50 possible values.). All the samples were added with Rician noise of different signal-to-noise ratios (SNRs). To learn the characteristics of noise, samples with noise of different SNRs mixed as one set. Among them, 80% of them were used as training set, the rest were validation set. The test set generated by a random way, which means the parameter sampled randomly instead of uniformly.

2.2. Training the CNN network

The CNN network we proposed is a multilayer network, including several convolutional layers, Pool layers and full connection layers. The input layer is an \( n \)-dimensional vector \( G(b) \), each element of \( G(b) \) representing the normalized DW signal \( G(b_n) \) at different b-values:

\[
G_{b_n} = \frac{S_b}{S_0} = Fe^{-b_nD} + (1 - F)e^{-b_nD}
\]

(2)

Where \( G_{b_n} \) is the normalized signal compared to that in Equation (1).

\[
G(b) = \begin{pmatrix}
G(b_1) \\
G(b_2) \\
\vdots \\
G(b_n)
\end{pmatrix}
\]

(3)

The output layer is a 2-dimensional vector \( R \), different element indicates high or low perfusion region.

\[
R = \begin{pmatrix}
0 \\
1
\end{pmatrix}
\]

(4)

For each convolution layer, the 1-D convolution kernel was used and the stride was 1. Each convolution layer follows a batch normalization and activation operation (Prelu). For each Pooling layer, MaxPool function was used for pooling operation. In the full connection layer, the dropout \((p=0.5)\) was used for reducing the effect of over-fitting. The detailed network structure is depicted in Fig. 1.

For the training, cross entropy loss function was used for learning the network parameters. The batch size is set to 500, the optimizer used in this paper is Adam with learning rate of 0.001. To reduce the effect of over-fitting, early stop was performed in the training process.

Using the trained CNN to analysis the influence of low b-values on distinguishing the DW signals in different perfusion regions. On this basis, initially determine the acquisition strategy of low b-values. Subsequently, two common fitting methods [13] named nonlinear least squares (LSQ) and Bayesian shrinkage prior (BSP), were used for evaluation the effect of low b-values on diffusion or perfusion parameter estimation. According to this, the optimized b-value acquisition strategy were determined.
The experiments were performed on both simulation and real brain data. The simulation data for CNN is the test set mentioned above. In addition, the simulation of brain were performed for the analysis of the dependence of fitting methods on low b-values. And the real DW brain data is composed of 5 normal brains and 5 brain tumors. The acquisition protocol is as follows: field of view (FOV)=256×256 mm, matrix size=128×128, slice thickness=5 mm, repetition time (TR)=2800 ms, echo time (TE)=77 ms, b-values=(0, 10, 20, 30, 40, 50, 70, 100, 200, 400, 600, 800 and 1000 s/mm²).

3. Results and Discussions

3.1. Simulation results
To analysis the influence of low b-values on distinguishing the DW signals in different perfusion regions, the CNN model classifies the DW signals generated by different number of low b-values according to high and low perfusion regions. The results were summarized in Fig. 2. In this figure, different colors represent different number of low b-values. The first and second row show the results obtained when the low b-value was sampled in random or uniform way. The first and second column represent the results of high perfusion region and low perfusion region, respectively. Similar results were obtained when the low b-values sampled in random or uniform way. No matter in high perfusion region and in low perfusion region, the classification accuracy of DW signals depend on the number of low b-values, especially in high perfusion region. The classification accuracy decreased with the decrease of number of low b-values. In the high perfusion region, more than 75% accuracy should be guaranteed in any SNR, so 4 low b-values were required to ensure the accuracy of classification. As respect to low perfusion region, at least 2 low b-values were required for identifying low perfusion DW signals. On this basis, initial b-value acquisition strategy should contains 4 low b-values.

Fig.2 Performance comparison of CNN models trained from different numbers of low b-value distribution data in distinguishing DW signals from high and low brain perfusion regions.

Not only the DW signals of different perfusion regions are sensitive to low b-values, the performance of different fitting methods are also sensitive to low b-values when estimating diffusion and perfusion parameters. The comparison of the dependence of fitting methods on low b-values was show in Fig. 3. Two fitting methods, LSQ and BSP were used in this experiment. It can be seen that whether it is high perfusion region (first row) or low perfusion region (second row), the mean value of the parameter $D^*$ will decrease as the number of low b-values decreases, especially in the high perfusion region. Compared with LSQ, the $D^*$ result obtained by the BSP method is closer to the ground-truth. The estimation of parameters $D$ and $F$ is not affected by the low b-values. The results show that the LSQ is more dependent on low b-values than BSP. For accurate estimation of model...
parameter, at least 2 low b-values were required when using BSP method and 3 low b-values were required for LSQ method.

![Fig. 3 Mean values of IVIM model parameters estimated by LSQ and BSP methods using different number of low b-values.](image)

3.2. Real brain results

In order to verify the dependence of different fitting methods on the low b-value, in addition to the simulation data, experiments were also carried out on the real brain DW data. IVIM model parameters obtained by different fitting methods on a meningioma ROI were shown in Fig. 5. Fig. 5 (a) is the diffusion-weighted image of brain, the red circled region represent Meningioma region. The images from left to right are the diffusion-weighted images acquired when b=0 s/mm², b=200 s/mm² and b=1000 s/mm². Fig.4 (b) shows the IVIM model parameter maps of meningioma ROI. It can be seen that the parameter maps generated by BSP method is clearer and smoother than those of the LSQ method. In terms of the influence of low b-value, the experimental results of real data are similar to simulation results. Compared with the \(D^*\) results, the parameter maps of tumor region like \(D\) and \(F\) are not sensitive to the number of low b-values. The \(D^*\) value will decrease as the number of low b-values decreases. The histogram of the obtained IVIM model parameters in the ROI is shown in Fig.4 (c). The distribution of IVIM parameters in the tumor ROI obtained by BSP method is more uniform than the results of LSQ, which mainly reflects the narrower parameter distribution. And the LSQ results have more outliers near the boundary of the parameter range.

![Fig. 4 (a) DWI image of brain with ROI of meningioma. (b) IVIM model parameter maps in tumor ROI. (c) The histogram of parameters in ROI.](image)
More results about brain tumors summarized in Fig. 5. In this figure, the mean and standard deviation of IVIM model parameters over all the tumor ROIs obtained by different number of b-values and fitting methods were compared. The results are similar to the simulation experiment. The estimation of the parameter $D^*$ is affected by the number of low b-values, and the result of $D^*$ estimation decreases with the decrease of the number of low b-values, especially when the LSQ method is used. Compared with parameter $D^*$, the estimates of parameters $D$ and $F$ are not sensitive to the number of low b-values. The BSP methods show superior in IVIM model parameter estimation, which reflect in lower dependence on low b-values and fewer outlying estimates. However, the BSP method is based on Bayesian theory, the assumption of prior distribution of model parameters is necessary, which leads the tissue structure information missing of BSP results at low SNRs and verified in other studies.

Fig. 5 Statistics of the mean and standard deviation of IVIM model parameters for all tumor ROIs.

4. Conclusion
Based on the results and discussions presented above, the conclusions are obtained as below:

1) DW signals in high perfusion region is more sensitive to number of low b-values than those in low perfusion region.

2) The dependences of different fitting methods on low b-values are different. For example, the BSP method requires at least 2 low b-values for accurate estimation of parameter in brain tumor and 4 low b-values are requires for LSQ method.

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