Preliminary Research on Multi-Material Decomposition of Spectral CT Using Deep Learning

Zhengyang Chen, Liang Li*

***Abstract*—Material decomposition is an important application of spectral Computed Tomography (CT). However, traditional post-processing material decomposition algorithms are based on voxel-local of reconstruction image, which leads two problems. First, ignoring the beam hardening problem. Second, not taking advantage of priori knowledge well. In order to solve these two problems processing spatial specificity, inspired by the work, we import Deep Learning technique to deal with multi-material decomposition. After been trained by plenty of samples, Deep Learning network can break the limit of voxel, reducing the influence of beam hardening and modeling the human body. We build a Convolutional Neural Network (CNN) which is a simplified version of VGG16 net, and simulate some reconstruction data of spectral CT to train the network. Compared to the results of solving linear equations, the CNN method turns out to work much better in the test samples. As the conclusion, we think CNN is useful in the multi-material decomposition, but there still remains many researches to work, such as the source of training data, the balance between the priori knowledge and measurement. On the other hand, this work focuses on post-processing, but using Deep Learning to deal with the pre-processing multi-material decomposition is also a potential direction.**

***Index Terms*—spectral CT, material decomposition, CNN, deep learning**

I. Introduction

The appearance of spectral CT enables CT to distinguish photon by different energy, which makes using the reconstruction images of CT at difference energy bins to do post-processing become possible. However, the reconstruction images of CT, or the linear attenuation coefficient of scanned object cannot reflect its inner information directly. In general, we concern more about the distribution of specific materials in the scanned object, such as fat, contrast agent, etc. For example, in clinic, using the result of material decomposition can measure the body fat rate, or in the case needed contract agent, can isolate the agent individually as the blank test [1].

Many material decomposition algorithms have been proposed with the popularity of spectral CT. These algorithms can be divided into two kinds roughly. One is the pre-process method which takes the measurement from detectors as the input data, and the other one reconstructs the image at different energy first, then uses the image as the input of the material decomposition algorithm, which is called post-process method. However, traditional material decomposition algorithms are based on voxel-local of reconstruction image, which leads some problems. In order to solve these problems, inspired by the work [4], we import the Deep Learning technique and propose a post-processing method with CNN.

Recently, the Deep Learning technique has become more in more popular in many fields [4, 6]. In image analysis, the CNN can extract the features in the image, which has turned out to be effective in image classification [5-7]. Therefore, we can model the result of material decomposition of a cross section with CNN to solve the problems in traditional material decomposition algorithms. In this work, we build a CNN and train it to deal with the decomposition problem, and it shows some advantages.

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II. Method

As we know, the reconstructed image of CT is the X-ray linear attenuation coefficient $\mu(\vec{x}, E)$ of the scanned object, where $\vec{x}$ is the spatial position and E is energy bin.

In the post-processing, knowing $\mu(\vec{x}, E)$ of scanned object by reconstruction algorithm, we need a set of basis functions to solve $\eta(\vec{x}, l)$. In the situation of duel-energy CT, since the information comes from only two energy bins, two kinds of materials are chosen as basis materials. By adopting the empirical formula between the adoption cross-section of X-ray and the relative atomicity, $\eta(\vec{x}, l)$ can be presented as a linear combination of these two basis materials [2]. But in the case of multi-energy CT, we can set all the materials of scanned object as the basis materials (generally speaking, the number of materials should be less than the number of energy bins), which can be presented as [3]:

$$\mu(\vec{x}, E) = \sum_{l=1}^{N_l} \eta(\vec{x}, l)\mu_l(E)\,, E = 1 \dots N_E \qquad (1)$$

where N_l is the number of materials, N_E is the number of energy bins, and $\mu_l(E)$ is the linear attenuation coefficient of material l at energy bin E, which is a known quantity. Intuitively, if $N_E \geq N_l$, by solving the equations (1) simultaneously at different energy bins, $\eta(\vec{x}, l)$ can be figured out.

However, there are two problems with traditional material decomposition algorithms which based on (1).

First, ignoring the beam hardening problem. Although the beam hardening is caused by reconstruction, which should not be classified into decomposition task, it's an important source of the error of material decomposition. Because the dose of X-ray used in CT, especially the medical CT, is limited, which

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leads the detector has to balance between the number of energy bins and statistical noise [8]. If the energy bins are too many, the number of photons stored in every energy bin become fewer, which makes the statistical noise become higher. On the other hand, if the number of energy bins is too few, the information can be gotten from different energy bins becomes less, and the beam hardening problem becomes more serious. That's because the X-ray used in CT is generated by bremsstrahlung, which has certain energy distribution, and the adoption of X-ray from scanned object also has distribution. After the X-ray goes across a certain thickness of the scanned object and reaches its inside, the energy distribution has changed. Obviously, the wider of energy bins' width, the bigger of the beam hardening error. What's more, in the medical CT, since the attenuation coefficient of the materials in human body is close, the system consisted of (1) is ill conditioned, the beam hardening will cause a bigger error in decomposition.

Second, not taking advantage of priori-knowledge well. Among these traditional material decomposition algorithms, in order to reduce error, most of them import the regularization terms artificially. These regularization terms, no mater of which have the form of Gibbs energy function, or the form of total variation, are based on the priori-knowledge that the images in nature should be piecewise smooth [9], then impose punishment on the drastic change part in the decomposition result. However, in the medical images, there is no too much difference in the same cross section of human body, so it's deducible that there is a good deal of priori knowledge which isn't used well. For instance, when a post-processing decomposition algorithm calculating the result of a voxel, and the reconstruction result of it happens to be wrong (which is unavoidable) for noise or beam hardening, if we have some priori knowledge like "this part should belong to bones", the error could be reduced. However, traditional algorithms are based on voxel, what they can consider is the voxel itself or its neighborhood, and it's hard to model the whole cross section, which doesn't take advantage of priori knowledge well.

In the case of medical CT reconstructing a certain cross section of human body, the two problems mentioned above have a kind of spatial specificity. For the same position of different people and the same cross section, the causes of bean hardening are similar, meanwhile, the priori information of the same position is also similar.

In order to avoid the spatial specificity problems, we should enlarge our visual field instead of considering voxel or its neighborhood only. On the other hand, spatial specificity means it's a feature of the image, which can be model in the CNN. Using large number of the result of reconstruction and their decomposition results as the training data and labels, CNN can find the features of the spatial distribution and stored them in the network abstractly, once input a new reconstruction image, CNN can use the priori information to predict the decomposition of a voxel, which may reduce the influence of beam hardening and statistical noise. What's more, having trained over, the forward process of CNN is quite fast, which is another advantage of using CNN to work out the decomposition problem.

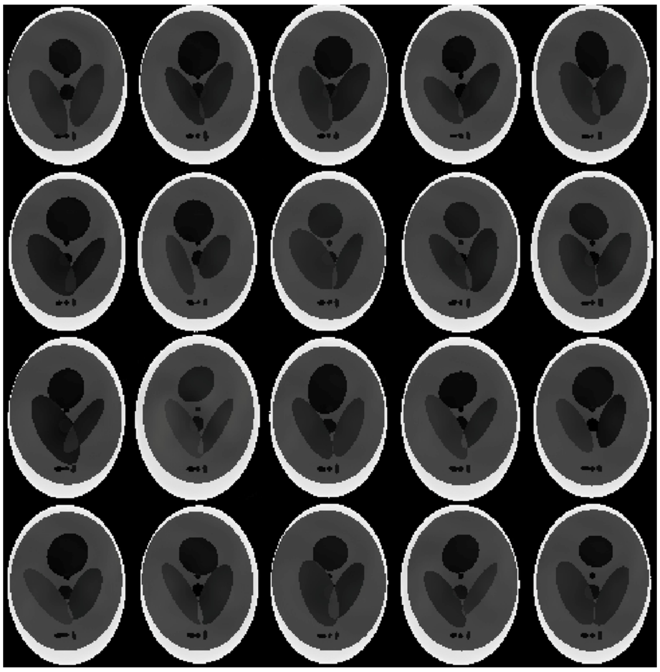


Fig.1. The phantoms used in this work. All the phantoms are similar to each other, but the size, position, direction of every ellipse and the concentration of the five materials are different (but close).

III. NUMERICAL SIMULATION AND RESULTS

In order to get the training data, we generate 20 phantoms shown in Fig.1. All phantoms are similar, and have five materials. The $\mu_l(E)$ is from the work [8], and shown in the Table.1. Inspired by the work [3], the generating phantoms meet the constraints:

$$\sum_{l=1}^{N_l} \eta(\vec{x}, l) = 1 \qquad (2)$$
$$0 \leq \eta(\vec{x}, l) \leq 1$$

The X-ray tube spectrum used in this work is the same as the work [8], which is divided into 8 energy bins. In the simulation, we adopt the fan-beam mode of X-ray source. The phantoms are 2*2cm, discretized into a 128*128 grid. There 512 detectors line in 4.5cm long, and they are apart from the center of the grid for 5cm. The number of views over 360 degrees is 360.

Table.1. The ID of materials in this work and in the work [8]

This work (the order in Fig.4)	Work [8] (the indexes in Fig.4)
1	3
2	2
3	7
4	4
5	1

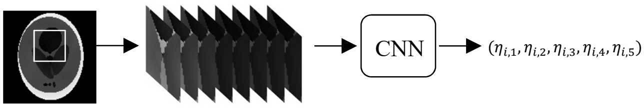


Fig.2. The flow chart shows that the 8*32*32 pieces are cut from a reconstruction images, whose size is 8*128*128, and the CNN maps a piece to the material decomposition result of the central voxel of that piece.

We iterate ART algorithm for 20 times to reconstruct these phantoms at each energy bin individually. After reconstruction, we get 20 images, whose size is 8*128*128.

As the function (1) shows, although the decomposition problem is almost a voxel-local problem, considering beam hardening, we cut the image into 8*32*32 pieces, and set the material decomposition result of its central voxel as its supervising label of the output of CNN, which is shown in Fig.2. In this way, we get 20*128*128 samples, and we can get the result of material decomposition of an image by scan it with CNN piece by piece.

CNN is coded by the Keras frame using the Theano as the backend. We use a structure similar to the VGG16 net [5], which shown in Fig 3. We build the training set by 15*128*128 samples from 15 phantoms to train CNN, the validation set by 3*128*128 samples from other 3 phantoms to prevent over-fitting, and the test set by the rest 2*128*128 samples from the rest 2 phantoms to evaluate the effect of CNN. Since this is not a classification problem, we use the Mean Square Error as the loss function, and use Adagrad algorithm as the optimizer to train CNN.

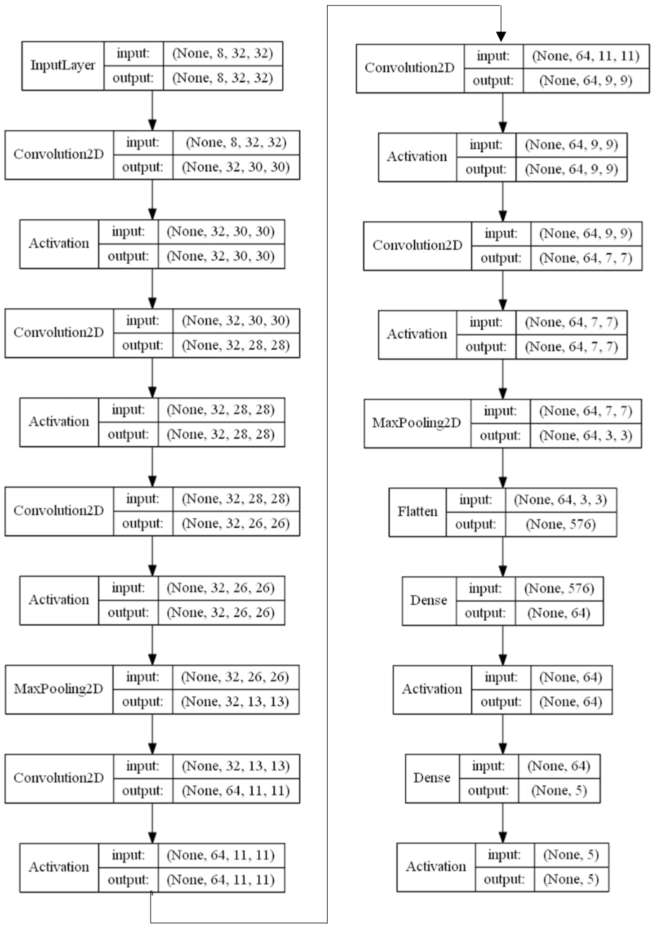
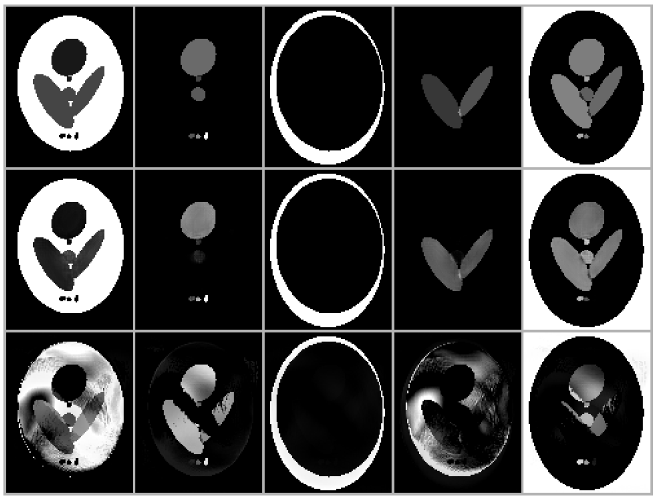
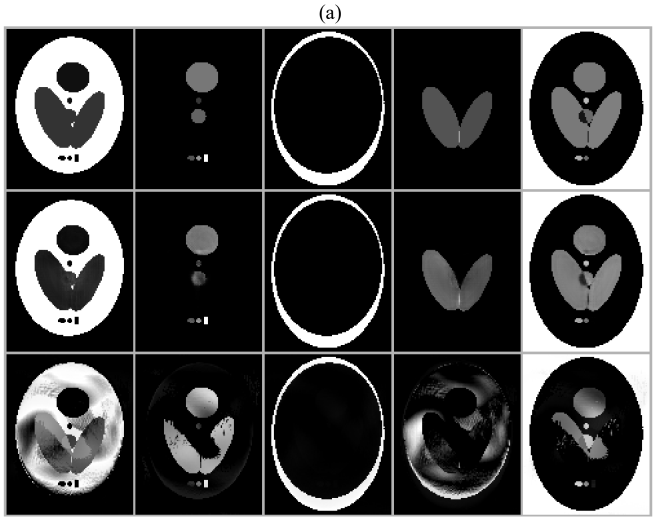


Fig.3. The CNN used in this work. All the convolutional kernels' size is 3*3, and the activation function is ReLU except the last one is Softmax. In order to increase the linearity of CNN, we remove the dropout layer in VGG16 net [5].

The results of 2 test set is shown in Fig.4. After training, the MSE reaches 4.33E-4 for training set, 5.93E-4 for validation set and 5.25E-4 for test set. As a contrast, we solve (1) with the constraint (2) in least square voxel by voxel. The MSE of decomposition result for the test set is 2.85E-2.



(a)



(b)

Fig.4. The material decomposition results of CNN method and solving equations. The first line is the generated phantom, and its five materials is in Table.1. The second line is the results of CNN, and the last line is the results of solving equations. Obviously, the quality of the second line is much better than the third line.

By heightening the contrast of reconstruction images, we can observe that there are similarities of the beam hardening among different phantoms, as shown in Fig.5. The spatial specificity of beam hardening exists indeed. This is one of the reasons that CNN can be effective in the material decomposition problem.

Fig.5. There are similarities in the same material of different phantoms.

We test different coefficient of reconstruction in the simulation. For example, decreasing the times of ART while increase the times of TV [9] can make images dimmed. But we observe that as long as the samples of test set and training set are generated on the same reconstruction coefficient, CNN can predict a decent result, which is another reflect of the availability of Deep Learning.

IV. CONCLUSION

From this preliminary research, CNN shows its availability in the material decomposition problems, which is a voxel-local partly linear problem. But there are some problems remaining to be solved. The most important problem is in the CT system in reality, how can we get the supervising label? Here are some possible ways. Use model (real or virtual), or use monochrome X-ray source to get the result of material decomposition without beam hardening problem, then reconstruct this result to get the training samples.

On the other hand, CNN may erase the situation that doesn't appear in the training set (for example, some rare tumors), how to balance the priori knowledge and the measurement is a considerable problem.

In the future, we can try some other network to do the material decomposition (for example, the Deep Residual Network, which displays better than VGG16 in the image classification [7]). Oh the other hand, if we can skip the reconstruction and deal with the measurement from the detector directly, which turns the post-processing into pre-processing, we may avoid the beam hardening problem. But this is not a voxel-local problem, which cannot be solved by CNN. We may need some methods like Recurrent Neural Network (RNN) to generate the material decomposition from sinograms.

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