Reduction of computed tomography ring artifacts via radial basis function neural network

Zhen Chao*, Hee-Joung Kim*,†

Department of Radiation Convergence Engineering, College of Health Science, Yonsei University, Wonju, Korea*
Department of Radiological Science, College of Health Science, Yonsei University, Wonju, Korea†
1.1. Causes of CT ring artifacts

- Hardware-based factor

A mis-calibrated or defective detector element, which results in rings centered on the center of rotation.
1.1. Causes of CT ring artifacts

- **Parameter-based factor**
  - Pitch = 0.075 (10 bpm)
  - Pitch = 0.150 (20 bpm)
  - PMMA ellipse ~40 cm across

- **Physics-based factor**
  - (normal X-ray)
  - (weak X-ray)

Ring artifacts occur when a weak X-ray (low dose) or improper pitch is used

- Boas et al., *Imaging in Medicine*, 2012
1.2. Adverse effects of CT ring artifacts

<table>
<thead>
<tr>
<th>Image aspect</th>
<th>Clinical aspect</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Destruction of effective Information</td>
<td>• Interfering diagnosis effect</td>
</tr>
<tr>
<td>• Reduction of image quality</td>
<td>• Increasing cost</td>
</tr>
</tbody>
</table>

Ring artifacts destroy valid information

Therefore, removing the ring artifacts and keeping the image resolution is hot topic

- Boas et al., Imaging in Medicine, 2012
### 1.3. Approaches of artifacts removal

<table>
<thead>
<tr>
<th>Category</th>
<th>Features</th>
<th>limitation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-processing</td>
<td><img src="image1.png" alt="pre-processing" /></td>
<td>▪ Restricting the applicability</td>
</tr>
<tr>
<td></td>
<td><img src="image2.png" alt="pre-processing" /></td>
<td>▪ Large difficulty</td>
</tr>
<tr>
<td></td>
<td><img src="image3.png" alt="pre-processing" /></td>
<td></td>
</tr>
<tr>
<td>post-processing</td>
<td><img src="image4.png" alt="post-processing" /></td>
<td>▪ Reducing image resolution</td>
</tr>
<tr>
<td></td>
<td><img src="image5.png" alt="post-processing" /></td>
<td></td>
</tr>
</tbody>
</table>

By comprehensive consideration, our research focuses on **post-processing**.

- Liang et al., *Physics in Medicine & Biology*, 2017
- Wang et al., *Neural Computing and Applications*, 2019
1.4. Previous works for solving the problems

<table>
<thead>
<tr>
<th>Problem list</th>
<th>Previous solutions</th>
<th>Limitations of previous studies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low image resolution</td>
<td>1) Artifact extraction and image subtraction</td>
<td>- Difficult to extract artifact-only</td>
</tr>
<tr>
<td></td>
<td>2) The application of interpolation technology</td>
<td></td>
</tr>
<tr>
<td>Normal information loss and artifact residues</td>
<td>1) The application of total variation-based method</td>
<td>- Difficult to choose parameter</td>
</tr>
<tr>
<td></td>
<td>2) Increasing the targeting of artifacts</td>
<td>- Difficult to make stopping criteria</td>
</tr>
<tr>
<td></td>
<td>3) The application of deep learning</td>
<td>- Huge training data</td>
</tr>
</tbody>
</table>

Therefore, The problems of extracting artifacts **on the whole** have not been solved

- Yan et al., *Physics in Medicine & Biology*, 2016
- Liang et al., *Physics in Medicine & Biology*, 2017
1.5. Research direction statement

‘point-to-point’ and ‘pixel-to-pixel’ instead of ‘on the whole’

- It is based on:

  - Finding the exact positions of all artifacts by **two smoothers and image subtraction**.
  - Analyzing and processing each artifacts pixels by **radial basis function neural network (RBFNN)**.
2.1. Polar coordinate transformation

- in Cartesian coordinates, suppose $M$ as $(x, y)$
- in Polar coordinates, suppose $M$ as $(\rho, \theta)$

\[ x = \rho \cos \theta, \quad y = \rho \sin \theta \]

In order not to lose spatial resolution, we adopted **nearest interpolation**.

- Yan et al., *Physics in Medicine & Biology*, 2016
2.2. Finding the positions of line artifacts

- Applying the relative total variation (RTV):

\[
\lambda \cdot \left( \frac{\sum_{q \in R(p)} g_{p,q} \cdot (\partial_x S)_q}{\sum_{q \in R(p)} g_{p,q} \cdot (\partial_x S)_q} + \varepsilon \right) + \left( \frac{\sum_{q \in R(p)} g_{p,q} \cdot (\partial_y S)_q}{\sum_{q \in R(p)} g_{p,q} \cdot (\partial_y S)_q} + \varepsilon \right)
\]

- \( R(p) \): window \( p \) in pending image \( S \)
- \( (\partial_x S)_q \): Partial Derivatives of Pixel \( q \) in \( x \) direction
- \( q \): the central pixel of \( R(p) \)
- \( g(p, q) = \exp \left( -\frac{(x_p-x_q)^2+(y_p-y_q)^2}{2\sigma^2} \right) \)
- \( \sigma \): the variance of window \( p \)
- \( \varepsilon \): a small positive number
- \( \lambda \): smoothing weight

- Liang et al., Physics in Medicine & Biology, 2017
2.2. Finding the positions of line artifacts

- **Image subtraction:**
  - Subtracting the image obtained by RTV from the original line artifacts image.

- **Further smoothing the obtained image:**

\[ A = \left(\frac{1, 1, 1, \ldots, 1}{W}\right) \]

Lateral smoothing template A, the value of w is 30-100

Finding line artifacts by increasing **artifact recognition**
2.3. Radial basis function neural network (RBFNN)

- Connections between two neurons in input layer and hidden layer:

\[ R(x_i, c_{pi}, \sigma_{pi}) = \exp\left( -\frac{1}{2\sigma_{pi}^2} \| x_i - c_{pi} \| ^2 \right) \]

- The expression of neurons in hidden layer:

\[ M(x, c_p, \sigma_p) = \prod_{i=1}^{k} R(x_i, c_{pi}, \sigma_{pi}) \]

- Connections between two neurons in hidden layer and output layer:

\[ y = \sum_{p=1}^{l} \omega_p M(x, c_p, \sigma_p) \]

\( \omega \): weight factor
2.3. Proposed RBFNN

- Selection of neurons in input layer

(What we need to do)

Two aspects are considered:

1. The effect of pending pixel itself
2. The effect of the surrounding normal pixels on artifact pixel
## Materials & Methods

### 2.3. Proposed RBFNN

- **Selection of neurons in input layer**

<table>
<thead>
<tr>
<th>Pixel value</th>
<th>Gradient direction</th>
<th>The sum of difference set</th>
<th>The mean of difference set</th>
<th>The variance of difference set</th>
<th>The sum of weight set</th>
<th>The mean of weight set</th>
<th>The variance of weight set</th>
</tr>
</thead>
</table>

**Input variables (eight neurons)**

- (8 normal pixel values and artifact pixel value)
- (Difference values between normal pixels and artifact pixel)
- (Weight values of normal pixels by inverse distance weighting (IDW))
2.3. Proposed RBFNN

- **Selection**
  - It depends on the training data selected.
  - The larger the number is, the better the effect is.
  - However, the time consumption and generalization also need to be considered.

Here, we chose 40 as the number of neurons in the hidden layer.

**Proposed RBFNN**

- Qasem et al. Knowledge-Based Systems, 2012
- Aljarah et al. Neural Computing and Applications, 2018
2.4. Training of proposed RBFNN

- Connections between two neurons in input layer and hidden layer:
  \[ R(x_i, c_{pi}, \sigma_{pi}) = \exp\left( -\frac{1}{2\sigma_{pi}^2} \| x_i - c_{pi} \|^2 \right) \]
  - \( i \) represents the \( \text{th} \) neuron in input layer
  - \( p \) represents the \( \text{th} \) neuron in hidden layer

- The expression of neurons in hidden layer:
  \[ M(x, c_p, \sigma_p) = \sum_{i=1}^{k} R(x_i, c_{pi}, \sigma_{pi}) \]

- Connections between two neurons in hidden layer and output layer:
  \[ y = \sum_{p=1}^{l} \omega_p M(x, c_p, \sigma_p) \]
  - \( \omega \): weight factor

According to the structure of our NN:

\[ X = (c^1, \ldots, c^{320}, \sigma^{321}, \ldots, \sigma^{640}, \omega^{641}, \ldots, \omega^{680}) \]

We proposed the hybrid of gradient descent method (GDM) and gravitational searching algorithm (GSA) for training.
2.4. Training of proposed RBFNN

- **Gravitational searching algorithm (GSA)**

Base on this:

- We regard 

\[ X = (c^1, \ldots, c^{320}, \sigma^{321}, \ldots, \sigma^{640}, \omega^{641}, \ldots, \omega^{680}) \]

as **planet (object)**

- GSA is to find the most suitable orbit (position) of an planet (object) by Newton's law.

\[ \text{Rashedi et al., Information sciences, 2009} \]
2.4. Training of proposed RBFNN

- **Gravitational searching algorithm (GSA)**

Generate initial arrays

\[ X = (X_1^1, ..., X_i^d, ..., X_i^{680}) \]

\[ V = (V_1^1, ..., V_i^d, ..., V_i^{680}) \]

\[ i = 1, 2, ..., 50 \]

Obtained by gradient descent method (GDM)

**Mass calculation**

\[ m_i(t) = \frac{\text{fit}_i(t) - \text{worst}(t)}{\text{best}(t) - \text{worst}(t)} \]

\[ M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{50} m_j(t)} \]

Fitness function:

\[ \text{fit}_i = \frac{\sum_{k=1}^{N} (A_i^k - B^k)^2}{N} \]

B: the ideal output

A: the actual output

**Gravitation calculation**

\[ F_{ij}^d(t) = G(t) \frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t) + \varepsilon} (x_{ij}^d(t) - x_i^d(t)) \]

\[ G(t) = G_0 e^{-\alpha t / T} \]

\[ F_i^d(t) = \sum_{j \in k \text{best}, j \neq i} \text{rand}_j F_{ij}^d(t) \]

**Acceleration calculation**

\[ a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} \]

**Position and velocity update**

\[ v_i^d(t+1) = \text{rand}_i \times v_i^d(t) + a_i^d(t) \]

\[ x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \]

Stop if \( t = 50 \)

By fitness function, find the optimal array

- Rashedi et al., Information sciences, 2009

---

**Results & Discussions**
2.5. Experimental data

- **Training data and test data**

<table>
<thead>
<tr>
<th></th>
<th>Training data</th>
<th>Test data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data</td>
<td>160 images</td>
<td>40 images</td>
</tr>
<tr>
<td>Notes</td>
<td>300 images</td>
<td>80 images</td>
</tr>
<tr>
<td>Type</td>
<td>(simulated artifacts)</td>
<td>(real artifacts)</td>
</tr>
</tbody>
</table>

- **Further explanation for training**

- **Experimental data**
  - Training data: 160 images
  - Test data: 40 images (simulated artifacts)

- **Further explanation for training**
  - Training data: 300 images
  - Test data: 80 images (real artifacts)

Size: 512×512

So, Training **pixels** what we need, no whole **images**
2.6. Quantitative evaluation

**Image quality and distortion evaluation**
(Peak signal-to-noise ratio (PSNR))

\[
PSNR = 10 \times \log_{10} \left( \frac{2^8 - 1)^2}{\frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=1}^{n-1} (X(i, j) - Y(i, j))^2} \right)
\]

- \( m, n \): the size of \( X, Y \)
- \( X \): reference image
- \( Y \): corrected image

**Similarity evaluation with reference images**
(Structural similarity (SSIM))

\[
SSIM(X, Y) = \left[ \frac{L(X, Y)}{L(X, Y)} \right] \left[ \frac{C(X, Y)}{C(X, Y)} \right] \left[ \frac{S(X, Y)}{S(X, Y)} \right]
\]

\[
l(x, y) = \frac{2 \mu_x \mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}, \quad s(x, y) = \frac{\sigma_{xy} + C_3}{\sigma_x \sigma_y + C_3}
\]

\[
c(x, y) = \frac{2 \sigma_x \sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2},
\]

- \( \mu_x, \mu_y \): the mean values of images \( X, Y \)
- \( \sigma_x, \sigma_y \): the standard deviations of images \( X, Y \)
- \( \sigma_{xy} \): the covariance of images \( X, Y \)

- Unidirectional total variation (UTV) method and Relative total variation-iterative (RTVI) method were implemented for comparison.
3.1. Brain data
3.2. The performances of PSNR and SSIM values

For all 40 CT brain data, The PSNR and SSIM performances of proposed method outperform those of other two methods.
3.3. Chest data

Original image with real ring artifacts

UTV

RTVI

Proposed
Results & Discussions

3.3. The performances of pixel profiles

The performances of pixel profiles for Ring artifacts image are shown in the graph. The pixel value is plotted against the pixel number. The proposed method shows better performance compared to Artifacts, UTV, and RTVI.
In this study, a proposed method which is based on the radial basis function neural network (RBFNN) for removing CT ring artifacts.

- **New style**: the point-to-point and pixel-to-pixel processing style, which increases the practicability of the method and enables it to act on all kind of cases.

- **New construction**: Although RBF neural networks are not new, the whole construction, mainly the selection of input neurons, is new. Moreover, we successfully applied it to ring artifact removal.

- **New training method**: the hybrid of gradient descent method (GDM) and gravitational searching algorithm (GSA).

By comparing with the other two recent methods, based on complicated data, it proves that our method has strong practicability and effectiveness.
Thanks for your attention

Presenter’s e-mail address: chaozhen1000@yonsei.ac.kr