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

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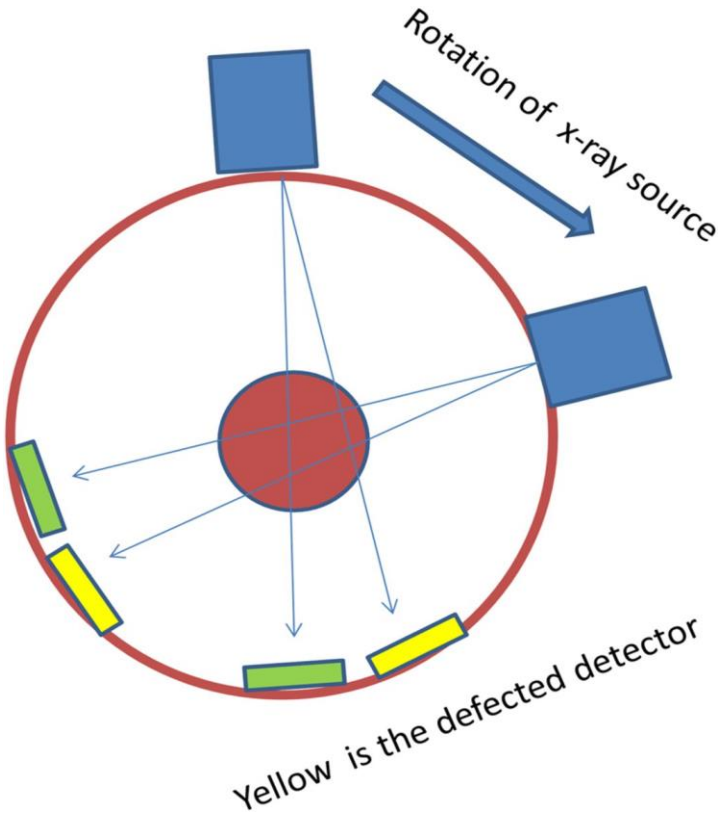
International Workshop 21st iWoRiD on Radiation Imaging Detectors

(Yonsei University)
(Medical Physics & Imaging Lab.)

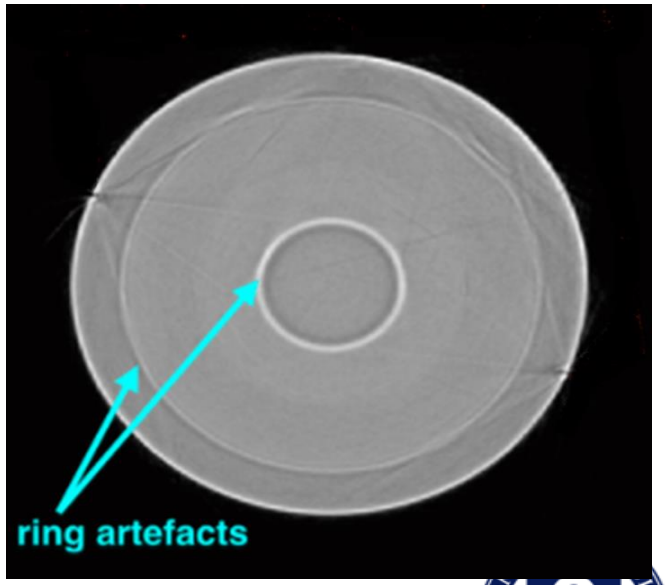
1.1. Causes of CT ring artifacts

- Hardware-based factor



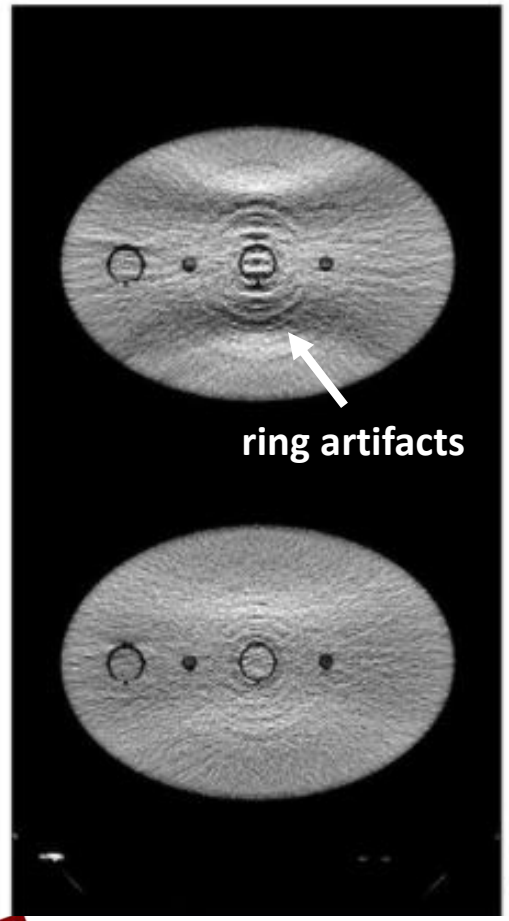
Schematic picture showing how ring artifact is produced

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

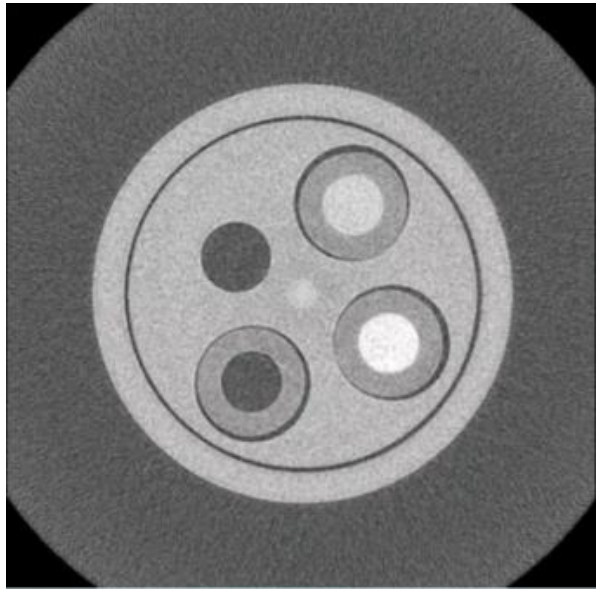


Pitch = 0.075
(10 bpm)

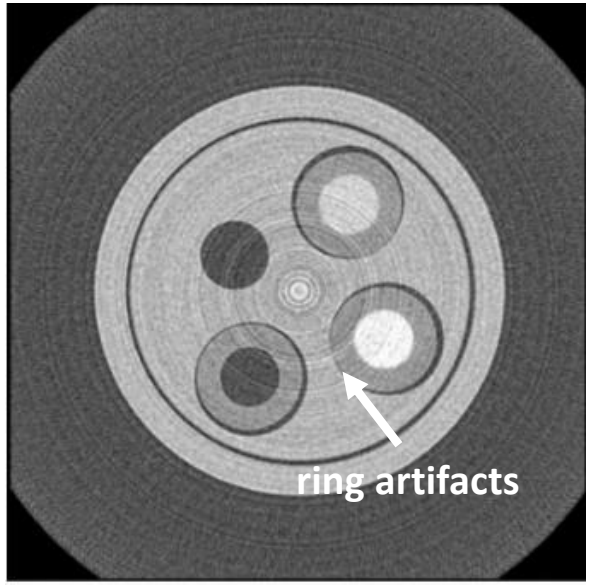
Pitch = 0.150
(20 bpm)

PMMA ellipse
~40 cm across

- Physics-based factor



(normal X-ray)



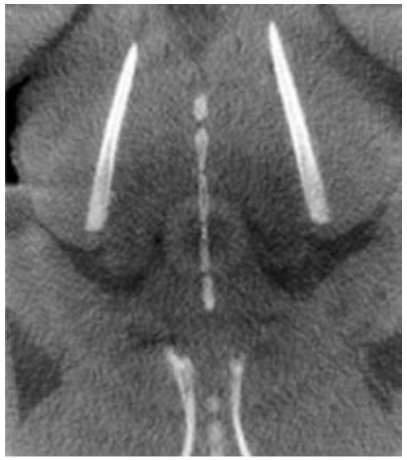
(weak X-ray)

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

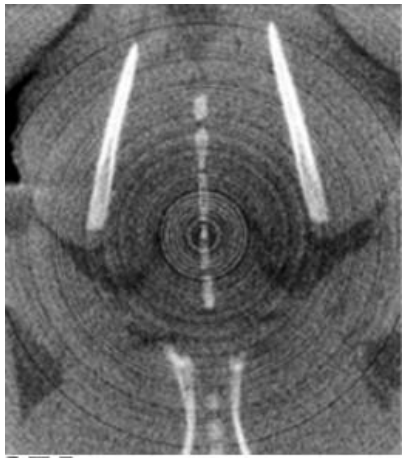
- *Boas et al., Imaging in Medicine,2012*

1.2. Adverse effects of CT ring artifacts

Image aspect	Clinical aspect
▪ Destruction of effective Information	▪ Interfering diagnosis effect
▪ Reduction of image quality	▪ Increasing cost



(normal)



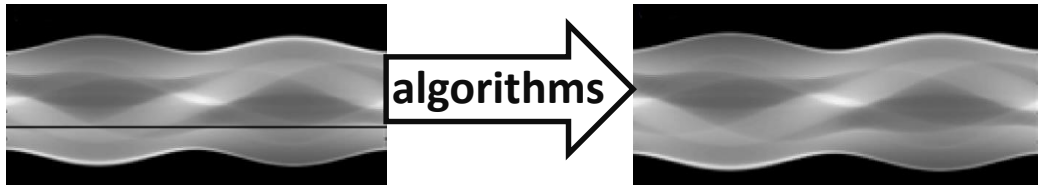
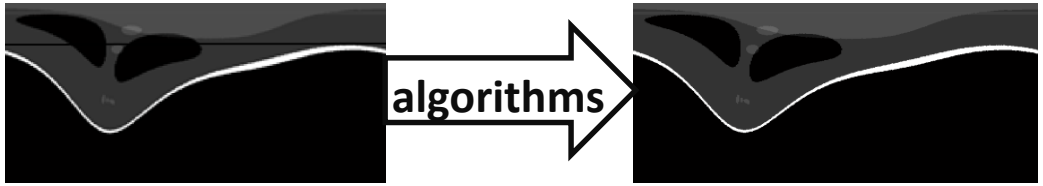
(ring artifacts)

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

Category	Features	limitation
▪ Pre-processing	 (sinogram-domain)	▪ Restricting the applicability ▪ Large difficulty
▪ post-processing	 (polar coordinate-domain)	▪ Reducing image resolution

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

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

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

- Yan et al., *Physics in Medicine & Biology,* 2016
- Huo et al., *Electronics Letter, 2016*
- Liang et al., *Physics in Medicine & Biology,* 2017
- *Wang et al Neural Computing and Applications, 2019*

1.5. Research direction statement

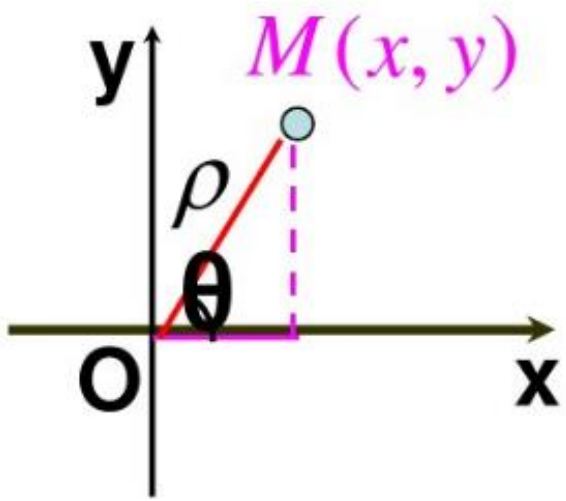
'point-to-point' and **'pixel-to-pixel'** instead of **'on the whole'**

- **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)** .

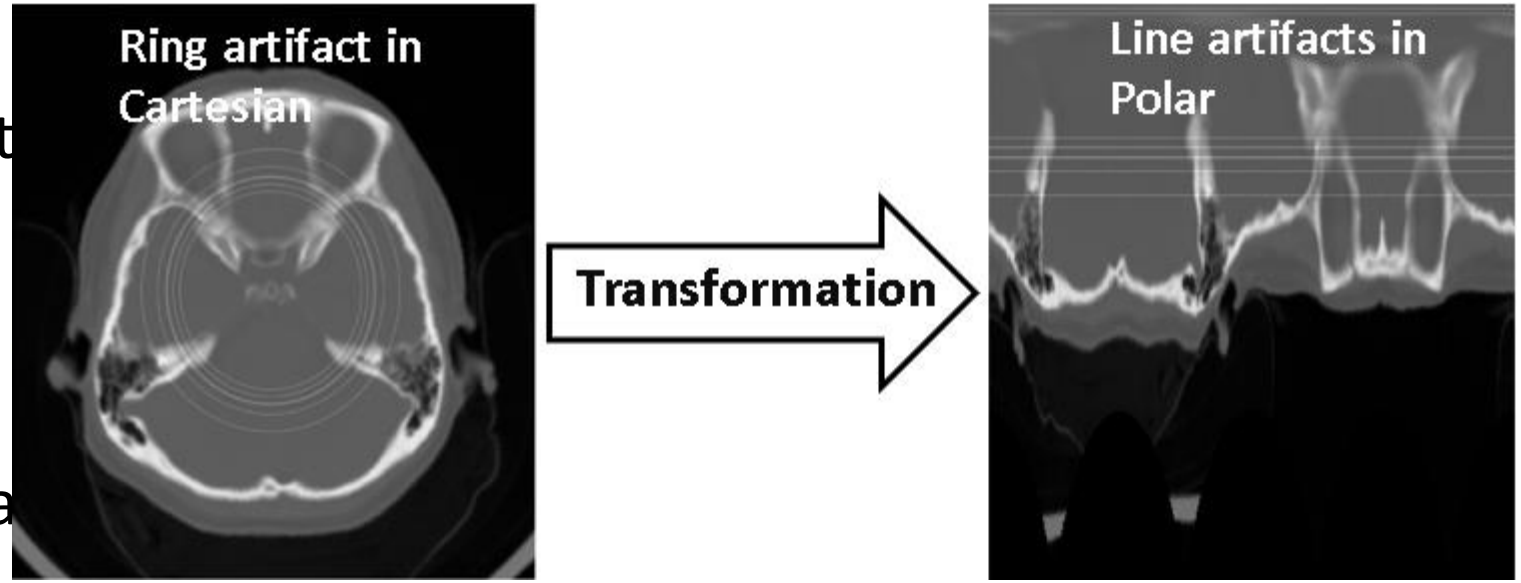
2.1. Polar coordinate transformation



- in Cartesian coordinates , suppose M as (x, y)
- in Polar coordinates, suppose M as (ρ, θ)

Cart

Pola



$$x=\rho\cos\theta,\quad y=\rho\sin\theta$$

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

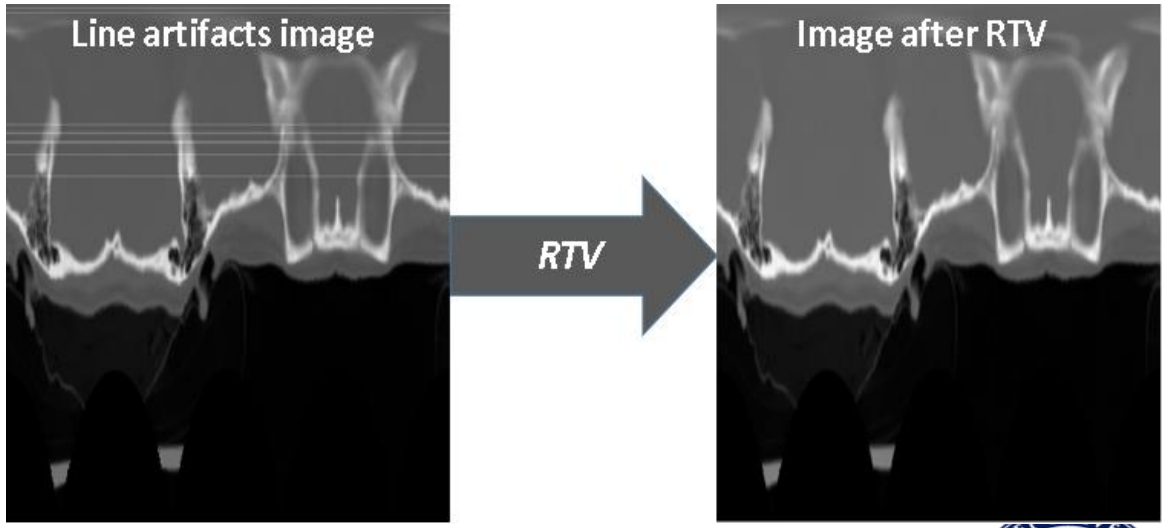
- Yan et al., *Physics in Medicine & Biology*, 2016

2.2. Finding the positions of line artifacts

- **Applying the relative total variation (RTV):**

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

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



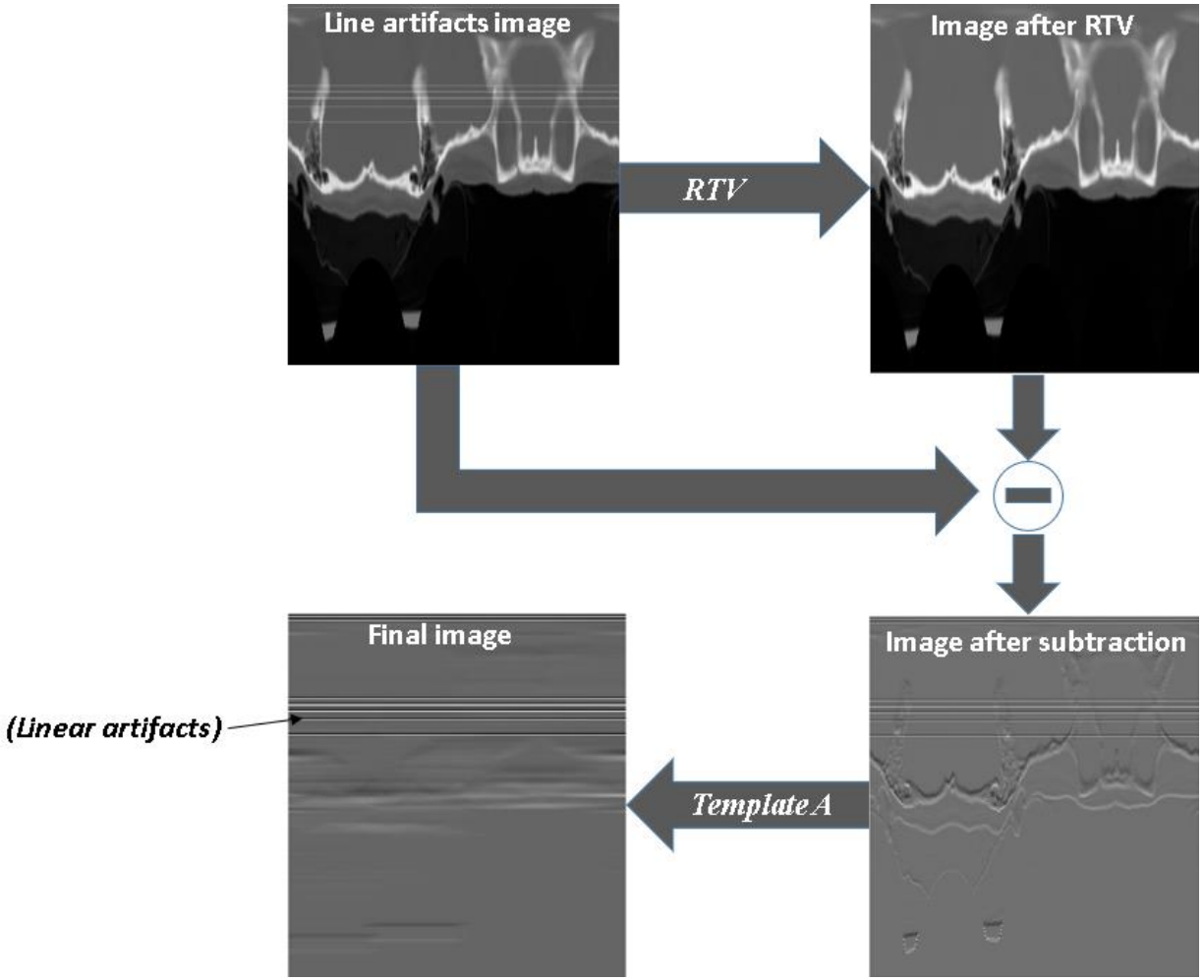
- *Liang et al., Physics in Medicine & Biology, 2017*

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:**

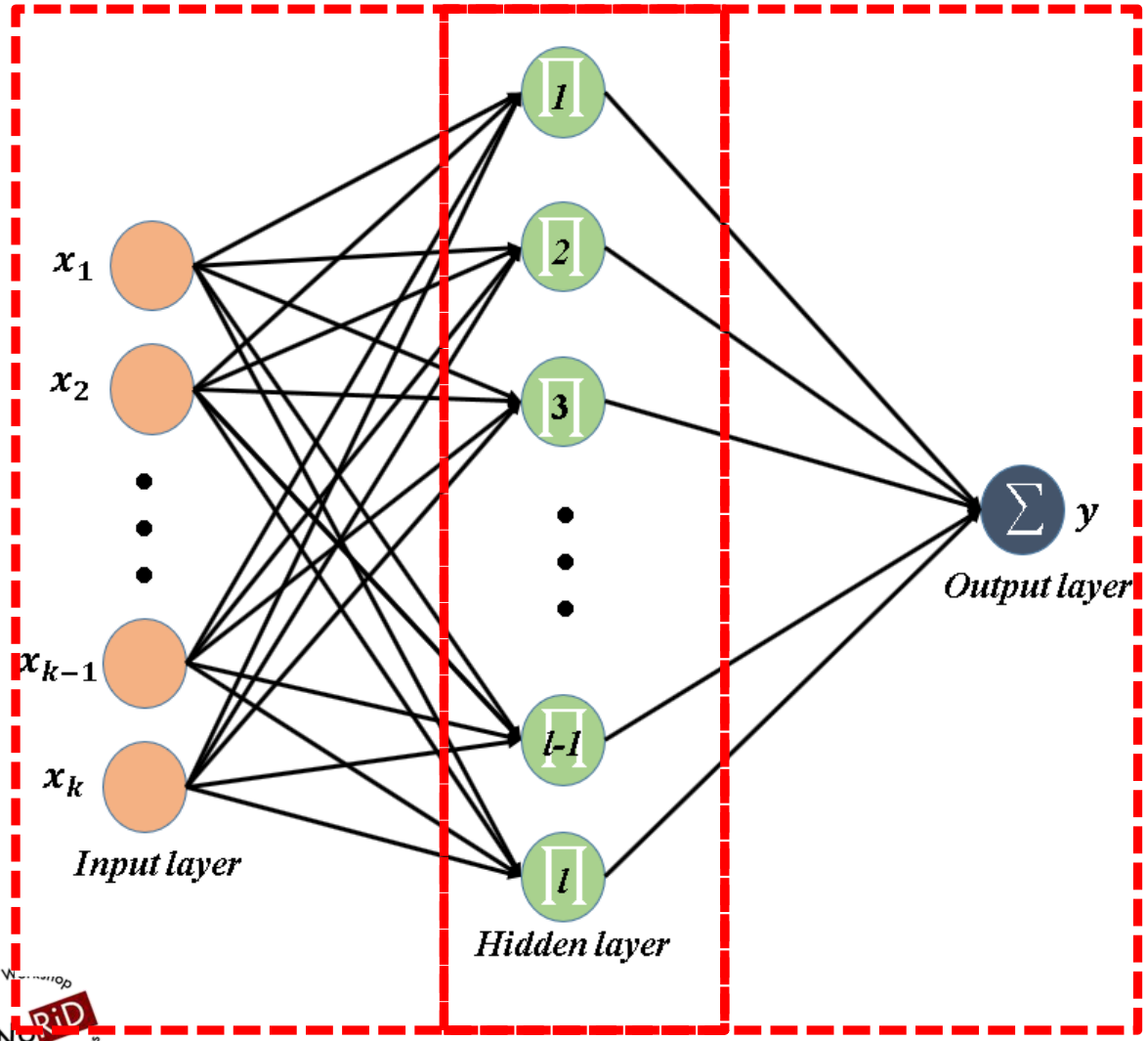
$$A = \underbrace{(1,1,1,1,\ldots,1)}_{W}/W$$

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:

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

  - ✓ *i* represent i^{th} neuron in input layer
  - ✓ *p* represent p^{th} neuron in hidden layer

- 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:

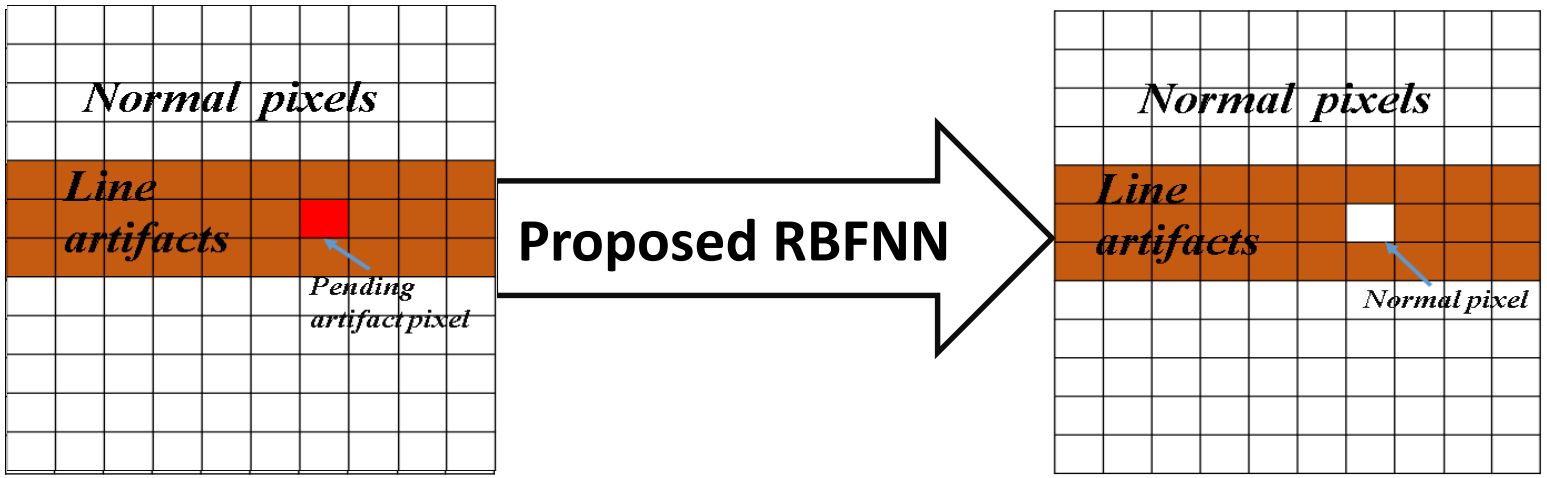
$$y = \sum_{p=1}^{l} \omega_p M(x, c_p, \sigma_p)$$

  - ✓ ω : *weight factor*

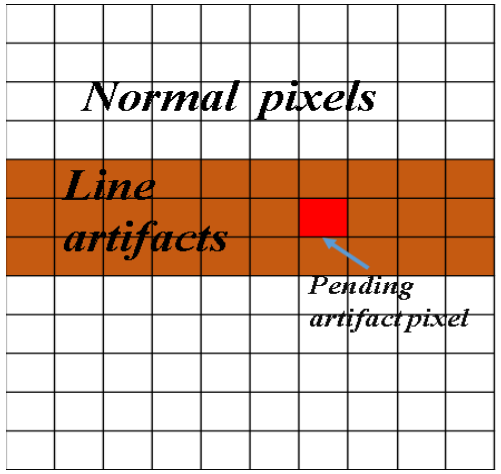
2.3. Proposed RBFNN

- **Selection of neurons in input layer**

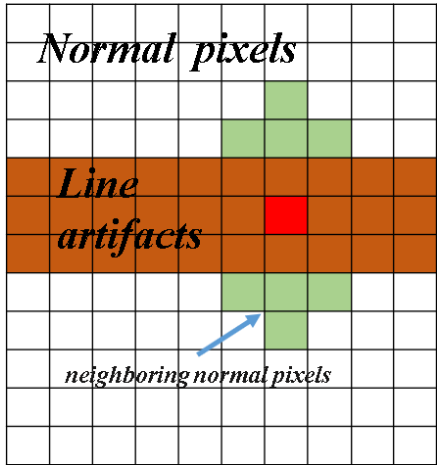
(What we need to do)



Two aspects are considered:



1. The effect of pending **pixel itself**



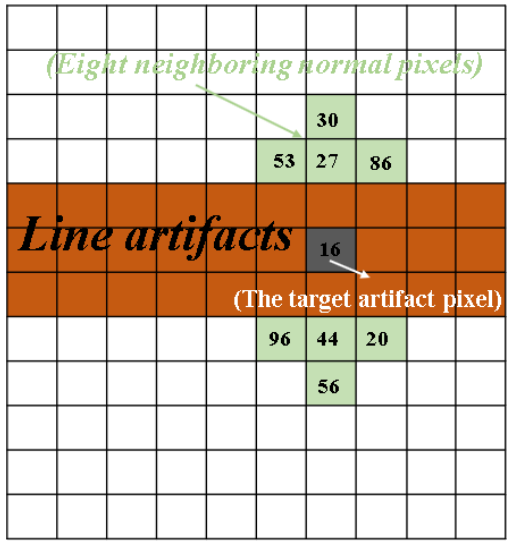
2. The effect of **the surrounding normal pixels on artifact pixel**

2.3. Proposed RBFNN

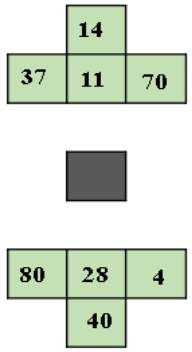
- **Selection of neurons in input layer**

Pixel value	Gradient direction	The sum of difference set	The mean of difference set	The variance of difference set	The sum of weight set	The mean of weight set	The variance of weight set

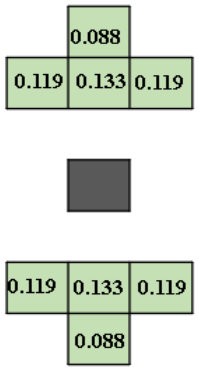
input variables (eight neurons)



(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))

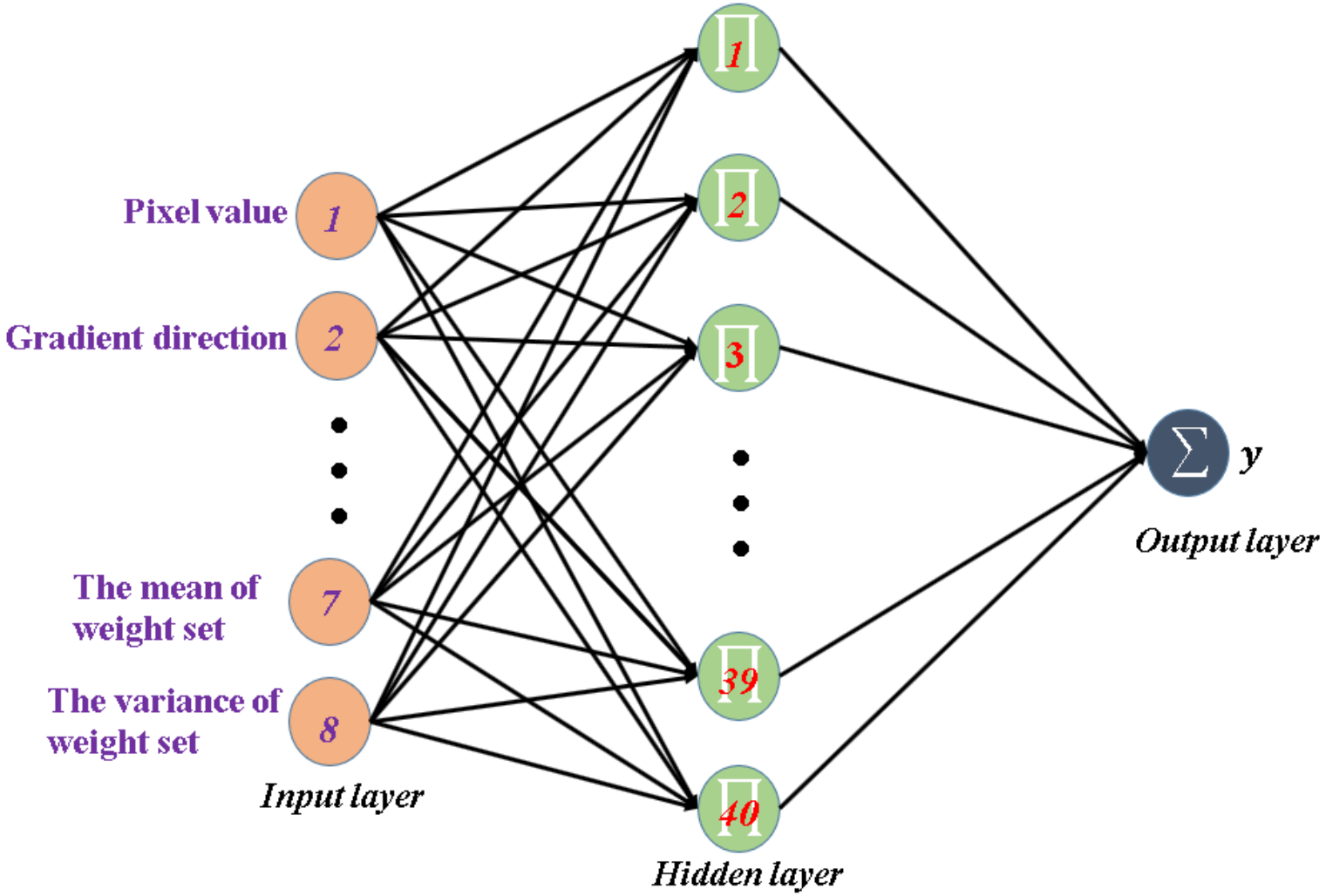
2.3. Proposed RBFNN

- **Selectic**
  - ❑ It d
  - ❑ The
  - ❑ Hov

considered.

Here

lden 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 represent i^{th} neuron in input layer
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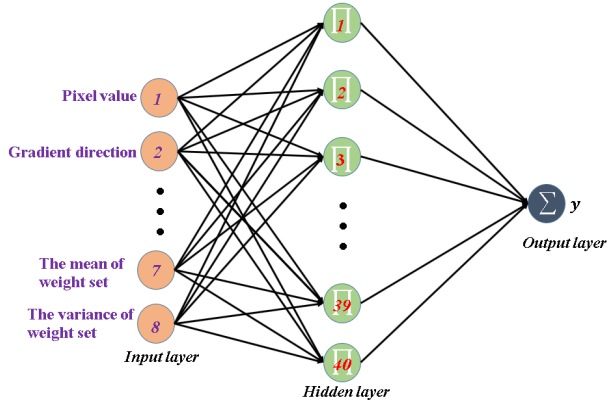
$$y = \sum_{p=1}^{l} \omega_p M(x, c_p, \sigma_p)$$

✓ ω : weight factor

According to the structure of our NN:



$$X = (c^1, \cdots, c^{320}, \sigma^{321}, \cdots, \sigma^{640}, \omega^{641}, \cdots, \omega^{680})$$

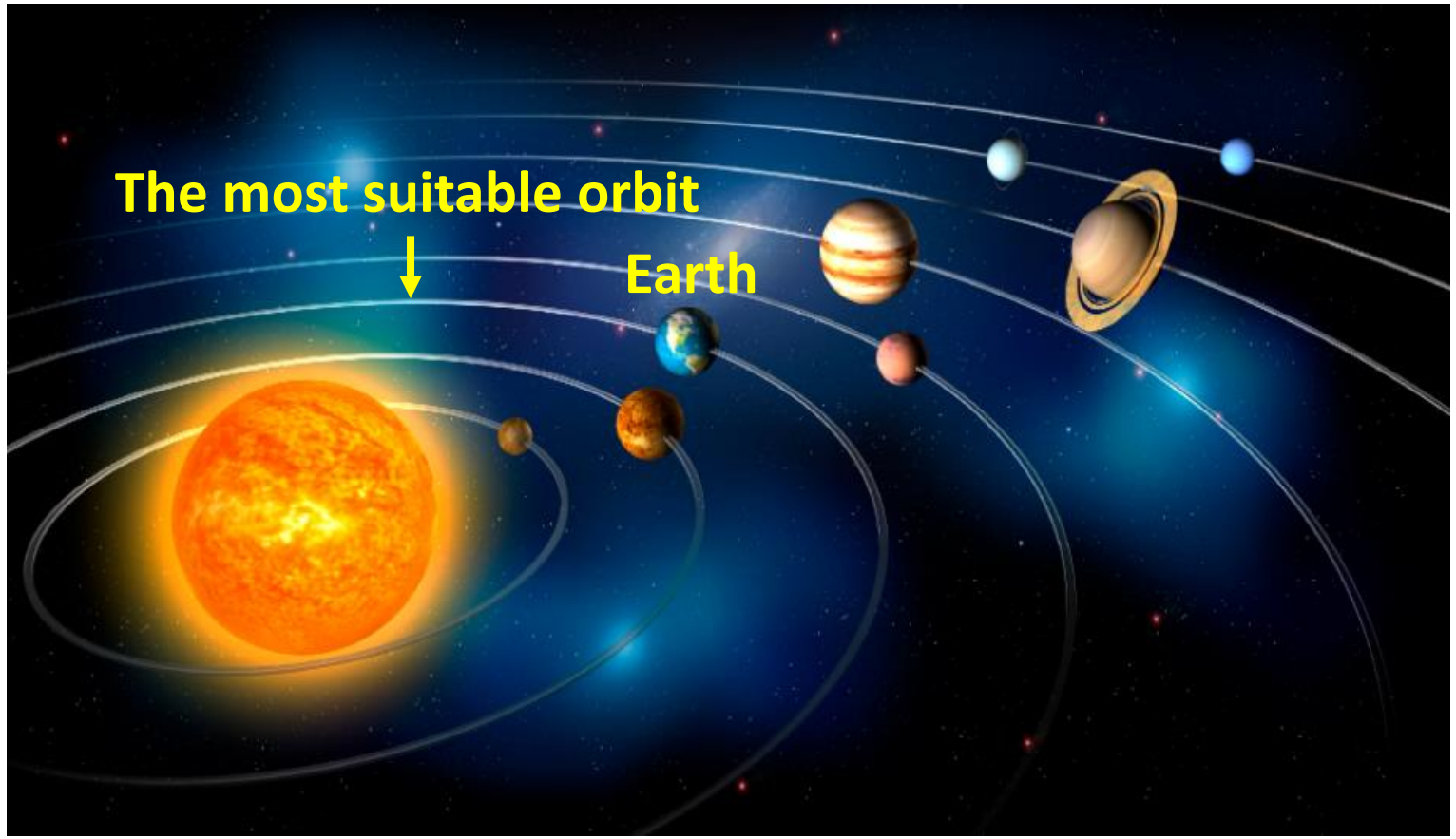
Training algorithm

Updated $X = (c^1, \cdots, c^{320}, \sigma^{321}, \cdots, \sigma^{640}, \omega^{641}, \cdots, \omega^{680})$

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)**



(Solar System)

Base on this:

- **We regard**

$$X = (c^{1}, \cdots, c^{320}, \sigma^{321}, \cdots, \sigma^{640}, \omega^{641}, \cdots, \omega^{680})$$

as planet (object)

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

- *Rashedi et al., Information sciences, 2009*

2.4. Training of proposed RBFNN

- **Gravitational searching algorithm (GSA)**

Generate initial arrays

$X = (X_i^1, \dots, X_i^d, \dots, X_i^{680})$

$V = (V_i^1, \dots, V_i^d, \dots, V_i^{680})$

i = 1, 2, ..., 50

Obtained by gradient descent method (GDM)

Mass calculation

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)}$$

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

Fitness function: $fit_i = \frac{\sum_{k=1}^{N}\left(A_i^k - B^k\right)^2}{N}$

B: the ideal output

A: the actual output

Gravitation calculation

$$F_{ij}^d(t) = G(t)\frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t) + \varepsilon}\left(x_j^d(t) - x_i^d(t)\right)$$

$$G(t) = G_0 e^{\frac{-\alpha \times t}{T}}$$

$$F_i^d(t) = \sum_{j \in kbest, j \neq i} rand_j F_{ij}^d(t)$$

Acceleration calculation

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

Position and velocity update

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1)$$

Stop if t =50

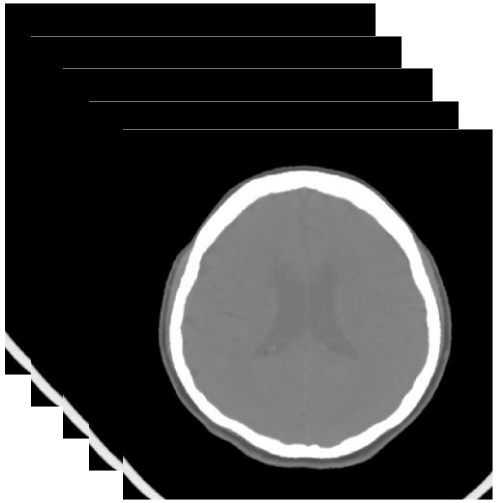
Stop or Back?

By fitness function, find the optimal array

- *Rashedi et al., Information sciences, 2009*

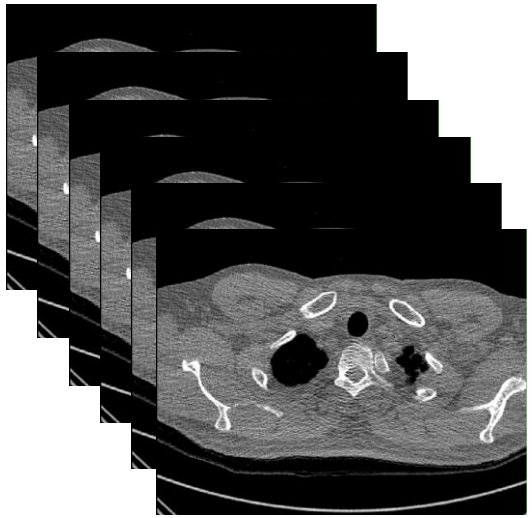
2.5. Experimental data

- **Training data and test data**



(brain data)

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

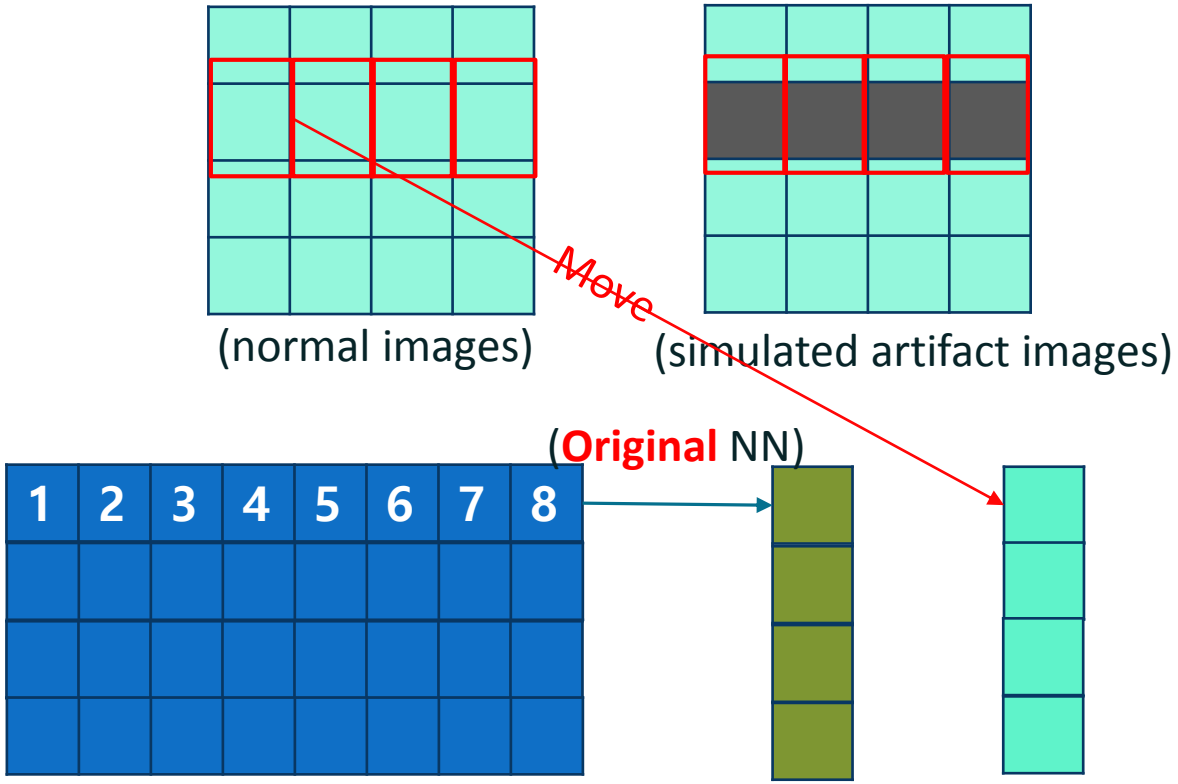


(Chest data)

- training data: **300** images
- Test data: **80** images (real artifacts)

Size: 512×512

- **Further explanation for training**



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))

$$SSIM(x,y) = [\, l(x,y) \,]\cdot[\, c(x,y) \,]\cdot[\, s(x,y) \,]$$

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

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

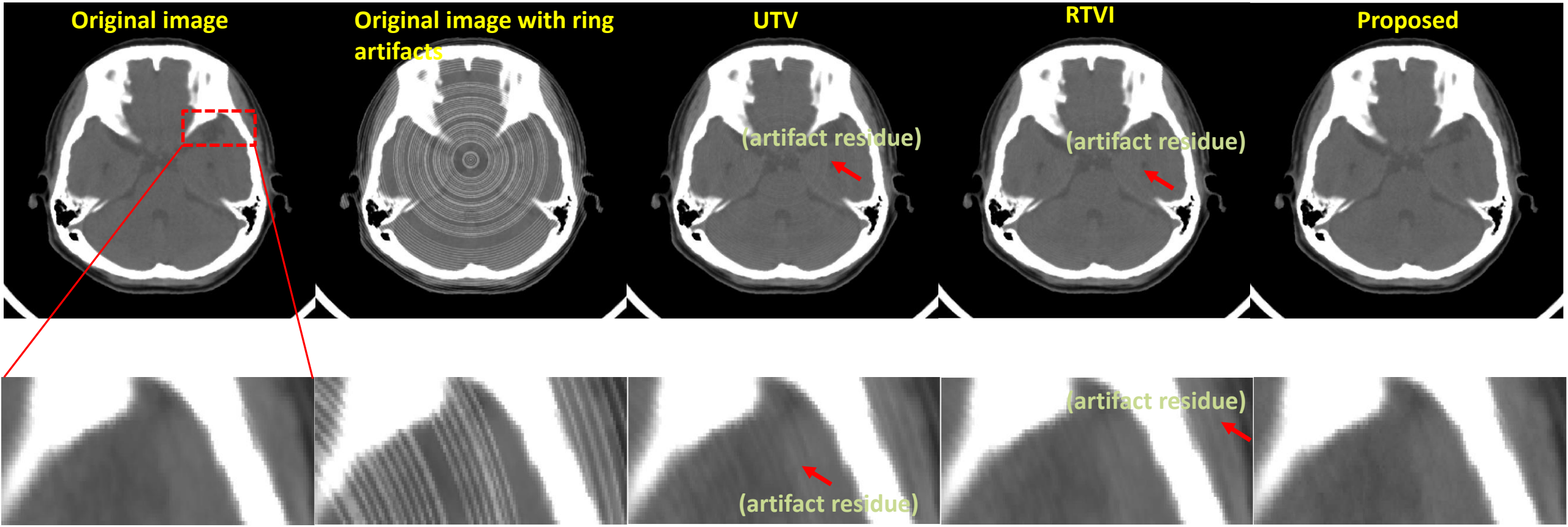
- ✓ μ_x, μ_y: the mean values of images *X*, *Y*
- ✓ σ_x, σ_y : the standard deviations of images *X*, *Y*
- ✓ σ_{xy} : the covariance of images *X*, *Y*

❖ **Unidirectional total variation (UTV) method and Relative total variation-iterative (RTVI) method were implemented for comparison.**

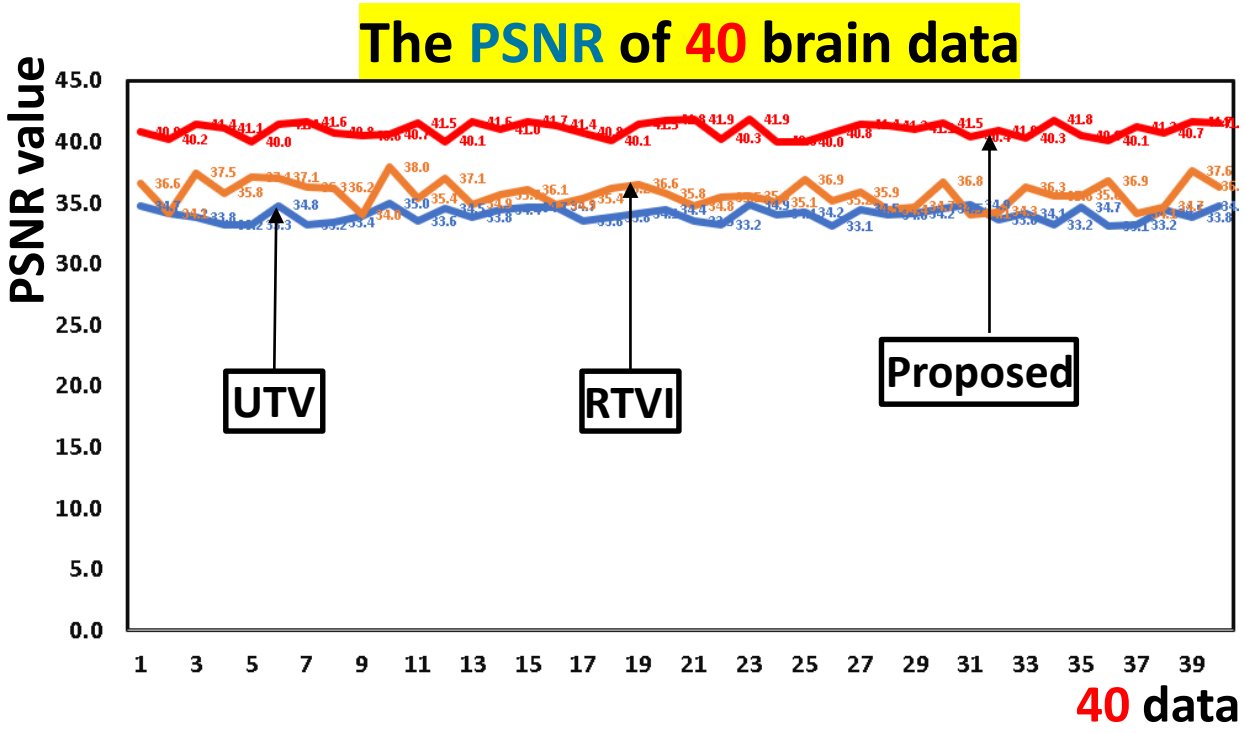
- Huo et al., *Electronics Letter, 2016*
- *Liang et al., Physics in Medicine & Biology, 2017*

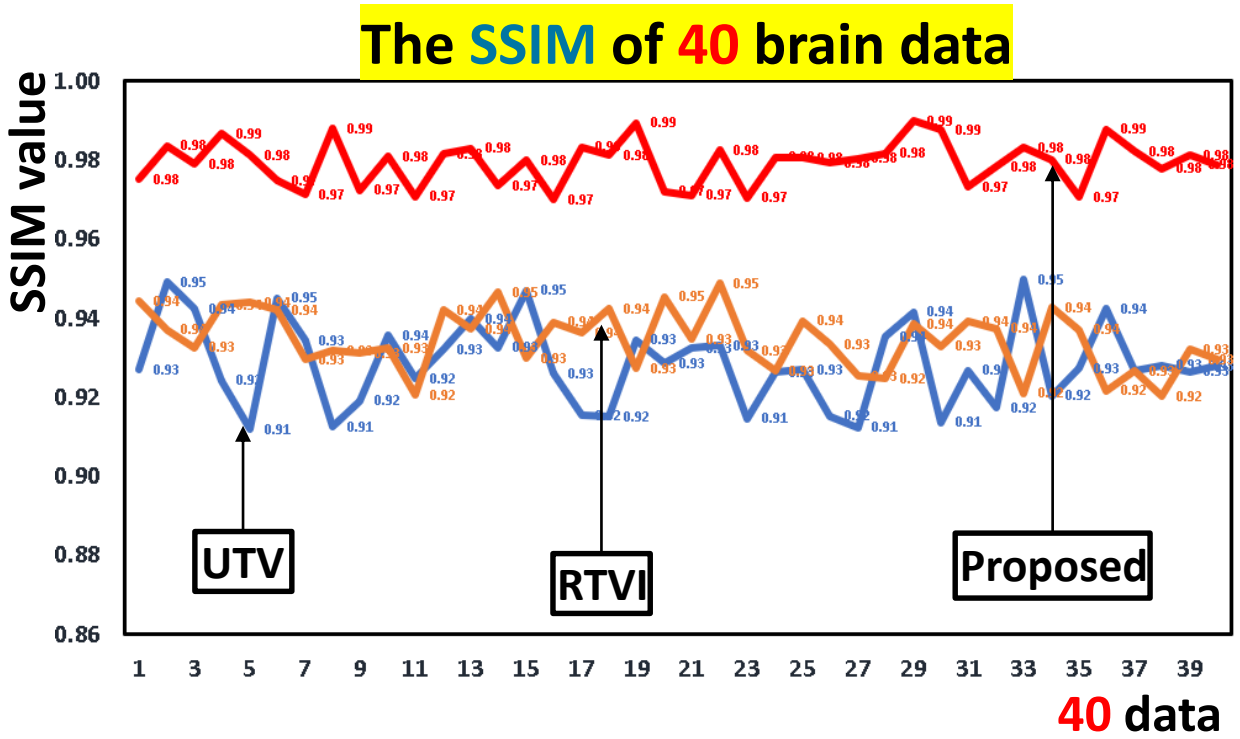
Results & Discussions

3.1. Brain data



3.2. The performances of PSNR and SSIM values

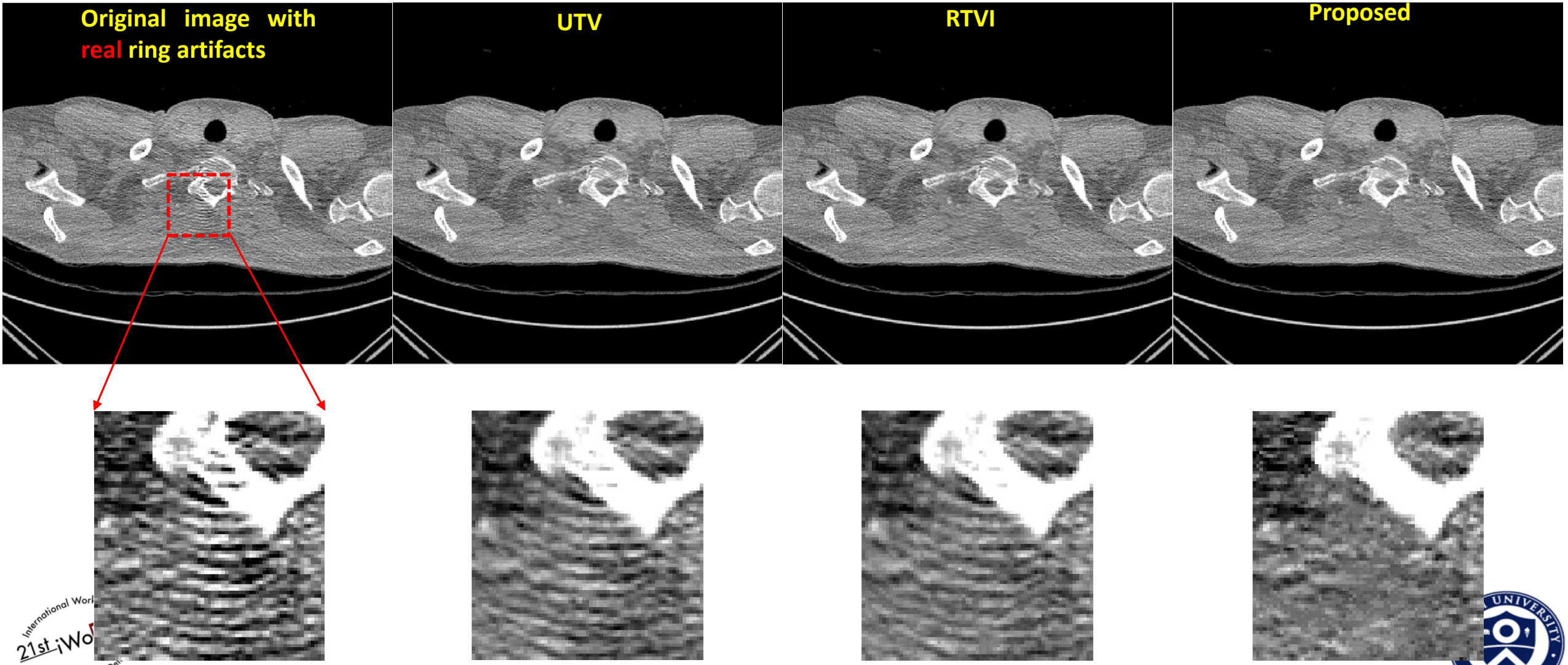




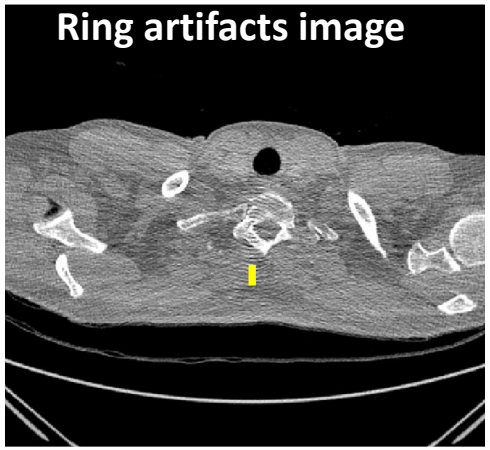
UTV RTVI Proposed

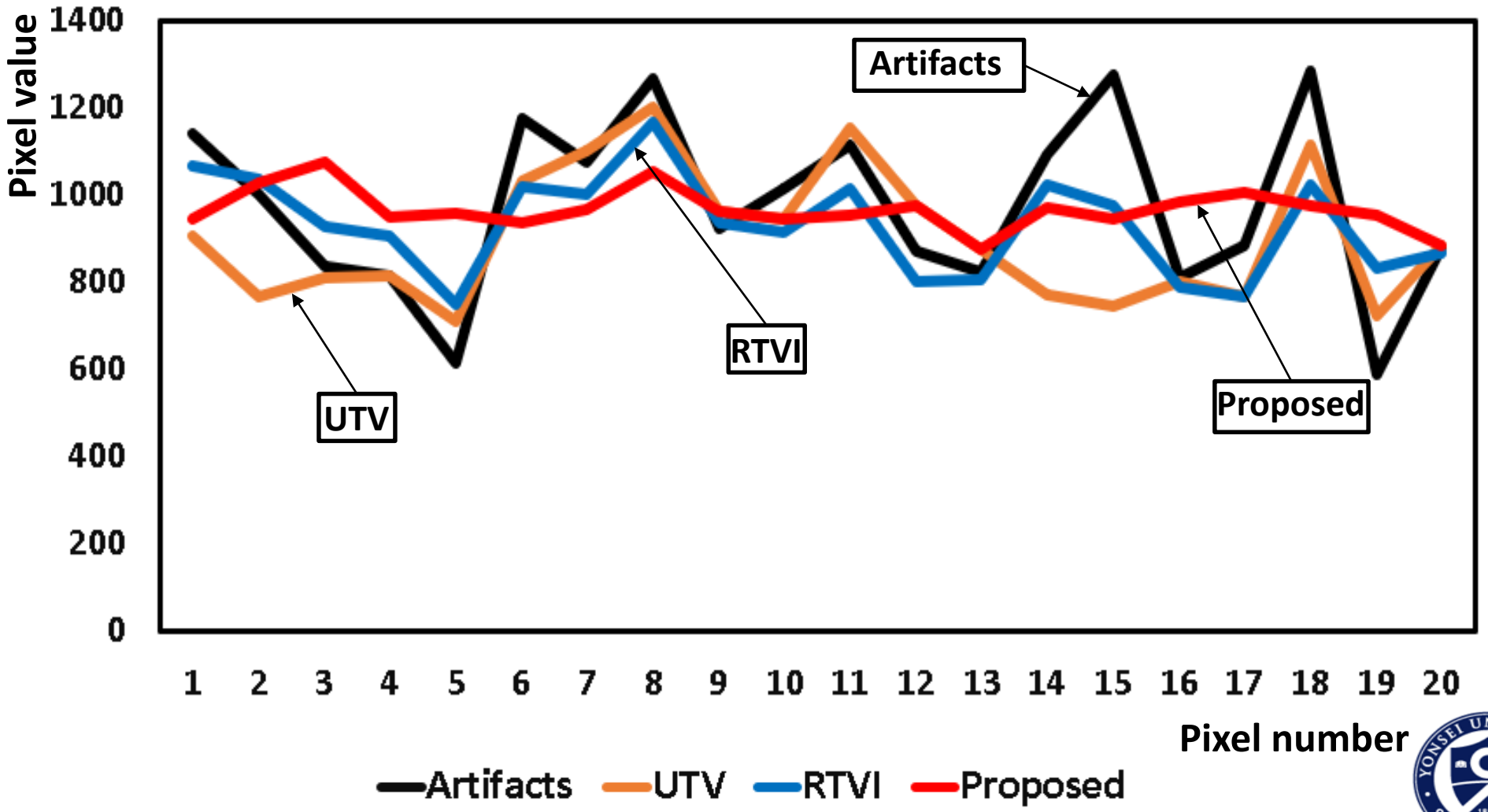
❖ For all 40 CT brain data, The PSNR and SSIM performances of proposed method **outperform** those of other two methods.

3.3. Chest data



3.3. The performances of pixel profiles

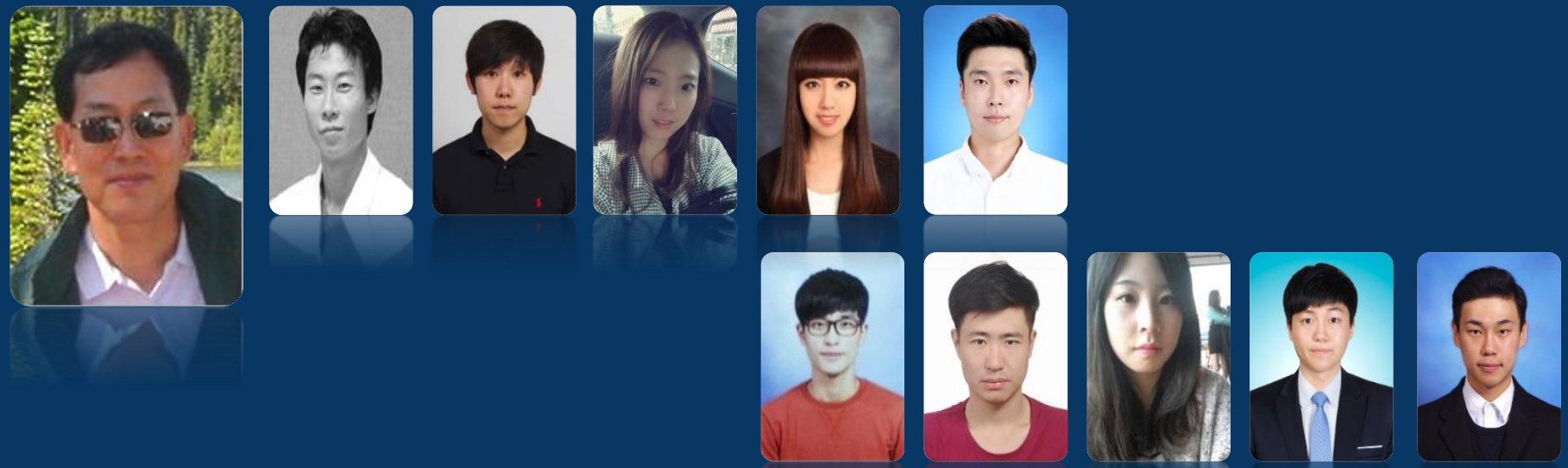




Conclusion

- 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



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