【研讨论文1】

K. Zhang, W. Zuo， *et al*, Beyond a Gaussian Denoiser: Residual Learningof Deep CNN for Image Denoising,

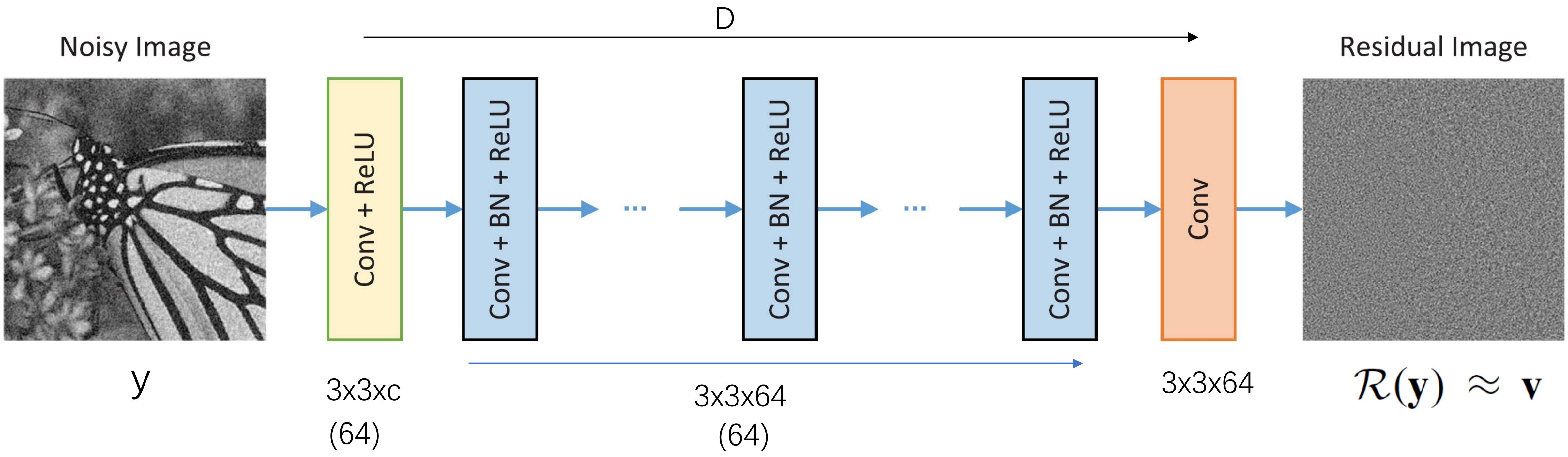
IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 26, NO. 7, JULY 2017:3142-3155

采样图像: y
目标图像: x
加性白噪声图像: v
(additive white Gaussian noise [AWGN])

$$y = x + v$$

denoising convolutional neural network (DnCNN)

- 训练网络输出噪声图像



$$\mathbf{x} = \mathbf{y} - \mathcal{R}(\mathbf{y})$$

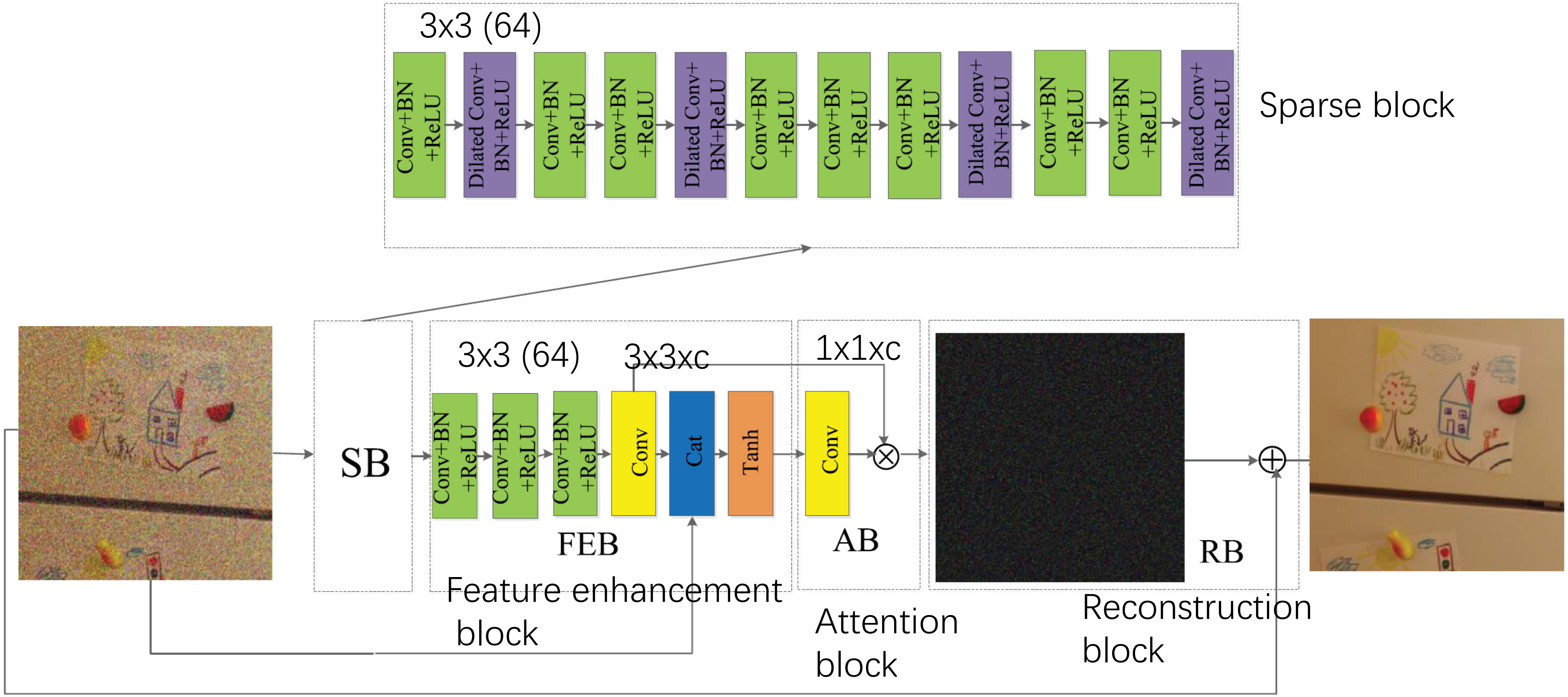
损失函数：

$$\ell(\Theta) = \frac{1}{2N} \sum_{i=1}^{N} \| \mathcal{R}(\mathbf{y}_i; \Theta) - (\mathbf{y}_i - \mathbf{x}_i) \|_F^2$$

【研讨论文2】

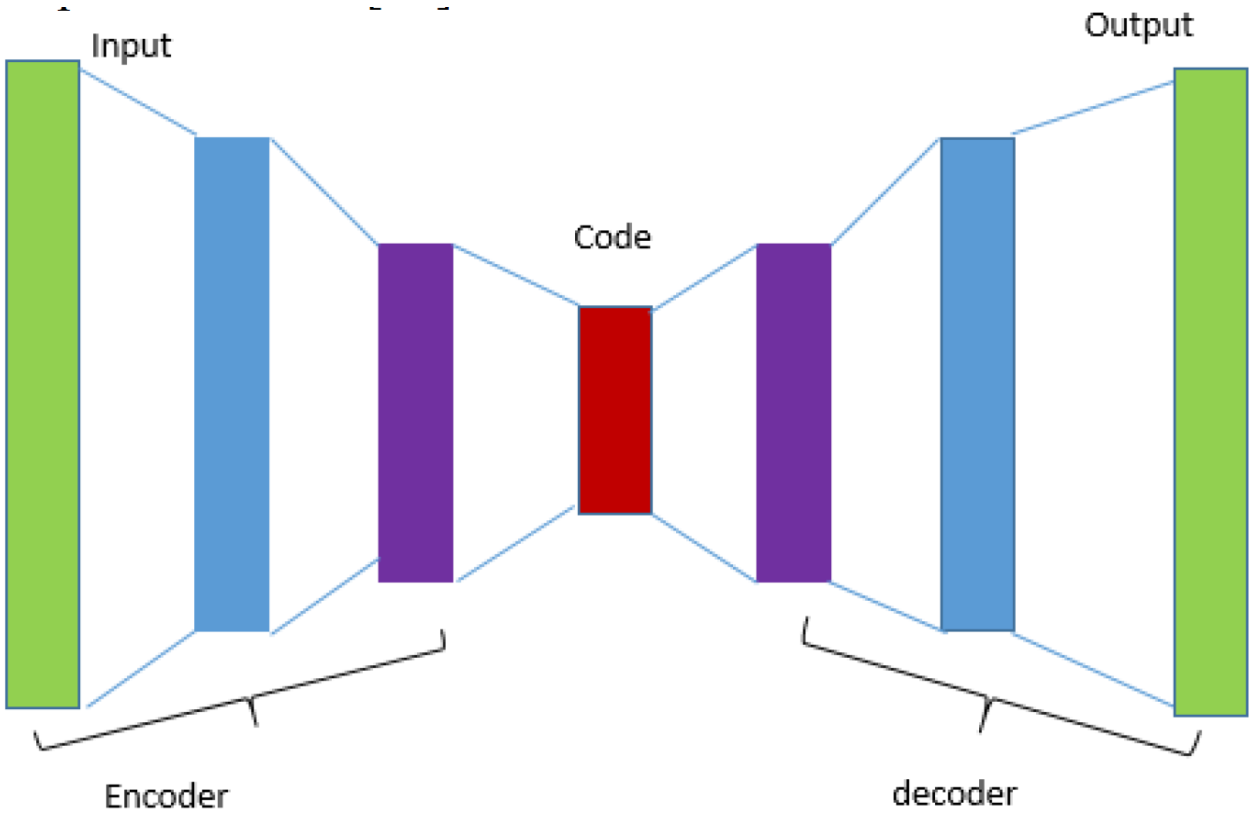
C.Tian, Y.Xu, *et al*, Attention-guided CNN for image denoising,
Neural Networks, 124 (2020): 117-129

ADNet

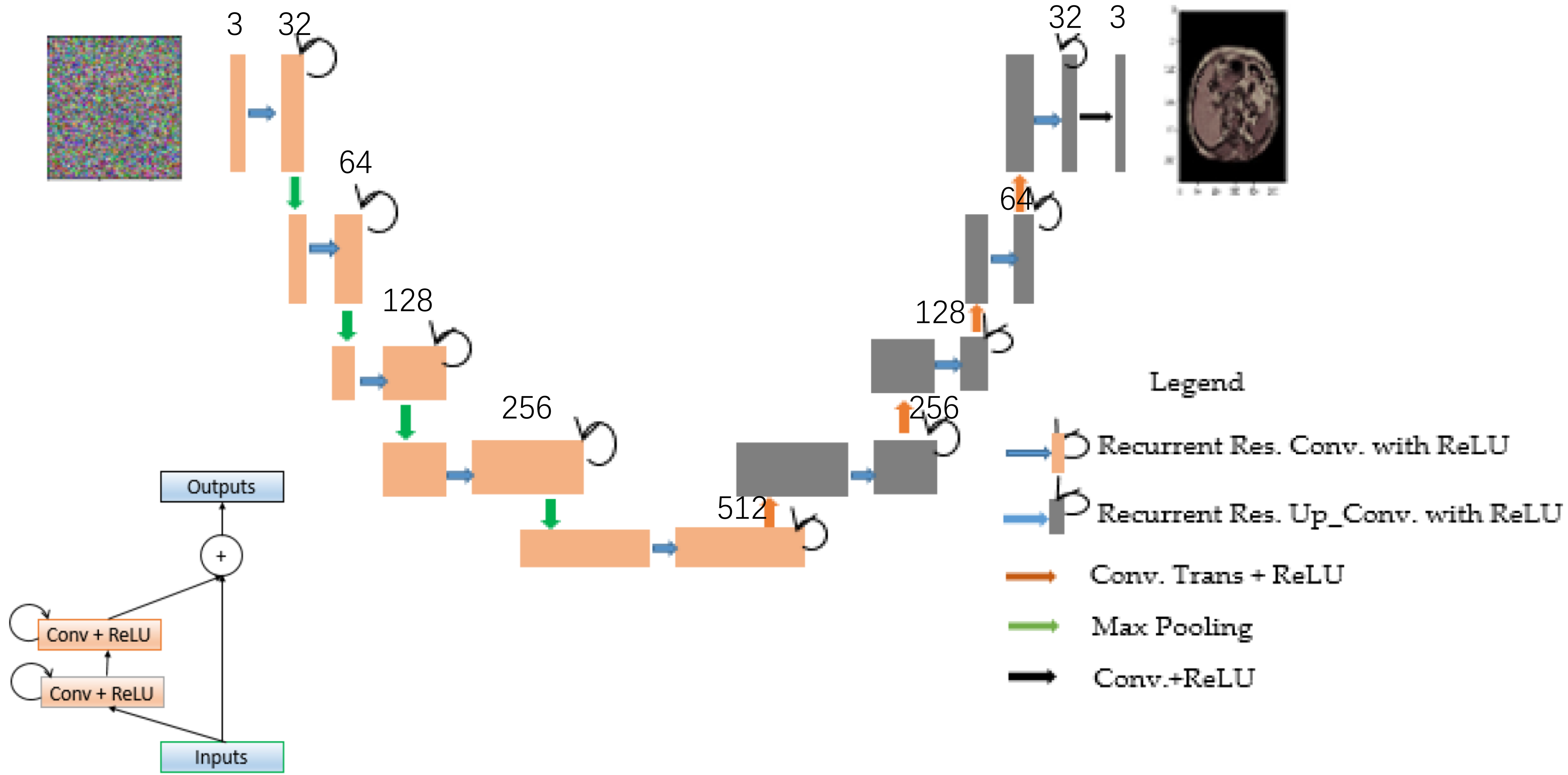


【研讨论文3】

S.Nasrin, Z.Alom, *el al*, Medical image denoising with recurrent residual U-net (R2U-Net) base auto-encoder, Proc. IEEE National Aerospace and Electronics Conf. ‘2019 : pp 345-350



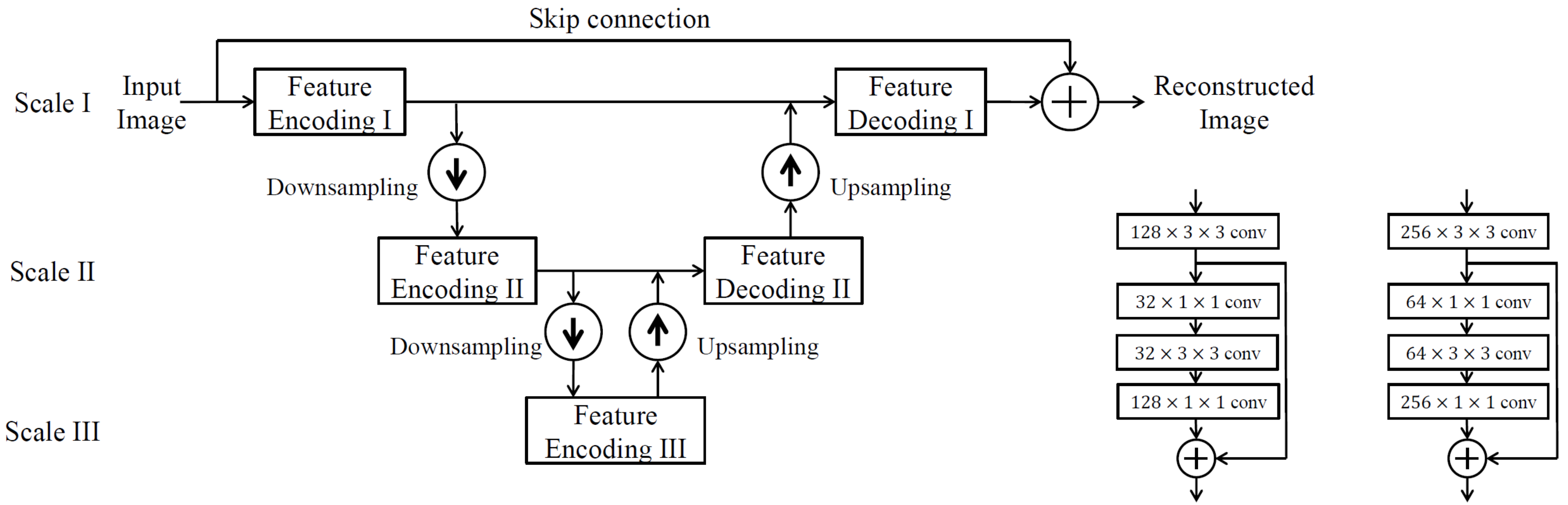
autoencoder



3
32
64
128
256
512
256
128
64
32
3
Outputs
+
Conv + ReLU
Conv + ReLU
Inputs
Legend
Recurrent Res. Conv. with ReLU
Recurrent Res. Up_Conv. with ReLU
Conv. Trans + ReLU
Max Pooling
Conv.+ReLU

【研讨论文4】

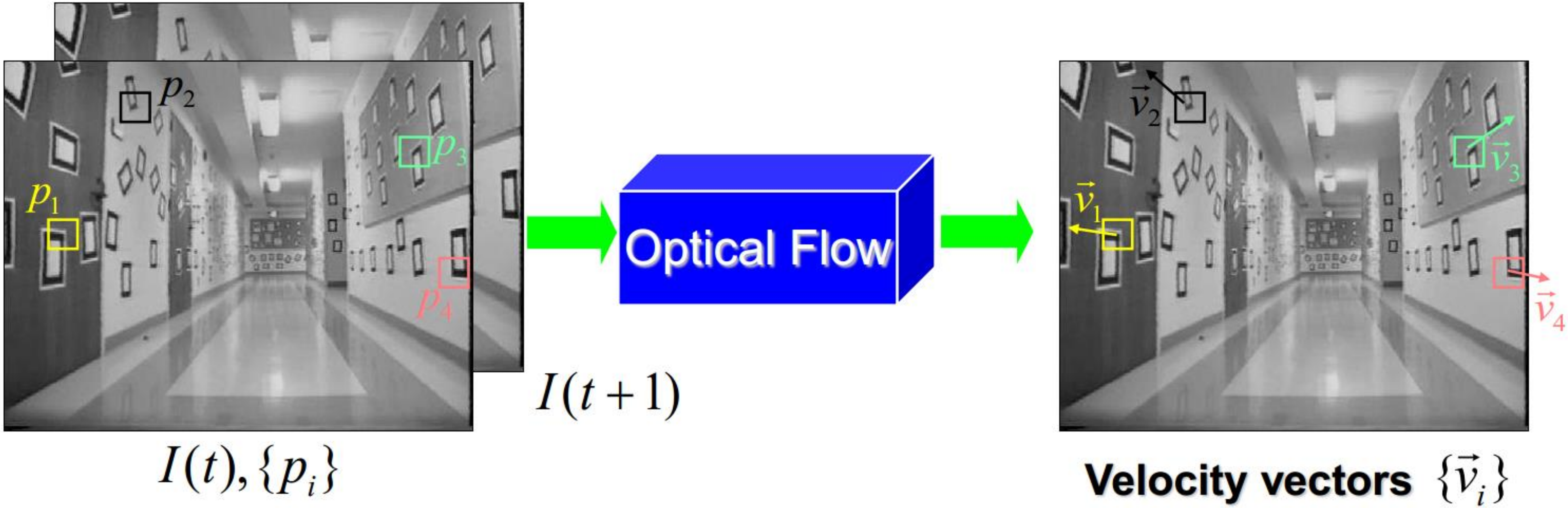
D.Liu, B.Wen, *et al*, When Image Denoising Meets High-Level Vision Tasks: A Deep Learning Approach, Proc. the 27th International Joint Conference on Artificial Intelligence, 2018



encoding

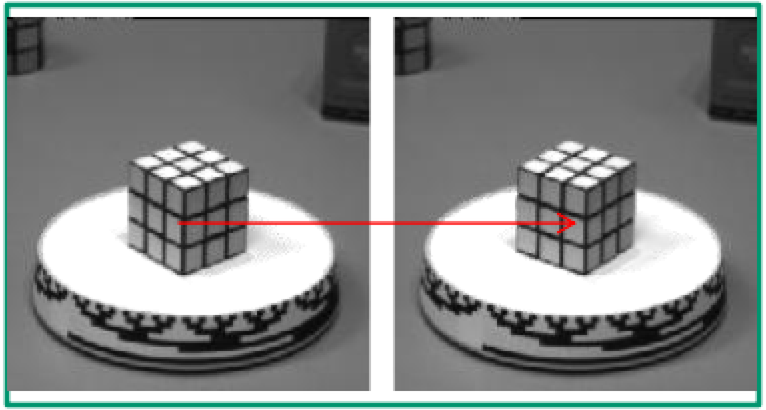
decoding

Optical Flow



$$I(p_i, t) = I(p_i + \vec{v}_i, t+1)$$

Start with an Equation: Brightness Constancy



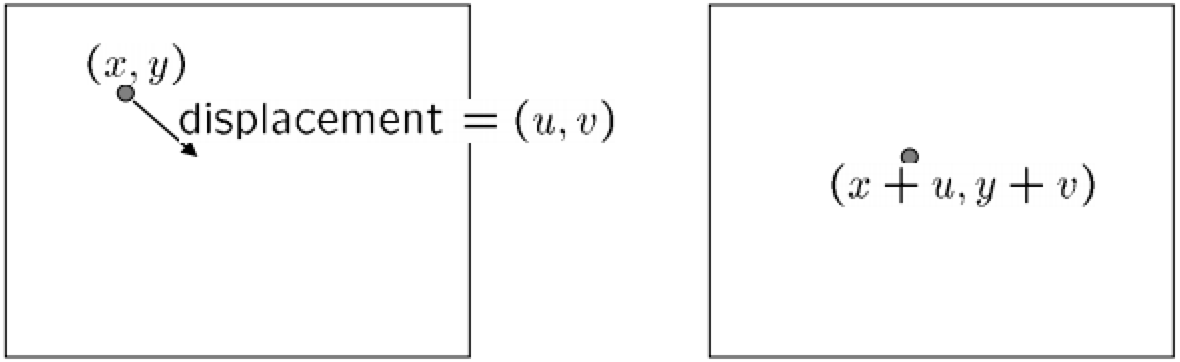
Time: t

Time: t + dt

Point moves (small), but its brightness remains constant:

$$I_{t1}(x, y) = I_{t2}(x + u, y + v)$$

$$I = constant \rightarrow \frac{dI}{dt} = 0$$



I_1 I_2

Mathematical formulation

$I\ (x(t),y(t),t)$ = brightness at (x,y) at time t

Brightness constancy assumption (shift of location but brightness stays same):

$$I(x + \frac{dx}{dt}\delta t, y + \frac{dy}{dt}\delta t, t + \delta t) = I(x, y, t)$$

Optical flow constraint equation (chain rule):

$$\frac{dI}{dt} = \frac{\partial I}{\partial x}\frac{dx}{dt} + \frac{\partial I}{\partial y}\frac{dy}{dt} + \frac{\partial I}{\partial t} = 0$$

The aperture problem

$$u = \frac{dx}{dt}, \qquad v = \frac{dy}{dt}$$

$$I_x = \frac{\partial I}{\partial x}, \qquad I_y = \frac{\partial I}{\partial y}, \qquad I_t = \frac{\partial I}{\partial t}$$

$$\boxed{I_x u + I_y v + I_t = 0}$$

Horn and Schunck optical flow equation

1 equation in 2 unknowns

Optical Flow: 1D Case

Brightness Constancy Assumption:

$$f(t) \equiv I\underbrace{(x(t),t)}_{} = I(x(t+dt), t+dt)$$

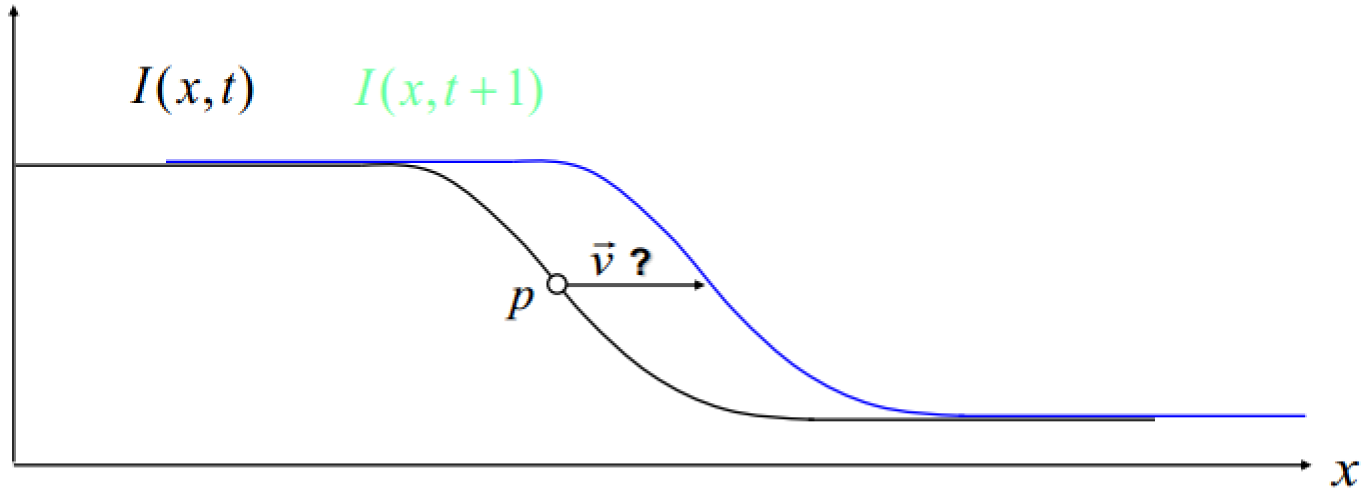
$$\frac{\partial f(x)}{\partial t} = 0$$ Because no change in brightness with time

$$\left.\frac{\partial I}{\partial x}\right|_t \left(\frac{\partial x}{\partial t}\right) + \left.\frac{\partial I}{\partial t}\right|_{x(t)} = 0$$

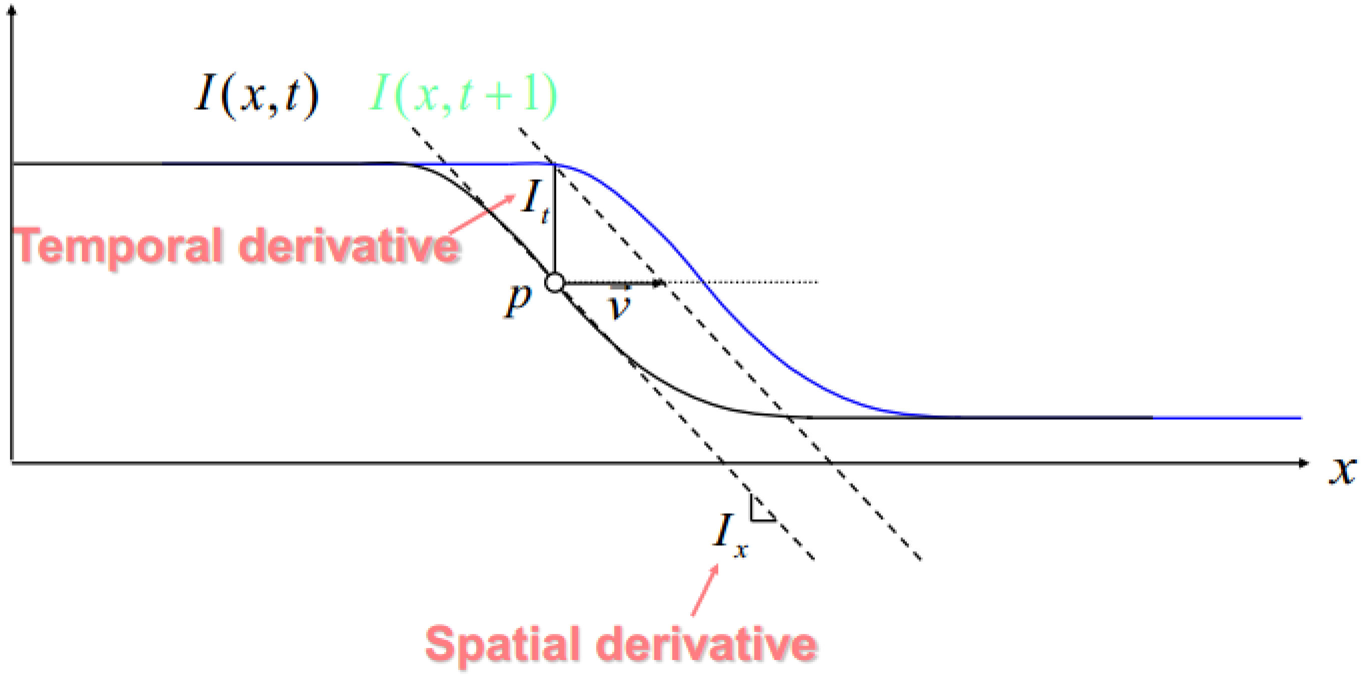
I_x $\quad$ v $\quad$ I_t

$$\Longrightarrow v = -\frac{I_t}{I_x}$$

Tracking in the 1D case:



Tracking in the 1D case:



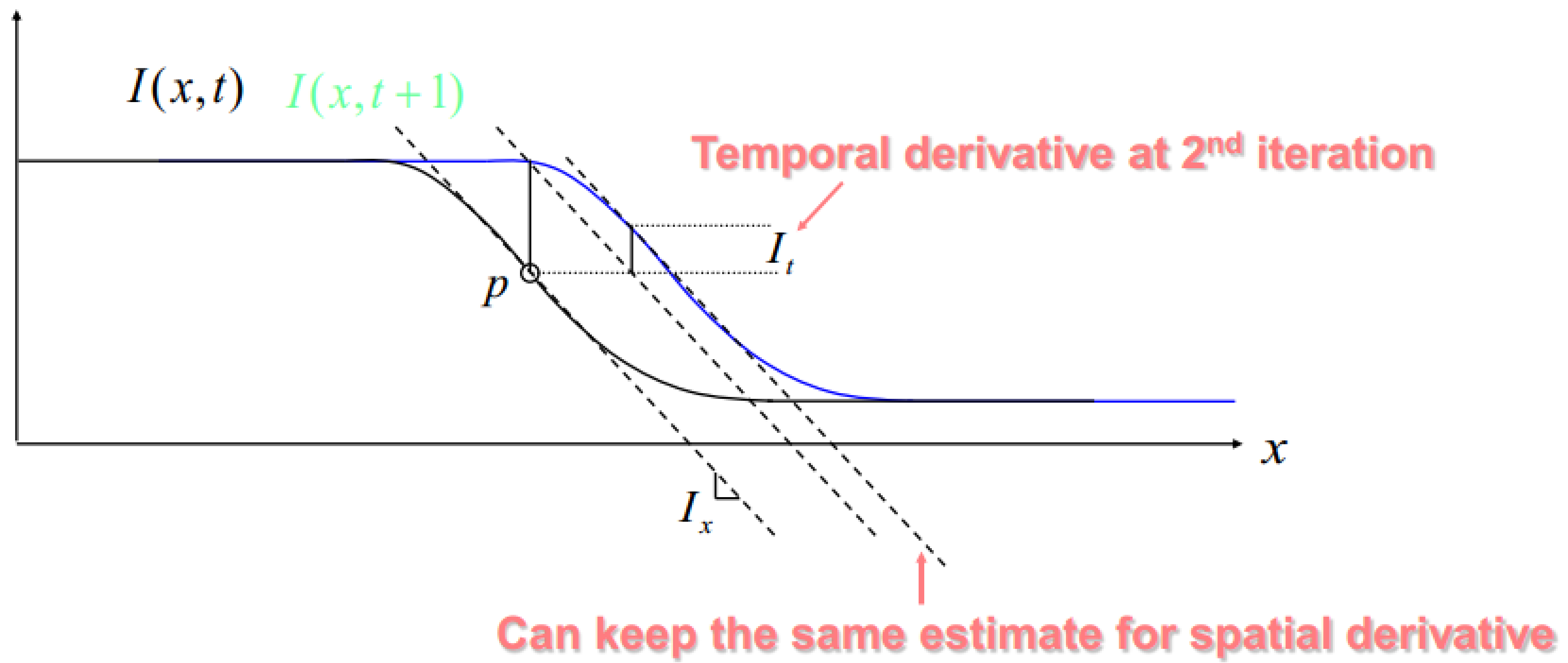
$$I_x = \left.\frac{\partial I}{\partial x}\right|_t \qquad I_t = \left.\frac{\partial I}{\partial t}\right|_{x=p} \qquad \Rightarrow \qquad \vec{v} \approx -\frac{I_t}{I_x}$$

Assumptions:

- **Brightness constancy**
- **Small motion**

Tracking in the 1D case:

Iterating helps refining the velocity vector



$$\vec{v} \leftarrow \vec{v}_{previous} - \frac{I_t}{I_x}$$

Converges in about 5 iterations

From 1D to 2D tracking

1D: $$\left.\frac{\partial I}{\partial x}\right|_t \left(\frac{\partial x}{\partial t}\right) + \left.\frac{\partial I}{\partial t}\right|_{x(t)} = 0$$

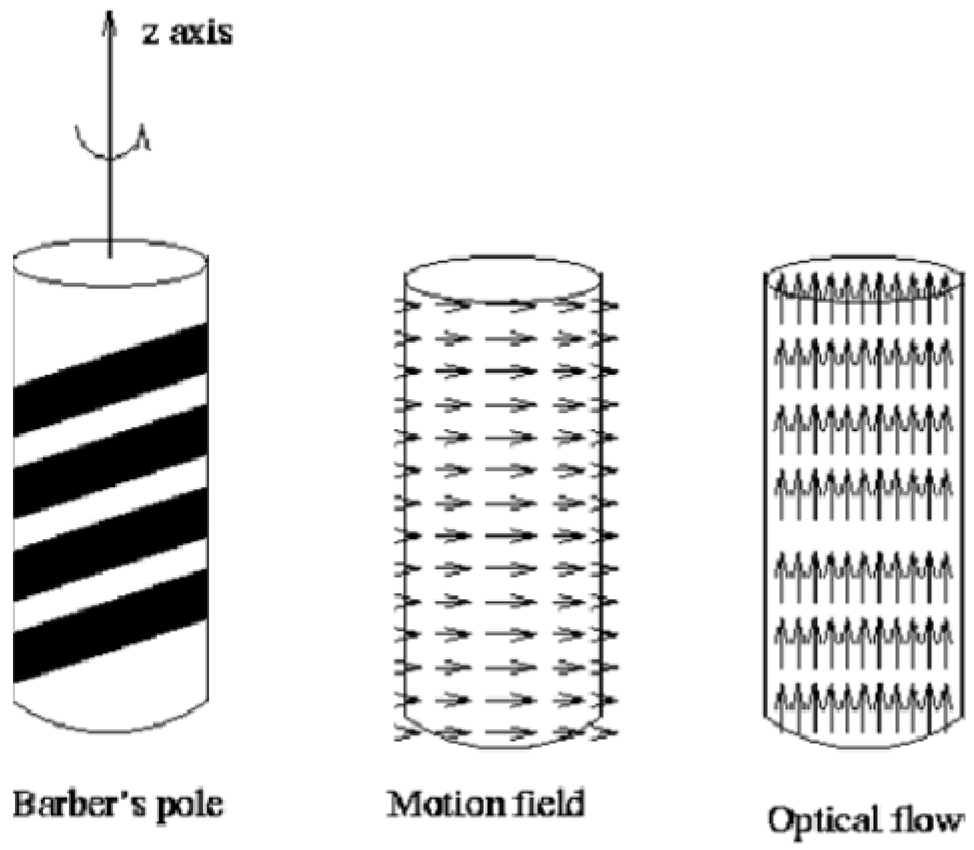
2D: $$\left.\frac{\partial I}{\partial x}\right|_t \left(\frac{\partial x}{\partial t}\right) + \left.\frac{\partial I}{\partial y}\right|_t \left(\frac{\partial y}{\partial t}\right) + \left.\frac{\partial I}{\partial t}\right|_{x(t)} = 0$$

$$\left.\frac{\partial I}{\partial x}\right|_t u + \left.\frac{\partial I}{\partial y}\right|_t v + \left.\frac{\partial I}{\partial t}\right|_{x(t)} = 0$$

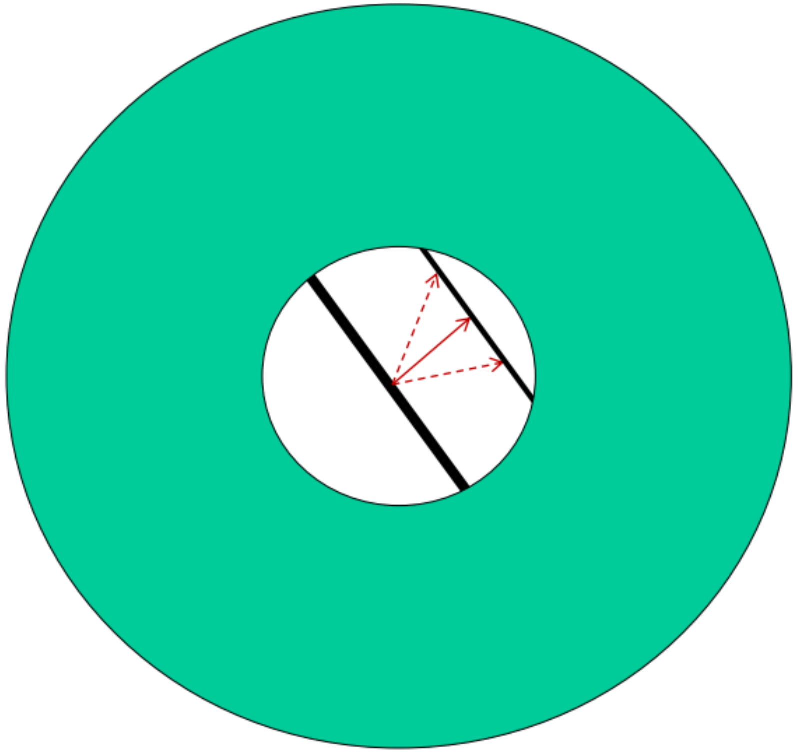
One equation, two velocity *(u,v)* unknowns…

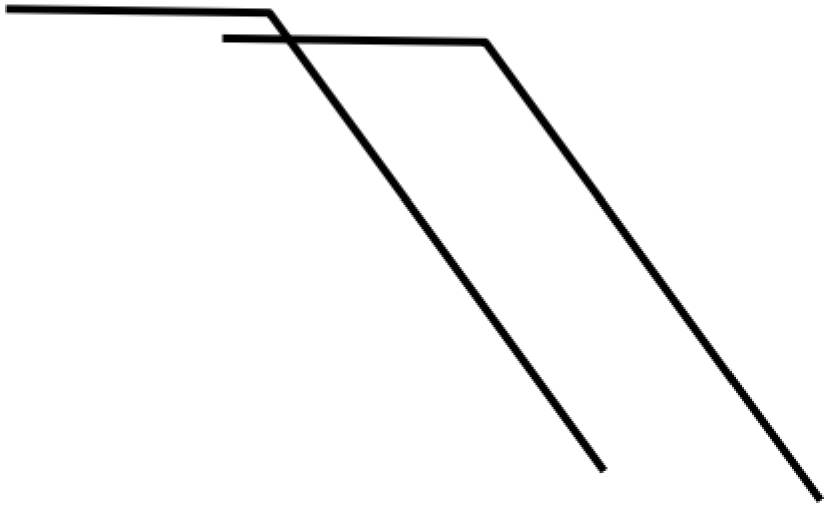
Optical Flow vs. Motion: Aperture Problem

Barber pole illusion



Aperture Problem





Normal Flow

Notation

$$I_x u + I_y v + I_t = 0$$

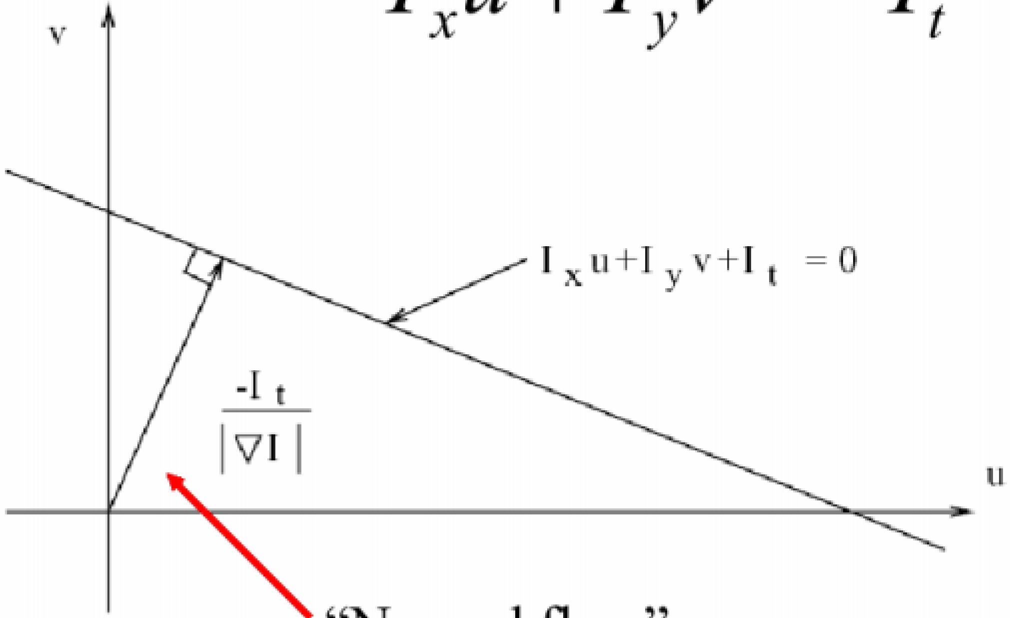
$$\downarrow$$

$$\nabla I^T \mathbf{u} = -I_t$$

$$\mathbf{u} = \begin{bmatrix} u \\ v \end{bmatrix} \quad \nabla I = \begin{bmatrix} I_x \\ I_y \end{bmatrix}$$

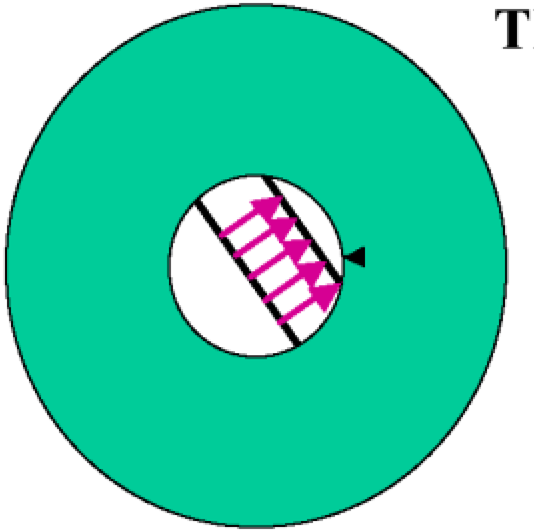
At a single image pixel, we get a line:

$$I_x u + I_y v = -I_t$$



"Normal flow"

Aperture Problem and Normal Flow

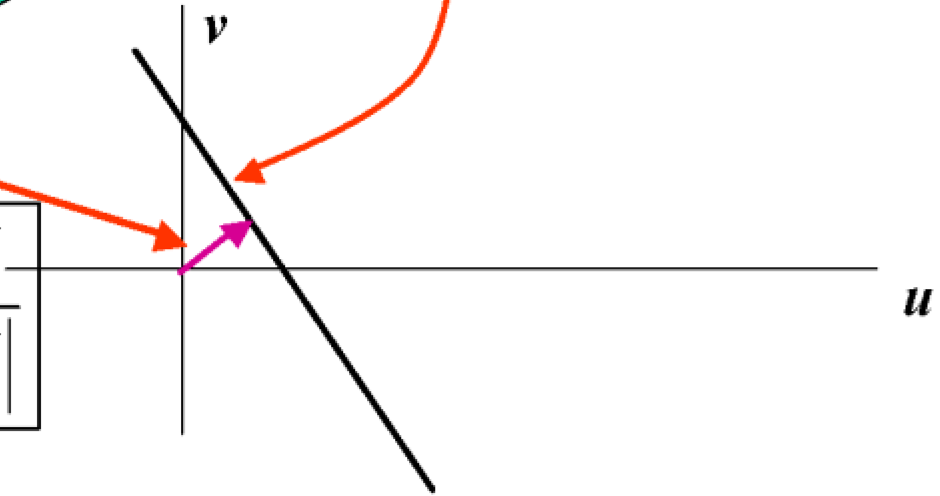


The gradient constraint:

$$I_x u + I_y v + I_t = 0$$

$$\nabla I \bullet \vec{U} = 0$$

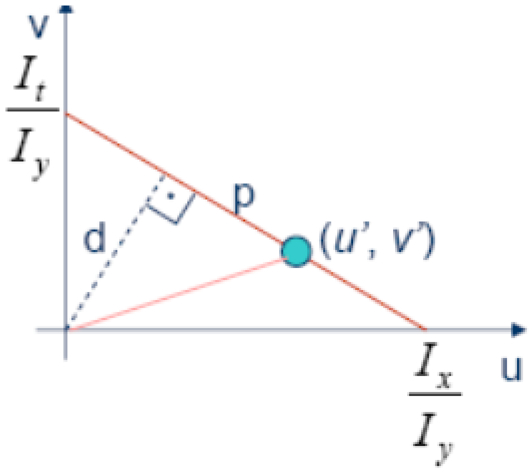
Defines a line in the *(u,v)* space



Normal Flow:

$$u_\perp = -\frac{I_t}{|\nabla I|}\frac{\nabla I}{|\nabla I|}$$

Aperture Problem and Normal Flow



$$v = u\frac{I_x}{I_y} + \frac{I_t}{I_y}$$

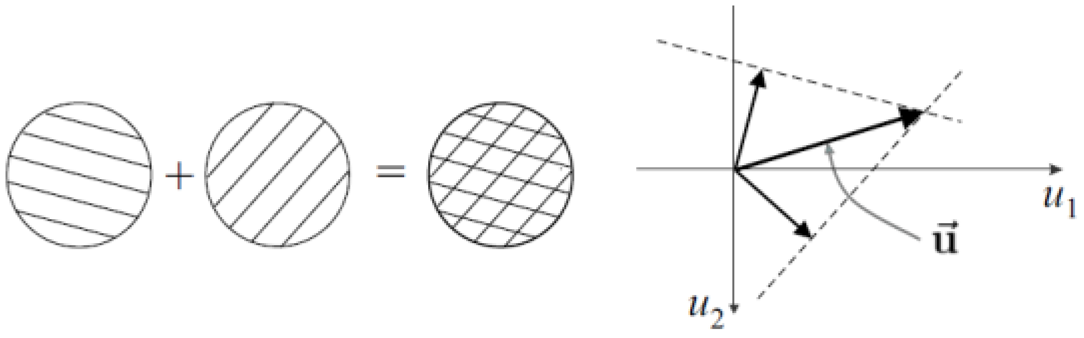
- Let (u', v') be true flow
- True flow has two components
  - Normal flow: *d*
  - Parallel flow: *p*
- Normal flow **can be** computed
- Parallel flow **cannot**

Possible Solution: Neighbors

Two adjacent pixels which are part of the same rigid object:

- we can calculate normal flows $\mathbf{v}_{n1}$ and $\mathbf{v}_{n2}$
- Two OF equations for 2 parameters of flow: $\bar{v} = \begin{pmatrix} v \\ u \end{pmatrix}$

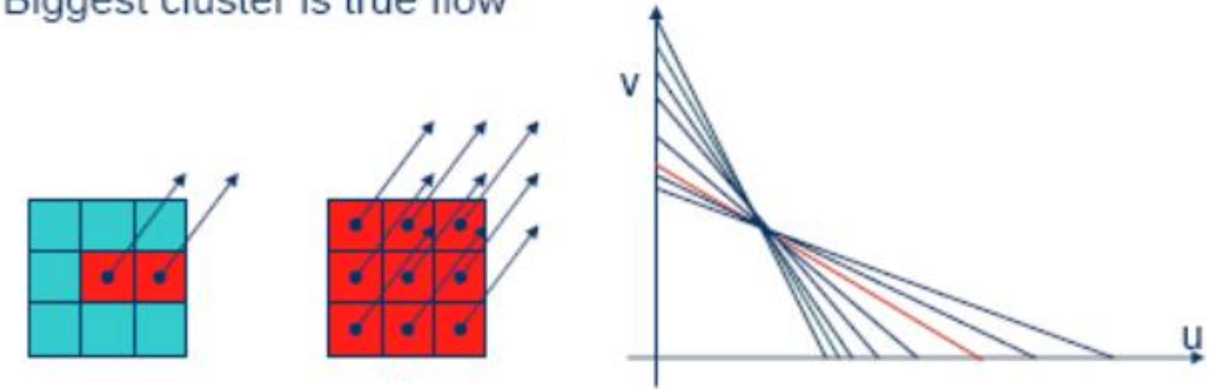
$$\nabla I_1 . \bar{v} - I_{t1} = 0$$
$$\nabla I_2 . \bar{v} - I_{t2} = 0$$



Considering Neighbor Pixels

Schunck

- If two neighboring pixels move with same velocity
  - Corresponding flow equations intersect at a point in (u,v) space
  - Find the intersection point of lines
  - If more than 1 intersection points find clusters
  - Biggest cluster is true flow



Horn & Schunck algorithm

Horn and Schunck's approach — Regularization

Two terms are defined as follows:

- Departure from smoothness

$$e_s = \int\int_{\Omega}((u_x^2 + u_y^2) + (v_x^2 + v_y^2))dxdy$$

- Error in optical flow constaint equation

$$e_c = \int\int_{\Omega}(E_x u + E_y v + E_t)^2 dxdy$$

The formulation is to minimize the linear combination of e_s and e_c,

$$e_s + \lambda e_c$$

where λ is a parameter.
Note: In this formulation, u and v are functions of x and y. Physically, u is the x-component of the motion, and v is the y-component of the motion.

Horn & Schunck algorithm

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Horn & Schunck

The Euler-Lagrange equations :

$$F_u - \frac{\partial}{\partial x} F_{u_x} - \frac{\partial}{\partial y} F_{u_y} = 0$$

$$F_v - \frac{\partial}{\partial x} F_{v_x} - \frac{\partial}{\partial y} F_{v_y} = 0$$

In our case ,

$$F = (u_x^2 + u_y^2) + (v_x^2 + v_y^2) + \lambda(I_x u + I_y v + I_t)^2,$$

so the Euler-Lagrange equations are

$$\Delta u = \lambda(I_x u + I_y v + I_t) I_x,$$

$$\Delta v = \lambda(I_x u + I_y v + I_t) I_y,$$

$$\Delta = \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2}$$ is the Laplacian operator

Horn & Schunck

Remarks :

1. Coupled PDEs solved using iterative methods and finite differences

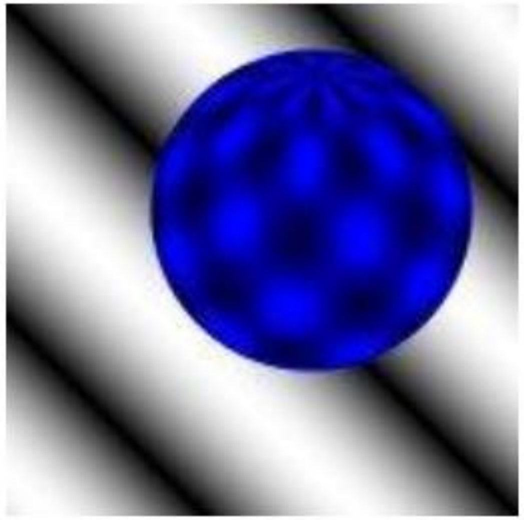
$$\frac{\partial u}{\partial t} = \Delta u - \lambda(I_x u + I_y v + I_t) I_x,$$

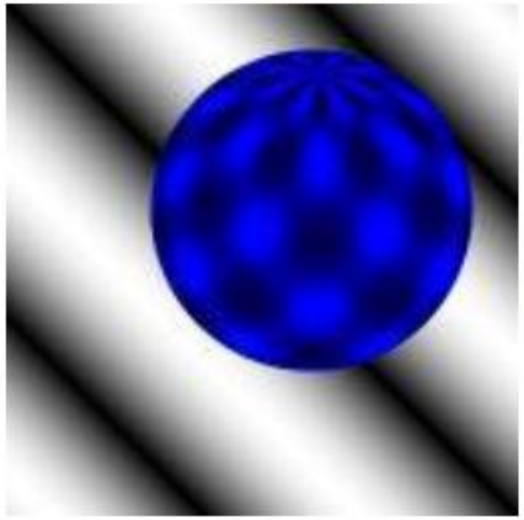
$$\frac{\partial v}{\partial t} = \Delta v - \lambda(I_x u + I_y v + I_t) I_y,$$

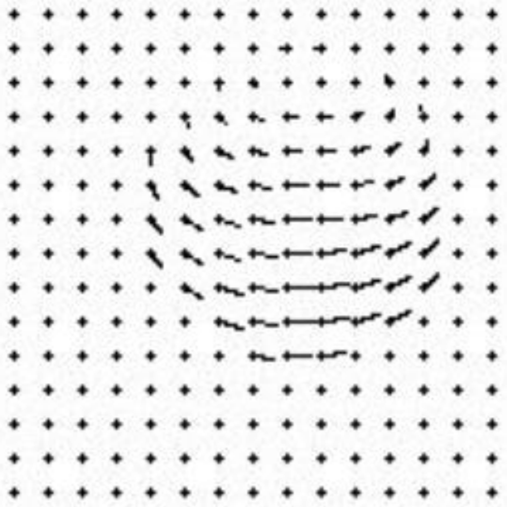
2. More than two frames allow a better estimation of I_t

3. Information spreads from corner-type patterns

Example







超分辨图像重建（superresolution)

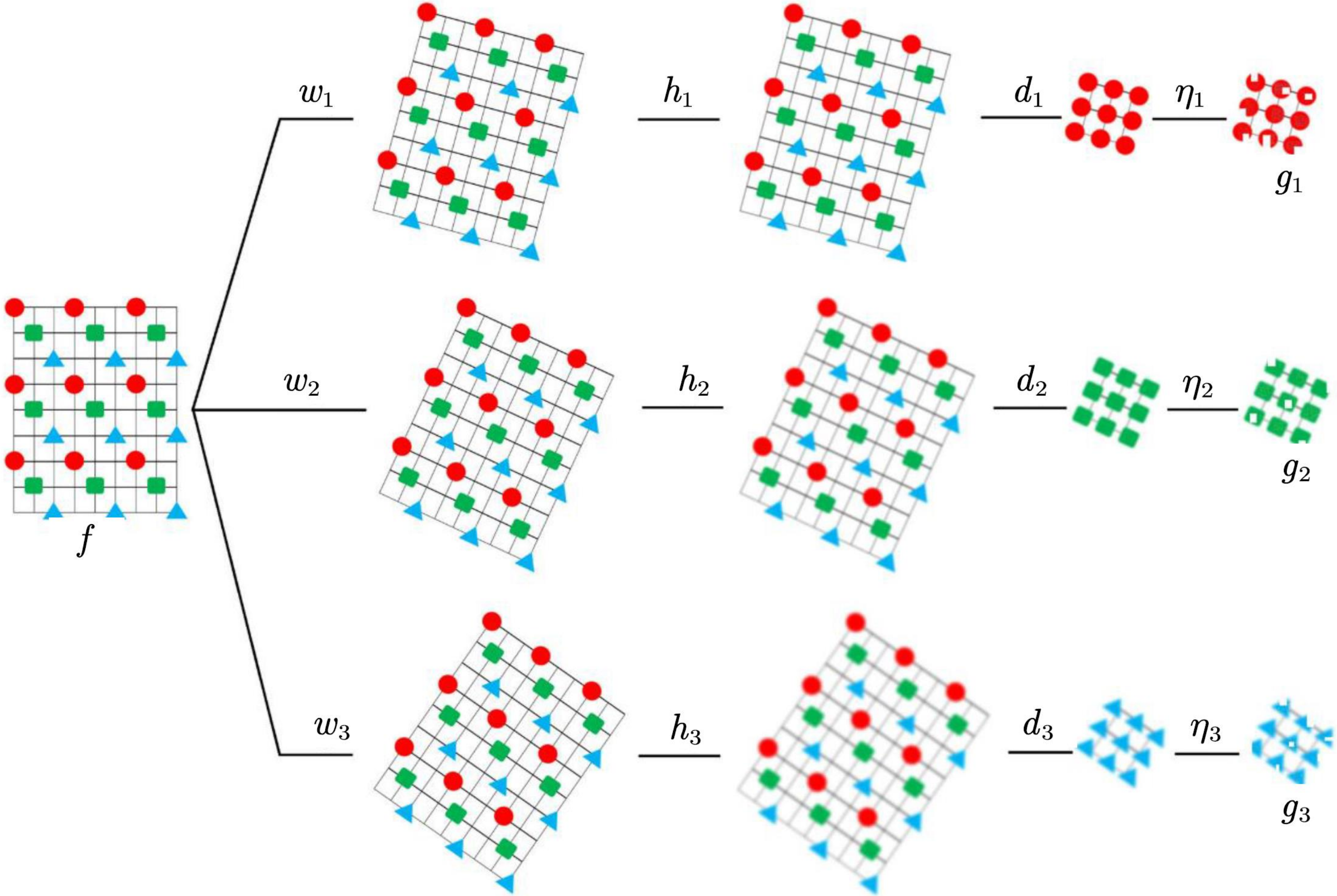
高分辨(HR)场景图像 f(x,y)

低分辨(LR)场景图像 g(m,n)

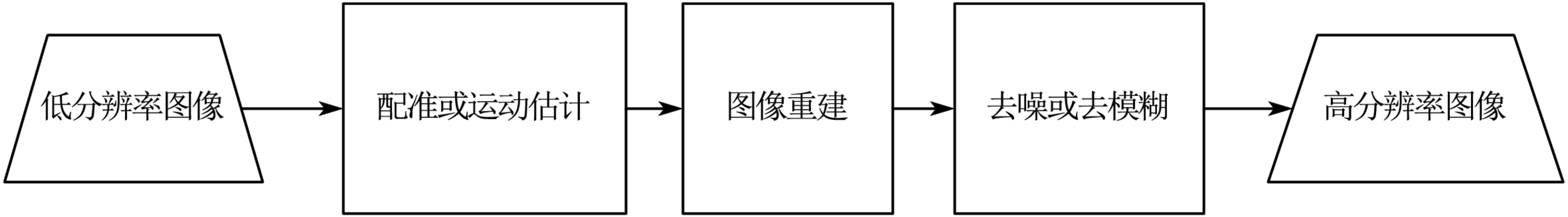
$$g(m,n) = d\Big(h\Big(w\big(f(x,y)\big)\Big)\Big) + \eta(m,n)$$

d() : 降采样，h() : 模糊算子，w() : 形变矩阵

$$g = Af + \eta$$

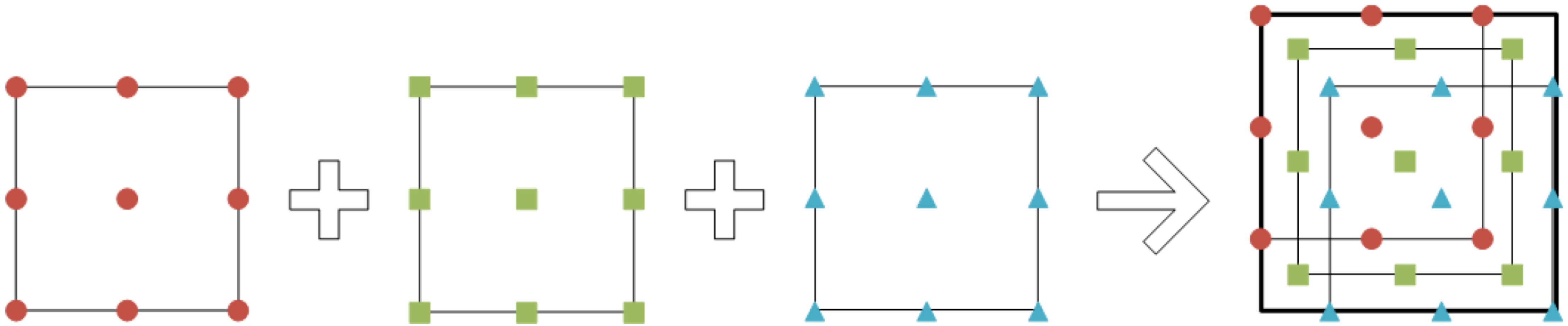


f
w1
w2
w3
h1
h2
h3
d1
d2
d3
η1
η2
η3
g1
g2
g3



单图像超分辨率 → 根据经验（模型）估计HR图像

多图像超分辨率 → 图像之间的亚像素位移补充HL图像中缺失的高频信息

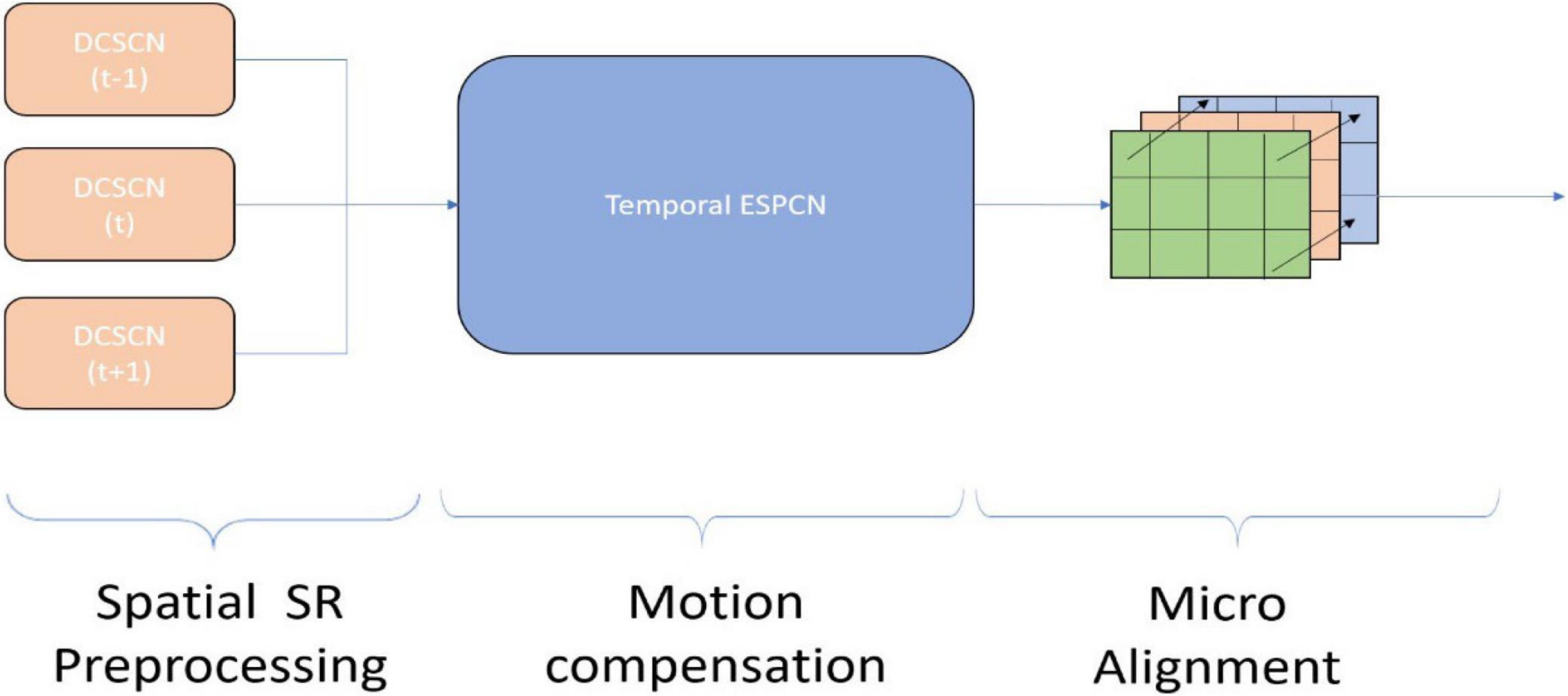


位移估计：光流场估计

$$I(\vec{x},t) = I(\vec{x}+\vec{u},t+1)$$

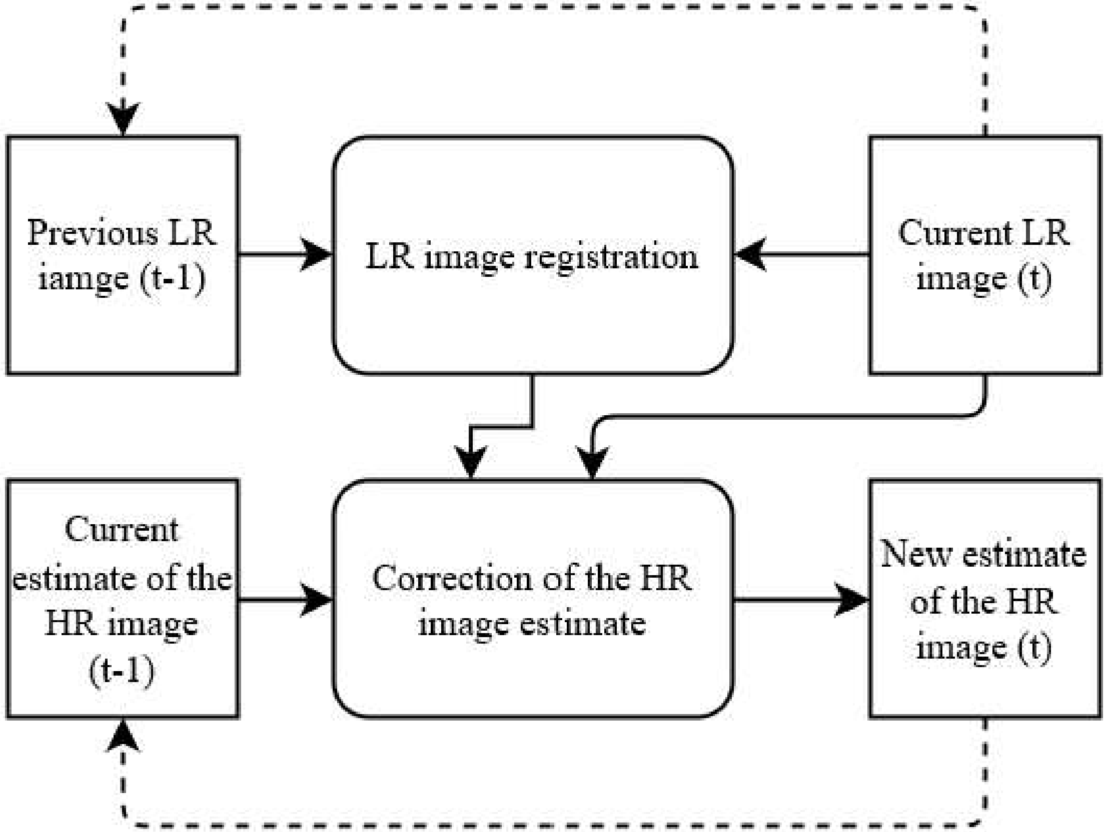
$$\frac{d}{dt}I(\vec{x}(t),t) = \frac{\partial I}{\partial x}\frac{\partial x}{\partial t} + \frac{\partial I}{\partial y}\frac{\partial y}{\partial t} + \frac{\partial I}{\partial t}\frac{\partial t}{\partial t} = \nabla I \cdot \vec{u} + I_t = 0$$

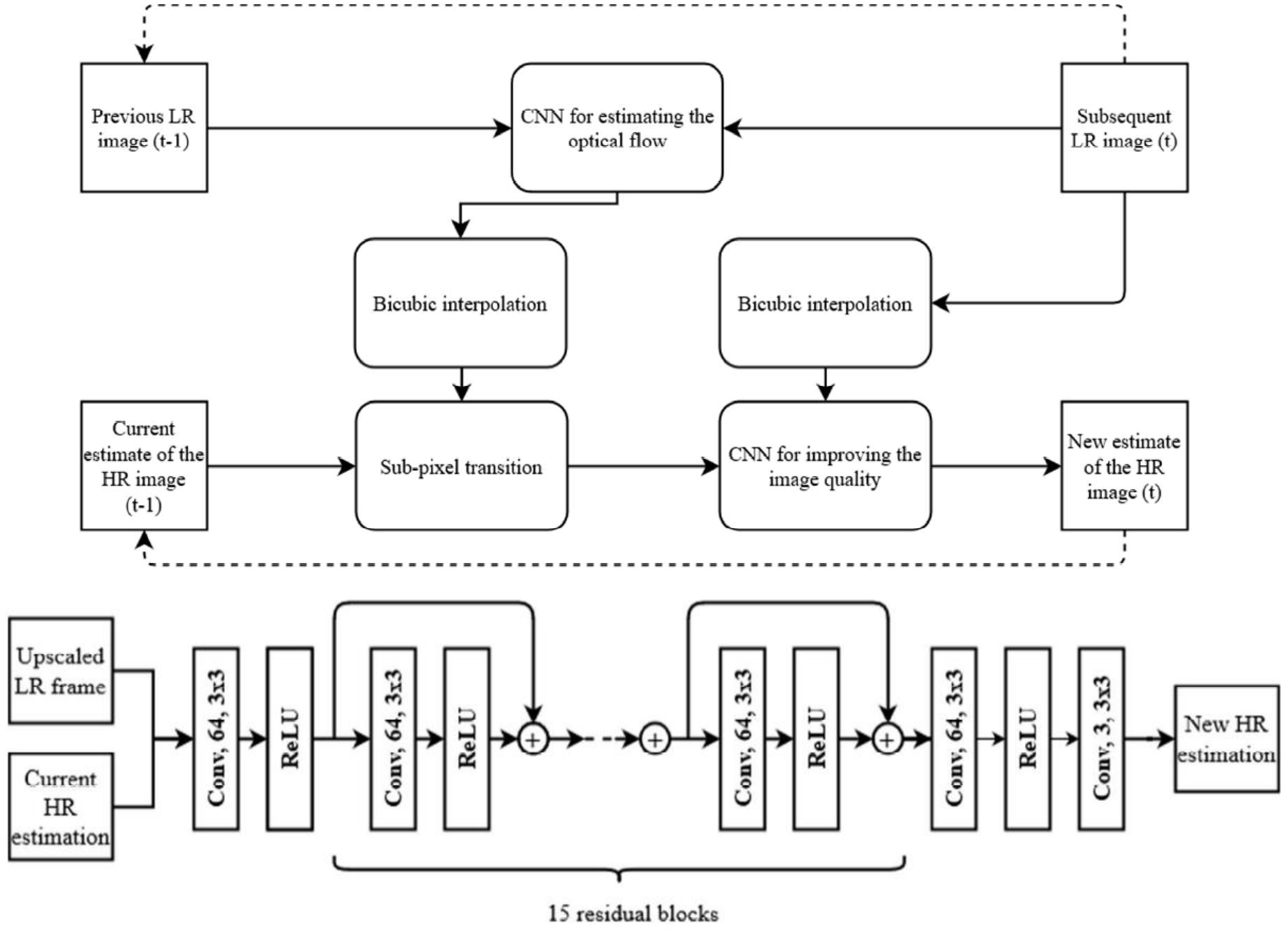
J.Mojoo, M.Sabri, T.Kurita, Video Super Resolution with Estimation of Motion Information by Using Higher Resolution Images Obtained by Single Image Super Resolution, Proc. International Joint Conference on Neural Networks, 2019


DCSCN
(t-1)
DCSCN
(t)
DCSCN
(t+1)
Temporal ESPCN
Spatial SR
Preprocessing
Motion
compensation
Micro
Alignment

【研讨论文5】

S.Savvin, A.Sirota, **An Algorithm for Multi-Fame Image Super-Resolution Under Applicative Noise Based on a Convolutional Neural Network,** proc. international conf. on Control Systems, Mathematical Modeling, Automation and Energy Efficiency, 2020, pp 422-424


Previous LR iamge (t-1)
LR image registration
Current LR image (t)
Current estimate of the HR image (t-1)
Correction of the HR image estimate
New estimate of the HR image (t)


Previous LR image (t-1)
CNN for estimating the optical flow
Subsequent LR image (t)
Bicubic interpolation
Bicubic interpolation
Current estimate of the HR image (t-1)
Sub-pixel transition
CNN for improving the image quality
New estimate of the HR image (t)
Upscaled LR frame
Current HR estimation
Conv, 64, 3x3
ReLU
Conv, 64, 3x3
ReLU
Conv, 64, 3x3
ReLU
Conv, 64, 3x3
ReLU
Conv, 3, 3x3
New HR estimation
15 residual blocks