



2010年、交替方向乘子法 (ADMM) 求解图像复原ROF-TV模型

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1、符号说明

2. Basic notation. Without loss of generality, we represent a grayscale image as an $N \times N$ matrix. The Euclidean space $\mathbb{R}^{N \times N}$ is denoted as V . The discrete gradient operator is a mapping $\nabla : V \rightarrow Q$, where $Q = V \times V$. For $u \in V$, ∇u is given by

$$(\nabla u)_{i,j} = ((\mathring{D}_x^+ u)_{i,j}, (\mathring{D}_y^+ u)_{i,j}),$$

with

$$\begin{aligned} (\mathring{D}_x^+ u)_{i,j} &= \begin{cases} u_{i,j+1} - u_{i,j}, & 1 \leq j \leq N-1, \\ u_{i,1} - u_{i,N}, & j = N, \end{cases} \\ (\mathring{D}_y^+ u)_{i,j} &= \begin{cases} u_{i+1,j} - u_{i,j}, & 1 \leq i \leq N-1, \\ u_{1,j} - u_{N,j}, & i = N, \end{cases} \end{aligned}$$

We denote the usual inner product and Euclidean norm of V as $(\cdot, \cdot)_V$ and $\|\cdot\|_V$, respectively. We also equip the space Q with inner product $(\cdot, \cdot)_Q$ and norm $\|\cdot\|_Q$, which are defined as follows. For $p = (p^1, p^2) \in Q$ and $q = (q^1, q^2) \in Q$,

$$(p, q)_Q = (p^1, q^1)_V + (p^2, q^2)_V$$

and

$$\|p\|_Q = \sqrt{(p, p)_Q}.$$

In addition, we mention that at each pixel (i, j) ,

$$|p_{i,j}| = |(p_{i,j}^1, p_{i,j}^2)| = \sqrt{(p_{i,j}^1)^2 + (p_{i,j}^2)^2},$$



2、图像复原ROF-TV模型

2.1、图像复原问题

$$(3.1) \quad f = Ku + n,$$

图像恢复的目标是从 f 恢复 u ，由于问题通常是病态的，我们不能直接从(3.1)解出 u 。

应考虑解的正则化，其中最基本也是最成功的图像正则化模型是ROF模型：

2.2、ROF-TV模型

$$(3.2) \quad \min_{u \in V} \left\{ F_{\text{rof}}(u) = R_{\text{rof}}(\nabla u) + \frac{\alpha}{2} \|Ku - f\|_V^2 \right\},$$

where

$$(3.3) \quad R_{\text{rof}}(\nabla u) = \text{TV}(u) = \sum_{1 \leq i, j \leq N} |(\nabla u)_{i,j}|$$



3、ADMM求解TV-L2

3.1、变量分离

求解ROF恢复模型(3.2)的困难在于TV项的不可微性，为此，对于 ∇u 引入一个辅助变量 $p \in Q$ ，我们可以将不可微项和2-范数平方项的计算分离。令 $p = \nabla u$ ，模型(3.2)等价于

$$(3.5) \quad \begin{aligned} \min_{u \in V, p \in Q} \quad & \left\{ G_{\text{rof}}(u, p) = R_{\text{rof}}(p) + \frac{\alpha}{2} \|Ku - f\|_V^2 \right\} \\ \text{s.t.} \quad & p = \nabla u, \end{aligned}$$

3.2、ADMM求解

对凸优化问题 (3.5)，ADMM求解步骤：

(1)、构建增广拉格朗日函数

$$\mathcal{L}_{\text{rof}}(v, q; \lambda) = R_{\text{rof}}(q) + \frac{\alpha}{2} \|Kv - f\|_V^2 + (\lambda, q - \nabla v)_Q + \frac{\gamma}{2} \|q - \nabla v\|_Q^2$$



3、ADMM求解TV-L2

3.2、ADMM求解

(2)、迭代计算

$$\mathcal{L}_{\text{rof}}(v, q; \lambda) = R_{\text{rof}}(q) + \frac{\alpha}{2} \|kv - f\|_v^2 + (\lambda, q - \nabla v)_Q + \frac{\gamma}{2} \|q - \nabla v\|_Q^2$$

固定拉格朗日乘子 λ^k .

在给定 q^k , 更新 v .

$$v^{k+1} = \arg \min_{v \in V} \left\{ \frac{\alpha}{2} \|kv - f\|_v^2 - (\lambda^k, \nabla v)_Q + \frac{\gamma}{2} \|q^k - \nabla v\|_Q^2 \right\}.$$

在给定 v^k , 更新 q

$$q^{k+1} = \arg \min_{q \in Q} \left\{ R_{\text{rof}}(q) + (\lambda^k, q)_Q + \frac{\gamma}{2} \|q - \nabla v^k\|_Q^2 \right\}.$$

更新拉格朗日乘子

$$\lambda^{k+1} = \lambda^k + \gamma (q^{k+1} - \nabla v^{k+1}).$$



3、ADMM求解TV-L2

3.2、ADMM求解

$$(4.1) \quad \mathcal{L}_{\text{rof}}(v, q; \mu) = R_{\text{rof}}(q) + \frac{\alpha}{2} \|Kv - f\|_V^2 + (\mu, q - \nabla v)_Q + \frac{r}{2} \|q - \nabla v\|_Q^2,$$

where $\mu \in Q$ is the Lagrange multiplier and r is a positive constant. For the augmented Lagrangian method for (3.5), we consider the following saddle-point problem:

$$(4.2) \quad \begin{aligned} &\text{Find } (u, p; \lambda) \in V \times Q \times Q \\ &\text{s.t. } \mathcal{L}_{\text{rof}}(u, p; \mu) \leq \mathcal{L}_{\text{rof}}(u, p; \lambda) \leq \mathcal{L}_{\text{rof}}(v, q; \lambda) \quad \forall (v, q; \mu) \in V \times Q \times Q. \end{aligned}$$

Algorithm 4.1. Augmented Lagrangian method for the ROF model.

1. *Initialization:* $\lambda^0 = 0$;
2. *For* $k = 0, 1, 2, \dots$: compute (u^k, p^k) as an (approximate) minimizer of the augmented Lagrangian functional with the Lagrange multiplier λ^k , i.e.,

$$(4.7) \quad (u^k, p^k) \approx \arg \min_{(v, q) \in V \times Q} \mathcal{L}_{\text{rof}}(v, q; \lambda^k),$$

where $\mathcal{L}_{\text{rof}}(v, q; \lambda^k)$ is defined in (4.1); update

$$(4.8) \quad \lambda^{k+1} = \lambda^k + r(p^k - \nabla u^k).$$

3、ADMM求解TV-L2

3.3、子问题求解



We separate (4.7) into the following two subproblems:

$$(4.9) \quad \min_{v \in V} \frac{\alpha}{2} \|Kv - f\|_V^2 - (\lambda^k, \nabla v)_Q + \frac{r}{2} \|q - \nabla v\|_Q^2$$

for a given q , and

$$(4.10) \quad \min_{q \in Q} R_{\text{rof}}(q) + (\lambda^k, q)_Q + \frac{r}{2} \|q - \nabla v\|_Q^2$$

for a given v .

3、ADMM求解TV-L2

3.3、子问题求解

对v子问题 (4.9)，可用FFT求解



$$f(v) = \frac{\alpha f(k^*) f(f) + f(\nabla^*) [f(\lambda^k) + r f(q)]}{\alpha f(k^*) f(k) + r f(\nabla^* \nabla)}$$

$$v = f^{-1} \left[\begin{array}{c} \downarrow \\ \end{array} \right]$$

若令 $\nabla^* = -\text{div}$, $\nabla^* \nabla = -\Delta$, 有:

$$(4.11) \quad v = \mathcal{F}^{-1} \left(\frac{\alpha \mathcal{F}(K^*) \mathcal{F}(f) - \mathcal{F}(\dot{D}_x^-) \mathcal{F}((\lambda^1)^k + r q^1) - \mathcal{F}(\dot{D}_y^-) \mathcal{F}((\lambda^2)^k + r q^2)}{\alpha \mathcal{F}(K^*) \mathcal{F}(K) - r \mathcal{F}(\Delta)} \right),$$

where $\lambda^k = ((\lambda^1)^k, (\lambda^2)^k)$ and $q = (q^1, q^2)$; Fourier transforms of operators such as $K, \dot{D}_x^-, \dot{D}_y^-$,



3、ADMM求解TV-L2

3.3、子问题求解

对q子问题 (4.10)

For (4.10), we actually have the following closed form solution [8, 40, 39]:

$$(4.12) \quad q_{i,j} = \begin{cases} \left(1 - \frac{1}{r} \frac{1}{|w_{i,j}|}\right) w_{i,j}, & |w_{i,j}| > \frac{1}{r}, \\ 0, & |w_{i,j}| \leq \frac{1}{r}, \end{cases}$$

where

$$(4.13) \quad w = \nabla v - \frac{\lambda^k}{r}.$$

4、ADMM求解TV-L1



4.1、图像复原ROF模型

$$(2) \quad \min_{u \in V} \{E(u) = R(\nabla u) + F(Ku)\},$$

where

$$(3) \quad R(\nabla u) = \text{TV}(u) = \sum_{1 \leq i, j \leq N} |(\nabla u)_{i,j}|,$$

不同噪声的保真项形式:

1. Gaussian noise:

$$F(Ku) = \frac{\alpha}{2} \|Ku - f\|^2,$$

2. Impulsive noise:

$$F(Ku) = \alpha \|Ku - f\|_{L^1},$$

3. Poisson noise (assuming $f_{i,j} > 0, \forall i, j$, as in [36]):

$$F(Ku) = \begin{cases} \alpha \sum_{1 \leq i, j \leq N} ((Ku)_{i,j} - f_{i,j} \log(Ku)_{i,j}), & (Ku)_{i,j} > 0, \forall i, j \\ +\infty, & \text{otherwise} \end{cases},$$

4、ADMM求解TV-L1



$$\min_{u \in V} \{ F_{\text{rof}}(u) = R_{\text{rof}}(\nabla u) + \alpha \|Ku - f\|_1 \} \quad (1).$$

若只引入辅助变量 $p = \nabla u$.

$$\min_{u \in V, p \in Q} \{ G_{\text{rof}}(u, p) = R_{\text{rof}}(p) + \alpha \|Ku - f\|_1 \} \quad (2).$$

$$\text{s.t. } p = \nabla u.$$

其 ALF:

$$\mathcal{L}_{\text{rof}}(u, p; \lambda) = R_{\text{rof}}(p) + \alpha \|Ku - f\|_1 + (\lambda, p - \nabla u) + \frac{\gamma}{2} \|p - \nabla u\|_Q^2 \quad (3).$$

u -子问题

$$\min_{u \in V} \{ \alpha \|Ku - f\|_1 - (\lambda, \nabla u)_Q + \frac{\gamma}{2} \|p - \nabla u\|_Q^2 \}$$

不可微.



4、ADMM求解TV-L1



$$\min_{u \in V} \{ F_{\text{rof}}(u) = R_{\text{rof}}(\nabla u) + \alpha \|ku - f\|_1 \} \quad (1)$$

引入辅助变量 $p = \nabla u \in Q$, $z = ku - f \in V$.

转化为优化问题:

$$\begin{aligned} \min_{u \in V, p \in Q, z \in V} \{ G_{\text{rof}}(u, p, z) = R_{\text{rof}}(p) + \alpha \|z\|_1 \} \\ \text{s.t.} \quad \begin{aligned} p &= \nabla u \\ z &= ku - f \end{aligned} \end{aligned} \quad (2)$$

(2)的 ALF:

$$\begin{aligned} \mathcal{L}_{\text{rof}}(u, p, z; \lambda_p, \lambda_z) = R_{\text{rof}}(p) + \alpha \|z\|_1 + (\lambda_p, p - \nabla u) \\ + (\lambda_z, z - (ku - f)) + \frac{\gamma_p}{2} \|p - \nabla u\|^2 + \frac{\gamma_z}{2} \|z - (ku - f)\|^2 \end{aligned} \quad (3)$$

4、ADMM求解TV-L1



$$\mathcal{L}_{\text{ref}}(u, p, z; \lambda_p, \lambda_z) = R_{\text{ref}}(p) + \alpha \|z\|_1 + (\lambda_p, p - \nabla u) + (\lambda_z, z - (ku - f)) + \frac{\gamma_p}{2} \|p - \nabla u\|^2 + \frac{\gamma_z}{2} \|z - (ku - f)\|^2 \quad (3)$$

(3) 转化为如下三个子问题.

u -子问题: 给定 p, z .

$$\min_{u \in V} \{ (\lambda_p^k, p - \nabla u) + (\lambda_z^k, z - (ku - f)) + \frac{\gamma_p}{2} \|p - \nabla u\|^2 \} \quad (4)$$

p -子问题: 给定 u, z

$$\min_{p \in \mathbb{R}} \{ R_{\text{ref}}(p) + (\lambda_p^k, p) + \frac{\gamma_p}{2} \|p - \nabla u\|^2 \} \quad (5)$$

z -子问题: 给定 u, p

$$\min_{z \in V} \{ \alpha \|z\|_1 + (\lambda_z^k, z) + \frac{\gamma_z}{2} \|z - (ku - f)\|^2 \} \quad (6)$$



4、ADMM求解TV-L1



u-子问题, 由FFT可求得

$$f(u) = \frac{f(k^*)[f(\lambda_z^k) + \gamma_z f(z) + \gamma_z f(f)] + f(p^*)[f(\lambda_p^k) + \gamma_p f(p)]}{\gamma_z f(k^*) f(k) + \gamma_p f(p^*) f(p)}$$

p-子问题有解 $f_{ij} = \max(0, 1 - \frac{1}{\gamma_p |w_{ij}|}) w_{ij}$

$$w = \nabla u - \frac{\lambda_p^k}{\gamma_p} \in Q$$

z-子问题有解 $z_{ij} = \max(0, 1 - \frac{\alpha}{\gamma_z |h_{ij}|}) h_{ij}$

$$h = ku - f - \frac{\lambda_z^k}{\gamma_z} \in V$$

4、ADMM求解TV-L1



4.1.2. *Solving the p -sub problem (12).* Similarly to [7, 56, 54, 57], (12) has the following closed form solution

$$(15) \quad p_{i,j} = \max(0, 1 - \frac{1}{r_p |\mathbf{w}_{i,j}|}) \mathbf{w}_{i,j}, \quad \forall i, j$$

where

$$(16) \quad \mathbf{w} = \nabla u - \frac{\lambda_p^k}{r_p} \in Q.$$

Here we would like to provide a geometric interpretation of the formulae (15), which is different from the view point of sub-differential [56]. According to the definition of $R(p)$ and $\|\cdot\|_Q$, we rewrite the problem (12) as

$$\min_{p \in Q} \left\{ \sum_{1 \leq i,j \leq N} |p_{i,j}| + \frac{r_p}{2} \sum_{1 \leq i,j \leq N} |p_{i,j} - (\nabla u - \frac{\lambda_p^k}{r_p})_{i,j}|^2 + \text{Constant} \right\}.$$

As one can see, the above problem is decomposable and at each pixel (i, j) , the problem takes the form as follows

$$(17) \quad \min_{q \in \mathbb{R}^2} \left\{ |q| + \frac{r_p}{2} |q - w|^2 \right\},$$

where $w \in \mathbb{R}^2$; see Fig. 1.

4、ADMM求解TV-L1

首先，可以验证(和想象)潜在的最小值应该位于实心圆的内部。通过构造对称点，我们可以进一步证明，潜在的最小值应该位于与 w 相同的象限。因此，只需要考虑那些位于实心圆内部和第一象限的点，例如:对于这样一个点 q ，我们画一个虚线圆，以 O 为圆心， $|q|$ 为半径。假设这个圆在 q^* 处与线段 Ow 相交。由三角不等式得到

$$|q| + |q - w| \geq |w| = |q^*| + |q^* - w|.$$

Since $|q| = |q^*|$, we obtain

$$|q - w| \geq |q^* - w|,$$

indicating

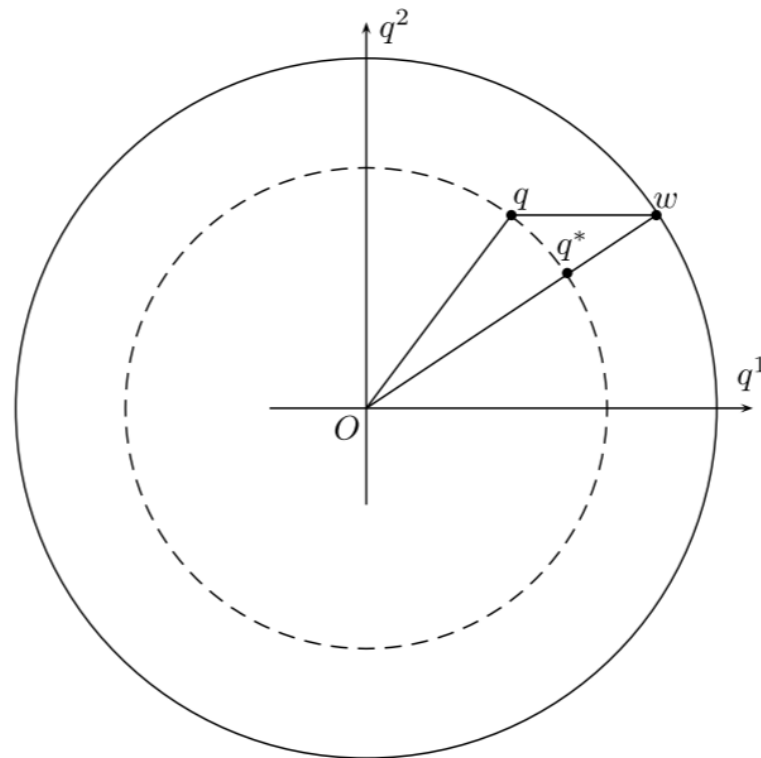
$$|q| + \frac{r_p}{2}|q - w|^2 \geq |q^*| + \frac{r_p}{2}|q^* - w|^2.$$

This means the solution of the problem (17) will locate on the line segment Ow . Denoting $q = \beta w$ with $0 \leq \beta \leq 1$, we hence simplify (17) to be the following 1-dimensional problem

$$(18) \quad \min_{0 \leq \beta \leq 1} \{ \beta |w| + \frac{r_p}{2}(\beta - 1)^2 |w|^2 \}.$$

The above (18) can be solved exactly, with a closed form solution as

$$\beta^* = \max(0, 1 - \frac{1}{r_p |w|}).$$



5、实验结果



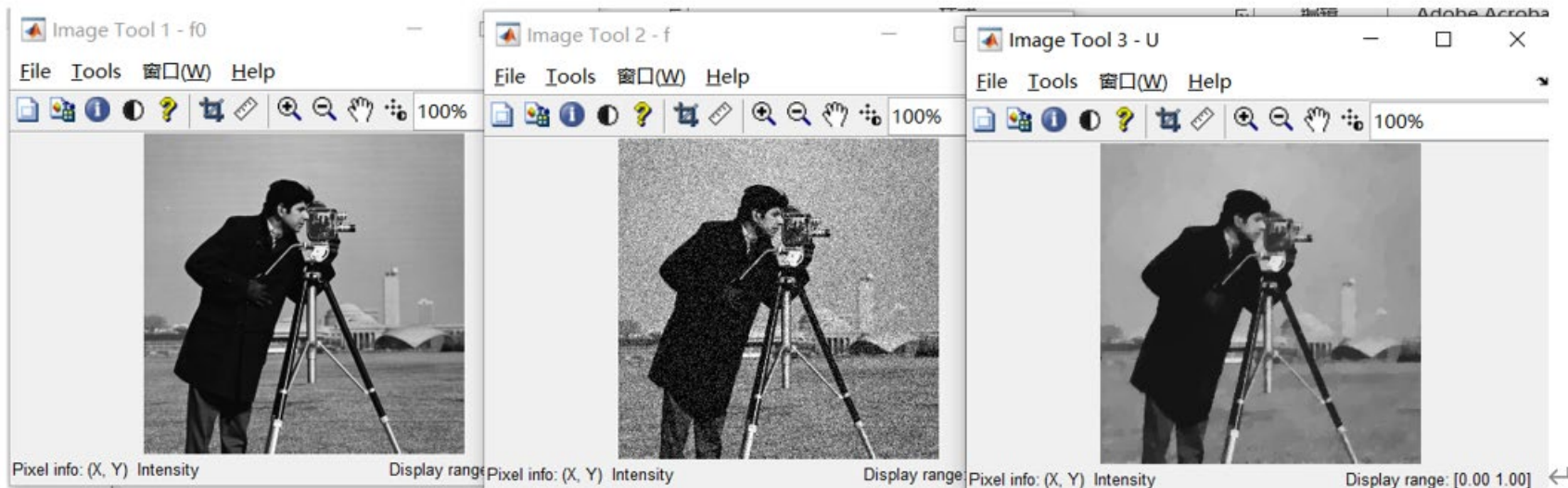
(1)、复原高斯噪声 (TV-L2) ←

```
f = imnoise(f0, 'gaussian', 0.01); ←
```

```
factPSNR =
```

```
20.3166
```

```
The alpha is 10, r_P is 5, SNR1 is 14.2815, PSNR1 is 26.5168, ←
```



5、实验结果

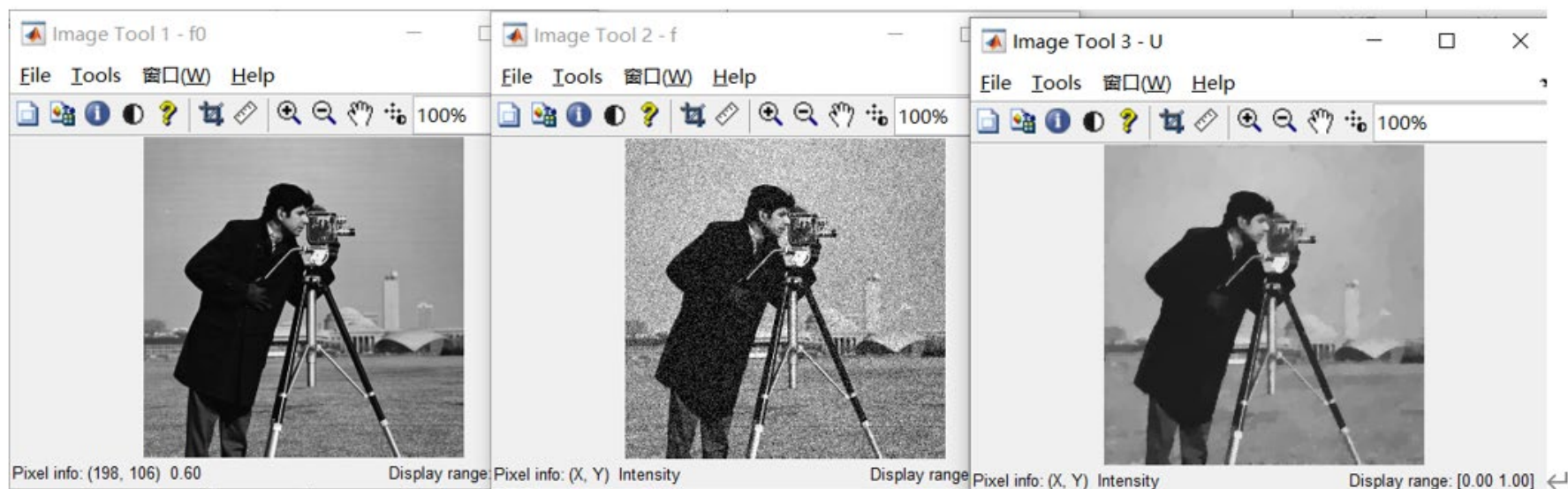


```
f = imnoise(f0, 'gaussian', 0.05);
```

```
factPSNR =
```

```
19.2126
```

```
The alpha is 10, r_P is 5, SNR1 is 11.1238, PSNR1 is 23.3591,
```



5、实验结果



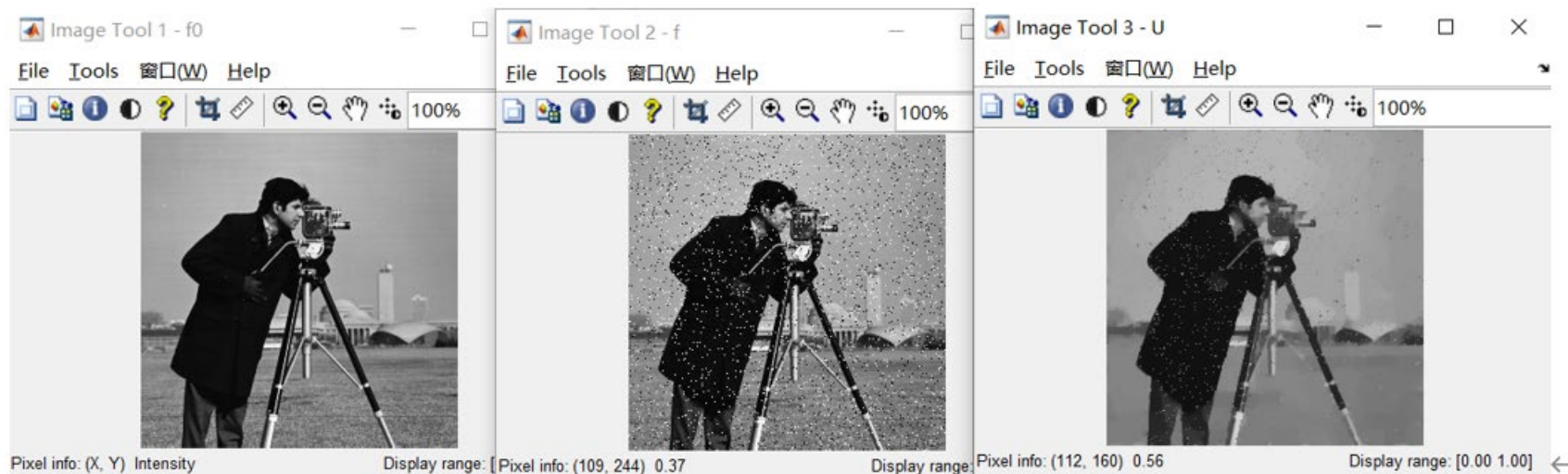
(2)、复原脉冲噪声（椒盐）（TV-L1）←

```
f = imnoise(f0, 'salt & pepper', 0.05);←
```

factPSNR =

18.0849|

The alpha is 7, r_P is 10, SNR1 is 11.3517, PSNR1 is 23.5869,←



5、实验结果



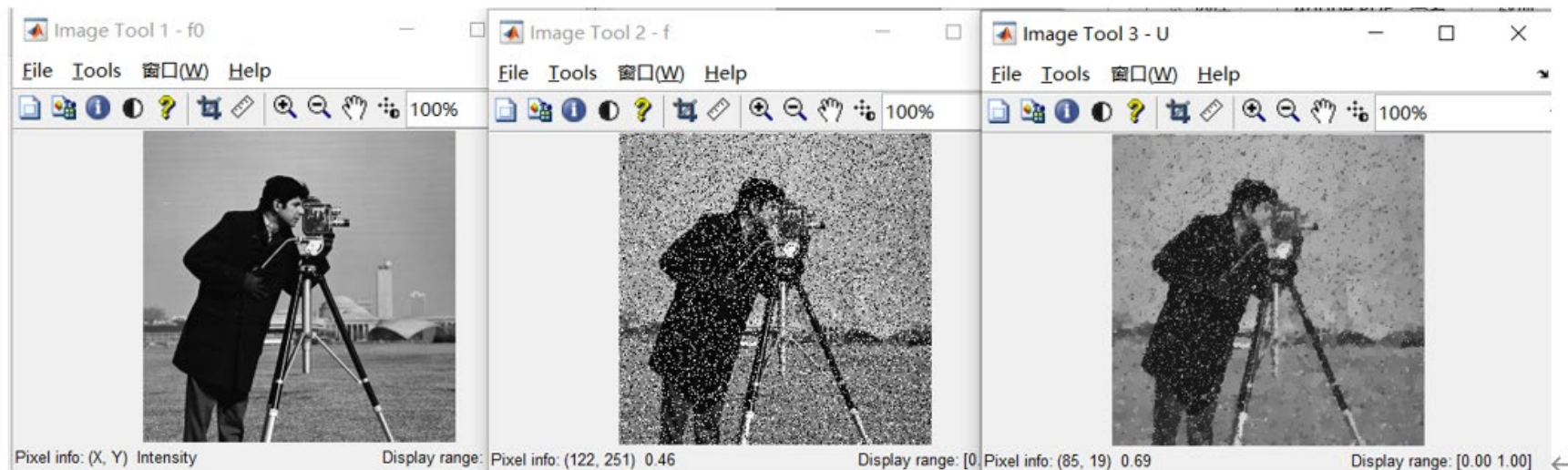
```
f = imnoise(f0, 'salt & pepper', 0.2);
```

```
←
```

```
factPSNR =
```

```
12.0611
```

```
The alpha is 7, r_P is 10, SNR1 is 7.3963, PSNR1 is 19.6316, ←
```





感谢老师的悉心指导

THANK YOU!

汇报人 | XXX

指导老师 | XXX