Stereo Matching

运行环境:

```
yqm@yqm:~$ lsb_release -a
No LSB modules are available.
Distributor ID: Ubuntu
Description: Ubuntu 14.04.3 LTS
Release: 14.04
Codename: _ trusty
```

Linux version 3.19.0-25-generic
Opencv 3.0
cmake version 2.8.12.2
gcc version 4.8.4
g++ (Ubuntu 4.8.4-2ubuntu1~14.04) 4.8.4

运行指令:

cmake . make

运行说明:

实验把测例图片所在文件夹命名为 images,与源码放在同一根目录下

运行后,程序生成文件夹 resultImages,存放运行结果

文件说明:

运行的结果都储存"result"文件夹中,其中 resultImages_v0 是"ASW: size=11*11, rc=7,rp=36; SSD&NCC:size=5*5" 跑出来的图片, resultImages_v1 是 "ASW: size=11*11, rc=36, rp=7; SSD&NCC:size=5*5"跑的图片, 然后文本文档是各部分运行的结果坏点率。

2.1 Basic Task

- 1.实现一个估计视差图坏像素率的函数
- a) 在 disparity.h 中,声明估计函数

void Evaluate(Mat standard, Mat myMap);

b) 在 disparity.cpp 中实现函数,遍历标准图和自己生成的视差图作比较

c) 最后保留两位小数输出

```
cout <<setiosflags(ios::fixed);
cout <<setprecision(2) << result * 100 << '%' << endl;</pre>
```

- 2.用"Sum of Squared Difference (SSD)"来计算匹配代价,做视差匹配
- a) 视差匹配
 - i. 匹配代价叠加

$$D_L(x, y) = \underset{d \in \{0, 1, \dots, d_{\max}\}}{\arg \min} \operatorname{dist} (F_L(x, y), F_R(x - d, y))$$

部分代码实现:

设定一个 5*5 的滑块,当匹配左眼图的视差图 DL 时,对每一个 d 的取值都计算滑块方框内的左右视图同一水平,垂直位置相差 d 的像素差值的平方,与对应的 d 值一起存放到 vector 中,最后取最小 SSD 值对应的 d 值做为 DL (x, y) 的值。(最后还需要乘上三,增强显示效果)

函数:

把图片转成灰度图:

Mat turnIntoGray(Mat input)

取三通道平均值做为灰度值

生成左右视差图:

Mat SSD(Mat Left, Mat Right, bool LeftOrRight, int size)

其中,Left、Right 分别时左右视图,布尔值 LeftOrRight=true 则返回 左视差图,反之返回右视差图,size 表示滑动窗口 patch 的大小。

- b) 不同的灰度值转换算法,优化
 - i. RGB 取平均值转为灰度图



Aloe 左视差图坏像素率为:^{24.83%}

ii. 用 opencv 自带 API 实现彩色图转灰度图

Mat disparityLeft; cvtColor(Left, disparityLeft, CV_BGR2GRAY);

Aloe 左视差图坏像素率为:^{24.68%}

iii. 利用一个转化公式

```
Gray = R*0.299 + G*0.587 + B*0.114
```

Aloe 左视差图坏像素率为: 24.72%

坏点率和灰度转化方式的关系不大。

- c) 保存图片和坏点率到固定文件夹中 e.g. "resultImage"
 - i. 创建一个 string 数组保存文件夹目录

```
//文件夹下的目录
string name[FileNumber]= {"Aloe", "Baby1", "Baby2", "Baby3", "Bowling1", "Bowling2", "Cloth1", "Cloth2", "Cloth3", "Cloth4", "Flowerpots", "Lampshade1", "Lampshade2", "Midd1", "Midd2", "Monopoly", "Plastic", "Rocks1", "Rocks2", "Wood1", "Wood2"};
```

ii. 对于每一个测例的处理:生成一个对应的文件夹,把 disparity map 存入,并且计算坏点率

```
//在目的文件夹中创建相应的文件夹,以便存入图片
string str = "resultImages/" + name[i];
const char * dir = str.c_str();
mkdir(dir, S_IRWXU);
```

```
Mat resultLeft = SSD(disparityLeft, disparityRight, true, 5);
imwrite( "resultImages/" + name[i] + "/" + name[i] + "_disp1_SSD.png", resultLeft );
Mat resultRight = SSD(disparityLeft, disparityRight, false, 5);
imwrite( "resultImages/" + name[i] + "/" + name[i] + "_disp5_SSD.png", resultRight );

//evaluate the quality of the disparity maps
Mat standardLeft = imread("images/" + name[i] + "/disp1.png", -1);
Evaluate(standardLeft, resultLeft);
Mat standardRight = imread("images/" + name[i] + "/disp5.png", -1);
Evaluate(standardRight, resultRight);
```

iii. 最后的坏点率

yqm@yqm:~ 24.72%

25.78%

33.65%

33.31%

38.97%

39.25%

43.15%

43.08%

69.00%

69.41%

50.76% 50.46%

10.35%

8.47%

31.50%

31.86%

15.92%

14.38%

22.86%

24.85%

59.34%

59.46%

61.43%

60.47%

73.89%

73.35%

62.81%

62.50%

70.74%

71.26%

67.26%

65.99%

82.16%

82.99%

24.52%

23.80%

23.66%

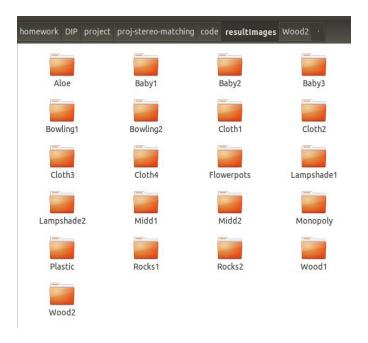
21.92%

41.51%

40.64%

50.02%

50.35%



最后跑完全部测例大概 5 mins

- 3.Normalized Cross Correlation (NCC)计算匹配代价,做视差匹配
- a) 原理

$$NCC(x, y, d) = \frac{\sum_{i=-n}^{n} \sum_{j=-m}^{m} I_{R}(x+i, y+j) I_{L}(x+i, y+d+j)}{\sqrt{\sum_{i=-n}^{n} \sum_{j=-m}^{m} I_{R}^{2}(x+i, y+j) \sum_{i=-n}^{n} \sum_{j=-m}^{m} I_{L}^{2}(x+i, y+d+j)}}$$

- b) 函数实现
 - i. 函数原型

Mat NCC(Mat Left, Mat Right, bool LeftOrRight, int size);

Left: 左视图灰度图

Right:右视图灰度图

LeftOrRight:为真,计算DL;反之,计算DR

Size: patch 窗口大小

ii. 套用公式计算

1. 计算分子

```
for (int x = i - size_; x <= i + size_; x ++) {
    for (int y = j - d - size_; y <= j - d + size_; y ++) {
        if (x < 0 || y < 0 || x >= row || y >= col || y + d < 0 || y + d >= col)continue;
        double temp1;
        double temp2;
        if (LeftOrRight) {
            temp1 = static_cast < double > (Right.ptr < uchar > (x)[y]);
            temp2 = static_cast < double > (Left.ptr < uchar > (x)[y + d]);
        }
        else {
            temp1 = static_cast < double > (Right.ptr < uchar > (x)[y + d]);
            temp2 = static_cast < double > (Left.ptr < uchar > (x)[y]);
        }
        temp2 += temp1 * temp2;
    }
}
```

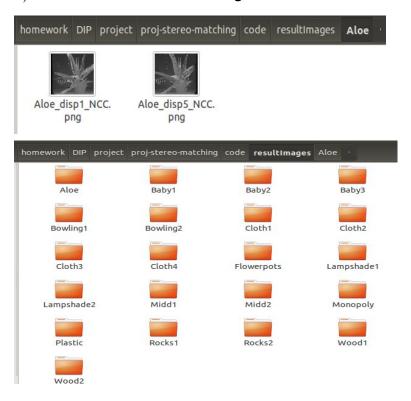
2. 计算分母

3. 最后把结果和 d 一起存入 vector, 取最大值作为 DL/DR 在该点的像素值,最后强度*3

```
double result = tempZ / tempM;
if (!LeftOrRight)d = -d;
v.push_back(make_pair(result, d));
```

4. 当 LeftOrRight=false 的时候表示计算右视图的视差图,此时 d 要取反

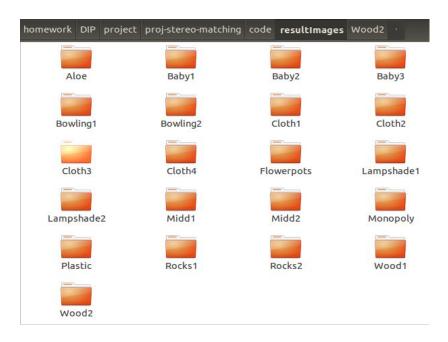
c) 运行结果储存在 resultImages 中:全部测例运行约 15 mins



d) 把 SSD 和 NCC 一起跑一遍

总耗时:15 mins 左右





坏点率,总体情况比SSD好:

Aloe Left SSD: 24.72% Aloe Left NCC: 23.64% Aloe_Right_SSD: 25.78% Aloe_Right_NCC: 24.20% Baby1_Left_SSD: 33.65% Baby1 Left NCC: 20.70% Baby1_Right_SSD: 33.31% Baby1_Right_NCC: 20.78% Baby2_Left_SSD: 38.97% Baby2_Left_NCC: 28.33% Baby2 Right SSD: 39.25% Baby2_Right_NCC: 29.19% Baby3 Left SSD: 43.15% Baby3_Left_NCC: 29.24% Baby3 Right SSD: 43.08% Baby3_Right_NCC: 29.34% Bowling1_Left_SSD: 69.00% Bowling1 Left NCC: 44.21% Bowling1_Right_SSD: 69.41% Bowling1 Right NCC: 44.25% Bowling2_Left_SSD: 50.76% Bowling2 Left NCC: 32.08% Bowling2 Right SSD: 50.46% Bowling2_Right_NCC: 32.29% Cloth1_Left_SSD: 10.35%

Cloth1_Left_NCC: 10.37% Cloth1 Right SSD: 8.47% Cloth1_Right_NCC: 8.50%

Cloth2 Left SSD: 31.50%

Cloth2 Left NCC: 19.39%

Cloth2_Right_SSD: 31.86%

Cloth2 Right NCC: 19.87%

Cloth3_Left_SSD: 15.92%

Cloth3_Left_NCC: 14.80%

Cloth3_Right_SSD: 14.38%

Cloth3 Right NCC: 13.04%

Cloth4_Left_SSD: 22.86%

Cloth4_Left_NCC: 18.96%

Cloth4_Right_SSD: 24.85%

Cloth4_Right_NCC: 20.97%

Flowerpots_Left_SSD: 59.34%

Flowerpots_Left_NCC: 39.52%

Flowerpots_Right_SSD: 59.46%

Flowerpots_Right_NCC: 40.28%

Lampshade1_Left_SSD: 61.43%

Lampshade1 Left NCC: 48.94%

Lampshade1_Right_SSD: 60.47%

Lampshade1 Right NCC: 48.93%

Lampshade2_Left_SSD: 73.89%

Lampshade2_Left_NCC: 50.19%

Lampshade2_Right_SSD: 73.35%

Lampshade2 Right NCC: 50.67%

Midd1_Left_SSD: 62.81%

Midd1_Left_NCC: 58.65%

Midd1 Right SSD: 62.50%

Midd1_Right_NCC: 58.60%

Midd2 Left SSD: 70.74%

Midd2_Left_NCC: 59.35%

Midd2 Right SSD: 71.26%

Midd2 Right NCC: 58.87%

Monopoly Left SSD: 67.26%

Monopoly Left NCC: 51.81%

Monopoly_Right_SSD: 65.99%

Monopoly Right NCC: 48.26%

Plastic_Left_SSD: 82.16%

Plastic Left NCC: 71.18%

Plastic Right SSD: 82.99%

Plastic_Right_NCC: 70.66%

Rocks1_Left_SSD: 24.52%

Rocks1_Left_NCC: 18.64%

Rocks1 Right SSD: 23.80%

Rocks1_Right_NCC: 18.06%
Rocks2_Left_SSD: 23.66%
Rocks2_Left_NCC: 17.95%
Rocks2_Right_SSD: 21.92%
Rocks2_Right_NCC: 16.43%
Wood1_Left_SSD: 41.51%
Wood1_Left_NCC: 24.38%
Wood1_Right_SSD: 40.64%
Wood1_Right_NCC: 21.78%
Wood2_Left_SSD: 50.02%
Wood2_Left_NCC: 26.82%
Wood2_Right_SSD: 50.35%
Wood2_Right_NCC: 27.21%

- 4. Add a small constant amount of intensity (e.g. 10) to all right eye images, and re-run the above two methods.
- a) 实现
- b) 强度增加 5

i. Result

Aloe Right SSD: 32.88% Aloe Right NCC: 24.31% Baby1 Right SSD: 60.14% Baby1_Right_NCC: 21.17% Baby2 Right SSD: 58.17% Baby2 Right NCC: 29.60% Baby3 Right SSD: 69.26% Baby3 Right NCC: 30.17% Bowling1 Right SSD: 80.66% Bowling1 Right NCC: 44.73% Bowling2_Right_SSD: 67.33% Bowling2 Right NCC: 32.88% Cloth1 Right SSD: 9.53% Cloth1 Right NCC: 8.53% Cloth2 Right SSD: 27.43% Cloth2 Right NCC: 20.49% Cloth3 Right SSD: 20.97% Cloth3 Right NCC: 13.19% Cloth4 Right SSD: 30.55% Cloth4_Right NCC: 24.97% Flowerpots Right SSD: 79.68% Flowerpots_Right_NCC: 41.67% Lampshade1_Right_SSD: 81.28% Lampshade1_Right_NCC: 49.50% Lampshade2_Right_SSD: 83.64% Lampshade2_Right_NCC: 51.42%

Midd1 Right SSD: 70.54% Midd1 Right NCC: 59.01% Midd2 Right SSD: 64.57% Midd2 Right NCC: 59.47% Monopoly Right SSD: 61.00% Monopoly Right NCC: 48.36% Plastic Right SSD: 82.50% Plastic Right NCC: 71.16% Rocks1 Right SSD: 38.83% Rocks1 Right NCC: 18.30% Rocks2 Right SSD: 31.33% Rocks2 Right NCC: 16.64% Wood1 Right SSD: 63.96% Wood1 Right NCC: 22.28% Wood2 Right SSD: 80.38% Wood2 Right NCC: 27.56%

c) 强度增加 10

i. Result

Aloe Right SSD: 42.73% Aloe Right NCC: 24.46% Baby1 Right SSD: 82.48% Baby1 Right NCC: 21.71% Baby2 Right SSD: 78.84% Baby2 Right NCC: 30.20% Baby3 Right SSD: 84.03% Baby3_Right NCC: 31.33% Bowling1_Right_SSD: 90.46% Bowling1 Right NCC: 46.32% Bowling2 Right SSD: 81.67% Bowling2 Right NCC: 33.80% Cloth1 Right SSD: 16.46% Cloth1_Right_NCC: 8.54% Cloth2 Right SSD: 60.61% Cloth2 Right NCC: 22.14% Cloth3 Right SSD: 43.07% Cloth3 Right NCC: 13.52% Cloth4 Right SSD: 50.16%

Cloth4_Right_NCC: 29.13% Flowerpots_Right_SSD: 94.22% Flowerpots_Right_NCC: 43.82% Lampshade1_Right_SSD: 91.23% Lampshade1_Right_NCC: 50.16% Lampshade2_Right_SSD: 94.76% Lampshade2_Right_NCC: 54.29%

Midd1 Right SSD: 80.01% Midd1 Right NCC: 59.77% Midd2 Right SSD: 78.87% Midd2 Right NCC: 60.41% Monopoly Right SSD: 57.41% Monopoly Right NCC: 48.58% Plastic Right SSD: 91.24% Plastic Right NCC: 71.86% Rocks1_Right_SSD: 59.16% Rocks1 Right NCC: 18.81% Rocks2 Right SSD: 56.84% Rocks2 Right NCC: 16.89% Wood1 Right SSD: 88.92% Wood1 Right NCC: 22.98% Wood2 Right SSD: 91.86% Wood2 Right NCC: 28.30%

d) 强度增加 20

i. Result

Aloe Right_SSD: 79.63% Aloe Right NCC: 28.20% Baby1 Right SSD: 95.23% Baby1 Right NCC: 23.29% Baby2 Right SSD: 93.84% Baby2 Right NCC: 34.08% Baby3 Right SSD: 95.11% Baby3 Right NCC: 34.43% Bowling1 Right SSD: 95.24% Bowling1 Right NCC: 52.17% Bowling2 Right SSD: 93.45% Bowling2 Right NCC: 36.86% Cloth1 Right SSD: 66.16% Cloth1 Right NCC: 8.61% Cloth2_Right SSD: 91.11% Cloth2 Right NCC: 24.42%

Cloth3 Right SSD: 80.49% Cloth3 Right NCC: 15.86% Cloth4 Right SSD: 90.09% Cloth4 Right NCC: 40.31% Flowerpots Right SSD: 96.57% Flowerpots Right NCC: 48.61% Lampshade1 Right SSD: 96.70% Lampshade1 Right NCC: 55.43% Lampshade2 Right SSD: 97.61% Lampshade2 Right NCC: 59.49% Midd1 Right SSD: 87.14% Midd1 Right NCC: 62.31% Midd2 Right SSD: 86.96% Midd2 Right NCC: 62.72% Monopoly Right SSD: 79.35% Monopoly Right NCC: 49.33% Plastic Right SSD: 96.06% Plastic Right NCC: 73.44% Rocks1 Right SSD: 87.18% Rocks1 Right NCC: 20.43% Rocks2 Right SSD: 86.72% Rocks2 Right NCC: 17.88% Wood1 Right SSD: 95.84% Wood1 Right NCC: 25.18% Wood2 Right SSD: 95.17% Wood2 Right NCC: 30.74%

结论:在增加强度时,SSD 算法处理的视差图质量下滑严重,坏点率增加非常明显,NCC 算法的处理效果会好一些,坏点率前后对比增加幅度不大,但是也有所增加。

5.ASW 算法的实现

- a) 算法实现
 - i. 原理

$$E(p,\bar{p}_d) = \frac{\sum_{q \in N_p, \bar{q}_d \in N_{\bar{p}_d}} w(p,q) w(\bar{p}_d, \bar{q}_d) e_0(q, \bar{q}_d)}{\sum_{q \in N_p, \bar{q}_d \in N_{\bar{p}_d}} w(p,q) w(\bar{p}_d, \bar{q}_d)}$$

111

$$d_p = \arg\min_{d \in S_d} E(p, \bar{p}_d)$$

where $S_d = \{d_{min}, \dots, d_{max}\}$ is a set of all possible disparity values.

$$e_0(q, \bar{q}_d) = \sum_{c \in \{r, g, b\}} |I_c(q) - I_c(\bar{q}_d)|$$

$$w(p,q) = k \cdot \exp \left(-(\frac{\Delta c_{pq}}{\gamma_c} + \frac{\Delta g_{pq}}{\gamma_p}) \right)$$

 Δc pq and Δg pq represent the color difference and the spatial distance between pixel p and q.

 Δc pq represents the Euclidean distance between two colors, cp = [Lp , ap , bp] and cq = [Lq , aq , bq],in the CIELab color space

$$\Delta c_{pq} = \sqrt{(L_p - L_q)^2 + (a_p - a_q)^2 + (b_p - b_q)^2}$$

yp is determined empirically

yc is typically 7

因为 K 最后会在表达式中约去, 所以可以忽略

ii. 代码实现

1. 函数原型

Mat ASW(Mat Left, Mat Right, bool LeftOrRight, int size, int rc, int rp);

Left:三通道左视图

Right:三通道右视图

LeftOrRight :true ,返回 left disparity map ;false , 返回 right disparity

map

Size: size of patch

rc\rp:表达式中的参数

2. 处理

a) 先转成 Lab 彩色模型

```
//change into Lab mode
Mat LeftLab;
cvtColor(Left, LeftLab, CV_BGR2Lab);
Mat RightLab;
cvtColor(Right, RightLab, CV_BGR2Lab);
```

这里需要注意使用的时 CV_BGR2Lab,而不是 CV_RGB2Lab,因为

Mat 默认的彩色图片三通道顺序为 B、G、R

b) 表达式的处理

对于每一隔 patch 内:

```
double Cpq = 0;
double Cp_q_ = 0;
double Gpq = 0;
double Gp_q_ = 0;
double Wpq = 0;
double Wp_q_ = 0;
double e0qq_ = 0;
```

```
//calculate Gpq\Gp_q_
Gpq = sqrt(pow((x - i), 2) + pow((y + d - j), 2));
Gp_q_ = sqrt(pow((x - i), 2) + pow((y - j + d), 2));
```

```
//gain value of Wpq\Wp_q_
Wpq = exp( - (Cpq / rc + Gpq / rp));
Wp_q_ = exp( - (Cp_q_ / rc + Gp_q_ / rp));
```

i. 分子

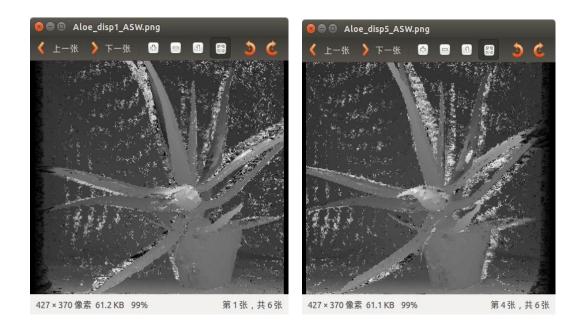
ii. 分母

b) 单个测例 Aloe 效果

ods [18], are shown in Figs. 7–8. The proposed algorithm is run with a constant parameter setting across all four images: the size of a support window = (33×33) , $\gamma_c = 7$, $\gamma_p = 36$. As shown in Figs. 7–8, the proposed method

为了可以比较之前的结果, size=5, rc=7, rp=36

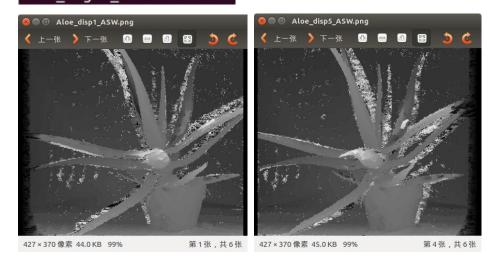
duration = 206 seconds
Aloe_Left_ASW: 31.33%
Aloe_Right_ASW: 31.39%



这是跑两张图的效果,确实很慢...

Size=11, rc=7, rp=36:

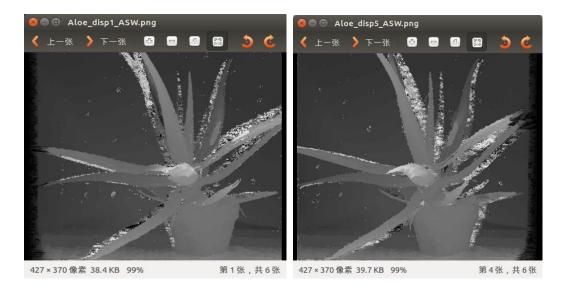
duration = 1050 seconds Aloe_Left_ASW: 24.06% Aloe_Right_ASW: 24.72%



试跑 size=33 , rc=7, rp=36:

跑了 2 个多小时....效果提升得不是很明显...如下图..

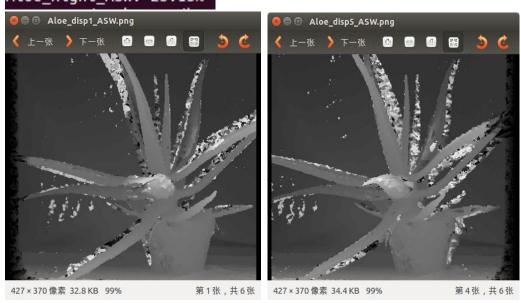
duration = 9123 seconds
Aloe_Left_ASW: 22.16%
Aloe_Right_ASW: 23.08%



把 rc\rp 的值交换,再取:

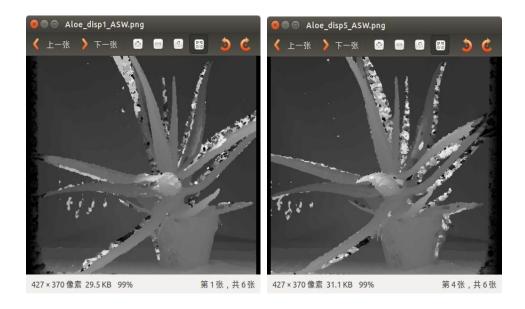
size=5, rc=36, rp=7:(坏点率相对 NCC 有所下降)

duration = 225 seconds Aloe_Left_ASW: 21.95% Aloe_Right_ASW: 23.13%



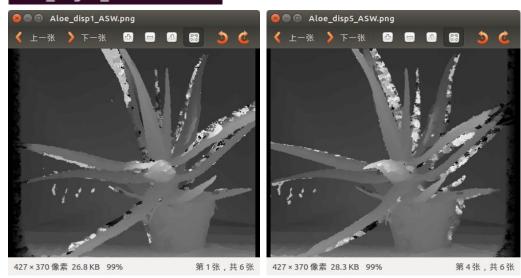
Size=7,rc=36,rp=7: (坏点率下降不明显)

duration = 433 seconds Aloe_Left_ASW: 21.00% Aloe_Right_ASW: 22.25%



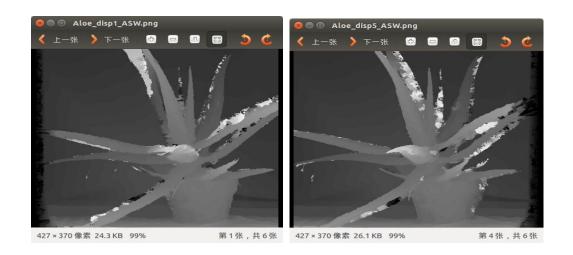
Size=11,rc=36,rp=7:

duration = 1045 seconds Aloe_Left_ASW: 20.19% Aloe_Right_ASW: 21.55%



Size=33*33, rc=36, rp=7

duration = 9242 seconds Aloe_Left_ASW: 19.44% Aloe_Right_ASW: 20.75%



由此可知 ,ASW 的效果在 11*11 以内的效果都是不明显 ,当 patch 的大小>=11*11 时 , 会的到比较好的效果。

c) 全部测例比较

i. Test1

参数设置:

SSD&NCC:size = 5*5

ASW:size = 11*11, rc = 7, rp = 36

Aloe_Left_ASW: 24.06% Aloe Left SSD: 24.72% Aloe Left NCC: 23.64% Aloe Right ASW: 24.72% Aloe Right SSD: 25.78% Aloe Right NCC: 24.20% Baby1 Left ASW: 34.32% Baby1_Left_SSD: 33.65% Baby1 Left NCC: 20.70% Baby1 Right ASW: 34.82% Baby1 Right SSD: 33.31% Baby1 Right NCC: 20.78% Baby2 Left ASW: 41.70% Baby2_Left_SSD: 38.97% Baby2 Left NCC: 28.33% Baby2 Right ASW: 41.85% Baby2_Right_SSD: 39.25% Baby2 Right NCC: 29.19% Baby3 Left ASW: 46.33% Baby3 Left SSD: 43.15% Baby3 Left NCC: 29.24% Baby3 Right ASW: 44.66% Baby3 Right SSD: 43.08% Baby3 Right NCC: 29.34% Bowling1 Left ASW: 64.82% Bowling1 Left SSD: 69.00% Bowling1 Left NCC: 44.21% Bowling1 Right ASW: 65.79% Bowling1 Right SSD: 69.41% Bowling1 Right NCC: 44.25% Bowling2 Left ASW: 44.85% Bowling2 Left SSD: 50.76% Bowling2 Left NCC: 32.08% Bowling2 Right ASW: 44.62% Bowling2 Right SSD: 50.46% Bowling2 Right NCC: 32.29% Cloth1 Left ASW: 14.02% Cloth1 Left SSD: 10.35% Cloth1 Left NCC: 10.37% Cloth1 Right ASW: 12.38% Cloth1 Right SSD: 8.47% Cloth1 Right NCC: 8.50% Cloth2 Left ASW: 30.65% Cloth2 Left SSD: 31.50% Cloth2 Left NCC: 19.39% Cloth2 Right ASW: 30.72% Cloth2 Right SSD: 31.86% Cloth2 Right NCC: 19.87% Cloth3 Left ASW: 17.12% Cloth3 Left SSD: 15.92% Cloth3 Left NCC: 14.80% Cloth3 Right ASW: 15.82% Cloth3 Right SSD: 14.38% Cloth3 Right NCC: 13.04% Cloth4 Left ASW: 24.18% Cloth4 Left SSD: 22.86% Cloth4 Left NCC: 18.96% Cloth4 Right ASW: 25.81% Cloth4 Right SSD: 24.85% Cloth4 Right NCC: 20.97% Flowerpots Left ASW: 57.87% Flowerpots Left SSD: 59.34%

Flowerpots_Left_NCC: 39.52%
Flowerpots_Right_ASW: 57.61%
Flowerpots_Right_SSD: 59.46%
Flowerpots_Right_NCC: 40.28%
Lampshade1_Left_ASW: 57.70%
Lampshade1_Left_SSD: 61.43%
Lampshade1_Left_NCC: 48.94%
Lampshade1_Right_ASW: 56.86%
Lampshade1_Right_SSD: 60.47%
Lampshade1_Right_NCC: 48.93%
Lampshade2_Left_ASW: 69.81%
Lampshade2_Left_SSD: 73.89%
Lampshade2_Left_NCC: 50.19%

Lampshade2_Right_ASW: 70.14% Lampshade2_Right_SSD: 73.35% Lampshade2_Right_NCC: 50.67%

Midd1_Left_ASW: 60.68% Midd1_Left_SSD: 62.81% Midd1_Left_NCC: 58.65% Midd1_Right_ASW: 60.63% Midd1_Right_SSD: 62.50%

Midd1_Right_NCC: 58.60% Midd2_Left_ASW: 70.45%

Midd2_Left_SSD: 70.74% Midd2_Left_NCC: 59.35% Midd2_Right_ASW: 70.89% Midd2_Right_SSD: 71.26%

Midd2_Right_NCC: 58.87% Monopoly_Left_ASW: 78.42% Monopoly_Left_SSD: 67.26% Monopoly_Left_NCC: 51.81% Monopoly_Right_ASW: 78.99%

Monopoly_Right_SSD: 65.99% Monopoly_Right_NCC: 48.26%

Plastic_Left_ASW: 79.93%
Plastic_Left_SSD: 82.16%
Plastic_Left_NCC: 71.18%
Plastic_Right_ASW: 81.46%
Plastic_Right_SSD: 82.99%
Plastic_Right_NCC: 70.66%
Rocks1_Left_ASW: 26.06%
Rocks1_Left_SSD: 24.52%

Rocks1_Left_NCC: 18.64% Rocks1_Right_ASW: 25.37% Rocks1 Right SSD: 23.80% Rocks1 Right NCC: 18.06% Rocks2 Left ASW: 26.27% Rocks2 Left SSD: 23.66% Rocks2 Left NCC: 17.95% Rocks2 Right ASW: 24.86% Rocks2 Right SSD: 21.92% Rocks2 Right NCC: 16.43% Wood1 Left ASW: 35.25% Wood1 Left SSD: 41.51% Wood1 Left NCC: 24.38% Wood1 Right ASW: 33.72% Wood1 Right SSD: 40.64% Wood1 Right NCC: 21.78% Wood2 Left ASW: 41.13% Wood2 Left SSD: 50.02% Wood2 Left NCC: 26.82% Wood2 Right ASW: 40.52% Wood2 Right SSD: 50.35% Wood2 Right NCC: 27.21%

比较结果,似乎 ASW 处理过后的视差图质量仅比 SSD 的稍微好一点,

而且也是普遍地比 NCC 差,决定在做一个 Test2

ii. Test2

参数设置:

SSD&NCC:size = 5*5

ASW:size = 11*11, rc = 36, rp = 7

duration = 25281 seconds

Aloe_Left_ASW: 20.19%
Aloe_Left_SSD: 24.72%
Aloe_Left_NCC: 23.64%
Aloe_Right_ASW: 21.55%
Aloe_Right_SSD: 25.78%
Aloe_Right_NCC: 24.20%
Baby1_Left_ASW: 23.75%
Baby1_Left_SSD: 33.65%
Baby1_Left_NCC: 20.70%
Baby1_Right_ASW: 23.23%

Baby1 Right SSD: 33.31% Baby1 Right NCC: 20.78% Baby2 Left ASW: 30.75% Baby2 Left SSD: 38.97% Baby2 Left NCC: 28.33% Baby2 Right ASW: 31.75% Baby2 Right SSD: 39.25% Baby2 Right NCC: 29.19% Baby3 Left ASW: 36.20% Baby3 Left SSD: 43.15% Baby3 Left NCC: 29.24% Baby3 Right ASW: 35.19% Baby3 Right SSD: 43.08% Baby3 Right NCC: 29.34% Bowling1 Left ASW: 61.11% Bowling1 Left SSD: 69.00% Bowling1 Left NCC: 44.21% Bowling1 Right ASW: 61.72% Bowling1 Right SSD: 69.41% Bowling1 Right NCC: 44.25% Bowling2 Left ASW: 40.55% Bowling2 Left SSD: 50.76% Bowling2 Left NCC: 32.08% Bowling2 Right ASW: 40.05% Bowling2 Right SSD: 50.46% Bowling2 Right NCC: 32.29% Cloth1 Left ASW: 9.87% Cloth1 Left SSD: 10.35% Cloth1 Left NCC: 10.37% Cloth1 Right ASW: 8.01% Cloth1 Right SSD: 8.47% Cloth1 Right NCC: 8.50% Cloth2 Left ASW: 23.81% Cloth2 Left SSD: 31.50% Cloth2 Left NCC: 19.39% Cloth2 Right ASW: 23.80% Cloth2 Right SSD: 31.86% Cloth2 Right NCC: 19.87% Cloth3 Left ASW: 12.69% Cloth3 Left SSD: 15.92% Cloth3 Left NCC: 14.80% Cloth3 Right ASW: 10.95% Cloth3 Right SSD: 14.38% Cloth3 Right NCC: 13.04%

Cloth4 Left ASW: 19.59% Cloth4 Left SSD: 22.86% Cloth4 Left NCC: 18.96% Cloth4 Right ASW: 21.38% Cloth4_Right SSD: 24.85% Cloth4 Right NCC: 20.97% Flowerpots Left ASW: 55.40% Flowerpots Left SSD: 59.34% Flowerpots Left NCC: 39.52% Flowerpots Right ASW: 55.14% Flowerpots Right SSD: 59.46% Flowerpots Right NCC: 40.28% Lampshade1 Left ASW: 53.89% Lampshade1 Left SSD: 61.43% Lampshade1 Left NCC: 48.94% Lampshade1 Right ASW: 52.80% Lampshade1 Right SSD: 60.47% Lampshade1 Right NCC: 48.93% Lampshade2 Left ASW: 66.81% Lampshade2 Left SSD: 73.89% Lampshade2 Left NCC: 50.19% Lampshade2 Right ASW: 67.17% Lampshade2 Right SSD: 73.35% Lampshade2 Right NCC: 50.67% Midd1 Left ASW: 56.32% Midd1 Left SSD: 62.81% Midd1 Left NCC: 58.65% Midd1 Right ASW: 56.19% Midd1 Right SSD: 62.50% Midd1 Right NCC: 58.60% Midd2 Left ASW: 65.54% Midd2 Left SSD: 70.74% Midd2 Left NCC: 59.35% Midd2 Right ASW: 65.59% Midd2 Right SSD: 71.26% Midd2 Right NCC: 58.87% Monopoly Left ASW: 62.96% Monopoly Left SSD: 67.26%

Monopoly_Right_NCC: 48.26% Plastic_Left_ASW: 76.73% Plastic_Left_SSD: 82.16%

Monopoly_Left_NCC: 51.81% Monopoly_Right_ASW: 62.80% Monopoly_Right_SSD: 65.99% Plastic Left NCC: 71.18% Plastic Right ASW: 77.13% Plastic Right SSD: 82.99% Plastic Right NCC: 70.66% Rocks1 Left ASW: 21.75% Rocks1 Left SSD: 24.52% Rocks1 Left NCC: 18.64% Rocks1 Right ASW: 21.06% Rocks1 Right SSD: 23.80% Rocks1 Right NCC: 18.06% Rocks2 Left ASW: 20.86% Rocks2 Left SSD: 23.66% Rocks2 Left NCC: 17.95% Rocks2 Right ASW: 18.88% Rocks2 Right SSD: 21.92% Rocks2 Right NCC: 16.43% Wood1 Left ASW: 28.97% Wood1 Left SSD: 41.51% Wood1 Left NCC: 24.38% Wood1 Right ASW: 26.91% Wood1 Right SSD: 40.64% Wood1 Right NCC: 21.78% Wood2 Left ASW: 38.27% Wood2 Left SSD: 50.02% Wood2 Left NCC: 26.82% Wood2 Right ASW: 37.63% Wood2 Right SSD: 50.35% Wood2 Right NCC: 27.21%

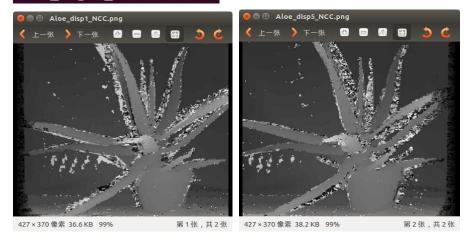
从上面可以看出,11*11 的 ASW 处理效果还不是很理想,虽然总体上处理效果优于 SSD,并且一部分的图像处理效果优于 NCC,但也有很多测例处理效果比 NCC 差的。其实很想跑一下 33*33 的测例,看看整体效果,但是估计了一下时间,大概需要 2-3 days,太慢了,ASW 的算法需要五个循环嵌套计算,暂时还想不出该怎么优化。

6.与 NCC 之间比较

A) NCC

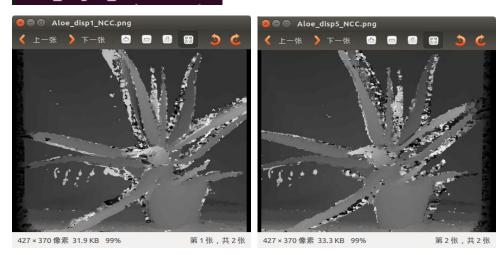
i. 5*5

duration = 29 seconds
Aloe_Left_NCC: 23.64%
Aloe_Right_NCC: 24.20%



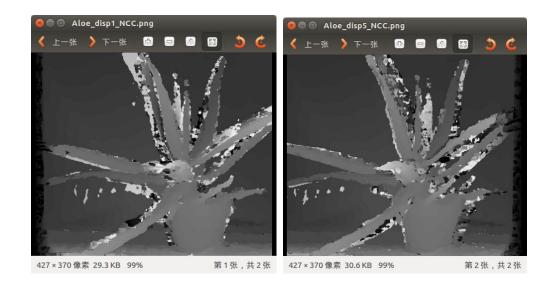
ii. 7*7

duration = 57 seconds
Aloe_Left_NCC: 24.67%
Aloe_Right_NCC: 25.34%



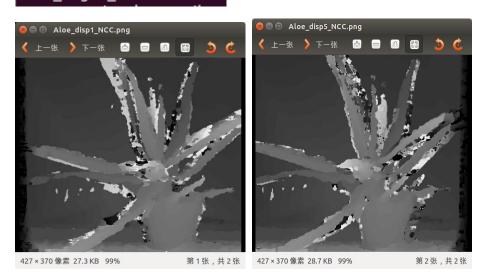
iii. 9*9

duration = 89 seconds Aloe_Left_NCC: 26.08% Aloe_Right_NCC: 26.79%



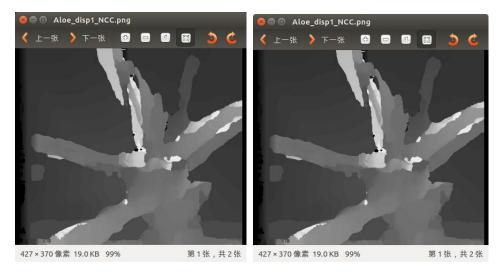
iv. 11*11

duration = 133 seconds
Aloe_Left_NCC: 27.35%
Aloe_Right_NCC: 28.08%



v. 33*33

duration = 1107 seconds
Aloe_Left_NCC: 37.25%
Aloe_Right_NCC: 36.87%



B)结论

从以上的比较可以看出,NCC的主要优点在于,强度增加时并不明显影响视图匹配的效率和质量,但是 patch 窗口增大的时候,视差匹配图的效果就越来越差,坏点率也一直增加。对比 ASW 算法的匹配,小窗口下的 ASW 匹配并不如 NCC、SSD 的效果好,如 3*3、5*5,随着 patch 窗口增大,其处理的视察匹配结果越好,到了 33*33时,aloe 测例的图形坏点率能达到 20%以下,但是,事实上窗口大小过了 11*11 之后,处理结果的质量上升得也不明显了,对比 11*11、33*33 的结果其实相差不大。

最后的总结:

- 1. 这次 project 因为对性能有要求,需要比较,所以增加了一些 API 来实现这些功能,用 time () 计数,测试各 SSD、NCC、ASW 的性能,同事也有用到 mkdir (dir,mode) 函数来创建文件夹,存储测试结果。
- 2. 关于坏点率的得到,因为 evaluate 函数是有直接输出结果的,可以利用重定向直接写入目标文档。