Written Assignment 3

1. Open "conesNoise.txt". What combination of match cost functions and smoothing give you the best error score? Why do these work best?

Any combination involves Gaussian filtering or bilateral filtering than could remove the noise.

2. Open "conesGainOffset.txt". What combination of match cost functions and smoothing give you the best error score? Why do these work best?

Any combination involves NCC which could be more robust when dealing gain.

3. Open "SouthSister.txt". What combination of match cost functions and smoothing give you the best results when rendering? Do the same parameters work best for "Garfield.txt"?

Generally the parameters for both test data will not be the same.
South Sisters has minor gain difference in its images and is more background with gradual change depth, Garfield has more foreground-baground object separation but because the focus is on the foreground, the background appear to has higher disparity. Although what's the same in these two data sets is both of them are having inconsistent sharp edges introduced by grass, leaves and trees, but they better be treated as noise and not take too much into calculation. On the other hand, Garfield has more consistent edges on the chair, car, bus and the wooden plate. So edge preserving method like those with bilateral filtering would work better in Garfield while noise removal method like those with Gaussian filtering would perform well in South Sisters. With so many details, method with large window size might not be preferable.

4. Download and read the following papers: Write a paragraph (6-8 sentences) on each paper describing the benefits and drawbacks of each approach.

Large Occlusion Stereo, IJCV 1999
Aaron F. Bobick and Stephen S. Intille
Pro: constraint setting for complexity reduction
Cons: images that contain small foreground object generating a large occlusion region is a violation of the ordering constraint, and images that only have short match regions interspersed with many disparity jumps won't work well.

Stereo Matching Using Belief Propagation, PAMI 2003
Jian Sun, Nan-Ning Zheng, Heung-Yeung Shum
Pros: lowest possible error, better results when using multiview stereo
Cons: generally computationally expensive, still hard to work on textureless (need even more iteration/time)

Adaptive Support-Weight Approach for Correspondence Search, PAMI 2006
Kuk-Jin Yoon, In So Kweon
Pros: generally very good depth/edge representation and low error (see the lamp swing arm in Tsukuba), does not depend on the initial disparity estimation, fairly robust against different sized support windows
Cons: computationally intensive, not work that well in highly textured and repetitive textured areas

Which approach would be best for realtime applications?
Speed Comparison:
Large Occlusion Stereo ? Stereo Matching Using Belief Propagation > Adaptive Support-Weight Approach for Correspondence Search **(Point will also be given because of good reasoning)**

Large Occlusion Stereo:
(Quoted from the paper) Running on a HP 730 workstation with a 515 x 512 image using nine 7x7 filters and a maximum disparity shift of 100 pixels, our current implementation takes a few seconds per scanline. However, since the most time consuming operations are simple window-based cross-correlation, the entire procedure could be made to run near real time with simple dedicated hardware. Furthermore, this step was used solely to provide GCPs; a faster high confidence match detector would eliminate most of this overhead.

Stereo Matching Using Belief Propagation:
(Quoted from the paper)

TABLE 3
Running Time of BP Algorithm on Tsukuba Data

Iterations	Time(seconds)		Tsukuba
	standard	speedup	$B_{\bar{0}}$
1	1.4	1.1	19.67
8	10.2	7.9	4.24
16	21.6	15.7	2.53
32	40.4	28.4	1.69
64	82.8	51.6	1.15
64 (Dual CPU)	43.1	27.4	1.15

Adaptive Support-Weight Approach for Correspondence Search:
(Quoted from the paper) The proposed method, however, is computationally a little more expensive than other area-based local methods because of the pixel-wise adaptive support-weight computation. For instance, the running time for the “Tsukuba” image with a (35 35) support window is about one minute on the AMD 2700+ machine. Fortunately, however, the runtime of the proposed method can be reduced by using parallel processors because the support-weights can be computed in parallel.

Since everyone would be more familiar with certain methodologies than others, it is possible to have different conclusions toward possible speed up when comparing between these papers. However, based on the result and evaluation data from the paper, “Large Occlusion Stereo” uses ground control points to greatly reduce complexity in calculate disparity. This is the only paper described that it is possible to replace the most computation-intensive process by hardware support. If taking this paper’s publication time into consideration, it is very likely to be implemented into realtime application nowadays. If the hardware realization isn’t true, the second candidate would be “Stereo Matching Using Belief Propagation” because it provides a trade-off between speed and accuracy. If a few errors are permitted, it is likely to gain a fair amount of speed-up by reducing iterations. Points will be give if reason supports either of the two methods.

Which paper is best for image-based rendering?

What we're looking for is the algorithm that could smoothly separate the object in order to produce visually pleasant result in rendering. The nature of Adaptive Support-Weight Approach would produce most promising edges on object. If multiview stereo is used, Belief Propagation could also achieve similar outcome.

Adaptive Support-Weight Approach for Correspondence Search:

Stereo Matching Using Belief Propagation:

Stereo Matching Using Belief Propagation with multiview stereo:

Which produces the lowest disparity errors?

Based on the result and table provided by the papers, “Stereo Matching Using Belief Propagation” and “Adaptive Support-Weight Approach for Correspondence Search” are competitive in lowest disparity errors, but “Stereo Matching Using Belief Propagation” seems to be able to reduce the error even further.

Stereo Matching Using Belief Propagation:

Algorithms	Tsukuba			Sawtooth			Venus			Map	
	$B_{\bar{O}}$	$B_{\bar{T}}$	B_D	$B_{\bar{O}}$	$B_{\bar{T}}$	B_D	$B_{\bar{O}}$	$B_{\bar{T}}$	B_D	$B_{\bar{O}}$	B_D
Belief prop. (seg)	1.15	0.42	6.31	0.98	0.30	4.83	1.00	0.76	9.13	0.84	5.27
Belief prop.	1.61	0.66	9.17	0.85	0.37	7.92	1.17	1.00	12.87	0.67	3.42
Graph cuts [30]	1.94	1.09	9.49	1.30	0.06	6.34	1.79	2.61	6.91	0.31	3.88
GC+occl. [22]	1.27	0.43	6.90	0.36	0.00	3.65	2.79	5.39	2.54	1.79	10.08
Graph cuts [8]	1.86	1.00	9.35	0.42	0.14	3.76	1.69	2.30	5.40	2.39	9.35
Realtime SAD [16]	4.25	4.47	15.05	1.32	0.35	9.21	1.53	1.80	12.33	0.81	11.35
Bay. diff. [30]	6.49	11.62	12.29	1.43	0.69	9.29	3.89	7.15	18.17	0.20	2.49
SSD+MF [30]	5.23	3.80	24.66	2.21	0.72	13.97	3.74	6.82	12.94	0.66	9.35
Scanl. opt. [30]	5.08	6.78	11.94	4.06	2.64	11.90	9.44	14.59	18.20	1.84	10.22
Dyn. prog. [30]	4.12	4.63	12.34	4.84	3.71	13.26	10.10	15.01	17.12	3.33	14.04

With multiview:

TABLE 4
The Performance of Our BP Multiview Stereo Algorithm on “Tsukuba” Sequence

Algorithms	Tsukuba		
	$B_{\bar{O}}$	$B_{\bar{T}}$	B_D
Belief prop. (multi-view)	0.95	0.25	5.40
Belief prop. (two-view)	1.15	0.42	6.31

Adaptive Support-Weight Approach for Correspondence Search:

	Tsukuba			Sawtooth			Venus			Map	
	nonocc.	untex.	disc.	nonocc.	untex.	disc.	nonocc.	untex.	disc.	nonocc.	disc.
Adapt. Weights	**1.29**	**0.61**	**6.72**	**0.97**	**0.34**	**4.82**	**0.99**	**0.89**	**6.66**	**1.13**	**11.55**
variable win. [4]	2.35	1.65	12.17	1.28	0.23	7.09	1.23	1.16	13.35	0.24	2.98
compact win. [3]	3.36	3.54	12.91	1.61	0.45	7.87	1.67	2.18	13.24	0.33	3.94
cooperative [20]	3.49	3.65	14.77	2.03	2.29	13.41	2.57	3.52	26.38	0.22	2.37
Bay. diff. [19]	6.49	11.62	12.29	1.45	0.72	9.29	4.00	7.21	18.39	0.20	2.49
shiftable win. [7]	5.23	3.80	24.66	2.21	0.72	13.97	3.74	6.82	12.94	0.66	9.35

Also from http://vision.middlebury.edu/stereo/eval/, one can see that BP method are generally better.

Finally, write a paragraph on how you might improve upon their results by either using a new idea, or by combining the approaches.

Points will be given if the proposed method is reasonable.