# Final Project Topics

CS6550 Computer Vision



# List of Final Topics

Image Classification

Image Saliency Detection

Image Segmentation (Learning Based)

Image Restoration

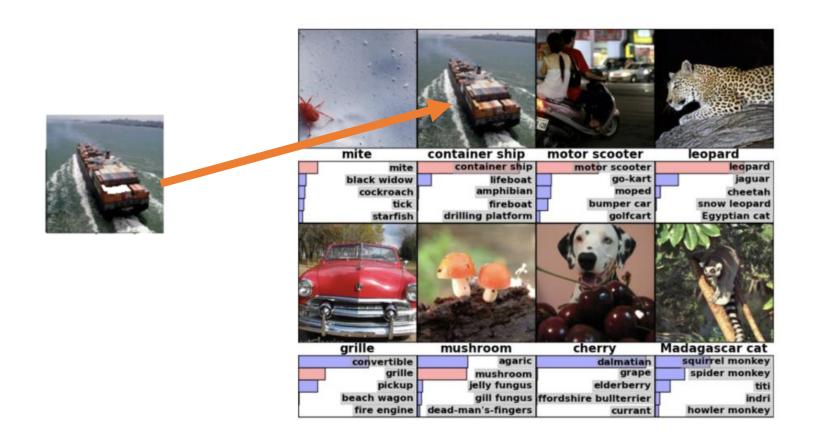
Object Detection

Facial Expression Recognition

Gesture Recognition

Stereo Matching

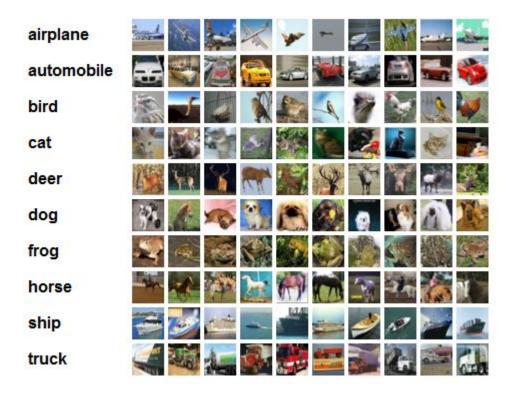
Categorize or detect text in the picture.



References: https://blog.acolyer.org/2016/04/20/imagenet-classification-with-deep-convolutional-neural-networks/

- How to do "Classification"?
  - 1. Preprocessing
  - 2. Feature extraction
  - 3. Modeling
    - Description of each class in mathematical form
  - 4. Classification
    - The classifier divides the feature space into class regions

- Datasets
  - ImageNet : http://image-net.org/
  - CIFAR : https://www.cs.toronto.edu/~kriz/cifar.html



References: https://www.cs.toronto.edu/~kriz/cifar.html

#### References

- https://papers.nips.cc/paper/4824-imagenetclassification-with-deep-convolutional-neuralnetworks.pdf
- http://vision.cse.psu.edu/seminars/talks/2009/random\_ \_tff/bosch07a.pdf
- http://cs.utsa.edu/~qitian/seminar/Spring11/02\_18\_11/ECCV10.pdf

• Finding salient objects in the source image.

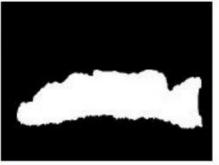








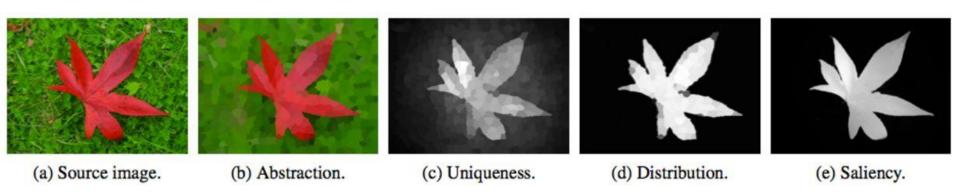








- Contrast Based Filter Saliency
  - Abstraction: decomposes an image into compact represented by their mean color.
  - Uniqueness: regions which stand out from other regions should be labeled more salient.
  - Distribution: foreground objects are generally more compact, thus we measure the spatial distribution.



References: https://graphics.ethz.ch/~perazzif/saliency\_filters/

- Datasets
  - https://graphics.ethz.ch/~perazzif/saliency\_filters/files /SF\_maps.zip
  - http://saliency.mit.edu/datasets.html







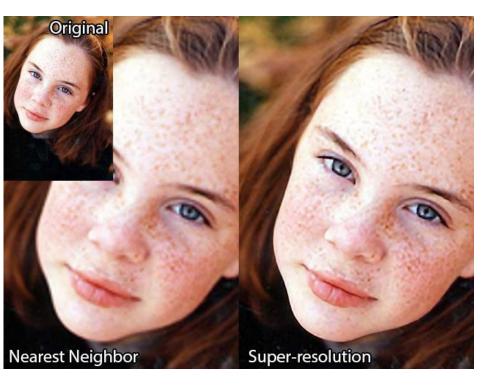
#### References

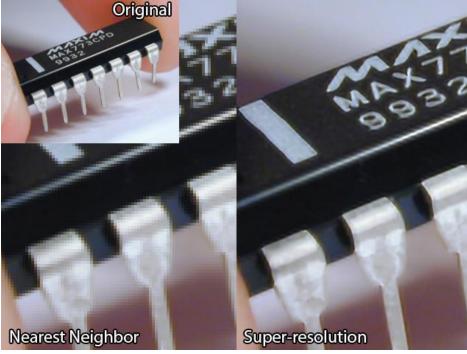
- https://graphics.ethz.ch/~perazzif/saliency\_filters/files /saliency\_filters\_cvpr\_2012.pdf
- http://www.cse.cuhk.edu.hk/leojia/projects/hsaliency/ papers/hsaliency.pdf
- https://arxiv.org/pdf/1505.01173v1.pdf

Super-Resolution
Inpainting / Completion

## Super-Resolution

- What is Super-Resolution?
  - Upscale the image to desire size (x2, x4, x8...)
- Possible solutions
  - Interpolations: Nearest Neighbor / Bicubic / Bilinear
  - Learning-based: Sparse Representation / Deep Learning



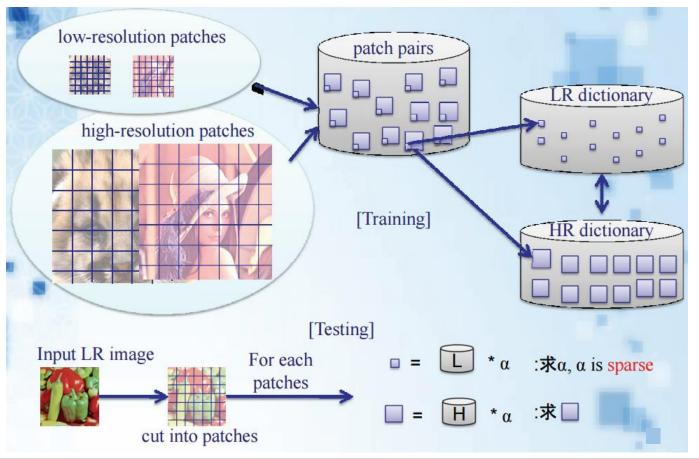


## Super-Resolution

- Sparse Representation [1]
  - 1. Training: Learned HR-LR pair dictionaries
  - 2. Testing: Solve the sparse coding
  - Reconstruct HR image

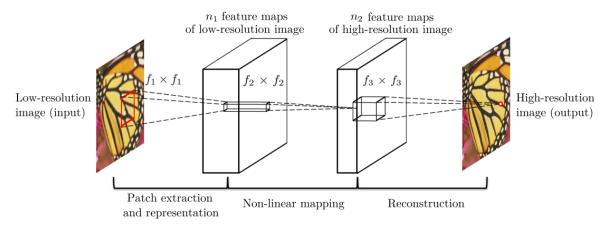
#### References

[1] <u>Image Super-Resolution</u>
<u>via</u>
Sparse Representation

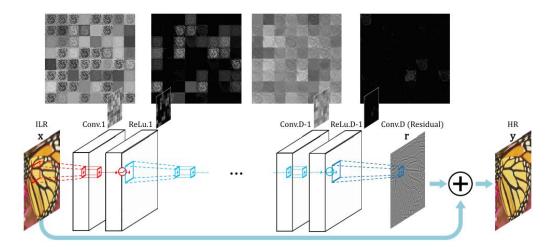


## Super-Resolution

- Deep Learning
  - SRCNN [2] Image Super-Resolution Using Deep Convolutional Networks



• VDSR [3] Accurate Image Super-Resolution Using Very Deep Convolutional Networks



### Super-Resolution

Training Datasets

The Berkeley Segmentation

Dataset and Benchmark (BSD 200)



Yang 91 Images



ImageNet (Not Suggested)



# Super-Resolution

Testing Datasets



Set 5



**Set 14** 



Urban 100



BSD 100



Sun-Hays 80

- **GitHub Resources:**
- Comparison with the state-of-the-art datasets
- Super-Resolution-Benchmarks

## Inpainting / Completion

- What is Inpainting or Completion?
  - To fill or complete the lost or unwanted regions in the images
- Related solutions
  - Vision-based (Patch Inpainting) / Numerical Optimization (TNNR)
  - MRF (Field of Experts) / Autoencoders / Deep Learning







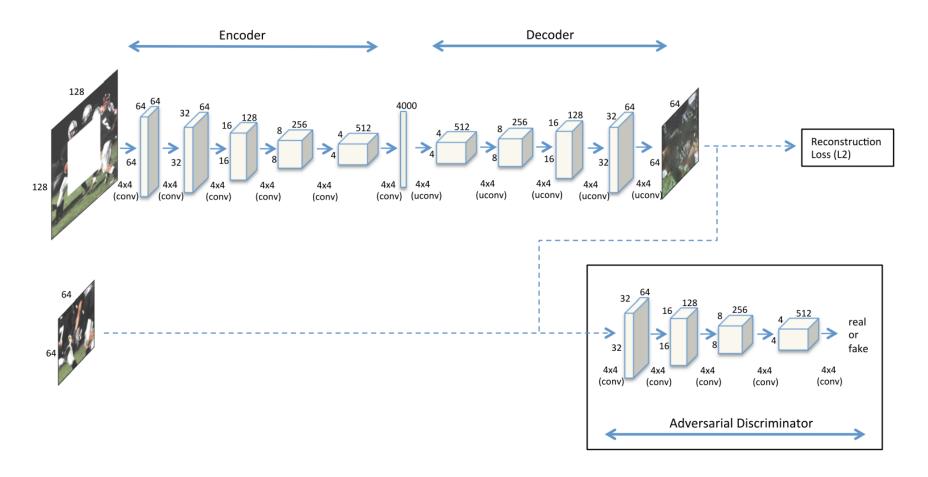






## Inpainting / Completion

- Autoencoders / Deep Learning
  - Conditional GANs
  - Context Encoder [1] Context Encoders: Feature Learning by Inpainting



### Inpainting / Completions

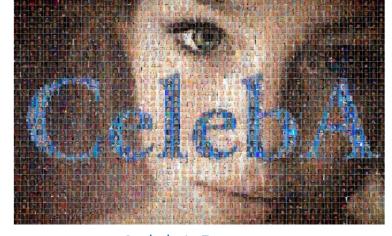
Datasets



TUM-Image Inpainting Database



Google Street View Data Set



CelebA Datasets

<u>The Berkeley Segmentation</u>

<u>Dataset and Benchmark</u> (BSD 200)



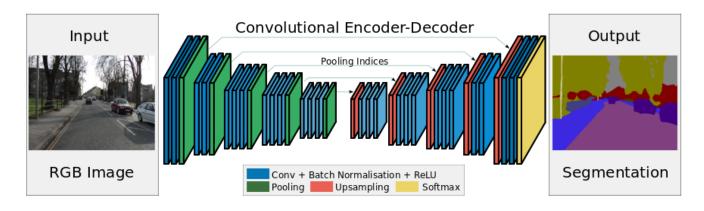


Focusing on Learning-based methods

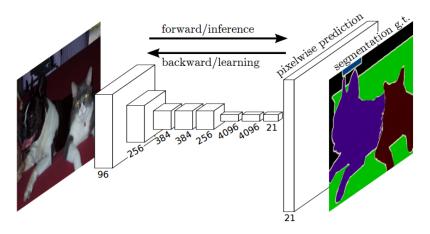
- What is Image Segmentation?
  - the process of partitioning a digital image into multiple segments (sets of pixels, also known as super-pixels).
  - The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.
- Related solutions
  - Grouping Super-Pixels / Kmeans
  - Deep Learning



- Deep Learning Methods: Directly generate segmentation results
  - SegNet [1]



Fully Convolutional Networks for Semantic Segmentation [2]



Datasets

The Berkeley Segmentation

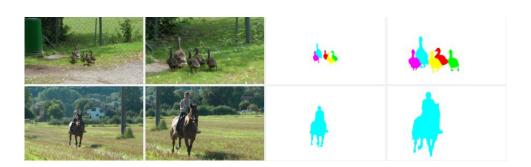
Dataset and Benchmark (BSD 200)



Visual Object Classes Challenge 2012



<u>Freiburg-Berkeley Motion</u> <u>Segmentation Dataset (FBMS-59)</u>



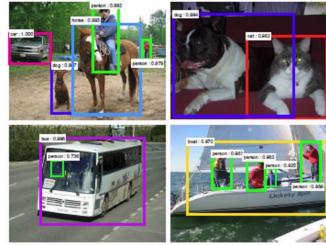
#### Problem

-Given an image, find all objects and mark them up with bounding

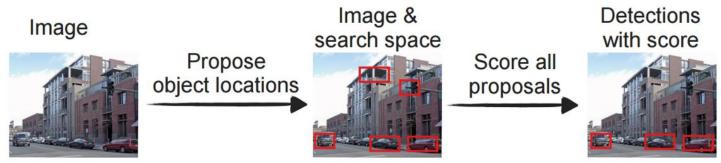
boxes and categories

#### Sub-problems

- Object proposal
- Image Classification



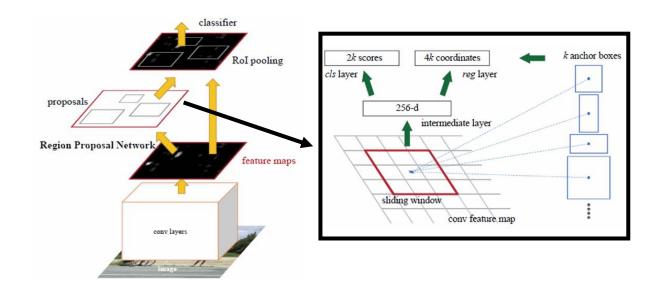
**Example of detection results** 



**Basic framework of object detection (FER)** 

#### Framework of Faster R-CNN

- Deep learning model
- -Shared CNN
- Region Proposal Network
- -Rol pooling



Faster R-CNN, NIPS2015

#### Evaluation dataset

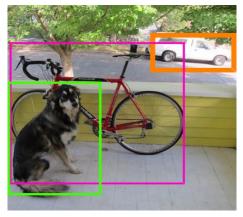
-MIT Street Scenes

http://cbcl.mit.edu/software-datasets/streetscenes/

-PASCAL VOC dataset

http://host.robots.ox.ac.uk/pascal/VOC/

-KITTI dataset



**Example of PASCAL VOC** 

http://www.xrce.xerox.com/Our-Research/Computer-Vision/Proxy-Virtual-Worlds











**Example of MIT Street Scenes** 

**Example of KITTI** 

#### Reference

- —Redmon, Joseph, et al. "You only look once: Unified, real-time object detection." *arXiv* preprint arXiv:1506.02640 (2015).
- Girshick, Ross. "Fast r-cnn." *Proceedings of the IEEE International Conference on Computer Vision*. 2015
- —Kye-Hyeon Kim, et al. "PVANET: Deep but Lightweight Neural Networks for Real-time Object Detection" arXiv:1608.08021.
- Dai, Jifeng, et al. "R-FCN: Object Detection via Region-based Fully Convolutional Networks." *arXiv preprint arXiv:1605.06409* (2016).

#### Tools

- Caffe http://caffe.berkeleyvision.org/
- —Tensorflow https://www.tensorflow.org/
- —Torch http://torch.ch/

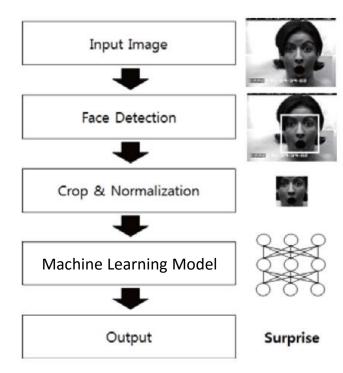
#### Problem

—Predict the emotion category (Anger, Disgust, Fear, Happiness, Sadness or Surprise) from a still-image or an

Approaches

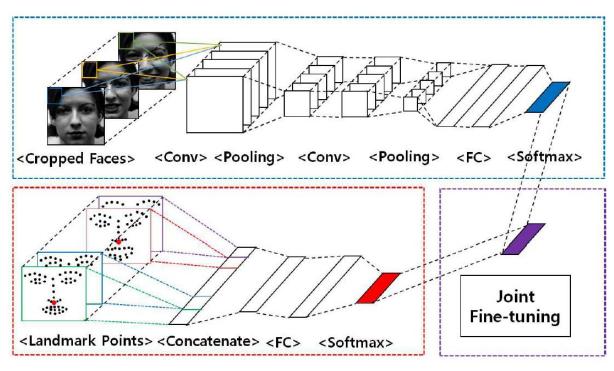
image sequence

- Image based framework
- Sequence based framework
- Preprocess
- Face detection
- —Face alignment



Basic framework of facial expression recognition (FER)

- Framework of image sequence approach
- Deep learning model
- —Appearance feature(CNN)
- Geometry feature(NN)
- Joint fine-tuning



**Joint Fine-Tuning Method, ICCV2015** 

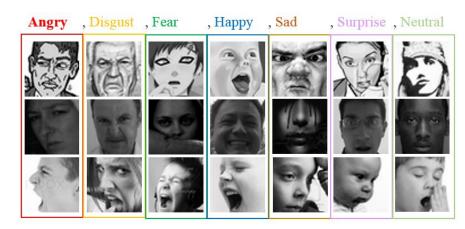
- Evaluation dataset
- -JAFFE database

http://www.kasrl.org/jaffe.html

-The CK+ database

http://www.consortium.ri.cmu.edu/ckagree/

-FER2013 dataset



**Example of the FER2013 dataset** 

https://www.kaggle.com/c/challenges-in-representation-learning-facial-expression-recognition-challenge/data



**Example of the JAFFE dataset** 



**Example of the CK+ dataset** 

#### References

- -Jung, Heechul, et al. "Joint fine-tuning in deep neural networks for facial expression recognition." *Proceedings of the IEEE International Conference on Computer Vision*. 2015.
- —Zhao, Xiangyun, et al. "Peak-piloted deep network for facial expression recognition." *European Conference on Computer Vision*. Springer International Publishing, 2016.
- Fabian Benitez-Quiroz, C., Ramprakash Srinivasan, and Aleix M. Martinez. "EmotioNet: An accurate, real-time algorithm for the automatic annotation of a million facial expressions in the wild." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2016.
- —Liu, Ping, et al. "Facial expression recognition via a boosted deep belief network." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2014.

#### • Tools

- Dlib C++ Library http://dlib.net/
- OpenCV http://opencv.org/

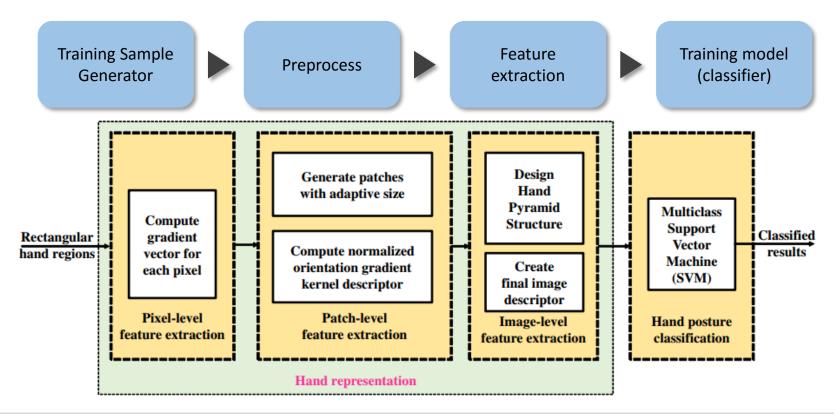
# Gesture Recognition

- Problem description
  - Given depth or RGB images with a specific hand pose
  - The goal is to solve a classification problem that seeks the pre-defined gesture classes which is most similar to the input data



- Sensor-based approach
- Vision-based approach
  - Model-based approach
  - Appearance-based approach

- Framework of hand posture recognition
  - Components
    - Training images
    - Testing images
    - Model

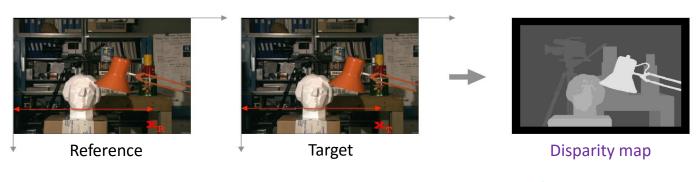


- Datasets
  - Multimedia Technology and Telecommunications Laboratory, University of Padova
    - http://lttm.dei.unipd.it/downloads/gesture/
  - ICVL Hand Posture Dataset
    - http://www.iis.ee.ic.ac.uk/~dtang/hand.html
  - IEEE Computer Society Workshop on Observing and understanding hands in action (HANDS 2015)
    - http://www.ics.uci.edu/~jsupanci/HANDS-2015/#

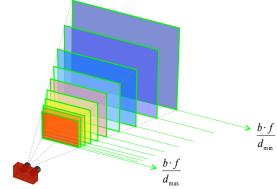
#### References

- G. Marin, F. Dominio, P. Zanuttigh, "Hand gesture recognition with Leap Motion and Kinect devices", IEEE International Conference on Image Processing (ICIP), Paris, France, 2014
- G. Marin, F. Dominio, P. Zanuttigh, "Hand Gesture Recognition with Jointly Calibrated Leap Motion and Depth Sensor", Multimedia Tools and Applications, 2015
- D. Tang, H.J. Chang\*, A. Tejani\*, T-K. Kim
   Latent Regression Forest: Structured Estimation of 3D Hand Posture, Proc. of IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)
- D. Tang, T.H. Yu and T-K. Kim
  Real-time Articulated Hand Pose Estimation using Semi-supervised
  Transductive Regression Forests, Proc. of IEEE Int. Conf. on Computer
  Vision (ICCV), Sydney, Australia, 2013
- Van-Toi NGUYEN et al, A New Hand Representation Based on Kernels for Hand Posture Recognition

- Problem description
  - It is a technique aimed at inferring depth from two or more cameras.
  - The **disparity** is the difference between the x coordinate of two corresponding points.
    - It is typically encoded with greyscale image (closer points are brighter).



 Depth measured by a stereo vision system is discretized into parallel planes (one for each disparity value)

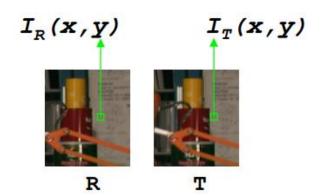


- According to [1] most stereo algorithms perform these steps:
  - 1. Matching cost computation
  - 2. Cost aggregation
  - 3. Disparity computation/optimization
  - 4. Disparity refinement
- Local algorithms
- Global algorithms

#### Matching cost computation

- Pixel-based matching costs
  - E.g. squared differences

$$E(x, y, d) = (I_R(x, y) - I_T(x + d, y))^2$$



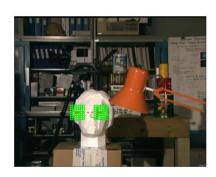
#### Cost aggregation

- Sum of squared differences (SSD)
  - E.g. squared differences

$$\sum_{(x,y)\in w} (I_R(x,y) - I_T(x+d,y))^2$$



Reference



Target

### Disparity computation/optimization

- Energy function  $E(d) = E_{data}(d) + E_{smooth}(d)$
- Relevant approaches are:
  - Graph Cuts
  - Belief Propagation

### Disparity refinement

- Raw disparity maps computed by correspondence algorithms contain outliers that must be identified and corrected
  - Sub-pixel interpolation
  - Image filtering techniques
  - Bidirectional Matching

- Evaluation & Datasets
  - Middlebury Stereo Datasets:
    - http://vision.middlebury.edu/stereo/data/
  - MPI Sintel Datasets :
    - http://sintel.is.tue.mpg.de/stereo

#### References

- Q. Yang, L. Wang, R. Yang, H. Stewénius, and D. Nistér. Stereo matching with color-weighted correlation, hierarchical belief propagation and occlusion handling. PAMI 2008.
- X. Mei, X. Sun, M. Zhou, S. Jiao, H. Wang, and X. Zhang. On building an accurate stereo matching system on graphics hardware. GPUCV 2011.
- Z. Wang and Z. Zheng. A region based stereo matching algorithm using cooperative optimization. CVPR 2008.
- D. Scharstein and R. Szeliski, A taxonomy and evaluation of dense two-frame stereo correspondence algorithms
- http://vision.deis.unibo.it/~smatt/Seminars/StereoVision.pdf
- H. Ha. et al High-quality Depth from Uncalibrated Small Motion Clip

# End

You can still choose other interesting topics