

# CVPR 2019 Notes

## Long Beach, CA, USA

Shuai Chen  
[shuaic92@gmail.com](mailto:shuaic92@gmail.com)

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This documents contains notes I took during CVPR 2019 conference in Long Beach, CA, USA. My motivation of making this document came from the inspiration of David Abel<sup>1</sup>. Please feel free to distribute it as well as correcting my typos and mistakes. My email is [shuaic92@gmail.com](mailto:shuaic92@gmail.com).

## 1 Conference Highlights

This was my first time took part in such an awesome academic conference. Most of my time spent in Deep Learning & Computational Photography related topics. However, I would also update some topics that I found interesting.

1. Around 10,000 people attend this year's conference. About 1300 papers were accepted in CVPR 2019. Reports saying number of attendees projected in 2035 will be over 1 million :). See Figure 1.

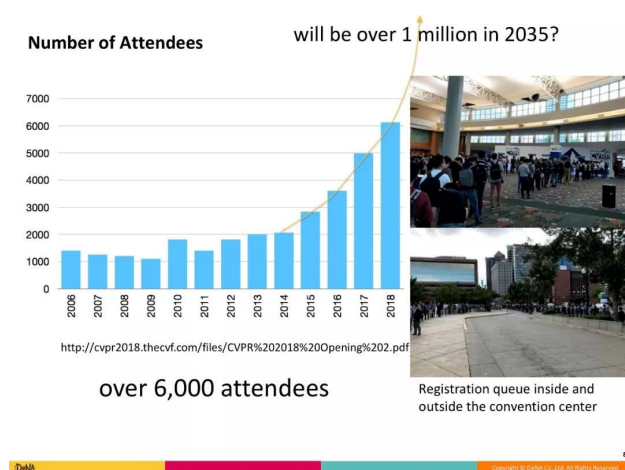


Figure 1: projection of attendees to reach 1 million by 2035

2. Comparing to last year, the number of papers accepted in CVPR 2019 increased about 30%. However, due to the fact that the number of papers submitted this year has increased 56.2%, thus the paper acceptance rate reduced 4% this year. See Figure 2.

<sup>1</sup><http://david-abel.github.io>

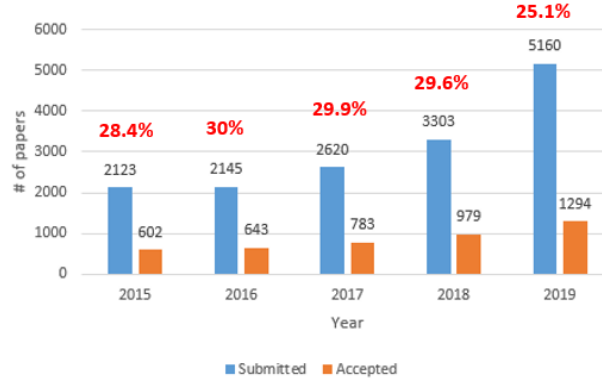


Figure 2: papers acceptance rate is 4% lower in CVPR 2019

3. Some of hot keywords in CVPR 2019 submission: Image, detection, 3d, object, video, segmentation, adversarial, recognition, visual. See Figure 3
4. More Meta-learning, One-shot/Few-shots learning, Graph Neural Networks papers started to emerge this year.
5. It's great to see a lot of fast pace improvement towards real-life low level image processing field.
6. Network Architecture Search was also another very popular topic. Great to see a burst of diverse solutions in this field.
7. Generative Adversarial Network was a hot topic again. Exciting progress were made again this year.

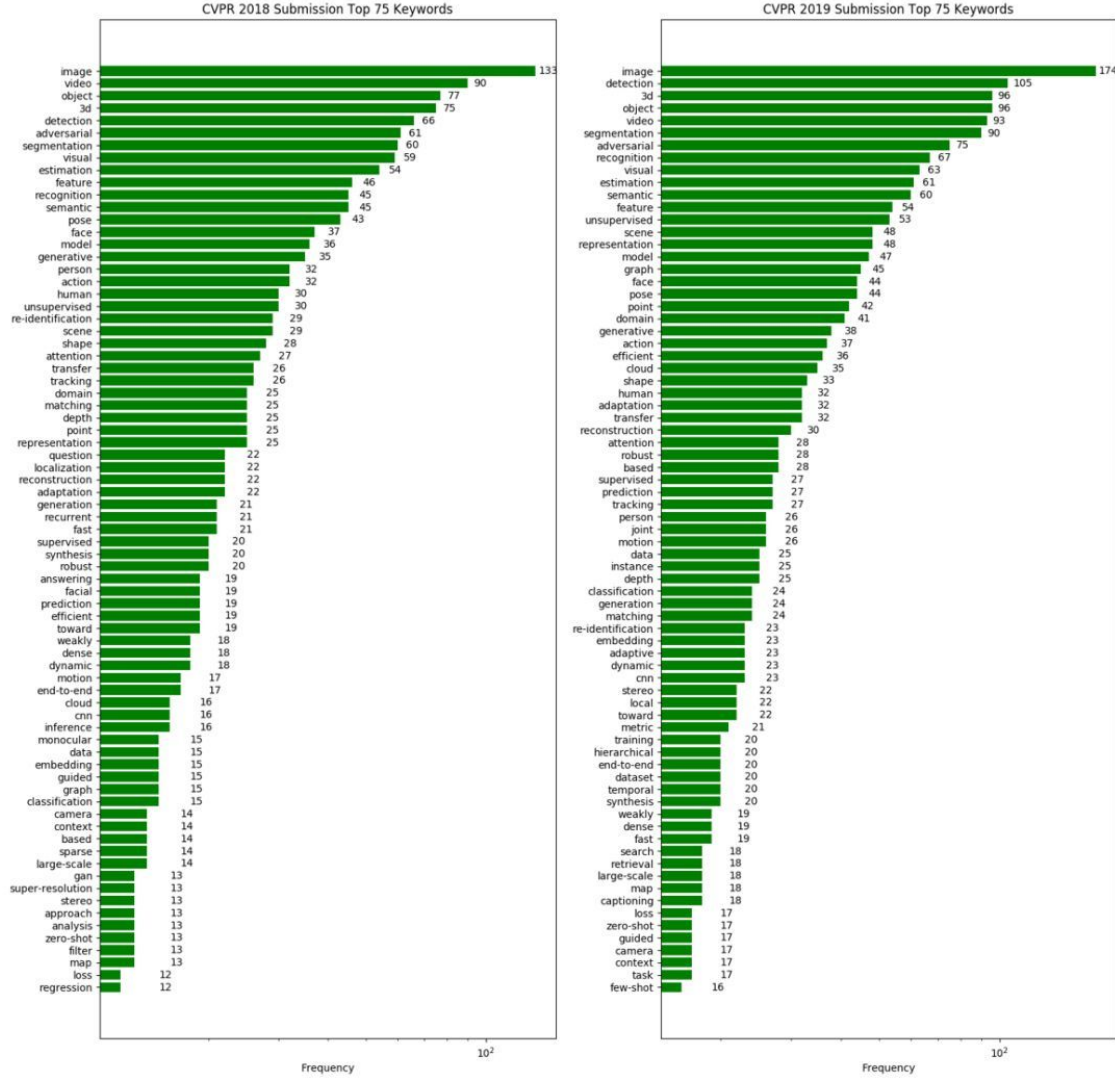


Figure 3: hot submission keywords CVPR 2018 vs. CVPR 2019

## 2 Sunday June 16th: Tutorials & Workshops

Caught up part of Deep-Vision workshop. I was a little bit confused on overwhelming tutorials and workshops. I also spent a lot of time trying to find the correct room. So first day's note was not really good. Please feel free to contact me and add some notes.

### 2.1 Workshop: Deep-Vision

#### 2.1.1 Topic: AI on Medicine, Speaker: Serena Yeung

Arrived at the end of the talk on this topic.

Talked about Towards full realization of an AI-assisted hospital: Integration of multimodal data sources.

Talked about Jointly Learning Energy Expenditures and Activities using Egocentric Multimodal Signals (CVPR 2017)

Will add a short paper summary here...

### **2.1.2 Topic: Video Re-Id, Speaker: Prof. Dr. Laura Leal-Taixé**

Tractor++ (reId+CMC)

CMC = motion camera model

### **2.1.3 Topic: Video Super-resolution, Speaker: Prof. Dr. Laura Leal-Taixé**

Designed new Temporal Loss to improve video SR performance. Great results.

### **2.1.4 Topic: Google Brain Pierre Sermanet: Self-Supervision and Play**

-Label Free

-Time-Contrastive Networks (TCN)

-Object-contrastive Networks

## 3 Monday June 17th: Tutorials & Workshops

### 3.1 Workshop: Computational Photography

Light Field Super-Resolution A Benchmark

Low Rank Poisson Denoising(LRPD)

#### 3.1.1 Professor Peyman Milanfar: Computation + Photography How the mobile phone became a camera

- Modern Mobile Imaging: Burst Photography. ?Burst Video?
- Classical camera pipeline -demosaiicing (Merging)
- Replace demosaicing with multiple frames
- Pixel Shifting
- Merge: Nonlinear Kernel Regression
- Merge High-res Grid -¿ up to 2x
- Source of motion imaging: 1. OIS, 2. (rough) alignment by (Natural) Physiological Tremor
- use OIS simulate tremor!!!!
- Aliasing + Phase diversity -¿ Multi-frame Super-res
- Visual System also appears to do super-resolution
- Handheld Multi-Frame Super-Resolution (Why not using GAN)
- Zoom Use Case: to zoom more: Upscale SISR, using RAISR
- Other Challenge in Computational Photography: Curation (NIMA for Aesthetic Quality, NIMA for Technical Quality)
- Camera Understand the Scene and the User
- Night Sight Mode: Super Night Sight on Merge Methods. ML on White Balance

#### 3.1.2 SuperSR

- Overfitting in Super Resolution
- MixUp: Data Synthesis with Learned Degradation

#### 3.1.3 Denoising

- Hanyang University
- Hierarchical Structure
- Iterative down-sampling and up-sampling
- Down-up Block
- Noise Level



### **3.1.4 Style-based GAN: Keras**

- Progressive GAN
- BigGAN
- Pose-Guided Face Rotation
- Mask-Guided Portrait Editing

### **3.1.5 Image Coloring Challenge**

### **3.1.6 Opportunity Chiuman Ho, Director of AI: Imaging in the Dark**

- $l_1$  &  $l_2$  since  $l_2$  penalize a lot on large loss
- Feature Loss

### **3.1.7 Blind Deconvolution: Professor Paolo Favaro**

- Learning to Extract Flawless Slow Motion from Blurry Videos CVPR 2019.
- $f = k * u + n$

### **3.1.8 EDVR**

### **3.1.9 Towards Versatile Image Restoration: Chen-Change LOY**

...

## **4 Tuesday June 18th: Main Conference Day 1**

### **4.1 CVPR Main Day 1**

Oral:

#### **4.1.1 GNN**

1. Few Shot Learning: EGNN
2. Few Shot Classification

#### **4.1.2 Kervolutional Neural Network**

1. Introduce nonlinearity in convolution

#### **4.1.3 Relu with high confident**

1. Adversarial confidence enhanced training (ACET)

#### **4.1.4 Structural Sensitivity of DCN to the Directions of FOurier Basis Functions**

#### **4.1.5 neural rejuvenation**

#### **4.1.6 On the Structural Sensitivity of Deep Convolution**

#### **4.1.7 Hardness aware Deep Metric Learning**

#### **4.1.8 Auto-Deeplab: NAS for Semantic Image Segmentation**

#### **4.1.9 Learning Loss for Active Learning**

1. Active Learning

#### **4.1.10 Striking the Right Balance With Uncertainty**

#### **4.1.11 Auto Augment**

#### **4.1.12 Zero Shot**

1. Domain Loss
2. Triplet Loss
3. Semantic Loss

#### **4.1.13 Zero-shot Task Transfer**

1. Regress the unknown zero-shot task

#### **4.1.14 C-MIL: sWeakly Supervised Object Detection**

1. Solve non-convex loss function problem

#### **4.1.15 Weakly Supervised Learning of Instance Segmentation**

1. Learning Displacements to Centroid (Find Instance)
2. Learning Class Boundaries (Find Shape)

#### **4.1.16 Attention-Based Dropout Layer for Weakly Supervised Object Localization**

1. Adversarial Erasing
2. Spatial Attention Transformation
3. Attention-based Dropout layer
4. attention-based, efficient, State of the art localization accuracy

#### **4.1.17 Domain Generalization by Sol Jigsaw Puzzles**

1. Recognition -¿ Jigsaw Puzzles
2. Domain Generalization
3. Multitask deep learning model

#### **4.1.18 Transferable Prototypical Networks for Unsupervised Domain Adaptation**

1. Most methods are cascaded model
2. Multitask into one network
3. Supervised classification loss, class-level discrepancy loss, sample-level discrepancy loss

#### **4.1.19 Blending-target Domain Adaptation**

1. Source-target domain discrimination, still lack of target domain area
2. Adaptation among Meta-sub-targets

#### **4.1.20 ELASTIC: Improving CNNs with dynamic Scaling Policies**

1. **Problem:** CNN image scaling are handcrafted
2. **Solution:** CNN to learn dynamic scaling policies

3. **Result:** Consistent improvement

#### 4.1.21 ScratchDet: Training Single-Shot Object Detectors From Scratch

1. **Problem:** High Computational cost on ImageNet, Learning bias from classification to detection, inconvenient to change the architecture of network
2. **Contribution:**
  1. Batch Norm
  2. Replace 7x7 by stacking 3x3 3x3...
  3. BatchNorm in the backbone key for detection to train from scratch

#### 4.1.22 SFNet: Learning Object-aware Semantic Correspondence

1. **Problem:** Lack of dataset semantic correspondences
2. **Solution:** 3.Loss functions: Mask consistency, smoothness, and ...
3. **Result:**

#### 4.1.23 Deep Metric Learning Beyond Binary Supervision

1. **Problem:** most metric learning are same or not (binary). Population pos and neg are unbalanced
2. **Solution:**
  1. Log-ratio loss.
  2. Dense Triplet Sampling
3. **Result:**
  1. Three retrieval: surpass state of the art

#### 4.1.24 Learning to Cluster Faces on an Affinity Graph

1. **Problem:** Clustering human faces, complex structure are difficult to use kmeans or spectral
2. **Solution:** Generate Proposal - GCN-Detection - GCN-Segmentation
3. **Result:** state of the art F-score

#### 4.1.25 C2AE: Class Conditioned Auto-Encoder for Open-Set

1. **Problem:** Open set recognition
2. **Solution:**
  1. Closed set training
  2. Open set training, Decoder
  3. Open-set Testing (k-Inference Algorithm)
3. **Results:**
  1. F-measure highest

## 1. Quantitative Analysis

### 4.1.26 Samsung: Learning to Quantize Deep Networks by Optimizing

1. **Problem:** Reducing bit-widths while minimizing accuracy drop
2. **Solution:** Find meaningful dynamic range for quantization
  1. Activation Quantizer
  2. Weight Quantizer
3. **Result:**
  1. better than others
  2. Heterogeneous training

### 4.1.27 Transfer Learning for Semantic Segmentation via Hierarchical Region Selection

1. **Problem:**
  1. Insufficient real data + a lot of unreal data
2. **Solution:**
  1. Source Image with Weighting Mask
  2. Feed in Source & target domain
  3. Use GAN to reduce domain differences

### 4.1.28 Unsupervised Learning of Dense Shape Correspondence

1. **Problem:** traditional supervised, want unsupervised
2. **Solutions:**
  1. No expensive annotations
  2. Geometric Invariants
3. **Result:**
  1. Achieve same result with Supervised
  2. Achieve state of the art accuracy without seen label
  4. Self-supervised Training Regime

### 4.1.29 Unsupervised Visual Domain Adaptation: A Deep Max-Margin Gaussian Process Approach

1. **Problem:** Traditional, learning source & target distributions. Fail at lack of domain labels -i  
No guarantee
2. **Solution:**
  1. Source-driven Gaussian Process posterior (H) inference
  2. Target domain Max Margin Separation

#### 4.1.30 Balanced Self-Paced Learning for Generative Adversarial Clustering Network

1. **Problem:**
2. **Solution:** Deep GAN Clustering Network
1. Entropy Minimization Loss

#### 4.1.31 Parallel Optimal Transport GAN

1. **Problem**

## 5 Wednesday June 19th: Main Conference Day 2

### 5.1 Photography Oral: (Day2)

#### 5.1.1 Photon-Flooded Single-Photon 3D Cameras

1. **Problem:** Sunlight disturb Ambient light
2. **Solution:**
  1. Find Optimal Filtering: low distortion, high SNR
3. **Result:**
  1. Long Range Low Power 3D Imaging

#### 5.1.2 High Flux Passive Imaging with Single-Photon Sensors

1. SPADs
2. **Problem:** Noise PF-SPAD, High Flux fail to catch Photons
3. **Solution:** PF-SPAD Sensor can catch High Dynamic Range
4. **Result:** PF-SPAD: SPADs as General-Purpose, Passive Sensors.

#### 5.1.3 Acoustic Non Line of sight Imaging

1. **Problem:** Expensive
2. **Solution:** Acoustic, cheap. Use Wall as mirror.

#### 5.1.4 Steady-State Non Line of Sight Imaging

1. **Problem:** Large setup size. Expensive
2. **Solution:**

#### 5.1.5 A Theory of Fermat Paths for Non line of sight shape reconstruction (CVPR19 best paper)

1. **Problem:** Non line of sight
2. **Solution:** Scanning the wall
  1. Fermat path lengths = discontinuities
  2. Fermat path = specula or boundary
  3. Add regularization term
  4. Optical Coherence Tomography to high resolution
3. **Result:**
  1. High resolution

### 5.1.6 Projector Photometric Compensation

1. **Problem:** Projection distort image
2. **Contribution:**
  1. CompenNet CNN
  2. Premarin method
  3. Benchmark
3. **Solution:**
  1. Capture Surface image and camera image
  2. Train CompenNet
4. **Result:**
  1. Surpass State of the art

### 5.1.7 Bringing a Blurry Frame Alive at High Frame-Rate With an Event Camera

1. **Problem:** Event camera likely to capture blur image
2. **Solution:**
  1. Double Integral while feeding in event.
  2. Find gradient descent by Fibonacci search
3. **Result:**
  1. Sharp Video Sequence

### 5.1.8 Bringing Alive Blurred Moments

1. **Problem:** unsuitable for realtime, Too many unknowns, estimate only in one image
2. **Solution:**
  1. Learn Extract motion from a sharp frame sequence
  2. Recurrent Video Encoder decoder

### 5.1.9 Learning to Synthesize Motion Blur

1. **Problem:** Motion During Exposure Causes Blur, accidental , Purposefully
  1. Optical Flow Blur unwanted object
2. **Solution:** Synthetic Motion Blur
  1. Train Model to synthesize
  2. Could learn occlusion
  3. Training Data Generation:
    1. Train Frame interpolation network
    2. Average for motion blur
3. **Result:**
  1. High dB
  2. Short Time
  3. Handling Complex Motions Better than Optical flow method



#### **5.1.10 Underexposed Photo Enhancement Using Deep Illumination Estimation**

1. **Problem:** Pixel-wise mapping has limitation
2. **Solution:**
  1. Illumination Map
  2. Smoothness loss

#### **5.1.11 Blind Visual Motif Removal From a Single Image**

1. **Solution:**
  1. 1 encoder, 3 decoders
  2. A bunch of losses
2. **Test Result:**

#### **5.1.12 Non-Local Meets Global: an integrated Paradigm for Hyper-spectral Denoising**

1. **Problem:**
  1. More spectral bands, more computation burden
2. **Solution:**
  1. Non-local similarity and global spectral low-rank property

#### **5.1.13 Neural Rendering in the wild**

1. **Solution:** Train Neural Render. Multiple stage training

#### **5.1.14 GeoNet: Deep Geodesic Networks for Point Cloud Analysis**

## 6 Thursday June 20th: Main Conference Day 3

### 6.1 Low-level & Optimization Oral: (Day3)

#### 6.1.1 Unprocessing Images for Raw Denoising

**Problem:** Traditional: Synthetic Data Denoising. Not Real

1. Real Camera Data: a high quality denoising dataset for smartphone cameras: best is BM3D
2. SRGB image + additive Gaussian noise
3. Raw + noise

**Solution:**

1. Find Unprocessed Data
2. Raw sensor data → Denoise & demosaic → Color Correction → gamma compression → Tone mapping → sRGB image
3. Unprofessional images reverse the pipeline
4. Realistic Training data

**Results:**

1. Best in DND

**Takeaways:**

1. Realistic Training data
2. Unprocessing data → better training results

#### 6.1.2 Residual Network for Light field image super resolution

1. **Problem:**

1. 2. **Solution:**

1. Extract subpixel in four direction
2. Combine with ...

3. **Result:**

1. Best result in Buddha and Mona
2. Surpass EDSR

#### 6.1.3 Modulating image restoration with Continual Levels via adaptive feature Modification Layers

1. **Problem:**

1. Degradation levels of real world image are continuous
2. Deep restoration is discontinuous
3. Cannot train large model to handle all degradation levels

2. **Solution:**

1. Propose AdaFM (Adaptive Feature Modification layer)
2. 1. Train basic layer, 2. Insert AdaFM, 3....
3. 7x7 filter achieve better than 5x5 3x3.
4. Arbitrary Result for Style transfer

#### 6.1.4 Second-Order Attention Network for Single Image Super-Resolution

1. **Problem:** neglect rich feature correlations (most work)
2. **Solution:**
  1. Attention based mechanism
  1. Spatial Attention
  2. Channel Attention
  2. Use Spatial & Channel attention simultaneously
1. Second-order attention network SAN
2. Use Newton Schulz iteration to solve eigenvalue decomposition (is not well supported on GPU platform)
3. **Result:**
  1. Better than VDSR

#### 6.1.5 Devil is in the Edges: learning Semantic Boundaries from noisy annotation

1. **Problem:**
  1. Boundary annotation imprecise, current SOTA
  2. Annotation Hard
2. **Solution:**
  1. Propose STEAL
  2. Semantic Thinning Edge Alignment layer
3. **Result:**
  1. SBD dataset achieve state of the art
  2. CITYSCAPES: 4.24. Dataset Refinement, annotate coarse masks fast, refine masks with STEAL

#### 6.1.6 Path-Invariant Map Networks

1. **Problem:**
  1. Invariant map problem
2. **Solution:**
  1. Path Invariance provides a regularization for training neural networks
  2. Supervised loss + unsupervised loss
3. **Result:**
  1. Leverage additional training data
  2. Fuse attention...
  3. ...

#### 6.1.7 FilterReg: Robust and Efficient Point-set registration

1. **Problem:**
  1. Iterative Closest Point: relatively fast but sensitive to..
2. **Solution:**
  1. Filter-based Correspondence

**3. Result:**

1. 40ms runtime
2. 303. Feature-based Registration

**6.1.8 Probabilistic Permutation Synchronization Using the Riemannian Structure of the Birkhoff Polytope**

**1. Problem:**

1. Synchronization of Multiview Correspondences
2. Correct Mistakes + Estimate Match Confidence

**2. Solution:**

1. Encode Pairwise Correspondence as total permutations
2. Minimize the cycle consistency loss over the entire (hyper-) graph
3. Propose Birkhoff Riemannian Langevin Monte Carlo

**3. Result:**

1. Achieve state of the art of L-BFGs algorithm

**6.1.9 Lifting Vectorial Variation Problems:**

**1. Problem:**

1. Global energy minimization

**2. Solution:**

3. OK I gave up

**6.1.10 A Sufficient Condition for Convergences of Adam and RMSProp**

**1. Problem:**

**2. Solution:**

1. Modify Adam to Generic Adam
2. Weighted AdaEMA
3. Propose Sufficient condition

**6.1.11 Guaranteed Matrix Completion Under Multiple Linear Transformation**

**1. Problem:**

1. Significant low-rank structure appears under some transformations
2. The conventional theoretical analysis for guarantee is no longer suitable

**2. Solution:**

1. Propose generalization the problem as Matrix Completion under Multi linear-Transformations MCMT
2. The upper-bound of the reconstruction error is linearly controlled by the condition number of the transformations

### 6.1.12 MAP inference via Block-Coordinate Frank-Wolfe Algorithm

#### 1. Problem:

### 6.1.13 A convex relaxation for multigraph matching

#### 1. Problem:

1. Multi-graph matching
2. Cycle consistency matching

#### 2. Contribution:

1. Partial matching
2. Quadratic costs
3. Higher order costs
4. Optimization: LP formulation
5. Convergence: Lower bounds & optimization gap
6. Scalability: Linear

#### 3. Result

## 7 Notes Under Construction...