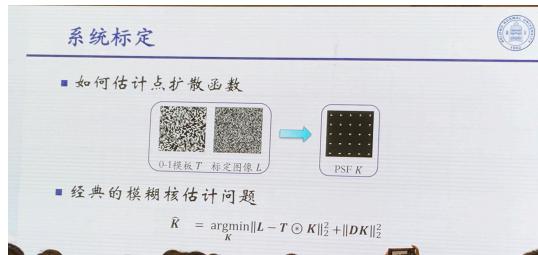


Workshop 1 计算光谱成像(本质与IR一致)

光传输函数

物镜没有 ~ 中继镜有模糊

系统标定

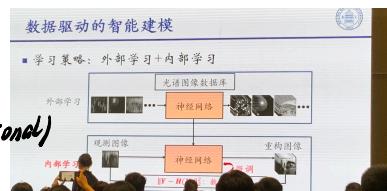


模糊核估计问题

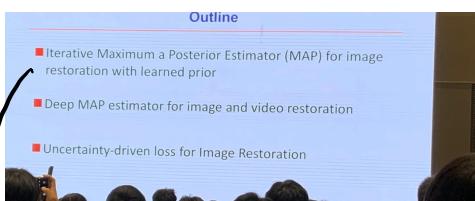
↑ 低频平滑相似
↑ 空谱联合
} 先验: 压缩解空间
} ~ 模型

先验
知识驱动
数据驱动

光滑先验
稀疏先验: 有效信息有稀疏性
低秩 ~ 有效信息自表示
自相似 ~ Non-local self similarity
未考虑物理成像模型: (解空间没约束)
⇒ 学习策略
网络结构: 深度展开
自相似、低秩性 (combined with traditional)



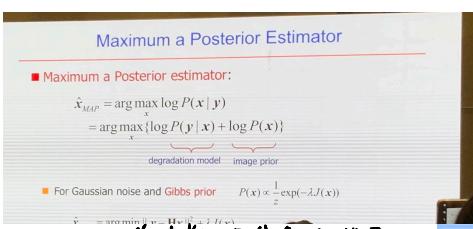
Workshop 2 董伟生



问题: 先验与迭代相互独立。
2. 迭代过程展开成神经网络

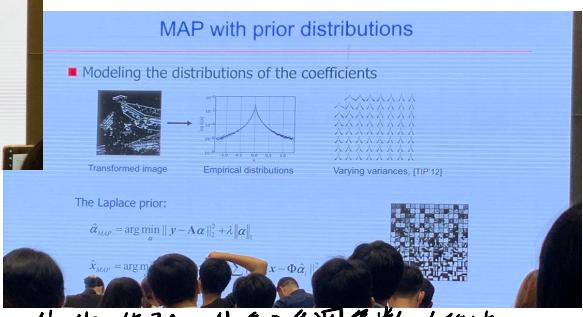
3. Uncertainty - loss IR

传统: L_1 / L_2 损失式 $\xrightarrow{\text{bayesian}}$ likely hood
 $\hat{x}_i = \bar{u}_i + \varepsilon_i$; 除方差均值外还对不确定项。
 又引入了一个方差的先验。



从训练集学数据分布 ⇒ 先验
均值偏差

TV: 全变差

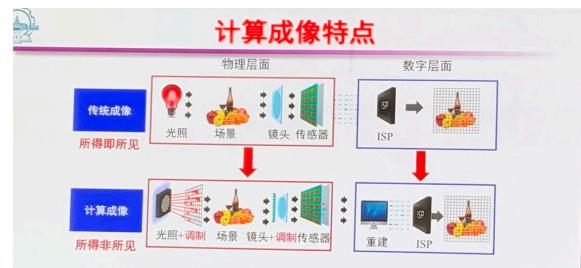


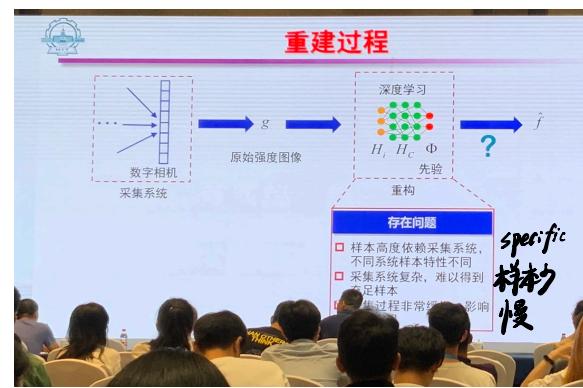
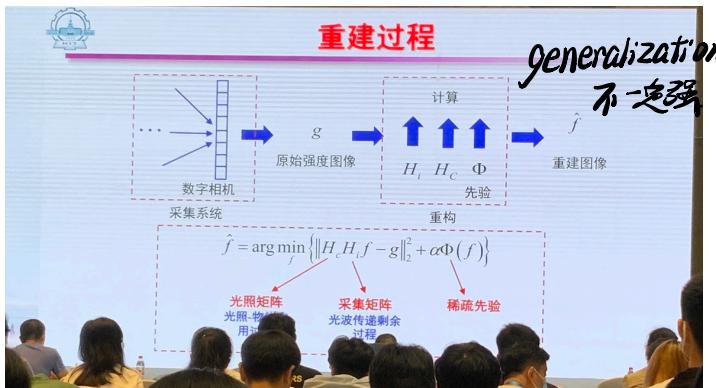
传统先验: 分布 → 手调参数 / 估计

Workshop 3 张永庆

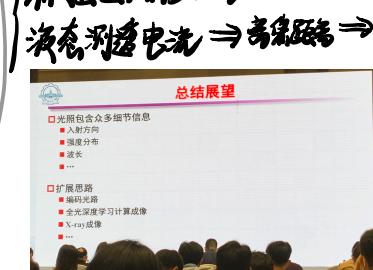
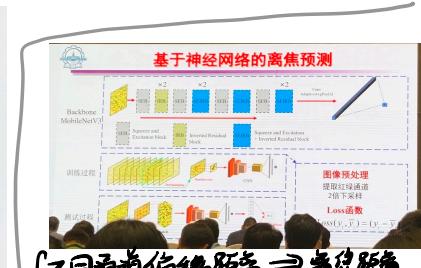
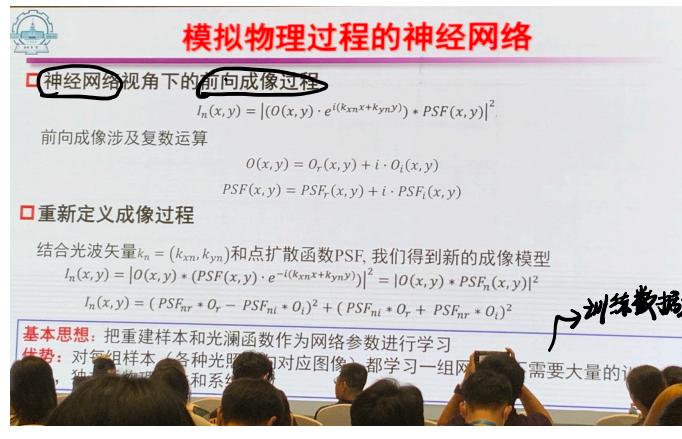
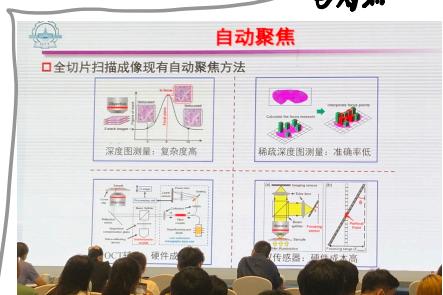
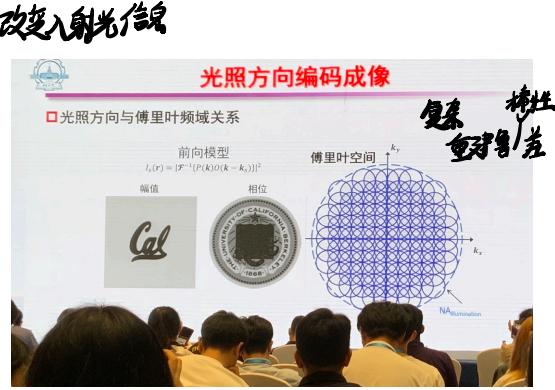
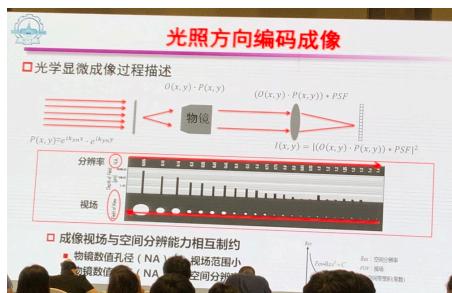


传统成像
↓
计算成像
↑
数字 : ISP

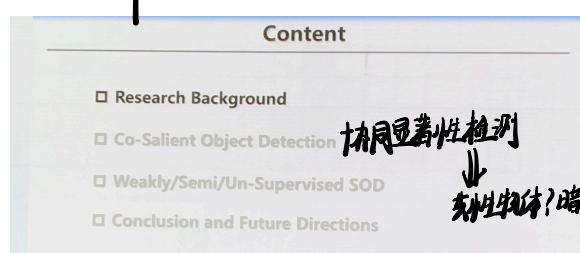




二显微成像
扫描成像
①加帧插过透
②对焦



Workshop 4 张景文



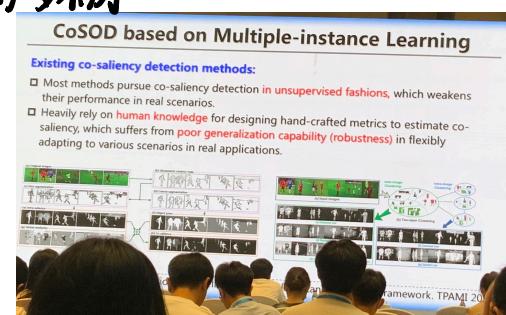
二、协同显著性检测

(1) 多示例

CoSOD based on Multiple-instance Learning

Existing co-saliency detection methods:

- Most methods pursue co-saliency detection in unsupervised fashions, which weakens their performance in real scenarios.
- Heavily rely on human knowledge for designing hand-crafted metrics to estimate co-saliency, which suffers from poor generalization capability (robustness) in flexibly adapting to various scenarios in real applications.



(2) 复杂场景: {② 物体关系纹理
introduction foreground
复杂场景的纹理}



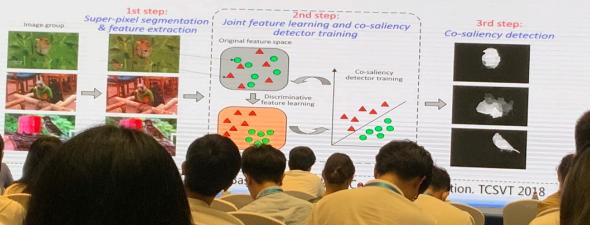
foreground - background similarity

三. 无/弱半监督 SOD

CoSOD based on Metric Learning

Overall solution:

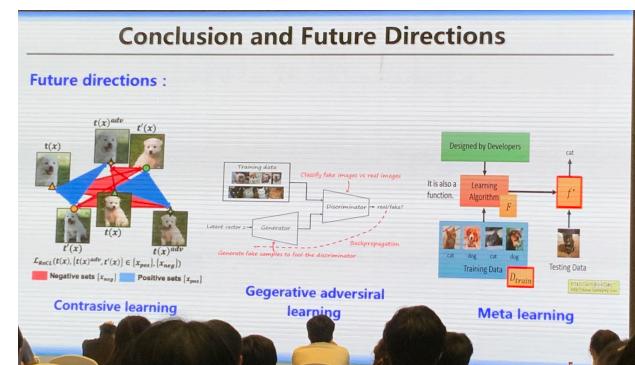
- Use metric learning to reduce the scatter within co-salient objects and enlarge the separation between foregrounds and backgrounds
- Design unified framework to jointly optimize metric learning matrix and SVM classifier via optimizing a new loss function



四. 结论

Conclusion and Future Directions

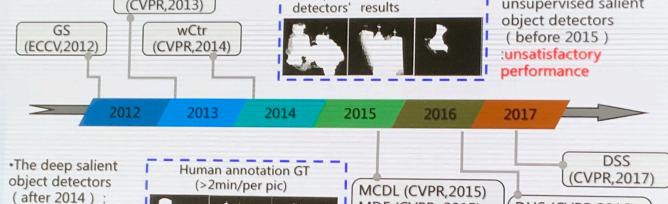
Future directions :



Weakly/Semi/Un-Supervised SOD

Weakly/Semi/Un-Supervised SOD

GS (ECCV, 2012) wCtr (CVPR, 2014)



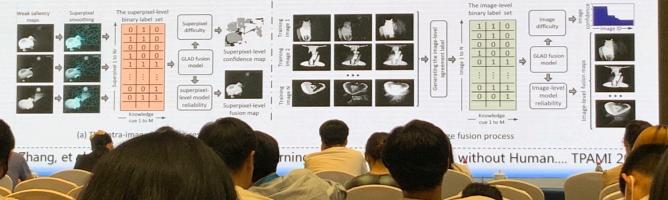
Weakly/Semi/Un-Supervised SOD

Supervision by Fusion:

- Fusing multiple saliency priors to generate reliable guidance for training deep SOD model.
- Considering the prior reliability and sample difficulty in GLAD-based fusion process.

$$p(l_j = z_j | \alpha_i, \beta_j) = \frac{1}{1 + e^{-\alpha_i \beta_j}}$$

Fusing priors in both image level and superpixel level.



Weakly/Semi/Un-Supervised SOD

The knowledge source transition mechanism :

- Priors from the existing saliency models are considered as the external knowledge source.
- The internal knowledge source are also considered for synthesizing supervision.
- The two kinds of knowledge source are used in a pre-defined curriculum to guide the whole learning process.



Workshop 5 任务

Content

Motivation

- Learning with Inconsistent Illumination for Face Frontalization
- Learning with Misalignment for RAW-to-sRGB
- Learning Temporal Consistency for Video Super-resolution
- Learning Progressive Dual-Pixel Alignment for Defocus Deblurring

Summary

- .1 数据 / motivation

Learning with Color-inconsistent Supervision

- Face Frontalization
- Limitation of existing methods

光屏条件不一致和对齐问题



光屏条件不一致和对齐问题

修正

Learning with Non-ideal Supervision

- Fortunately, some kind of supervision can still be attained, but is non-ideal



Learning with Non-ideal Supervision

Illumination Misalignment

Spatial Misalignment



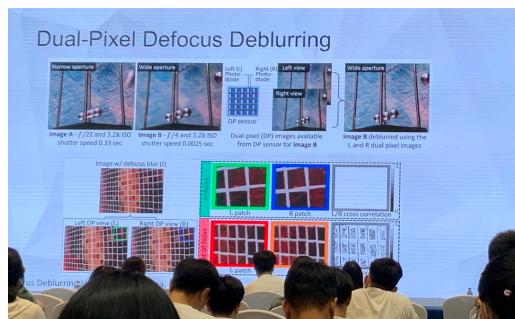
二. raw 2 RGB : LSP (NN) raw2rgb



三. SR Video



四. Dual-Pixel



Dual-Pixel Misalignment

- Spatially variant defocus blur brings difficulty for alignment in regions out of DoF
 - Neither image in left view nor right view is aligned with latent all-in-focus image
-

