Pix2Pose: Pixel-Wise Coordinate Regression of Objects for 6D Pose Estimation

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Hanyang univ. AILAB 정지은

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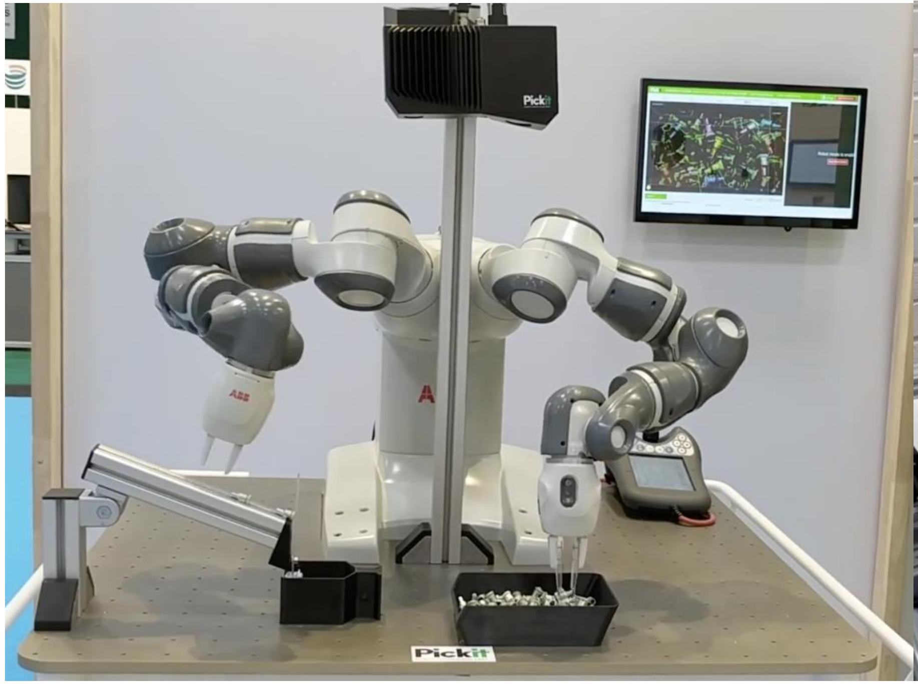
1. Introduction

Introduction

- **Bin picking**



https://m.blog.naver.com/PostList.nhn?blogId=rubenautomation

Introduction

- **6D Pose estimation task**

Introduction

- **Challenges**

1) 3D models **with high-quality textures** are required

Special device / manual adjustment

BigBIRD Object Scanning Rig*

Sufficient for
Synthetic rendering

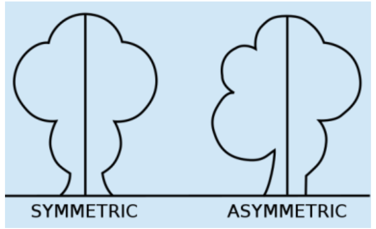
Real environment (e.g., robots)
Noisy odometry, varied lighting, limited viewpoints

3D reconstruction using a mobile robot

Not sufficient!

2) Occlusion

3) Symmetric objects

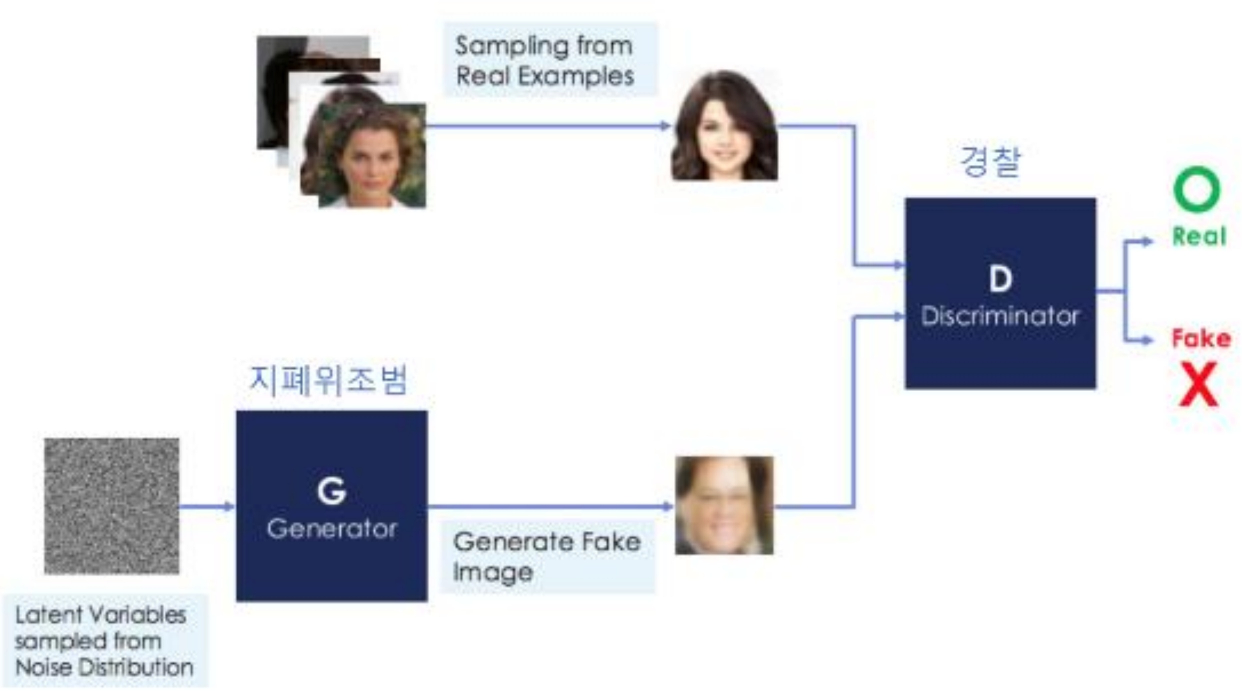


*Calli et al., IJRR (2017)

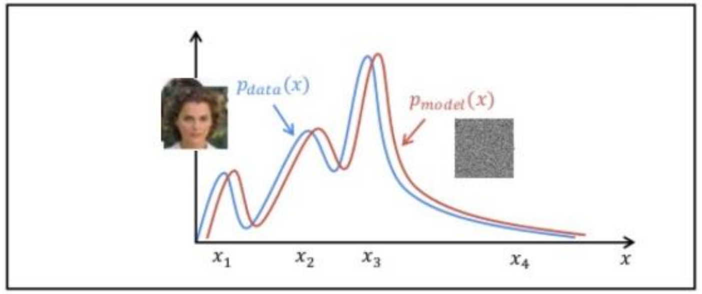
2. Related work

Related work : GAN (Generative Adversarial Network)

- **두개의 모델** (Generator & Discriminator)을 **적대적으로 경쟁**시키면서 서로의 성능을 발전시키는 방식으로 실제 이미지와 비슷한 이미지를 만드는 **생성모델**



The purpose of the GAN



최적화를 통해 서로 다른 확률분포 간의 차이 줄이기

Related work : GAN loss

Discriminator loss function

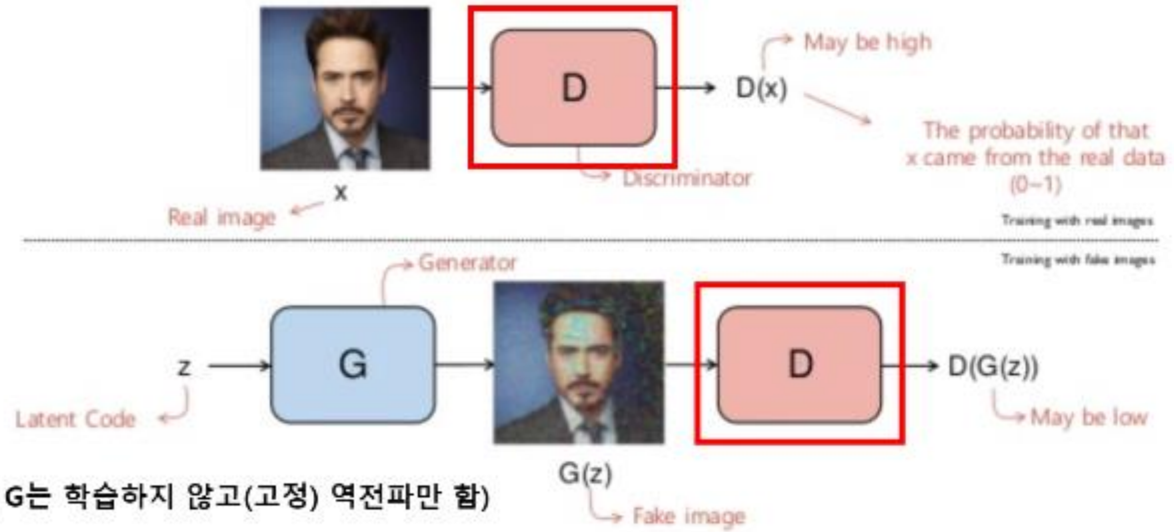
Sample x from real data distribution

Sample z from Gaussian distribution

$$\min_G \boxed{\max_D V(D,G)} = E_{x\sim p_{data}(x)}[\log D(x)] + E_{z\sim p_z(z)}[\log(1-D(G(z)))]$$

D(x) = 1일때 Maximum

D(G(z)) = 0일때 Maximum



(단, D 학습시에는 G는 학습하지 않고(고정) 역전파만 함)

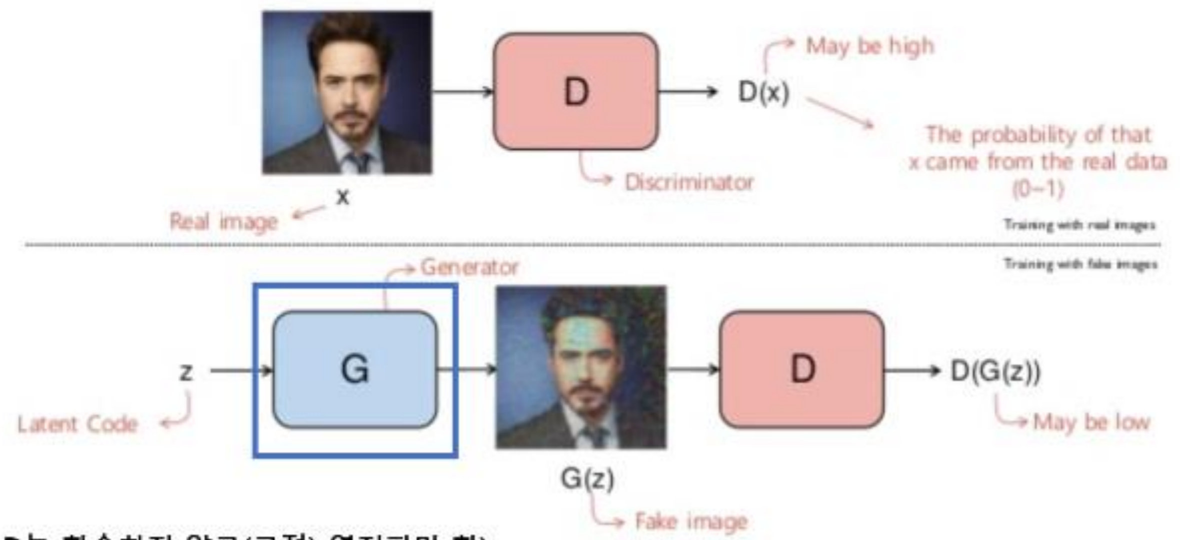
Related work : GAN loss

Generator loss function

$$\boxed{\min_G}\max_D V(D,G) = \cancel{E_{x\sim p_{data}(x)}[\log D(x)]} + E_{z\sim p_z(z)}[\log(1 - D(G(z)))]$$

G is independent

D(G(z)) = 1일때 Minimum



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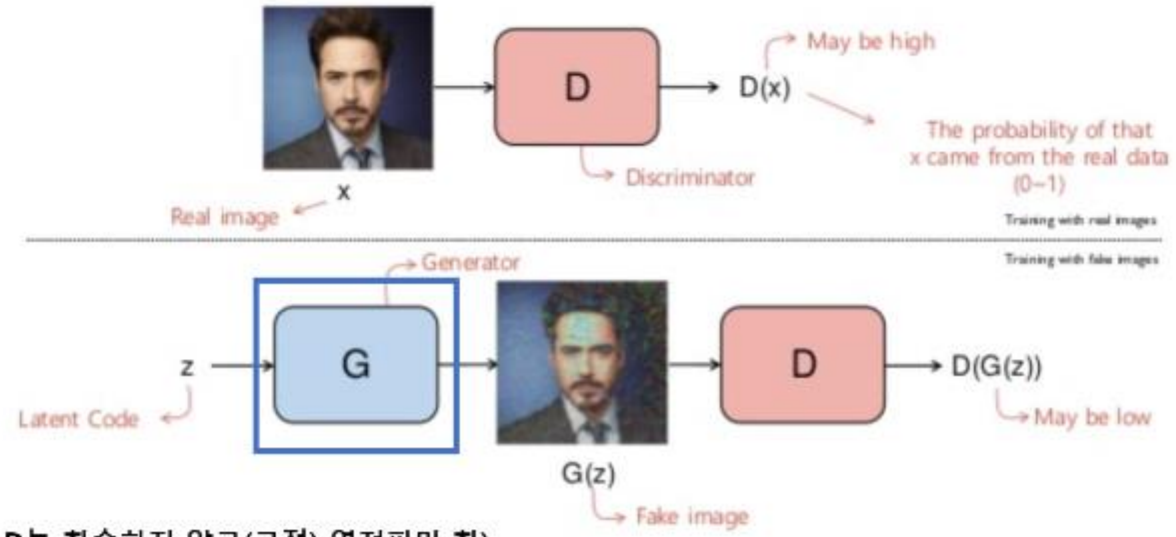
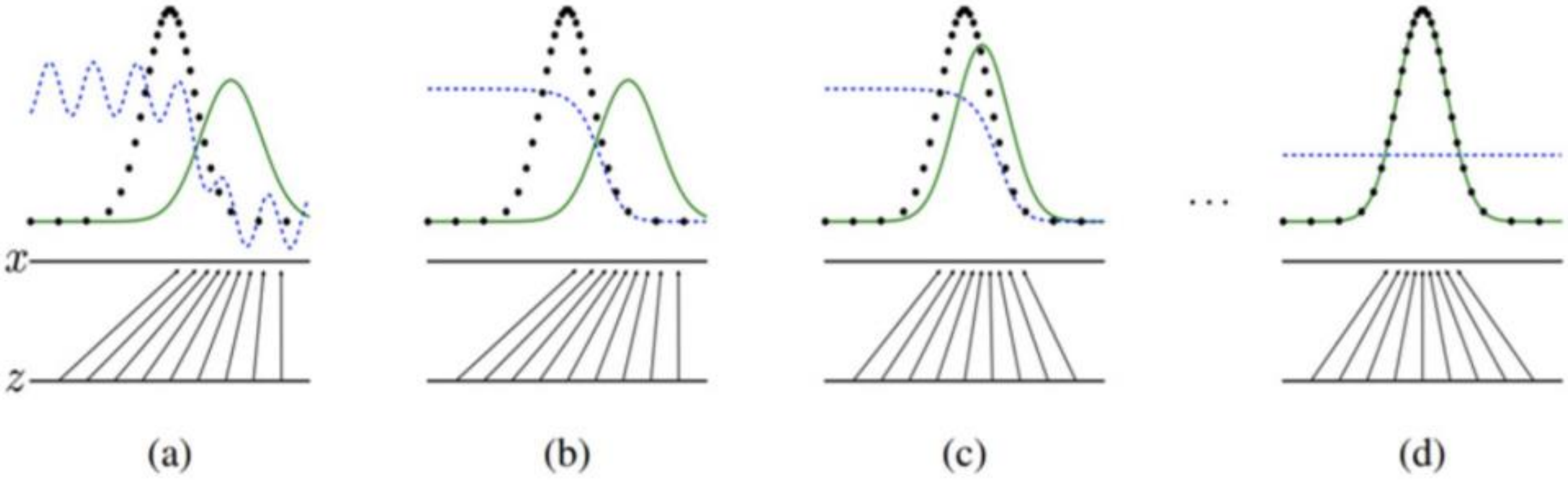


(단, G 학습시에는 D는 학습하지 않고(고정) 역전파만 함)

1 epoch 완료

Related work : GAN (Generative Adversarial Network)

The purpose of the GAN



※ **검은 점선**: 원 데이터의 확률분포, **녹색 점선**: GAN이 만들어 내는 확률분포, **파란 점선**: 분류자의 확률분포

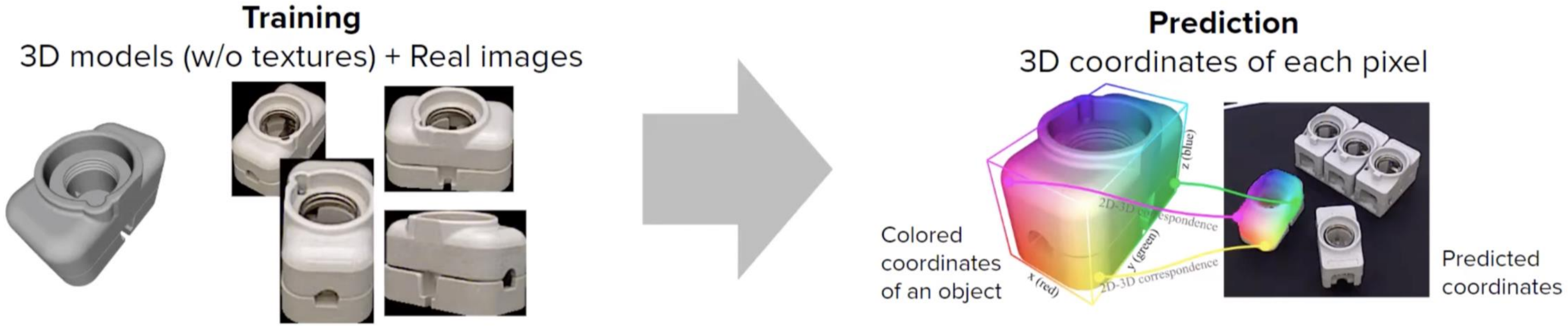
위로 뻗은 화살표 : x = G(z)의 mapping

<GAN에서 학습을 통해 확률분포를 맞추어 나가는 과정>

3. Method

Method : Pix2Pose

- **기본 아이디어 :**
  GAN의 image-to-image translation 방식처럼 물체의 가려진 부분을 복원하면서
  이미지 -> 좌표값 으로 translation

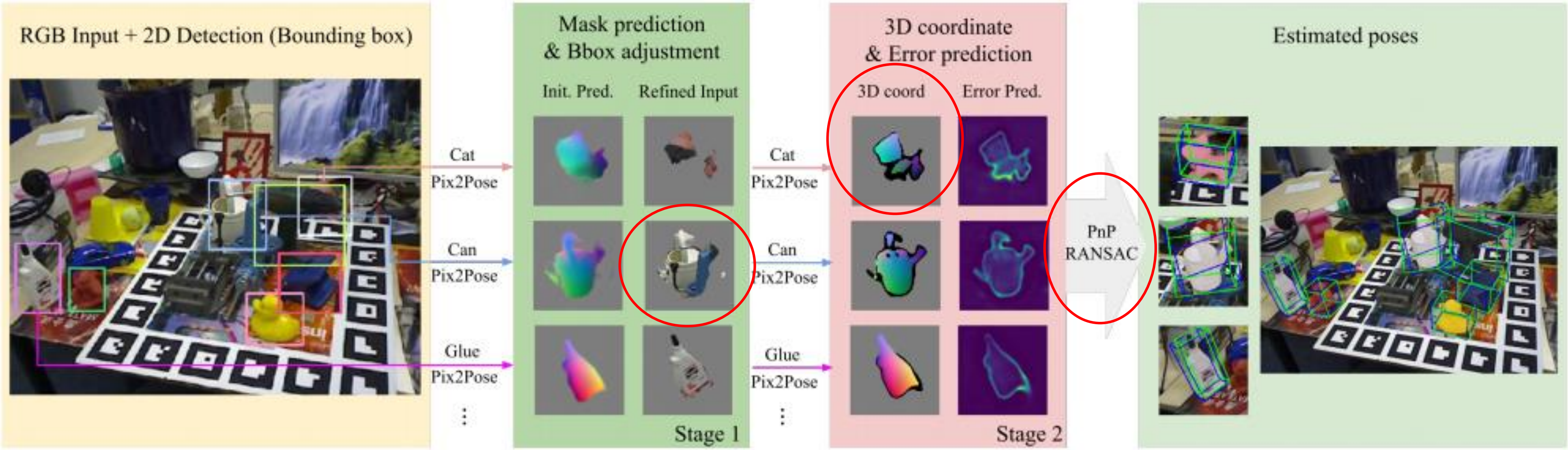


- Annotation = 6D 포즈 좌표값
- Ground truth = CAD 모델에 6D 좌표값을 대응시킨 3D Color 이미지

- 3D 좌표값이 색상으로 렌더링된 2D 이미지가 됨

Entire Architecture

- A single network is trained and used for each object class.



Method : Pix2Pose

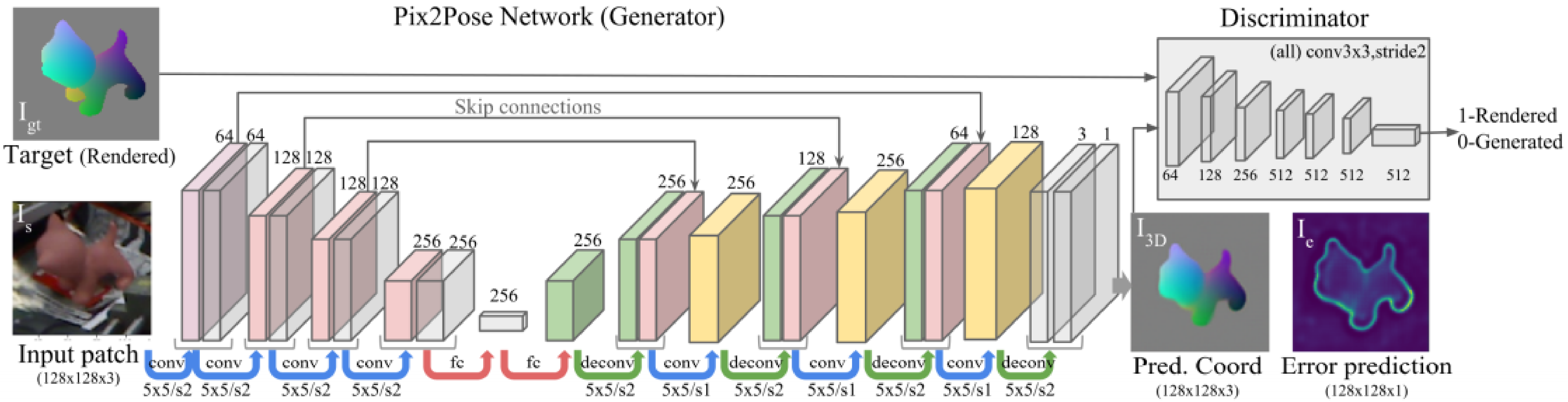


Figure 2. An overview of the architecture of Pix2Pose and the training pipeline.

- **Input** : **A cropped image** Is using a bounding box of a detected object class
- **Output** : **Normalized 3D coordinates** of each pixel I3D in the object coordinate and estimated errors

Network training : Loss

$$G^* = \arg\min_G \max_D \mathcal{L}_{\mathrm{GAN}}(G, D) + \lambda_1 \mathcal{L}_{\mathrm{3D}}(G) + \lambda_2 \mathcal{L}_{\mathrm{e}}(G)$$

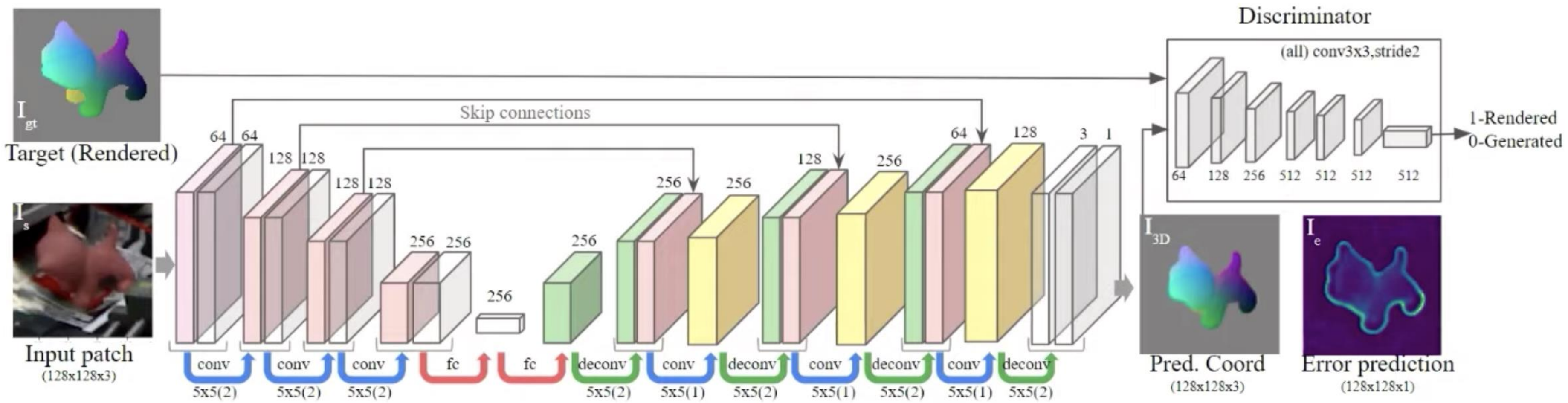
- 전체 손실함수는 3가지로 구성되어 있음

(1) GAN loss : Occlusion 문제 해결

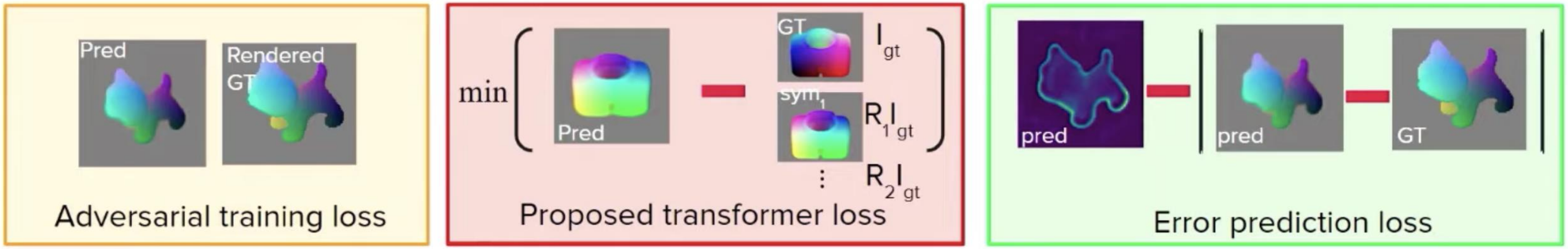
(2) Transformer loss : Symmetric objects 문제 해결

(3) Error loss : <u>외곽부분</u>을 보완적으로 보정해서 정밀한 이미지 생성

Network training : Loss



Training objective: $G^* = \arg\min_G \max_D \mathcal{L}_{\mathrm{GAN}}(G, D) + \lambda_1 \mathcal{L}_{\mathrm{3D}}(G) + \lambda_2 \mathcal{L}_{\mathrm{e}}(G)$



For occlusion objects For symmetric objects For Inliers and outliers

Network training : Loss

(1) GAN loss: 이미지의 가려진 부분을 복원해서 알맹이 만들기 (Occlusion 문제 해결)

$$\mathcal{L}_{\text{GAN}} = \log D(I_{gt}) + \log(1 - D(G(I_{\text{src}})))$$

- G : 가짜 이미지 생성
- D : 가짜 생성 이미지와 GT 이미지 판별

- I_src : source img(input)
- I_gt : GT

Network training : Loss

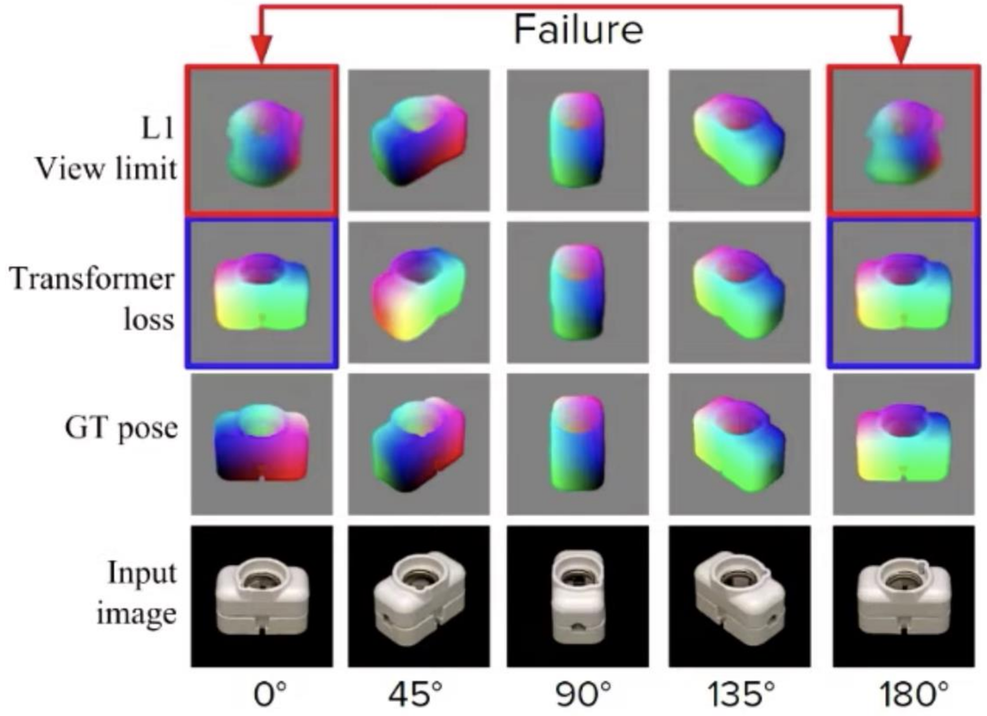
(2) **Standard loss**: 기본 L1 로스

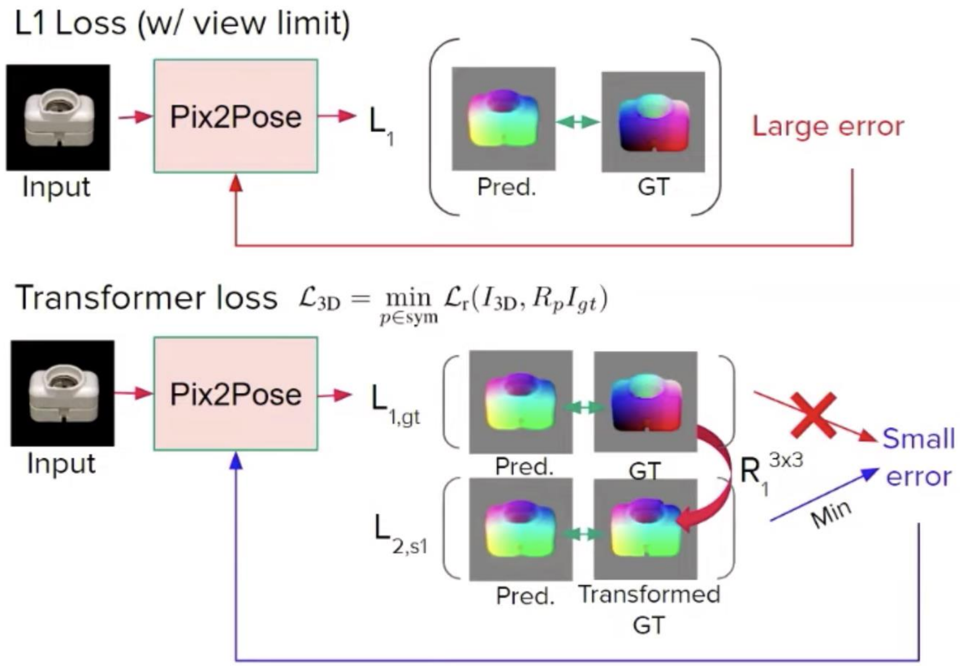
$$\mathcal{L}_{\mathrm{r}} = \frac{1}{n}\left[\beta \sum_{i \in M} ||I_{\mathrm{3D}}^{i} - I_{\mathrm{gt}}^{i}||_1 + \sum_{i \notin M} ||I_{\mathrm{3D}}^{i} - I_{\mathrm{gt}}^{i}||_1\right]$$

- n : 이미지 전체 픽셀의 개수
- M : GT 이미지의 오브젝트 마스크

Network training : Loss

(2) Standard loss: 대칭 물체에서 문제 발생

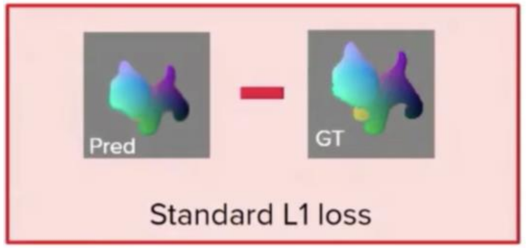




Network training : Loss

(2) Standard loss: 기본 L1 로스

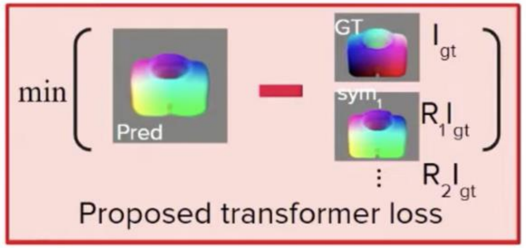
$$\boxed{\mathcal{L}_{\mathrm{r}}} = \frac{1}{n}\Big[\beta \sum_{i\in M} ||I^i_{3\mathrm{D}} - I^i_{\mathrm{gt}}||_1 + \sum_{i\notin M} ||I^i_{3\mathrm{D}} - I^i_{\mathrm{gt}}||_1\Big]$$



- n : 이미지 전체 픽셀의 개수
- M : GT 이미지의 오브젝트 마스크

(2-1) Transformer loss: 회전시킨 GT들과의 가장 작은 L1 Loss (Symmetric objects 문제 해결)

$$\mathcal{L}_{3\mathrm{D}} = \min_{p\in\mathrm{sym}} \mathcal{L}_{\mathrm{r}}(I_{3\mathrm{D}}, R_p I_{gt}),$$



- R_p : transformed matrix
- Sym : symmetric pool

Network training : Loss

(3) Error loss: 외곽부분을 따로 잡아주는 손실함수(더욱 정밀한 pose 근사가 가능하도록 함)

$$\mathcal{L}_\mathrm{e} = \frac{1}{n}\sum_i ||I^i_\mathrm{e} - \min[\mathcal{L}^i_\mathrm{r}, 1]||^2_2, \beta = 1.$$

초록색 부분 = 에러율이 높음

Error prediction loss

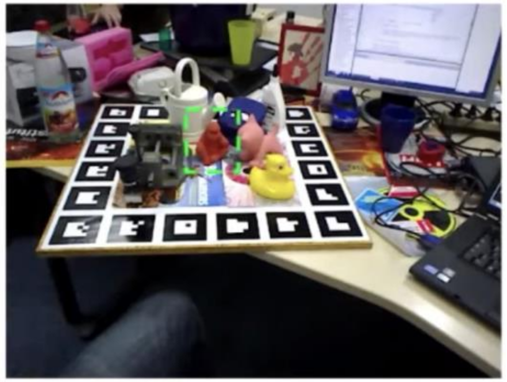
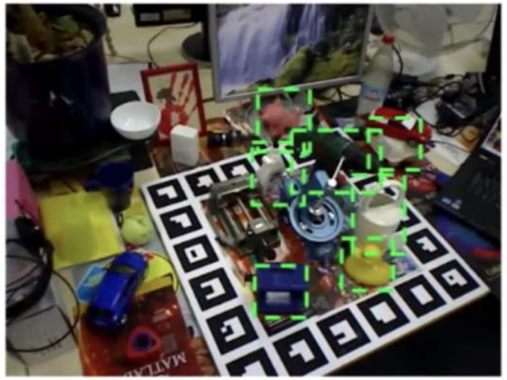
- I_e : predicted error
- min 은 Lr을 0~1 사이로 정규화 하는 효과

$$\begin{bmatrix} & & & & \\ & & 1 & & \\ 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} - \left| \begin{bmatrix} & & & & \\ & & 1 & & \\ & 1 & 1 & 1 & \\ & 1 & 1 & 1 & \\ & & & & \end{bmatrix} - \begin{bmatrix} & & & & \\ & & 1 & & \\ -1 & 1 & 1 & 1 & -1 \\ -1 & 1 & 1 & 1 & -1 \\ -1 & -1 & -1 & -1 & -1 \end{bmatrix} \right| = \begin{bmatrix} & & & & \\ & & 1 & & \\ 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

Ex) 극단적으로 외곽을 잘 예측한 경우

4. Experiments

Dataset

	LineMOD	LineMOD Occlusion	T-Less
			
	13 Objects	8 Objects	30 Objects
Training images	Sub-sampled **real images**	**Real images** in LineMOD	**Real training** images
Symmetric objects	2 Objects	2 Objects	**All**
Occlusion	No	Yes	**Yes**

Experiments : LineMOD

	ape	bvise	cam	can	cat	driller	duck	e.box*	glue*	holep	iron	lamp	phone	avg
Pix2Pose	**58.1**	**91.0**	**60.9**	**84.4**	**65.0**	**76.3**	**43.8**	**96.8**	79.4	**74.8**	**83.4**	**82.0**	45.0	**72.4**
Tekin [30]	21.6	81.8	36.6	68.8	41.8	63.5	27.2	69.6	**80.0**	42.6	75.0	71.1	**47.7**	56.0
Brachmann [2]	33.2	64.8	38.4	62.9	42.7	61.9	30.2	49.9	31.2	52.8	80.0	67.0	38.1	50.2
BB8 [25]	27.9	62.0	40.1	48.1	45.2	58.6	32.8	40.0	27.0	42.4	67.0	39.9	35.2	43.6
Lienet$^{30\%}$ [4]	38.8	71.2	52.5	86.1	66.2	82.3	32.5	79.4	63.7	56.4	65.1	89.4	65.0	65.2
BB8^{ref} [25]	40.4	91.8	55.7	64.1	62.6	74.4	44.3	57.8	41.2	67.2	84.7	76.5	54.0	62.7
Implicit^{syn} [29]	4.0	20.9	30.5	35.9	17.9	24.0	4.9	81.0	45.5	17.6	32.0	60.5	33.8	31.4
SSD-6D$^{syn/ref}$ [15]	65	80	78	86	70	73	66	100	100	49	78	73	79	76.7
Rad$^{syn/ref}$ [26]	-	-	-	-	-	-	-	-	-	-	-	-	-	***78.7***

Experiments : LineMOD Occlusion

Method	**Pix2Pose**	Oberweger† [23]	PoseCNN† [33]	Tekin [30]
ape	**22.0**	17.6	9.6	2.48
can	44.7	**53.9**	45.2	17.48
cat	**22.7**	3.31	0.93	0.67
driller	44.7	**62.4**	41.4	7.66
duck	15.0	19.2	**19.6**	1.14
eggbox*	25.2	**25.9**	22.0	-
glue*	32.4	**39.6**	38.5	10.08
holep	**49.5**	21.3	22.1	5.45
Avg	**32.0**	30.4	24.9	6.42

- Texture 정보 사용
- Pose variation 많음

Experiments : T-Less

Input	RGB only		RGB-D	
Method	**Pix2Pose**	Implicit [29]	Kehl [16]	Brachmann [2]
Avg	**29.5**	18.4	24.6	17.8

5. Conclusion

Conclusion

- **Pix2Pose : RGB 이미지를 이용한 물체의 6D Pose estimation model**
  - Texture정보 필요 없음
  - GAN 학습방식 사용 : Occlusion에 강건
  - Transformer Loss 제안 : 유한개의 대칭 포즈를 가진 물체에 대한 문제 해결

Thank You

Reference

- Paper : https://arxiv.org/pdf/1908.07433.pdf
- ICCV 2019 Oral presentation : https://www.youtube.com/watch?v=zem03fZWLrQ
- GAN : https://www.slideshare.net/NaverEngineering/1-gangenerative-adversarial-network