Alpha Matte Generation from Single Input for Portrait Matting

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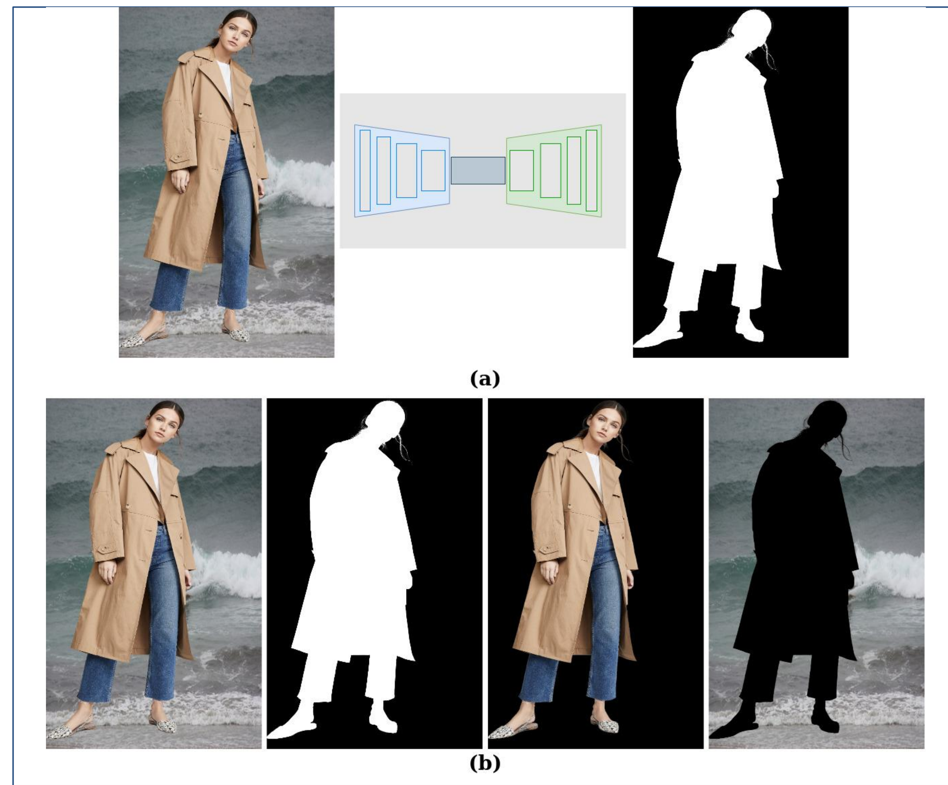
Motivation



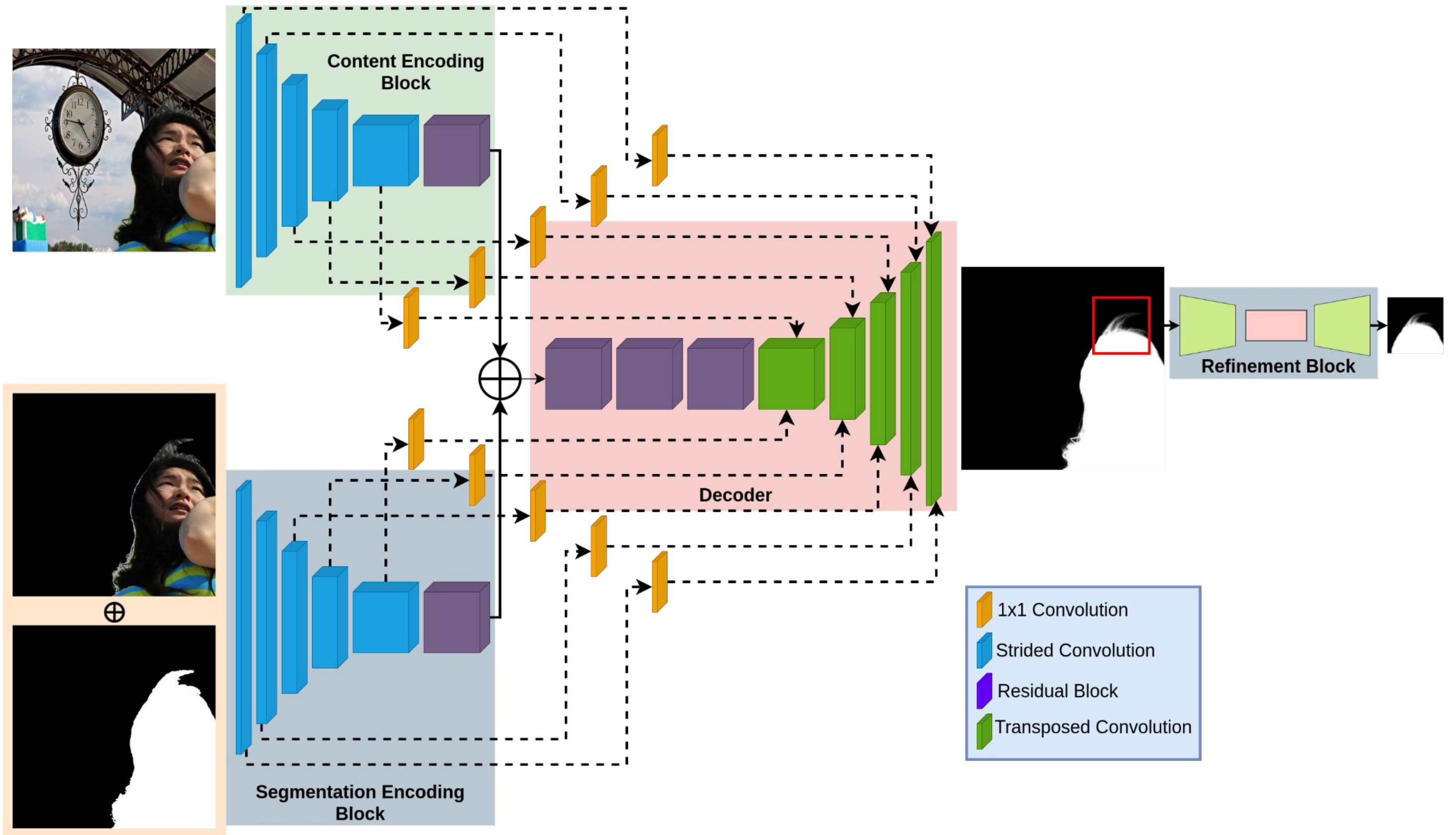
- Distinguish background and foreground subject by predicting alpha matte
- **Applications:** Image/video editing, background modification, video/movie post-production
- **Task definition:** Generate alpha matte for the subject.

$$I_i = \alpha_i F_i + (1-\alpha_i)\, B_i$$

Proposed Model

- **Content Encoding Block:** Encode the content of the image.
- **Segmentation Encoding Block:** Encode the **extracted subject** and **segmentation map**. Provides better feature representation.
- **Refinement Block:** Enhance the details of the alpha matte.
- **Segmentation map:** Obtain with a pretrained person segmentation model.
- **Extracted subject:** Obtain with the predicted segmentation map.
- Split standard alpha loss into two different losses to penalize separately ad adjust their effects..
  - **Alpha loss:** Calculate for only pixels that have one or zero values.
  - **Alpha coefficient loss:** Only use pixels that have neither zero nor one values.
- **Border loss:** Penalize only the area around the border of the subject.

$$L = L_{GAN}(G,D) + \lambda L_{percep}(G) + BL_{alpha}(G) + \gamma L_{border}(G) + \theta L_{ac}(G)$$

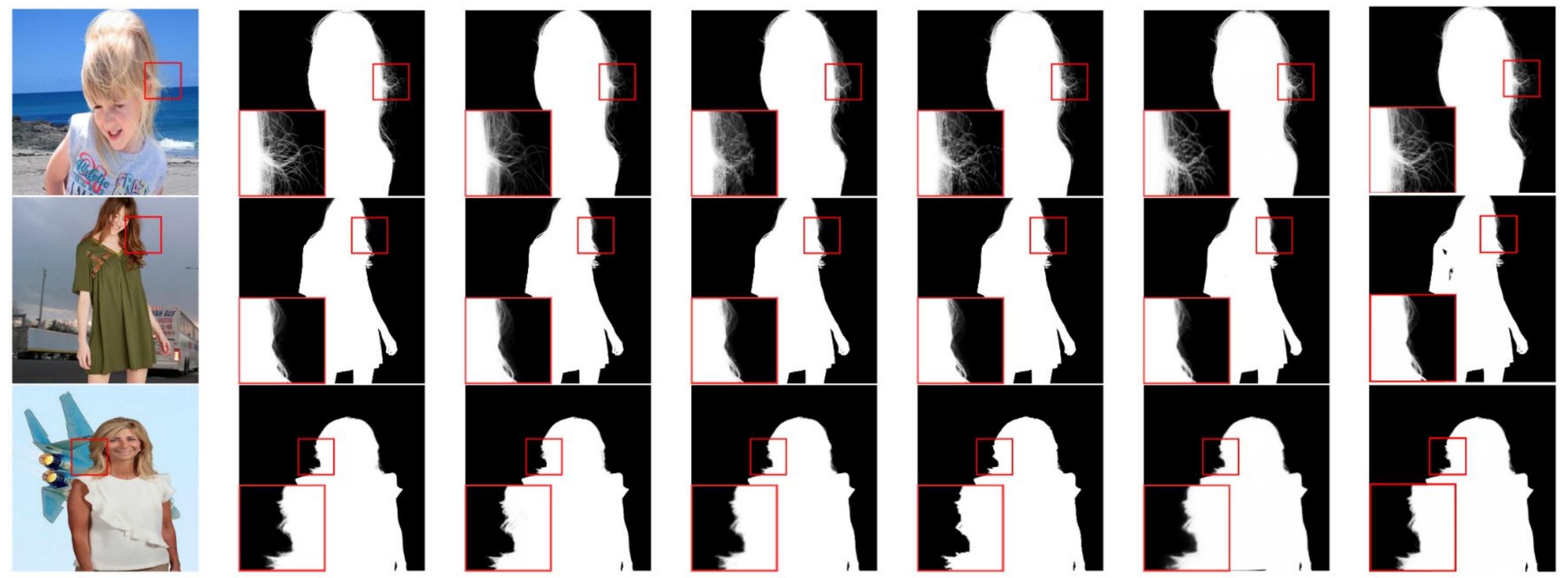


Experimental Results

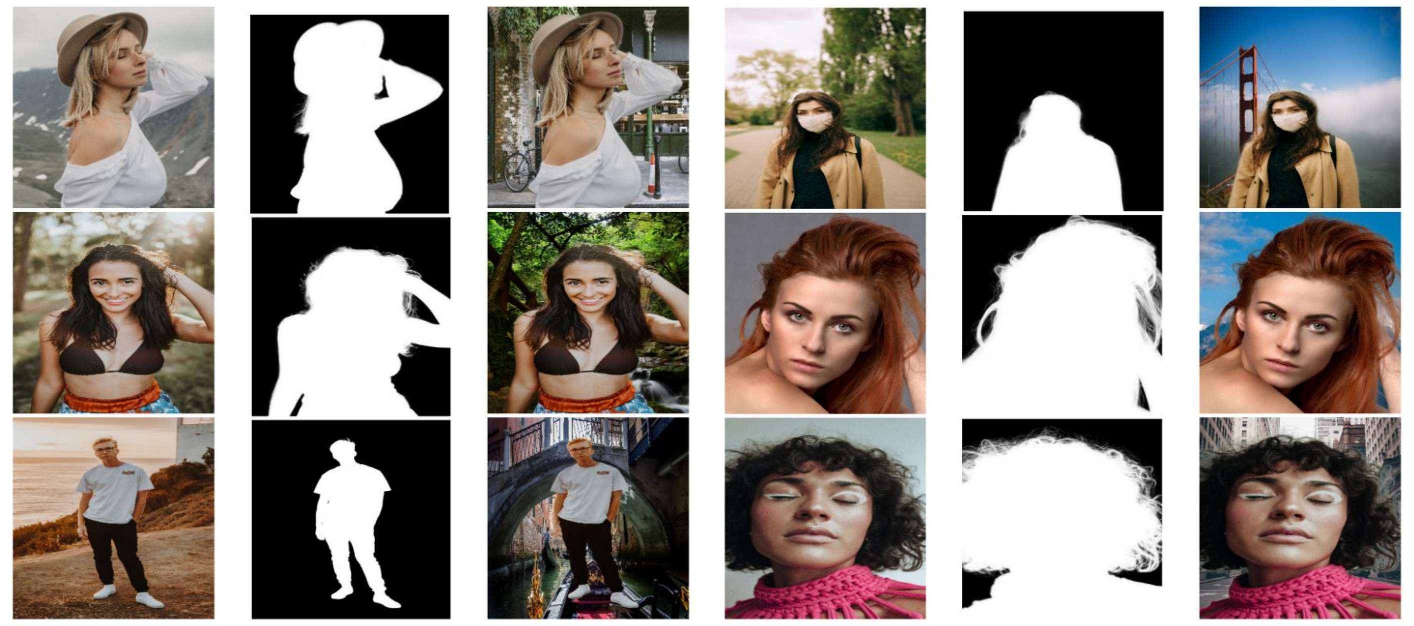
Method	Extra Input	Dataset	MSE	SAD	Grad	Conn
BGM-V2 [1]	Background	AIM	2.12	9.04	8.32	9.21
FBA [2]	Trimap	AIM	0.40	3.98	1.19	3.11
MODNet [3]	-	AIM	21.65	33.93	44.24	35.45
MGM [4]	-	AIM	1.48	6.21	4.74	6.55
Ours	**-**	**AIM**	**1.06**	**5.04**	**4.22**	**5.39**
BGM-V2 [1]	Background	PM85	0.37	1.45	1.28	2.38
FBA [2]	Trimap	PM85	1.01	2.55	3.50	2.75
MODNet [3]	-	PM85	2.32	7.23	12.17	9.48
MGM [4]	-	PM85	0.38	2.91	1.32	2.04
Ours	**-**	**PM85**	**0.19**	**1.19**	**0.65**	**1.16**
BGM-V2 [1]	Background	D646	0.98	4.83	3.78	5.30
FBA [2]	Trimap	D646	0.44	3.25	1.70	2.38
MODNet [3]	-	D646	3.51	10.27	13.54	18.98
MGM [4]	-	D646	0.88	5.42	3.40	4.76
Ours	**-**	**D646**	**0.71**	**3.99**	**2.74**	**3.84**
FBA [2]	Background	PPM100	0.96	2.41	4.20	2.70
MODNet [3]	Trimap	PPM100	4.60	11.59	12.48	22.16
MGM [4]	-	PPM100	1.15	5.31	5.04	5.29
Ours	**-**	**PPM100**	**0.84**	**4.70**	**3.67**	**4.46**

Datasets: AIM, PM85, D646, PPM100

- **Training:**
  - Combine AIM and D646 datasets.
  - In total, 564 subjects.
  - Use 100 background images from MSCOCO dataset for each subject.
  - 56400 training images in total
- **Test:**
  - AIM test set, PM85, D646 test set, PPM100
  - Combine each subject with 20 different background images from PASCAL VOC dataset.



Input GT Ours BGM-V2 FBA MODNet MGM



Input Alpha Combined Input Alpha Combined

Ablation Studies

- Using combination of segmentation and foreground as an input to the segmentation encoding block improves the result.
- Using combination alpha matte and foreground as an input to the discriminator makes the training more stable and accurate.
- SE block and refinement network provide more accurate alpha matte prediction.
- Each loss function allows us to obtain better performance by enhancing the predicted alpha matte.

Cases	MSE
Segmentation map	1.86
Segmentation + Foreground	1.41
Alpha matte + Foreground	1.06

Cases	MSE
Base model	2.20
Base model + SE block	1.57
Base model + SE block + refinement network	1.06

Loss	MSE
$L_{cGAN} + L_{alpha}$	7.24
$L_{cGAN} + L_{per} + L_{alpha}$	3.78
$L_{cGAN} + L_{per} + L_{alpha} + L_{border}$	1.76
$L_{cGAN} + L_{per} + L_{alpha} + L_{border} + L_{ac}$	1.06
α	3.14
α, F	1.06

Conclusions

- Proposed conditional GAN-based additional input-free two-stage approach.
  - First stage: person segmentation with DeepLabV3+
  - Second stage: alpha matte prediction using the input image and predicted segmentation map
- Proposed refinement network enhanced the quality of the predicted alpha matte.
- Proposed alpha coefficient loss and border loss improved the performance of alpha matte prediction.
- Segmentation encoding block improved the performance by providing more useful feature representation to the decoder network.
- Using combination of segmentation map and extracted subject with it as an input to the segmentation encoding block increased the performance.

Acknowledgement

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References

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