

Matte Anything: Interactive Natural Image Matting with Segment Anything Models

Jingfeng Yao, Xinggang Wang*, Lang Ye, and Wenyu Liu

School of EIC, HUST

Project page: <https://github.com/hustvl/Matte-Anything>

Abstract. Natural image matting algorithms aim to predict the transparency map (alpha-matte) with the trimap guidance. However, the production of trimaps often requires significant labor, which limits the widespread application of matting algorithms on a large scale. To address the issue, we propose Matte Anything model (MatAny), an interactive natural image matting model which could produce high-quality alpha-matte with various simple hints. The key insight of MatAny is to generate pseudo trimap automatically with contour and transparency prediction. We leverage task-specific vision models to enhance the performance of natural image matting. Specifically, we use the segment anything model (SAM) to predict high-quality contour with user interaction and an open-vocabulary (OV) detector to predict the transparency of any object. Subsequently, a pretrained image matting model generates alpha mattes with pseudo trimaps. MatAny is the interactive matting algorithm with the most supported interaction methods and the best performance to date. It consists of orthogonal vision models without any additional training. We evaluate the performance of MatAny against several current image matting algorithms, and the results demonstrate the significant potential of our approach.

Keywords: Image Matting, Image Segmentation, Segment Anything Model, Open Vocabulary

1 Introduction

Natural image matting is a prominent computer vision task with significant implications [1, 4, 14, 17, 37]. Its primary objective is to accurately predict the transparency map, commonly referred to as the alpha matte, for an object in a given image. Unlike image segmentation [6, 7, 15], natural image matting offers more precise predictions and excels in handling transparent objects, such as glasses. Consequently, it finds widespread applications in the generation of posters and the creation of visual effects for movies. Recently, image matting algorithms [10, 22, 28, 32, 40, 43, 45] with deep learning have achieved remarkable performance.

* Corresponding author: Xinggang Wang (xgwang@hust.edu.cn).

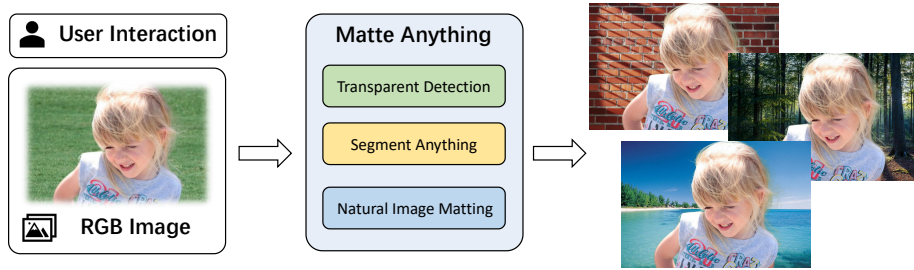


Fig. 1. Matte Anything Model is an interactive image matting system which unleashes the potential of the vision foundation model in image matting.

These image matting algorithms aim to predict the transparency of an object by utilizing the guidance provided by a trimap. As shown in Figure 2, the trimap is a hint map that is manually labeled for the purpose of image matting. It effectively divides an image into three distinct regions: foreground, background, and an unknown region. In the current state-of-the-art natural image matting methods [43], both the original image and its corresponding trimap are simultaneously used as input. However, despite the excellent matting results achieved by these methods, they have not yet become mainstream approaches widely adopted on a large scale. One crucial limitation of these methods is the high labor cost associated with generating trimaps.

Several previous methods have attempted to address this problem. One approach [33, 50] involves performing image matting using only RGB images without any guidance. However, a significant drawback of these methods is that they treat the result of image matting as an image-level task. A significant challenge would arise when faced with multiple instances, as it becomes difficult for them to determine which object should be matted. Another approach [9, 39, 42] is to incorporate additional inexpensive cues, such as bounding boxes, to guide image matting. These methods often utilize the same training dataset [40] as trimap-based methods. The problem with such a scheme is that after losing the information-rich trimap, a single network is required to simultaneously tackle the challenging tasks of image segmentation, transparency assessment, and image matting using a single dataset. This severely restricts the overall performance and generalization capabilities of the network.

To address the aforementioned challenges, we propose Matte Anything model (MatAny). Our underlying hypothesis is that the trimap’s fundamental role lies in providing explicit edge information and transparent object assessment to the matting network. Accordingly, we approach image matting as a downstream task of image segmentation and transparent object detection. In MatAny, we leverage task-specific vision models to enhance the performance of natural image matting. Firstly, we employ the Segment Anything Model (SAM) [16] to generate a high-quality mask for the target instance. Subsequently, we utilize the open-vocabulary object detection model, i.e., GroundingDINO [25] to detect commonly

occurring transparent objects. Pseudo-trimaps are then generated based on the segmentation and transparent object detection results, which are subsequently inputted into natural image matting models, e.g., ViTMatte [43]. The ViTMatte model is the state-of-the-art class-agnostic matting method, is implemented by efficiently adapting pre-trained ViTs, and has strong generalization ability. The three parts, SAM, GroundingDINO, and ViTMatte, are decoupled and require no additional training.

Since the strong capability of these task-specific models, MatAny yields unprecedented matting capabilities. It first supports various matting guidance including text. It is interactive and could be easily refined with just a few clicks. It could serve as a natural image matting method and could also generalize to other class-specific matting tasks [19, 20]. We evaluate MatAny on four image matting datasets and demonstrate its potential. On Composition-1k, our method outperforms other x -guided matting methods (x could be points, boxes, and so on) and achieves competitive results to trimap-based matting methods with simple refinement. To sum up, our contributions could be summarized as follows:

- We present Matte Anything, an interactive matting system composed of decoupled vision models that require no additional training. This system is designed to support various user interactions.
- We propose a trimap generation strategy based on vision foundation models. This strategy enables the generation of high-quality and adaptive pseudo trimaps with minimal user input, significantly reducing the manual effort required for trimap production.
- We evaluate the performance and generalization ability of Matte Anything using various image matting benchmarks. The results demonstrate its significant potential in achieving high-quality matting results across diverse datasets.

2 Related Work

2.1 Natural Image Matting

Natural image matting is class-agnostic, as it aims to segment any selected instances within an image. Deep learning algorithms [10, 22, 28, 32, 40, 43, 45], represented by DIM [40] (Deep Image Matting), have achieved significant advancements in image matting. However, these algorithms have a common requirement for trimap as guidance information, which restricts their applicability to a wide range of scenarios. Some methods [9, 39, 42] attempt to perform image matting using simplistic guidance, such as points or bounding boxes, and there are even attempts [33, 50] to achieve matting without any explicit guidance. However, these methods often experience notable performance degradation and poor generalization capabilities, primarily due to the limited datasets available for training and the restricted number of parameters employed. There is an urgent need for an efficient and high-performance natural image matting algorithm with just simple guidance.



Fig. 2. RGB image and its corresponding trimap.

2.2 Foundation Model

Large Language Models (LLMs) [2, 31, 38] have garnered significant attention in both the Natural Language Processing (NLP) and Computer Vision (CV) fields, as exemplified by models like GPT-4 [31] and LLaMA [38]. Researchers have observed the immense power of scaling up deep learning models, where foundational models trained on extensive data can unlock boundless possibilities for downstream tasks. Recently, Kirillov et al. have introduced the Segment Anything Model (SAM) [16] as a segmentation foundation model in computer vision, capable of segmenting any object based on user prompts. Researchers have successfully leveraged SAM to enhance various downstream tasks, such as image inpainting [46], image generation [35, 49], and so on [3, 8, 23, 26, 29, 30, 36, 41, 47]. However, to the best of our knowledge, there has been no prior investigation into the potential of SAM in the context of image matting tasks.

2.3 Open Vocabulary Detection

Open Vocabulary (OV) detection [11, 12, 44, 48] focuses on identifying the bounding box of diverse categories without predefined constraints. Leveraging the foundation model CLIP [34], researchers have achieved notable zero-shot performance on detection datasets [13, 18, 24], showcasing its robust generalization capability. Furthermore, recent advancements in the field, such as GroundingDINO [25], have demonstrated impressive results, surpassing 50 mAP on the COCO [24] dataset through the fusion of vision and language modalities at multiple stages. These innovations have found broad applications in image generation, image editing, and image segmentation. Building upon these achievements, our work in Matte Anything introduces a novel perspective on OV detection for image matting tasks.

3 Method

3.1 Preliminary: Trimap in Natural Image Matting

For ease of comprehension, we first give a brief introduction to trimap in image matting. As discussed above, trimap is a hint map to provide information on the foreground, background, and unknown region for a given image. There are

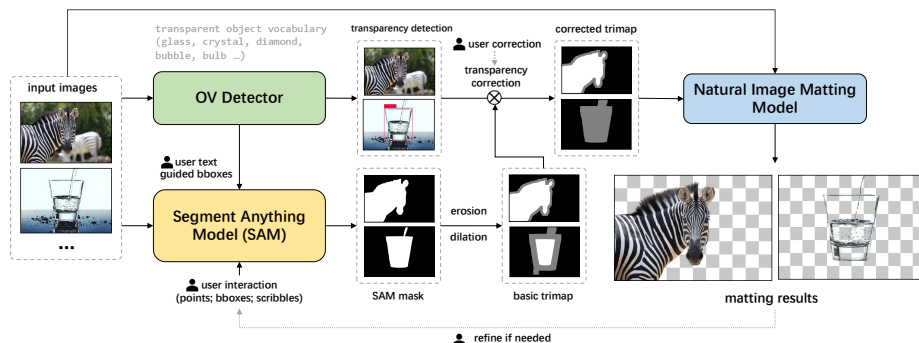


Fig. 3. Overall architecture of Matte Anything model (MatAny). It could process both opaque and transparent objects. Please zoom in for the best view.

two main priors of an accurate trimap. *Prior 1, an image matting algorithm will predict only in unknown regions of trimap.* That means a predicted alpha matte will be like Equation 1:

$$\alpha(x, y) = \begin{cases} 1 & \text{if } (x, y) \in F \\ M(i, t) & \text{if } (x, y) \in U \\ 0 & \text{if } (x, y) \in B \end{cases} \quad (1)$$

where F , U , and B denote the regions of foreground, unknown, and background in trimap respectively. M denotes the image matting model, i, t denotes input image and trimap. *Prior 2, a transparent region will not be the foreground region in trimap.* Since the pixel’s alpha value in the transparent region should be in $[0, 1)$. If a transparent region is labeled as foreground in trimap, it will conflict with Equation 1.

Based on these two main priors, we start to introduce our Matte Anything model.

3.2 Overall Architecture

In this section, we introduce our proposed model called MatAny (Matte Anything model). As depicted in Figure 3, MatAny comprises three key components: a natural image matting model, a Segment Anything Model (SAM) [16], and an Open Vocabulary (OV) detector [25]. We use the OV detector to generate a bounding box with given text for SAM and detect common transparent objects. Then SAM could produce high-quality masks with various guidance, including points, boxes, scribbles and texts. Subsequently, we generate pseudo trimaps with SAM mask and transparency detection. The natural image matting model [43] will predict alpha mattes with pseudo trimaps and original RGB images. Besides, since each component of the Matte Anything model (MatAny) is accessible, users can easily refine alpha mattes with just a few clicks.

3.3 Segment with User Interaction

We utilize the Segment Anything Model (SAM) [16] as the foundation model for segmentation in our approach. SAM is capable of producing high-quality masks through user interactions, including the use of points, bounding boxes, and scribbles. Additionally, we incorporate GroundingDINO [25] as our open vocabulary detector to enhance image matting using textual guidance. GroundingDINO is adept at detecting objects based on provided text prompts. Leveraging SAM and GroundingDINO, our proposed method, MatAny, can generate high-quality masks using more cost-effective guidance methods compared to the traditional trimap.

3.4 Pseudo Trimap Generation

The objective of this part is to generate pseudo trimaps for natural image matting models [43] that closely resemble manually created trimaps.

Our trimap generation could be divided into two main steps. In the first step, we generate a basic trimap with SAM mask. We treat each object to be opaque in this part and just simply erode and dilate its mask. Specifically, given a binary input mask m . We first erode and dilate it to m_e and m_d . Then we generate a basic trimap t_b with the Equation 2:

$$t_b(x, y) = \begin{cases} 1 & \text{if } (x, y) \in m_e \\ 0.5 & \text{if } (x, y) \in m_d, (x, y) \notin m_e \\ 0 & \text{if } (x, y) \notin m_d, (x, y) \notin m_e \end{cases} \quad (2)$$

However, when using Equation (2) for opaque objects, the pseudo trimap may *conflict with Prior 2* mentioned in Section 3.1. To address this issue, in the second step, we propose a transparency correction method for the basic trimap, resulting in a corrected trimap denoted as t_c . We provide two options for the user. The first option is fully automatic: we utilize a Large Language Model (LLM) [31] to generate a list of common transparent objects. Subsequently, we employ an Open Vocabulary (OV) detector [25] to identify transparent objects based on the generated list. If the detection results are empty, we consider t_b as the final trimap, i.e., $t_c = t_b$. However, if we detect transparent objects and obtain their corresponding bounding boxes B_t , the basic trimap will be refined using Equation (3).

$$t_c(x, y) = \begin{cases} t_b(x, y) & \text{if } (x, y) \notin B_t \\ 0.5 & \text{if } (x, y) \in B_t \end{cases} \quad (3)$$

Incorrect transparency predictions can significantly affect the final performance. When there is an error in the OV detector, we give another very simple solution to refine. Users can determine whether an object is transparent or not with just one click. If it is transparent, we generate a corrected pseudo trimap with Equation (4).

$$t_c(x, y) = \begin{cases} 0.5 & \text{if } t_b(x, y) > 0 \\ 0 & \text{if } t_b(x, y) = 0 \end{cases} \quad (4)$$

3.5 Natural Image Matting

After the steps above, we generate a pseudo trimap with a mask and transparent prediction. We choose to use a natural image matting model [43] to predict the final alpha-matte of the input image. Specifically, we use state-of-the-art natural image matting methods without any additional finetuning. We observe that with proper trimap, they could achieve remarkable results in the wild to matte anything.

4 Experiments

4.1 Implementation Details

The MatAny comprises three pretrained models: the interactive segmentation model SAM [26], the open-world detection model GroundingDINO [25], and the natural image matting model ViTMatte [43]. In terms of model sizes, we utilize the ViT-H SAM model, GroundingDINO-B, and ViTMatte-B. When generating the initial trimap using erosion and dilation, we set the kernel size to 15 and allow users to fine-tune it within the range of [1, 100]. The number of iterations of erosion and dilation is fixed at 5. For transparency prediction, we define an initial vocabulary of transparent objects and require GroundingDINO to correct basic trimap with Equation 3. Users are also given the ability to correct any errors made by GroundingDINO through a single click. The majority of our interactive processes can be completed with just a few mouse clicks, eliminating the need for complex tasks such as trimap drawing.

4.2 Datasets

We assess the performance of the Matte Anything model (MatAny) by conducting evaluations on four distinct datasets that span various dimensions. These datasets include synthetic natural image data, real natural image data, real human image data, and real animal image data.

Composition-1k [40] is an extensively utilized benchmark in the field of natural image matting. It consists of a synthetic dataset comprising 50 distinct foreground objects combined with 1000 diverse backgrounds sourced from the COCO [24] dataset. This dataset serves as an evaluation platform for assessing the performance of MatAny on synthetic datasets and enables direct comparisons with previous matting methods based on trimaps and approaches based on other guidance.

AIM-500 [21] is a dataset comprising real natural images. It consists of 500 high-quality natural images along with their corresponding foreground objects and alpha mattes. The foreground objects in this dataset encompass both opaque entities such as humans and animals, as well as transparent objects like glass cups. AIM-500 serves as a valuable resource for evaluating algorithmic performance in terms of generalization on real images, as well as assessing the capability to handle foreground objects with diverse attributes.

P3M-500 [19] and *AM-2k* [20] These two datasets have been curated to focus on specific foreground objects, such as humans and animals, along with their corresponding alpha mattes. It is important to note that these datasets exist in both synthetic and real image versions; for our testing purposes, we exclusively utilize the real image variants. These two datasets effectively capture the most commonly encountered objects in the context of image matting, enabling the evaluation of algorithms’ performance and generalization capabilities in real-world scenarios with specific targets.

4.3 Experiments on Synthetic Image

To address the scarcity of training data for image matting, a series of deep learning matting methods, exemplified by DIM [40], have adopted randomly synthesized datasets for training and testing purposes. Consequently, the synthetic dataset Composition-1k [40] has emerged as the most widely utilized benchmark for evaluating image matting techniques. We evaluate our MatAny on Composition-1k with various matting methods, as shown in Table 1. Figure 4 shows our visualization results. Our experiments reflect the following facts.

Table 1. Composition-1k

methods	interactive	guidance	SAD↓			MSE↓		
			<i>all</i>	<i>transparent</i>	<i>opaque</i>	<i>all</i>	<i>transparent</i>	<i>opaque</i>
DIM [40]		<i>trimap</i>	59.6	122.5	14.0	8.5	17.9	1.7
IndexNet [28]		<i>trimap</i>	45.7	92.9	11.6	5.2	10.9	1.1
MatteFormer [32]		<i>trimap</i>	23.8	46.7	7.2	1.3	2.6	0.4
ViTMatte [43]		<i>trimap</i>	20.4	39.8	6.3	1.1	1.9	0.5
LFMatting [50]		-	58.3	-	-	11.0	-	-
UIMatting [42]		<i>point, bbox</i> <i>scribble</i>	49.9	-	-	6.0	-	-
HAttMatting [33]		-	44.1	-	-	7.0	-	-
ClickMatting [39]	✓	<i>point</i>	16.8*	-	-	3.1*	-	-
MatAny(Ours)	✓	<i>point, bbox</i> <i>scribble, text</i>	54.62	107.57	16.28	11.0	21.2	3.62
MatAny(Ours)†	✓	<i>point, bbox</i> <i>scribble, text</i>	28.3 6.1*	54.0 11.4*	9.6 2.3*	2.6 2.3*	5.5 4.4*	0.48 0.7*

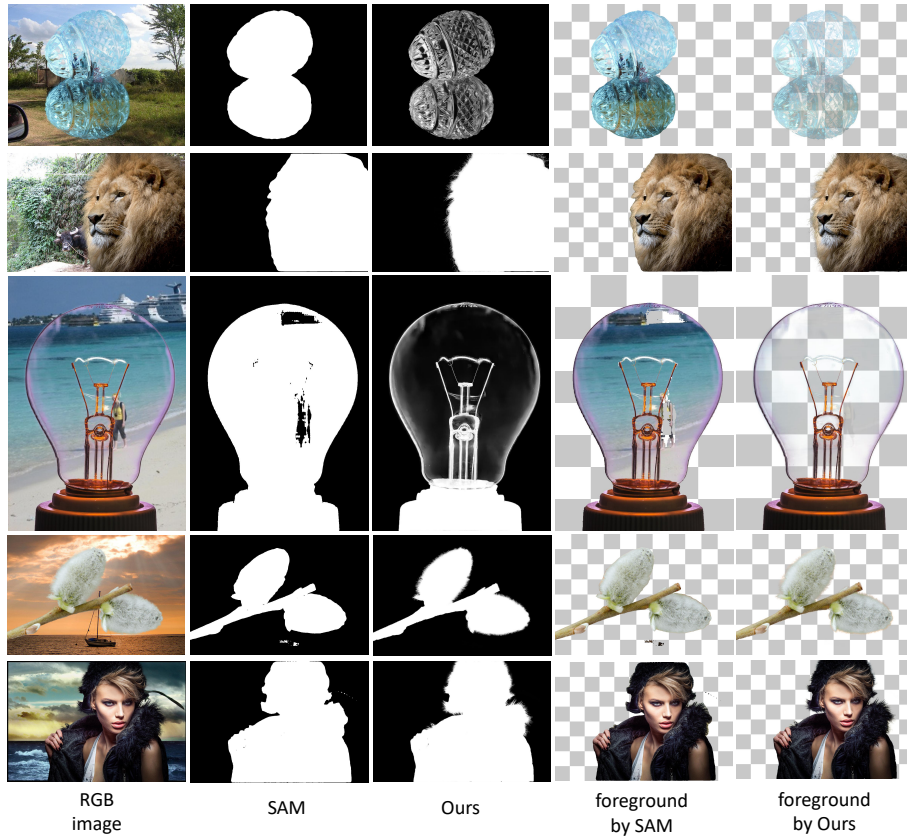


Fig. 4. Visualization of SAM and MatAny on Composition-1k. Please zoom in for the best view.

MatAny is an interactive matting method, its performance could be significantly refined through simple user interactions. In Table 1, *MatAny* and *MatAny \hat{f}* respectively denote the first results and the results after a secondary refinement. Specifically, we first obtain a high-quality mask through user interaction and generate a pseudo-trimap based on Equation 2 and 3, resulting in outcome *MatAny*. However, we observe that GroundingDINO achieves a transparency prediction accuracy of 74.9% on the Composition-1k dataset. Incorrect predictions of transparency can lead to substantial performance degradation. In MatAny, users can correct these erroneous predictions with just a single click. By applying this simple correction with Equation 4, we obtain result *MatAny \hat{f}* . It is evident that *MatAny \hat{f}* exhibits a significant improvement over *MatAny*, with a SAD improvement of over 50 and an MSE improvement of over 15 for transparent objects.

MatAny with user refinement stands out as the top-performing x -guided interactive method in terms of performance. We conducted a comparative analysis between MatAny and other matting methods, including the trimap-free method LFM [50], HAttMatting [33], as well as x -guided matting methods ClickMatting [39] and UIMatting [42]. The results demonstrate that MatAny surpasses all of them, achieving new state-of-the-art performances. Notably, MatAny exhibits significant improvements of 21.6 in SAD and 3.4 in MSE compared to the previous best results. To ensure fair comparison with ClickMatting [39], we resize the images in Composition-1k dataset, and our MatAny achieved improvements of 10.7 in SAD and 0.8 in MSE. Furthermore, MatAny achieves competitive results when compared to trimap-based methods. It even outperforms DIM [40], IndexNet [28], and GCAMatting [28]. Compared to the previous state-of-the-art method ViTMatte [43], MatAny exhibits only a 1.5 decrease in MSE, demonstrating the effectiveness of our pseudo-trimap generation strategy.

4.4 Experiments on Real Image

To evaluate the generalization capability of our model on real-world natural images, we conducted experiments on the AIM-500 dataset using our proposed MatAny approach. Due to the unavailability of code for some methods mentioned in Table 1, we focused our comparison exclusively on high-performance trimap-based matting methods. Furthermore, as previously discussed, we applied a straightforward refinement process to our results.

The effectiveness of our approach on the AIM-500 dataset is demonstrated in Table 2. Our method showcases the promising performance, surpassing certain previous trimap-based matting methods [22, 28] and achieving competitive results with MatteFormer [32].

Table 2. AIM-500

methods	interactive	guidance	SAD↓			MSE↓		
			<i>all</i>	<i>transparent</i>	<i>opaque</i>	<i>all</i>	<i>transparent</i>	<i>opaque</i>
GCAMatting [22]		<i>trimap</i>	34.93	198.72	13.44	12.08	74.87	3.84
IndexnetMatting [28]		<i>trimap</i>	28.38	150.17	12.40	8.55	50.90	3.00
MatteFormer [32]		<i>trimap</i>	26.87	146.99	11.11	8.74	54.45	2.74
ViTMatte [43]		<i>trimap</i>	17.21	80.90	8.86	3.80	21.27	1.51
MatAny(Ours)†	✓	<i>point, bbox scribble, text</i>	27.83	110.50	16.98	9.36	35.30	5.95

4.5 Experiments on Class-Specific Image

To validate the generalization capability of our proposed method in specific real-world contexts, we selected two specific category datasets, namely P3M-500 [19] and AM-2k [20]. These datasets respectively reflect the ability of MatAny in performing image matting for portraits and animal subjects. As shown in

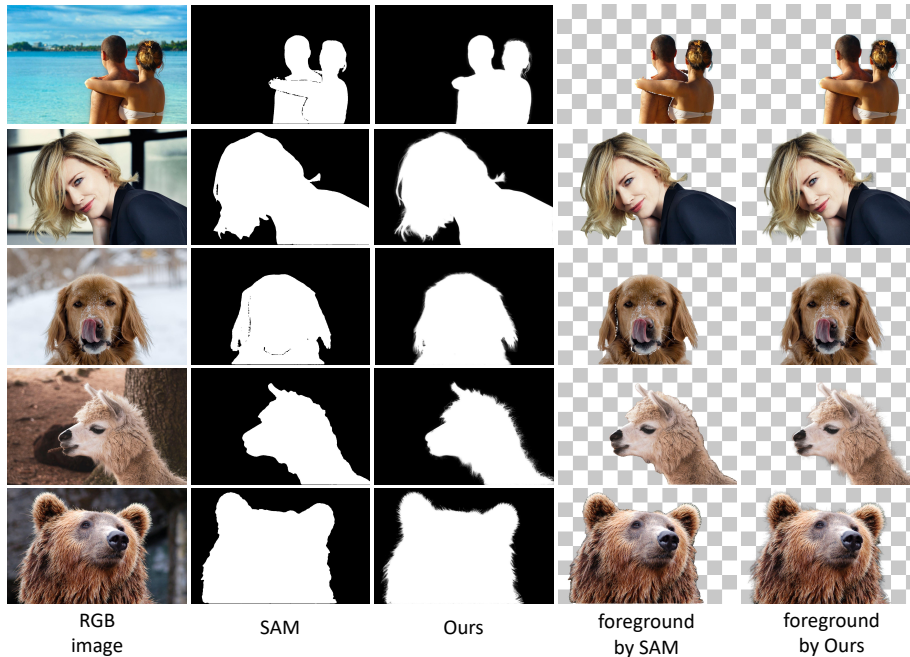


Fig. 5. Visualization of SAM and MatAny on real-world data from AM-2K [20] and P3M-500 [19]. Please zoom in for the best view.

Table 3. AM-2k-testset

methods	training data	interactive	guidance	SAD↓	MSE↓	Conn↓	Grad↓
LFM [50]	AM-2k		-	36.12	11.60	21.06	33.62
SHM [5]	AM-2k		-	17.81	6.80	12.54	17.02
GFM [20]	AM-2k		-	9.66	2.40	9.37	8.98
GCAMatting [22]	DIM		<i>trimap</i>	8.93	1.84	8.03	9.03
MatteFormer [32]	DIM		<i>trimap</i>	8.69	1.77	7.77	8.38
ViTMatte [43]	DIM		<i>trimap</i>	7.94	1.17	6.65	7.11
MatAny(Ours)†	DIM	✓	<i>point, bbox scribble, text</i>	11.92	3.29	10.92	11.73

Table 4. P3M-500

methods	training data	interactive	guidance	SAD↓	MSE↓	Conn↓	Grad↓
LFM [50]	P3M		-	32.59	13.10	19.50	31.93
SHM [5]	P3M		-	20.77	9.30	17.09	20.30
GFM [20]	P3M		-	15.50	5.60	18.03	14.82
P3M [19]	P3M		-	9.06	2.80	-	-
GCAMatting [22]	DIM		<i>trimap</i>	7.90	1.62	7.37	12.44
MatteFormer [32]	DIM		<i>trimap</i>	7.81	1.51	7.16	12.40
ViTMatte [43]	DIM		<i>trimap</i>	7.26	1.24	6.47	11.32
MatAny(Ours)†	DIM	✓	<i>point, bbox scribble, text</i>	10.68	2.80	9.97	17.31

Table 3 and 4, we have compared the two types of methods. Figure 5 shows our visualization results.

We conduct an evaluation of the generation ability of MatAny using class-specific data. The matting model employed in MatAny is adapted from the state-of-the-art matting model, ViTMatte [43], which was pretrained on the DIM dataset [40]. We directly applied our MatAny to the AM-2k and P3M-500 test datasets, demonstrating its robust generation capability. Our method outperforms LFM [50], SHM [5], and achieves competitive results with state-of-the-art trimap-free models [19, 20] trained on the corresponding datasets.

Furthermore, we compared our methods with previous trimap-based matting techniques [22, 32, 43]. Our model exhibits comparable performance to the trimap-based approaches. Overall, the differences between our method and these approaches are only around 3 in terms of SAD and approximately 1.5 in terms of MSE. This highlights the strong potential of our method.

5 Ablations

5.1 User Interaction

MatAny is an interactive matting system that emphasizes the importance of user interaction in achieving the desired alpha matte, especially when dealing with multiple objects.

As illustrated in Figure 6, the resulting mattes vary based on different user interactions. For example, if the user clicks on only one cat on the left or right, MatAny will matte only that specific cat as instructed. Conversely, if the user clicks on both cats, MatAny will matte both of them accordingly. This unique advantage of MatAny showcases its ability to matte any desired instance through simple user clicks, which is challenging to achieve using traditional trimap-based methods.

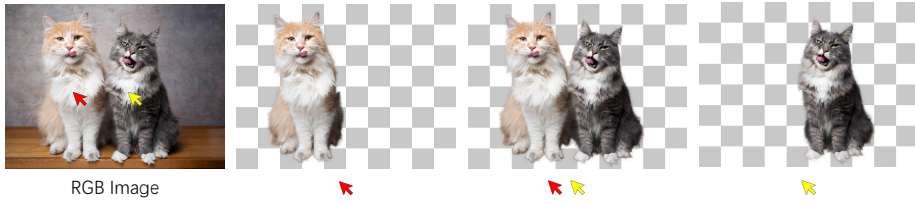


Fig. 6. Matte with user interaction.

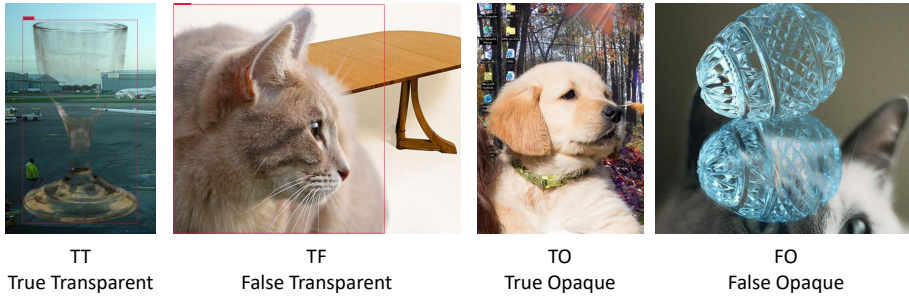


Fig. 7. Results of GroundingDINO [25]. The red bounding boxes refer to detected transparent objects.

Table 5. Accuracy of OV detector on Composition-1k

transparent object vocabulary	box threshold	backbone	TT	FT	TO	FO	accuracy
['glass']	0.5	Swin-T [27]	0.180	0.027	0.553	0.240	73.3%
['glass', 'web']	0.5		0.237	0.126	0.454	0.183	69.1%
['glass', 'web', 'wine']	0.5		0.179	0.038	0.542	0.241	72.1%
['glass']	0.4		0.280	0.061	0.519	0.140	79.9%
['glass']	0.6		0.118	0.020	0.560	0.302	67.8%
['glass']	0.5	Swin-B [27]	0.252	0.231	0.349	0.168	60.1%
['glass', 'web']	0.5		0.248	0.098	0.482	0.172	73.0%
['glass', 'web', 'wine']	0.5		0.236	0.092	0.488	0.184	72.4%
['glass']	0.4		0.326	0.410	0.170	0.094	49.6%
['glass']	0.6		0.190	0.110	0.470	0.230	66.0%

5.2 OV Detector

In this section, we mainly ablate the open-vocabulary detector in different dataset. We observe that different vocabularies given to the OV detector in MatAny result in different transparency detection abilities. Though we give a refine strategy with Equation 4, it is still necessary to verify the validity of the OV detector.

As shown in Table 5, we evaluate GroundingDINO with different backbones, box thresholds, and vocabularies. Some of the test results are shown in Figure 7. We have obtained the following two observations: Firstly, the OV detector is able to achieve an accuracy rate exceeding or approaching 70% in most cases. The highest accuracy rate recorded is 79.9%. Secondly, there are significant differences in the hyperparameter settings among different OV detectors. For instance, the table reflects that GroundingDINO with Swin-T tends to have smaller thresholds and a smaller vocabulary, whereas GroundingDINO with Swin-B exhibits the opposite behavior. Overall, we believe that a carefully tuned OV detector, combined with minor user corrections, can serve as a solution for determining transparent objects in matting.

6 Conclusion

In this paper, we present Matte Anything model (MatAny), a highly performant interactive matting system designed to address the labor-intensive process of trimap generation. Our approach leverages the potential of vision foundation models in the field of image matting. MatAny comprises three pretrained models, including the segment anything model, open-vocabulary detector, and natural image matting model, eliminating the need for additional training. Additionally, we propose a pseudo trimap generation strategy based on two key priors for accurate trimap estimation.

We evaluate the performance of MatAny on four benchmark datasets. Through simple refinement, our method outperforms all existing x -guided methods and achieves competitive results with trimap-guided methods on the Composition-1k dataset. Moreover, MatAny demonstrates robust generation capability in various real-world scenarios. We hope that our work could inspire future advancements in interactive image matting and find wide application in numerous real-world tasks.

References

1. Boda, J., Pandya, D.: A survey on image matting techniques. In: 2018 International Conference on Communication and Signal Processing (ICCSP). pp. 0765–0770 (2018). <https://doi.org/10.1109/ICCSP.2018.8523834> 1
2. Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J.D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D., Wu, J., Winter, C., Hesse, C., Chen, M., Sigler, E., Litwin, M., Gray, S., Chess, B., Clark, J., Berner, C., McCandlish, S., Radford, A., Sutskever, I., Amodei, D.: Language models are few-shot learners. In: Larochelle, H., Ranzato, M., Hadsell, R., Balcan, M., Lin, H. (eds.) Advances in Neural Information Processing Systems. vol. 33, pp. 1877–1901. Curran Associates, Inc. (2020) 4
3. Cen, J., Zhou, Z., Fang, J., Shen, W., Xie, L., Zhang, X., Tian, Q.: Segment anything in 3d with nerfs. arXiv:2304.12308 (2023) 4

4. Chen, Q., Li, D., Tang, C.K.: Knn matting. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **35**(9), 2175–2188 (2013). <https://doi.org/10.1109/TPAMI.2013.18> **1**
5. Chen, Q., Ge, T., Xu, Y., Zhang, Z., Yang, X., Gai, K.: Semantic human matting. In: *Proceedings of the 26th ACM international conference on Multimedia*. pp. 618–626 (2018) **11, 12**
6. Cheng, B., Misra, I., Schwing, A.G., Kirillov, A., Girdhar, R.: Masked-attention mask transformer for universal image segmentation (2022) **1**
7. Cheng, B., Schwing, A., Kirillov, A.: Per-pixel classification is not all you need for semantic segmentation. *Advances in Neural Information Processing Systems* **34**, 17864–17875 (2021) **1**
8. Cheng, Y., Li, L., Xu, Y., Li, X., Yang, Z., Wang, W., Yang, Y.: Segment and track anything. *arXiv preprint arXiv:2305.06558* (2023) **4**
9. Ding, H., Zhang, H., Liu, C., Jiang, X.: Deep interactive image matting with feature propagation. *IEEE Transactions on Image Processing* **31**, 2421–2432 (2022) **2, 3**
10. Forte, M., Pitié, F.: f, b , alpha matting. *arXiv preprint arXiv:2003.07711* (2020) **1, 3**
11. Gao, P., Geng, S., Zhang, R., Ma, T., Fang, R., Zhang, Y., Li, H., Qiao, Y.: Clip-adapter: Better vision-language models with feature adapters. *arXiv preprint arXiv:2110.04544* (2021) **4**
12. Gu, X., Lin, T.Y., Kuo, W., Cui, Y.: Open-vocabulary object detection via vision and language knowledge distillation. *arXiv preprint arXiv:2104.13921* (2021) **4**
13. Gupta, A., Dollar, P., Girshick, R.: Lvis: A dataset for large vocabulary instance segmentation. In: *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. pp. 5356–5364 (2019) **4**
14. He, K., Rhemann, C., Rother, C., Tang, X., Sun, J.: A global sampling method for alpha matting. In: *CVPR 2011*. pp. 2049–2056 (2011). <https://doi.org/10.1109/CVPR.2011.5995495> **1**
15. Jain, J., Li, J., Chiu, M., Hassani, A., Orlov, N., Shi, H.: OneFormer: One Transformer to Rule Universal Image Segmentation (2023) **1**
16. Kirillov, A., Mintun, E., Ravi, N., Mao, H., Rolland, C., Gustafson, L., Xiao, T., Whitehead, S., Berg, A.C., Lo, W.Y., Dollár, P., Girshick, R.: Segment anything. *arXiv:2304.02643* (2023) **2, 4, 5, 6**
17. Levin, A., Lischinski, D., Weiss, Y.: A closed-form solution to natural image matting. *IEEE transactions on pattern analysis and machine intelligence* **30**(2), 228–242 (2007) **1**
18. Li, C., Liu, H., Li, L., Zhang, P., Aneja, J., Yang, J., Jin, P., Hu, H., Liu, Z., Lee, Y.J., et al.: Elevater: A benchmark and toolkit for evaluating language-augmented visual models. *Advances in Neural Information Processing Systems* **35**, 9287–9301 (2022) **4**
19. Li, J., Ma, S., Zhang, J., Tao, D.: Privacy-preserving portrait matting. In: *Proceedings of the 29th ACM International Conference on Multimedia*. p. 3501–3509. *MM '21*, Association for Computing Machinery, New York, NY, USA (2021). <https://doi.org/10.1145/3474085.3475512>, <https://doi.org/10.1145/3474085.3475512> **3, 8, 10, 11, 12**
20. Li, J., Zhang, J., Maybank, S.J., Tao, D.: Bridging composite and real: towards end-to-end deep image matting. *International Journal of Computer Vision* **130**(2), 246–266 (2022) **3, 8, 10, 11, 12**
21. Li, J., Zhang, J., Tao, D.: Deep automatic natural image matting. In: Zhou, Z.H. (ed.) *Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence, IJCAI-21*. pp. 800–806. *International Joint Conferences on Artificial*

- Intelligence Organization (8 2021). <https://doi.org/10.24963/ijcai.2021/111>, <https://doi.org/10.24963/ijcai.2021/111>, main Track 8
22. Li, Y., Lu, H.: Natural image matting via guided contextual attention. In: Proceedings of the AAAI Conference on Artificial Intelligence. vol. 34, pp. 11450–11457 (2020) 1, 3, 10, 11, 12
 23. Li, Y., Wang, H., Duan, Y., Li, X.: Clip surgery for better explainability with enhancement in open-vocabulary tasks. arXiv preprint arXiv:2304.05653 (2023) 4
 24. Lin, T.Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., Dollár, P., Zitnick, C.L.: Microsoft coco: Common objects in context. In: European conference on computer vision. pp. 740–755. Springer (2014) 4, 7
 25. Liu, S., Zeng, Z., Ren, T., Li, F., Zhang, H., Yang, J., Li, C., Yang, J., Su, H., Zhu, J., et al.: Grounding dino: Marrying dino with grounded pre-training for open-set object detection. arXiv preprint arXiv:2303.05499 (2023) 2, 4, 5, 6, 7, 13
 26. Liu, Y., Zhang, J., She, Z., Kheradmand, A., Armand, M.: Samm (segment any medical model): A 3d slicer integration to sam. arXiv preprint arXiv:2304.05622 (2023) 4, 7
 27. Liu, Z., Lin, Y., Cao, Y., Hu, H., Wei, Y., Zhang, Z., Lin, S., Guo, B.: Swin transformer: Hierarchical vision transformer using shifted windows. In: Proceedings of the IEEE/CVF International Conference on Computer Vision. pp. 10012–10022 (2021) 13
 28. Lu, H., Dai, Y., Shen, C., Xu, S.: Indices matter: Learning to index for deep image matting. In: Proceedings of the IEEE/CVF International Conference on Computer Vision. pp. 3266–3275 (2019) 1, 3, 8, 10
 29. Ma, J., Wang, B.: Segment anything in medical images. arXiv preprint arXiv:2304.12306 (2023) 4
 30. Mohapatra, S., Gosai, A., Schlaug, G.: Sam vs bet: A comparative study for brain extraction and segmentation of magnetic resonance images using deep learning. arXiv preprint arXiv:2304.04738 2 (2023) 4
 31. OpenAI, R.: Gpt-4 technical report. arXiv (2023) 4, 6
 32. Park, G., Son, S., Yoo, J., Kim, S., Kwak, N.: Matteformer: Transformer-based image matting via prior-tokens. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 11696–11706 (2022) 1, 3, 8, 10, 11, 12
 33. Qiao, Y., Liu, Y., Yang, X., Zhou, D., Xu, M., Zhang, Q., Wei, X.: Attention-guided hierarchical structure aggregation for image matting. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 13676–13685 (2020) 2, 3, 8, 10
 34. Radford, A., Kim, J.W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., Sastry, G., Askell, A., Mishkin, P., Clark, J., et al.: Learning transferable visual models from natural language supervision. In: International conference on machine learning. pp. 8748–8763. PMLR (2021) 4
 35. Rombach, R., Blattmann, A., Lorenz, D., Esser, P., Ommer, B.: High-resolution image synthesis with latent diffusion models (2021) 4
 36. Seo, J., Jang, W., Kwak, M.S., Ko, J., Kim, H., Kim, J., Kim, J.H., Lee, J., Kim, S.: Let 2d diffusion model know 3d-consistency for robust text-to-3d generation. arXiv preprint arXiv:2303.07937 (2023) 4
 37. Shahrian, E., Rajan, D., Price, B., Cohen, S.: Improving image matting using comprehensive sampling sets. In: 2013 IEEE Conference on Computer Vision and Pattern Recognition. pp. 636–643 (2013). <https://doi.org/10.1109/CVPR.2013.88> 1

38. Touvron, H., Lavril, T., Izacard, G., Martinet, X., Lachaux, M.A., Lacroix, T., Rozière, B., Goyal, N., Hambro, E., Azhar, F., Rodriguez, A., Joulin, A., Grave, E., Lample, G.: Llama: Open and efficient foundation language models. arXiv preprint arXiv:2302.13971 (2023) [4](#)
39. Wei, T., Chen, D., Zhou, W., Liao, J., Zhao, H., Zhang, W., Yu, N.: Improved image matting via real-time user clicks and uncertainty estimation. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 15374–15383 (2021) [2](#), [3](#), [8](#), [10](#)
40. Xu, N., Price, B., Cohen, S., Huang, T.: Deep image matting. In: Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 2970–2979 (2017) [1](#), [2](#), [3](#), [7](#), [8](#), [10](#), [12](#)
41. Yang, J., Gao, M., Li, Z., Gao, S., Wang, F., Zheng, F.: Track anything: Segment anything meets videos. arXiv preprint arXiv:2304.11968 (2023) [4](#)
42. Yang, S., Wang, B., Li, W., Lin, Y., He, C., et al.: Unified interactive image matting. arXiv preprint arXiv:2205.08324 (2022) [2](#), [3](#), [8](#), [10](#)
43. Yao, J., Wang, X., Yang, S., Wang, B.: Vitmatte: Boosting image matting with pretrained plain vision transformers. arXiv preprint arXiv:2305.15272 (2023) [1](#), [2](#), [3](#), [5](#), [6](#), [7](#), [8](#), [10](#), [11](#), [12](#)
44. Yao, L., Han, J., Wen, Y., Liang, X., Xu, D., Zhang, W., Li, Z., Xu, C., Xu, H.: Detclip: Dictionary-enriched visual-concept paralleled pre-training for open-world detection. arXiv preprint arXiv:2209.09407 (2022) [4](#)
45. Yu, Q., Zhang, J., Zhang, H., Wang, Y., Lin, Z., Xu, N., Bai, Y., Yuille, A.: Mask guided matting via progressive refinement network. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 1154–1163 (2021) [1](#), [3](#)
46. Yu, T., Feng, R., Feng, R., Liu, J., Jin, X., Zeng, W., Chen, Z.: Inpaint anything: Segment anything meets image inpainting. arXiv preprint arXiv:2304.06790 (2023) [4](#)
47. Yu, T., Feng, R., Feng, R., Liu, J., Jin, X., Zeng, W., Chen, Z.: Inpaint anything: Segment anything meets image inpainting. arXiv preprint arXiv:2304.06790 (2023) [4](#)
48. Zareian, A., Rosa, K.D., Hu, D.H., Chang, S.F.: Open-vocabulary object detection using captions. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 14393–14402 (2021) [4](#)
49. Zhang, L., Agrawala, M.: Adding conditional control to text-to-image diffusion models (2023) [4](#)
50. Zhang, Y., Gong, L., Fan, L., Ren, P., Huang, Q., Bao, H., Xu, W.: A late fusion cnn for digital matting. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. pp. 7469–7478 (2019) [2](#), [3](#), [8](#), [10](#), [11](#), [12](#)