Screentone-Preserved Manga Retargeting

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As a popular comic style, manga offers a unique impression by utilizing a rich set of bitonal patterns, or screentones, for illustration. However, screentones can easily be contaminated with visual-unpleasant aliasing and/or blurriness after resampling, which harms its visualization on displays of diverse resolutions. To address this problem, we propose the first manga retargeting method that synthesizes a rescaled manga image while retaining the screentone in each screened region. This is a non-trivial task as accurate region-wise segmentation remains challenging. Fortunately, the rescaled manga shares the same region-wise screentone correspondences with the original manga, which enables us to simplify the screentone synthesis problem as an anchor-based proposals selection and rearrangement problem. Specifically, we design a novel manga sampling strategy to generate aliasing-free screentone proposals, based on hierarchical grid-based anchors that connect the correspondences between the original and the target rescaled manga. Furthermore, a Recurrent Proposal Selection Module (RPSM) is proposed to adaptively integrate these proposals for target screentone synthesis. Besides, to deal with the translation insensitivity nature of screentones, we propose a translation-invariant screentone loss to facilitate the training convergence. Extensive qualitative and quantitative experiments are conducted to verify the effectiveness of our method, and notably compelling results are achieved compared to existing alternative techniques.

Fig. 1. The goal of manga retargeting is to retain the screentone resolution while allowing the overall manga scale to change. This avoids the blurriness and the aliasing introduced by naive resampling. Comparing to existing applicable methods (b)-(d), our proposed retargeting model in (e) can better preserve the original screentones.

1 INTRODUCTION

The popular Japanese-style comic or manga makes use of various black-and-white patterns, or screentones, to illustrate the regional tonal and texture characteristics, and better differentiate regions, as color is missing. With the popularity of mobile digital devices, such as smartphones, tablets, etc., readers are now enjoying the manga on displays of various sizes. However, to fit the display resolution, manga images are usually resampled bilinearly or bicubicly, which inevitably causes blurriness and aliasing artifacts [Xie et al. 2021a] on these screentones, especially with the reduced resolution. A typical example is demonstrated in Fig. 2. In this scenario, a screentone-preserved manga retargeting technique is urgently needed in order to preserve the visual fidelity of manga when presented in different resolutions.
Unlike the existing natural image retargeting techniques [Dong et al. 2015; Lei et al. 2017] aiming at preserving the prominent content when the image aspect ratio changes, our manga retargeting focuses on preserving the screentones when the overall image resolution changes. In other words, we want to retain the screentone resolution within the screened region while the overall structure is allowed to rescale (compare Fig. 2(a) to (c)). Apparently, applying existing natural image retargeting methods to manga will damage the screentone patterns. Matsui et al. [2011] made attempts to generate manga for other aspect ratios, but they only consider line drawing while the more challenging screentone is ignored. An intuitive solution to generate retargeted manga is to first segment the screentones regions and then applied screentone patches to the corresponding regions [Tsubota et al. 2019; Yao et al. 2016]. However, these methods can only handle screentones in a predefined set and may not generate consistent screentone within the same region, as demonstrated in Fig. 3(b). Another possible solution is to adopt an interpolative representation, such as the ScreenVAE map generated by Screentone Variational AutoEncoder [Xie et al. 2020]. This representation can be resampled and used to reconstruct screentones that resemble the original ones. However, the reconstructed screentones (Fig. 3(c)) may not match well with the originals. Manga inpainting technique [Xie et al. 2021b] may also be employed for retargeting purpose, but their model is tailored for inpainting manga (both screentone and outline) at a single scale. Retargeting at arbitrary scales may fail their model, as demonstrated by their inconsistent screentones in changed scales Fig. 4.

In this paper, we propose a learning-based model for screentone-preserved manga retargeting. As screentones tolerate no interpolation, we aim at retaining the screentone in each shrunked (enlarged) region in a shrunked (enlarged) manga. Fig. 5 illustrates the intuition of our model. Intuitively speaking, we patch-wisely copy-and-paste the screentone from the input image to form a shrunked (enlarged) screened region in the shrunked (enlarged) manga. The core challenge is to ensure the generated screentone is visually well-aligned (Fig. 5(c)). Previous learning-based method [Xie et al. 2021b] suffers from the poor alignment problem (Fig. 5(b)) and cannot generate satisfactory results, as demonstrated by the misalignment seams within the generated screentone especially the shrunked and enlarged mangas in Fig. 4(b).

To achieve the goal, we adopt the semantic representation, consisting of structural line and ScreenVAE map, to represent the retargeted manga image, similar to [Xie et al. 2021b]. However, when the scale of the manga is changed, such semantic representation is not sufficient to accurately reconstruct the original screentones. The ScreenVAE map is not helpful to align screentone during a patch-wise copy-and-paste process, as all ScreenVAE values in the same screened region are equal. This means we need to utilize the input screentone in spatial domain to align the patches during our screentone synthesis. To determine patches and align them, we propose a hierarchical anchor-based proposal sampling scheme to build the correspondences between the original and the retargeted screentone layouts. These proposals are intuitively our “patches for copy-and-paste” and they are aligned in this module. Next, we design a Recurrent Proposal Selection Module (RPSM) to fuse (“paste”) these proposals one by one and, simultaneously, hold an accumulated confidence map to avoid the regions already fused with high-confidence proposal features to be fused again. To make it works,
we also propose a translation-invariant screentone loss to allow
the generated screentones to match one feasible solution, which
is practically useful to guarantee sharp screentone patterns.

To evaluate our method, extensive experiments are conducted,
including qualitative and quantitative results of synthetic data. Con-
vincing results are obtained in terms of visual quality and qua-
titative evaluation. Also, we apply our method on various real-world
manga images to generate manga with diverse resolutions, and
visually plausible results are obtained. Our contributions can be
summarized as follows:

- We propose the first manga retargeting method, which gen-
erates manga with structures resampled while screentones
maintaining at the original scale.
- We propose a Manga Retargeting Network with sampled pro-
posalsto select and rearrange appropriate ones for screentone
synthesis.
- We propose a translation-invariant screentone loss to tolerate
the screentone misalignment and enable the learning from
multiple solutions.

2 RELATED WORK

2.1 Image Retargeting

Retargeting is the process of adapting an image from one screen res-
solution to another, often with the change of the aspect ratio as well
[Shamir and Sorkine 2009]. In real-time applications, global visual
effects of the image can be preserved using scaling operators when
interpolation scaling methods are employed. But, these methods
may produce distortion of important contents. Plenty of content-
aware retargeting approaches have been proposed to improve the
visual quality of the resized images [Dong et al. 2015; Lei et al.
2017]. The existing content-aware image retargeting algorithms
can be mainly categorized into two types: discrete approaches and
continuous approaches.

In the discrete approaches, an input image is resized by cropping
or seam carving. Cropping-based methods [Liu and Gleich 2006;
Suh et al. 2003] select an optimal rectangle from the image and
remove the content outside the rectangle. Still, they may lead to
noticeable information loss and not perform well with images con-
taining multiple salient objects. Seam carving [Avidan and Shamir
2007; Shamir and Sorkine 2009] is another typical discrete approach,
which achieves image resizing by removing or inserting one seam
with the least energy each time until reaching the target size. How-
ever, it will cause obvious distortion if too many seams passing
through important objects are involved. Rubinstein et al. [2009]
present a multi-operator algorithm and get more pleasing results
than other single operators by combining cropping, linear scaling,
and seam carving. Pritch et al. [2009] regards image retargeting as
geometric rearrangement of images and discretely removes repeated
patterns in homogenous regions instead of scaling and stretching
images. Although these approaches can generate pleasing results for
many cases, it should be noted that all the above discrete methods
may lead to noticeably jagged edges and discontinuous artifacts in
image objects.

Instead of eliminating redundant contents directly, continuous
methods optimize a mapping or warping using several deformation
and smoothness constraints. Liu et al.,[2005] propose a non-linear
warping scheme to preserve important content. However, contents
outside the region of interest may suffer from significant distortions.
Wolf et al. [2007] propose to reduce distortion by merging less im-
portant pixels. However, the distortion still propagates along the
resizing direction. To refine the distortion propagation, Wang et
al. [2008] propose an optimized scale-and-stretch approach which
divides an image into uniform mesh grand and resizes the image by
iteratively computing optimal local scaling factors of local regions.
But this method may lead to inconsistent deformation for objects oc-
cupying several mesh. To ease this problem, some approaches [Guo
et al. 2009; Jin et al. 2010; Zhang et al. 2009] propose to combine
saliency information to protect salient objects. These methods per-
form well on preserving the shape of local objects while inconsistent
distortions may still occur on structure lines.

Deep learning techniques have achieved astonishing advances
in recent years and also promoted the development of image retar-
ting. Liu et al. [2018] use deep neural networks to extract seman-
tic components, which are then fused with the original image to
generate the target image. Cho et al. [2017] first applied deep learn-
ing in image retargeting in an end-to-end manner. A weakly- and
self-supervised deep convolutional neural network (WSSDCNN) is
proposed to predict attentive shift maps which are used to warp
the input image into an image of target size. However, these meth-
ods require image-level annotations when training. Tan et al. [2019]
proposed a deep cyclic image retargeting approach, called Cycle-IR,
without relying on any explicit user annotations, but it cannot per-
form well when important areas are too large or scattered or with
low contrast. DeepIR [Lin et al. 2019] first constructs the semantic
structures with a deep neural network and then applies uniform
resampling in feature level to preserve these structures in the re-
targeted image, while it may over squeeze the important regions
or over maintain the less important ones. All above image retar-
ting methods cannot handle manga as they all involve scaling
operations on image contents which will destroy the appearance of
screentones.

2.2 Screentone Extraction and Manga Screening

Some attempts have been made to extract screentones from manga
and generate new screentone patches. Yao et al. [2016] considered
how to extract screentones from manga by modeling three specific

![Copy-and-paste](image-url)
3 OVERVIEW

Given a high-quality manga image $I$ of size $H \times W$, we aim at synthesizing a retargeted version $\hat{I}$ of size $kH \times kW$ (where $k \in \mathbb{R}_+$), which has the structure lines resampled accordingly while preserves the screentones at the original scale. As screentone is vulnerable to interpolation, we follow the practice of [Xie et al. 2021b] and adopt semantic representation of manga images, including structure line and ScreentoneVAE map, so that we can approximately represent the desired manga by interpolating in this domain. Anyhow, such representation is not informative enough to reconstruct the original screentones, possibly because of the dataset bias learned by the ScreentoneVAE map generator [Xie et al. 2020]. Regarding this, we additionally exploit the original screentone to extract proposals based on a hierarchical anchor sampling scheme, which provides effective guidance to promote the screentone reconstruction fidelity.

The overview diagram of our system is illustrated in Figure 6, including three functional blocks. Firstly, the input manga image $I$ is decomposed into a structural line map $L$ and a screentone image $I^s$ through [Li et al. 2017]. The screentone image is further encoded as the ScreentoneVAE map $S$ with smooth values within each screentone region [Xie et al. 2020]. $L$ and $S$ together forms the semantic representation of $I$. Then, we feed the resampled semantic representation $\tilde{L}$ and $\tilde{S}$ to the screentone reconstruction network $G$. To supplement screentone details, a special feature extractor $E_p$ is employed to encode region-wise screentone features $F_p$ from the input manga image $I$ and $S$. $F_p$ will be integrated with the bottleneck features $F_b$ of $G$ through the Recurrent Proposal Selection Module (RPSM). Note that, $F_p$ and $F_b$ are under different resolutions and directly resampling $F_b$ may ruin the embedded high-frequency screentone details. So, to construct proposals of the same resolution, we propose to regularly scatter a grid of anchors $A = \{a_{i,j}\}^{I,J}$ and crop the local patches of $F_p$ that are centralized on these anchors. Particularly, we construct multiple groups of such proposals by changing the anchor-grid interval (i.e. the anchor numbers), which offer more rich information for screentone reconstruction. Considering these proposal patches may not fully match the target regions, we propose Recurrent Proposal Selection Module (RPSM) to progressively select appropriate proposals, and the fused features are exploited to generate the resultant manga image.

As consisting of periodic or aperiodic discrete patterns, screentones are perceptually insensitive to pattern translation, as demonstrated in Fig. 7. These characteristic poses challenge to the training of screentone synthesis because one given ground-truth actually

![Fig. 6. Overview diagram of our manga retargeting system. Given a high-quality manga image $I$, we first decompose it into structural line $L$ and ScreentoneVAE map $S$, which are resampled to the target size via bilinear interpolation, and then fed to the screentone synthesis network. Meanwhile, the input manga $I$ and its ScreentoneVAE map are fed to another feature extractor $E_p$ that offers screentone features for hierarchical anchor-based proposal sampling. Then, the proposal screentone features are integrated by the Recurrent Proposal Selection Module (RPSM) in a progressive manner, and the fused features are finally used to reconstruct the retargeted manga image $\hat{I}$.](image-url)
corresponds to lots of other variants of the same essence. Both pixel-wise measurement or using window averaged features will cause blurry results as a kind of average effect. To tackle this issue, we proposed a Translation-Invariant Screentone Loss that allows the generated screentones to match one possible solution within a tolerance window. It comes out to be essential for generating discrete high-frequency screentones. The detailed model architectures and loss functions are described in Section 4.

### 4 OUR APPROACH

In this section, we first describe the network architecture logically, and then introduce two key technical designs in detail. After that, the loss function will be presented.

#### 4.1 Network Architecture

Our manga retargeting network contains two branches, namely the screentone reconstruction branch $G$ and the screentone encoder branch $E_p$. The screentone reconstruction network $G$ adopts an encoder-decoder structure, implemented with a series of convolution layers and dilated residual blocks[Yu et al. 2017]. It takes the resampled semantic components (structural line map $L$ and ScreenVAE map $S$) as input and generate the screentone-preserved manga image $I$ under the guidance of the original screentone proposals. Particularly, the screentone proposals are fused in the bottleneck of $G$ and through the Recurrent Proposal Selection Module (RPSM) that will be expatiated in section 4.2.

Since the semantic representation is not informative enough to reconstruct the original screentone precisely, we employ a special screentone encoder $E_p$ to extract screentone appearance features from the original manga image $I$ and its ScreenVAE map $S$, which will be sampled under a hierarchical anchor-based proposal sampling scheme (detailed in Section 4.2) to provide guidance for $G$. The screentone encoder $E_p$ shares the same architecture with the encoder of $G$, and the decoder $D$ is with symmetric architecture with the encoder $E$. Skip connections are adopted between $E$ and $D$ to preserve the spatial information of regions. The detailed network architectures are provided in the supplementary material.

#### 4.2 Hierarchical Proposal based Recurrent Fusion

**Hierarchical anchor-based proposal sampling.** Given the screentone feature $F_s = E_p(I, S)$ of size $HF \times WF$, we can not fuse it with the backbone features $F_b = E(L, S)$ directly, because of the misalignment caused by inconsistent resolutions. Furthermore, resampling $F_s$ to the same resolution of $F_b$ (i.e. $kHF \times kW_F$) may destroy the high-frequency pattern information embedded in. Instead, to ensure the intactness of local patches, we regularly scatter a $I \times J$ grid of anchors $A = \{a_{ij}\}^{IJ}$ on $F_s$ and sample the local patches around them. Specifically, for an arbitrary anchor $a_{ij}$, the sampled feature patch can be denoted as $F_{s,ij} = P(F_s, a_{ij})$, where $P(\cdot)$ denotes a cropping function that takes the patch centralized on $a_{ij}$ and sized $kHF \times kW_F$. For the case of $k > 1$, where some cropping patches may cover regions beyond $F_s$, we simply extend $F_s$ by padding empty value. Then, we can combine these grid-anchor based local patches $\{F_{s,ij}\}^{IJ}$ as input and generate the screentone-preserved manga image $\hat{I}$ under the guidance of the original screentone proposals.

![Fig. 8. Illustration of the grid-anchor-based proposal sampling. Local feature patch around each anchor is cropped, and all the patches are combined to form a feature proposal.](image)

**Recurrent selection of hierarchical proposals.** Once the multiple proposals of screentone features are constructed, the screentone reconstruction network $G$ takes them as guidance to reconstruct the region-wise screentones according to the semantic information represented by $L$ and $S$. A naive solution is to simply concatenate all these proposal feature sets $\{\hat{F}_l\}_{l=0}^N$ and the backbone feature $F_b$, which are then fed to decoder $D$. However, our experiment shows that such feature concatenation causes blurry reconstruction or even artifacts because the network might be confused by the case that multiple proposals provide equally-qualified solutions for certain regions. A visual example is compared in Fig. 9. To address this issue, we propose an explicit proposal feature selection module, namely Recurrent Proposal Selection Module (RPSM), whose working diagram is illustrated in Fig. 6. The primary motivation is to force the block only to choose one feasible solution from the provided proposals. We select proposal features by computing spatial attention maps in a recurrent manner. Particularly, we manage to avoid the regions that are already fused with high-confidence proposal features to be covered again by holding an accumulated confidence map $C$, which
We formulate four loss terms to train our network, namely translation-invariant screentone loss, ScreenVAE map loss, attention loss, and adversarial loss.

Translation-invariant screentone loss. As demonstrated in Fig. 7, screentones are translation-insensitive to Human Vision System (HVS), which indicates multiple acceptable candidates exist for given ground truth. To allow such ambiguity in similarity measurement, we propose the translation-invariant screentone loss $L_{\text{sir}}$. Specifically, for a region $p$ of the generated manga image $I$, we first search an optimal offset $\delta \in \mathbb{R}^2$ for the provided ground-truth screentone template $I_{t(p)}$, which is of the same size with $I$ but only filled with the ground-truth screentone type $t(p)$, so that the pixel-wise difference of the screentones is minimized in this region. Apparently, the measurement for each region is performed separately because their optimal offset is different. Formally, the translation-invariant screentone loss is then defined as:

$$
L_{\text{sir}} = \sum_p \min_{\delta \in \mathbb{W}} \| M_p \odot (I - \text{Shift}(I_{t(p)}, \delta)) \|_2, \tag{1}
$$

where $w$ is a window of $11 \times 11$ and $\text{Shift}(\cdot, \delta)$ denotes to shift an image with offset $\delta$. Meanwhile, as there are some screentones with width frequency, a small window may not cover all solutions while a larger window may make the model hard to converge. Thus, we adopt a multiscale scheme to progressively find the optimal offset. We introduce a half-size resampled version of the generated output and ground truth image, and then obtain the offset $\delta'$ for the resampled version. The offset $\delta'$ can be used to refine the ground truth image $I_{t(p)}' = \text{Shift}(I_{t(p)}, \delta')$, which are further used to calculate translation-invariant screentone loss. In particular, we use a 1-by-1 window size for the original scale to preserve the screentone appearance.

ScreenVAE map loss. Empirically, under the translation-invariant screentone loss only, the model may generate screentones with visually similar but spatially incoherent patterns. Such pattern inconsistency significantly hurts the visual quality. So, the ScreenVAE map loss $L_{\text{scr}}$ is employed to further ensure the generated manga image is filled with the same screentone types as the ground truth. It is formulated as the difference between the screenVAE map of generated manga and the ground-truth ScreenVAE map $S$.

$$
L_{\text{scr}} = \| \text{SVAE}(I) - S \|_2, \tag{2}
$$

where SVAE denotes the pretrained ScreenVAE model [Xie et al. 2020] that computes the ScreenVAE map from the input manga image.

Attention loss. The attention loss $L_{\text{atn}}$ is developed to guide the Recurrent Proposal Selection Module (RPSM) to be more decisive. When applying the spatial attention $\{M^l_t\}_{l=4}^0$ to proposals, each pixel value of the fused features is represented as a weighted sum of pixels in the proposals (as presented in Algorithm 1). Considering the extracted feature proposals $\{\hat{F}^l_t\}_{l=0}^L$ may have inconsistent screentone-translation bias, for each region, we encourage the model to choose only one of the proposals through the attention loss:

$$
L_{\text{atn}} = \sum_t \| M^l_t - 0.5 \| - 0.5 \| \tag{3}
$$

where $\cdot$ denotes the operation to take the element-wise absolute value. In particular, for synthetic data, we can directly construct the ground-truth attention mask $\hat{M}^l_t$, and reformulate the attention loss as:

$$
L_{\text{atn}} = \sum_t \| M^l_t - \hat{M}^l_t \|_2 \tag{4}
$$

To be specific, $\hat{M}^l_t$ is the overlapped regions of the resampled label map and the anchor-based sampled label map.
Adversarial loss. The adversarial loss encourages the generated manga to follow the appearance distribution as the real-world manga, e.g., clear and binary-valued appearance, conditioned on the structural line and ScreentoneVAE map. We adopt Conditional GAN [Mirza and Osindero 2014] to impose this constraint, with a discriminator $D_{mg}$ with 5 strided downscaling blocks employed. The adversarial loss is formulated as:

$$L_{adv} = \sum \{ \log (1 - D_{mg}(I, \mathbf{L}, \mathbf{S})) + \log D_{mg}(I, \mathbf{L}, \mathbf{S}) \}$$

The overall loss function for our network is defined as the weighted sum of the above terms:

$$L = \beta_{sis} L_{sis} + \beta_{sct} L_{sct} + \beta_{atn} L_{atn} + \beta_{adv} L_{adv},$$

where $\beta_{sis}$, $\beta_{sct}$, $\beta_{atn}$ and $\beta_{adv}$ are the weight coefficients for different loss terms. We empirically set $\beta_{sis} = 10$, $\beta_{sct} = 100$, $\beta_{atn} = 5$, and $\beta_{adv} = 1$ in our experiments.

5 RESULTS AND DISCUSSION

5.1 Implementation Details

Data Preparation. We use two types of data to train our model, including synthetic manga data and real manga data. We manually collected 100 line drawings and 125 types of screen tones to synthesize a manga image. Screen tones are randomly picked and laid onto each closed region by following the method [Li et al. 2017]. We synthesized a total number of 6000 manga images and their corresponding per-pixel labels (i.e., screen tone type). The labels are used to calculate the translation-invariant screen tone loss $L_{sis}$ and $L_{atn}$. For the real-world data, we manually collected 20,000 screened manga of resolution 2,048×1,536 to train our model. Note that there are no annotations for real manga data. The translation-invariant screen tone loss $L_{sis}$ is not calculated for these data. All training images are cropped to 512×512 resolution during training.

Training Scheme. We implemented our model in the PyTorch framework [Paszke et al. 2017] and trained with the loss function defined in Eq. 6. The hyper-parameters in the loss function are set as following: $\beta_{sis} = 10$, $\beta_{sct} = 100$, $\beta_{atn} = 5$, and $\beta_{adv} = 1$. The network weights are randomly initialized using the method of [He et al. 2015]. We used 512×512 images for the training and a scaling factor range from 0.5 to 1.25. The Adam solver [Kingma and Ba 2014] is applied to our model with a batch size of 1 and an initial learning rate of 0.0001. The synthetic data was first used during the training to use the appearance information of multiple proposals adaptively. Then, the whole framework was trained with both synthetic and real data to improve generalization. We empirically found that this strategy helps to converge and improves the overall performance.

5.2 Comparison

There is no existing method developed for generating retargeted manga with different resolutions. To evaluate the performance of our method, we adopt three related works for comparison: (i) [Tsubuta et al. 2019], first classifies the screen tone types and then applied the screen tone back to the line drawings; (ii) [Xie et al. 2020], which proposes Screentone Variational AutoEncoder(ScreentoneVAE) to encode manga into an interpolative representation that can be used to reconstruct the input manga; and (iii) [Xie et al. 2021b], which reuses the screen tone in known area to fill up the content-missing regions by exploiting semantic correlation. We directly use the publicly released code of [Tsubuta et al. 2019] and [Xie et al. 2020] to generate retargeted manga. As [Xie et al. 2021b] it is not tailored for inpainting the whole image, we make certain adaptation that enables the applicability to our manga retargeting problem. To be specific, we remove the semantic inpainting network and directly feed the resampled ScreentoneVAE map and structure lines, together with the original manga image, into the appearance synthesis network, which will generate a manga image of the retargeted resolution. The adapted model is retrained on our dataset, under the same training scheme as ours.

Fig. 11 shows the visual results produced by the competitors mentioned above and our methods. When retargeting the manga to other resolutions, we need to guarantee consistent screen tones on corresponding regions. We can see that, in general, our method shows plausible results with homogenous screen tones over regions to show a great visual impression. The results generated by [Tsubuta et al. 2019] may generate inconsistent screen tones over the same screen tone region if the screen tones cannot match well with the screen tones in predefined sets. Meanwhile, their method often cannot generate the same labels for the same screen tone regions. We also compared the manga filling style translation method proposed by Xie et al. [2020] and Monyan and Zisserman [2014]. Specifically, these metrics all monotonically increase according to the retargeted resolution. We can see that, in general, our method reconstructs high-fidelity screen tones whatever the retargeted resolution changes.

Besides the qualitative comparison, we quantitatively evaluate the visual quality of the results produced by various methods. We first generate 500 synthetic manga images with screen tone labels. These images are further retargeted to fit resolution range from 50% and 125% by these methods. We adopt 3 metrics to evaluate the quality of these retargeted images, including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM) [Wang et al. 2004], and Learned Perceptual Image Patch Similarity (LPIPS) [Zhang et al. 2018]. We evaluate the LPIPS metric based on the VGG16 [Simonyan and Zisserman 2014] model. Specifically, these metrics all have limitations in evaluating the retargeted images with multiple acceptable results. These metrics may over-penalize a slight shift of screen tone as they are alignment-sensitive. Thus, we measure each result with the best-matched ground truth by aligning each screen tones separately. The quantitative evaluation is listed in Table 1. We can see that our method quantitatively outperforms other methods.
Fig. 11. Comparison with existing methods on real-world cases.
5.3 Ablation Study
To verify the effectiveness of each individual loss term, we conduct ablation studies for each module by visually and quantitatively comparing their generated outputs. Fig. 12 shows the generated manga image of the trained model without individual loss terms. Without the translation-invariant screentone loss $L_{\text{sis}}$, the original periodic information of screentones may not be restored (Fig. 12(b)). The screentone types may not be reproduced without the ScreenVAE map loss $L_{\text{scr}}$ (Fig. 12(c)). The attention loss $L_{\text{atn}}$ is essential for model training and it helps the retargeted features to be replaced with the appropriate proposals (Fig. 12(d)). Without the adversarial loss $L_{\text{adv}}$, the network may fail to generate tidy and binarized results (Fig. 12(e)). In comparison, the combined loss can help the network generate clear and aligned screentones (Fig. 12(f)). The quantitative evaluation in Table 2 also shows that the combined loss quantitatively outperforms the others variants of our method.

5.4 Limitations
Our framework still has some limitations. Firstly, our model may fail to generate screentones for some tiny or narrow regions, which are hard to extract periodic information. For example, in Fig. 13(a), the screentones between the hair and the balloon failed to generate. In addition, our proposed method might generate distorted patterns for irregular screentones. An example can be found in Fig. 13(b), and the irregular patterns in the background cannot be appropriately retargeted. This is because the candidates for irregular patterns cannot be aligned with translation.

6 CONCLUSION
In this paper, we made the first attempt to tackle the screentone-preserved manga retargeting task and obtain plausible results. We simplify the screentone synthesis problem as an anchor-based proposals selection and rearrangement problem. Hierarchical anchors-based proposal sampling is proposed to generate aliasing-free screentone proposals which are then adaptively fused to generate retargeted images through a Recurrent Proposal Selection Module. Besides, as there can be multiple solutions for manga retargeting, we propose a translation-invariant screentone loss to tolerant the misalignment of multiple possible solutions. Both the visual comparison and the quantitative experiments show the superiority of our proposed method.
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