Vectorization of Raster Manga by Deep Reinforcement Learning

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\textbf{Abstract}

Manga is a popular Japanese-style comic form that consists of black-and-white stroke lines. Compared with images of real-world scenarios, the simpler textures and fewer color gradients of mangas are the extra natures that can be vectorized. In this paper, we propose Mang2Vec, the first approach for vectorizing raster mangas using Deep Reinforcement Learning (DRL). Unlike existing learning-based works of image vectorization, we present a new view that considers an entire manga as a collection of basic primitives "stroke line", and the sequence of strokes lines can be deep decomposed for further vectorization. We train a designed DRL agent to produce the most suitable sequence of stroke lines, which is constrained to follow the visual feature of the target manga. Next, the control parameters of strokes are collected to translated to vector format. To improve our performances on visual quality and storage size, we further propose an SA reward to generate accurate stokes, and a pruning mechanism to avoid producing error and redundant strokes. Quantitative and qualitative experiments demonstrate that our Mang2Vec can produce impressive results and reaches the state-of-the-art level.

\textbf{1. Introduction}

Manga is a popular Japanese-style comic form in the world. Typical mangas are composed of black-and-white stroke lines and represented as raster images on digital multimedia. As shown in Figure 1, compared with images of real-world scenarios, mangas have the extra natures to be vectorized, i.e., having simpler structures and fewer color gradients. The advantages of vectorizing raster manga are four-fold. First, vector graphics are resolution-independent
and readily displayed on digital devices with different resolutions. Second, allowing easily edit the stroke lines and colors. Third, for showing some contents, vector graphics have higher compression ratios for storage than raster images. Fourth, offering convenience for content retrieval, and allowing retrieval for particular shape objects.

Vectorization of raster images has been studied extensively in image processing, graphics, vision, and other areas. Recent representative works for vectorizing images are mainly divided into two categories. The first category of works is based on pre-designed algorithms, which analyzes pixels and calculates parameters to construct vector graphics (e.g., [2, 5, 14, 16, 21, 22, 31]). The other category of works is based on deep learning (DL) (e.g., [4, 6, 8, 18, 23, 27–29]), which trains neural models to produce vector graphics utilizing the features of target raster images. However, the DL-based methods typically vectorize an entire image in one step, and the one-step manner makes the DL model cannot handle too many parameters of vector format accurately. Therefore, these methods only work well in vectorizing targets with simpler structures (e.g., icons, fonts), and get trouble in vectorizing mangas with complex structures.

Unlike these works, our proposed Mang2Vec is a vectorization approach based on Deep Reinforcement Learning (DRL). In Mang2Vec, we propose a new view that considers an entire manga as a collection of basic primitives “stroke line”, and the sequence of strokes lines can be deep decomposed for further vectorization. First, start with a blank canvas, we train a DRL agent to produce the most suitable stroke line at each step by the designed rewards. After enough steps, the combination of sequential stroke lines will appear as the input manga. Then, the control parameter of each stroke is collected to be converted to the designed vector format. Since stroke lines can be infinitely added by the DRL model, our approach has better performance on vectorizing mangas with complex textures. To improve our performance on visual quality and storage size, in Mang2Vec, we propose an SA reward to generate accurate strokes, and a pruning mechanism to avoid producing error and redundant strokes. Extensive quantitative and qualitative experiments demonstrate that our Mang2Vec can produce impressive results and has achieved the state-of-the-art level.

To summarize, our main contributions are three-fold:

• We propose Mang2Vec, the first DRL-based approach for vectorizing raster mangas. Mang2Vec presents a new view that considers an entire manga as a sequential of basic primitives “stroke line” that can be deep decomposed for further vectorization.

• We propose a new SA reward to improve the accuracy of generated stroke lines in colors and positions, and propose a pruning module to avoid error strokes and reduce the storage size.

• Experiments show that Mang2Vec can produce impressive results, and prove the effectiveness in vectorizing numerous types of mangas with complex structures (e.g., with intensive, sparse, wide, or thin stroke lines).

2. Related Work

Below we summarize the most related works that mainly involve methods of learning-based image vectorization, generative model of vector graphics, and image decomposition.

Learning-based vectorization: the goal of learning-based vectorization methods is to convert a target image to the vector format with high visual similarity. Egiiazarian et al. [6] propose a transformer-based architecture for translating technical line drawings to vector parameters. Gao et al. [8] produce parametric line drawings utilizing the extracted image features and a designed hierarchical recurrent network. Guo et al. [18] first utilize a network to convert an image to junctions, and then address an integer program that obtains the vectorized floorplans as a set of architectural primitives. Reddy et al. [23] propose Im2Vec, a VAE-based method to predict vectorize parameters of input images, and the network can be trained without vector supervision.

Generative model of vector graphic: the motivation of generative vector graphic models is to produce vector graphics by inputting some heuristic information (e.g., incomplete sketches, conditional parameters, random noises), where inputs and outputs do not need accurate correspondences in appearance. SketchRNN [11] propose a method for both unconditional and conditional vector generation. All sketches are translated to pen positions and states, and an LSTM is trained to produce parameters of a density function, where the parameters can be sampled to produce a new sketch. Similar to SketchRNN, Sketchformer [24] presents a framework to encode vector form sketches using the transformer. SVG-VAE [19] is the first generative approach for estimating vector graphics parameters. They fix the weights of pre-trained Variational Auto Encoder (VAE) weights and train a decoder that predicts vector parameters from the latent variable learned on images. DeepSVG [3] shows that the hierarchical networks are useful to reconstruct diverse vector graphics, and do well in interpolation and generation tasks. For font glyphs vectorization, [1, 9] can produce results from partial observations in a low-resolution raster.
domain. Li et al. [17] present a differentiable rasterizer to edit and produce vector parameters by raster-based target functions and machine learning.

**Image decomposition:** these methods decompose an image into an assembly of primitives in pixel-wise, which aims to benefit understanding scenes, assisting in classify, reproducing painting processes, and so on. Prior works [7, 13, 20, 32] train DRL drawing agents, and circumvent the requirement of supervision on the painting process by simulating a rendering engine. CSGNet [26] propose a deep model that constructs complex shapes by recursively applying boolean operations on primitives. It designs a neural encoder and recurrent decoder to map shapes to modeling instructions, and trains the network by policy gradient algorithm.

Unlike the above methods, our work combines the merits of image vectorization and image decomposition, and considers an entire manga image as a combination of vector primitives, and generates the sequence of vector primitives that is visually similar to the input manga by the DRL technique.

### 3. Method

#### 3.1. Overview

Given a raster manga image $M$, our Mang2Vec is modeled as a function $\Psi$ to generate a vector graphic $V = \Psi(M)$. For appearance, $V$ is similar to $M$ accurately. For format, $V$ is a vector graphic that can be zoomed freely without distortion.

As shown in Figure 2, our Mang2Vec $\Psi = \{\Psi_l, \Psi_v\}$ is composed of two parts, the learning part $\Psi_l$ (Figure 2 left) and the vectorization part $\Psi_v$ (Figure 2 right). $\Psi_l$ is designed to learn an accurate DRL model for decomposing $M$ to a sequence of primitives parameters, and $\Psi_v$ is designed to further vectorize the primitives parameters. Specifically, in $\Psi_l$, our goal is to train a DRL model to produce an action sequence $A = \Psi_l(M)$, where $A = \{a_0, a_1, ..., a_t\}$ can be translated to the stroke line sequence $L = \{l_0, l_1, ..., l_t\}$ by a designed drawing model $D$, and the combination of all strokes in $L$ are constrained to compose $M$ visually. Right: the vectorization part $\Psi_v$ that aims to covert action sequence $A$ to vector format $V$ in a designed manner.

The details of learning phase $\Psi_l$ and vectorization phase $\Psi_v$ are described in Section 3.2 and Section 3.3 respectively.

#### 3.2. DRL Model Learning

In phase $\Psi_l$, our goal is to train a DRL model $\pi$ to produce a suitable action sequence $A = \{a_0, a_1, ..., a_t\}$, and the action $a_t = \pi(s_t)$ is predict by the observed state $s_t$ in each timestep $t$. Each $a_t$ can be converted to a stroke line $l_t = D(a_t)$ by the drawing module $D$, and all strokes can be combined into $M$ visually. To improve the accuracy of each stroke, the stroke generation is designed to follow the **Markov Decision Process** and **Greedy Strategy**. In other words, the defined state space is independent of the timestep. In each timestep, according to the current state, the model only needs to find the next stroke line that is most suitable, and regardless of future strokes and final strokes combination.

**Policy:** as shown in Figure 2 left, our DRL model basically employs the model-based Deep Deterministic Pol-
ICY Gradient (DDPG) that follows the actor-critic architecture [13]. There are two networks, the actor $\pi(s_t)$ and critic $Q(s_t)$. The actor models a policy $\pi$ that maps state $s_t$ to action $a_t$, and the critic predicts the expected reward and is trained by

$$Q(s_t) = \mathcal{R}_t(a_t, s_t) + \gamma Q(s_{t+1}),$$

where $\mathcal{R}_t(a_t, s_t)$ is the current reward calculated by $a_t$ and $s_t$, $\gamma$ is the discount factor, and actor $\pi(s_t)$ is trained to maximize $Q(s_t)$.

**State:** our defined state $s_t$ is independent from timestep $t$, and $s_t$ consists of two parts: the current canvas $c_t$ and the target manga $M$, represented as $s_t = (c_t, M)$. Initialize with a blank canvas $c_0$, the actor $\pi$ produces action $a_t = \pi(s_t)$ according to $s_t$, and $(t+1)$-th canvas $c_{t+1} = c_t + D(a_t)$ is rendered by the drawing module $D$. Then, the next state $s_{t+1}$ is represented as $s_{t+1} = [D(\pi(s_t)), M]$.

**Action and drawing module:** the drawing module $D$ is designed to convert an action $a_t$ to a stroke line $l_t$. Formally, $l_t = D(a_t), a_t \in [0, 1]$. Although training a neural renderer to map $a_t$ to $l_t$ is flexible (e.g., [13]), it will compromise strokes’ accurateness (e.g., irregular or blurring edges, missing pixels) and the inaccuracy strokes are fatal to our task. Therefore, we design an image rendering program as the drawing module $D$.

As shown in Fig. 3(a)(b), the path of a stroke line $l_t$ follows the rules of quadratic Bézier curve (QBC) $\mathcal{B}$, and the thickness of $l_t$ is controlled by a sequence of circles. Each circle $g_k$ is defined as $g_k(\xi_k, \eta_k, \rho_k)$, where $\xi_k, \eta_k$, and $\rho_k$ indicate $x, y$ coordinates, and radius of $g_k$ respectively. Then, $\xi_k(\xi'_k, \eta'_k, \rho'_k)$ is calculated by

$$\xi'_k = (1 - k)^2 P^x_0 + 2(1 - k) k P^x_1 + k^2 P^x_2,$$
$$\eta'_k = (1 - k)^2 P^y_0 + 2(1 - k) k P^y_1 + k^2 P^y_2,$$
$$\rho'_k = (1 - k)^2 P^r_0 + 2(1 - k) k P^r_1 + k^2 P^r_2,$$

where $P_0, P_1, P_2$ are the three control points of a QBC. Correspondingly, the designed action $a_t$ consists of nine control parameters of a QBC, defined as

$$a_t = (P^x_0, P^y_0, P^x_1, P^y_1, P^x_2, P^y_2, P^r_0, P^r_2, g)_t,$$

where $(P^x_0, P^y_0, P^x_1, P^y_1, P^x_2, P^y_2)$ indicate the $(x, y)$ coordinates of $P_0, P_1, P_2$ respectively. $(P^r_0, P^r_2)$ control a stroke’s thickness, and $g$ control a stroke’s color in 1-channel grayscale space.

**Reward:** for designing the reward, our main goal is to select the most suitable and accurate stroke line $l_t$ in each timestep $t$. The previous strokes generating work [13] shows that employing the L2 reward $r_t$ can encourage the agent to gradually draw the target image, and the reward $r_t$ is defined as

$$r_t = \|c_t - M\|^2 - \|c_{t+1} - M\|^2.$$

However, as shown in Figure 4, we observe in experiments that the original reward in Eq.(4) will make the trained model produce inaccurate strokes. On the one hand, for dense strokes in the target image, the actor will produce inaccurate strokes. On the other hand, for a larger stroke in the target image, the agent may cover the region with numerous smaller strokes repeatedly.

![Figure 4](image-url)
our SA (Stroke Accurateness) reward $R_A$ as:

$$
R_A = \lambda_1 r_1^I + \lambda_2 r_2^I + \lambda_3 r_3^I + \lambda_4 r_4^I
$$

$$
r_1^I(l_t) = \frac{1}{C HW} \cdot \text{Sum}(l_t^I)
$$

$$
r_2^I(l_t) = 1 - \frac{1}{|\mathcal{G}|} \cdot \text{Unique}(l_t^I \times M)
$$

where $\lambda_1$ to $\lambda_3$ are used to balance the multiple objectives. 

\textbf{Sum()} and \textbf{Unique()} functions to calculate the sum and different elements number in parentheses. $l_t$, $l_t^I$, $c_t$, and $c_{t+1}$ have the same shape of $C \times H \times W$. $\{r_1^I, r_2^I, r_3^I, r_4^I\} \subseteq \{0, 1\}$. The meaning of $r_1^I$ to $r_4^I$ are as following:

- $r_1^I$ is increasing with the coverage $l_t^I$ of stroke.
- $r_2^I$ is decreasing with the category number of colors in $(l_t^I \times M)$.
- $r_3^I$ is increasing with the difference between $l_t^I \times c_t$ and $l_t^I \times c_{t+1}$.
- $r_4^I$ is increasing with the similarity between $l_t^I \times c_t$ and $l_t^I \times M$.

\textbf{Network Architecture:} as shown in Figure 3(e), in order to produce accurate strokes to better handle mangas with complex textures, the actor and critic follow the network architectures of residual structures similar to ResNet-18 [12], and the critic uses WN [25] with Translated ReLU (TReLU) [31] to stabilize the learning. Referencing the method of model-based DDPPG [13], we utilize the soft target network that constructs a copy for the actor and critic and updating their weights by making them slowly track the learned networks.

\section{3.3. Vectorization}

In the vectorization phase $\Psi_{\nu}$, as shown in Figure 2 right, utilizing the well trained actor $\pi$, $\Psi_{\nu}$ can be modeled as $\Psi_{\nu} = \{\Phi_{m2a}, \Phi_{e2v}\}$. First, $\Phi_{m2a}$ generates an action sequence $A = \{a_0, a_1, ..., a_t\}$ following the content of manga $M$. Then, $\Phi_{e2v}$ translates action sequence $A$ to a vector graphic sequence $\mathcal{V} = \{v_0, c_1, ..., v_t\}$. Formally, $\mathcal{V} = \Psi_{\nu}(\pi, M) = \Phi_{e2v}(\Phi_{m2a}(\pi, M))$.

\textbf{Design of vectorized stroke:} as shown in Figure 3(b), in drawing module $D$, a stroke is rendered as hundreds of continuous circles (red) $\{q_1, q_2, ..., q_k\}$, where the path of circle centers follow a QBC $B$ as Eq.(2), and radiiuses of start and end circle are $P_0^I$ and $P_2^I$ defined in Eq.(2)(3). Although it is easy to vectorize a stroke by vectorizing each of these circles, the storage of the final vector graphic will be particularly large.

\begin{algorithm}
\caption{Pruning Algorithm.}
\begin{algorithmic}[1]
\Input{$A, M, \xi$;}
\State Initialize $t = |A|$;
\State $\mathcal{V} \leftarrow \Phi_{e2v}(A)$;
\State $\delta \leftarrow \frac{\|M-I(\mathcal{V})\|_2}{C HW}$;
\While{$t > 0$}
\State $\mathcal{V}' \leftarrow \mathcal{V}$;
\State Remove $v_t$ in $\mathcal{V}'$;
\State $\delta' \leftarrow \frac{\|M-I(\mathcal{V}')\|_2}{C HW}$;
\If{$\delta' \leq \delta + \xi$}
\State $\delta \leftarrow \delta'$;
\State $\mathcal{V} \leftarrow \mathcal{V}'$;
\State $t \leftarrow t - 1$;
\Else
\State $t \leftarrow t - 1$;
\EndIf
\EndWhile
\Output{$\mathcal{V}$;}
\end{algorithmic}
\end{algorithm}

To represent a vectorized stroke $v_t$ in a light-weight manner, as shown in Figure 3(c), we define $v_t$ as three parts, i.e., the start and end circles (yellow) and a enclosed path $p$ (green). Since the widely used vector format (e.g., SVG, PDF) can only represent a curve as a QBC path, we must calculate the fitted QBC path of $p$'s edges.

As shown in Figure 3(c)(d), first, we obtain $p_k$'s radiuses that are perpendicular to $B$, and then find the intersection $p_k$ of the radius and circle, calculated by

$$
p_k^x = q_k^x \pm \cos(\theta) \cdot q_k^y, \quad p_k^y = q_k^y \pm \sin(\theta) \cdot q_k^x,
$$

where $(p_k^x, p_k^y)$ is the coordinate of $p_k$, $\theta = \arctan\{(B')^{-1}\}$, and $B'$ indicates the derivative of $B$, calculated by

$$
B' = \frac{d(q_k^y)}{d(q_k^x)} = \frac{(1-k)(P_1^y - P_2^y) + k(P_0^y - P_1^y)}{(1-k)(P_1^x - P_2^x) + k(P_0^x - P_1^x)}
$$

where $P_0, P_1, P_2$ are defined in Eq.(2)(3). The obtained $p_k$ is a point on the curve edge of $p$, and we further calculate five points on each edge of $p$ to fit a QBC paths.

\textbf{Pruning Mechanism:} in $\Phi_{m2a}$, there are two points compromise the performance on vectorization. First, $\pi$ may produces some error strokes to increase the difference between generated vector graph and the ground truth. Second, the strokes are stacked together where may have repeated or redundant strokes to increase the storages of vectorization results. To address these two issues, as shown in Algorithm 1, we propose a pruning mechanism to optimize the redundant strokes and the storage sizes.

In Algorithm 1, we input the action sequence $A$ and out put the pruned vector sequence $\mathcal{V}$, where $|A|$ indicate the cardinality of $A$, $M$ is the ground truth, $I(\mathcal{V})$ means converting $\mathcal{V}$ to a raster image, and $M$ and $I(\mathcal{V})$ have the same
Table 1: Vectorization Accuracy

| Method | DeepManga | Fonts | MSE | SSIM |
|--------|-----------|-------|-----|------|
| SVG-VAE | 0.3815 | × | 0.4328 | × |
| DeepSVG | 0.3433 | × | 0.5238 | × |
| Im2Vec | 0.0532 | 0.2445 | 0.8083 | 0.3879 |
| Ours | **0.0261** | **0.0905** | **0.9303** | **0.7468** |

Figure 5: Vectorization on dataset Fonts with simple structure. The observed results demonstrate that compared with the leading learn-based vectorization methods, our Mang2Vec can produce accurate results for vectorizing raster images with simple structure (e.g., fonts).

Figure 6: Vectorizations on mangas with complex structures. **Left:** comparison with the leading learning-based vectorization method Im2Vec trained by the same dataset DeepManga with us. **Right:** Our vectorization results in different zooming scales.

size of \( C \times H \times W \). \( v_i \) is the vectorized strokes produced by \( a_i \), \( \delta \) is the measured difference between \( I(V) \) and \( M \), and \( \xi \) indicates the tolerable error which is used to balance the visual similarity and the storage size of \( V \).

4. Experiment

In the following experiments, we mainly evaluate the performance of Mang2Vec on two aspects, the vectorization accurateness and the storage sizes of vectorization results.

4.1. Experimental Setting

Our Manga2Vec is implemented in PyTorch, and all experiments are performed on a computer with an NVIDIA Geoforce RTX 2080 GPU. The dataset DeepManga used in experiments is collected from popular manga works and contains 42599 raster manga with 1024×1024 resolution. For training the DRL agent of Manga2Vec, each training data is converted to 1-channel grayscale space, and we randomly cut 128×128 images from original data as the inputs. The learning rate of actor or critic is \( \{3 \times 10^{-3}, 1 \times 10^{-4}\} \) or \( \{1 \times 10^{-3}, 3 \times 10^{-4}\} \), learning rate decays after \( 1 \times 10^5 \) training batches, and the optimizer is Adam. We set 1 action per timestep, 40 timesteps per episode, and the reward discount factor is 0.955. In all experiments, by default, we set \( \delta_1, \delta_2, \delta_3, \delta_4 = 1 \) in Eq.(5), the max numbers of strokes \( S = 40 \), and the number of patches \( P = 32 \times 32 \).

4.2. Vectorization Accurateness

**Vectorization on simple structure:** we first measure the vectorization performance of the related learn-based methods (including SVG-VAE [19], DeepSVG [3], and Im2Vec [23]) and ours on the dataset with simple structures (e.g., Fonts). As shown in Figure 5 and Table 1, the results are compared in subjective visual perception and objective indexes of MSE (Mean Square Error) and SSIM [30] (Structural SIMilarity). MSE and SSIM are employed to measure the similarity between targets and outputs. MSE indexes are computed by \( \frac{\| I - O \|^2}{C \cdot H \cdot W} \in [0, 1] \), where \( I \) and \( O \) indicate targets and outputs of sizes \( C \times H \times W \), and \( I, O \in [0, 255] \). SSIM indexes are in \( [-1, 1] \), and the similarity between two images is proportional to the SSIM index. In comparing similarities, each method’s results in vector space are rasterized to 512×512 by CairoSVG [15].

Figure 5 and Table 1 demonstrate that compared with other learning-based methods, our method can produce vectorization results with high accuracy, and achieves the state-of-the-art level for vectorizing targets with simple structures.

**Vectorization on complex structure:** we also measure the vectorization performance on mangas with complex structures, and results are shown in Figure 6 and Table 1. We compare our method with the leading method Im2Vec [23] which trained by the same dataset DeepManga with us. Note that we do not compare with DeepSVG [3] and SVG-VAE [19], since they cannot be trained without the supervision of vector ground truth. Moreover, Reddy et al. [23] have proved that Im2Vec outperforms DeepSVG and SVG-VAE on the accurateness of vector reconstruction. Results in Figure 6 and Table 1 show that our method outperforms the referenced methods on the accurateness of vectorization mangas with complex structures.

Although the reference learn-based methods have the advantage of reproducing the intended vector parametrization,
they can only handle targets with simple structures or textures (e.g., icons, fonts) due to the limitation of processable vector parameters. By contrast, our method is better at handling targets with complex textures since the strokes can be added infinitely by the DRL agent.

**Influence of patches and strokes:** In the vectorization phase, a result with higher accuracy can be produced by dividing the target image into small patches and vectorizing each of them respectively. In Figure 7, we display the vectorization results under the settings of different numbers of patches and strokes. The observed results show that vectorization accuracy is proportional to the number of patches and strokes. Moreover, after the stroke number reaches a threshold, the influence of stroke number increasing on the accuracy will be less and less.

**Accuracy of strokes:** For evaluating the accuracy of strokes, we mainly compare our performance with the baseline [13] of producing neural strokes. Comparisons in visual and quantification as shown in Figure 8, we observed that the stroke accuracy in positions and colors of our method is significantly higher than that of the baseline, and our method does better in the task of manga vectorization.

4.3. Storage Size and Time Cost

**Storage size:** In Mang2Vec, the pruning module (PM) is designed to reduce the storage size of vectorization results. Leveraging 100 random vectorization samples, we evaluate the performance of PM on two aspects, the reduced storage size and the influence of size reduction on visual similarity. As shown in Figure 9 upper, using PM is able to reduce about 50% of the storage sizes when \( S = 40 \), and the effectiveness is proportional to the maximum numbers of strokes. In Figure 9 bottom, we display the visual similarity between target and vectorization results. The scatter charts show that the reduction of storage size preserves or even improves the visual similarity since PM removes the redundant and error stroke lines.

To summarize, PM effectively reduces the storage sizes of outputs without compromising the visual similarity of vectorization.

**Time cost:** We evaluate the time cost of Mang2Vec on vectorization without PM and the time cost of PM. Let \( P \) and \( S \) indicate the patch number patch and the stroke number respectively, and the calculated time costs (in seconds) are shown in Table 2. The results demonstrate that the time costs of our method are increasing with \( P \) and \( S \), and the maximum vectorization time is an acceptable few minutes. Empirically, setting \( P = 16, S = 20 \) is enough to produce results in high accuracy, and setting \( P = 32, S = 40 \) can already handle mangas with extremely complex structures.

5. Advantage and Limitation

According to the advantages of images vectorization aforementioned in Section I, our vectorized mangas are resolution-independent and readily displayed on digital devices with different resolutions, and have smaller storage sizes than raster images when representing some target contents.
Figure 9: Influences of using pruning module (PM) on storage size and visual similarity. Upper: average storage sizes (kilobyte) of vectorized results (in 100 random samples) generating without PM (red) and with PM (green). Bottom: Quantitative similarity between targets and outputs in 100 random cases. The results show that PM effectively reduces the storage sizes of outputs without compromising the visual similarity.

Table 2: Time costs (seconds) under different numbers of patch $P$ and stroke $S$. Upper: time costs of Mang2Vec w/o pruning module. Bottom: time costs of the pruning module.

| P, S | 1  | 5  | 10 | 15 | 20 | 25 | 30 | 35 | 40 |
|------|----|----|----|----|----|----|----|----|----|
| 1^2  | 1.22| 1.28| 1.31| 1.35| 1.39| 1.45| 1.50| 1.54| 1.58|
| 4^2  | 1.37| 1.74| 2.22| 2.70| 3.19| 3.67| 4.06| 4.51| 4.97|
| 8^2  | 1.72| 3.43| 5.18| 7.18| 8.91| 10.72|12.54|14.35|16.96|
| 12^2 | 2.45| 6.59|12.36|16.32|21.84|26.34|29.12|34.12|37.43|
| 16^2 | 3.34|10.11|18.15|23.62|33.68|39.24|49.46|53.24|68.60|
| 20^2 | 4.65|13.25|27.46|37.58|52.63|63.24|76.67|83.14|92.32|
| 24^2 | 5.92|21.62|39.65|55.28|75.68|91.35|109.43|113.43|118.53|
| 28^2 | 7.46|28.12|52.38|83.03|102.71|134.62|150.87|189.41|201.99|
| 32^2 | 9.36|35.89|69.81|98.60|116.35|148.35|185.65|225.32|257.34|

| P, S | 1  | 5  | 10 | 15 | 20 | 25 | 30 | 35 | 40 |
|------|----|----|----|----|----|----|----|----|----|
| 1^2  | 0.02| 0.08| 0.18| 0.22| 0.47| 0.8 | 1.08| 1.22| 2.33|
| 4^2  | 0.18| 0.61| 1.54| 2.75| 5.18| 7.82|12.76|18.12|26.53|
| 8^2  | 0.58| 2.11| 5.32|10.98|18.95|32.34|49.56|71.31|97.61|
| 12^2 | 1.53| 7.18|12.34|22.98|34.17|50.37|69.25|95.34|189.18|
| 16^2 | 2.94|11.75|20.48|31.63|48.23|93.24|123.85|165.76|323.71|
| 20^2 | 4.94|20.13|33.53|64.55|101.34|143.71|198.35|256.37|358.35|
| 24^2 | 8.31|28.74|46.08|92.96|144.79|203.84|283.63|372.54|517.37|
| 28^2 | 12.83|34.97|69.77|125.74|197.36|279.56|387.19|503.87|697.64|
| 32^2 | 20.23|51.54|98.14|165.25|257.23|367.95|506.45|658.32|921.61|

6. Conclusion

In this paper, we propose Mang2Vec, the first approach for vectorizing raster mangas based on Deep Reinforcement Learning. We present a new view that regards an entire manga as a collection of primitives “stroke line”, and the sequence of strokes lines can be deep decomposed for vectorization. To improve our performance on vectorization accuracy and storage size, we further propose an SA reward and a pruning mechanism in Mang2Vec. Quantitative and qualitative experiments demonstrate that our Mang2Vec can produce impressive results and reaches the state-of-the-art level.

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