Residual-Recursion Autoencoder for Shape Illustration Images

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Abstract

Shape illustration images (SIIs) are common and important in describing the cross-sections of industrial products. Same as MNIST, the handwritten digit images, SIIs are gray or binary and containing shapes that are surrounded by large areas of blanks. In this work, Residual-Recursion Autoencoder (RRAE) has been proposed to extract low-dimensional features from SIIs while maintaining reconstruction accuracy as high as possible. RRAE will try to reconstruct the original image several times and recursively fill the latest residual image to the reserved channel of the encoder’s input before the next trial of reconstruction. As a kind of neural network training framework, RRAE can wrap over other autoencoders and increase their performance. From experiment results, the reconstruction loss is decreased by 86.47% for convolutional autoencoder with high-resolution SIIs, 10.77% for variational autoencoder and 8.06% for conditional variational autoencoder with MNIST.

1. Introduction

Recently, (Zhou et al., 2018) proposed a method for computer-aided design (CAD) which can find efficient and innovative CAD models automatically. The method will first describe the target product by a shape illustration image (SII), Figure 1 for example; second compress the SII to get a low dimensional latent code \( z \); third modify \( z \) by a random searching algorithm to get a new latent code \( z_{\text{new}} \); fourth reconstruct a new SII from \( z_{\text{new}} \) and test its performance by a computer-aided engineering software. A highly efficient SII will be found automatically by replacing \( z \) with \( z_{\text{new}} \) and doing the third and the fourth steps repeatedly. The image encoding and decoding techniques are the bottlenecks of the CAD method. A high compression rate can get low dimensional \( z \) that will lead to shorter optimization periods. But current encoding techniques are all sacrificing details to get a high compression rate which is unacceptable to SIIs whose details are highly correlated to their performance.

Figure 1. An example of the SII-based CAD method (Zhou et al., 2018). First, use the cross section as the SII to describe the rotor. Second, compress the SII by 2D discrete cosine transformation. Third, use a Genetic Algorithm to generate a new code from the old one. Forth, use inverse 2D discrete cosine transformation to reconstruct the new SII.

Because SIIs are usually generated by following predefined principals, they are similar to each other even though they are containing sharp edges and/or lots of small shapes. It is possible to learn the principals by deep learning-based autoencoders and express them with low dimensional features. Most autoencoders (Chen et al., 2016; Nalisnick & Smyth, 2016; Xu et al., 2019; Qi et al., 2014; Dong et al., 2018; Bojanowski et al., 2017; Sønderby et al., 2016; Wang et al., 2012; Creswell & Bharath, 2018; Kiasari et al., 2018; Wang et al., 2016) are using the traditional structure where images are encoded into low dimensional features and then decoded into the reconstructed images. When dealing with
SIIs, the traditional autoencoders are shot-handed because of the lack of mechanics to emphasize hard patterns. The hard patterns are part of details that distinguish an SII from the others and are difficult to be captured by autoencoders. (Zhao & Li, 2018) proposed to learn features with image pyramids generated by smoothing and down-sampling operations. Although image pyramids can highlight details, the details are found by non-trainable operations that are not necessarily capable of identifying the hard patterns.

In this work, a framework, namely Residual-Recursion Autoencoder (RRAE), has been proposed to encode SIIs into low dimensional latent code recursively. RRAE will try to reconstruct the original image \( T \) times. The input of the autoencoder has \( T \) channels whose first channel is the original image. The residual between the reconstructed image and the original image will be filled to its reserved channel in the input. The updated input will be used to encode and reconstruct the original image again. At \( T \)th autoencoder forward propagation, the output of the encoder will be kept as the latent code and the decoder output will be the final reconstructed image. By the residual-recursion mechanic, the hard patterns are detected by a trainable operator, the autoencoder itself. The hard patterns will be highlighted in each channel of the input except the first channel. RAE can wrap over different autoencoders and increase their performance. From the experiment results, the reconstruction loss is decreased by 86.47% for convolutional autoencoder with high-resolution SIIs, 10.77% for variational autoencoder (VAE) (Kingma & Welling, 2013) and Conditional Variational Autoencoder (CVAE) (Sohn et al., 2015) as the autoencoder \( f(.) \) respectively whose networks are consisted of Linear and ReLU layers. The encoding and decoding part is wrapped by RAE where the autoencoder will try reconstruct the image \( T \) times and return the reconstructed image \( y_T \), the latent code \( z_T \), the natural logarithm of latent code variance \( \text{ln} (\sigma^2) \), and the latent code \( \text{ln} (\mu) \) of the last trial. Before every trial, the latest residual function is \( re(x, y) = (x - y)/2 \), total epoch number is 300.

3.1. MNIST

MNIST (LeCun et al., 1998) is a handwritten digital dataset in which 60000 images for training and 10000 for testing. Images of MNIST are similar to SIIs except the resolution is much lower than SIIs’. In this experiment, code from Github 1 has been modified to run RRAE on MNIST with Variational Autoencoder (VAE) (Kingma & Welling, 2013) and Conditional Variational Autoencoder (CVAE) (Sohn et al., 2015) as the autoencoder \( f(.) \) respectively whose networks are consisted of Linear and ReLU layers. The encoding and decoding part is wrapped by RAE where the autoencoder will try reconstruct the image \( T \) times and return the reconstructed image \( y_T \), the latent code \( z_T \), the natural logarithm of latent code variance \( \text{ln} (\sigma^2) \), and the latent code \( \text{ln} (\mu) \) of the last trial. Before every trial, the latest residual function is \( re(x, y) = (x - y)/2 \), total epoch number is 300.

3. Experiments

All experiments have run on 1080ti GPU and Pytorch (Paszke et al., 2019) framework. As default, the optimization function is Adam (Kingma & Ba, 2014) with default configurations, learning rate is 1e-4, weight decay is 1e-5, the residual function is \( re(x, y) = (x - y)/2 \), total epoch number is 300.

1 https://github.com/timbmg/VAE-CVAE-MNIST  
2 Please refer to the uploaded code in VAE-CVAE folder for implementation details.
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![Figure 2](image.png)

Figure 2. An example of the RRAE algorithm. X is an SII dataset consisted of cross-sectional images of Savonius rotors. Three autoencoders \( f(.) \)s share the same set of weights. The residual function is \( r(x, y_t) = (x - y_t)/2 + 0.5 \) where pixel value is range from 0 to 1. The loss function \( l(.) \) is the L1 loss of \( x \) and \( y_3 \).

result). From Table 1, it is obvious that the RRAE helps a lot in decreasing reconstruction error without increasing the dimension of the latent code. Usually, bigger \( T \) leads to better performance. But too many trials will consume too much computation with little improvements. So, in the following experiments, the upper limit of \( T \) is 3.

\[
BCE(x, y) = -\sum (x \ln(y) + (1 - x) \ln(1 - y)) \quad (1)
\]

\[
KLD(m, n) = -0.5 \sum (1 + n - m^2 - \exp(n)) \quad (2)
\]

Convolutional autoencoders have been tested on MNIST and its high-resolution version \(^3\). The autoencoders are piled up by layers of 2D convolution, Group Normalization (Wu & He, 2018) and ReLU without skipping links. The high-resolution MNIST is a 512x512 binary image dataset that is generated by bilinear interpolation in which 60000 images for trianing and 10000 for testing. The images are binarized with threshold 127.5. All images are mean and std normalized. The loss function \( l(.) \) of the original MNIST is \( L1 \). For high resolution, the loss function is \( l(.) = NMS(.) = (1 - MS(.)) + 100 \) (Mentzer et al., 2018) where \( MS(.) \) is MS-SSIM (Wang et al., 2003). Table 2 shows the best testing results from which we can conclude that the RRAE is much more efficient for high-resolution images than low-resolution images.

| Table 2. Convolutional autoencoders with MNIST and its high-resolution version. |
|-------------|-------------|-------------|-------------|-------------|
| \( z \) | \( T \) | \( L1 \) | \( DR/\% \) | \( z \) | \( T \) | \( NMS(.) \) | \( DR/\% \) |
|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| 1 | 1 | 0.07645 | 0 | 1 | 50 | 2.851 | 0 |
| 1 | 2 | 0.07895 | -3.27 | 2 | 50 | 1.800 | 36.86 |
| 2 | 1 | 0.06544 | 0 | 2 | 50 | 1.534 | 46.19 |
| 2 | 2 | 0.06358 | 2.84 | 3 | 100 | 1.399 | 0 |
| 2 | 3 | 0.06425 | 1.82 | 4 | 100 | 0.4281 | 69.40 |

3.2. SIIs of Savonius Rotors

A SII dataset has been constructed according to (Zhou et al., 2018) which is consisted of cross-sectional images of Savonius Rotors. Since the shape of a Savonius Rotor is controlled by a parabolic curve that is specified by four enumerable variables, 26973 SIIs have been generated by enumerating the height \( h_1 = 100, 125, \ldots, 1000 \), the length \( l = 400, 425, \ldots, 600 \), the down left point \((x_1, y_1)\) where \( x_1 = -100, -75, \ldots, 100 \) and \( y_1 = -100, -75, \ldots, 100 \). Figure 3 shows some random samples of the SII dataset. The resolution is 512x512. 1 out of 7 images are selected ran-
A convolutional autoencoder that wrapped by RRAE is used to encode the cross-sectional images. The autoencoder is piled up by layers of 2D convolution, batch normalization (Ioffe & Szegedy, 2015) and ReLU without skipping links. The input cross-sectional image is mean and std normalized. The output of the last transposed convolution layer is denormalized to get the reconstructed image. The reconstructed image and the original cross-sectional image are used to calculate the residual image and the NMS(\cdot) loss.

Table 3 shows the results of the cross-sectional autoencoding experiment in which the best test results have been listed. From the results, RRAE has improved the reconstruction accuracy significantly. When the latent code dimension is low, 2 for example in this experiment, too many trials (e.g. \( T = 3 \)) will harm the performance of RRAE. The performance decreasing can also be observed in Table 2. Figure 4 shows the results of each trial that are from one test run of the \( z = 5 \) & \( T = 3 \) experiment. The reconstructed images are clamped to the range from 0 to 1. To illustrate the residual images, they are added by the bias 0.5 to keep the pixel value in the range from 0 to 1. From Figure 4, it is obvious that the residual gets smaller after each trial. The final reconstructed image \((t = T)\) is very close to the original image which has been encoded into just 5 float variables.

The L1 loss of the final reconstructed image is 0.0020 in Figure 4. Figure 5 shows the results of different image compression algorithm with the same original image. The DCT method is same as the one introduced in (Zhou et al., 2018) where a image will be encoded into latent codes by 2D discrete cosine transformation and Zigzag reordering. Jpeg and Jpeg2000 are provided by MATLAB2014a. The DCT method needs 119157 double variables to reconstruct the image with L1 loss 0.0020. Jpeg has the loss 0.0024 with file size 5177 bytes. Jpeg2000 has the loss 0.0021 with file size 3333 bytes. Although L1 losses are close to each other, the code length of image compression methods are much longer than RRAE. From the residual images of Figure 5, there are obvious noises in the reconstructed images. Comparing to Figure 5, the final reconstructed image in Figure 4 has smoother and cleaner edges that are important in describing CAD shapes.

Table 3. The cross-sectional image autoencoding experiment.

| z  | T  | NMS(\cdot) | DR/% | z  | T  | NMS(\cdot) | DR/% |
|----|----|------------|------|----|----|------------|------|
| 2  | 1  | 5.0069     | 0    | 4  | 1  | 0.2821     | 0    |
| 2  | 2  | 3.665      | 27.70| 4  | 2  | 0.05777    | 79.52|
| 2  | 3  | 4.910      | 3.14 | 4  | 3  | 0.04142    | 85.32|
| 3  | 1  | 0.7347     | 0    | 5  | 1  | 0.2081     | 0    |
| 3  | 2  | 0.2983     | 59.40| 5  | 2  | 0.04240    | 79.63|
| 3  | 3  | 0.2591     | 65.73| 5  | 3  | 0.02815    | 86.47|

Please refer to code in folder CNN for implementation details.

Please refer to code in folder DCT for implementation details.
Figure 4. Results of each trial. (a) is the original image. (b) is the reconstructed image of the first trial. (c) and (d) are the reconstructed images of the second and third trials. (e) is the residual image of the first trial. (f) and (g) are the residual images of the second and third trials.

4. Conclusion

An autoencoder framework, Residual-Recursion Autoencoder (RRAE), has been proposed to boost the performance of any autoencoder that encodes the target image into a latent code and reconstructs the image from the latent code. RRAE can endow the autoencoders with the ability of learning, capturing and highlighting hard patterns of the target image. When wrapped by RRAE, autoencoders will try to reconstruct the target image several times. After each trial, the residual between the reconstructed image and the target image will be filled to the reserved channel of the input tensor. Recursively, the input tensor will be full of residual images in which hard patterns may be repeated several times. With the fully filled input tensor, autoencoder can reconstruct the target image accurately with low dimensional latent code. The significant improvements over the baseline autoencoders have verified the performance of RRAE.

The target image should contain lots of hard patterns, for example, shape illustration images that consist of binary or gray shapes with sharp edges and large areas of blanks. Otherwise, RRAE will not bring in any significant improvements. This conclusion is supported by the comparative experiments of MNIST and its high-resolution version. RRAE with the high-resolution MNIST that contains much more hard patterns yielded more significant improvement than the original MNIST.

Supposing the computational cost of an autoencoder is $O(n)$, the cost will be $T \cdot O(n)$ after the wrapping of RRAE. According to the experiment results, the upper limit of $T$ is 3. In our experiments, RRAE increased computation cost by 2 times and decreased the reconstruction error by 86.47%.

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Figure 5. Image compression results.

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