VQBB: Image-to-image Translation with Vector Quantized Brownian Bridge

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Abstract

Image-to-image translation is an important and challenging problem in computer vision. Existing approaches like Pixel2Pixel [7], DualGAN [12] suffer from the instability of GAN and fail to generate diverse outputs because they model the task as a one-to-one mapping. Although diffusion models can generate images with high quality and diversity, current conditional diffusion models still cannot maintain high similarity with the condition image on image-to-image translation tasks due to the Gaussian noise added in the reverse process. To address these issues, a novel Vector Quantized Brownian Bridge (VQBB) diffusion model is proposed in this paper. On one hand, Brownian Bridge diffusion process can model the transformation between two domains more accurately and flexibly than the existing Markov diffusion methods. As far as the authors know, it is the first work for Brownian Bridge diffusion process proposed for image-to-image translation. On the other hand, the proposed method improves the learning efficiency and translation accuracy by confining the diffusion process in the quantized latent space. Finally, numerical experimental results validated the performance of the proposed method.

1. Introduction

Image-to-image translation refers to building a mapping between two distinct domains. Numerous problems in computer vision can be regarded as image-to-image translation tasks, for example, style transfer, grayscale image colorization, edge-to-image, etc.

A natural approach for image-to-image translation is to learn the conditional distribution of output images given the samples from the input domain. Pixel2Pixel [7] is one of the most popular image-to-image translation methods. It is a typical conditional Generative Adversarial Networks (GANs) [9], and the domain translation is accomplished by learning a mapping from input image to output image. In addition, a specific adversarial loss function is also trained to constrain the domain mapping. Despite of the high fidelity translation performance, they are notoriously hard to train due to training instabilities and mode collapse. In addition, GANs-based image-to-image translation methods are also suffered from lack of diverse translation results.

Recently, diffusion models [2] have shown the competitive performance on producing high-quality images compared with GAN based models. Several conditional diffusion models including CDiffE [1] and Pallete [10] have been proposed for image-to-image translation tasks. These methods treat image-to-image translation as conditional image generation. The forward diffusion process of these methods coincides with the original Markov diffusion model [2], and accomplishes conditional generation by utilizing either clean or perturbed condition image in the reverse process to predict the diffusion direction based on the condition. However, most of these methods are suffered from model generalization, and can only be adapted to some specified applications. In addition, most diffusion models are conducted in image space, resulting in high computation complexity in both training and inference stages.

In this paper, we propose a novel image-to-image translation framework based on Brownian Bridge diffusion process. Compared with the existing diffusion methods, the proposed method directly builds the mapping between the input and the output domain, rather than a conditional generation process.

The main contributions of this paper include:

1. A novel image-to-image translation method based on Brownian Bridge diffusion process is proposed in this paper. As far as the authors know, it is the first work for Brownian Bridge diffusion process proposed for image-to-image translation.

2. The proposed method improved the learning efficiency and model generalization by performing the diffusion process in the quantized latent space.
3. The proposed VQBB model achieved competitive results on different image-to-image translation tasks.

2. Related work

Image-to-image translation. Isola [7] firstly propose a unified framework for image-to-image translation based on conditional GANs. Wang [11] extended Pixel2Pixel framework to generate high-resolution images. DualGAN [12] used two GANs separately on two domains and train them together with dual learning [4]. But they suffer from the training instabilities and mode collapse problems of GAN. There were also several multimodal methods [13, 6] for image-to-image translation.

Brownian Bridge A Brownian Bridge is a continuous-time stochastic process whose probability distribution is the conditional probability distribution of a standard Wiener process. Specifically, the density of a Brownian bridge process starting from point \( x_0 \sim q_{data}(x_0) \) at \( t = 0 \) and ending at point \( x_T \) at \( t = T \) can be formulated as:

\[
p(x_t | x_0, x_T) = \mathcal{N}\left(\frac{1 - t}{T} x_0 + \frac{t}{T} x_T, \frac{t(T - t)}{T}\right)
\]  

(1)

Denoising Diffusion Probabilistic Models (DDPM) [5]. A T-step DDPM model consists of two processes: the forward process also referred to diffusion process, and the reverse prediction process.

The forward process from data \( x_0 \sim q_{data}(x_0) \) to the latent variable \( x_T \) can be formulated as a fixed Markov chain:

\[
q(x_1, ..., x_T | x_0) = \prod_{t=1}^{T} q(x_t | x_{t-1})
\]

(2)

where \( q(x_t | x_{t-1}) = \mathcal{N}(x_t; \sqrt{1-\beta_t} x_{t-1}, \beta_t I) \), \( \beta_t \) is a small positive constant. The forward process gradually perturbs \( x_0 \) to a latent variable with an isotropic Gaussian distribution \( p_{\text{latent}}(x_T) = \mathcal{N}(0, I) \). The sampling distribution of \( x_t \) can be derived as the following distribution conditioned on \( x_0 \):

\[
q(x_t | x_0) = \mathcal{N}(x_t; \sqrt{\alpha_t} x_0, (1 - \alpha_t) I)
\]

(3)

where \( \alpha_t = 1 - \beta_t \) and \( \bar{\alpha}_t = \prod_{s=1}^{t} \alpha_s \).

The reverse process strives to predict the original data \( x_0 \) from the latent variable \( x_T \sim \mathcal{N}(0, I) \) through another Markov chain:

\[
p_\theta(x_0, ..., x_{T-1} | x_T) = \prod_{t=1}^{T} p_\theta(x_{t-1} | x_t)
\]

(4)

The training objective of DDPM is to optimize ELBO.

\[
E_q[D_K L (q(x_T | x_0) | p(x_T))] + \sum_{t>1} D_K L (q(x_{t-1} | x_t, x_0) | p_\theta(x_{t-1} | x_t)) - \log p_\theta(x_0 | x_1)
\]

(5)

Combining Eq. (2) and Eq. (4), the objective can be simplified as optimize:

\[
\mathbb{E}_{x_0, \epsilon} \| \epsilon - \epsilon_\theta(x_t, t) \|_2^2
\]

(6)

where \( \epsilon \) is the Gaussian noise in \( x_t \), \( \epsilon_\theta \) is the model trained to estimate \( \epsilon \).

Conditional Diffusion Processes. Wang. [8] proposed CDiffuSE which is a kind of conditional diffusion process for speech enhancement. CDiffuSE define the conditional diffusion process as:

\[
q_{\text{diff}}(x_t | x_0, y) = \mathcal{N}(x_t; (1 - m_t) \sqrt{\alpha_t} x_0 + m_t \sqrt{\alpha_t} y, \delta_t I)
\]

(7)

where \( m_t \) starts from \( m_0 = 0 \) and is gradually increased to \( m_T \approx 1 \), \( y \) is the conditional information. And when \( \delta_t = (1 - \bar{\alpha}_t - m_t^2 \bar{\alpha}_t) \), \( q_{\text{diff}}(x_t | x_0) \) becomes equivalent to the original diffusion process as DDPM.

The training objective can be derived as:

\[
\mathbb{E}_{x_0, x_0, \epsilon, y} \| m_t \sqrt{\alpha_t} (y - x_0) + \sqrt{\delta_t} (\epsilon - \epsilon_\theta(x_t, y, t)) \|_2^2
\]

(8)

3. Method

Given two datasets \( \mathcal{X}_A \) and \( \mathcal{X}_B \) sampled from domains \( A \) and \( B \), image-to-image translation aims to learn a mapping from domain \( A \) to domain \( B \). In this paper, a novel image-to-image translation method based on Brownian Bridge process is proposed. In order to improve the learning efficiency and model generalization of the existing diffusion based methods, we propose to accomplish the diffusion process by utilizing the VQGAN latent space. Given an image \( I_A \) from domain \( A \), we can extract the latent feature \( L_A \), and the Brownian Bridge maps \( L_A \) to the corresponding latent representation \( L_{A \rightarrow B} \) of domain \( B \). Finally, the translated image \( I_{A \rightarrow B} \) is generated by the decoder of the pretrained VQGAN, as shown in Figure 1.

3.1. Brownian Bridge

The forward diffusion process of DDPM [5] starts from clean data \( x_0 \sim q_{data}(x_0) \) and ends at standard normal distribution. Similarly, the forward diffusion process of CDiffuSE [8] starts from clean data \( x_0 \sim q_{data}(x_0) \) and ends at the conditional input \( y \) with variance \( \delta_T > 0 \). Instead of ending at the conditional input with some variance, Brownian Bridge takes the clean conditional input \( y \) as its destination.

We convert the latent expressions between domain \( A \) and \( B \) by the Brownian Bridge. To take similar notations as DDPM and CDiffuSE, let \( x_0 = L_B \) and \( y = L_A \). The forward diffusion process of Brownian Bridge can be defined...
where the mean in each reverse step aims to predict $x_t$.

In the reverse process, Brownian Bridge simply starts from $t = T$ and ends at $t = 0$.

### 3.1.2 Reverse process

Given the interpolation formulation in Eq.(9), we can derive the distribution $q_{BB}(x_t|x_{t-1}, y)$ as:

$$q_{BB}(x_t|x_{t-1}, y) = \mathcal{N}(x_t; \frac{1 - m_t}{1 - m_{t-1}} x_{t-1}, \delta_t I)$$

where $m_t = \frac{t}{T}$ and $\delta_t = \frac{t(T-t)}{T} \frac{4\delta_{max}}{T}$.

### 3.1.3 Simplified training objective

The ELBO for the conditional diffusion process can be formulated as:

$$ELBO = -\mathbb{E}_q(D_{KL}(q_{BB}(x_T|x_0, y)|p(x_T|y)) + \sum_{t=2}^{T} D_{KL}(q_{BB}(x_{t-1}|x_t, x_0, y)|p_\theta(x_{t-1}|x_t, y)) - \log p_\theta(x_0|x_1, y))$$

Since $x_T$ is equal to $y$ in Brownian Bridge, $D_{KL}(q_{BB}(x_T|x_0, y)||p(x_T|y))$ can be seen as a constant and ignored. And by combining Eq.(9) and Eq.(12), $q_{BB}(x_{t-1}|x_t, x_0, y)$ can be derived through Bayes’ theorem and the Markov chain property:

$$q_{BB}(x_{t-1}|x_t, x_0, y) = \frac{q_{BB}(x_t|x_{t-1}, y)q_{BB}(x_{t-1}|x_0, y)}{q_{BB}(x_t|x_0, y)}$$

where $q_{BB}(x_{t-1}|x_0, y)$ is a linear combination of $x_t$ and $y$.

### 3.2 Brownian Bridge in latent space

With the aim of improving the learning efficiency and model generalization, we propose to accomplish Brownian Bridge diffusion between domains in the latent space...
of VQGAN [3]. Given two VQGAN model $VQGAN_A$ and $VQGAN_B$ seperately pretrained on domain $A$ and $B$, paired training images $I_A$ and $I_B$ are encoded into latent space by the encoder of VAGAN model. Then we use the paired latent expression to train Brownian Bridge.

**4. Experiments**

**4.1. Experiment Setup**

Model Architecture: The VQBB framework contains three parts: two pretrained VQGAN model and Brownian Bridge. We implement Brownian Bridge based on the same UNet architecture as DDPM [5].

Dataset: We evaluate the VQBB framework on several datasets, including face2comic, edges2shoes, edges2handbags [7].

**4.2. Experiment results**

We conduct several experiments on the above-mentioned datasets and the experiments in Figure 2 3 4, show that VQBB framework can produce promising results with diversity.

**5. Conclusion and limitations**

We proposed a new method for conversion between different domains based on Brownian Bridge. To extend the applications of Brownian Bridge, we combined Brownian Bridge with VQGAN and proposed a new framework for image-to-image translation tasks. We showed that our VQBB framework can generate promising results on several different tasks. Nevertheless, there is still much room for the improvement of VQBB, so one of the important future directions is to modify the VQBB to produce high quality samples. Meanwhile, it would also be interesting to try our framework on various tasks that have paired training data.

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