

Variational-Auto-Encoder for tooth image generation

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Abstract—Variational Autoencoder (VAE), as a kind of deep latent space generation model, has achieved great success in performance in recent years, especially in image generation. In this article, we expound on the application of VAE in tooth image generation. Variational-Auto-Encoder is a recently proposed excellent algorithm for data generation. We show that VAE also has a good generation effect in tooth image generation.

Keywords—Variational-Auto-Encoder, tooth image generation

I. INTRODUCTION

In recent years, deep learning has received increasing attention from researchers. Compared with traditional machine learning, the multi-layer network structure of the deep learning model can express complex functions more effectively, thereby learning features with stronger representation ability. Variational Autoencoder (VAE), as a branch of deep learning, has received extensive attention since its appearance[1]. VAE is of great significance to the development of generative models. The neural network structure adopted by VAE is not limited to the generation dimension, which greatly expands the range of generated data samples. In addition, VAE also has effective capabilities in the field of natural language processing, such as generating dialogue and generating images from text. This potential ability to generate unlimited samples separately has great application value in the fields of AI for image and visual computing, speech, and language processing, interconnection and large-scale system information security.

VAE is an important type of generative model, which was proposed by Diederik P. Kingma and Max Welling in 2013. Burda et al. proposed an importance-weighted autoencoder in 2015[2]. The important weighted autoencoder target is also the lower bound of $\log p_{\text{model}}(x)$, and it becomes tighter as k increases. In 2016, Sønderby, CK, Raiko, T., and others proposed Ladder variational autoencoders, which improve the generated distribution through the possibility of dependence between data in a ladder network[3].

Experiments show that it is compatible with hierarchical variational autoencoders. Compared with the pure bottom-up reasoning of other generative models, this model can obtain a more effective prediction likelihood function and a stricter lower bound of log-likelihood.

In just a few years, VAE has become the most popular method for unsupervised learning of complex distributions. VAE is attractive because they are built on standard function approximators (neural networks) and can be trained by stochastic gradient descent. VAE has demonstrated the effectiveness of generating a variety of complex data, including handwritten numbers, faces, house numbers, CIFAR images, physical models of scenes, segmentation, and predicting the future through static images.

II. TECHNICAL APPROACH

A. Data collection

Since there is no public dataset, we had to collect 451 images from hospital. We selected the images with different distances and lighting and the people with different genders and ages. This is a challenge for the network.

B. Variational Autoencoder

As a generative model, VAE transforms a bunch of real samples into an ideal data distribution through an encoder network, and then this data distribution is passed to a decoder network to get

a bunch of generated samples, and the generated samples are close enough to the real samples. If so, an autoencoder model is trained. Then VAE is to do further variational processing on the autoencoder model so that the output result of the encoder can correspond to the mean and variance of the target distribution, as shown in the following figure 1.

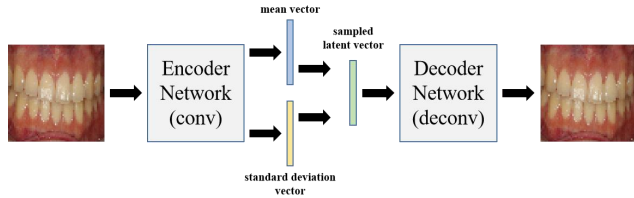


Figure 1. Variational Autoencoder Workflow

III. RESULTS

In Figure 2, we visualized the results. We found that our method could generate realistic translated images. It can be seen from the results that the teeth and the gums are clearly separated, and there is a clear boundary between each tooth in most images.



Figure 2. Results display

IV. CONCLUSION & FUTURE WORK

In this article, we show the results of VAE on tooth image generation. In tooth image analysis, image generation has a great effect on tooth orthodontics and dental disease detection. The VAE-based image generation model is easily adapted to improve performance without extensive modification or customization. In the future, VAE will combine more networks, not just image generation. It can also predict the occurrence of diseases, such as orthodontics, fillings, and assessing the health of teeth.

ACKNOWLEDGMENT

This work is financially supported by Korea Ministry of Land, Infrastructure and Transportation(MOLIT) as 「 Innovative Talent Education Program for Smart City」 .

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