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SATELLITE IMAGE TO GOOGLE MAP IMAGE-TO-IMAGE TRANSLATION USING DUAL GANS

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Abstract- Image translation has become widely used everywhere and it has been used for generating new images from existing images such as generating avatars, creating fake images, translation of images from one type to another and many more using various machine learning algorithms. One such machine learning technique for image translation is GAN (Generative Adversarial Networks). The classic GANs does the job of translation the images of a domain U to domain V, and the conditional GANs does the same but basing on a condition. These GANs are able to tell the discrimination between the objects accurately when training labeled data sets, and cannot perform well when training unlabeled data sets. So, we need a GAN that can train the unlabeled data sets well and able to translate the images of the domain U to domain V and vice-versa so that we can calculate the realness or fakeness of the image translated taking the original image as reference. For this purpose, we research dual GANs, which combine a primal GAN with another GAN. The inversion of the task of the primal GAN, which is comparable to the traditional GAN, is learnt by dual GAN,
Keywords- *Generative Adversarial Networks, Dual GANs, Classic GANS, Machine Learning, Generator, Discriminator, Image translation, Neural networks, Conditional GANs, Standardization*

1. INTRODUCTION

In this paper, we will study how actually Dual GANs work for translation of images. The dataset that is being trained for this paper is "maps". The data set consists of the satellite images and the corresponding Google map images. The size of each image is 600x600 pixels. The image translation involves translating satellite image to Google map images and Google map images to satellite images. The generator and the discriminator are the major parts of the architecture of the GAN model. The generator is an encoder-decoder which takes an input or source image (e.g. satellite image) and converts it into target image (e.g. Google map image) using a U-Net architecture [12]. Using a deep convolutional neural network i.e., the discriminator that discriminates the image generated with that of the source image and predicts the realness or fakeness of the translated image [12]. Basically, Dual GANs consists of a primal GAN which translates pictures from a domain U to domain V and inversion of the primal GAN is taken care of by the secondary GAN simultaneously. Dual GANs are used in this project because when training unlabeled data, they perform very well at generating some of the best images with high precision and accuracy compared to GANs and CGANs.

2. RELATED WORK

In this section, authors are reviewing the different algorithms related to image-to-image translation using various machine learning techniques like SPI-GAN, Link-GAN etc. Zili Yi et al. [1] when experimenting with four labelled datasets and two unlabeled, unpaired datasets and comparing their results in the qualitative analysis have shown that the DualGANs are able to produce much clear and accurate results compared to GANs and Conditional GANs. In addition to better preserving content structures in the inputs and capturing aspects (such as texture, colour, and/or style) of the target domain, DualGAN outcomes are less hazy, have less artefacts, and are less blurry. [1].

Table-1: Literature Review of Related Work

Ref. No.	Title of the Paper	Authors	Findings
[2]	SPI-GAN: Towards Single-Pixel Imaging through Generative Adversarial Network	Nazmul Karim and Nazanin Rahnavard	A generative adversarial network-based technique for single-pixel photography is called SPI-GAN. The generator learns usable representations using an architecture akin to ResNet, enabling the reconstruction of previously unknown things. The outcomes of the experiment show that SPI-GAN outperforms the current state-of-the-art method and has better generalization ability to completely unseen datasets. This method has the potential to enable low-cost and high-speed imaging, making it an exciting development in the field of image recovery.

[3]	LinkGAN: Linking GAN Latents to Pixels for Controllable Image Synthesis	Jiapeng Zhut, Ceyuan Yangt, Yujun Shent, Zifan Shi, Deli Zhao, Qifeng Chen	LinkGAN allows for local control of image synthesis by linking specific image regions to latent space axes during GAN training. The experimental results show that LinkGAN has several desirable properties, including the ability to link multiple regions to different latent axes independently and simultaneously, without sacrificing synthesis performance. This method improves spatial controllability in both 2-Dimensional and 3-Dimesional GAN models and enhances GAN-based image synthesis. This work is significant in the development of more spatially controllable and disentangled GAN latent spaces.
[4]	Attention-Guided Generative Adversarial Networks for Unsupervised Image-to-Image Translation	Hao Tang, Dan Xu, Nicu Sebe, Yan Yan	AGGAN is a GAN-based approach for semantic manipulation problems. The most discriminative semantic object is detected using AGGAN, and undesired alterations are minimized, resulting in high-quality images. AGGAN uses attention-guided generators and a novel attention-guided discriminator to produce attention masks and content masks. The results show that AGGAN outperforms existing models and has potential applications in various fields such as computer vision and medical imaging.
[5]	Image-To-Image Translation with Conditional Adversarial Networks	Phillip Isola, Jun-Yan Zhu ,Tinghui Zhou, Alexei A.Efros	The usage of conditional adversarial networks to solve the image-to-image translation problem is investigated by the authors. These networks have an input picture to output image mapping that can be trained using a loss function. Convolutional Neural Networks (CNN) are trained to minimize a loss function, which is simply an indicator of how well results were produced.

[6]	Unsupervised Cross-Domain Image Generation	Yaniv Taigman, Adam Polyak & Lior Wolf	An approach to computer network architecture called the Domain Transfer Network (DTN) aims to solve technical problems in heterogeneous networks that might not have constant network connectivity. In machine learning, generative modelling is a process that incorporates unsupervised learning in which regularities or patterns are automatically found and learned. Most notably in image to image translation tasks like translating photos of summer to winter or day to night, generative models excel at producing realistic examples across a variety of problem domains. They also produce accurate images of objects, scenes, and people.
[7]	Unpaired Deep Image Deraining Using Dual Contrastive learning	Xiang Chen, Jinshan Pan , Kui Jiang , Yufeng Li , Yufeng Huang , Chihuahua Kong , Long gang Dai , Zhentao Fan	Single Image Deraining (SID) is a technique used to forecast the rain layer from an input rainy image using residual learning. An encoder-decoder network that requires the encoder to encode a high-quality rain embedding, which determines the performance of the succeeding decoding stage to reconstruct the rain layer, is widely used for this purpose. This research presents an efficient DCD-GAN for SID unpaired learning method.
[8]	Unsupervised Pixel-Level Domain Adaption with Generative Adversarial Networks	Konstantinos Bousmalis , Nathan Silberman , David Dohan , Dumitru Erhan , Dilip Krishnan	Images from the source domain are used in the Generative Adversarial Network (GAN) based model to make them appear to be from the target domain. Unsupervised domain adaptation methods that try to convert representations across the two domains or discover domain-invariant feature extraction. The most recent technique is utilized to carry out supervised domain adaptation. When it comes to a collection of Unsupervised domain adaptation scenarios, PixelIDA models outperform prior research.

[9]	GAN based Object Removal in High Resolution Satellite Images	Hadi Mansourifar , Steven J.Simske	Compared to ground view photos, satellite images provide a substantial amount of sensitive information. Two key issues with GAN-based techniques have been identified: first, adding a new item to the scene to conceal a particular object or region may provide unrealistic merging images; second, utilizing masks on colour feature images has been shown to be ineffective for GAN-based object removal. In this article, the authors look into CFI's potential for one-shot CGAN-based object removal.
[10]	Discovering Class-Specific GAN Controls for Semantic Image	Edgar Schonfeld, Julio Borges, Vadim Sushko, Bernt Schiele, Anna Khoreva	Ctrl-SIS is a method for semantic image synthesis using conditional GANs. The method allows for class-specific edits without affecting other areas of the image. The discovered controls are semantically meaningful and enable diverse and high-quality class edits. The method outperforms prior methods in terms of the quality of class edits.
[11]	Discriminator-Cooperated Feature Map Distillation for GAN Compression	Tie Hu, Mingbao Lin, Lizhou You, Fei Chao, Rongrong Ji	DCD can be used for compressing GANs while maintaining performance. DCD uses a teacher discriminator to guide the student generator in producing similar outputs. The method also introduces collaborative adversarial training to mitigate mode collapse. Experimental results show that DCD outperforms existing GAN compression methods.

3. MATERIALS AND METHODS

When the generator A(GA) of primal GAN maps and translates an image from domain U to domain V, the generator B(GB) of the secondary GAN learns to map and translate the image from domain V to domain U. The discriminator DA of the primal GAN differentiates the image generated by the GA’s translated image with that of the image from the domain V. Inverting the challenge by learning a discriminator DB is what the dual GAN does.. As the name suggests, the discriminator generates a report on genuineness versus falsity of the image generated by comparing it with the actual image. This will help us understand to what extent the algorithm is helpful to generate images from the existing images.

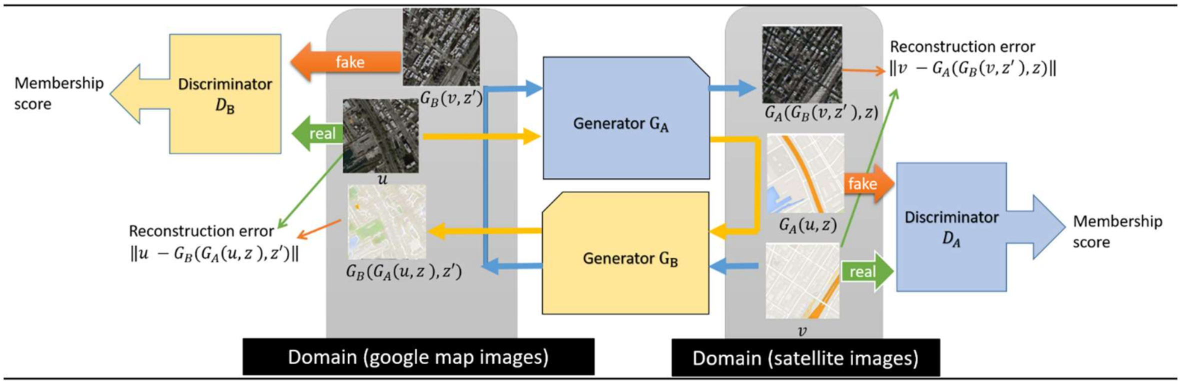

Fig-1: Architecture and work flow of the Dual GAN image-to-image translation

3.1. Algorithm:

Step-1:Import two sets of unlabeled, unpaired photos (x and y) drawn from the domains X and Y, respectively

Step-2: Learn a generator G_A: $X \rightarrow Y$ that maps an image $x \in X$ to an image $y \in Y$

Step-3: Train an inverse generator G_B: $Y \rightarrow X$ that learns to map an image $y \in Y$ to an image $x \in X$

Step-4: Learn a discriminator D_A that compares real image from domain Y with that of G_A's output

Step-5: Train an inverse discriminator D_B that compares real image from domain X with that of G_B's output

4. RESULTS

As a part of analysis, we collected samples of the statistics of the logs generated by the classic GAN and Dual GAN on the dataset "maps". The sample logs are then converted to meaningful datasets and then standardized using standardization filter under unsupervised learning. From the graphs, we can see that the classic GANs failed to produce accurate results as they cannot discriminate or distinguish between the true picture and the picture generated as most of the sample logs has the U domain's image difference and V domain's image difference as zero. Whereas, the Dual GANs did an exceptional job at detecting the difference between the images and the graph shows that they are able to detect the realness or the fakeness of the images generated very well.

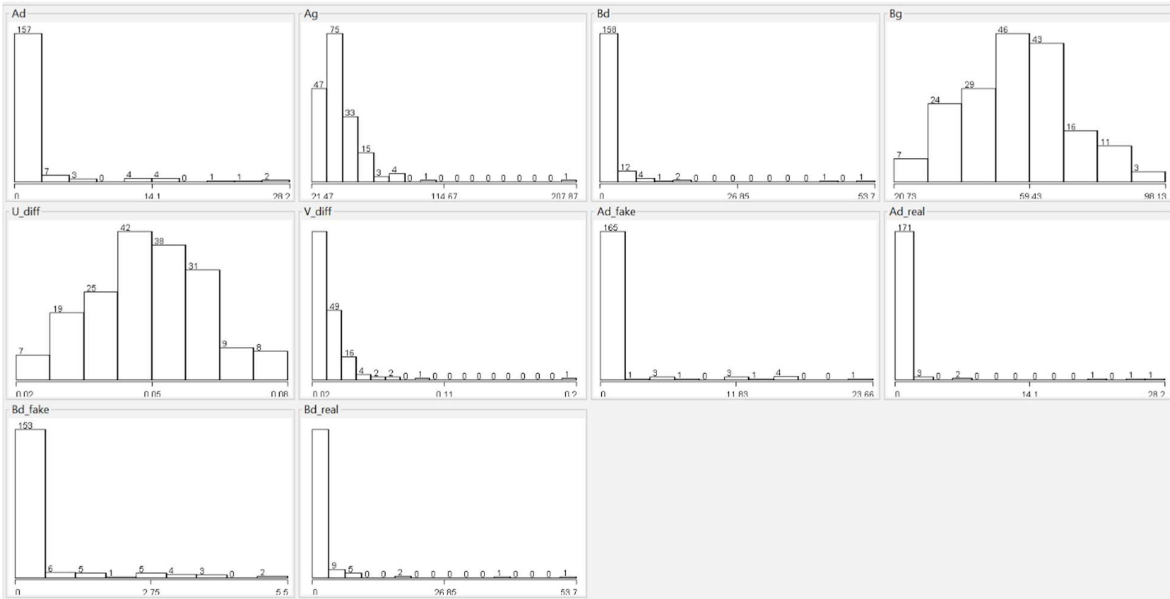

Fig-2: Statistics of the sample logs generated by the classic GAN

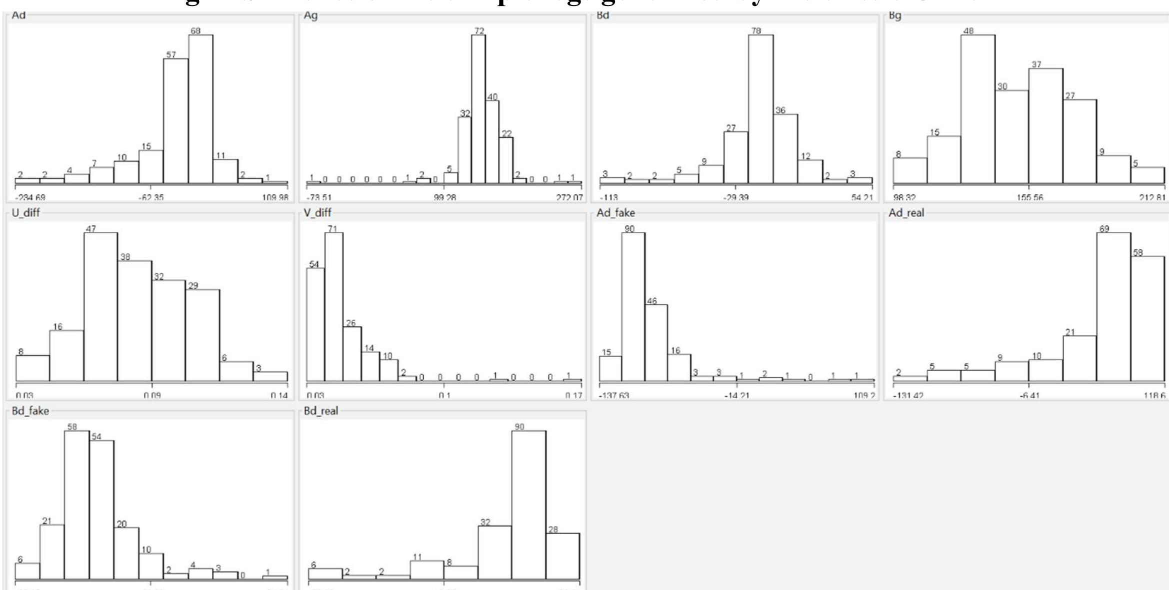

Fig-3: Statistics of the sample logs generated by the Dual GANs

5. DISCUSSION

Image translation is useful to generate new images from existing images by picking the features of the real images. From the experiments and the analysis done, we can say that the Dual GANs are reliable when we want to predict the likeliness of the images generated during the image translation of the unlabeled image datasets. Whereas the classic GANs and conditional GANs cannot outperform the Dual GANs at cross-domain translation and predicting the dissimilarities between the existing image and the image produced.

6. CONCLUSION

In image translation and analysis, we can say that Dual GANs can perform very well at generating images from one dataset to another and vice-versa when trained with unlabeled data. They can also discriminate the images generated up to some extent on labeled datasets. The Dual GANs can be improvised so that they can perform well when used with labeled datasets. In future, they can be extended to carry out 3D image to image translations and analysis.

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