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Research Article

Generation of Fake Mesh Structures Using GANs with SIFT-Based Feature Preservation

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ABSTRACT

The mechanism used in processing geometric information for graphs lies at the intersection of graph theory with engineering and data science; in this case, the structured graph data is processed and analyzed through topological and geometric concepts, thus generating artificial graphs that are similar to real data, taking into account when creating the data, the preservation of the existing properties of the original graphs, which are the basic features and structural patterns. The proposed approach uses a generative adversarial network (GAN) with the addition of a completely separate layer for each of the generator and discriminator networks, which is one of the deep learning techniques; in this way, the system is enabled to identify the patterns present in real data and reduce the possibility of overfitting resulting during the processing of data which is in the form of vectors. Applying this strategy, the model can build fake graphs with the number of points equal to the number of input data points and whose location is close to the points present in the real data graphs. This study aims to produce graphs that are simulated to the original graphs. The simulated graph data can be used in the field of algorithm development, benchmarking and other fields such as testing and data augmentation.

Keywords: GAN, mesh image generation, building of a fake mesh, synthetic mesh generation, Generative Adversarial Network, Deep learning, SIFT.

INTRODUCTION

The methods used in analyzing and managing graph data require a set of approaches and strategies in order to obtain useful results in solving problems [1]. Graphical data is a data structure where data is organized in the form of nodes and edges connecting the nodes (vertices) where edges (links) reflect the relationships and interactions between the elements (entities), such as biological networks, transportation networks, and social networks [2, 3]. Having access to the right tools necessary for studying graph data requires a thorough understanding of graph theory and the knowledge of the effective use of relevant algorithms. These tools are the techniques that help in finding hidden patterns and complex relationships formed by graph data and taking them into account in decision-making[4]. In general, deep learning is similar to human learning and has brought about a major transformational revolution within the concepts of artificial intelligence. The concept of deep learning has previously unimaginable effective techniques for decoding and analyzing complex data and is an effective catalyst in the innovation of a wide range of industries [5, 6].

Deep learning is the product of the development of machine learning and artificial intelligence, where the design of algorithms focuses on artificial neural networks inspired by the structure and function of the brain[3]. Artificial intelligence has succeeded in training computers and allowing them to learn from huge amounts of data and perform activities that were previously thought to be specific to human intelligence[7, 8]. One of the artificial intelligence techniques explained above is the GAN technique, which was used to create new data similar to the original data within unsupervised machine learning. This technique takes the competitive approach between the generator and discriminator networks to train neural networks, as the GAN technique consists of two parts that were introduced by Goodfellow[9]. The first part is the generator network, whose role is to produce synthetic data, which is called fake, such as images, which somewhat mimic the real data that the GAN network was trained on. The training process begins with random noise, and then the network gradually acquires the ability to produce samples closer to real data.

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In contrast, the discriminator works as a critic, assessing both the generator's bogus samples and the real data samples from the training set. Its job is to differentiate between synthetic and actual data[10, 11]. As illustrated in Figure (1).

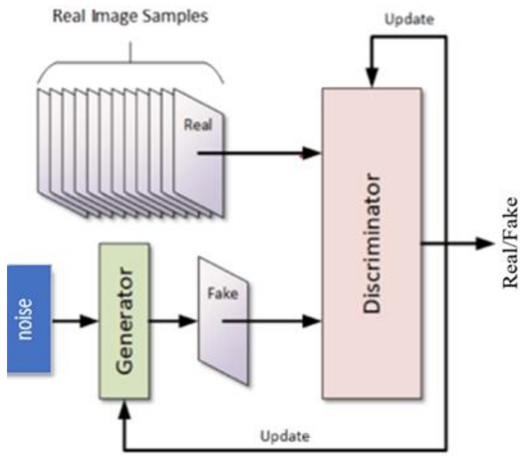

Figure (1) Architecture of Generative Adversarial Networks

In training, the discriminator continuously improves its ability to determine whether the data it receives is real, while the generator attempts to make more credible fake data to trick the discriminator. Until the generator generates data that the discriminator can't distinguish differently from the true data, this adversarial process is repeated[12]. A generative adversarial network (GAN), a deep learning technology, has been presented as a way to generate false graphs. In both the discriminator and generator networks of this model, there is just one completely linked layer. The Scale-Invariant Feature Transform (SIFT) approach is used to extract interest points from satellite images of the Earth's surface, which are then processed by the generative network as input vector data in the form of a binary matrix[13, 14].

The generator then provides fake graphs with the help of the fully connected layer, which plays the role of identifying patterns in the input data and avoiding overfitting that occurs during training[15, 16]. As for the discriminator network, whose structure has been modified by adding a fully connected layer, it also plays the role of evaluating the generator outputs, as the generator outputs and the real data are entered into the discriminator network to differentiate between them. In other words, the benefit of having the fully connected layer after the discriminator network is the classification of the generator outputs, which leads to obtaining a probability value (0,1). The data is entered into the proposed model in the form of a coordinate matrix structure (X, Y) that expresses the interest points found in the satellite image of the Earth's surface extracted by SIFT technology, and then a coordinate matrix of the locations of those coordinates is generated near the real points while preserving its features of topological and geometric. as Figure (2) illustrates.

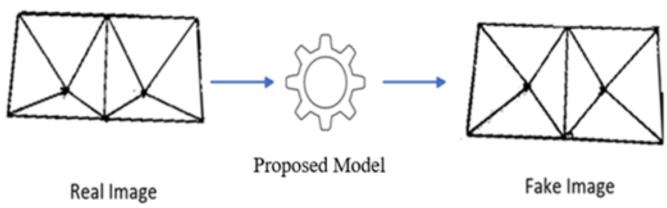

Figure (2) Study's Objective

RELATED WORK

Since Ian Goodfellow [9] and his colleagues first introduced Generative Adversarial Networks (GANs) in 2014, the area of generative modeling has dramatically changed. The general structure of the GAN technique consists of two neural networks, the generator and the discriminator, one working against the other as if it were a zero-sum game. The job of the generator is to create fake data and is an attempt to simulate real data, while the discriminator works to assessment whether the generator's outputs are real or fake over time. The essence of this competitive process is to produce increasingly realistic data.

Before GANs were created, generative models were unsupervised and looked for patterns in the input data that could be used to create new instances that closely resembled the original data[17]. This kind of unsupervised generation frequently takes a long time and produces poor-quality output. In contrast, GANs extended the generating process with a supervised task. During the training process of a GAN, the discriminator learns efficiently how to distinguish between synthetic and real samples, while the generator competes with the discriminator to generate data that the discriminator might examine as real data.

Constantly increase the depth of the ConvNet by adding more convolutional layers, all of which use very small (3×3) convolutional filters. In designing a deep convolutional neural network (ConvNet) to improve the accuracy of image classification by increasing the depth of the network [18]. In other words, the conventional ConvNet architecture, when made deeper, can achieve state-of-the-art performance on the ImageNet challenge dataset.

A recently developed geographic data translation (GDT) technique based on Generative Adversarial Networks (GANs) is called InstantCITY. Only street networks are used in the system's design to produce high-resolution vector-building data [19]; GANs can generate high-resolution, realistic-looking synthetic images of human faces, streetscapes, and satellite images. GANS are combined with sequential architectures, such as long- and short-term memory layers (LSTM) [20]. To give specific control over the produced data, GANs may also take in outside circumstances; Images can be synthesized using deep generative models. GANs are an example of a recent technique. There is conditional image synthesis based on the type of input data. Researchers have explored several models for generating images, including one based on text [21]. GANs have produced artificial satellite pictures of towns and landscapes for use in mapping[22]. Switching between different cartographic formats[23], converting satellite photos into graphical representations[24-26], and using geographic vector data to create cartographic representations[27].

THE PROPOSED SYSTEM

The proposed system includes two major modifications to the traditional generative adversarial network (GAN) architecture. First, an additional fully connected layer is introduced after both the generator and discriminator networks. This modification is added to the generator network to improve the extracted features and detect patterns in the input data, making it easier to generate fake data. The fully connected layer within the generator network serves two major functions: to enhance the gradient flow to stabilize training and to mitigate overfitting, thus improving the training accuracy.

Second, in the discriminator network, which differentiates between real and generated data, a fully connected similar layer is integrated. This layer helps in classifying generated and real variables by outputting probability values; thus, the output is then normalized using a sigmoid activation function within the range (0, 1). Observed in Figure (3).

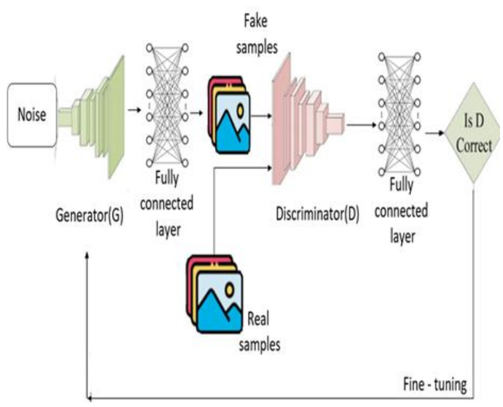

Figure (3) Updated GAN Model's Design

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The model was trained using a dataset of 1400 satellite images of Seattle, USA, divided into 1220 images for training and 280 for testing, with an 80% training section and a 20% testing section. The training samples were fed as the input data structure to the generator consisting of a matrix of (X, Y) coordinates extracted from the points of interest on the Earth's surface from satellite images using the SIFT technique, the generator network also outputs a matrix of fake (X, Y) coordinates, which were then evaluated by the network to distinguish between the real and generated data by the generator network. This block diagram provides a clear overview of the data flow from the initial dataset to the generation of a new mesh image using GAN, as shown in Figure (4).

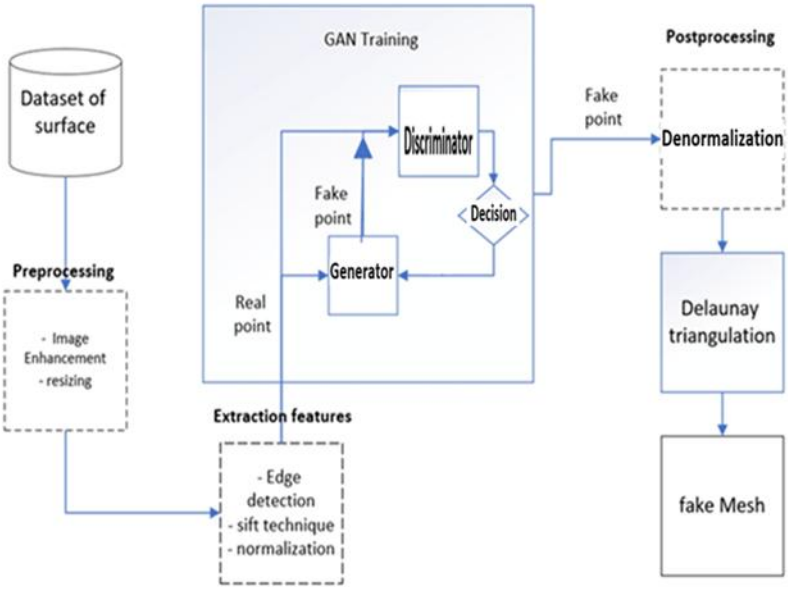

Figure (4) Proposes block diagram of the system

Training and testing phases demonstrate that the model's performance significantly improved with the suggested modifications to the standard generative adversarial network (GAN) design. The method successfully improved the quality of feature extraction by adding one additional fully connected layer after the feature networks and the generator. The reasons for making the creation of synthetic data easier are the presence of a fully connected layer which is necessary to reduce the dimensions of the matrix and to normalize the output, a sigmoid activation function is used to ensure that the output data remains within the restricted range (0,1).

In addition, this modification of the GAN network helps to provide a more stable training environment on real data and noise by enhancing the gradient flow and avoiding the possibility of overfitting.

This improvement produced more accurate results, in addition to stabilizing the training process. The discriminator network's corresponding fully connected layer improved the classification procedure more deeply, allowing the model to distinguish between real and artificial images more precisely. This improvement was critical for achieving higher probabilities for real versus synthetic data classification.

The important parts of the proposed model consist of:

Normalizing Data: Normalization transforms the input data into a range of [0,1] to stabilize and enhance the performance of the GAN. Let x be the original data point, xmin be the minimum value in the dataset, and xmax be the maximum value in the dataset. The normalized data x′ is given by:

$$x' = (x - xmin) / (xmax - xmin) \quad (1)$$

Denormalizing Data: Denormalization reverts the normalized data back to its original scale. Let x′ be the normalized data point. The denormalized data x is obtained using:

$$x = x' \times (xmax - xmin) + xmin \quad (2)$$

Building GAN Architecture:

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Generator: The generator model G creates fake data point $\hat{x}$ by using a random noise vector z as input:

$$\hat{x} = G(z; \theta G) \quad (3)$$

where the generator's parameters are denoted by θG.

Discriminator: A matrix of (x, y) coordinates, real and fake (either real x or fake $\hat{x}$), is fed into the discriminator model D, which returns a D(x) or D($\hat{x}$) indicating whether the output is real or fake:

$$D(x \text{ or } \hat{x} ;\ \theta D) \quad (4)$$

where the generator's parameters are denoted by θD.

Training the GAN: The generator and discriminator compete to improve their performance in training the GAN when it comes to successfully classifying real and fake data, where the role of the discriminator is to maximize the probability of identifying fake data while the role of the generator is to minimize the probability of identifying fake data. The objective functions for the discriminator VD and generator VG are defined as follows:

Discriminator Loss:

$$VD=Ex \sim pdata\,[\,\log D(x)] + Ez \sim pz\,[\log 1-D(G(z)))\,] \quad (5)$$

Generator Loss:

$$VG=Ez \sim pz\,[\,\log (1-D(G(z)))\,] \quad (6)$$

However, it is often beneficial to optimize log D(G(z)) instead for better gradients:

$$VG=Ez \sim pz\,[\,\log D(G(z))\,] \quad (7)$$

The training involves iterating over these steps:

Update Discriminator: Maximize VD by adjusting θD:

$$\theta D \leftarrow \theta D + \eta\, \nabla \theta D\ VD \quad (8)$$

Update Generator: Minimize VG by adjusting θG:

$$\theta G \leftarrow \theta G - \eta\, \nabla \theta G\ VG \quad (9)$$

where η is the learning rate.

Figure (5) illustrates the idea of the proposed model, where the mesh points are entered in the form of a (X, Y) coordinate matrix to the model, where a fake coordinate matrix is generated based on training the proposed GAN model. Then, these points are converted into mesh by applying the Delaunay triangulation technique, and this technique converts these points into non-overlapping triangles, where the idea of this technique is to form a triangle through three vertices so that these three vertices form a circle and these vertices are on the circumference of the circle, and it is required that the formed circle does not contain other points inside the formed circle, thus a triangle is formed from those three vertices. Delaunay triangulation is a geometric structure that works to divide a group of points into a network of non-overlapping triangles, and one of the characteristics of this triangulation is that any triangle in the triangulation forms a circle that passes through three vertices, provided that it does not contain any point inside the circle except the three points on the circumference[28].

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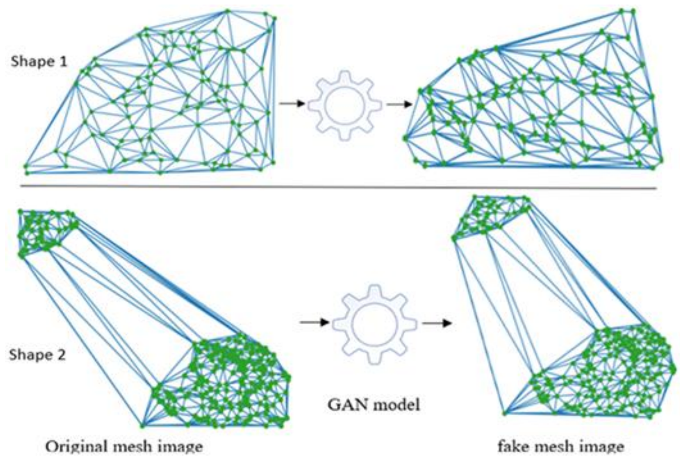

Figure (5) GAN Model's Input and Output

RESULT AND DISCUSSION

For graphical distributions, the Earth Moving Distance (EMD) [20] provides a robust comparison of the generated image and the real image by taking the distance between elements into account. We used the EMD measure to measure the difference between the real and fake histograms. EMD is a measure used to quantify the distance between two probabilities of graphical distributions within a given region D. It is based on the idea of finding the minimum amount of work required to transform one graphical distribution to another so that the distributions are similar or identical to an acceptable degree.

Formal Definition: Given two distributions, the EMD is the least amount needed to convert distribution P into distribution Q over an area D. Cost is defined as the sum of the masses moved times the distance traveled. This can be expressed mathematically as:

$$\text{EMD (P, Q)} = \min_{flow} \sum_{i,j} f_{i,j} d_{i,j} \tag{10}$$

where the distance between these points is di,j , and the flow is represented by fi,j from point i in P to point j in Q. The distributions' supply and demand limitations must be satisfied by the flow fi,j .

In Figure (5) there are two shapes the EMD of the shape (1) equal 132.470 and in shape (2) equal 125.130

CONCLUSION

The proposed modifications to the traditional GAN architecture, specifically the introduction of an additional fully connected layer after both the generator and feature networks—demonstrate significant advancements in the model's ability to generate realistic data. By improving feature extraction and dimensionality reduction within the generator network, the system effectively enhances gradient flow and mitigates overfitting, leading to greater training stability and accuracy. Additionally, the integration of a similar fully connected layer within the discriminator network allows for more precise classification of real and generated data. Using a dataset of satellite images, this model demonstrates how well it can produce fake data of high quality.

Future research will aim to improve the GAN model's strength and variety. To this end, experiments with other architectures, additions of data augmentation methods, and expansion of the model to deal with a wider range of complex network configurations will be necessary. Moreover, sophisticated evaluation standards will help evaluate generated image quality more accurately.

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