**Creating Enhanced Auto Stereograms Using Disparity Convolution and CNNs**

**1. Main Project Idea:**

In order to produce depth maps and textures that are richer, more dynamic, and more arresting, the main concept is to develop autostereograms "Magic Eye" images that incorporate sophisticated neural network techniques, particularly disparity convolution. This method uses a pipeline inspired by the NeuralMagicEye framework, improving the stereograms with contemporary computational techniques to produce superior depth perception and aesthetic value, in contrast to traditional stereograms that rely on basic repeating patterns.

**2. Proposed Approach:**

The pipeline consists of three interconnected modules:

**A. Graphic Renderer (GR):** It Converts 3D object models into 2D depth maps, where the brightness of each pixel represents the depth of the object brighter areas are closer, darker areas are farther. Use 3D object models from datasets like ShapeNetCore, Render depth maps with libraries like Pyrender, specifying camera angles, lighting, and field-of-view parameters to simulate real-world 3D scenes and the resulting depth maps serve as input for encoding depth in autostereograms.

**B. Autostereogram Generator (GA):** It Encodes depth information into a texture pattern to produce the final stereogram. Select a random texture or CNN-generated texture as the base, map depth values from the depth map to horizontal pixel shifts in the texture. For closer objects, the shift is greater, while for distant objects, the shift is smaller and combine the shifted textures into a single image, forming the autostereogram.

**C. Decoding Network with Disparity Convolution:** It Improves depth perception and texture clarity in the stereogram using a neural network.

**Key Features:**

1. Disparity convolution layers simulate human stereopsis by comparing adjacent pixels horizontally to estimate depth. This addresses the loss of spatial correspondence in standard convolutions.
2. Networks like ResNet and U-Net are used to process the disparity and refine the depth representation.

**Steps:**

1. **Disparity Calculation:** For each pixel, compute the difference between its feature vector and that of its horizontally adjacent neighbors.
2. **Feature Maps:** Store these differences in feature maps, which guide the creation of smoother depth transitions in the stereogram.
3. **CNN Processing:** Use the disparity-enhanced features in a CNN architecture to refine and optimize the textures and depth encoding.

I selected this method because it overcomes conventional constraints by fusing the visual appeal of autostereograms with the computational capability of CNNs and disparity convolution. Disparity convolution offers accurate depth encoding and smooth gradients by simulating human stereopsis, which makes concealed 3D shapes more readable and visually appealing. Creating dynamic textures with CNNs enhances the stereograms' visual appeal by adding originality and diversity. This method uses self-supervised learning to dynamically produce high-quality depth maps and textures, and it is scalable to a variety of datasets and resilient to noise. It supports both technological innovation and artistic inquiry, which is in line with my interests in machine learning, vision science, and creative technology.

**3. Input/Output Data:**

**Input Data:**

1. **3D Object Models:**

Models from datasets like ShapeNetCore, containing diverse shapes and categories e.g., vehicles, furniture.

These models are rendered into depth maps.

1. **Texture Patterns:**

Randomly generated patterns or procedurally designed ones.

CNN-extracted textures from real-world images, providing structured and dynamic backgrounds.

**Output Data:**

**Enhanced Autostereograms:**

Final images where the 3D shapes encoded in the depth maps are visible when viewed correctly.

These stereograms incorporate optimized textures for improved visual clarity and depth perception.

**4. Training Data:**

1. **3D Object Models:**

Use ShapeNetCore, a publicly available dataset with over 50,000 models covering 55 object categories.

Depth maps are rendered from these models’ using software like Pyrender.

1. **Textures:**

Collect textures from online repositories like free texture libraries or generate them procedurally.

Apply transformations e.g., blurring, compression to simulate real-world variations.

1. **Augmented Data:**

Enhance the training dataset with augmentation techniques such as cropping, flipping, rotation, and scaling, to make the network more robust to different conditions

**5. Evaluation Plan:**

1. Use PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) to measure the accuracy of depth encoding and recovery.
2. Test the stereograms with various degradation scenarios e.g., blurring, compression to assess robustness.
3. Compare traditional stereogram methods with the proposed approach in terms of clarity and 3D perception.
4. Analyze the impact of different CNN architectures ResNet vs. U-Net on the quality of stereograms.

**6.  Impact**

This project has broad implications across multiple fields:

1. **Art and Design:** Provides new creative tools for generating interactive 3D illusions with greater complexity and aesthetic appeal.
2. **Education:** Offers insights into the science of human stereopsis and machine-based depth perception, useful in teaching concepts of vision and computer graphics.
3. **Accessibility:** Could help individuals with difficulty perceiving traditional stereograms, as the disparity convolution process mimics human visual mechanisms differently.
4. **Technology and Research:** Demonstrates how deep learning techniques like disparity convolution can extend into unconventional areas of image synthesis and decoding.