3D OBJECT RECONSTRUCTION FROM 2D IMAGES

- BY

TEAM PAST THE PIXELS

- UNDER

PROF. CRYSTAL MAUNG

AGENDA

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Key Insights

Applications

Conclusion



INTRODUCTION

- Leveraged deep learning techniques to reconstruct high-fidelity 3D models from 2D images
- Transformed 2D representations into 3D objects is crucial for applications like gaming, simulations, and augmented reality.
- Used methods like voxel grids, point clouds, and mesh generation, making the process more efficient and accessible.
- Traditional methods of creating 3D models require extensive manual effort and technical expertise.
- 3D object reconstruction plays a transformative role across industries like gaming, AR/VR, animation, and healthcare.
- Achieve fine-grained reconstruction of details like fingers, facial features, and clothing textures.



OBJECTIVE



Recent advances in image-based 3D reconstruction have enabled applications like virtual avatars, gaming, and AR/VR.



PIFuHD introduces a novel multi-level architecture for generating high-resolution, realistic 3D models from a single image.



Leverage PyTorch3D to dynamically deform a simple 3D source shape (sphere) into complex, user-defined objects.



Mesh deformation allows reshaping 3D models to match target objects by minimizing geometric and structural differences.

2D VS 3D VIEW

	2 D	3D
Full Form	Two-Dimensional	Three-Dimensional
Definition	Represents an object with just two dimensions, i.e. length, and height.	Represents an object with three dimensions: Length, width, and height
Representation	Flat	Life-like
Aspects	Length, and height, no depth (width).	Length, width, and height
Mathematics	The x-axis and y-axis.	The x-axis, y-axis and the z-axis.
Geometry	Rectangle, square, triangle, polygon, etc.	Cylinder, sphere, cube, pyramid, prism, etc.

DATASETS

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Render People Dataset:

- High-resolution photogrammetry scans of clothed humans.
- Synthetic backgrounds using the COCO dataset for robustness against varied environments.

Data Augmentation:

 Random rotations, translations, and background changes to improve generalization.

Dataset for the objects are taken as the input from the user and image converted to obj file.

Human 3D Model

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PIFuHD - "Pixel-Aligned Implicit Function for High-Resolution 3D Human Digitization". It predicts 3D occupancy for any given point in the image space, allowing pixel-level alignment for better detail preservation

Architecture:

Coarse Module: Processes down sampled images to capture global 3D structure.

Fine Module: Uses high-resolution features to refine and enhance local details.

Input Image Course Module Fine Module Fine Module Fine Module

Steps for Human 3D Model:

- 1. Input Preparation
- A 2D image of a person is provided as input, resized to 512x512 pixels for consistency.
- A segmentation mask isolates the person from the background, ensuring only the subject is processed.
- 2. Feature Extraction
- The model uses convolutional neural networks (CNNs) to extract pixel-aligned features, preserving spatial relationships.
- These features capture global details (body structure) and local details (clothing folds, facial features).

3. Implicit Function Mapping

- Each pixel in the 2D image is mapped to a 3D coordinate (x, y, z) and a surface occupancy value (on/off the 3D surface).
- A hierarchical approach refines this mapping, starting with a rough geometry and adding finer details.
- 4. Depth and Surface Reconstruction
- The model predicts depth (z-coordinates) for each pixel, creating a 3D representation of the subject.
- It combines depth and pixel features to generate a detailed 3D surface mesh.

5. 3D Model Refinement

- The generated 3D mesh is smoothed and cleaned to remove inconsistencies.
- Optional textures or colors are added to make the model more realistic.
- 6. Rotation and Visualization
- The 3D model is rotated using mathematical transformations (e.g., rotation matrices) for viewing.
- Tools like Open3D or Blender are used to visualize the model interactively.

The final output is a high-resolution 3D mesh saved in .obj format.Applications include animation, gaming, VR/AR, and digital avatars.

The main advantage of this approach is that it helps overcome challenges like depth ambiguity and missing information.

Object 3D Model

Step 1: Input Handling

Path of .obj file

Step 2: Preprocessing

- Normalize the target 3D mesh to fit within a unit sphere for effective optimization.
- Center the target object at the origin.

Step 3: Source Mesh Initialization

Use an icosphere as the initial source shape for deformation.

Step 4: Optimization

- Define trainable parameters for the source mesh vertices.
- Use loss functions to compute discrepancies between the source and target:
- Chamfer Distance: Measures geometric similarity.
- Edge Loss: Ensures edges maintain uniform length.
- Normal Consistency: Preserves smooth surface normals.
- Laplacian Smoothing: Maintains mesh smoothness.

Step 5: Results and Output

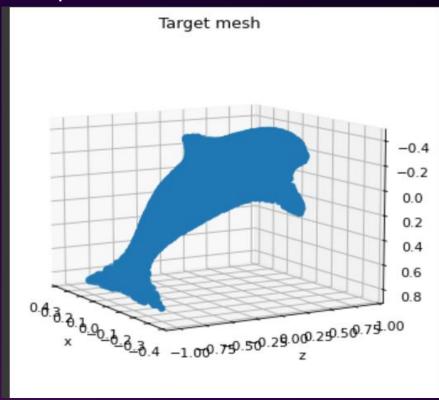
Iteratively deform the source shape to match the target mesh and save the .obj file 12

- Resolutions: Input resolution: 1k (1024x1024 pixels).
- 2. Feature resolution: Up to 512x512 in the fine module.
- 3. Framework: TensorFlow/PyTorch-based implementation.
- Training Details: Loss Function: Extended Binary Cross-Entropy Loss.
- 5. Sampling Strategy: Gaussian perturbation near surfaces for sharp reconstructions.

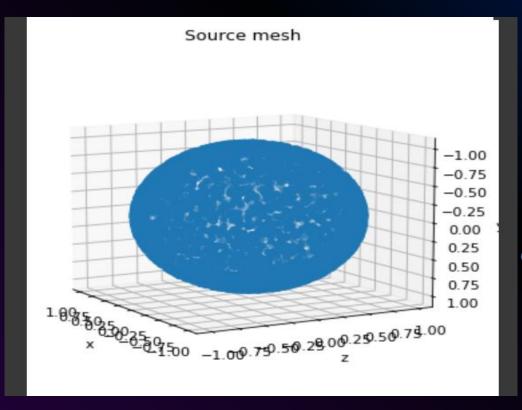




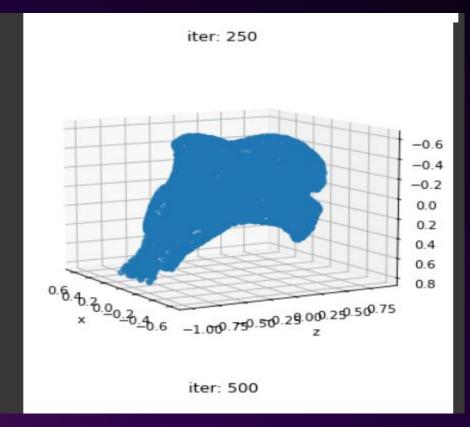
1. Input Mesh

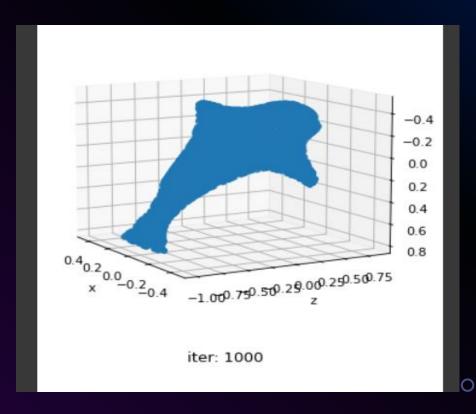


2. Source Mesh

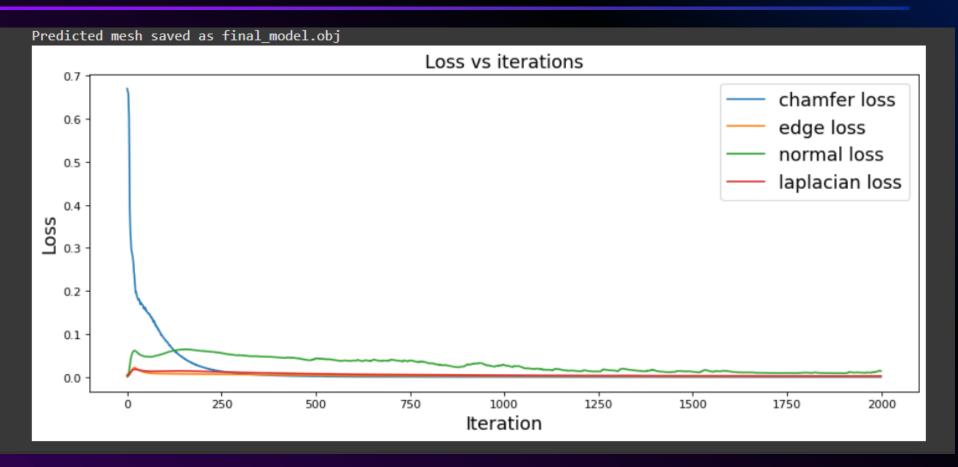


3. Optimization Process





4. Loss Graphs





KEY INSIGHTS

Dynamic Mesh Deformation

Optimization Techniques

User-Friendly Input

Real-Time Visualization

Scalability and Versatility

APPLICATIONS

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- 1. Animation and Gaming
- 2. Medical Imaging
- 3. Product Design and Prototyping
- Virtual and Augmented Reality (VR/AR)
- 5. Digital Art and Creative Industries
- 6. Education and Research
- 7. Robotics and Simulation

CHALLENGES

Memory Limitations: Handling high-resolution inputs (1k) requires significant computational resources.

Depth Ambiguity: Difficulties in reconstructing occluded body parts based solely on front-facing views.

Holistic vs. Local Reasoning: Balancing the need for global context and fine-grained detail extraction.

Approach to Challenges: Efficient memory usage through multi-level design. Using surface normal prediction for backside reconstruction.

CONCLUSION





The project demonstrates an efficient pipeline for transforming 2D representations into detailed 3D models using **PyTorch3D** and optimization techniques.

It highlights applications in gaming, AR/VR, and product design, offering a flexible solution for generating 3D content.

THANK YOU

Riya Badal Kapadia – rxk230132

Rajeswari Subramanian – rxs230174

Nandhana Suresh Kumar – nxs230139

Nivedha Shankar – nxs230138