gaussian_renderer directory and GaussianRasterizer class

- ./gaussian_renderer/
- render() method

```
# gaussian_renderer/__init__.py
...
from diff_gaussian_rasterization import GaussianRasterizationSettings,
GaussianRasterizer
...
def render(viewpoint_camera, pc : GaussianModel, pipe, bg_color : torch.Tensor,
scaling_modifier = 1.0, override_color = None):
    ...
    tanfovx = math.tan(viewpoint_camera.FoVx * 0.5)
    tanfovy = math.tan(viewpoint_camera.FoVy * 0.5)

    raster_settings = GaussianRasterizationSettings(
        image_height=int(viewpoint_camera.image_height),
        image_width=int(viewpoint_camera.image_width),
        tanfovx=tanfovx,
        tanfovy=tanfovy,
        bg=bg_color,
        scale_modifier=scaling_modifier,
        viewmatrix=viewpoint_camera.world_view_transform,
        projmatrix=viewpoint_camera.full_proj_transform,
        sh_degree=pc.active_sh_degree,
        campos=viewpoint_camera.camera_center,
        prefiltered=False,
        debug=pipe.debug
    )

    rasterizer = GaussianRasterizer(raster_settings=raster_settings)

    ...
    rendered_image, radii = rasterizer(
        means3D = means3D,
        means2D = means2D,
        shs = shs,
        colors_precomp = colors_precomp,
        opacities = opacity,
        scales = scales,
        rotations = rotations,
        cov3D_precomp = cov3D_precomp)

    return {"render": rendered_image,
            "viewspace_points": screenspace_points,
            "visibility_filter" : radii > 0,
            "radii": radii}
```

Rendering (渲染) and Rasterization (光栅化)

- Rendering: Rendering is the broader process of generating an image from a model. This model can include geometry (shapes and structures), texture (surface detail), lighting (how light interacts with surfaces), and shading (how colors and shadows are applied).
- Rasterization: **Rasterization is a specific method used within the rendering process** to convert 3D models into 2D images. It translates geometric data (like vertices and edges) into pixels or fragments.

Paramters for Rendering

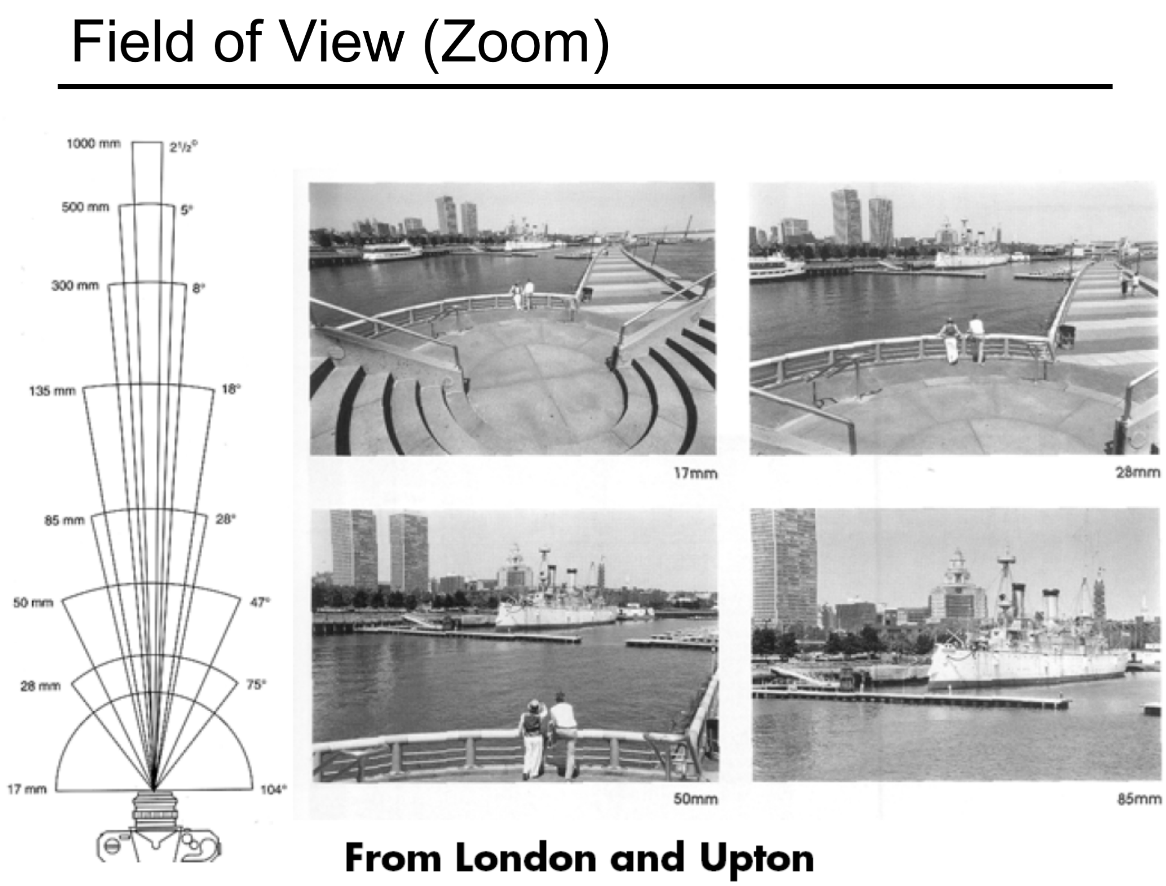
- viewpoint_camera: the rendered image will be based on the viewpoint_camera
- pc (point cloud): 3D gaussian points that will be **splatted** on to the viewpoint camera plane
- pipe: pipe is create as the training starts. The pipe contains attributes to determine whether certain operation should be performed at certain place, e.g.,:

```
# whether need to precompute 3D convariance
if pipe.compute_cov3D_python:
    cov3D_precomp = pc.get_covariance(scaling_modifier)
# whether need to convert SH to rgb before rasterization
if pipe.convert_SHs_python:
        shs_view = pc.get_features.transpose(1, 2).view(-1, 3,
(pc.max_sh_degree+1)**2)
        dir_pp = (pc.get_xyz -
viewpoint_camera.camera_center.repeat(pc.get_features.shape[0], 1))
        dir_pp_normalized = dir_pp/dir_pp.norm(dim=1, keepdim=True)
        sh2rgb = eval_sh(pc.active_sh_degree, shs_view, dir_pp_normalized)
        colors_precomp = torch.clamp_min(sh2rgb + 0.5, 0.0)
```

- bg_color: background color. Will occupy pixels that not have been rendered
- scaling_modifier: in the case that the resolution of the image is too large, may use scaling_modifier > 1 to downsample, similar to resolution_scales
- override_color: maybe a feature that can change the original color that whatever color we want

Paramters for GaussianRasterizationSettings

- image_height: height of the rendered image
- image_width: width of the rendered image
- tanfovx: tangent of field of view in x-axis
    - fov： field of view(视场角\视野), quantified by angle

- 

- tanfovy: tangent of field of view in y-axis
- bg: background color
- scale_modifier: in the case that the resolution of the image is too large, may use scaling_modifier > 1 to downsample, similar to resolution_scales
- viewmatrix: viewpoint_camera.world_view_transform, the matrix defines the relation between the world space (3D space) and the camera space (view space)
- projmatrix: viewpoint_camera.full_proj_transform, combining vorld_view_matrix and projection matrix
    - relevant code:

```
# scene/cameras.py
self.world_view_transform = torch.tensor(getWorld2View2(R, T, trans, scale)).transpose(0, 1).cuda()
self.projection_matrix = getProjectionMatrix(znear=self.znear, zfar=self.zfar, fovX=self.FoVx, fovY=self.FoVy).transpose(0,1).cuda()
self.full_proj_transform = (self.world_view_transform.unsqueeze(0).bmm(self.projection_matrix.unsqueeze(0))).squeeze(0)
self.camera_center = self.world_view_transform.inverse()[3, :3]


# utils/graphics_utils.py
def getWorld2View2(R, t, translate=np.array([.0, .0, .0]), scale=1.0):
    Rt = np.zeros((4, 4))
    Rt[:3, :3] = R.transpose()
    Rt[:3, 3] = t
    Rt[3, 3] = 1.0
```

```
    C2W = np.linalg.inv(Rt)
    cam_center = C2W[:3, 3]
    cam_center = (cam_center + translate) * scale
    C2W[:3, 3] = cam_center
    Rt = np.linalg.inv(C2W)
    return np.float32(Rt)

def getProjectionMatrix(znear, zfar, fovX, fovY):
    tanHalfFovY = math.tan((fovY / 2))
    tanHalfFovX = math.tan((fovX / 2))

    top = tanHalfFovY * znear
    bottom = -top
    right = tanHalfFovX * znear
    left = -right

    P = torch.zeros(4, 4)

    z_sign = 1.0

    P[0, 0] = 2.0 * znear / (right - left)
    P[1, 1] = 2.0 * znear / (top - bottom)
    P[0, 2] = (right + left) / (right - left)
    P[1, 2] = (top + bottom) / (top - bottom)
    P[3, 2] = z_sign
    P[2, 2] = z_sign * zfar / (zfar - znear)
    P[2, 3] = -(zfar * znear) / (zfar - znear)
    return P
```

- campos: the position of the camera (center of the viewpoint)
- prefiltered: refer to the low-pass filter in EWA splatting
  - relevant code: (this is a cuda function determine if a point in the screen. It seems that `prefiltered` indicates that the points have undergone some preprocessing, filtering points with `prefiltered=True` will trigger some warnings)
  - EWA splatting: We can either sample the continuous signal at a higher frequency or we eliminate frequencies above the Nyquist limit before sampling, which is called prefiltering.

```
__forceinline__ __device__ bool in_frustum(int idx,
const float* orig_points,
const float* viewmatrix,
const float* projmatrix,
bool prefiltered,
float3& p_view)
{
    float3 p_orig = { orig_points[3 * idx], orig_points[3 * idx + 1],
orig_points[3 * idx + 2] };

    // Bring points to screen space
    float4 p_hom = transformPoint4x4(p_orig, projmatrix);
    float p_w = 1.0f / (p_hom.w + 0.0000001f);
    float3 p_proj = { p_hom.x * p_w, p_hom.y * p_w, p_hom.z * p_w };
```

```
    p_view = transformPoint4x3(p_orig, viewmatrix);

    if (p_view.z <= 0.2f)// || ((p_proj.x < -1.3 || p_proj.x > 1.3 ||
p_proj.y < -1.3 || p_proj.y > 1.3)))
    {
        if (prefiltered)
        {
            printf("Point is filtered although prefiltered is set. This
shouldn't happen!");
            __trap();
        }
        return false;
    }
    return true;
}
```

- debug: whether enable debug setting

Many of the parameters are related to cameras

- an example camera setting:

```
[{"id": 0, "img_name": "DSC05572", "width": 1264, "height": 832, "position":
[3.1404339644832397, 0.18188197960281, -3.563482533678278], "rotation":
[[0.9979604943324005, 0.011462677284412257, -0.06279696474594969],
[-0.04072327873048568, 0.8718824481262268, -0.48801906849923030],
[0.049157566266748824, 0.4895810491419074, 0.8705710367338437]], "fy":
1040.192756666184, "fx": 1040.007303759328}]
```

- cameras will be loaded by `utils/camera_utils.py` and then initialized by `scene/cameras.py`

`submodules\diff-gaussian-rasterization`

- Differential Gaussian Rasterization
- A package contains functions that perform rasterization (rendering)
- Most of the parameters above will be used in this package to perform rasterization

Relation to EWA splatting

- EWA: the whole object model is a resampling of a continuous function
- 3DGS: the point cloud is a resampling of a continuous function
- Volume Resampling in EWA & Rasterization in 3DGS
    - two ways of volume rendering:
        - backward mapping (NeRF)
        - forward mapping (EWA & 3DGS)
    - EWA: Mapping the data onto the image plane involves a sequence of intermediate steps where the data is transformed to different coordinate systems
    - final goal: 3D points -> 2D images that can be perceived by human

Data Flow

- source space / object space / world space -> camera space -> ray space -> screen space (viewport coordinates)

Detailed Implementation

- `submodules\diff-gaussian-rasterization\diff_gaussian_rasterization\__init__.py` invokes C++/CUDA rasterizer
  - examples of invoking a C++/CUDA function:

```
from . import _C
...
# Invoke C++/CUDA rasterizer
if raster_settings.debug:
        cpu_args = cpu_deep_copy_tuple(args) # Copy them before they can be corrupted
        try:
            num_rendered, color, radii, geomBuffer, binningBuffer, imgBuffer = _C.rasterize_gaussians(*args)
        except Exception as ex:
            torch.save(cpu_args, "snapshot_fw.dump")
            print("\nAn error occured in forward. Please forward snapshot_fw.dump for debugging.")
            raise ex
    else:
        num_rendered, color, radii, geomBuffer, binningBuffer, imgBuffer = _C.rasterize_gaussians(*args)
...
# Compute gradients for relevant tensors by invoking backward method
if raster_settings.debug:
    cpu_args = cpu_deep_copy_tuple(args) # Copy them before they can be corrupted
    try:
        grad_means2D, grad_colors_precomp, grad_opacities, grad_means3D, grad_cov3Ds_precomp, grad_sh, grad_scales, grad_rotations = _C.rasterize_gaussians_backward(*args)
    except Exception as ex:
        torch.save(cpu_args, "snapshot_bw.dump")
        print("\nAn error occured in backward. Writing snapshot_bw.dump for debugging.\n")
        raise ex
else:
        grad_means2D, grad_colors_precomp, grad_opacities, grad_means3D, grad_cov3Ds_precomp, grad_sh, grad_scales, grad_rotations = _C.rasterize_gaussians_backward(*args)
...
def markVisible(self, positions):
    # Mark visible points (based on frustum culling for camera) with a boolean
    with torch.no_grad():
        raster_settings = self.raster_settings
```

```
            visible = _C.mark_visible(
                positions,
                raster_settings.viewmatrix,
                raster_settings.projmatrix)

        return visible
```

C++/CUDA rasterizer details

- directory hierachy:

```
diff-gaussian-rasterization/
├── cuda_rasterizer/        # C++/CUDA rasterizer implementation
│   ├── auxiliary.h         # Auxiliary functions and definitions
│   ├── backward.cu         # CUDA kernel for backward pass (gradient computation)
│   ├── backward.h          # Header file for backward pass
│   ├── forward.cu          # CUDA kernel for forward pass (rasterization)
│   ├── forward.h           # Header file for forward pass
│   ├── rasterizer_impl.cu # Main CUDA rasterizer implementation
│   ├── rasterizer_impl.h  # Header file for main rasterizer implementation
│   ├── rasterizer.h        # Header file for rasterizer interface
├── diff_gaussian_rasterization/   # Python initialization module
│   ├── __init__.py         # Python package initialization
├── third_party/            # Third-party packages
│   └── glm/                # OpenGL Mathematics library
├── CMakeLists.txt          # CMake configuration file for building the project
├── ext.cpp                 # C++ extension module definition for Python
├── rasterize_points.cu     # CUDA kernel for rasterizing points
├── rasterize_points.h      # Header file for point rasterization
├── setup.py                # Python setup script for building and installing the
package
```

- forward process (forward.cu & forward.h):
    - forward mapping mentioned in EWA splatting
    - the process of rendering and rasterization
    - obtain rendered image that can compute loss
- backward process (backward.cu & backward.h):
    - computing gradient for minimizing loss
    - optimize the parameters

EWA Splatting

Abstract

- high quality splatting using elliptical Gaussian kernel
- avoid aliasing artifacts (can refer to [常见的伪影])
    - image aliasing:

        - Moire Pattern (摩尔纹)
        - Jagged Edge (锯齿状边缘)
        - Pixelation (像素化)
    - video aliasing:
        - Temporal Aliasing: frame rate is too low
        - Flickering (闪烁效应)
- introduce the concept of a resampling fliter, combining a reconstruction kernel with a low-pass filter
- like EWA (elliptical weighted average) filter for texture mapping -> EWA splatting
- EWA splat primitives
- can be used in regular, rectilinear, and irregular dataset
- EWA volume reconstruction kernels can be reduced to surface reconstruction kernels

Introduction

Ideal Volume Rendering

- The ideal volume rendering algorithm **reconstructs a continuous function** in 3D, **transforms** this 3D function into screen space, and then **evaluates opacity integrals** along line-of-sights
    - Reconstructing a continuous function in 3D
        - The 3D data is often stored as a discrete set of samples (voxels). Reconstructing a continuous function means interpolating these discrete samples to create a smooth, continuous representation of the 3D volume
        - may use interpolation
    - Transforms to screen space
        - project the function to 2D space so that human can see
    - Evaluates opacity integrals
        - Imagine casting rays from the viewer's eye through each pixel on the screen into the 3D volume. Each ray represents a line of sight

Splatting Algorithm

- volume data -> set of particles absorbing and emitting light
- line integrals are precomputed across each particles separately -> **footprint functions / splats** -> final image
- elliptical weighted average texture filter
- concept of ray space:
    - a point in ray space: $x = (x_0, x_1, x_2)^T$
    - x_0, x_1 -> a point on the projection plane
    - synonyms: $\textbf{x}, (textbf{x}, x_2)^T, (x_0, x_1, x_2)^T$
    - light intensity:

$$I_\lambda(\mathbf{x}) = \int_0^L c_\lambda(\mathbf{x}, \xi) f_c'(\mathbf{x}, \xi) e^{-\int_0^\xi f_c'(\mathbf{x}, \mu)\, d\mu}\, d\xi, \tag{7}$$

- extinction function in ray space (after perform transformation from source space / object space):

$$f'_c(\mathbf{x}) = f_c(\varphi^{-1}(\phi^{-1}(\mathbf{x}))) = \sum_k w_k r'_k(\mathbf{x}), \tag{8}$$

  - where φ is the mapping from object space to camera space, ϕ is the mapping from camera space to ray space
- substituting (8) into (7) we obtain a reconstruction kernel call it g_c:

$$I(\mathbf{x}) = \sum_k w_k \Bigg(\int_0^L c(\mathbf{x}, \xi) r'_k(\mathbf{x}, \xi) \prod_j e^{-w_j \int_0^\xi r'_j(\mathbf{x}, \mu)\, d\mu}\, d\xi \Bigg), \tag{9}$$

- Assumption:
  - Usually, the reconstruction kernels $r_{k}'(x)$ have local support. The splatting approach assumes that these local support areas do not overlap along a ray x and the reconstruction kernels are ordered front to back
  - emission coefficient is constant in the support of each reconstruction kernel along a ray
  - approximate the exponential function with the first two terms of its Taylor expansion, thus $e^{-x} \approx 1 - x$
  - ignore self-occlusion
- yielding:

$$g_c(\mathbf{x}) = \sum_k w_k c_k(\mathbf{x}) q_k(\mathbf{x}) \prod_{j=0}^{k-1} (1 - w_j q_j(\mathbf{x})), \tag{10}$$

  where $q_k(\mathbf{x})$ denotes an integrated reconstruction kernel, hence:

$$q_k(\mathbf{x}) = \int_{\mathbb{R}} r'_k(\mathbf{x}, x_2)\, dx_2. \tag{11}$$

- $q_k(x)$: footprint function of each point on the screen is an ellipse whose shape and orientation depend on the point's properties and the viewing parameters