

```
In [1]: import os
import sys
import gc
import cv2
import random
import shutil
import numpy as np
from PIL import Image
from random import sample
from pyunpack import Archive
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
from scipy.ndimage import map_coordinates
```

```
In [2]: import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.nn.modules.utils as nn_utils
from torchvision.transforms import PILToTensor
from typing import Any, Callable, Dict, List, Optional, Union, Tuple
from diffusers.models.unet_2d_condition import UNet2DConditionModel
from diffusers import DDIMScheduler
from diffusers import StableDiffusionPipeline
```

```
2024-01-30 15:08:13.536613: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
To enable the following instructions: SSE4.1 SSE4.2 AVX AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
```

```
In [ ]: #Archive('FLoRI21_DataPort.zip').extractall(os.getcwd())
```

```
In [3]: #shutil.rmtree(os.path.join(os.getcwd(), 'FLoRI21_DataPort_Image_Registration_Result
```

```
In [4]: path = os.path.join(os.getcwd(), 'FLoRI21_DataPort_Image_Registration_Results/Homogr
os.makedirs(path, exist_ok=True)
```

```
In [5]: path = os.path.join(os.getcwd(), 'FLoRI21_DataPort_Image_Registration_Results/Polyno
os.makedirs(path, exist_ok=True)
```

```
In [6]: path = os.path.join(os.getcwd(), 'FLoRI21_DataPort_Image_Registration_Results/Homogr
os.makedirs(path, exist_ok=True)
```

Note:

Some of the code cells were referenced from the paper titled "Emergent Correspondence from Image Diffusion." Please cite their paper as follows:

```
@inproceedings{tang2023emergent,
    title={Emergent Correspondence from Image Diffusion},
    author={Luming Tang and Menglin Jia and Qianqian Wang and Cheng Perng
```

```
Phoo and Bharath Hariharan},
booktitle={Thirty-seventh Conference on Neural Information Processing
Systems},
year={2024},
url={https://openreview.net/forum?id=yp0iXjdfnU}
}
```

```
In [7]: class MyUNet2DConditionModel(UNet2DConditionModel):
    """
    Customized 2D U-Net conditioned model inherited from `UNet2DConditionModel`.

    This model extends the original `UNet2DConditionModel` to incorporate additional
    such as encoder hidden states, attention mask, and cross-attention keyword arguments.
    """

    def forward(
        self,
        sample: torch.FloatTensor,
        timestep: Union[torch.Tensor, float, int],
        up_ft_indices,
        encoder_hidden_states: torch.Tensor,
        class_labels: Optional[torch.Tensor] = None,
        timestep_cond: Optional[torch.Tensor] = None,
        attention_mask: Optional[torch.Tensor] = None,
        cross_attention_kwargs: Optional[Dict[str, Any]] = None):
        """
        Forward method for `MyUNet2DConditionModel`.

        Args:
            sample (torch.FloatTensor): Noisy inputs tensor with shape (batch, channels, height, width).
            timestep (torch.FloatTensor or float or int): Timesteps for each batch.
            up_ft_indices (list): List of upsampling indices.
            encoder_hidden_states (torch.FloatTensor): Encoder hidden states with shape (batch, channels, height, width).
            class_labels (Optional[torch.Tensor], default=None): Class labels tensor with shape (batch, num_classes).
            timestep_cond (Optional[torch.Tensor], default=None): Timestep condition tensor with shape (batch,).
            attention_mask (Optional[torch.Tensor], default=None): Mask to avoid attention at padding.
            cross_attention_kwargs (Optional[dict], default=None): Keyword arguments for cross-attention.

        Returns:
            dict: Dictionary containing upsampled features (`up_ft`).
        """

        # By default samples have to be AT LEAST a multiple of the overall upsample factor
        # The overall upsample factor is equal to 2 ** (# num of upsample layers)
        # However, the upsample interpolation output size can be forced to fit an
        # exact multiple if necessary.
        default_overall_up_factor = 2**self.num_upsamplers

        # upsample size should be forwarded when sample is not a multiple of `default_overall_up_factor`
        forward_upsample_size = False
        upsample_size = None

        if any(s % default_overall_up_factor != 0 for s in sample.shape[-2:]):
            # Logger.info("Forward upsample size to force interpolation output size")
            forward_upsample_size = True
```

```

# prepare attention_mask
if attention_mask is not None:
    attention_mask = (1 - attention_mask.to(sample.dtype)) * -10000.0
    attention_mask = attention_mask.unsqueeze(1)

# 0. center input if necessary
if self.config.center_input_sample:
    sample = 2 * sample - 1.0

# 1. time
timesteps = timestep
if not torch.is_tensor(timesteps):
    # TODO: this requires sync between CPU and GPU. So try to pass timestep
    # This would be a good case for the `match` statement (Python 3.10+)
    is_mps = sample.device.type == "mps"
    if isinstance(timestep, float):
        dtype = torch.float32 if is_mps else torch.float64
    else:
        dtype = torch.int32 if is_mps else torch.int64
    timesteps = torch.tensor([timesteps], dtype=dtype, device=sample.device)
elif len(timesteps.shape) == 0:
    timesteps = timesteps[None].to(sample.device)

# broadcast to batch dimension in a way that's compatible with ONNX/Core ML
timesteps = timesteps.expand(sample.shape[0])

t_emb = self.time_proj(timesteps)

# timesteps does not contain any weights and will always return f32 tensors
# but time_embedding might actually be running in fp16. so we need to cast
# there might be better ways to encapsulate this.
t_emb = t_emb.to(dtype=self.dtype)

emb = self.time_embedding(t_emb, timestep_cond)

if self.class_embedding is not None:
    if class_labels is None:
        raise ValueError("class_labels should be provided when num_class_em"

        if self.config.class_embed_type == "timestep":
            class_labels = self.time_proj(class_labels)

    class_emb = self.class_embedding(class_labels).to(dtype=self.dtype)
    emb = emb + class_emb

# 2. pre-process
sample = self.conv_in(sample)

# 3. down
down_block_res_samples = (sample,)
for downsample_block in self.down_blocks:
    if hasattr(downsampling_block, "has_cross_attention") and downsample_bloc
        sample, res_samples = downsample_block(
            hidden_states=sample,
            temb=emb,
            encoder_hidden_states=encoder_hidden_states,

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                attention_mask=attention_mask,
                cross_attention_kwargs=cross_attention_kwags,
            )
        else:
            sample, res_samples = downsample_block(hidden_states=sample, temb=emb)

            down_block_res_samples += res_samples

    # 4. mid
    if self.mid_block is not None:
        sample = self.mid_block(
            sample,
            emb,
            encoder_hidden_states=encoder_hidden_states,
            attention_mask=attention_mask,
            cross_attention_kwags=cross_attention_kwags,
        )

    # 5. up
    up_ft = {}
    for i, upsample_block in enumerate(self.up_blocks):

        if i > np.max(up_ft_indices):
            break

        is_final_block = i == len(self.up_blocks) - 1

        res_samples = down_block_res_samples[-len(upsample_block.resnets):]
        down_block_res_samples = down_block_res_samples[: -len(upsample_block.r

        # if we have not reached the final block and need to forward the
        # upsample size, we do it here
        if not is_final_block and forward_upsample_size:
            upsample_size = down_block_res_samples[-1].shape[2:]

        if hasattr(upsample_block, "has_cross_attention") and upsample_block.ha
            sample = upsample_block(
                hidden_states=sample,
                temb=emb,
                res_hidden_states_tuple=res_samples,
                encoder_hidden_states=encoder_hidden_states,
                cross_attention_kwags=cross_attention_kwags,
                upsample_size=upsample_size,
                attention_mask=attention_mask,
            )
        else:
            sample = upsample_block(
                hidden_states=sample, temb=emb, res_hidden_states_tuple=res_sam
            )

        if i in up_ft_indices:
            up_ft[i] = sample.detach()

    output = {}
    output['up_ft'] = up_ft
    return output

```

```

class OneStepSDPipeline(StableDiffusionPipeline):
    """
        One-step Stable Diffusion Pipeline.

        Provides a one-step stable diffusion process, integrating the VAE encoding and
    """

    @torch.no_grad()
    def __call__(
        self,
        img_tensor,
        t,
        up_ft_indices,
        negative_prompt: Optional[Union[str, List[str]]] = None,
        generator: Optional[Union[torch.Generator, List[torch.Generator]]] = None,
        prompt_embeds: Optional[torch.FloatTensor] = None,
        callback: Optional[Callable[[int, int, torch.FloatTensor], None]] = None,
        callback_steps: int = 1,
        cross_attention_kwarg: Optional[Dict[str, Any]] = None
    ):
        """
            Call method for `OneStepSDPipeline`.

            Args:
                img_tensor (torch.Tensor): Image tensor.
                t (torch.Tensor or int): Timesteps tensor.
                up_ft_indices (list): List of upsampling indices.
                negative_prompt (Optional[str or list], default=None): Negative prompts
                generator (Optional[torch.Generator or list], default=None): Torch gene
                prompt_embeds (Optional[torch.FloatTensor], default=None): Precomputed
                callback (Optional[Callable], default=None): Callback function invoked
                callback_steps (int, default=1): Frequency of invoking the callback.
                cross_attention_kwarg (Optional[dict], default=None): Keyword argument
        """

        Returns:
            dict: Dictionary containing output from U-Net.
        """

        device = self._execution_device
        latents = self.vae.encode(img_tensor).latent_dist.sample() * self.vae.config
        t = torch.tensor(t, dtype=torch.long, device=device)
        noise = torch.randn_like(latents).to(device)
        latents_noisy = self.scheduler.add_noise(latents, noise, t)
        unet_output = self.unet(latents_noisy,
                               t,
                               up_ft_indices,
                               encoder_hidden_states=prompt_embeds,
                               cross_attention_kwarg=cross_attention_kwarg)

        return unet_output

class SDFeaturizer:
    """
        Stable Diffusion Featurizer.

        Provides a mechanism to compute stable diffusion based features from an input i
    """

```

```

"""
def __init__(self, sd_id='stabilityai/stable-diffusion-2-1'):
    """
    Initializes `SDFeaturizer` with a given stable diffusion model ID.

    Args:
        sd_id (str, default='stabilityai/stable-diffusion-2-1'): Stable diffusi
    """
    unet = MyUNet2DConditionModel.from_pretrained(sd_id, subfolder="unet")
    onestep_pipe = OneStepSDPipeline.from_pretrained(sd_id, unet=unet, safety_c
    onestep_pipe.vae.decoder = None
    onestep_pipe.scheduler = DDIMScheduler.from_pretrained(sd_id, subfolder="sc
    gc.collect()
    onestep_pipe = onestep_pipe.to("cuda")
    onestep_pipe.enable_attention_slicing()
    onestep_pipe.enable_xformers_memory_efficient_attention()
    self.pipe = onestep_pipe

@torch.no_grad()
def forward(self,
            img_tensor, # single image, [1,c,h,w]
            t,
            up_ft_index,
            prompt,
            ensemble_size=8):
    """
    Forward method for `SDFeaturizer`.

    Args:
        img_tensor (torch.Tensor): Single input image tensor with shape [1, c,
        t (torch.Tensor or int): Timesteps tensor.
        up_ft_index (int): Index for upsampling.
        prompt (str): Textual prompt for conditioning.
        ensemble_size (int, default=8): Size of the ensemble for feature averag

    Returns:
        torch.Tensor: Stable diffusion based features with shape [1, c, h, w].
    """
    img_tensor = img_tensor.repeat(ensemble_size, 1, 1, 1).cuda() # ensem, c, h
    prompt_embeds = self.pipe._encode_prompt(
        prompt=prompt,
        device='cuda',
        num_images_per_prompt=1,
        do_classifier_free_guidance=False) # [1, 77, dim]
    prompt_embeds = prompt_embeds.repeat(ensemble_size, 1, 1)
    unet_ft_all = self.pipe(
        img_tensor=img_tensor,
        t=t,
        up_ft_indices=[up_ft_index],
        prompt_embeds=prompt_embeds)
    unet_ft = unet_ft_all['up_ft'][up_ft_index] # ensem, c, h, w
    unet_ft = unet_ft.mean(0, keepdim=True) # 1,c,h,w
    return unet_ft

```

In [8]: `class DFT:`

```

RetinaRegNet (RetinaRegNetwork) utilizes DFT (Diffusion Features) for identifying
and locations between images.

"""
def __init__(self, imgs, img_size, pts):
    """
    Initialize the DFT object.

    Parameters:
    - imgs (list): List of input image tensors.
    - img_size (int): Expected size of the image for processing.
    - pts (list): List of point tuples specifying coordinates.
    """

    self pts = pts
    self imgs = imgs
    self.num_imgs = len(imgs)
    self.img_size = img_size

def unravel_index(self, index, shape):
    """
    Converts a flat index into a tuple of coordinate indices in a tensor of the
    same shape.

    This function mimics numpy's `unravel_index` functionality, which is used to
    convert a flat index into a tuple of coordinate indices for an array of given shape. This is useful
    for dealing with multi-dimensional indices of a position in a flattened array.

    Parameters:
    - index (int): The flat index into the array.
    - shape (tuple of ints): The shape of the array from which the index is derived.

    Returns:
    - tuple of ints: A tuple representing the coordinates of the index in an
      n-dimensional space defined by the shape.

    Example:
    >>> obj = MyClass()
    >>> obj.unravel_index(22, (5, 5))
    (4, 2)
    >>> obj.unravel_index(52, (7, 8))
    (6, 4)

    Note:
    This function operates under the assumption that indexing starts from 0
    """
    out = []
    for dim in reversed(shape):
        out.append(index % dim)
        index = index // dim
    return tuple(reversed(out))

def compute_pooled_and_combining_feature_maps(self, feature_map, hierarchy_range):
    """
    Compute pooled and stacked feature maps.

    Parameters:
    - feature_map (torch.Tensor): Input feature map.
    - hierarchy_range (int, optional): Depth of hierarchical pooling. Defaults to 1.
    - stride (int, optional): Stride for pooling. Defaults to 1.
    """

```

```

    Returns:
    - torch.Tensor: Pooled and stacked feature map.
    """
    # List to store the pooled feature maps
    pooled_feature_maps = feature_map
    # Loop through the specified hierarchy range
    for hierarchy in range(1,hierarchy_range):
        # Average pooling with kernel size 3^k x 3^k
        win_size = 3 ** hierarchy
        avg_pool = torch.nn.AvgPool2d(win_size, stride=1, padding=win_size // 2)
        pooled_map = avg_pool(feature_map)
        # Append the pooled feature map to the list
        pooled_feature_maps+=pooled_map
    return pooled_feature_maps

def compute_batched_2d_correlation_maps(self, pts_list, feature_map1, feature_m
    """
    Computes 2D correlation maps between selected points in one feature map and
    This method takes two feature maps and a list of points. It extracts features at
    specified points, normalizes them, and then computes a batched 2D correlation
    The output is a set of correlation maps, each corresponding to a point in `pts_list`.
    A feature vector correlates across the spatial dimensions of the second feature
    Parameters:
        pts_list (list of tuples): List of points (y, x) for which the correlation
        feature_map1 (torch.Tensor): The first feature map tensor of shape (1,
        feature_map2 (torch.Tensor): The second feature map tensor of shape (1,
            and H2, W2 do not necessarily need to be equal
    Returns:
        torch.Tensor: A tensor of shape (NumPoints, H2, W2) where each slice corresponds
            for each point in `pts_list`.
    Notes:
        The function assumes that the first dimension of feature_map1 and feature_map2
        This method uses batch matrix multiplication and vector normalization for efficiency.
        Running this method on a GPU is recommended due to its computational cost.
    """
    # Convert the input tensors to float16
    feature_map1 = feature_map1.to(dtype=torch.float16)
    feature_map2 = feature_map2.to(dtype=torch.float16)
    _, C, H, W = feature_map2.shape

    # Flatten feature_map2 for batch matrix multiplication
    feature_map2_flat = feature_map2.view(C, H*W)

    # Prepare a batch of point features
    points_indices = torch.tensor(pts_list)
    point_features = feature_map1[0, :, points_indices[:, 0], points_indices[:, 1]]

    # Normalize the point features and feature_map2_flat
    point_features_norm = torch.norm(point_features, dim=1, keepdim=True)
    normalized_point_features = point_features / point_features_norm

```

```

feature_map2_norm = torch.norm(feature_map2_flat, dim=0, keepdim=True)
normalized_feature_map2 = feature_map2_flat / feature_map2_norm

# Compute the correlation map for each point
correlation_maps = torch.mm(normalized_point_features, normalized_feature_m

# Reshape the correlation maps to the desired output shape (NumPoints, H, W)
correlation_maps = correlation_maps.view(-1, H, W)

# Cleanup if needed
torch.cuda.empty_cache()

return correlation_maps

```



```

def compute_correlation_map_max_locations(self, pts_list, feature_map1, feature_map2):
    """
    Compute the maximum locations in the batched correlation maps between two feature maps.

    Parameters:
    - pts_list (list of tuples): List of points for which the correlation maps are computed.
    - feature_map1, feature_map2 (torch.Tensor): The input feature maps.

    Returns:
    - torch.Tensor: Tensor of maximum locations for each point.
    - torch.Tensor: Tensor of maximum values for each point.
    """
    enhanced_feature_map1 = self.compute_pooled_and_combining_feature_maps(feature_map1)
    enhanced_feature_map2 = self.compute_pooled_and_combining_feature_maps(feature_map2)
    # Compute the batched correlation maps
    batched_correlation_maps = self.compute_batched_2d_correlation_maps(pts_list)

    M, H2, W2 = batched_correlation_maps.shape
    #print(batched_correlation_maps.shape)

    # Find the maximum values and their locations along the last two dimensions
    max_values, max_indices_flat = torch.max(batched_correlation_maps.view(len(pts_list), -1), 1)

    x, y = zip(*[self.unravel_index(idx.item(), (H2, W2)) for idx in max_indices_flat])
    x = torch.tensor(x, device = 'cuda').view(M)
    y = torch.tensor(y, device = 'cuda').view(M)

    # Stack the coordinates to get a 2xHxW tensor
    max_locations = torch.stack((x, y)).t()

    return max_locations, max_values

def feature_upsampling(self, ft):
    """
    Upsample the feature to match the specified image size.

    Parameters:
    - ft (torch.Tensor): Feature tensor to be upsampled.

    Returns:
    - torch.Tensor: The upsampled feature tensor.
    """
    if ft.size(2) < 2 or ft.size(3) < 2:
        return ft
    else:
        return F.interpolate(ft, scale_factor=2, mode='bilinear')

```

```

        - tuple: Upsampled source and target feature maps.
    """
    with torch.no_grad():
        num_channel = ft.size(1)
        src_ft = ft[0].unsqueeze(0)
        src_ft = nn.Upsample(size=(self.img_size, self.img_size), mode='bilinear')
        gc.collect()
        torch.cuda.empty_cache()
        trg_ft = nn.Upsample(size=(self.img_size, self.img_size), mode='bilinear')
    return src_ft, trg_ft

def feature_maps(self, feature_map1, feature_map2, iccl):
    """
    Processes feature maps to extract points that meet the inverse consistency
    This method computes the maximum locations of correlation between feature maps.
    It checks for inverse consistency between the mapped points. It filters these
    specified inverse consistency criteria limit (iccl), keeping only those pairs
    whose distance between the original point and its double-mapped location is within
    Parameters:
        feature_map1 (torch.Tensor): The first feature map, used as the base for comparison.
        feature_map2 (torch.Tensor): The second feature map, used for reverse comparison.
        iccl (float): The maximum allowed distance (inverse consistency criteria) for a point
            to be considered consistent relative to its double-mapped location.
    Returns:
        tuple of (list, list, list):
            - pnts (list of tuples): The points from the original feature map that
                have a corresponding point in the second feature map.
            - rmaxs (list of floats): The maximum correlation values at these points.
            - rspts (list of tuples): The corresponding points in the second feature map
                that are within the specified distance from the `pnts`.
    """
    pnts, rmaxs, rspts = [], [], []
    pts = [(int(y), int(x)) for x, y in self.pts]
    max_indices_ST, max_values_ST = self.compute_correlation_map_max_locations(
        x_prime_y_prime = max_indices_ST
    )
    max_indices_TS, max_values_TS = self.compute_correlation_map_max_locations(
        x_prime_prime_y_prime_prime = max_indices_TS
    )
    for i, (pt, max_idx) in enumerate(zip(self.pts, x_prime_y_prime_prime)):
        # Calculate the distance between the point and the max correlation index
        if np.sqrt((pt[1] - max_idx.cpu()[0]) ** 2 + (pt[0] - max_idx.cpu()[1]) ** 2) < iccl:
            pnts.append((int(pt[0]), int(pt[1])))
            rmaxs.append(max_values_ST[i].cpu().item()) # Assuming max_values_ST[i] is valid
            rspts.append((x_prime_y_prime_prime[i][1].cpu().item(), x_prime_y_prime_prime[i][0].cpu().item()))
    return pnts, rmaxs, rspts

```

In [9]:

```

def compute_boundary(image, mean_intensity):
    """
    Compute the boundary of an image based on its mean intensity.
    Parameters:
        - image (numpy.array): The input grayscale image.
        - mean_intensity (float): Average intensity of the image to define boundaries.
    
```

```

    Returns:
    - tuple: upper, lower, left, and right boundaries of the image region with intensity threshold.

    # Compute the upper, lower, left, and right boundary
    upper_boundary = next((i for i, row in enumerate(image) if np.mean(row) > mean))
    lower_boundary = next((i for i, row in enumerate(image[::-1]) if np.mean(row) > mean))

    left_boundary = next((i for i, col in enumerate(image.T) if np.mean(col) > mean))
    right_boundary = next((i for i, col in enumerate(image.T[::-1]) if np.mean(col) > mean))

    return upper_boundary, image.shape[0]-lower_boundary, left_boundary, image.shape[1]-right_boundary

def is_within_boundary(kp, boundaries):
    """
    Check if a keypoint is within the specified boundaries.

    Parameters:
    - kp (cv2.KeyPoint): The keypoint to check.
    - boundaries (tuple): Tuple of (upper, lower, left, right) boundaries.

    Returns:
    - bool: True if the keypoint is within the boundaries, False otherwise.
    """
    upper, lower, left, right = boundaries
    return left <= kp.pt[0] <= right and upper <= kp.pt[1] <= lower

def SIFT_top_n_keypoints(image_path, N=250, img_shape=256, max_dist=25):
    """
    Detect top N keypoints in the given image using SIFT, considering constraints on their positions.

    Parameters:
    - image_path (str): Path to the input image.
    - N (int): Number of keypoints to select. Defaults to 250.
    - img_shape (int): The size to which the image should be resized. Defaults to 256.
    - max_dist (int): Minimum distance between selected keypoints. Defaults to 25.

    Returns:
    - list: List of selected keypoints (cv2.KeyPoint objects).
    - list: List of keypoints' positions in the form (x, y).
    """
    # Load image
    image1 = cv2.imread(image_path, cv2.IMREAD_GRAYSCALE)
    image1 = cv2.resize(image1, (img_shape, img_shape))
    clahe = cv2.createCLAHE(clipLimit=1.0, tileGridSize=(8, 8))
    image = clahe.apply(image1)

    # Initialize SIFT detector
    sift = cv2.SIFT_create()

    # Detect keypoints and compute descriptors
    keypoints, descriptors = sift.detectAndCompute(image, None)

    # Sort keypoints based on response (strength of the keypoint)
    keypoints = sorted(keypoints, key=lambda x: -x.response)

    # Determine the intensity threshold

```

```

mean_intensity = np.mean(image)
boundaries = compute_boundary(image, mean_intensity)

# Select top N keypoints
selected_keypoints = []
for keypoint in keypoints:
    # Check if the keypoint is within the boundary
    if is_within_boundary(keypoint, boundaries):
        # Check if the pixel intensity at the keypoint is greater than the threshold
        if image[int(keypoint.pt[1]), int(keypoint.pt[0])] > mean_intensity:
            # Check if the keypoint is far from existing selected keypoints
            if all(cv2.norm(np.array(keypoint.pt) - np.array(kp.pt)) > max_dist
                  for kp in selected_keypoints):
                selected_keypoints.append(keypoint)

    # Break if N keypoints are selected
    if len(selected_keypoints) == N:
        break

# Draw keypoints on the color image
image_with_keypoints = cv2.drawKeypoints(image1, selected_keypoints, None)
return selected_keypoints, [kp.pt for kp in selected_keypoints]

def select_random_points(img, num_points=100, img_size=1200, offset=0.01, window_size=51):
    """
    Selects a specified number of random points from an image, ensuring that each point
    meets a defined intensity threshold within the image. The image is resized to
    meet the requirements. Points are chosen randomly, with each potential point undergoing validation against
    criteria such as intensity and distance from other points.

    Parameters:
    img (str): Path to the image file.
    num_points (int, optional): The number of random points to select. Defaults to 100.
    img_size (int, optional): The size to which the image is resized (assumed square). Defaults to 1200.
    offset (float, optional): Proportional offset to exclude points near the boundary
        relative to the image dimensions. Defaults to 0.01.
    window_size (int, optional): Size of the square window used to check pixel
        intensity. Defaults to 51.
    max_attempts_per_point (int, optional): The maximum number of attempts allowed
        for a point to meet the criteria. Defaults to 100.

    Returns:
    list of tuples: A list where each tuple represents the (y, x) coordinates of a
        selected point.

    Notes:
    The function converts the image to grayscale and resizes it to img_size x img_size.
    It checks for points near the image boundary by applying a boundary offset calculated from
    the image size and the window size. Each point must be centered in a window (defined by 'window_size') where all
    pixels have an intensity greater than or equal to 5. If the function fails to find a suitable point
    after max_attempts_per_point attempts for any location, it stops and returns the points found up to that moment.
    """
    image = cv2.resize(cv2.imread(img, cv2.IMREAD_GRAYSCALE), (img_size, img_size))
    h, w = image.shape
    boundary_offset = int(offset * h)
    pts = []
    window_offset = window_size // 2 # Calculate the offset from the center of the

```

```

while len(pts) < num_points:
    attempts = 0
    while attempts < max_attempts_per_point:
        x = random.randint(boundary_offset + window_offset, h - boundary_offset)
        y = random.randint(boundary_offset + window_offset, w - boundary_offset)

        # Define the window boundaries
        x_lower = x - window_offset
        x_upper = x + window_offset + 1
        y_lower = y - window_offset
        y_upper = y + window_offset + 1

        # Check that no pixel in the window has an intensity less than 10
        if np.all(image[x_lower:x_upper, y_lower:y_upper] >= 5):
            pts.append((y, x))
            break # Successfully found a point, break the inner loop
        attempts += 1 # Increment attempts

    if attempts == max_attempts_per_point:
        print("Maximum attempts reached, unable to find sufficient points with")
        break # Break outer loop if max attempts is reached without finding a

return pts

```

In [10]:

```

def clahe(imag, clip):
    """
    Apply Contrast Limited Adaptive Histogram Equalization (CLAHE) to an image.

    This function converts an image to grayscale, applies CLAHE to enhance the image
    and then converts it back to RGB. It uses OpenCV for the CLAHE operation and PI
    conversions.

    Parameters:
        imag (np.array): The input image array. Expected to be in format suitable for
        clip (float): The clipping limit for the CLAHE algorithm, which controls the
                      contrast. Higher values increase contrast.

    Returns:
        np.array: The contrast-enhanced image in RGB format.

    Notes:
        - The tile grid size for CLAHE is set to (8, 8). Adjustments to this parameter
          change the granularity of the histogram equalization.
    """
    clahe = cv2.createCLAHE(clipLimit=clip, tileGridSize=(8, 8))
    imag = Image.fromarray(np.uint8(imag))
    imag = imag.convert('L')
    img = np.asarray(imag)
    image_equalized = clahe.apply(img)
    image_equalized_img = Image.fromarray(np.uint8(image_equalized))
    image_equalized = image_equalized_img.convert('RGB')
    image_equalized = np.asarray(image_equalized)
    return image_equalized

def compute_plot_Flori21_AUC(landmark_errors):
    """

```

```

Function to compute and plot the success rate curve and calculate the AUC for t

Parameters:
- landmark_errors: List of landmark errors including outliers.
"""

landmark_errors_sorted = sorted(landmark_errors) # includes all outliers as well
# Initialize lists for thresholds and success rates
thresholds = list(range(101)) # 0 to 100
success_rates = []
# Calculate success rate for each threshold
for threshold in thresholds:
    successful_count = sum([1 for error in landmark_errors_sorted if error <= threshold])
    success_rate = successful_count / len(landmark_errors_sorted)
    success_rates.append(success_rate * 100) # convert to percentage
# Plot the curve
plt.plot(thresholds, success_rates, label="Success Rate Curve")
plt.xlabel("Threshold")
plt.ylabel("Success Rate (%)")
plt.title("Success Rate vs. Threshold")
plt.legend()
plt.grid(True)
plt.show()
# Compute AUC
auc = np.sum(success_rates) / 10000 # normalize to 0-1
print("AUC:", auc)

def plot_landmark_errors(landmark_errors,rpth,chr='All'):
"""

Plots a graph of landmark errors over successive iterations to provide a visual
across samples. This function is designed to help in the assessment of registration
or computer vision tasks by plotting each landmark error against its iteration.
It also displays the average landmark error across all iterations.

Parameters:
    landmark_errors (list of float): A list containing numerical errors for each sample.
                                         Outliers (e.g., errors set to 10000) are automatically filtered.
    rpth (str): Path where the resulting plot image will be saved.
    chr (str, optional): Characteristic or description to include in the plot title.
                         Defaults to 'All'.

Returns:
    None: This function does not return any value but saves the plot to the specified path.

Notes:
    - This plot is useful for tracking improvements or deteriorations in landmark errors.
    - It automatically filters out error values set to 10000, considering them as outliers.
    - The function saves the plot in the directory specified by `rpth` and name.
"""

#excluding outliers
landmark_errors =[x for x in landmark_errors if x!=10000]
# Generate sample numbers (or indices) based on the number of errors recorded
samples = list(range(1, len(landmark_errors) + 1))
# Calculate the average Landmark error
avg_error = sum(landmark_errors) / len(landmark_errors)
# Plotting
plt.figure(figsize=(12, 7))

```

```

plt.plot(samples, landmark_errors, marker='o', linestyle='-', color="#2C3E50",
plt.axhline(y=avg_error, color='#E74C3C', linestyle='--', label=f"Average Error")
plt.title("Landmark Error vs. Iteration for Database Housing model {} images".format(db_name))
plt.xlabel("Iteration Number", fontsize=14)
plt.ylabel("Landmark Error", fontsize=14)
plt.xticks(samples, [f"Iteration {i}" for i in samples], rotation=45)
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.legend(fontsize=12)
plt.tight_layout()
plt.savefig(os.path.join(rpth, 'Landmark_Error_Plot.png'))
plt.show();

def keypoints_visualization(image, landmarks, img_size, rpth, num):
    """
    Visualize keypoints on a given image.

    Parameters:
    - image (ndarray): The input image on which the keypoints are to be visualized.
    - landmarks (list or array-like): Collection of keypoints to be drawn on the image.
    - img_size (tuple): The size (width, height) of the image.
    - rpth (str): The path where the image with keypoints will be saved.
    - num (int or str): An identifier for the saved image file.

    Notes:
    - The function assumes the existence of a coordinates_rescaling function.
    - The displayed image has the title 'Chosen Keypoints' and does not have any axis labels.
    """
    # Rescale the coordinates of the landmarks
    rescaled_landmarks = coordinates_rescaling(landmarks, img_size, img_size, 256)

    # Define color map based on the number of points
    num_points = len(rescaled_landmarks)
    if num_points > 15:
        cmap = plt.get_cmap('tab20') # Changed from 'tab10' to 'tab20' for more colors
    else:
        cmap = ListedColormap(['red', 'yellow', 'blue', 'lime', 'magenta', 'indigo',
                               'darkgreen', 'maroon', 'black', 'white', 'chocolate'])
    colors = np.array([cmap(i) for i in range(num_points)])

    # Create the figure and axis
    fig, ax1 = plt.subplots(1, 1, figsize=(6, 6))

    # Set title and turn off the axis
    ax1.set_title('Chosen Keypoints')
    ax1.axis('off')

    # Show the image
    ax1.imshow(image, cmap='gray') # Assuming image is grayscale; remove cmap if it's already set

    # Define the radii for the circles
    radius1, radius2 = 4, 1

    # Plot each rescaled landmark on the image
    for point, color in zip(rescaled_landmarks, colors):
        x, y = point

```

```

# Create two circles at each point
circ1 = plt.Circle((x, y), radius1, facecolor=color, edgecolor='white', alpha=0.5)
circ2 = plt.Circle((x, y), radius2, facecolor=color, edgecolor='white')
# Add the circles to the axis
ax1.add_patch(circ1)
ax1.add_patch(circ2)

# Save the figure
plt.savefig(os.path.join(rpth, 'Keypoints_Visualization_' + str(num) + '.png'))

# Display the plot
plt.show();

def image_point_correspondences(images, img_size, landmarks1, landmarks2, landmarks3, rpth, num):
    """
    Displays and compares point correspondences between three images using given landmarks.

    This function visualizes three images side-by-side with their respective landmarks. Landmarks of corresponding points across the images are marked with the same color for easy comparison. The function is designed to handle visualization for studies like image registration or similar tasks where landmark matching is crucial.

    Parameters:
        images (list of str): File paths to the three images (source, target, and result).
        img_size (int): The size to which images should be resized, specified as width.
        landmarks1 (list of tuples): Landmark points on the first image (source image).
        landmarks2 (list of tuples): Corresponding landmark points on the second image.
        landmarks3 (list of tuples): Corresponding landmark points on the third image.
        rpth (str): Path where the resultant visualization should be saved.
        num (int): An identifier number used to differentiate the output file name.

    Returns:
        None: The function directly displays the image using matplotlib and saves the figure to disk.

    Notes:
        - The function uses OpenCV for reading and resizing images, and the 'clahe' function from skimage.exposure for contrast enhancement.
        - Matplotlib is used for visualizing the images and landmarks. The colormap for landmarks; if there are more than 15 landmarks, a cyclic colormap is used.
        - This function is particularly useful for visualizing transformations and similar fields where point correspondence is critical.
        - It is assumed that the order of landmarks in `landmarks1`, `landmarks2`, and `landmarks3` is consistent.

    """
    image1 = cv2.resize(cv2.imread(images[0]),(256,256))
    image2 = cv2.resize(cv2.imread(images[1]),(256,256))
    #### enhance image contrast for visualization
    image1 = clahe(image1, 3)
    image2 = clahe(image2, 3)
    keypoints_visualization(image1, landmarks1, img_size, rpth, num)
    landmarks2 = coordinates_rescaling(landmarks2, img_size, img_size, 256)
    landmarks3 = coordinates_rescaling(landmarks3, img_size, img_size, 256)
    assert len(landmarks2) == len(landmarks3), f"points lengths are incompatible: {len(landmarks2)} != {len(landmarks3)}"
    num_points = len(landmarks2)
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 6))
    ax1.set_title('Source Image')
    ax2.set_title('Target Image')
    ax1.axis('off')

```

```

ax2.axis('off')
ax1.imshow(image1,cmap='gray')
ax2.imshow(image2,cmap='gray')
if num_points > 15:
    cmap = plt.get_cmap('tab20')
else:
    cmap = ListedColormap(["red", "yellow", "blue", "lime", "magenta", "indigo",
                           "maroon", "black", "white", "chocolate", "gray", "brown"])
colors = np.array([cmap(x) for x in range(num_points)])
radius1, radius2 = 4, 1
for point1, point2, color in zip(landmarks2, landmarks3, colors):
    x1, y1 = point1
    circ1_1 = plt.Circle((x1, y1), radius1, facecolor=color, edgecolor='white',
    circ1_2 = plt.Circle((x1, y1), radius2, facecolor=color, edgecolor='white')
    ax1.add_patch(circ1_1)
    ax1.add_patch(circ1_2)
    x2, y2 = point2
    circ2_1 = plt.Circle((x2, y2), radius1, facecolor=color, edgecolor='white',
    circ2_2 = plt.Circle((x2, y2), radius2, facecolor=color, edgecolor='white')
    ax2.add_patch(circ2_1)
    ax2.add_patch(circ2_2)
plt.savefig(os.path.join(rpth,'RetinaRegNet_Keypoints_Estimation_Results'+str(n
plt.show();

def original_image_point_correspondences(images, img_size, landmarks1, landmarks2,
    """
    Visualize point correspondences across three images typically representing fixed
    and deformed states in image processing tasks. This function plots and saves the
    showing landmark points overlaid on each image. The images are enhanced using CLAHE
    and the landmarks are scaled according to a given image size.

    Parameters:
        images (list of np.array): A list containing three images (as numpy arrays)
            and deformed image states.
        img_size (tuple): The original size (width, height) of the images before re-
            scaling.
        landmarks1 (list of tuples): Landmark coordinates for the first image.
        landmarks2 (list of tuples): Landmark coordinates for the second image.
        landmarks3 (list of tuples): Landmark coordinates for the third image.
        rpth (str): Path to the directory where the result image will be saved.
        num (int): A numeric label to differentiate the output file name.

    Raises:
        AssertionError: If the lengths of landmarks1, landmarks2, and landmarks3 do
            not match.

    Notes:
        - This function uses CLAHE for contrast enhancement of the images.
        - The landmarks are resized to fit a 256x256 image scale for visualization.
        - A colormap is used to differentiate points; if the number of points exceeds
            15, a specific 20-color map is applied.
    """
    assert len(landmarks1) == len(landmarks2) == len(landmarks3), "All landmarks lists must have the same length"
    num_points = len(landmarks1)
    fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(18, 6))

    ax1.set_title('Fixed Image')

```

```

ax2.set_title('Moving Image')
ax3.set_title('Deformed Image')

ax1.axis('off')
ax2.axis('off')
ax3.axis('off')

ax1.imshow(clahe(cv2.resize(images[0],(256,256)),1.2),cmap='gray')
ax2.imshow(clahe(cv2.resize(images[1],(256,256)),1.2),cmap='gray')
ax3.imshow(clahe(cv2.resize(images[2],(256,256)),1.2),cmap='gray')

landmarks1 = coordinates_rescaling(landmarks1,img_size,img_size,256)
landmarks2 = coordinates_rescaling(landmarks2,img_size,img_size,256)
landmarks3 = coordinates_rescaling(landmarks3,img_size,img_size,256)

if num_points > 15:
    cmap = plt.get_cmap('tab20')
else:
    cmap = ListedColormap(["red", "yellow", "blue", "lime", "magenta", "indigo",
                           "maroon", "black", "white", "chocolate", "gray", "bl

colors = np.array([cmap(x) for x in range(num_points)])
radius1, radius2 = 4, 1

for point1, point2, point3, color in zip(landmarks1, landmarks2, landmarks3, co
    # Landmarks for Image 1
    x1, y1 = point1
    circ1_1 = plt.Circle((x1, y1), radius1, facecolor=color, edgecolor='white',
    circ1_2 = plt.Circle((x1, y1), radius2, facecolor=color, edgecolor='white')
    ax1.add_patch(circ1_1)
    ax1.add_patch(circ1_2)

    # Landmarks for Image 2
    x2, y2 = point2
    circ2_1 = plt.Circle((x2, y2), radius1, facecolor=color, edgecolor='white',
    circ2_2 = plt.Circle((x2, y2), radius2, facecolor=color, edgecolor='white')
    ax2.add_patch(circ2_1)
    ax2.add_patch(circ2_2)

    # Landmarks for Image 3
    x3, y3 = point3
    circ3_1 = plt.Circle((x3, y3), radius1, facecolor=color, edgecolor='white',
    circ3_2 = plt.Circle((x3, y3), radius2, facecolor=color, edgecolor='white')
    ax3.add_patch(circ3_1)
    ax3.add_patch(circ3_2)

plt.savefig(os.path.join(rpth, 'RetinaRegNet_Original_Keypoints_Estimation_Resu
plt.show();

```

In [11]: `def estimate_affine_transformation(points):`
 `"""`
 `Estimate affine transformation matrix using point correspondences.`
 `Args:`
 `points (np.array): Array of point correspondences.`

```

    Returns:
    np.array: Affine transformation matrix.
    """
    src_pts = np.float32([point[0] for point in points])
    dst_pts = np.float32([point[1] for point in points])
    affine_matrix, _ = cv2.estimateAffinePartial2D(src_pts, dst_pts)
    return affine_matrix

def transform_points_affine(moving_points, affine_matrix):
    """
    Transform the moving points using the given affine matrix.

    Parameters:
    - moving_points: List of (x, y) tuples
    - affine_matrix: (3x3) affine matrix

    Returns:
    - List of (x, y) tuples representing transformed points
    """
    points_array = np.array(moving_points)
    homogeneous_points = np.hstack([points_array, np.ones((len(moving_points), 1))])
    transformed_points = np.dot(homogeneous_points, affine_matrix.T)
    return [tuple(point) for point in transformed_points[:, :2]]


def transform_points_homography(moving_points, homography_matrix):
    """
    Transform the moving points using the given homography matrix.

    Parameters:
    - moving_points: List of (x, y) tuples
    - homography_matrix: (3x3) homography matrix

    Returns:
    - List of (x, y) tuples representing transformed points
    """
    points_array = np.array(moving_points)
    homogeneous_points = np.hstack([points_array, np.ones((len(moving_points), 1))])
    transformed_points = np.dot(homogeneous_points, homography_matrix.T)
    transformed_points /= transformed_points[:, 2][:, np.newaxis] # Normalize by z
    return [tuple(point[:2]) for point in transformed_points]


def transform_points_third_order_polynomial(moving_points, coefficients):
    """
    Transform the moving points using the given third-order polynomial coefficients

    Parameters:
    - moving_points: List of (x, y) tuples
    - coefficients: Array of 20 coefficients for the third-order polynomial transfo

    Returns:
    - List of (x, y) tuples representing transformed points
    """
    if len(coefficients) != 20:
        raise ValueError("Coefficients should have a shape of (20,).")

```

```

# Extract the coefficients
a1, a2, a3, a4, a5, a6, a7, a8, a9, a10, \
a11, a12, a13, a14, a15, a16, a17, a18, a19, a20 = coefficients

transformed_points = []
for x, y in moving_points:
    # Compute new x' and y' for each point using third-order polynomial
    x_prime = (a1*x**3 + a2*x**2*y + a3*x*y**2 + a4*y**3 +
               a5*x**2 + a6*x*y + a7*y**2 + a8*x + a9*y + a10)
    y_prime = (a11*x**3 + a12*x**2*y + a13*x*y**2 + a14*y**3 +
               a15*x**2 + a16*x*y + a17*y**2 + a18*x + a19*y + a20)
    transformed_points.append((x_prime, y_prime))

return transformed_points

```



```

def transform_points_quadratic(points, coefficients):
    """
    Deform a set of points using given quadratic coefficients.

    :param points: A list of points, where each point is a tuple (x, y).
    :param coefficients: The coefficients to use for the deformation.
    :return: A list of deformed points.
    """
    if len(coefficients) != 12:
        raise ValueError("Coefficients should have a shape of (12,).")

    a1, a2, a3, a4, a5, a6, a7, a8, a9, a10, a11, a12 = coefficients

    deformed = []
    for x, y in points:
        x_prime = a1*x + a2*y + a3*x*y + a4*x**2 + a5*y**2 + a6
        y_prime = a7*x + a8*y + a9*x*y + a10*x**2 + a11*y**2 + a12
        deformed.append((x_prime, y_prime))

    return deformed

```



```

def compute_landmark_error_fixed_space(polynomial_matrix, fixed_points, moving_points):
    """
    Compute the landmark error between fixed points and transformed moving points.

    Parameters:
    - fixed_points: List of (x, y) tuples in the fixed image.
    - moving_points: List of (x, y) tuples in the moving image.
    - polynomial_matrix: (3x3) matrix used to transform points using a third-order
    - image_size: The original size of the images.
    - new_image_size: The size of the images after rescaling.

    Returns:
    - mle: Mean Landmark Error.
    """
    transformed_points = transform_points_third_order_polynomial(moving_points, pol
    transformed_points = coordinates_rescaling_high_scale(transformed_points, image_

```

```

    errors = np.linalg.norm(np.array(fixed_points) - transformed_points, axis=1)
    mle = np.mean(errors)
    return mle

def compute_third_order_polynomial_matrix(landmarks1, landmarks2):
    """
    Compute coefficients for the third-order polynomial transformation.

    Args:
        landmarks1 (list): List of (x, y) tuples of landmarks in the first image.
        landmarks2 (list): List of (x, y) tuples of landmarks in the second image.

    Returns:
        np.array: Coefficients of the third-order polynomial transformation.
    """
    if len(landmarks1) != len(landmarks2) or len(landmarks1) < 10:
        raise ValueError("Both landmarks should have the same number of points, and"

A = []
B = []

for (x, y), (x_prime, y_prime) in zip(landmarks1, landmarks2):
    # For x'
    A.append([x**3, x**2 * y, x * y**2, y**3, x**2, x * y, y**2, x, y, 1, 0, 0,
    # For y'
    A.append([0, 0, 0, 0, 0, 0, 0, 0, 0, x**3, x**2 * y, x * y**2, y**3, x**2 * y, y**2, x, y, 1, 0, 0])

    B.extend([x_prime, y_prime])

A = np.array(A)
B = np.array(B)

# Solve the linear system
coefficients, _, _, _ = np.linalg.lstsq(A, B, rcond=None)

return coefficients # The shape of coefficients is (20,)

def compute_quadratic_matrix(landmarks1, landmarks2):
    """
    Compute the quadratic matrix using provided landmarks.

    Parameters:
    - landmarks1: List of (x, y) tuples from the source image.
    - landmarks2: List of (x, y) tuples from the target image.

    Returns:
    - 3x3 homography matrix.
    """
    if len(landmarks1) != len(landmarks2) or len(landmarks1) < 6:
        raise ValueError("Both landmarks should have the same number of points, and"

A = []
B = []

for (x, y), (x_prime, y_prime) in zip(landmarks1, landmarks2):

```

```

        A.append([x, y, x*y, x*x, y*y, 1, 0, 0, 0, 0, 0, 0])
        A.append([0, 0, 0, 0, 0, 0, x, y, x*y, x*x, y*y, 1])

    B.append(x_prime)
    B.append(y_prime)

A = np.array(A)
B = np.array(B)

# Solve the linear system
coefficients, _, _, _ = np.linalg.lstsq(A, B, rcond=None)

return coefficients

def compute_homography_matrix(landmarks1, landmarks2):
    """
    Compute the homography matrix using provided landmarks.

    Parameters:
    - landmarks1: List of (x, y) tuples from the source image.
    - landmarks2: List of (x, y) tuples from the target image.

    Returns:
    - 3x3 homography matrix.
    """
    homography_matrix, _ = cv2.findHomography(np.array(landmarks1), np.array(landmarks2))
    return homography_matrix

def transform_points_third_order_polynomial_matrix(landmarks1, landmarks2, img_size,
    """
    Computes a third-order polynomial transformation matrix based on rescaled landmarks1
    to another. This transformation is typically used for tasks like geometric transformation
    alignment or registration of image features is necessary.

    Parameters:
        landmarks1 (list of tuples): List of original landmark points in the source
        landmarks2 (list of tuples): List of corresponding landmark points in the target
            The points in landmarks2 should correspond one-to-one with landmarks1.
        img_size (int): Original size of the images from which the landmarks were extracted.
            Rescale points for accurate computation of the transformation matrix.
        new_img_size (int): New size to which the points will be rescaled before computation.
            This should reflect the size of the image space into which the transformed
            points will be mapped.

    Returns:
        numpy.ndarray: A transformation matrix which can be used to map the points
            from the space defined by landmarks1 to the space defined by landmarks2. The matrix is represented
            as a 3x3 array where each row corresponds to the terms of a third-order polynomial.
    """
    landmarks1 = coordinates_rescaling(landmarks1, img_size, img_size, new_img_size)
    landmarks2 = coordinates_rescaling(landmarks2, img_size, img_size, new_img_size)
    third_order_polynomial_matrix = compute_third_order_polynomial_matrix(landmarks1, landmarks2)

```

```

    return third_order_polynomial_matrix

def transform_points_quadratic_matrix(landmarks1, landmarks2, img_size, new_img_size)
    """
    Computes a quadratic transformation matrix based on rescaled landmarks from one

    This function rescales the input landmarks from their original dimensions (img_
    It then calculates a quadratic transformation matrix that describes how points
    can be transformed to align with the second set (landmarks2). This matrix could
    be used to transform images or coordinates.

    Parameters:
        landmarks1 (list of tuples): List of (x, y) tuples representing original la
        landmarks2 (list of tuples): List of (x, y) tuples representing target land
            corresponding to landmarks1.
        img_size (int): The original size (width and height, assumed square) of the
        new_img_size (int): The new size (width and height, assumed square) to which
            the image should be scaled before computing the transformation matrix.

    Returns:
        numpy.ndarray: A matrix that contains the coefficients of the quadratic tra
            to transform points from the source image to the target image.

    Notes:
        - Ensure that the number of points in landmarks1 and landmarks2 are equal a
        - This function is essential in image processing tasks where precise transfo
    """
    landmarks1 = coordinates_rescaling(landmarks1, img_size, img_size, new_img_size)
    landmarks2 = coordinates_rescaling(landmarks2, img_size, img_size, new_img_size)
    quadratic_matrix = compute_quadratic_matrix(landmarks1, landmarks2)
    return quadratic_matrix

def warp_image_third_order_polynomial(image, coefficients):
    """
    Deform the image using given third-order polynomial coefficients.

    :param image: The image to deform, as a numpy array (height, width) or (height,
    :param coefficients: The coefficients to use for the deformation.
    :return: The deformed image.
    """
    if len(coefficients) != 20:
        raise ValueError("Coefficients should have a shape of (20,).")

    # Extract the coefficients
    a1, a2, a3, a4, a5, a6, a7, a8, a9, a10, \
    a11, a12, a13, a14, a15, a16, a17, a18, a19, a20 = coefficients

    # Check if the image is grayscale or colored
    if len(image.shape) == 2:
        height, width = image.shape
        output = np.zeros((height, width))
        channels = 1
        image = image[:, :, np.newaxis] # add an additional dimension for consistency
    else:
        height, width, channels = image.shape

    # Create a grid of points
    grid_x, grid_y = np.mgrid[0:height, 0:width]
    grid_x = grid_x.reshape(-1, 1)
    grid_y = grid_y.reshape(-1, 1)

    # Compute the transformed coordinates
    transformed_x = grid_x * a1 + grid_y * a2 + a3
    transformed_y = grid_x * a4 + grid_y * a5 + a6
    transformed_x = transformed_x * a7 + transformed_y * a8 + a9
    transformed_x = transformed_x * a10 + a11
    transformed_y = transformed_y * a12 + a13
    transformed_x = transformed_x * a14 + transformed_y * a15 + a16
    transformed_x = transformed_x * a17 + a18
    transformed_y = transformed_y * a19 + a20

    # Reshape the transformed coordinates
    transformed_x = transformed_x.reshape(height, width)
    transformed_y = transformed_y.reshape(height, width)

    # Warp the image
    warped_image = cv2.warpAffine(image, (transformed_x, transformed_y), (height, width))

    return warped_image

```

```

        output = np.zeros((height, width, channels))

    # Generate the coordinates
    coordinates = np.indices((height, width))
    x_coords = coordinates[1]
    y_coords = coordinates[0]

    # Compute new x' and y' for every x and y using third-order polynomial
    x_prime = (a1*x_coords**3 + a2*x_coords**2*y_coords + a3*x_coords*y_coords**2 +
               a5*x_coords**2 + a6*x_coords*y_coords + a7*y_coords**2 + a8*x_coords
    y_prime = (a11*x_coords**3 + a12*x_coords**2*y_coords + a13*x_coords*y_coords**2 +
               a15*x_coords**2 + a16*x_coords*y_coords + a17*y_coords**2 + a18*x_co

    # Map the old image pixels to the new deformed positions
    for c in range(channels): # for each channel
        output[:, :, c] = map_coordinates(image[:, :, c], [y_prime, x_prime], order

    if channels == 1:
        return output[:, :, 0] # return as 2D grayscale image
    else:
        return output


def warp_image_quadratic_matrix(image, coefficients):
    """
    Deform the image using given quadratic coefficients.

    :param image: The image to deform, as a numpy array (height, width) or (height,
    :param coefficients: The coefficients to use for the deformation.
    :return: The deformed image.
    """

    if len(coefficients) != 12:
        raise ValueError("Coefficients should have a shape of (12,).")

    a1, a2, a3, a4, a5, a6, a7, a8, a9, a10, a11, a12 = coefficients

    # Check if the image is grayscale or colored
    if len(image.shape) == 2:
        height, width = image.shape
        output = np.zeros((height, width))
        channels = 1
        image = image[:, :, np.newaxis] # add an additional dimension for consistency
    else:
        height, width, channels = image.shape
        output = np.zeros((height, width, channels))

    # Generate the coordinates
    coordinates = np.indices((height, width))
    x_coords = coordinates[1]
    y_coords = coordinates[0]

    # Compute new x' and y' for every x and y
    x_prime = a1*x_coords + a2*y_coords + a3*x_coords*y_coords + a4*x_coords**2 + a
    y_prime = a7*x_coords + a8*y_coords + a9*x_coords*y_coords + a10*x_coords**2 + a

```

```

# Map the old image pixels to the new deformed positions
for c in range(channels): # for each channel
    output[:, :, c] = map_coordinates(image[:, :, c], [y_prime, x_prime], order=3)

if channels == 1:
    return output[:, :, 0] # return as 2D grayscale image
else:
    return output

```

def compute_third_order_polynomial_matrix_and_plot(images, img_size, landmarks1, landmarks2, rpth, num, cll):

Computes the third-order polynomial transformation matrix between two sets of landmark points and applies this transformation to warp one image to align with another. The function displays and saves the fixed, moving, and deformed images with contrast enhancement.

Parameters:

- images (list of str): List containing the file paths of two images.
- img_size (int): The size (height and width) to which the images will be resized.
- landmarks1 (list of tuples): Landmark points (x, y) on the first image.
- landmarks2 (list of tuples): Corresponding landmark points (x, y) on the second image.
- rpth (str): The directory path where the resultant images will be saved.
- num (int): Identifier number used to differentiate the output file names.
- cll (float, optional): The clipping limit for the CLAHE algorithm used in contrast enhancement.

Raises:

- ValueError: If the landmarks1 list is empty.

Returns:

- tuple: A tuple containing three elements:
 - imags (list of np.array): List containing the original fixed and moving images.
 - imgs (list of str): File paths where the output images have been saved.
 - coefficients (np.array): Coefficients of the third-order polynomial transformation matrix.

Notes:

- The third-order polynomial transformation is a complex and computationally expensive method, suitable for fine-grained image registration tasks where simple affine transformations fail.
- The resultant 'Deformed Image' is the second image warped to align with the transformation defined by the third-order polynomial transformation matrix.

"""

```

imags,imgs = [],[]
img1 = cv2.resize(cv2.imread(images[0]), (img_size, img_size))
img2 = cv2.resize(cv2.imread(images[1]), (img_size, img_size))

imags.append(img1)
imags.append(img2)

# Check if the list is not empty
if not landmarks1:
    raise ValueError("Input list cannot be empty")

# Compute the third-order polynomial transformation matrix
coefficients = compute_third_order_polynomial_matrix(landmarks1, landmarks2)
coefficients_for_transform = compute_third_order_polynomial_matrix(landmarks2, landmarks1)

# Apply the transformation using third-order polynomial

```

```

transformed_image = warp_image_third_order_polynomial(img2, coefficients_for_tr
imgags.append(transformed_image)

# Display and save the images
plt.figure(figsize=(10, 5))

plt.subplot(131)
plt.imshow(clahe(img1.astype(np.uint8),cl1))
plt.title('Fixed Image')
plt.axis('off')

plt.subplot(132)
plt.imshow(clahe(img2.astype(np.uint8),cl1))
plt.title('Moving Image')
plt.axis('off')

plt.subplot(133)
plt.imshow(clahe(transformed_image.astype(np.uint8),cl1))
plt.title('Deformed Image')
plt.axis('off')

plt.show()

imgags.append(os.path.join(rpth, 'Deformed_Image_ ' + str(num) + '_png'))
imgags.append(os.path.join(rpth, 'Target_ ' + str(num) + '_png'))
cv2.imwrite(os.path.join(rpth, 'Target_ ' + str(num) + '_png'), img1)
cv2.imwrite(os.path.join(rpth, 'Source_ ' + str(num) + '_png'), img2)
cv2.imwrite(os.path.join(rpth,'Deformed_Image_'+str(num)+'_png'),transformed_i
return imgags,coefficients

```

def compute_affine_matrix(images, img_size, landmarks1, landmarks2, rpth, num, cl1=5):

"""

Computes an affine transformation matrix based on provided landmarks from two images. This transformation is used to visually compare the source, target, and transformed images.

This function takes pairs of landmarks from two images and computes the affine transformation that best maps the source image to align with the target image. It then applies this transformation to the source image and displays both the original (source and target) and the transformed image. The images are displayed after contrast enhancement and are saved to the specified directory.

Parameters:

- images (list of str): File paths for the source and target images.
- img_size (int): The size (width and height) to which the images will be resized.
- landmarks1 (list of tuples): Landmark points (x, y) on the source image.
- landmarks2 (list of tuples): Corresponding landmark points (x, y) on the target image.
- rpth (str): Directory path where the resultant images will be saved.
- num (int): Identifier number used to differentiate the output file names.
- cl1 (float, optional): Clipping limit for the CLAHE algorithm used in contrast enhancement.

Returns:

- tuple: Contains two items:
 - imgags (list of str): File paths where the images are saved.
 - affine_matrix (numpy.ndarray): The computed 3x3 affine transformation matrix.

```

    Raises:
        ValueError: If the landmarks list is empty, indicating insufficient data to

    Notes:
        - This function uses OpenCV for image processing tasks including reading, r
        - The affine transformation matrix is computed using a least squares method
        - This function is useful for image registration tasks where visual compari
    """
    imgs=[]
    img1 = cv2.resize(cv2.imread(images[0]),(img_size,img_size))
    img2 = cv2.resize(cv2.imread(images[1]),(img_size,img_size))

    # Check if the list is not empty
    if not landmarks1:
        raise ValueError("Input list cannot be empty")

    # Create the array with the specified format
    A = np.array([[xs, ys, 1] for xs, ys in landmarks1])

    X = np.array([xt for xt, yt in landmarks2])
    Y = np.array([yt for xt, yt in landmarks2])

    # Solve for the variables x1, y1, and z1
    sol1 = np.dot(np.dot(np.linalg.inv(np.dot(A.T,A)),A.T),X)
    sol2 = np.dot(np.dot(np.linalg.inv(np.dot(A.T,A)),A.T),Y)
    # Extract the variables
    x1, y1, z1 = sol1
    x2, y2, z2 = sol2
    affine_matrix = np.array([[x1,y1,z1],
                            [x2,y2,z2],
                            [0, 0, 1]])
    print("Affine Matrix:")
    print(affine_matrix)

    # Ensure the affine matrix is of type float32
    affine_matrix = affine_matrix.astype(np.float32)

    # Use only the top two rows for cv2.warpAffine
    affine_for_warp = affine_matrix[:2]

    # Apply the affine transformation using cv2.warpAffine
    transformed_image = cv2.warpAffine(img2, affine_for_warp, (img2.shape[1], img2.

    # Display the original and transformed images
    plt.figure(figsize=(10, 5))

    plt.subplot(131)
    plt.imshow(clahe(img1,c11))

    plt.title('Fixed Image')
    plt.axis('off')

    plt.subplot(132)
    plt.imshow(clahe(img2,c11))

```

```

plt.title('Moving Image')
plt.axis('off')

plt.subplot(133)
plt.imshow(clahe(transformed_image,c1))

plt.title('Deformed Image')
plt.axis('off')

plt.show();
imgs.append(os.path.join(rpth,'Deformed_Image_'+str(num)+'.png'))
imgs.append(os.path.join(rpth,'Target_'+str(num)+'.png'))
cv2.imwrite(os.path.join(rpth,'Target_'+str(num)+'.png'),img1);
cv2.imwrite(os.path.join(rpth,'Source_'+str(num)+'.png'),img2);
cv2.imwrite(os.path.join(rpth,'Deformed_Image_'+str(num)+'.png'),transformed_i

return imgs,affine_matrix

def warp_quadratic_matrix(images,img_size,landmarks1, landmarks2,rpth,num,c1=5):
"""
Computes a quadratic transformation matrix from source to target landmarks and to the source image. The transformed source image is displayed alongside the original images and all images are saved to disk.

This function takes pairs of corresponding landmarks from the source and target images and computes a quadratic transformation matrix. This matrix is then used to warp the source image to match the target image. The result, along with the original images, is displayed and saved for comparison.

Parameters:
    images (list of str): File paths for the source and target images.
    img_size (int): The size (width and height) to which the images will be resized.
    landmarks1 (list of tuples): Landmark points (x, y) on the source image.
    landmarks2 (list of tuples): Corresponding landmark points (x, y) on the target image.
    rpth (str): Directory path where the resultant images will be saved.
    num (int): Identifier number used to differentiate the output file names.
    c1 (float, optional): Clipping limit for the CLAHE algorithm used in contrast enhancement.

Returns:
    tuple: Contains three items:
        - imgs (list of str): File paths where the output images are saved.
        - imgs (list of np.array): List containing the numpy arrays of the original images.
        - quadratic_matrix (numpy.ndarray): The computed quadratic transformation matrix.

Raises:
    AssertionError: If the number of points in `landmarks1` and `landmarks2` are not equal. An equal number of points is required for matrix computation.

Notes:
    - The function uses OpenCV for image processing tasks such as reading, resizing, and writing images.
    - The quadratic transformation matrix is computed using a least squares method.
    - Matplotlib is used for visualizing the before and after effects of the transformation.
    - This function is particularly useful in applications such as image registration and warping.

"""

imgs,imgs=[],[]
img1 = cv2.resize(cv2.imread(images[0]),(img_size,img_size))

```

```

img2 = cv2.resize(cv2.imread(images[1]),(img_size,img_size))

imags.append(img1)
imags.append(img2)

assert len(landmarks1) == len(landmarks2), "landmarks lists must have the same

# Ensure the quadratic matrix is of type float32
quadratic_matrix = compute_quadratic_matrix(landmarks1, landmarks2)

quadratic_matrix_for_image_deformed = compute_quadratic_matrix(landmarks2, land

print("quadratic Matrix:")
print(quadratic_matrix)

# Apply the quadratic transformation using cv2.warpquadratic
transformed_image = warp_image_quadratic_matrix(img2, quadratic_matrix_for_im
transformed_image = cv2.resize(transformed_image, (img2.shape[1], img2.shape[0]

# Display the original and transformed images
plt.figure(figsize=(10, 5))

plt.subplot(131)
plt.imshow(clahe(img1,cll))

plt.title('Fixed Image')
plt.axis('off')

plt.subplot(132)
plt.imshow(clahe(img2,cll))

plt.title('Moving Image')
plt.axis('off')

plt.subplot(133)
plt.imshow(clahe(transformed_image.astype(int),cll))

plt.title('Deformed Image')
plt.axis('off')

plt.show();
imags.append(transformed_image)
imgs.append(os.path.join(rpth,'Deformed_Image_'+str(num)+'.png'))
imgs.append(os.path.join(rpth,'Target_'+str(num)+'.png'))
cv2.imwrite(os.path.join(rpth,'Target_'+str(num)+'.png'),img1);
cv2.imwrite(os.path.join(rpth,'Source_'+str(num)+'.png'),img2);
cv2.imwrite(os.path.join(rpth,'Deformed_Image_'+str(num)+'.png'),transformed_i
return imgs,imags,quadratic_matrix

def compute_and_apply_homography(images, img_size, landmarks1, landmarks2, rpth, nu
"""
Computes the homography transformation matrix based on landmark correspondences
and applies this transformation to the source image. The function displays the
target images along with the transformed source image. It also saves these imag

```

```

Parameters:
    images (list of str): Paths to the source and target images.
    img_size (int): The size to which both images will be resized (assumed square).
    landmarks1 (list of tuples): Landmark points (x, y) from the source image.
    landmarks2 (list of tuples): Corresponding landmark points (x, y) from the target image.
    rpth (str): The directory path where the resultant images will be saved.
    num (int): An identifier number used to differentiate the output file names.
    cl1 (float): The clipping limit for the CLAHE algorithm used in contrast enhancement.

Returns:
    tuple: A tuple containing the paths to the saved images, a list of image arrays, and the computed homography matrix.

Raises:
    ValueError: If the list of landmarks is empty, indicating that there are no corresponding points defined.

Notes:
    - The function uses OpenCV for image reading, resizing, and applying the homography transformation.
    - Matplotlib is used for displaying the images.
    - Ensure the landmarks are accurately defined as their correspondence directly.
    - Homography transformations are particularly useful for applications in image registration.

"""


```

```

plt.subplot(133)
plt.imshow(clahe(transformed_image.astype(np.uint8),cl1))
plt.title('Deformed Image')
plt.axis('off')

plt.show();

imags.append(transformed_image)
imgs.append(os.path.join(rpth,'Deformed_Image_'+str(num)+'.png'))
imgs.append(os.path.join(rpth,'Target_'+str(num)+'.png'))
cv2.imwrite(os.path.join(rpth, 'Target_ ' + str(num) + '_png'),img1)
cv2.imwrite(os.path.join(rpth, 'Source_ ' + str(num) + '_png'),img2)
cv2.imwrite(os.path.join(rpth,'Deformed_Image_'+str(num)+'.png'),transformed_i
return imgs,imags,homography_matrix

```

In [12]:

```

def landmark_error(point, transformed_point):
    """
    Compute the Euclidean distance between the original point and the transformed p

    Args:
    point (tuple): Original point (x, y).
    transformed_point (tuple): Transformed point (x, y).

    Returns:
    float: Euclidean distance.
    """
    return np.linalg.norm(np.array(point) - np.array(transformed_point))

def estimate_affine_transformation(points):
    """
    Estimate affine transformation matrix using point correspondences.

    Args:
    points (np.array): Array of point correspondences.

    Returns:
    np.array: Affine transformation matrix.
    """
    src_pts = np.float32([point[0] for point in points])
    dst_pts = np.float32([point[1] for point in points])
    affine_matrix, _ = cv2.estimateAffinePartial2D(src_pts, dst_pts)
    return affine_matrix

def estimate_homography_matrix(points):
    """
    Estimate the homography matrix given a set of point correspondences.

    Parameters:
    - points: A list of tuples, where each tuple contains two (x, y) tuples.
              The first tuple in each pair is from the first set of points (set1),
              and the second tuple is the corresponding point in the second set (se

    Returns:
    - homography_matrix: The estimated (3x3) homography matrix.
    """

```

```

import numpy as np
import cv2

# Separate the points into two sets
set1 = [point[0] for point in points]
set2 = [point[1] for point in points]

# Convert to numpy arrays
set1 = np.array(set1, dtype=np.float32)
set2 = np.array(set2, dtype=np.float32)

# Estimate the homography matrix
homography_matrix, _ = cv2.findHomography(set1, set2, cv2.RANSAC)

return homography_matrix

```

def remove_outliers_based_on_error_affine(set1, set2, threshold=20):

"""

Filters out outlier point pairs from two sets of points by applying an affine transformation matrix based on all given point pairs. Each point in the first set is transformed using this matrix, and the error is calculated as the Euclidean distance between the transformed point and the corresponding point in the second set. Points with an error greater than the specified threshold are considered outliers and are excluded from the results.

Parameters:

- set1 (list of tuples): A list of (x, y) tuples representing coordinates of the first image.
- set2 (list of tuples): A list of (x, y) tuples representing corresponding coordinates of the second image. The indices in `set1` and `set2` must correspond to each other.
- threshold (float, optional): The maximum allowed error distance between the transformed point and the corresponding point in the second set. Points with an error greater than this threshold are considered outliers and are excluded from the results. Default value is 20.

Returns:

- tuple of lists:** Returns two lists (updated_set1, updated_set2) containing the transformed versions of `set1` and `set2` respectively.

Notes:

- It is critical that `set1` and `set2` are of equal length and that the points correspond to each other. Any misalignment could result in incorrect calculations and poor results.
- This function is typically used in image processing and computer vision tasks where a transformation of point sets between images is required, particularly in stereo vision applications.

"""

```

points = list(zip(set1, set2))
affine_matrix = estimate_affine_transformation(points)
updated_set1 = []
updated_set2 = []

for point1, point2 in zip(set1, set2):
    transformed_point = transform_points_affine([point1], affine_matrix)[0]
    error = landmark_error(point2, transformed_point)

    if error <= threshold:
        updated_set1.append(point1)
        updated_set2.append(point2)

return updated_set1, updated_set2

```

```

def remove_outliers_based_on_error_homography(set1, set2, threshold=20):
    """
    Filters out outlier point pairs from two sets of points by applying a homograph
    and removing pairs that have an error greater than a specified threshold. The function
    estimates a homography transformation matrix based on all given point pairs. Each point in
    the first set is transformed using this matrix, and the error is calculated as the Euclidean distance
    between the transformed point and the corresponding point in the second set. Points with an error
    greater than the threshold are considered outliers and are excluded from the results.

    Parameters:
        set1 (list of tuples): A list of (x, y) tuples representing coordinates of points in the first set.
        set2 (list of tuples): A list of (x, y) tuples representing corresponding points in the second set.
        threshold (float, optional): The maximum allowed error distance between the transformed points and their
            corresponding points for them to be considered inliers. Default value is 20.

    Returns:
        tuple of lists: Returns two lists (updated_set1, updated_set2) containing the filtered
            `set1` and `set2` respectively.

    Notes:
        - Ensure that `set1` and `set2` are of equal length and that the points correspond
            correctly, as any misalignment could result in incorrect calculations and poor results.
        - This function is typically used in image processing and computer vision tasks where
            alignment and transformation of point sets between images are required, such as
            panorama stitching and object tracking.

    """
    points = list(zip(set1, set2))
    homography_matrix = estimate_homography_matrix(points)
    updated_set1 = []
    updated_set2 = []

    for point1, point2 in zip(set1, set2):
        transformed_point = transform_points_homography([point1], homography_matrix)
        error = landmark_error(point2, transformed_point)

        if error <= threshold:
            updated_set1.append(point1)
            updated_set2.append(point2)

    return updated_set1, updated_set2

def filter_outlier_cond(computed, original, criteria='affine', thresh=20):
    """
    Filter outliers based on a specified condition.

    This function processes two sets of points (computed and original) and filters
    out outliers based on the specified criteria and threshold.

    Parameters:
        - computed (list of tuples): List of computed points as (x, y) coordinates.
        - original (list of tuples): List of original points as (x, y) coordinates to compare against.
        - criteria (str, optional): The criteria to use for filtering outliers. Options include 'affine' and 'rANS'.
        - thresh (int, optional): Threshold value used in the outlier removal process.

    Returns:
        tuple of lists: Returns two lists (filtered_computed, filtered_original) containing the
            filtered `computed` and `original` sets respectively.
    """

    # Implementation logic for filtering outliers based on the specified criteria and threshold.
    # This part is omitted for brevity.

```

```

    - list: A list containing the filtered computed points after outlier removal.
    - list: A list containing the filtered original points after outlier removal.

    Raises:
    - AssertionError: If the length of the computed points is not 3.

    Notes:
    - If 'homography' is chosen as the criteria, the function estimates a homograph
    - If 'affine' is chosen, it removes outliers based on affine transformation err
    """
    assert len(computed) >= 3
    if criteria=='homography':
        computed,original = estimate_homography_matrix(computed,original,thresh)
    else:
        computed,original = remove_outliers_based_on_error_affine(computed,original)
    return computed,original

```

```
In [13]: def coordinates_rescaling_high_scale(pnts,H,W,img_shape):
    """
    Rescale a list of coordinates based on given height and width ratios.

    Parameters:
    - pnts (list of tuples): List of (x, y) coordinates to be rescaled.
    - H (int): Original height.
    - W (int): Original width.
    - img_shape (int): Desired image dimension (assumes square shape).

    Returns:
    - list of tuples: List of rescaled (x, y) coordinates.
    """
    scaled_points=[]
    for row in pnts:
        a = (row[0]/W)*img_shape[1]
        b = (row[1]/H)*img_shape[0]
        scaled_points.append((a,b))
    return scaled_points

def coordinates_rescaling(pnts,H,W,img_shape):
    """
    Rescale a list of coordinates based on given height and width ratios.

    Parameters:
    - pnts (list of tuples): List of (x, y) coordinates to be rescaled.
    - H (int): Original height.
    - W (int): Original width.
    - img_shape (int): Desired image dimension (assumes square shape).

    Returns:
    - list of tuples: List of rescaled (x, y) coordinates.
    """
    scaled_points=[]
    for row in pnts:
        a = (row[0]/W)*img_shape
        b = (row[1]/H)*img_shape
        scaled_points.append((a,b))
```

```

    return scaled_points

def CLAHE_Images(imgs, clip):
    """
    Applies Contrast Limited Adaptive Histogram Equalization (CLAHE) to a list of images.
    This method is particularly useful for improving the visibility of details in images
    that suffer from poor contrast.

    Parameters:
        imgs (list of str): List of paths to the image files that need contrast enhancement.
        clip (float): Clip limit for the CLAHE algorithm, which sets the threshold.
                      The higher the clip limit, the more aggressive the contrast enhancement.

    Returns:
        list of str: Returns a list of paths to the saved CLAHE-processed images. Each image is saved with a "CLAHE_" prefix in its filename to distinguish it.

    Notes:
        - This function uses OpenCV's `createCLAHE` method to apply the CLAHE algorithm. The images are first converted to grayscale as CLAHE is typically applied to single-channel images for visualization of detail.
        - The images are processed in-place and saved in the same directory as the original files, with a "CLAHE_" prefix added to their filenames.
        - It is recommended to adjust the `clip` parameter based on the specific requirements of the input images and the desired level of contrast enhancement.

    """
    imgs = []
    clahe = cv2.createCLAHE(clipLimit=clip, tileGridSize=(8, 8))
    for img in imgs:
        fn, _ = os.path.splitext(os.path.basename(img))
        ifn = 'CLAHE' + '_' + str(fn) + '.png'
        imag = cv2.imread(img)
        imag = Image.fromarray(np.uint8(imag))
        imag = imag.convert('L')
        img = np.asarray(imag)
        image_equalized = clahe.apply(img)
        image_equalized_img = Image.fromarray(np.uint8(image_equalized))
        image_equalized = image_equalized_img.convert('RGB')
        image_equalized = np.asarray(image_equalized)
        cv2.imwrite(ifn, image_equalized);
        imgs.append(ifn)
    return imgs

def Feature_padding(feature_maps, size):
    """
    Pad feature maps to a uniform size using bilinear interpolation.

    This function adjusts the size of each feature map in the input list to a specified target size.

    Parameters:
        feature_maps (list of tensors): A list of feature map tensors to be resized.
        size (tuple): The target size for the feature maps as (height, width).

    Returns:
        list: A list of uniformly sized feature maps.
    """

```

```

uniform_feature_maps=[]
for feature in feature_maps:
    uniform_feature_maps.append(F.interpolate(feature, size=size, mode='bilinear'))
return uniform_feature_maps

def multi_resolution_features(images, img_size, N, clip, offset, window_size, max_dist, timestep):
    """
    Generate multi-resolution features from images using SIFT, and Random Points.

    This function processes images to generate feature maps at multiple resolutions.

    Parameters:
    - images (list of str): List of paths to the images to be processed.
    - img_size (int): The size of the images for processing.
    - N (int): The number of keypoints to be used in SIFT.
    - clip (float): The clip limit for CLAHE.
    - max_dist (float): Maximum distance for keypoint selection in SIFT.
    - timestep (float): Timestep parameter for Diffusion Model initialization.
    - up_ft_indices (list): Indices for feature upsampling in the Diffusion Model.
    - multi_ch (bool): Flag to indicate multi-channel mode.
    - multi_img_size (int): The size of the images for multi-resolution processing.
    - multi_iter (int): Number of iterations for multi-resolution processing.

    Returns:
    - tuple: A tuple of source and target feature tensors.
    """
    if multi_ch:
        src_fts, trg_fts = [], []
        for i in range(multi_iter):
            sks, pts = SIFT_top_n_keypoints(images[0], N, multi_img_size*(i+1), max_dist)
            pts = pts + select_random_points(images[0], N, multi_img_size*(i+1), offset)
            if clip > 0:
                images = CLAHE_Images(images, clip = clip)
            dft = DFT(images, multi_img_size*(i+1), pts)
            src_ft1, trg_ft1 = dft.feature_upsampling(RetinaRegNet_Initialization(images, img_size))
            src_fts.append(src_ft1)
            trg_fts.append(trg_ft1)
        src_fts = Feature_padding(src_fts, (img_size, img_size))
        trg_fts = Feature_padding(trg_fts, (img_size, img_size))
        src_ft = torch.cat(src_fts, dim=1)
        trg_ft = torch.cat(trg_fts, dim=1)
    else:
        sks, pts = SIFT_top_n_keypoints(images[0], N, img_size, max_dist)
        pts = pts + select_random_points(images[0], N, img_size, offset, window_size)
        if clip > 0:
            images = CLAHE_Images(images, clip = clip)
        dft = DFT(images, img_size, pts)
        src_ft, trg_ft = dft.feature_upsampling(RetinaRegNet_Initialization(images, img_size))
    return src_ft, trg_ft

def landmarks_condition_check(orig_images, img_size, t, uft, landmarks1, landmarks2):
    """
    Iteratively attempts to improve image registration quality by enhancing image contrast
    until certain quality conditions are met or a maximum number of attempts is reached.
    for image contrast enhancement and uses various feature transformation and scaling
    """

```

of landmark correspondences between two images.

Parameters:

```
    orig_images (list of str): Paths to the original images to be processed.  
    img_size (int): Size of the images to be processed, assumed to be square.  
    t (float): Threshold parameter for initializing the Diffusion Model.  
    uft (float): Parameter for extracting diffusion features from the diffusion  
    landmarks1 (list of tuples): Initial landmarks as (x, y) coordinates in the  
    landmarks2 (list of tuples): Target landmarks as (x, y) coordinates in the  
    max_tries (int, optional): Maximum number of attempts to improve image regi-  
    num (int, optional): Minimum required number of landmarks. Defaults to 100.  
    clip (float, optional): Clip limit for CLAHE. Defaults to 1.0.  
    N (int, optional): Number of points to be chosen at random for processing.  
    offset (float, optional): Offset used in point selection to avoid edge effe-  
    window_size (int, optional): Size of the window used in point selection. De-  
    iccl (float, optional): Inverse consistency criteria limit used in landmark  
    outlier_cond (str, optional): Condition used to determine outliers. Default  
    thresh (float, optional): Threshold used for filtering outliers. Defaults to
```

Returns:

```
tuple: Depending on the success of the registration process, this function  
      - The original images and the best set of landmarks found, or  
      - The original images and a set of default landmarks if conditions are
```

Raises:

```
AssertionError: If the number of initial and target landmarks do not match.
```

Notes:

- This function is particularly useful in medical imaging or computer vision where registration is crucial for further analysis.
- The effectiveness of the registration process depends heavily on the quality of the input images.
- CLAHE and other image processing techniques may not always produce the desired results if the images are of poor quality or the initial landmarks are inaccurately defined.

```
"""
```

```
imgs,lim,land_marks1, land_marks2,list_landmarks_2, list_sim_scores,list_land-  
marks, ch, = 0, 0  
assert len(landmarks1) == len(landmarks2), f"Points lengths are incompatible: {  
    len(landmarks2),len(landmarks1)}  
    landmarks2,landmarks1 = filter_outlier_cond(landmarks2,landmarks1,outlier_cond,  
    print(len(landmarks2)))  
list_landmarks_1.append(landmarks1)  
imgs.append(orig_images)  
list_landmarks_2.append(landmarks2)  
if len(landmarks2) < num:  
    print("Image Registration Unsuccessful for Original Set of Images")  
    while len(land_marks2) < num and tries< max_tries:  
        print("Executing Trial", tries + 1)  
        images = orig_images  
        pts = select_random_points(orig_images[0], N, img_size,offset,window_si-  
        dft = DFT(images, img_size, pts)  
        src_ft,trg_ft = dft.feature_upsampling(RetinaRegNet_Initialization(image  
        land_marks1,sim_score, land_marks2 = dft.feature_maps(src_ft,trg_ft,icc  
        del src_ft  
        del trg_ft  
        torch.cuda.empty_cache()  
        gc.collect()  
        land_marks2,land_marks1 = filter_outlier_cond(land_marks2,land_marks1,o
```

```

        list_landmarks_1.append(land_marks1)
        imgs.append(images)
        list_landmarks_2.append(land_marks2)
        list_sim_scores.append(np.mean(sim_score))
        tries += 1
    for i in range(len(list_landmarks_2)):
        lim.append(len(list_landmarks_2[i]))
    idx = np.argmax(np.array(lim))
    return orig_images, list_landmarks_1[idx], list_landmarks_2[idx]
else:
    return orig_images, landmarks1, landmarks2

```

In [14]:

```

def folder_structure(path):
    """
    Create a directory structure for storing image registration results.

    Parameters:
    - path (str): Base path for the directory.
    """
    os.makedirs(os.path.join(path+'_'+Image_Registration_Results'), exist_ok=True)

def subject_organization(nfn, fls):
    """
    Organize subjects based on file naming conventions.

    Parameters:
    - nfn (list): List of subject names.
    - fls (list): List of filenames.

    Returns:
    - dict: Dictionary with subjects as keys and their corresponding files as value
    """
    result_lists = {f'Subject_{i + 1}': [] for i in range(len(nfn))}
    for i in fls:
        if '_'.join(map(str,i.split('.')[0].split('_')[-2:])) in nfn:
            result_lists['_'.join(map(str,i.split('.')[0].split('_')[-2:]))] .
        else:
            continue
    return result_lists

def elements_replication(fixed, temp):
    """
    Replicate elements of a list based on another list's elements.

    Parameters:
    - fixed (list): List containing elements to replicate.
    - temp (list): List containing numbers indicating how many times to replicate e
    Returns:
    - list: List with replicated elements.
    """
    fxd = []
    for i in range(len(fixed)):
        replicated_sublist = [fixed[i][0]] * temp[i]
        fxd.append(replicated_sublist)
    return fxd

```

```

def data_organizing(pth,fnf,result_lists):
    """
    Organize data based on filenames and subject names.

    Parameters:
    - pth (str): Base path to the dataset.
    - nfn (list): List of subject names.
    - fnf (list): List of file identifiers.
    - result_lists (dict): Dictionary with subjects as keys and their corresponding

    Returns:
    - tuple: Lists containing paths to fixed images, moving images, and point files
    """
    fixed,moving,pnts,temp=[],[],[],[]
    for i in nfn:
        a,b,c=[],[],[]
        for j in range(len(result_lists[i])):
            if result_lists[i][j].split('_')[1].startswith(str(fnn[1][0])):
                b.append(os.path.join(pth,str(i),fnf[1],result_lists[i][j]))
            elif result_lists[i][j].startswith(str(fnn[2][0])):
                #a += [os.path.join(pth,str(i),fnf[2],result_lists[i][j])] * N
                a.append(os.path.join(pth,str(i),fnf[2],result_lists[i][j]))
                #a.append(result_lists[i][j])
            else:
                c.append(os.path.join(pth,str(i),fnf[0],result_lists[i][j]))
                #c.append(result_lists[i][j])
        temp.append(len(b))
        fixed.append(sorted(a))
        moving.append(sorted(b))
        pnts.append(sorted(c))
    fixed = elements_replication(fixed,temp)
    return fixed,moving,pnts

def text_points_extraction(pnts):
    """
    Extract point coordinates from a text file.

    Parameters:
    - pnts (str): Path to the text file containing point coordinates.

    Returns:
    - tuple: Lists of fixed points and moving points.
    """
    fixed_pnts = []
    moving_pnts = []
    with open(pnts, 'r') as file:
        for line in file:
            points = [float(coord) for coord in line.strip().split(',')]
            fps = tuple(points[:2])
            lps = tuple(points[2:])
            fixed_pnts.append(fps)
            moving_pnts.append(lps)
    return fixed_pnts,moving_pnts

```

```

def info_extraction(fixed,moving, pnts):
    """
    Extract information from given lists to pair up images and their points.

    Parameters:
    - fixed (list): List of fixed image paths.
    - moving (list): List of moving image paths.
    - pnts (list): List of point file paths.

    Returns:
    - tuple: Lists of image pairs, fixed points, and moving points.
    """
    images,fixed_points,moving_points = [],[],[]
    assert len(fixed) == len(moving), f"Some Images do not have a pair: {len(fixed)}"
    for i in range(len(fixed)):
        for j in range(len(moving)):
            if i==j:
                for k in range(len(fixed[i])):
                    for l in range(len(moving[j])):
                        if k==l:
                            images.append([moving[j][l],fixed[i][k]])
                            p1,p2 = text_points_extraction(pnts[j][l])
                            fixed_points.append(p1)
                            moving_points.append(p2)
                        else:
                            continue
            else:
                continue
    return images,fixed_points,moving_points

def coordinates_processing(image1,image2,fpnts,mpnts,img_shape=256):
    """
    Process and rescale coordinates for two images.

    Parameters:
    - image1 (str): Path to the first image.
    - image2 (str): Path to the second image.
    - fpnts (list of tuples): List of (x, y) coordinates related to the first image
    - mpnts (list of tuples): List of (x, y) coordinates related to the second image
    - img_shape (int, optional): Desired image dimension for rescaling. Default is 256.

    Returns:
    - tuple: Scaled coordinates for the first and second images.
    """
    H1,W1,C1 = cv2.imread(image1).shape
    H2,W2,C2 = cv2.imread(image2).shape
    scaled_moving_points = coordinates_rescaling(mpnts,H1,W1,img_shape)
    scaled_fixed_points = coordinates_rescaling(fpnts,H2,W2,img_shape)
    scaled_original_moving_points = coordinates_rescaling(mpnts,H1,W1,max(max(H1,W1),
    return (H2,W2),max(max(H1,W1),max(H2,W2)),scaled_fixed_points,scaled_moving_points)

def feature_scaling(images,fixed_points,moving_points,img_shape):
    """
    Apply feature scaling to given images and their associated points.
    """

```

```

Parameters:
- images (list): List of image paths.
- fixed_points (list): List of fixed points.
- moving_points (list): List of moving points.
- img_shape (int): Desired image dimension for rescaling.

Returns:
- tuple: Scaled fixed and moving points.
"""
fixed_image_size,max_image_size,fixed_pointss,moving_pointss,scaled_moving_poin
for i in range(len(images)):
    fhs,mhs,fpnts,mpnts,scmpnts = coordinates_processing(images[i][0],images[i])
    fixed_image_size.append(fhs)
    max_image_size.append(mhs)
    fixed_pointss.append(fpnts)
    moving_pointss.append(mpnts)
    scaled_moving_points.append(scmpnts)
return fixed_image_size,max_image_size,fixed_points,fixed_pointss,moving_points

def data_preprocessing(path):
"""
Preprocess the dataset from a given path by organizing and extracting relevant

Parameters:
- path (str): Path to the dataset directory.

Returns:
- tuple: Images, fixed points, and moving points extracted from the dataset.
"""
fls,nfn,fnn=[],[],[]
pth = os.path.join(os.getcwd(),path,'data')
for i in os.listdir(pth):
    nfn.append(i)
    for j in os.listdir(os.path.join(os.getcwd(),path,'data',i)):
        fnn.append(j)
        for k in os.listdir(os.path.join(os.getcwd(),path,'data',i,j)):
            if k!='.ipynb_checkpoints':
                fls.append(k)
            else:
                continue
folder_structure(path)
result= subject_organization(nfn,fls)
fixed,moving,pnts = data_organizing(pth,nfn,np.unique(fnn),result)
images,fixed_points,moving_points=info_extraction(fixed,moving,pnts)
return images,fixed_points,moving_points

```

In [15]:

```

def RetinaRegNet_Initialization(filelist,img_size = 256,timestep = 75,up_ft_index =
"""
Initialize RetinaRegNet by processing a list of image files.

Parameters:
- filelist (list of str): List of paths to image files for feature extraction.
- img_size (int, optional): Desired size for resizing images. Default is 256.
- timestep (int, optional): Time step for the initializing the diffusion model.
- up_ft_index (int, optional): Index for the extracting diffusion features from

```

```

Returns:
- ft (torch.Tensor): A tensor containing the Diffusion features of the images i

Notes:
The function uses the SDFeatrizer from the 'stabilityai/stable-diffusion-2-1'
from each image. After processing all images, the extracted features are concat
To avoid memory issues, the function cleans up resources after processing.
"""

ft = []
imglist = []
dfm = SDFeatrizer(sd_id='stabilityai/stable-diffusion-2-1')
for filename in filelist:
    img = Image.open(filename).convert('RGB')
    img = img.resize((img_size, img_size))
    imglist.append(img)
    img_tensor = (PILToTensor()(img) / 255.0 - 0.5) * 2
    ft.append(dfm.forward(img_tensor,
                          timestep,
                          up_ft_index,
                          prompt='FLORI21',
                          ensemble_size=8))
ft = torch.cat(ft, dim=0)

del dfm
torch.cuda.empty_cache()
gc.collect()
return ft

```

In [16]:

```

def main(images,rpth,ifn,img_size=256,up_ft_indices = 1,timestep = 75,N=50,offset=0
        """
        Perform image registration and point correspondence using a series of processin

Parameters:
- images (list): A list of input images for registration.
- rpth (str): Path to save the resulting registered images.
- ifn (str): File name prefix for the saved images.
- img_size (int, optional): Size of the input images (default is 256).
- up_ft_indices (int, optional): Up-sampling factor for feature indices (default is 1).
- timestep (int, optional): Time step for feature extraction (default is 75).
- N (int, optional): Number of keypoints to extract (default is 50).
- offset (float, optional): Offset parameter for feature extraction (default is 0.0).
- window_size (int, optional): Size of the window for feature extraction (default is 5).
- max_dist (int, optional): Maximum distance for feature matching (default is 5).
- iccl (int, optional): ICC level for feature matching (default is 3).
- outlier_cond (str, optional): Condition for outlier removal (default is 'affine').
- thresh (int, optional): Threshold value for outlier removal (default is 20).
- max_tries (int, optional): Maximum number of attempts for matching features (default is 5).
- num (int, optional): Number of iterations for matching features (default is 5).
- clip (float, optional): Clip parameter for image enhancement (default is 1.0).
- multi_ch (bool, optional): Flag indicating whether to use multi-channel processing.
- multi_iter (int, optional): Number of iterations for multi-channel processing (default is 5).
- multi_img_size (int, optional): Size of images for multi-channel processing (default is 256).

Returns:
- original (list): List of original image points.

```

- computed (list): List of computed image points after registration.

Note:

- This function performs various processing steps including feature extraction, outlier removal, and image registration.
- It saves the resulting registered images in the specified directory.
- If the image registration is unsuccessful, empty lists are returned for both ""

```

sks,pts = SIFT_top_n_keypoints(images[0],N,img_size,max_dist)
pts = pts+select_random_points(images[0],N,img_size)
if clip > 0:
    images = CLAHE_Images(images, clip = clip)
dft = DFT(images,img_size,pts)
src_ft,trg_ft = multi_resolution_features(images,img_size,N,clip,offset>window_
pnts,rmaxs, rspts = dft.feature_maps(src_ft,trg_ft,iccl)
del src_ft
del trg_ft
torch.cuda.empty_cache()
gc.collect()
images,original,computed = landmarks_condition_check(images, img_size, timestep
if len(computed)!=0:
    image_point_correspondences(images,img_size,pts,original,computed,rpth,ifn)
    return original,computed
else:
    print("Image Registration is Unsuccessful for the presented Images due to u
    return [],[]
torch.cuda.empty_cache()
```

In [17]:

```
img_size= 1024
images,fixed_points,moving_points = data_preprocessing('FLoRI21_DataPort')
fixed_image_size,max_image_size,fixed_points,scaled_fixed_points,scaled_moving_poin
```

In [18]:

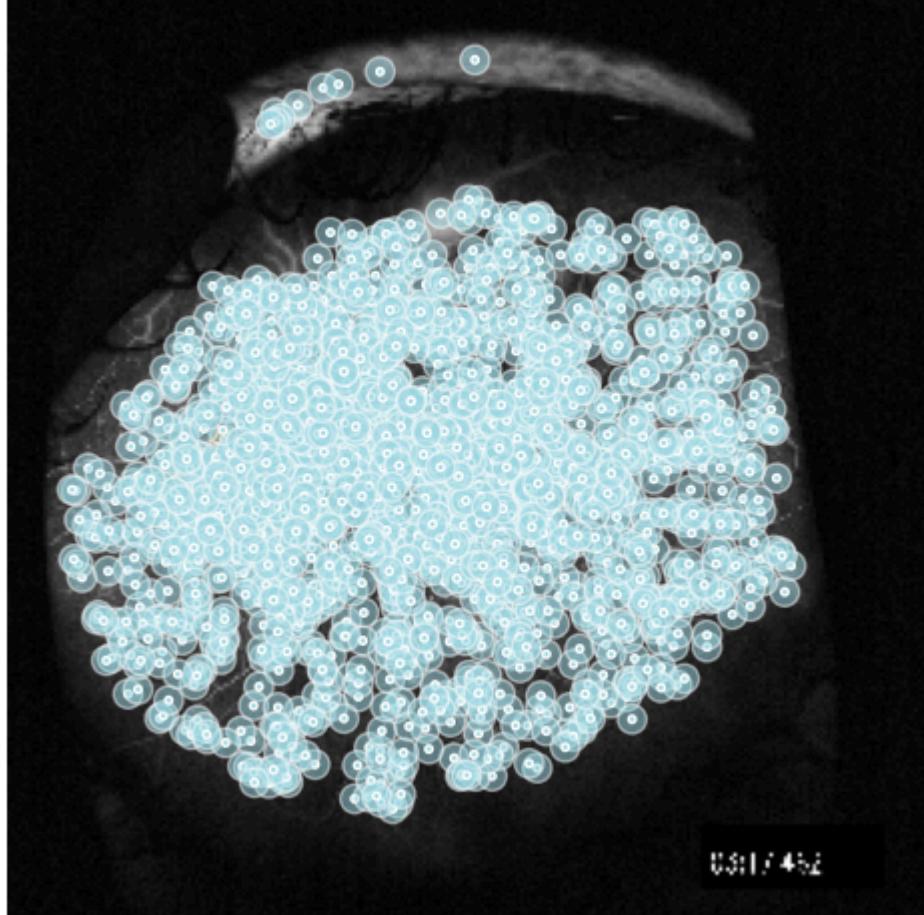
```
landmark_errors=[]
for i in range(len(images)):
    print("Iteration {}".format(i+1))
    print("Loading Source Images {} ,Target Image{} to the framework".format(imag
    original_low_res,computed_low_res = main(images[i],os.path.join(os.getcwd(),'FL
    imgs,homography_matrix_low_res = compute_and_apply_homography(images[i][:]
    if len(homography_matrix_low_res) !=0:
        transformed_points_hom = transform_points_homography(scaled_moving_points[i]
        transformed_points_high_res_hom = coordinates_rescaling(transformed_points
        original_low_res,computed_low_res = main(imgs,os.path.join(os.getcwd(),'FL
        imgs,quadratic_matrix_low_res = compute_third_order_polynomial_matrix_
        if len(quadratic_matrix_low_res) !=0:
            ## rescaled version for dispaly purposes
            transformed_points_poly = transform_points_third_order_polynomial(trans
            original_image_point_correspondences(imag,img_size, scaled_fixed_points
            ### Original Version for computation of errors
            polynomial_matrix = transform_points_third_order_polynomial_matrix(orig
            error = compute_landmark_error_fixed_space(polynomial_matrix,fixed_poin
            print("Recorded Landmark Error for Iteration {} is {}".format(i+1,err
            landmark_errors.append(error)
        else:
            landmark_errors.append(10000)
```

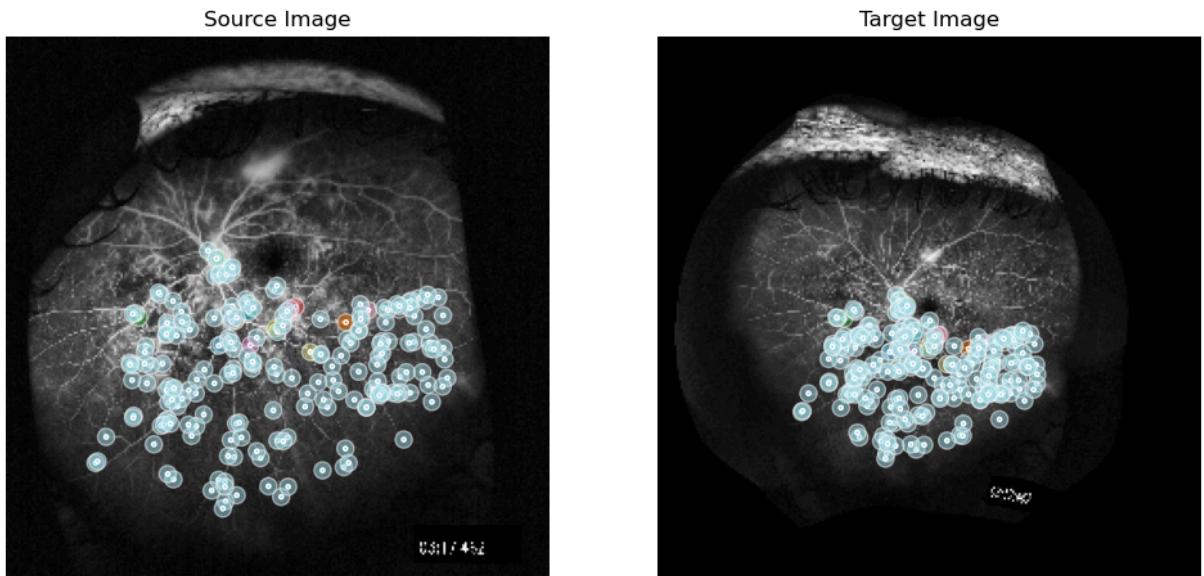
```
    else:  
        landmark_errors.append(10000)
```

Iteration 1
Loading Source Images /blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_2/Montage/Montage_Subject_2.tif ,Target Image/blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_2/FA/Raw_FA_1_Subject_2.tif to the framework
Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
/blue/weishao/vi.sivaraman/conda/envs/VBS_HRC/lib/python3.11/site-packages/torch/nn/modules/conv.py:459: UserWarning: Applied workaround for CuDNN issue, install nvrtc.so (Triggered internally at ../../aten/src/ATen/native/cudnn/Conv_v8.cpp:80.)
 return F.conv2d(input, weight, bias, self.stride,
/scratch/local/22569018/ipykernel_1623912/2877224606.py:74: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requires_grad_(True), rather than torch.tensor(sourceTensor).
 points_indices = torch.tensor(pts_list)

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Chosen Keypoints





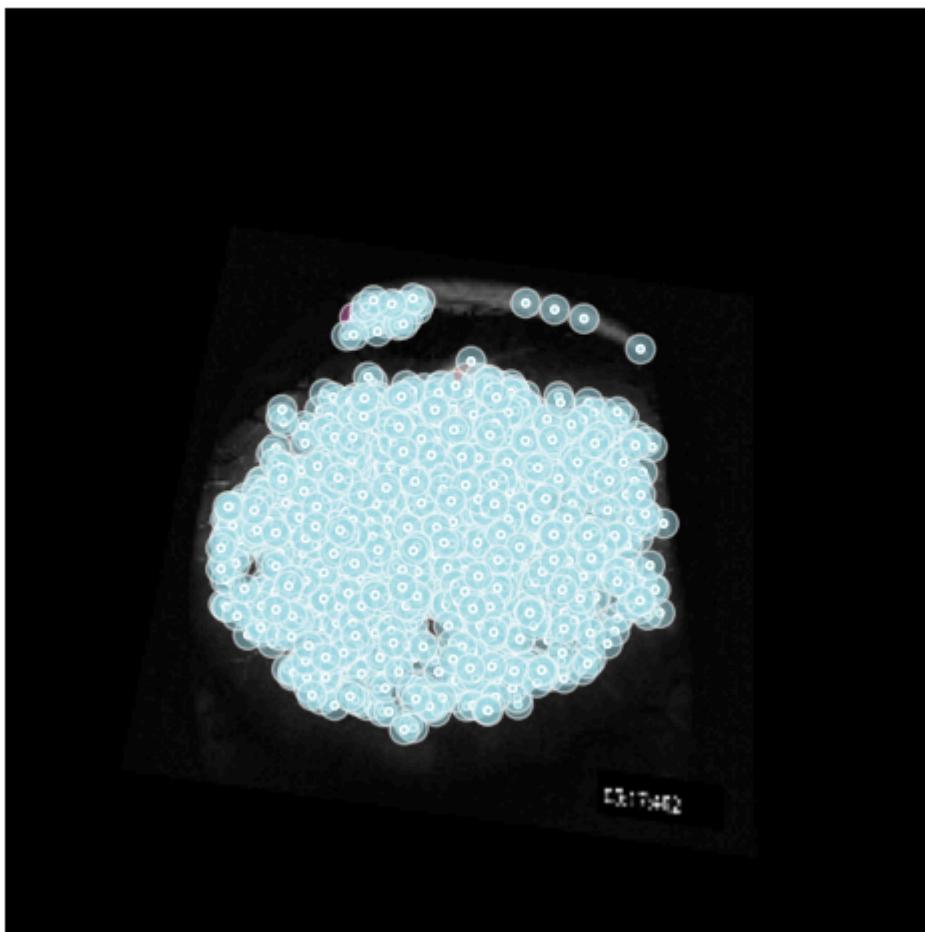
Homography Matrix:

```
[[ 5.61061207e-01 -1.41432074e-01  2.50466914e+02]
 [ 7.48336292e-02  4.40905276e-01  2.41829394e+02]
 [-1.93660443e-06 -1.73865167e-04  1.00000000e+00]]
```

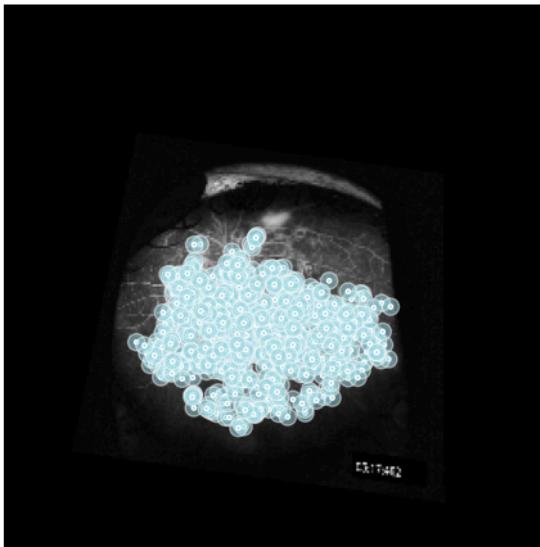


Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
710

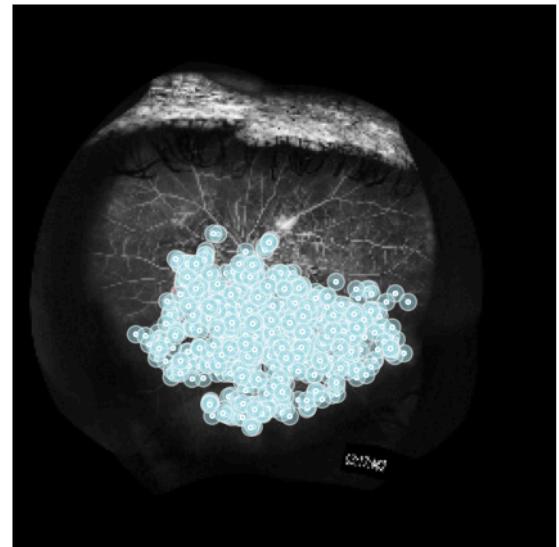
Chosen Keypoints

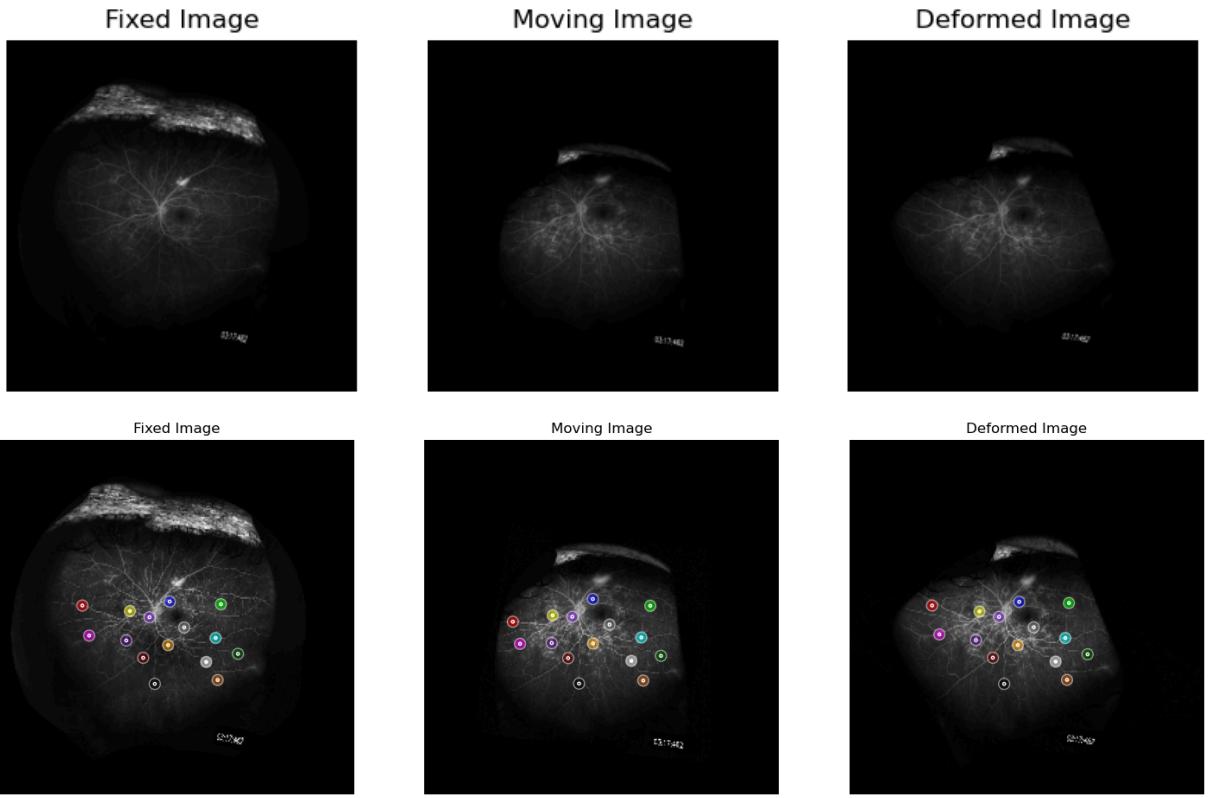


Source Image



Target Image





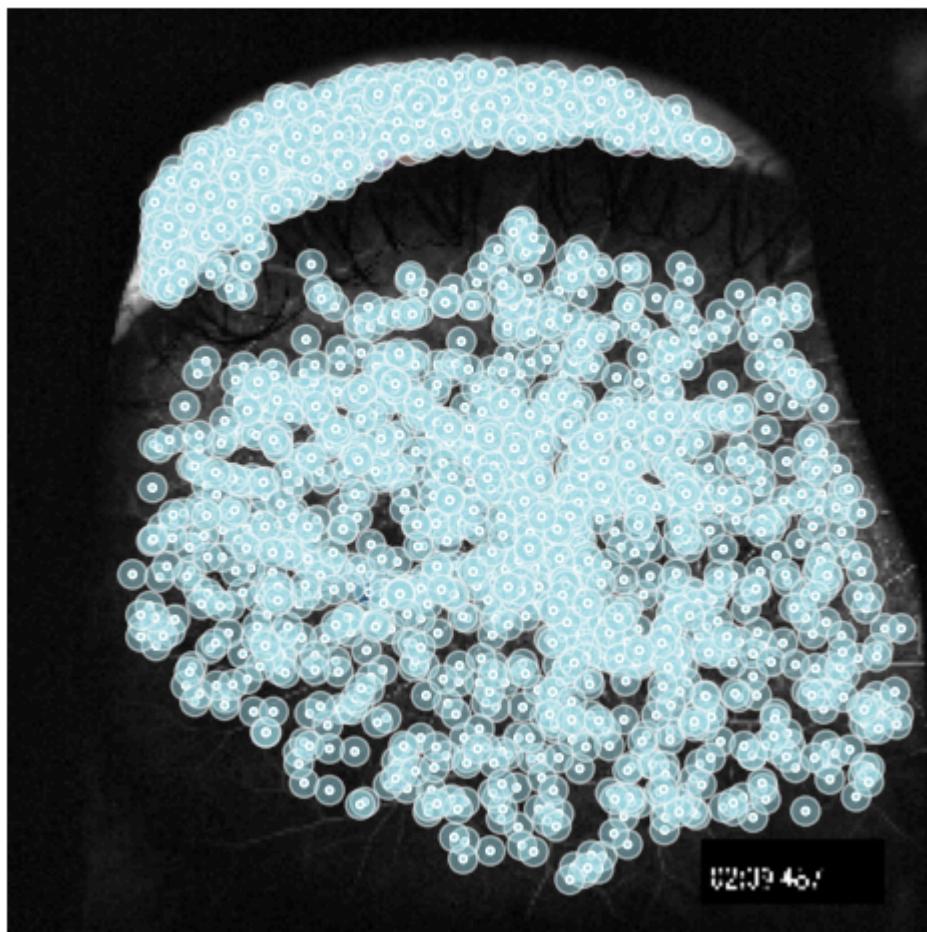
Recorded Landmark Error for Iteration 1 is 8.749038446032909

Iteration 2

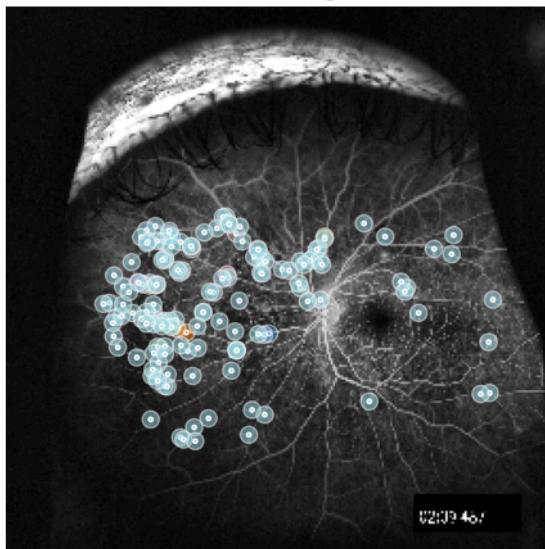
```
Loading Source Images /blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_R
egistration/FLoRI21_DataPort/data/Subject_2/Montage/Montage_Subject_2.tif ,Target Im
age/blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21
_DataPort/data/Subject_2/FA/Raw_FA_2_Subject_2.tif to the framework
Loading pipeline components...:  0%| 0/6 [00:00<?, ?it/s]
153
```

153

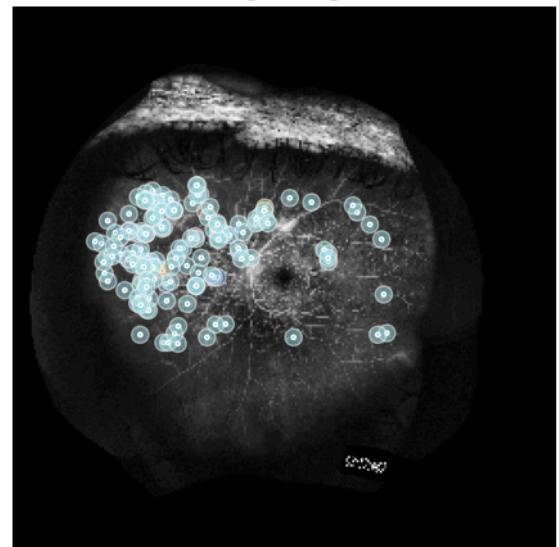
Chosen Keypoints



Source Image

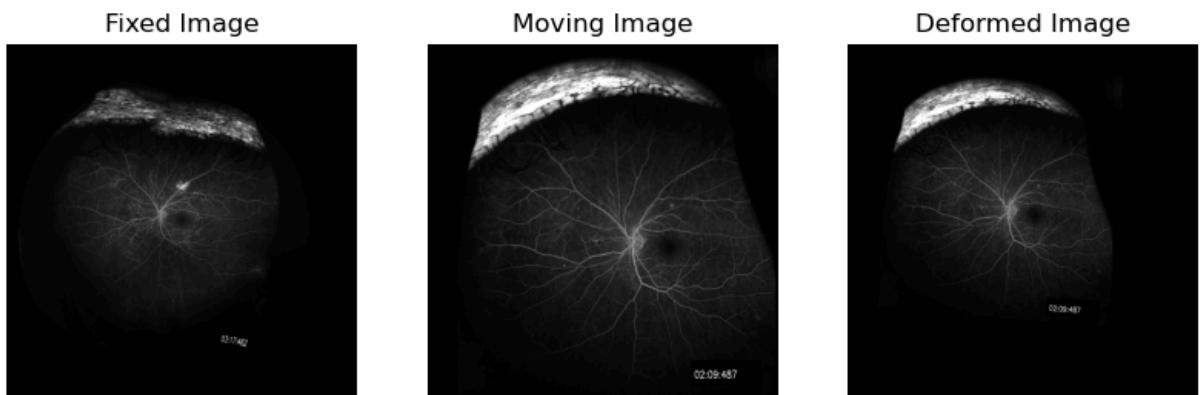


Target Image



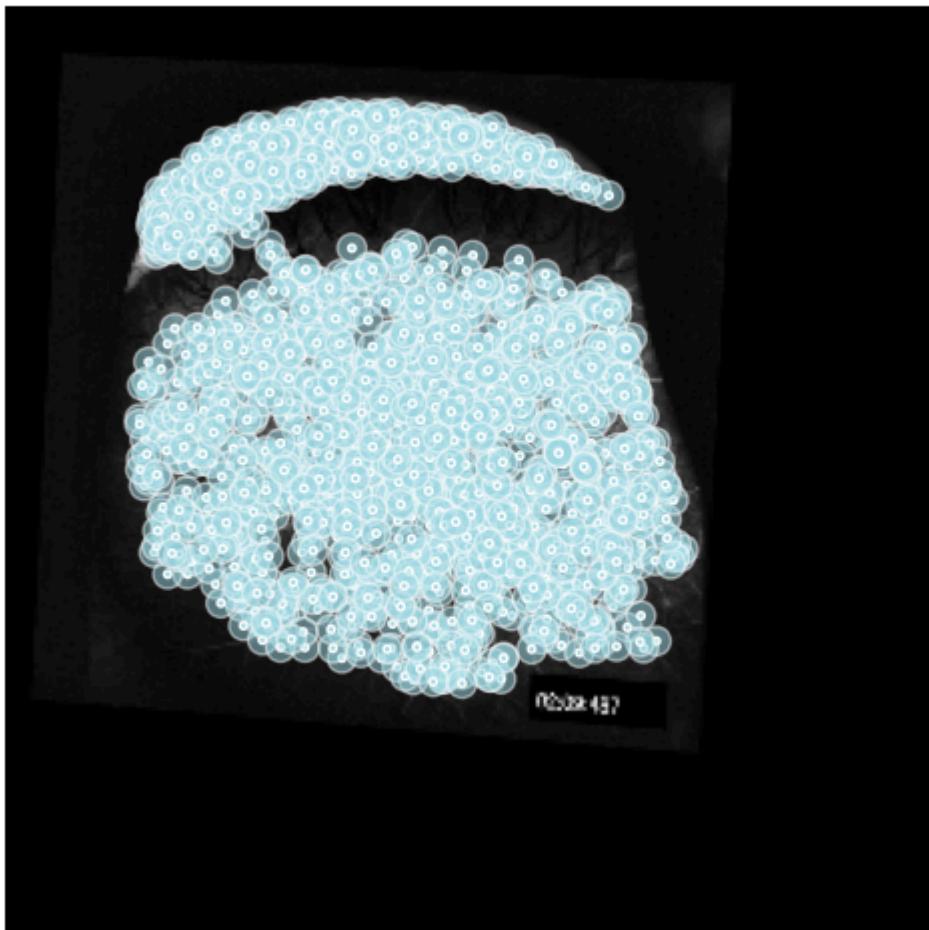
Homography Matrix:

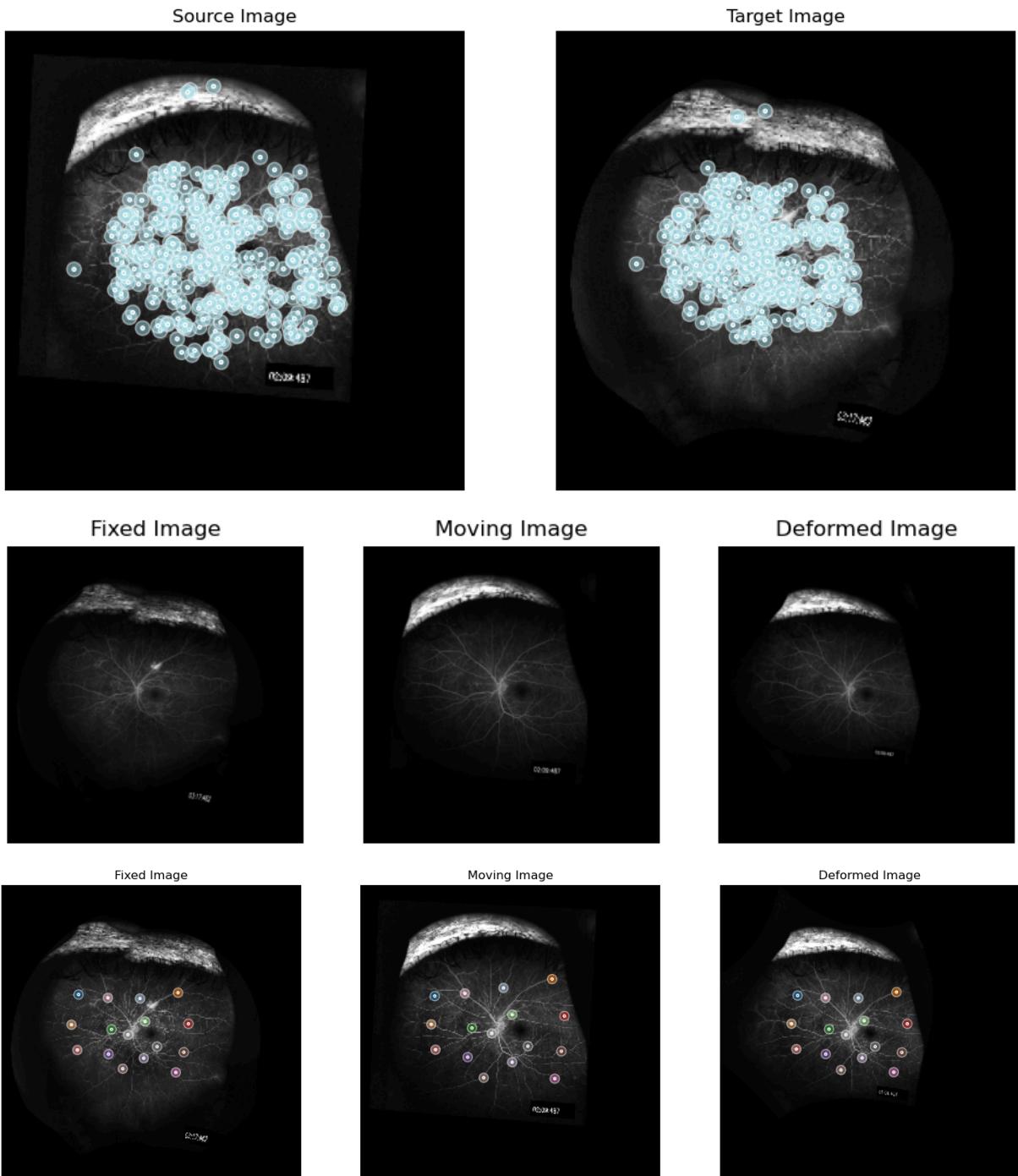
```
[[ 6.97182568e-01 -3.30054245e-02  6.34819242e+01]
 [ 2.98053207e-02  7.00984237e-01  5.23725037e+01]
 [-3.50091534e-05  3.82990449e-06  1.00000000e+00]]
```



Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
485

Chosen Keypoints





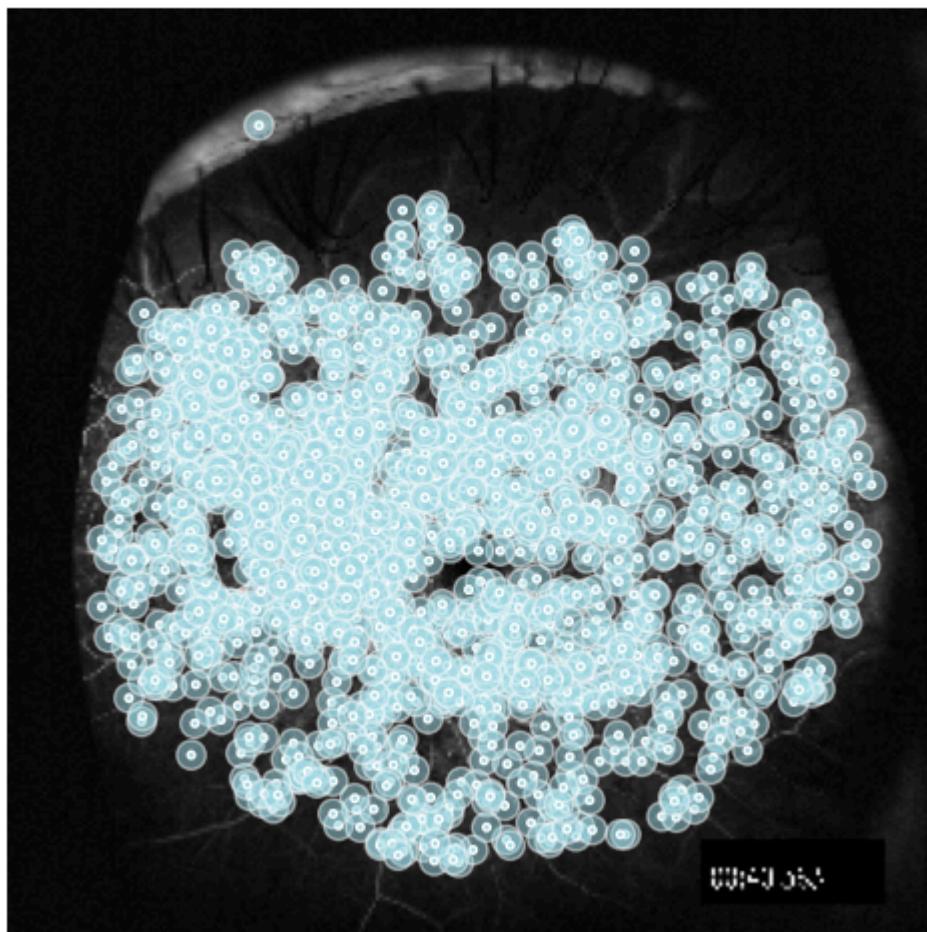
Recorded Landmark Error for Iteration 2 is 10.66290389511247

Iteration 3

```
Loading Source Images /blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_2/Montage/Montage_Subject_2.tif ,Target Image/blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_2/FA/Raw_FA_3_Subject_2.tif to the framework
Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
```

239

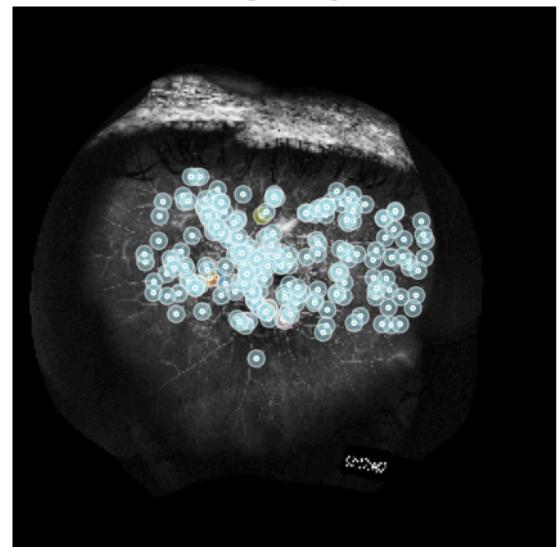
Chosen Keypoints



Source Image

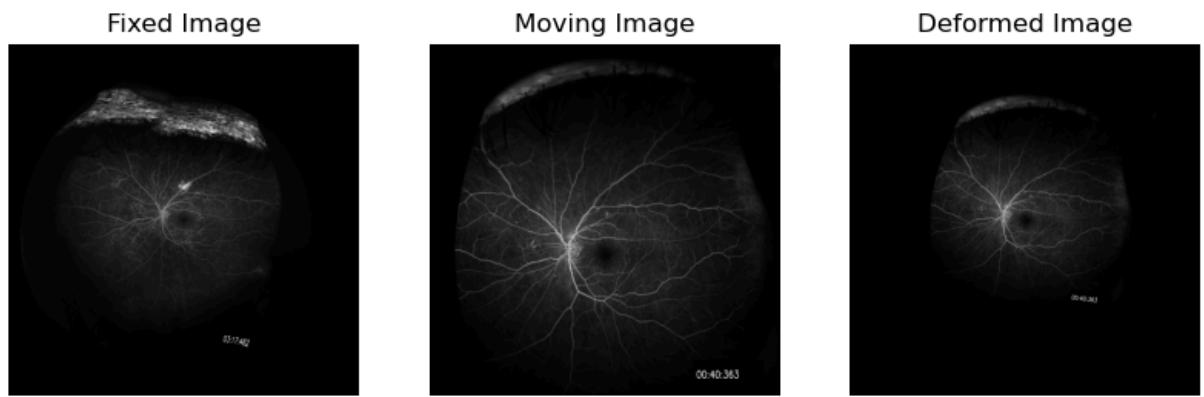


Target Image

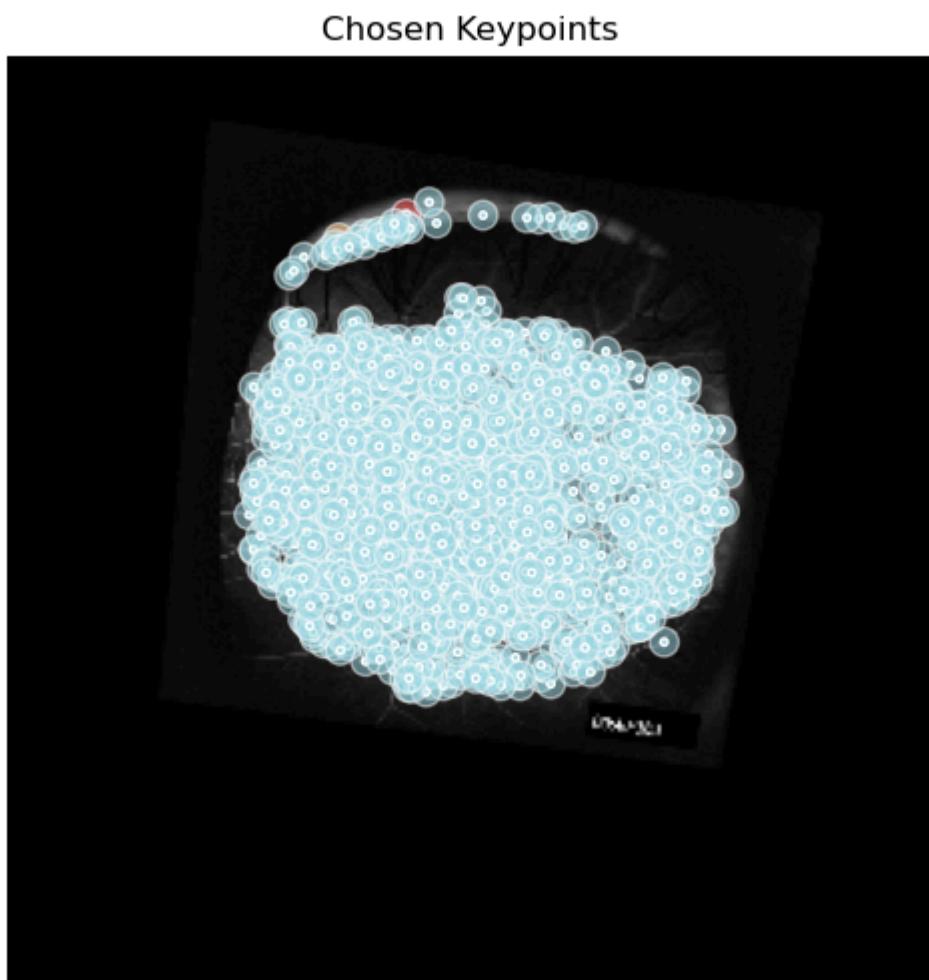


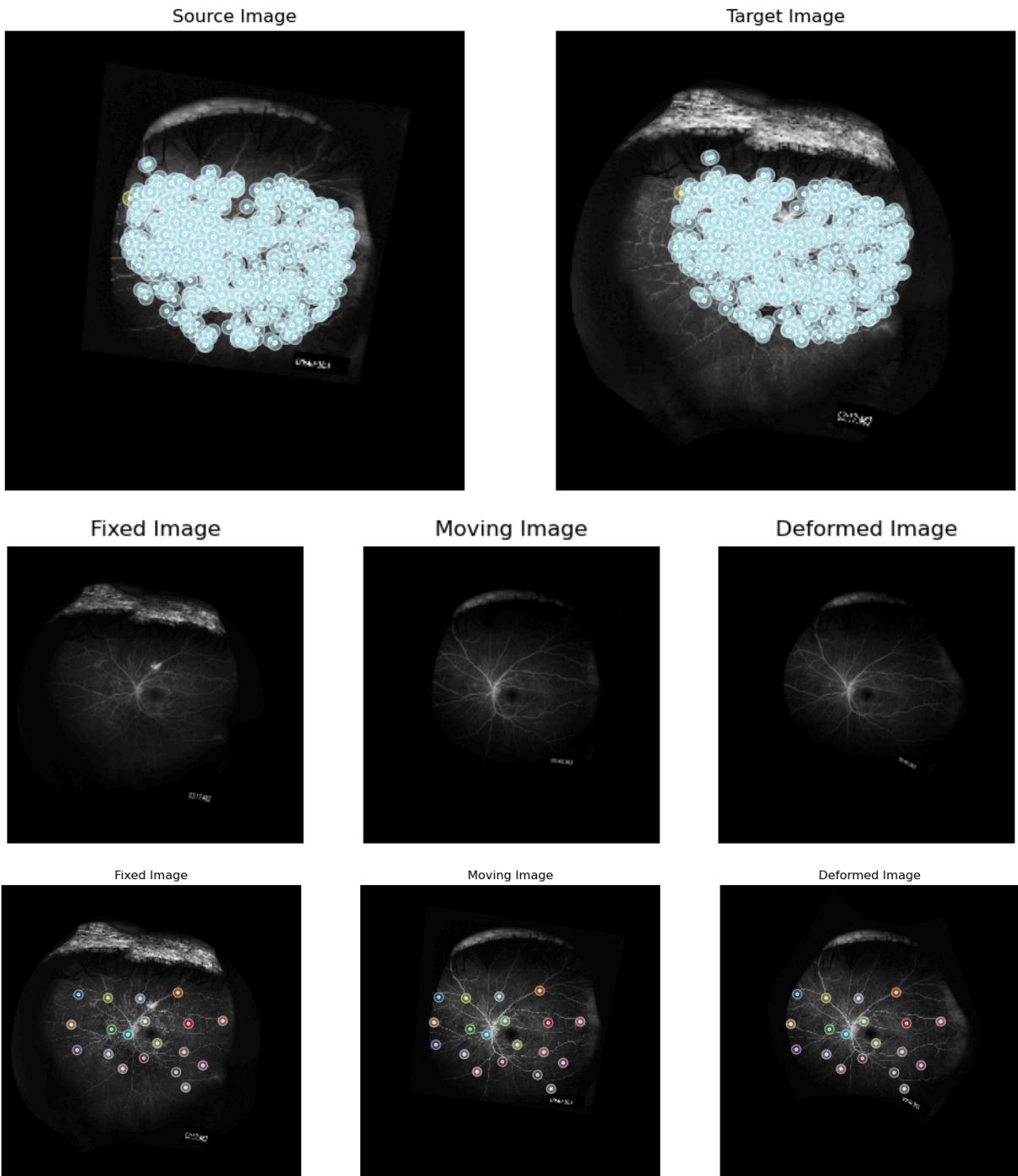
Homography Matrix:

```
[[ 6.90923060e-01 -3.71556824e-02  2.23843744e+02]
 [ 1.06891836e-01  6.97986371e-01  6.98996409e+01]
 [ 2.92173489e-05  1.00562885e-04  1.00000000e+00]]
```



Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
759





Recorded Landmark Error for Iteration 3 is 12.173661032414424

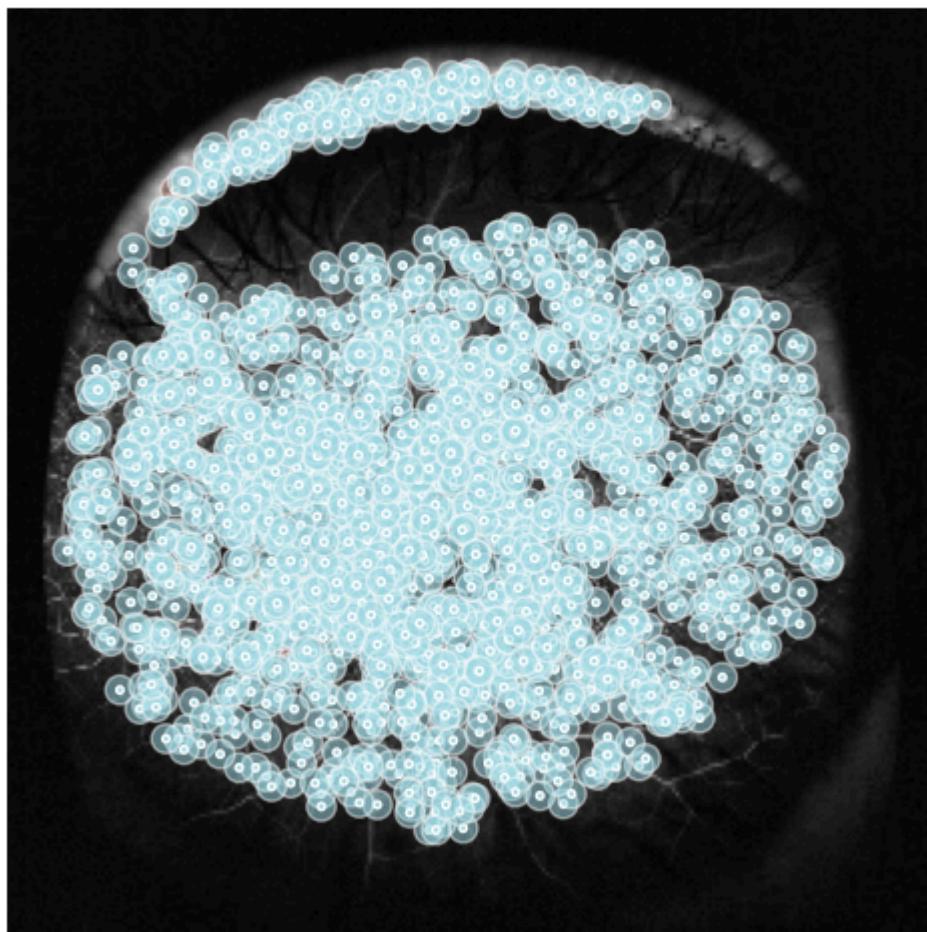
Iteration 4

```
Loading Source Images /blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_2/Montage/Montage_Subject_2.tif ,Target Image/blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_2/FA/Raw_FA_4_Subject_2.tif to the framework
```

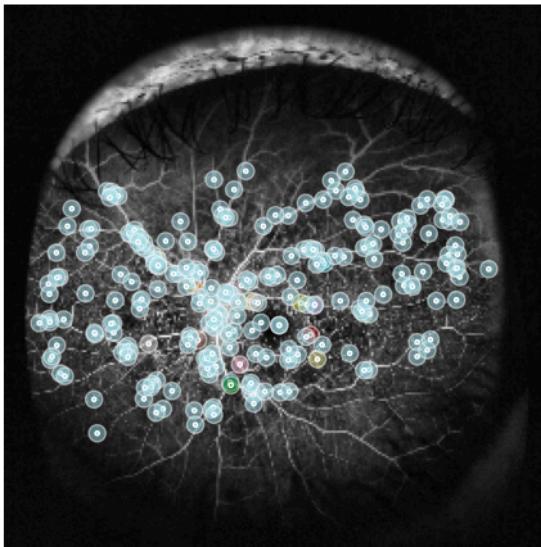
```
Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
```

246

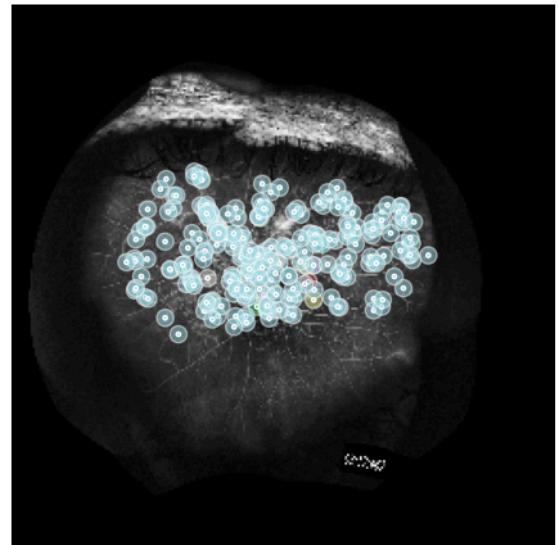
Chosen Keypoints



Source Image

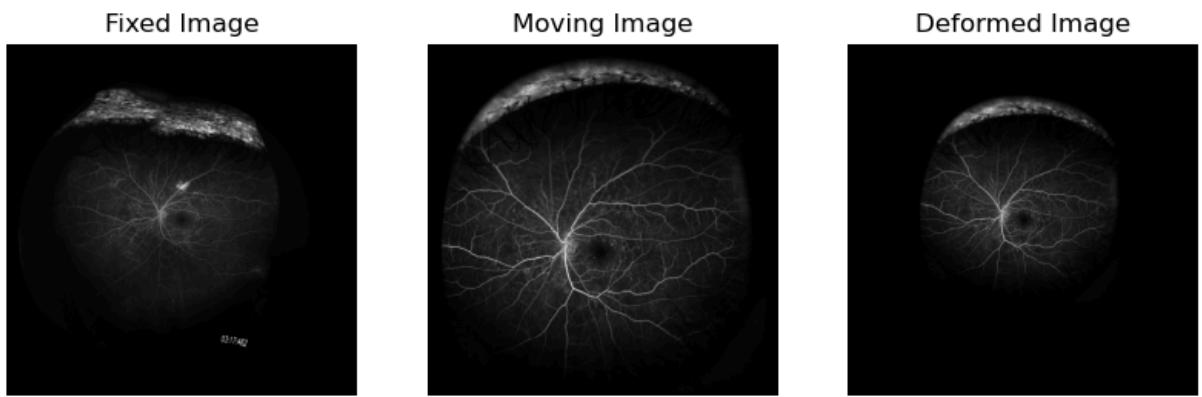


Target Image

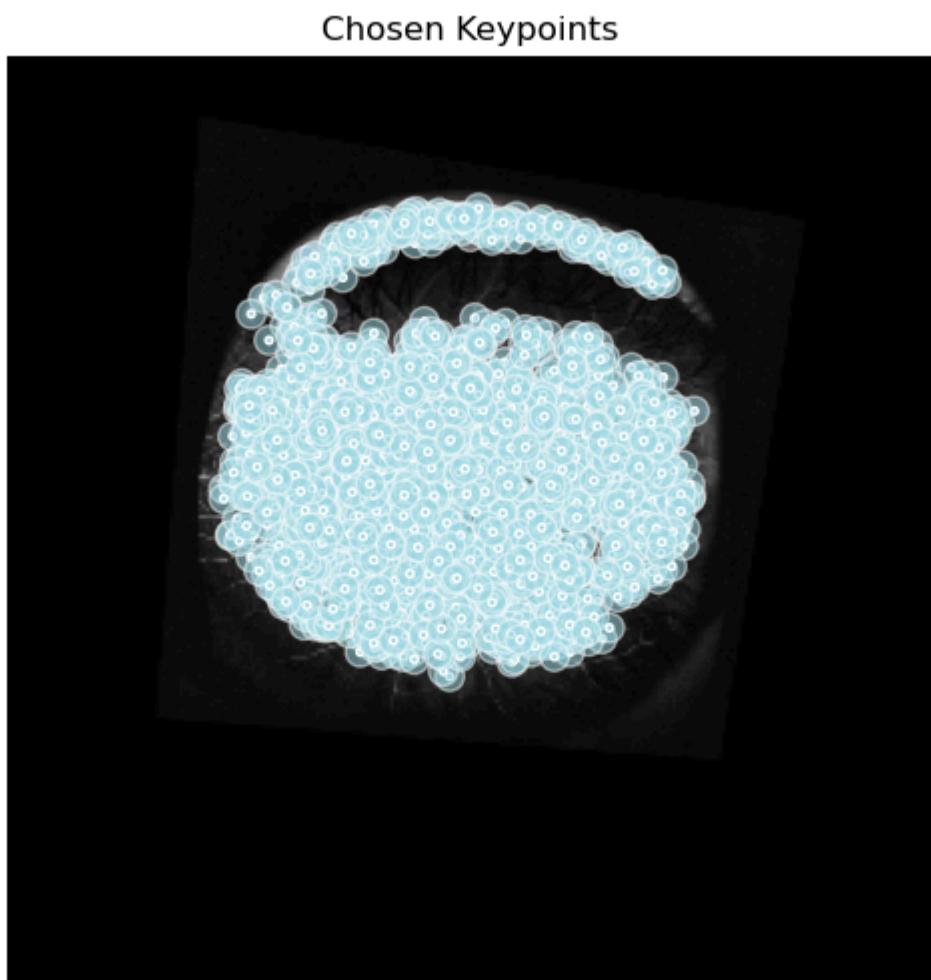


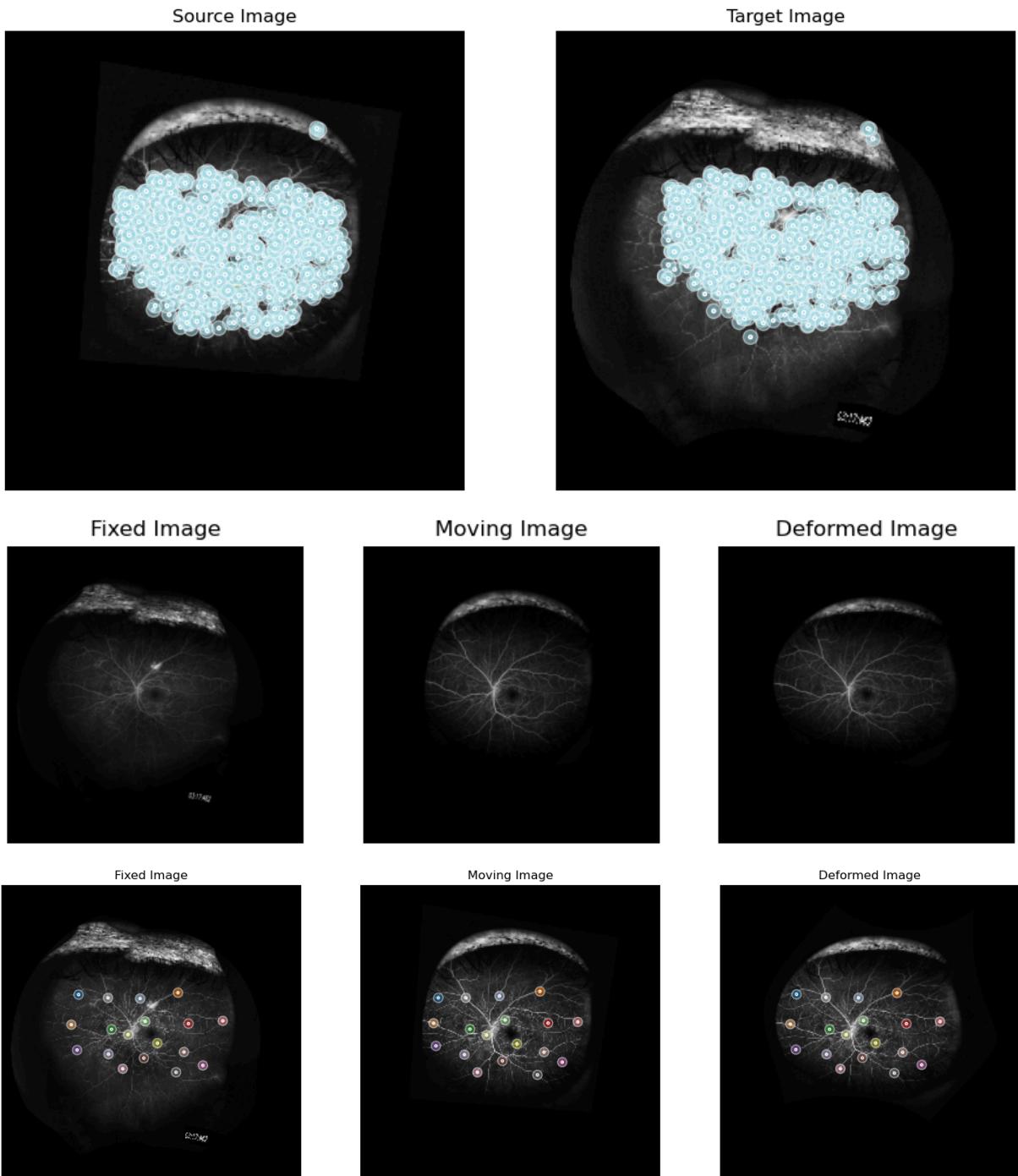
Homography Matrix:

```
[[ 7.43350656e-01 -3.32135363e-02  2.14034752e+02]
 [ 1.29448692e-01  7.13142268e-01  6.70666933e+01]
 [ 1.01583656e-04  8.64135296e-05  1.00000000e+00]]
```



Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
930





Recorded Landmark Error for Iteration 4 is 12.930191960013286

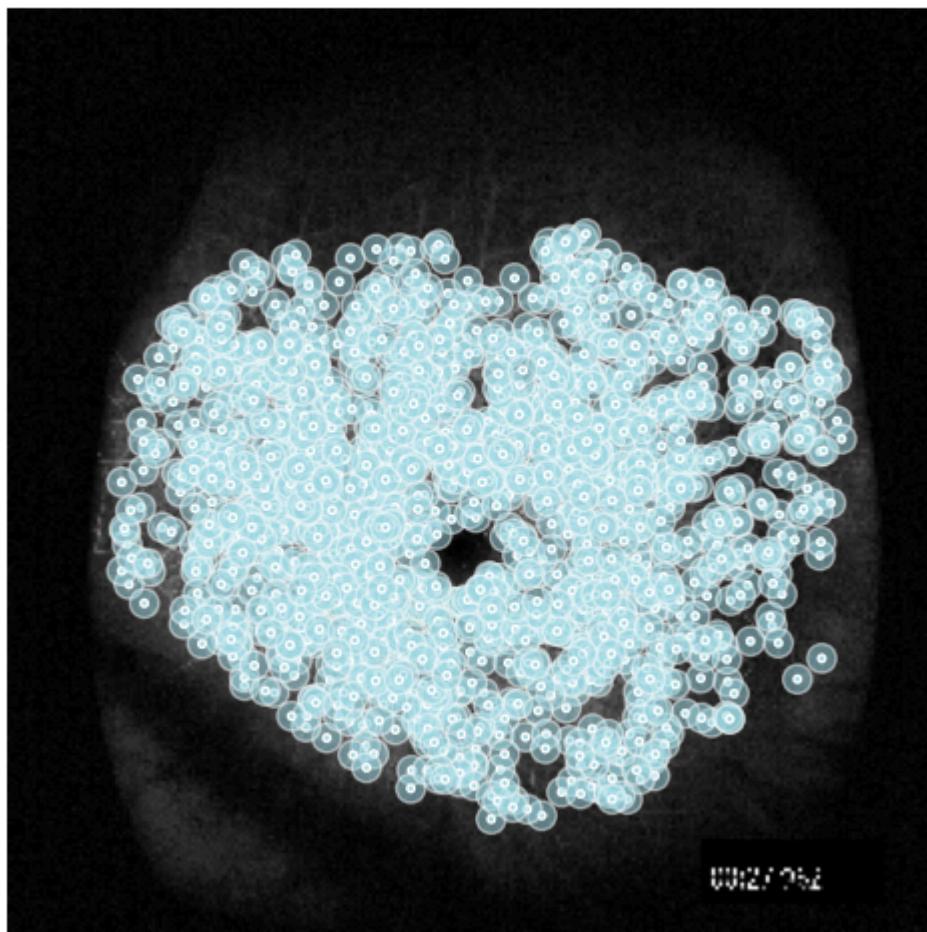
Iteration 5

```
Loading Source Images /blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_4/Montage/Montage_Subject_4.tif ,Target Image/blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_4/FA/Raw_FA_1_Subject_4.tif to the framework
```

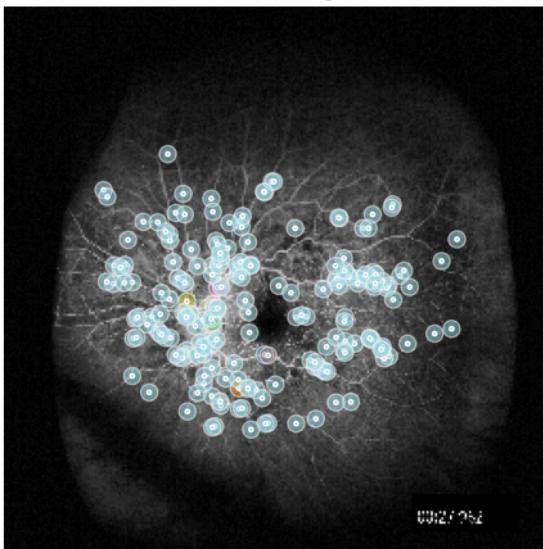
```
Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
```

207

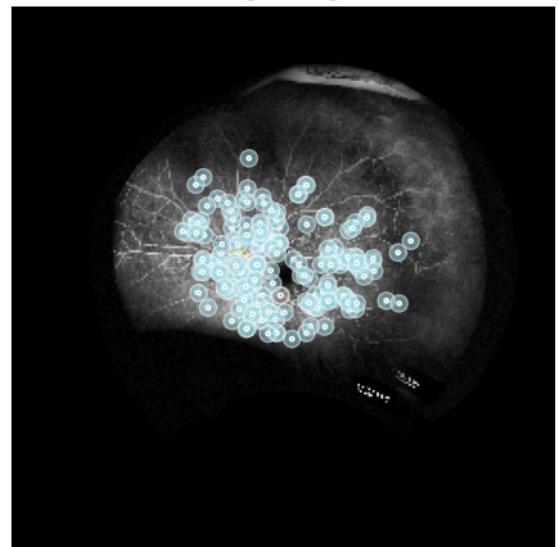
Chosen Keypoints



Source Image



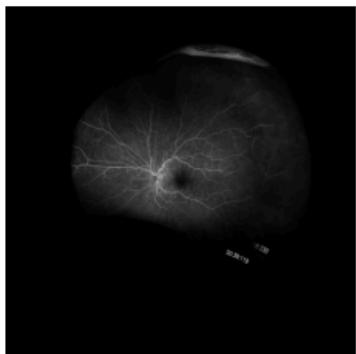
Target Image



Homography Matrix:

```
[[ 7.10751419e-01 -1.05944534e-02  2.36522902e+02]
 [ 1.49087923e-01  7.52782504e-01  5.38568251e+01]
 [ 6.36777932e-05  1.74113686e-04  1.00000000e+00]]
```

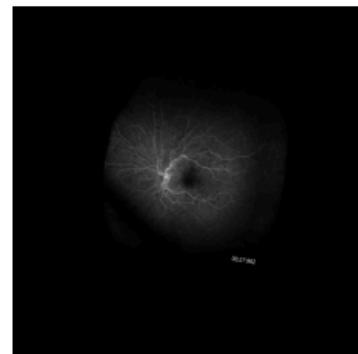
Fixed Image



Moving Image



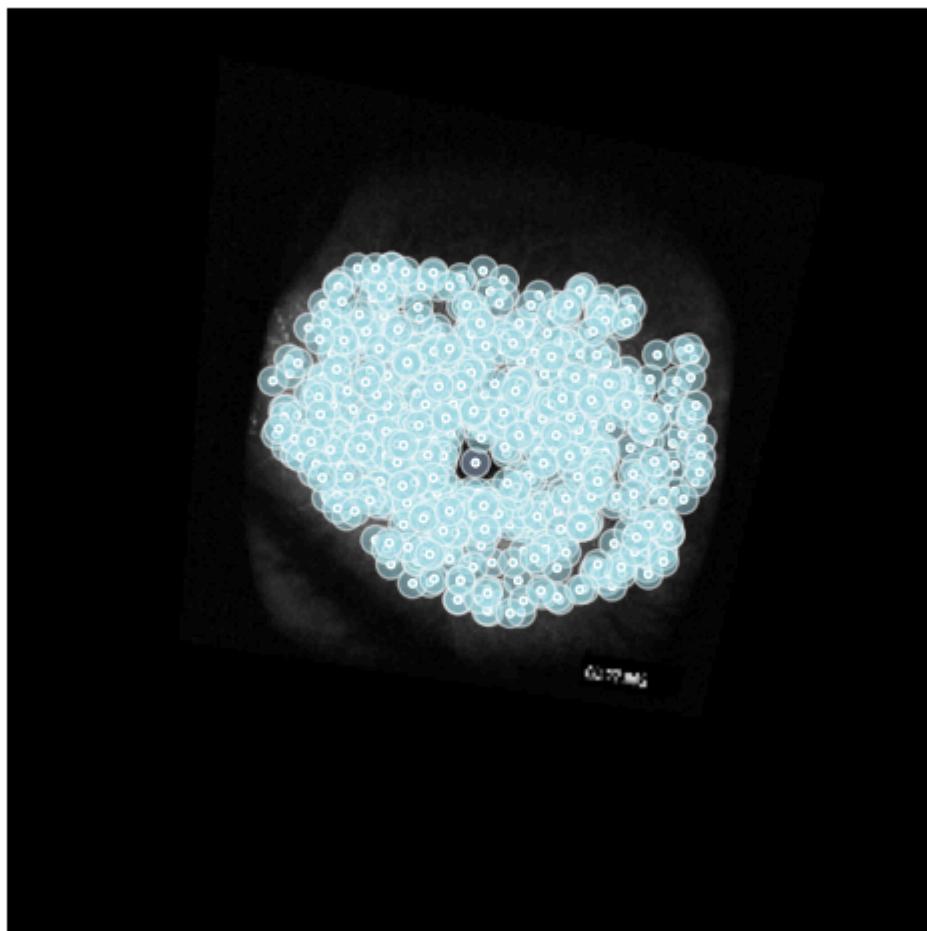
Deformed Image

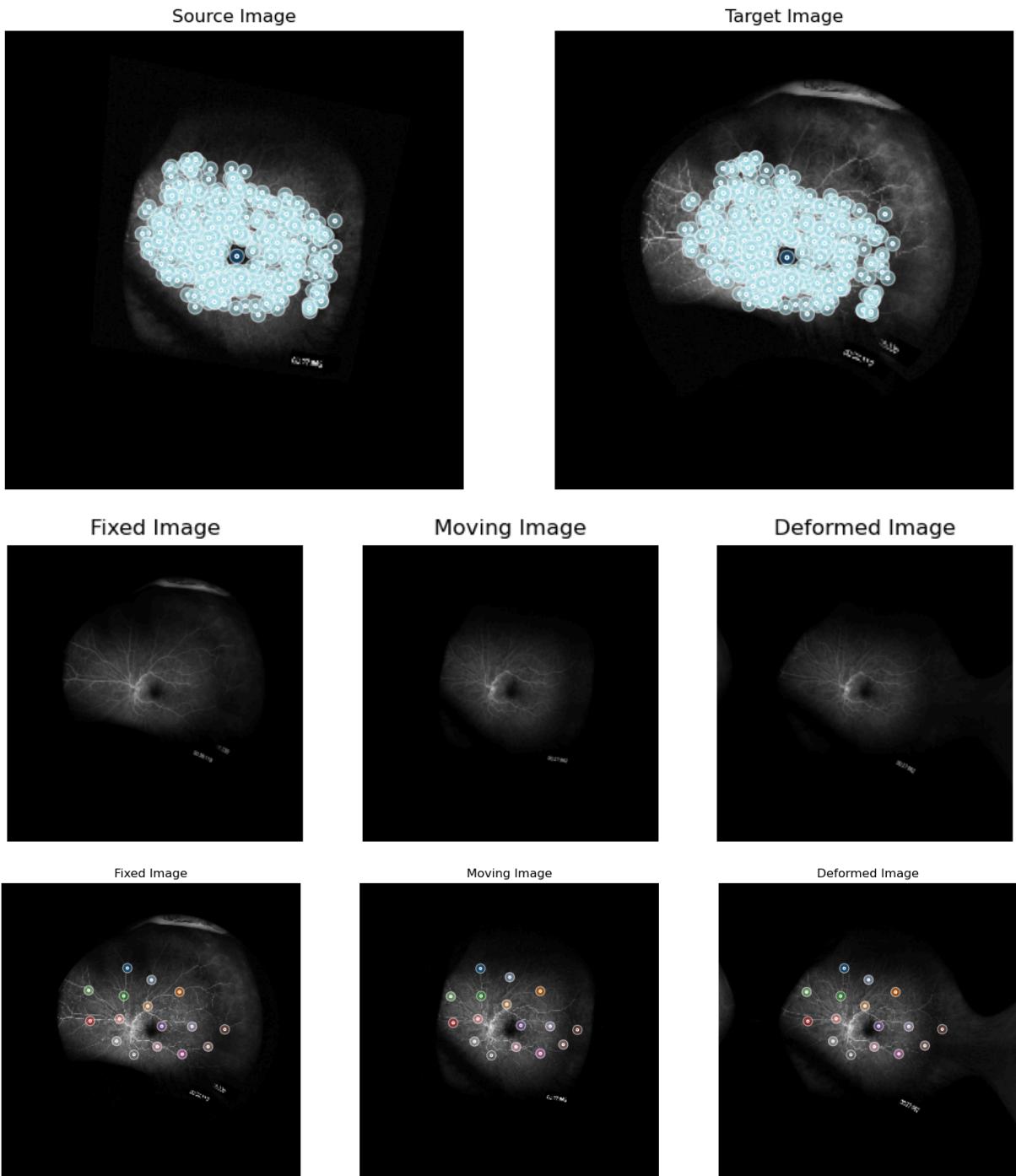


Maximum attempts reached, unable to find sufficient points with the specified criteria.

Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
497

Chosen Keypoints





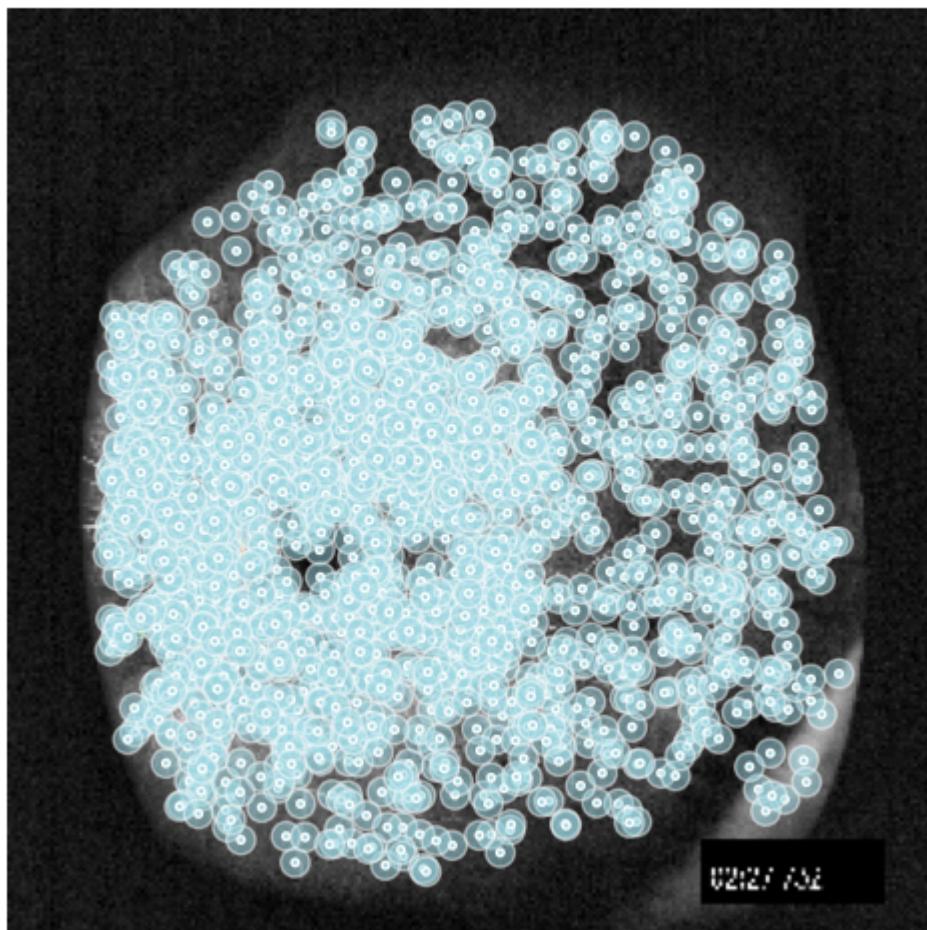
Recorded Landmark Error for Iteration 5 is 6.759529169360167

Iteration 6

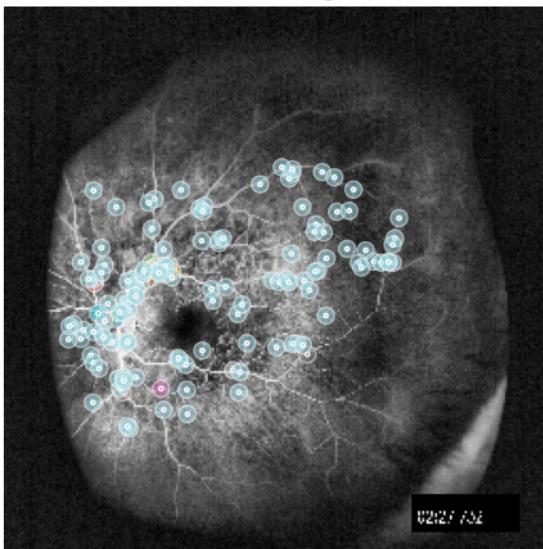
```
Loading Source Images /blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_4/Montage/Montage_Subject_4.tif ,Target Image/blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_4/FA/Raw_FA_2_Subject_4.tif to the framework
Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
```

138

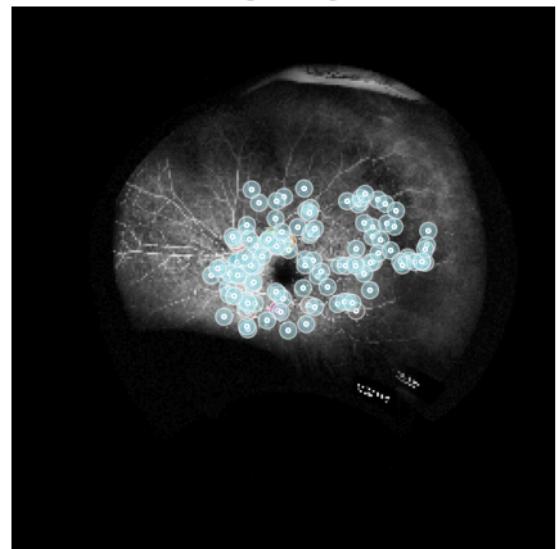
Chosen Keypoints



Source Image

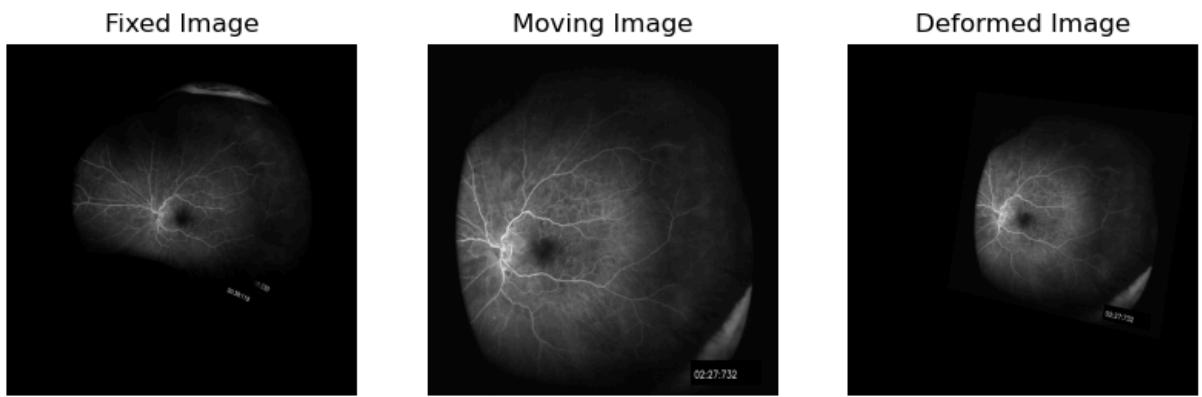


Target Image



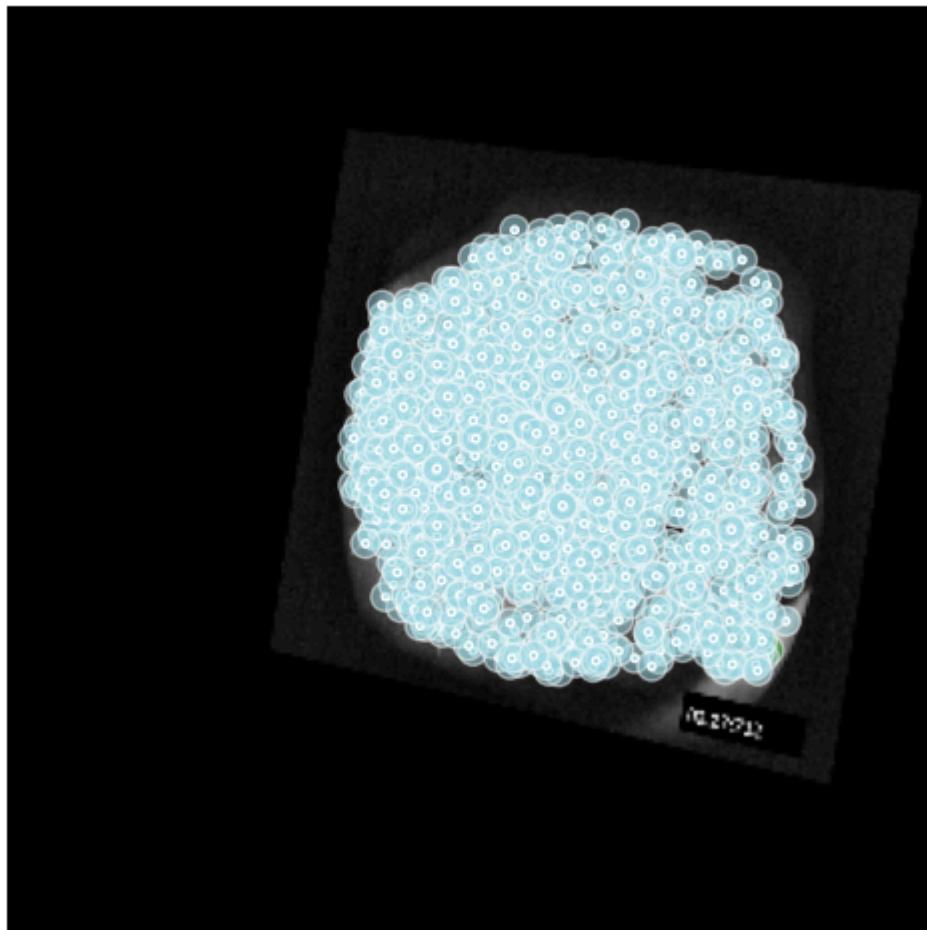
Homography Matrix:

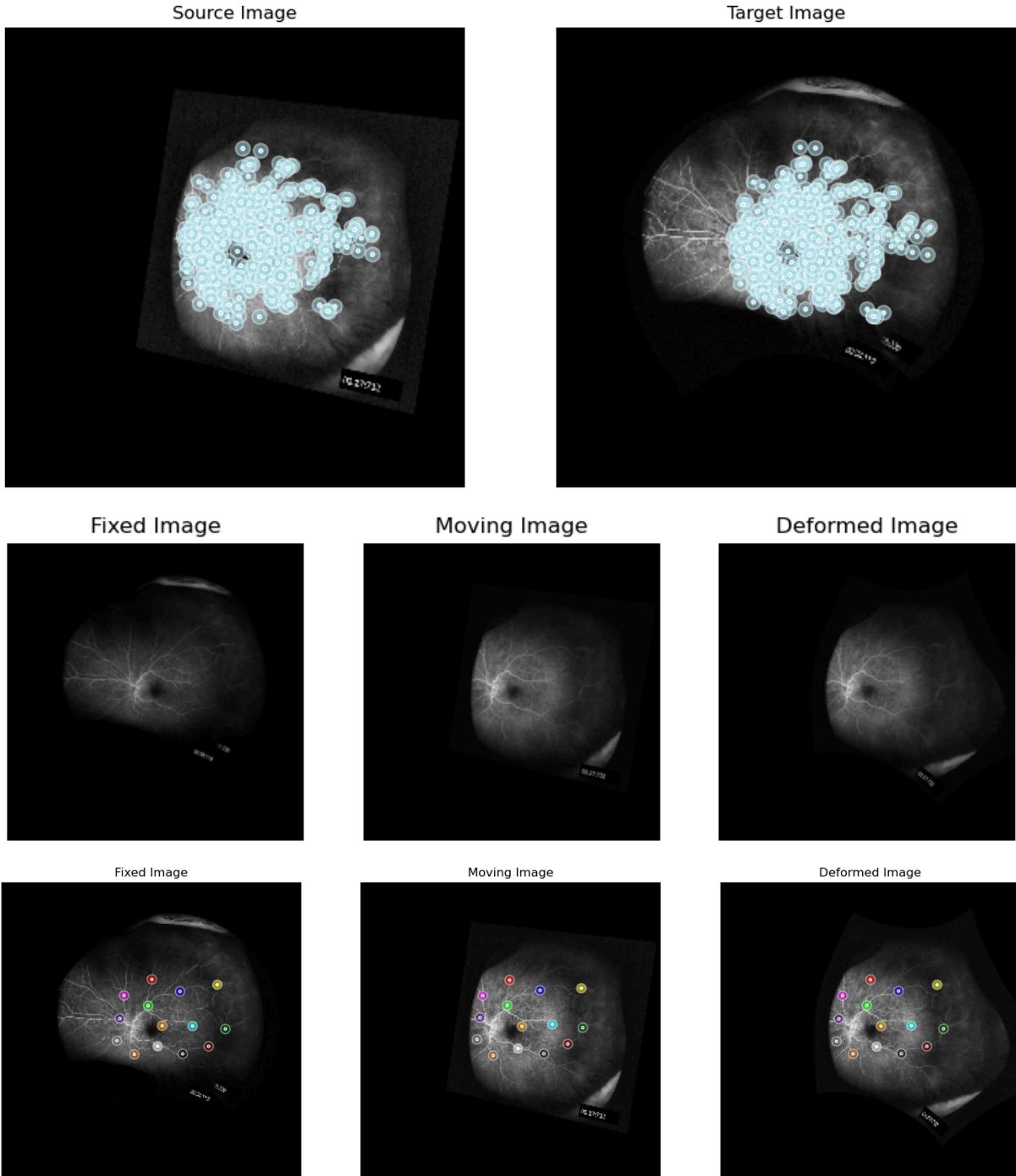
```
[[ 5.0075555e-01 -8.19523012e-02  3.76277891e+02]
 [ 4.43979272e-02  5.66042031e-01  1.36262431e+02]
 [-1.18480918e-04  4.92888940e-06  1.00000000e+00]]
```



Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
507

Chosen Keypoints





Recorded Landmark Error for Iteration 6 is 7.769554363418775

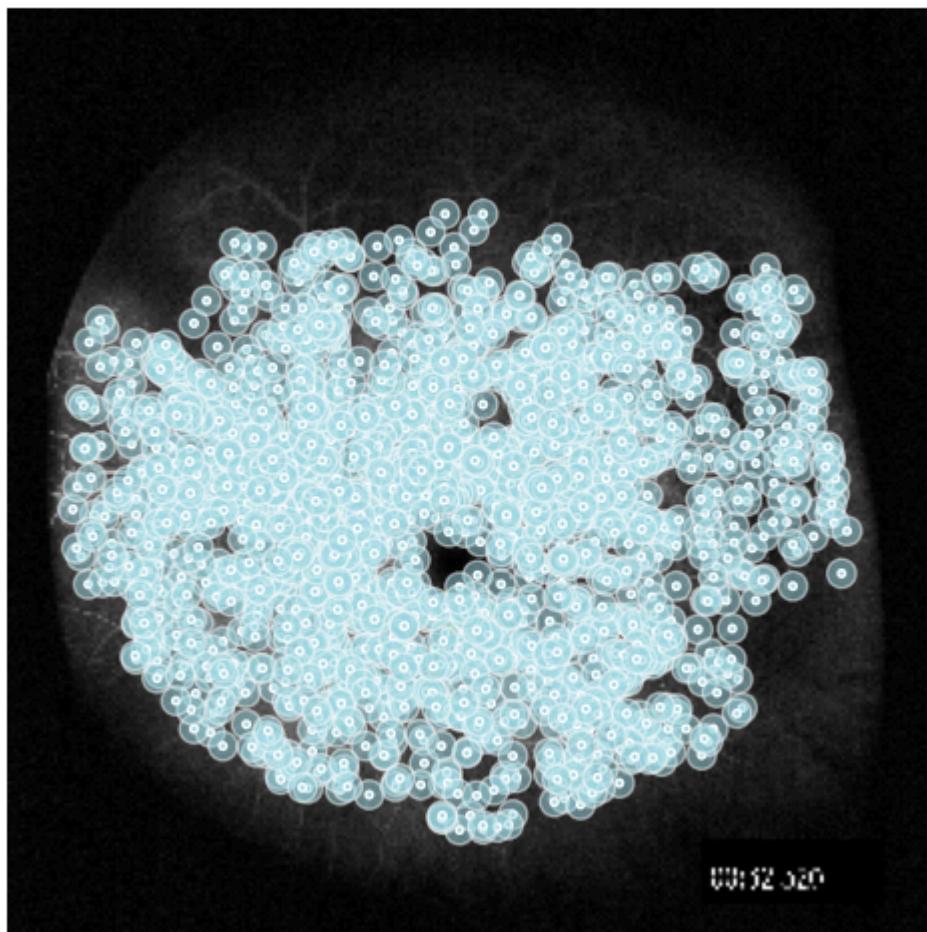
Iteration 7

```
Loading Source Images /blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_4/Montage/Montage_Subject_4.tif ,Target Image/blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_4/FA/Raw_FA_3_Subject_4.tif to the framework
```

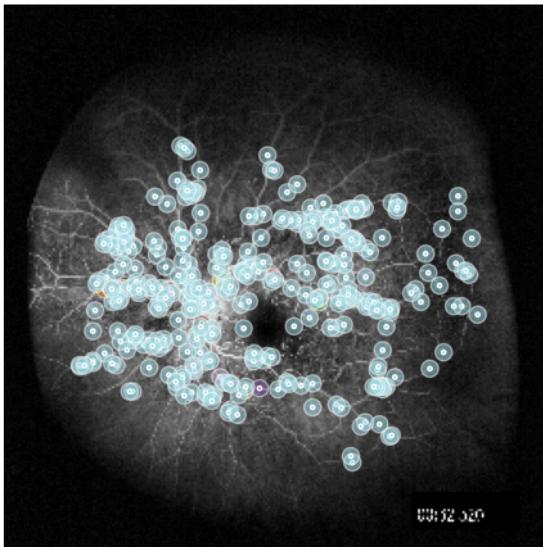
```
Loading pipeline components...: 0%| 0/6 [00:00<?, ?it/s]
```

346

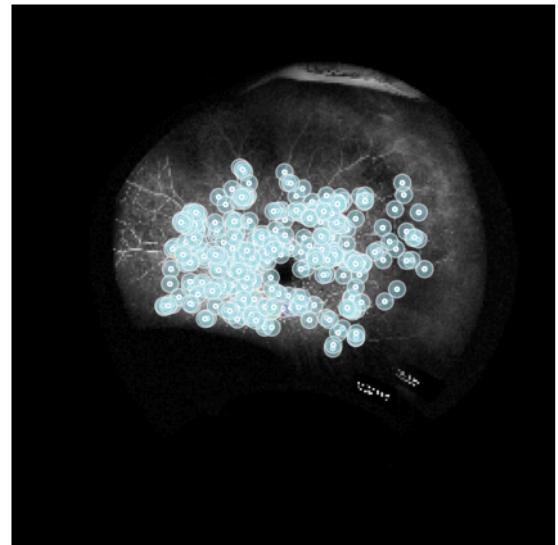
Chosen Keypoints



Source Image



Target Image

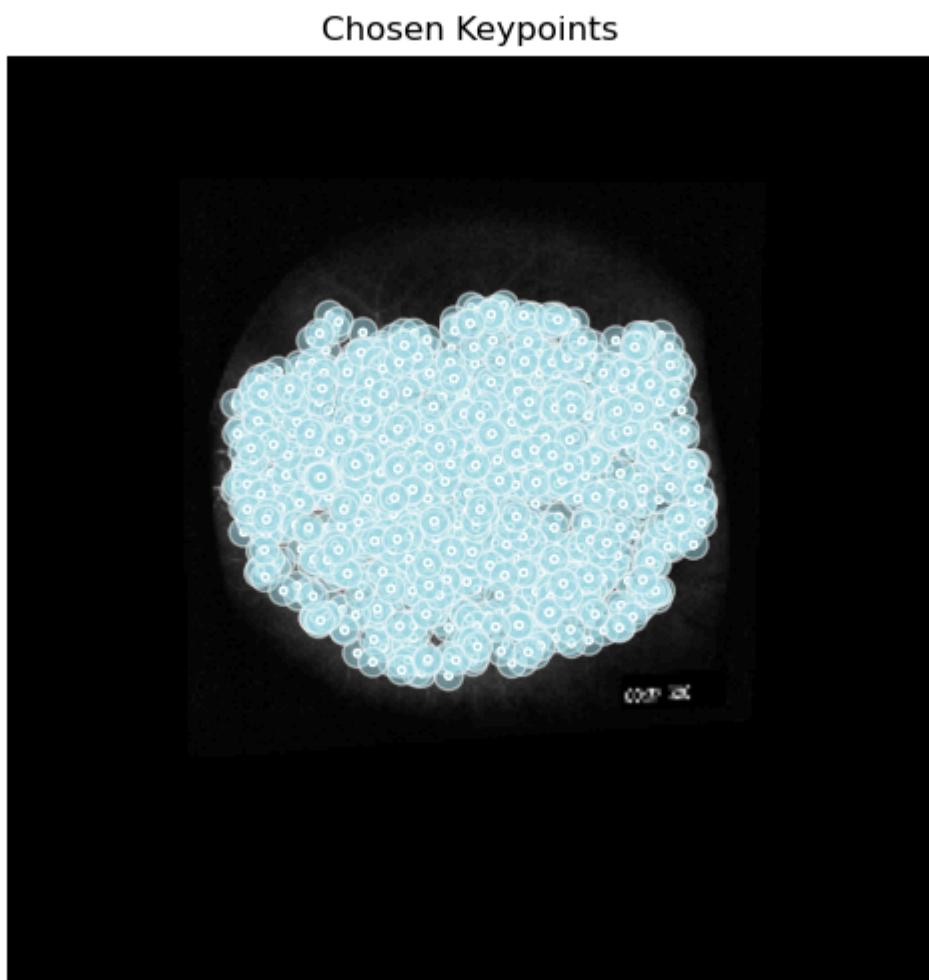


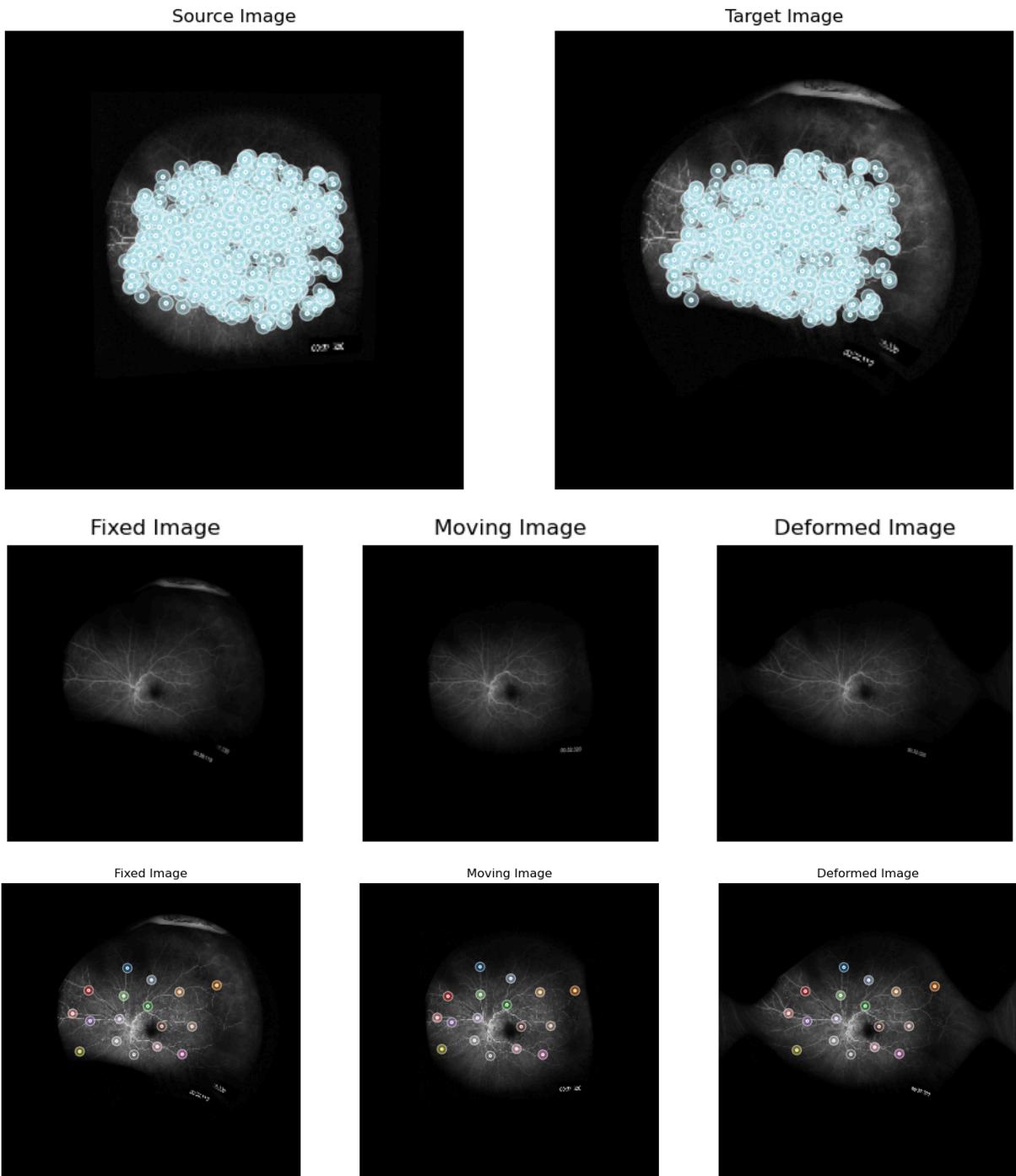
Homography Matrix:

```
[[7.03264585e-01 1.98972435e-02 1.90334265e+02]
 [1.67179000e-02 6.60301667e-01 1.35100557e+02]
 [8.23555659e-05 4.32838897e-05 1.00000000e+00]]
```



Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
840





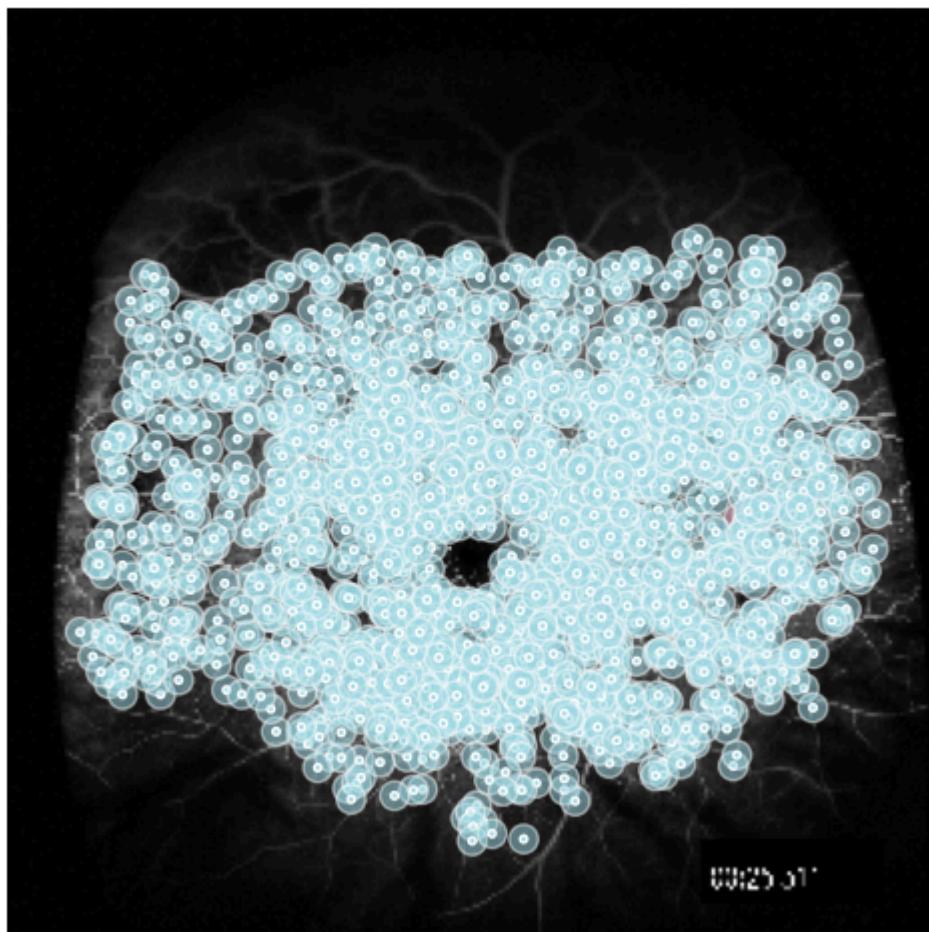
Recorded Landmark Error for Iteration 7 is 14.708587917366152

Iteration 8

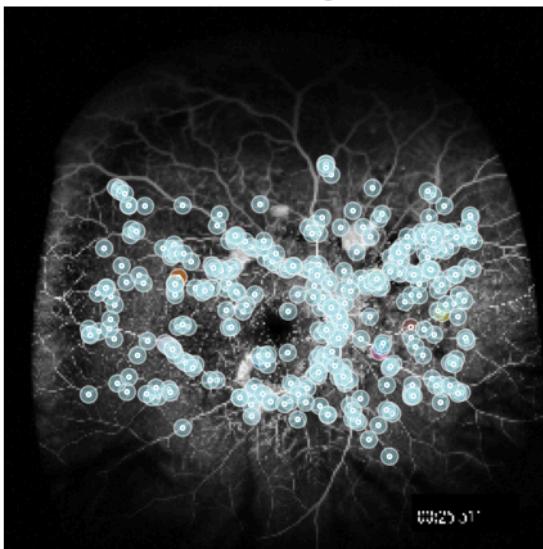
```
Loading Source Images /blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_3/Montage/Montage_Subject_3.tif ,Target Image/blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_3/FA/Raw_FA_1_Subject_3.tif to the framework
Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
```

361

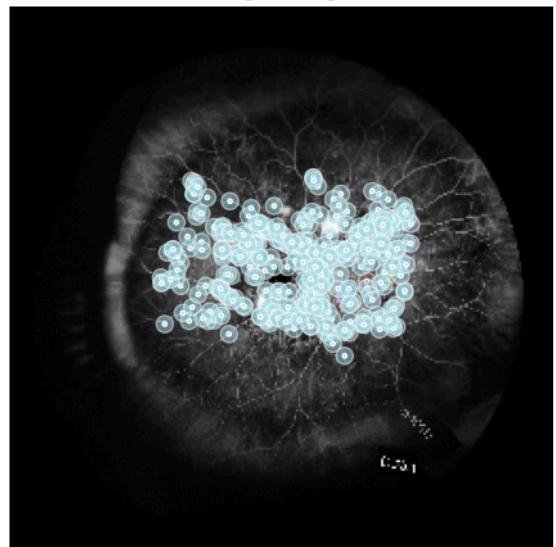
Chosen Keypoints



Source Image

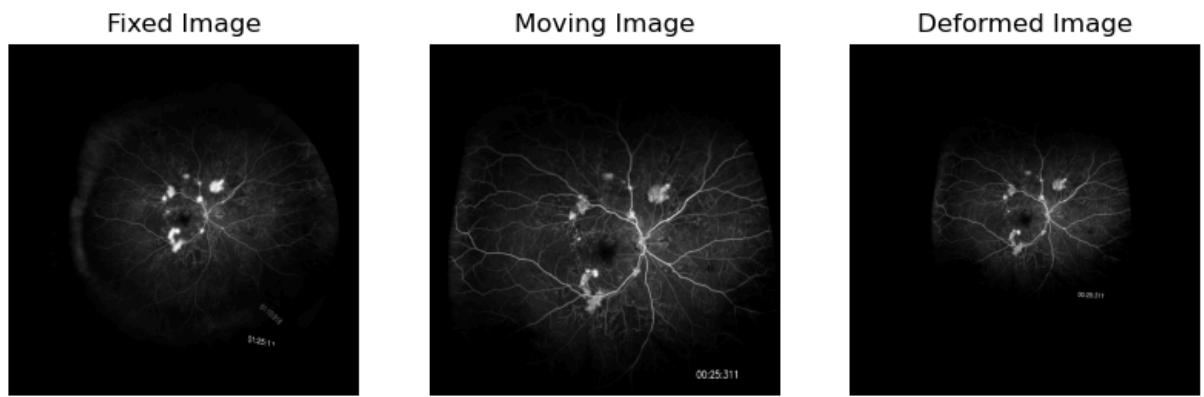


Target Image



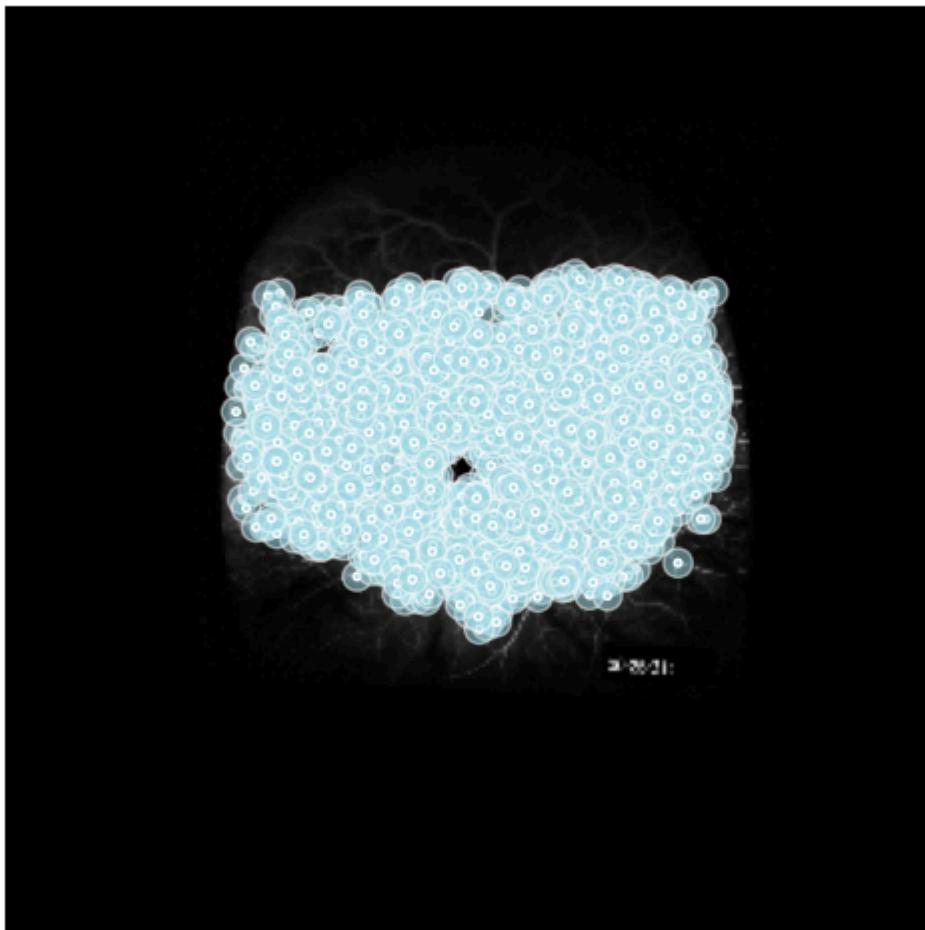
Homography Matrix:

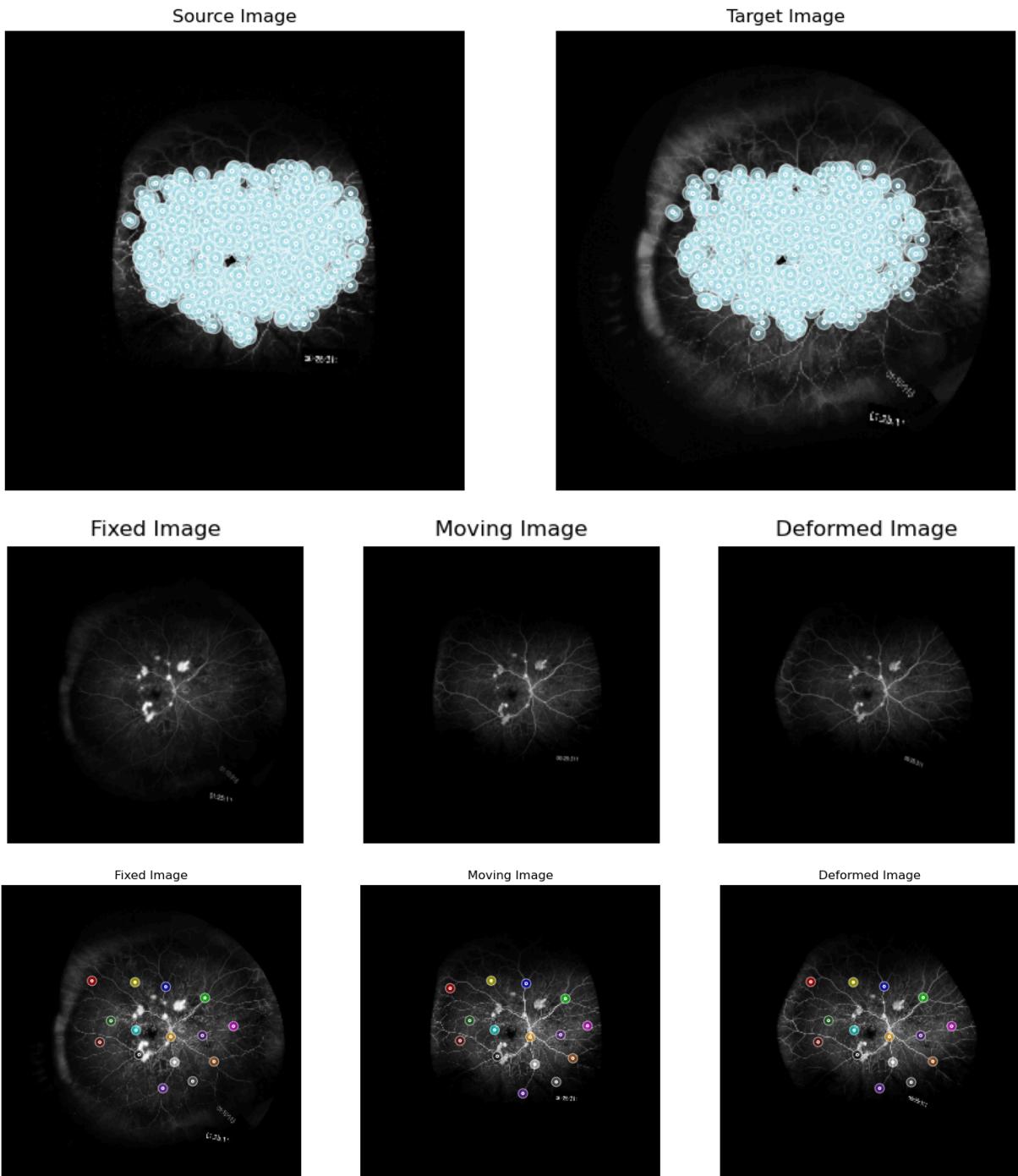
```
[[ 5.95139254e-01  3.16401047e-02  1.99392701e+02]
 [-1.22940162e-02  6.66896211e-01  1.25509137e+02]
 [-6.18260419e-05  9.10222909e-05  1.00000000e+00]]
```



Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
1208

Chosen Keypoints





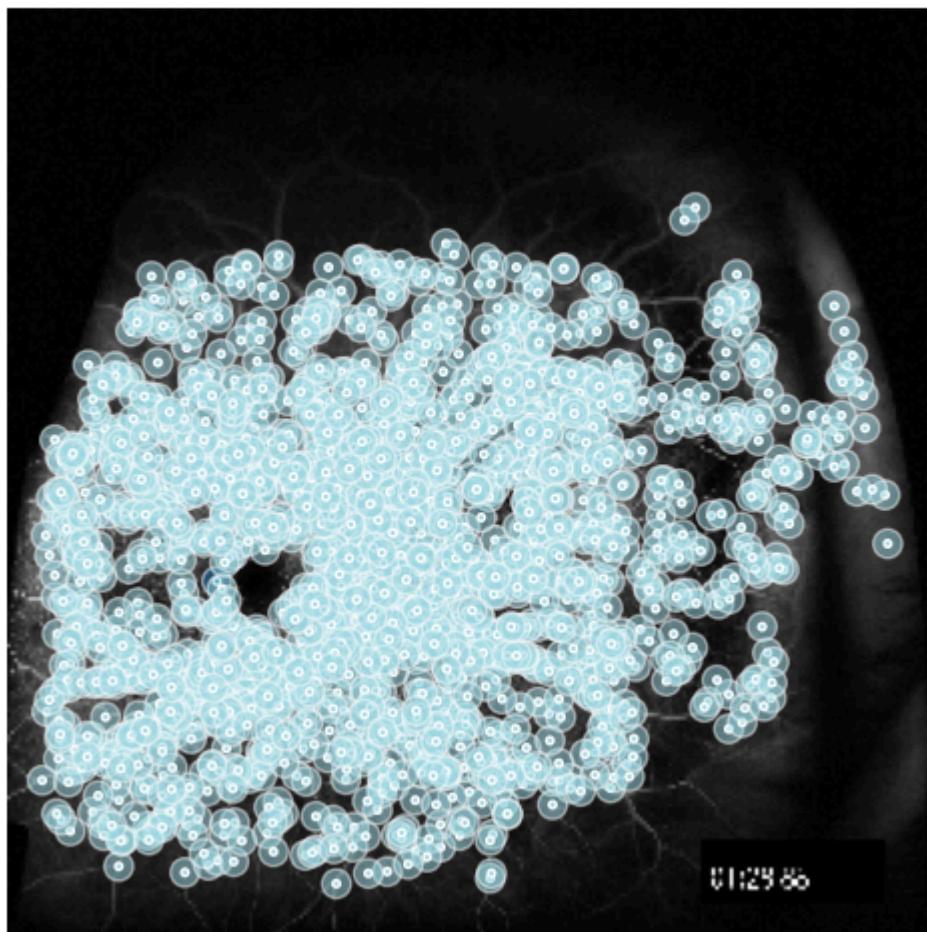
Recorded Landmark Error for Iteration 8 is 19.67213024057926

Iteration 9

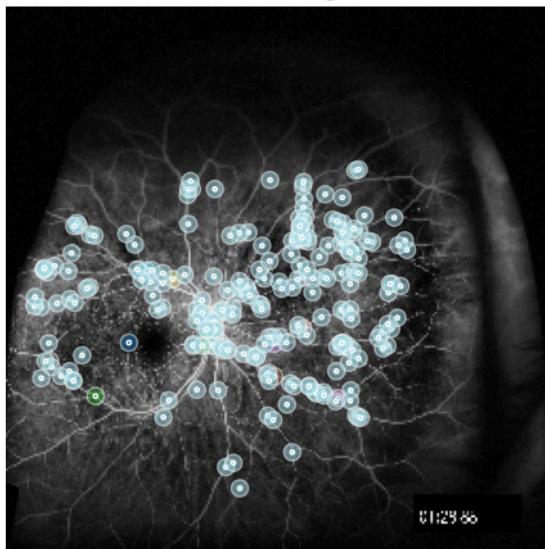
```
Loading Source Images /blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_3/Montage/Montage_Subject_3.tif ,Target Image/blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_3/FA/Raw_FA_2_Subject_3.tif to the framework
Loading pipeline components...:    0%|          | 0/6 [00:00<?, ?it/s]
```

240

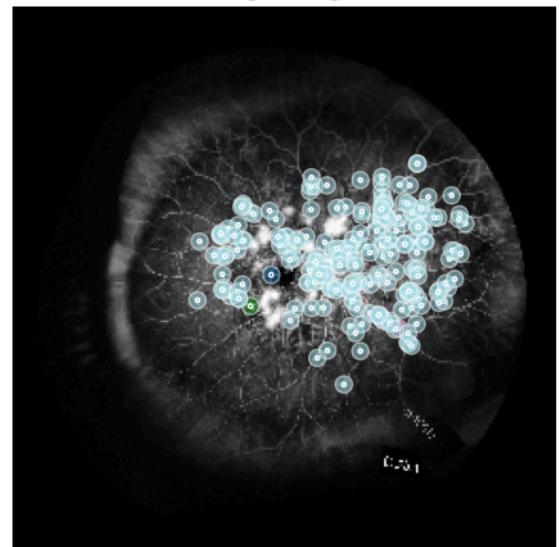
Chosen Keypoints



Source Image

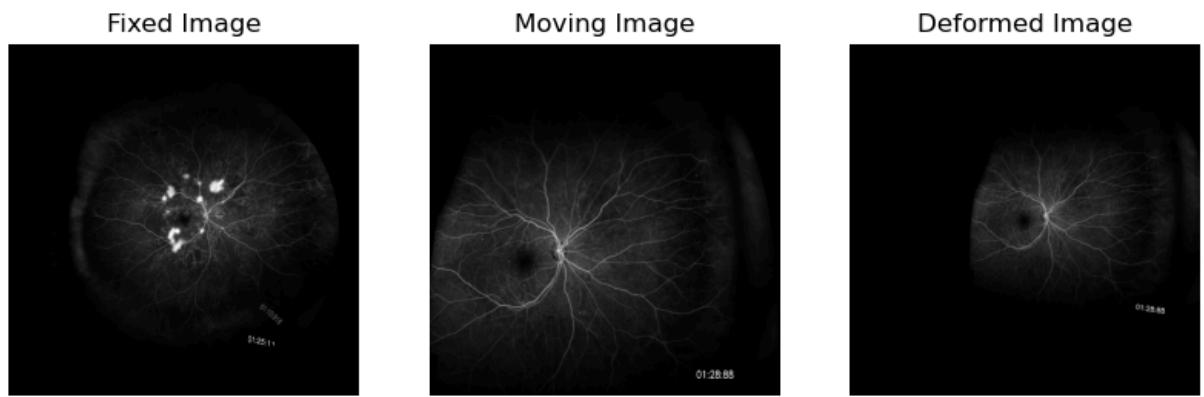


Target Image



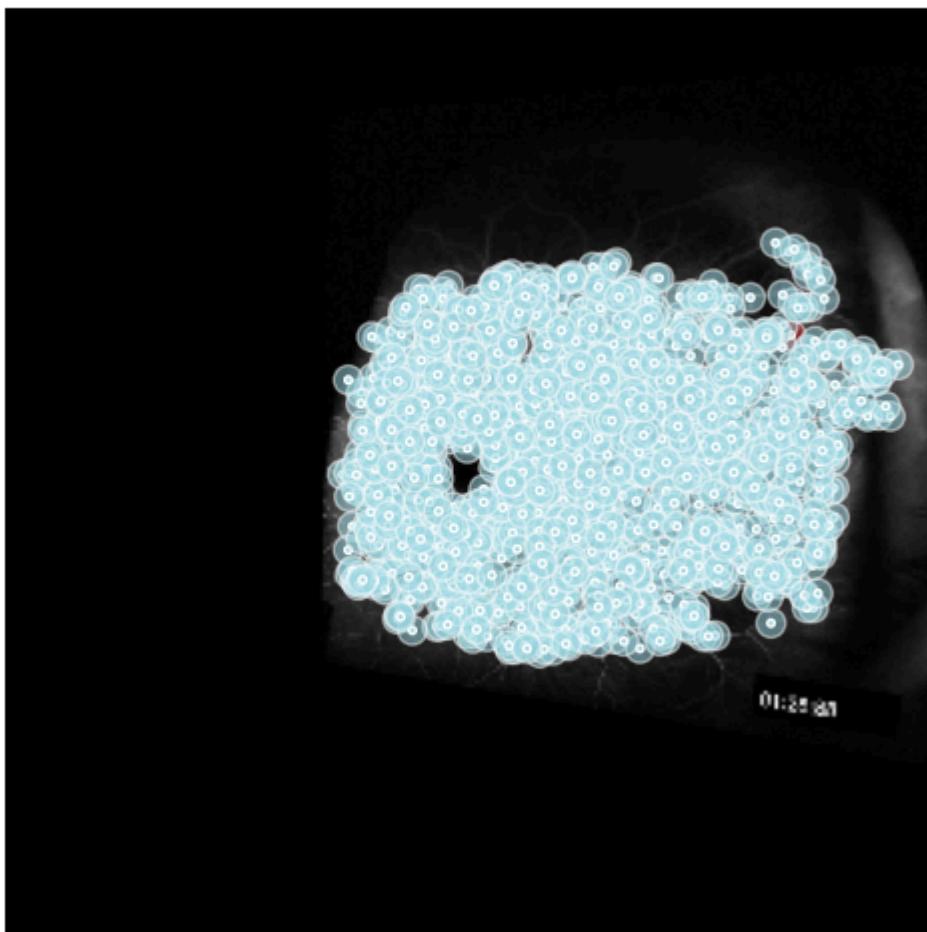
Homography Matrix:

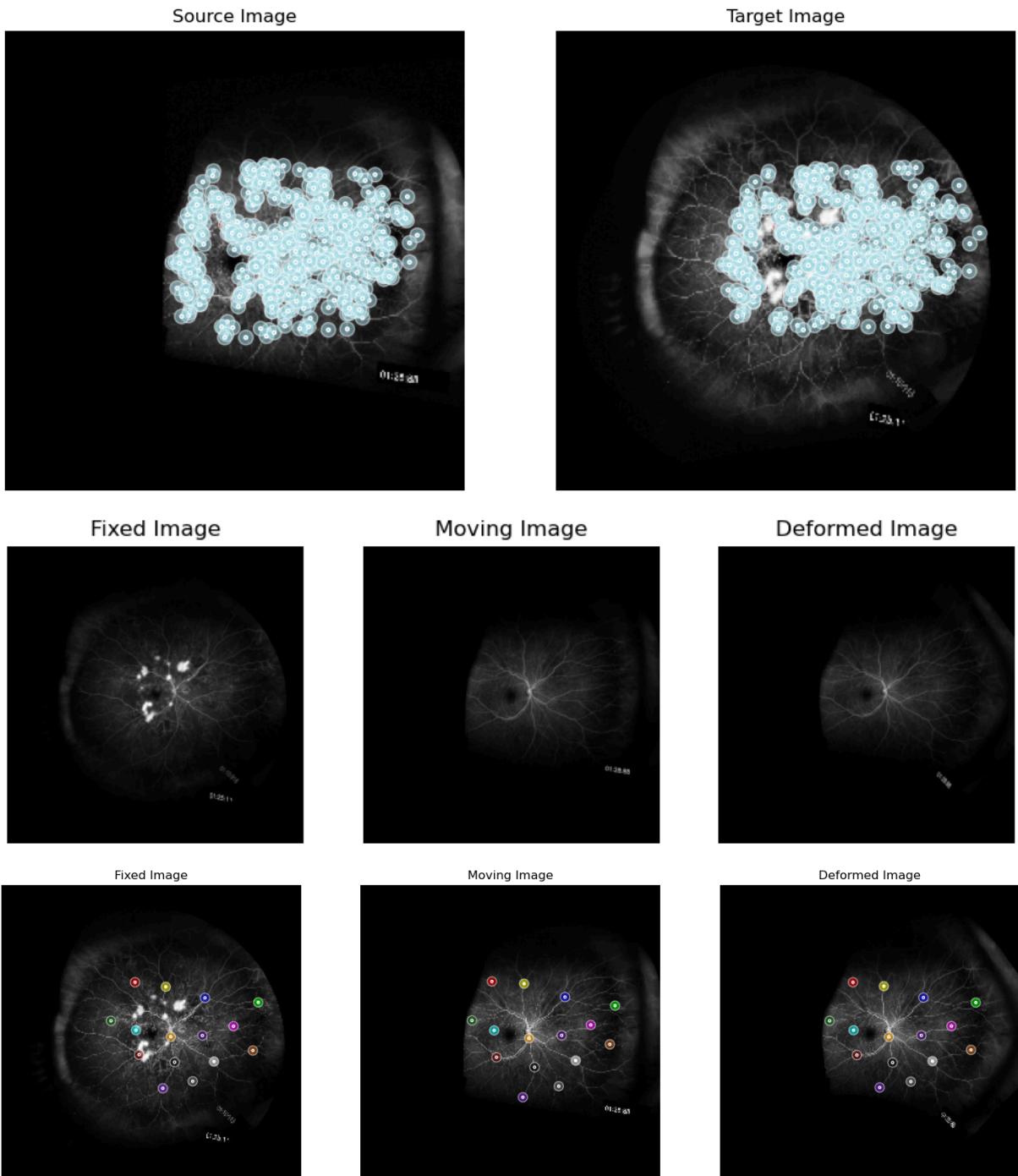
```
[[ 4.71634809e-01  1.56899535e-02  3.60032279e+02]
 [-7.84514268e-02  6.46447194e-01  1.17906857e+02]
 [-2.38292830e-04  7.63805793e-05  1.00000000e+00]]
```



Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
573

Chosen Keypoints





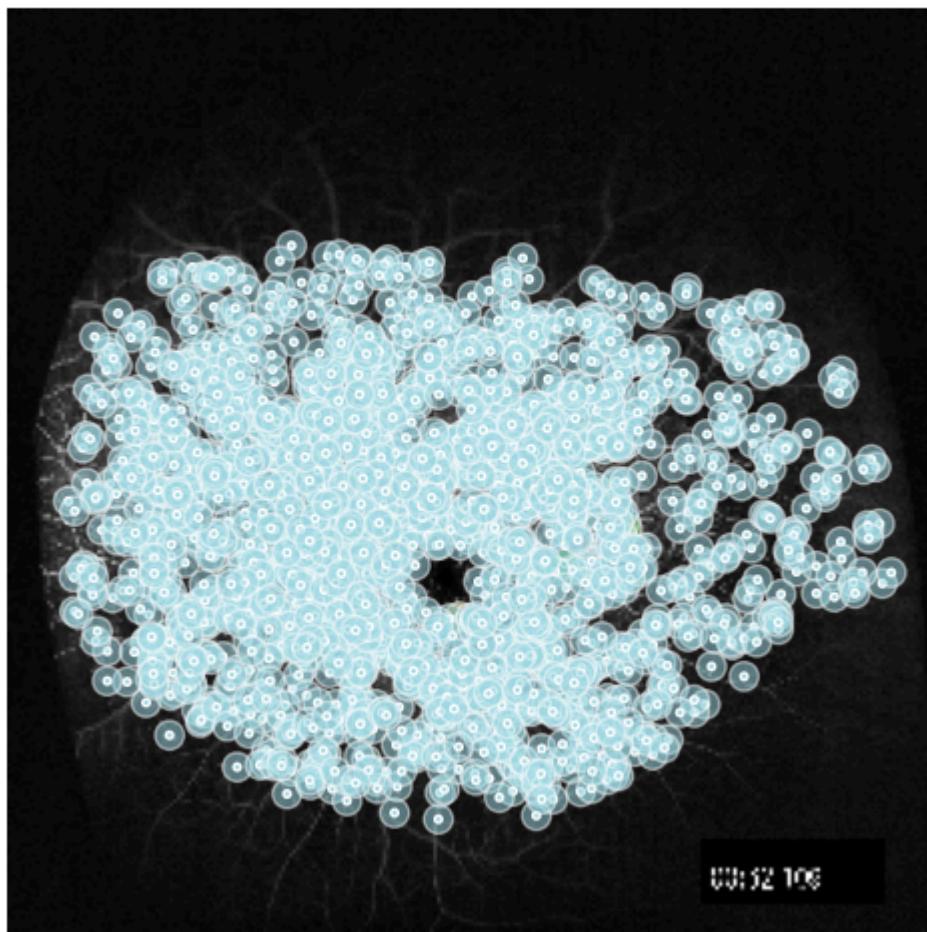
Recorded Landmark Error for Iteration 9 is 11.877064069272913

Iteration 10

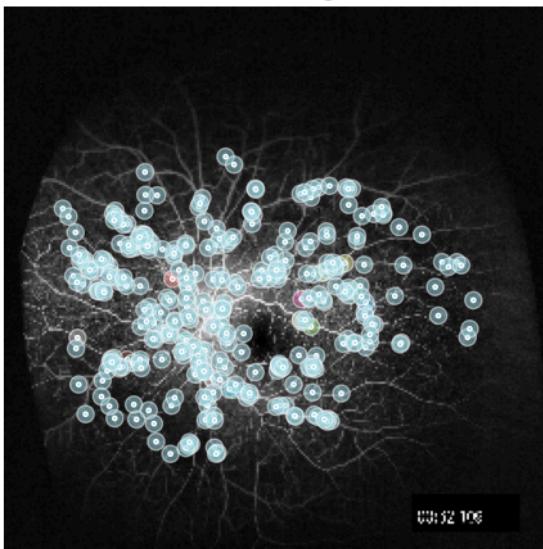
```
Loading Source Images /blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_1/Montage/Montage_Subject_1.tif ,Target Image/blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_1/FA/Raw_FA_1_Subject_1.tif to the framework
Loading pipeline components...: 0%| 0/6 [00:00<?, ?it/s]
```

331

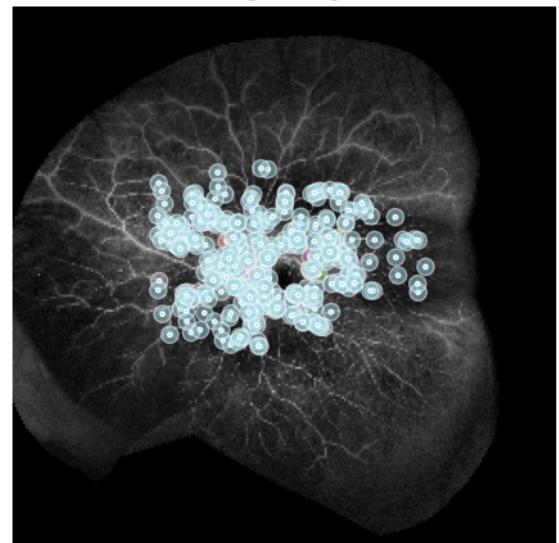
Chosen Keypoints



Source Image

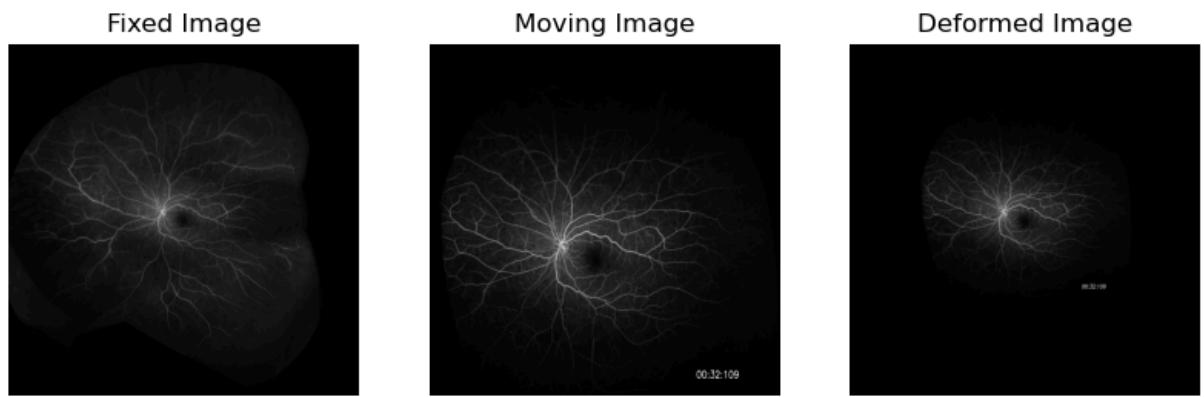


Target Image

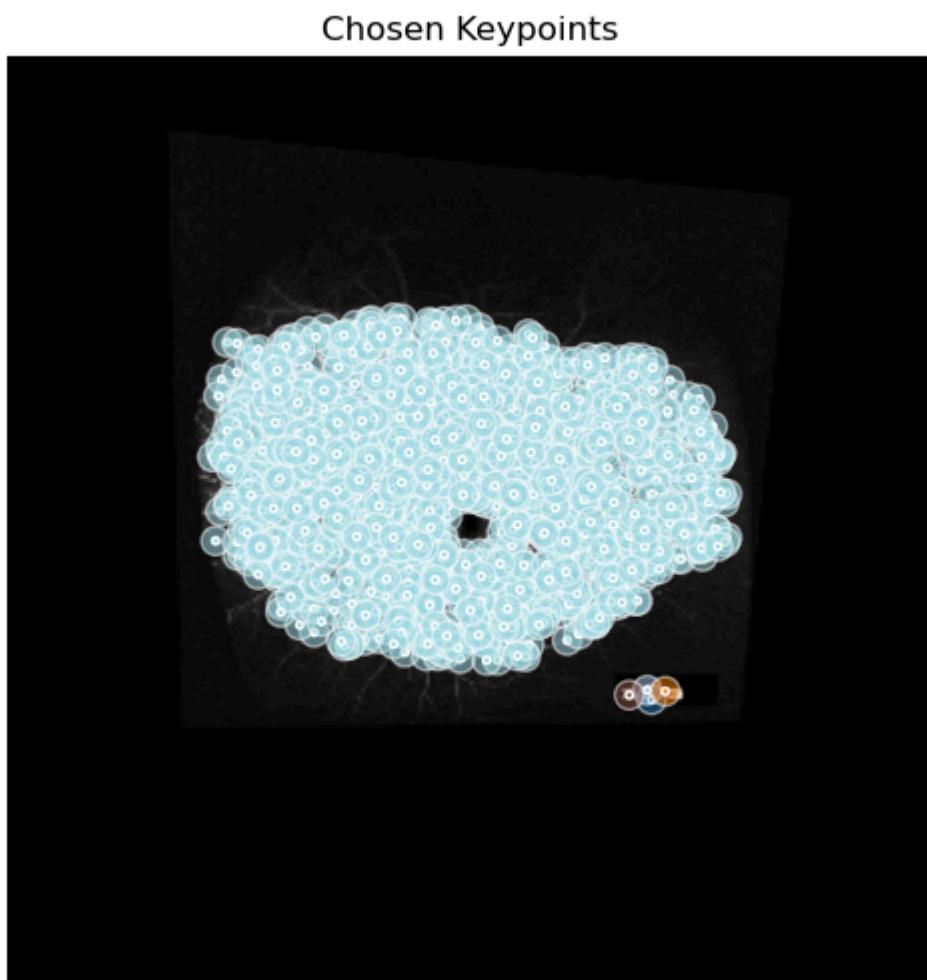


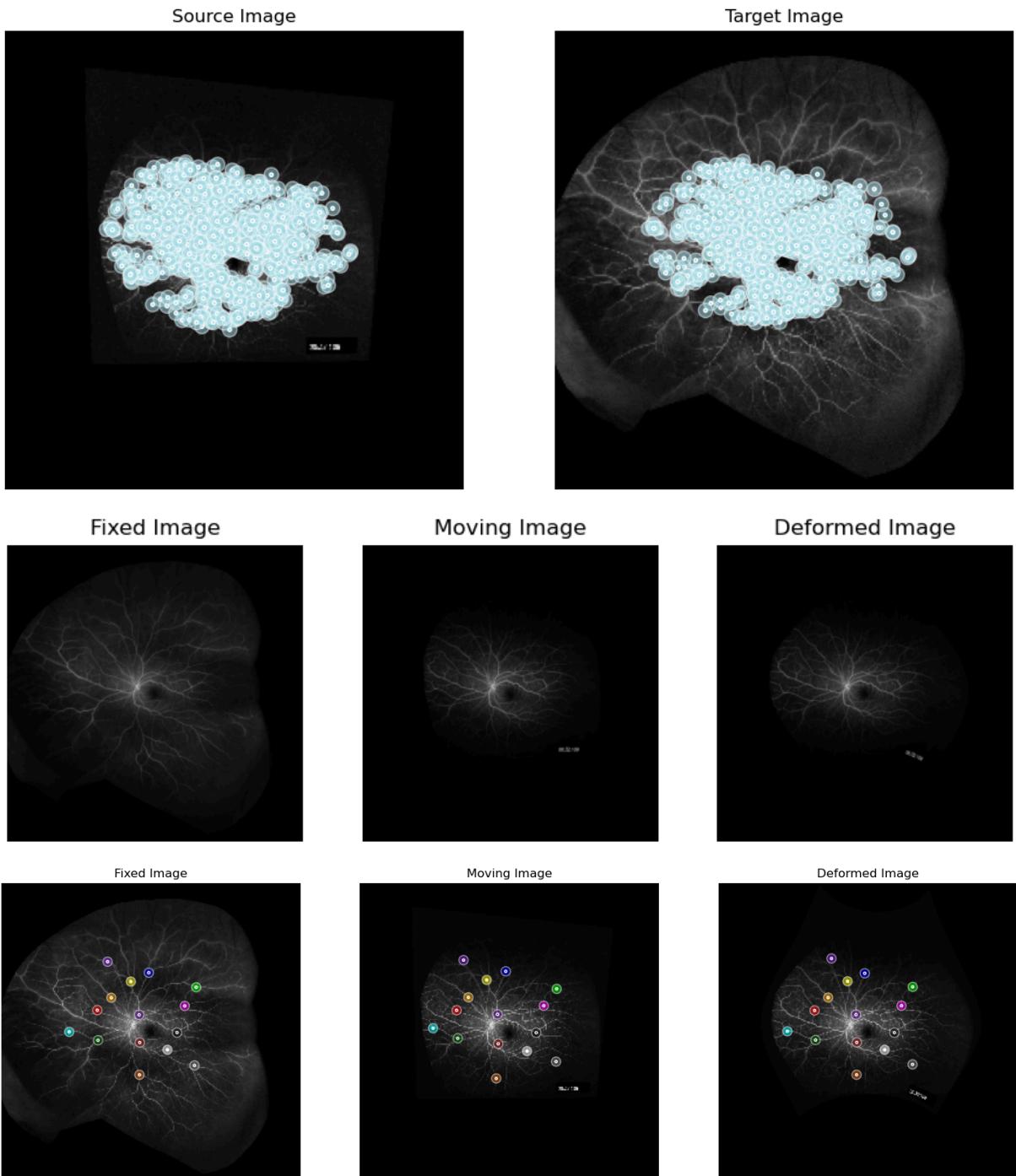
Homography Matrix:

```
[[7.92116801e-01 3.93065893e-02 1.78313558e+02]
 [9.35385789e-02 7.39573886e-01 8.18451278e+01]
 [1.37492727e-04 1.25432925e-04 1.00000000e+00]]
```



Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
882





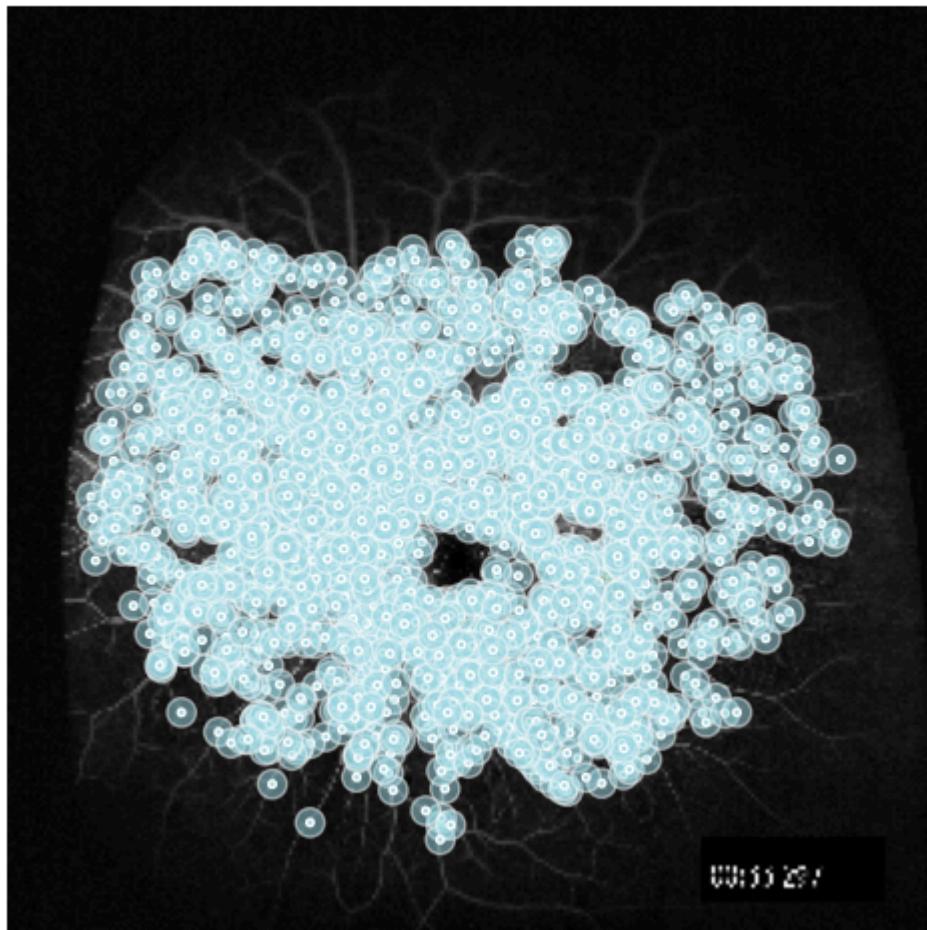
Recorded Landmark Error for Iteration 10 is 16.697139474300744

Iteration 11

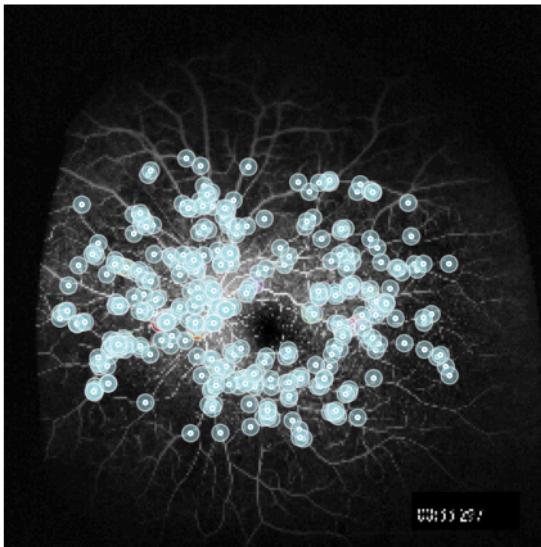
```
Loading Source Images /blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_1/Montage/Montage_Subject_1.tif ,Target Image/blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_1/FA/Raw_FA_2_Subject_1.tif to the framework
Loading pipeline components...: 0%| 0/6 [00:00<?, ?it/s]
```

358

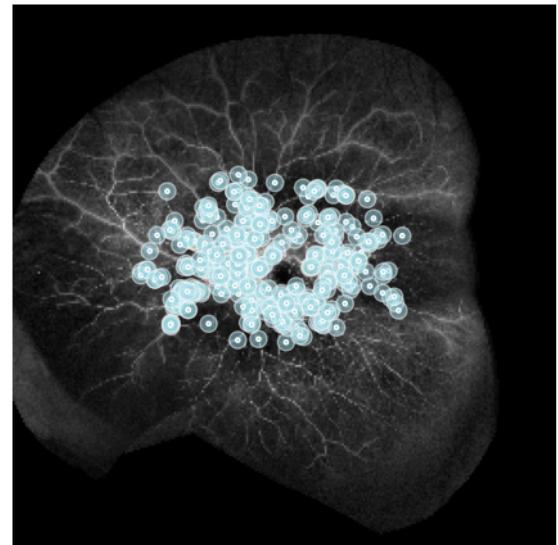
Chosen Keypoints



Source Image

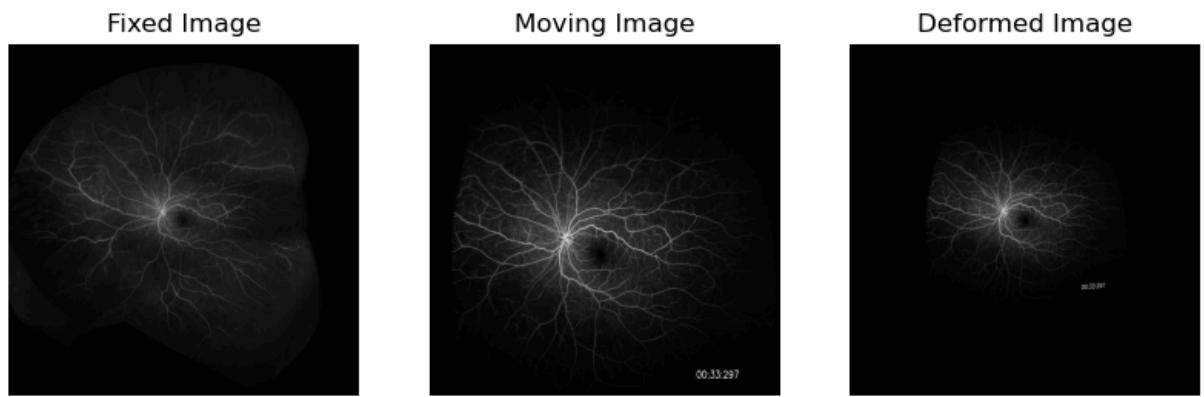


Target Image

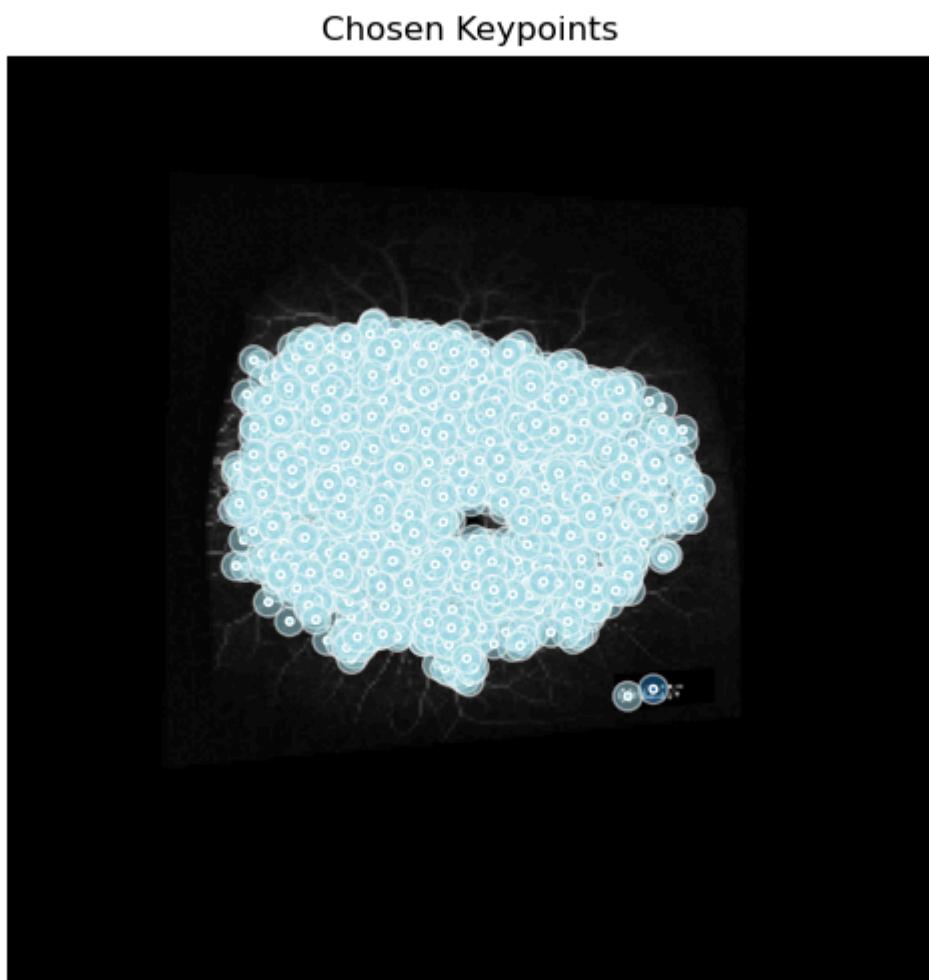


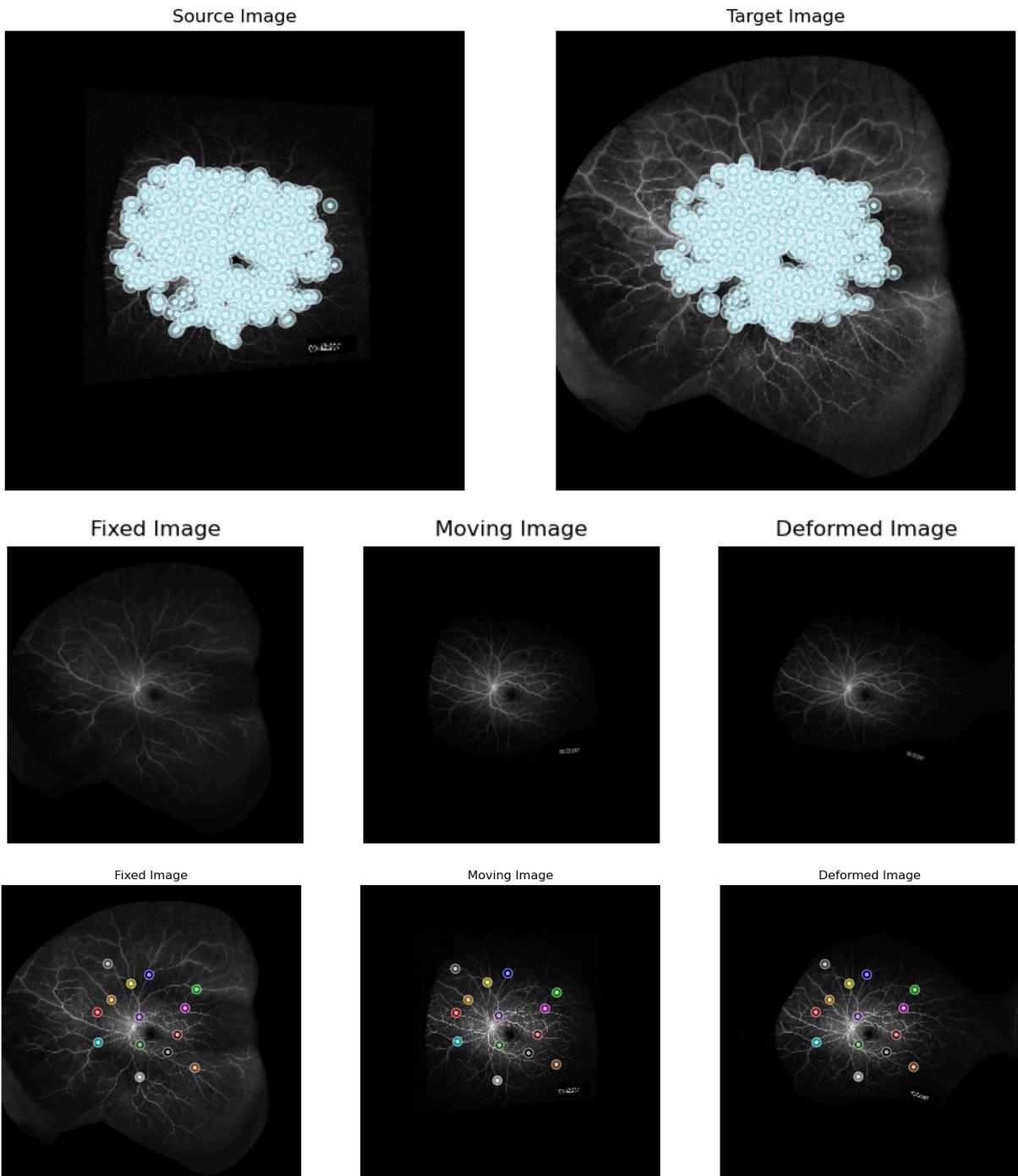
Homography Matrix:

```
[ [ 7.62427676e-01 -7.93999848e-03 1.81686540e+02]
  [ 6.90747642e-02 6.44927869e-01 1.28282144e+02]
  [ 1.71301682e-04 8.61617945e-07 1.00000000e+00] ]
```



Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
1019





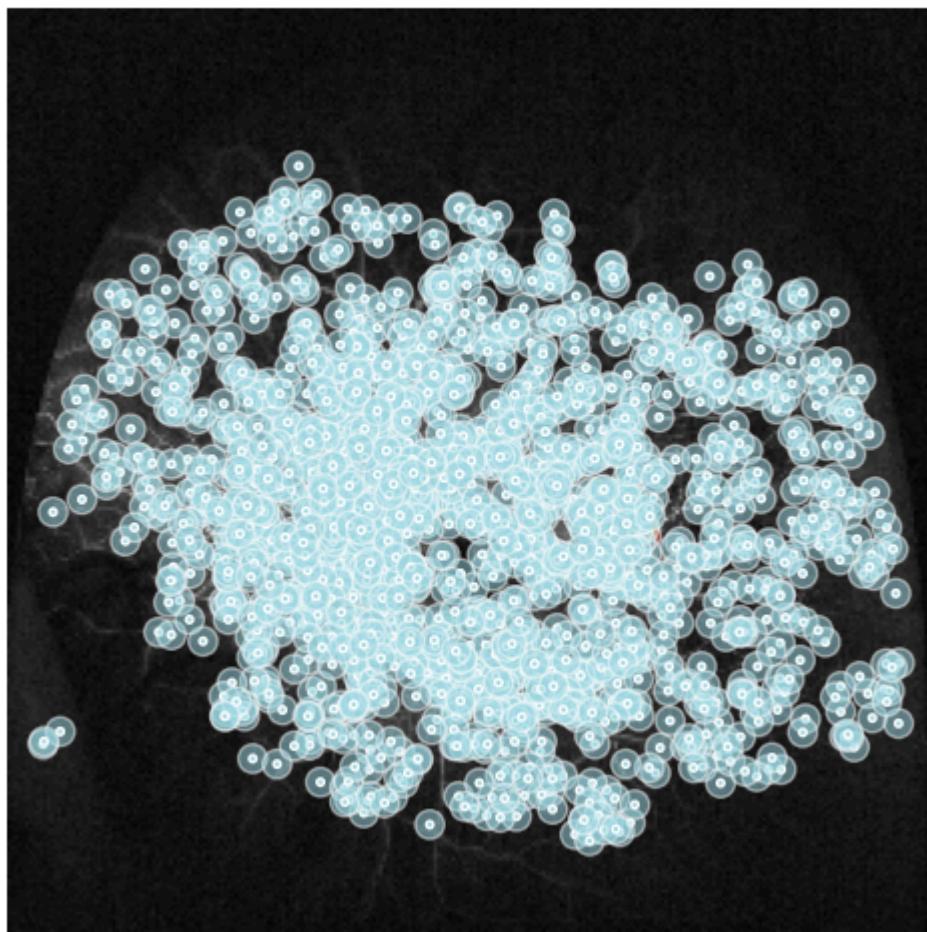
Recorded Landmark Error for Iteration 11 is 18.30264639174361

Iteration 12

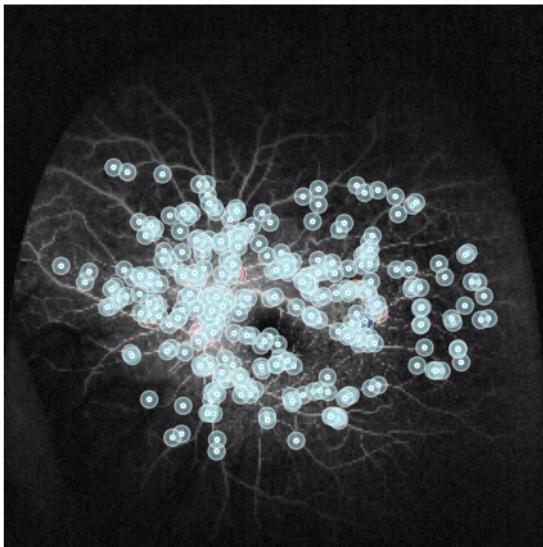
```
Loading Source Images /blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_1/Montage/Montage_Subject_1.tif ,Target Image/blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_1/FA/Raw_FA_3_Subject_1.tif to the framework
Loading pipeline components...:  0%|          | 0/6 [00:00<?, ?it/s]
```

337

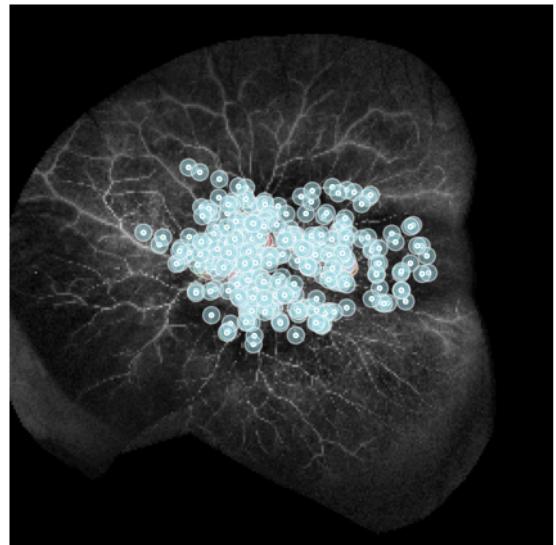
Chosen Keypoints



Source Image

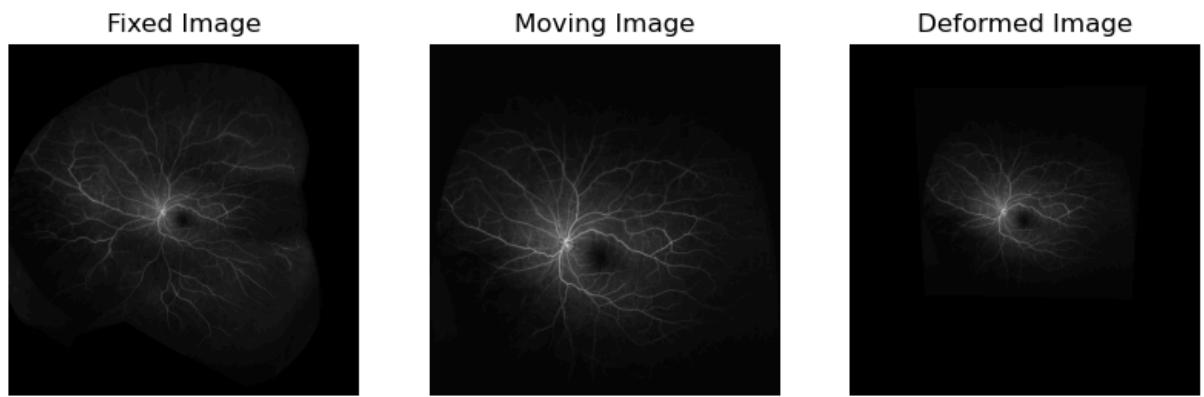


Target Image



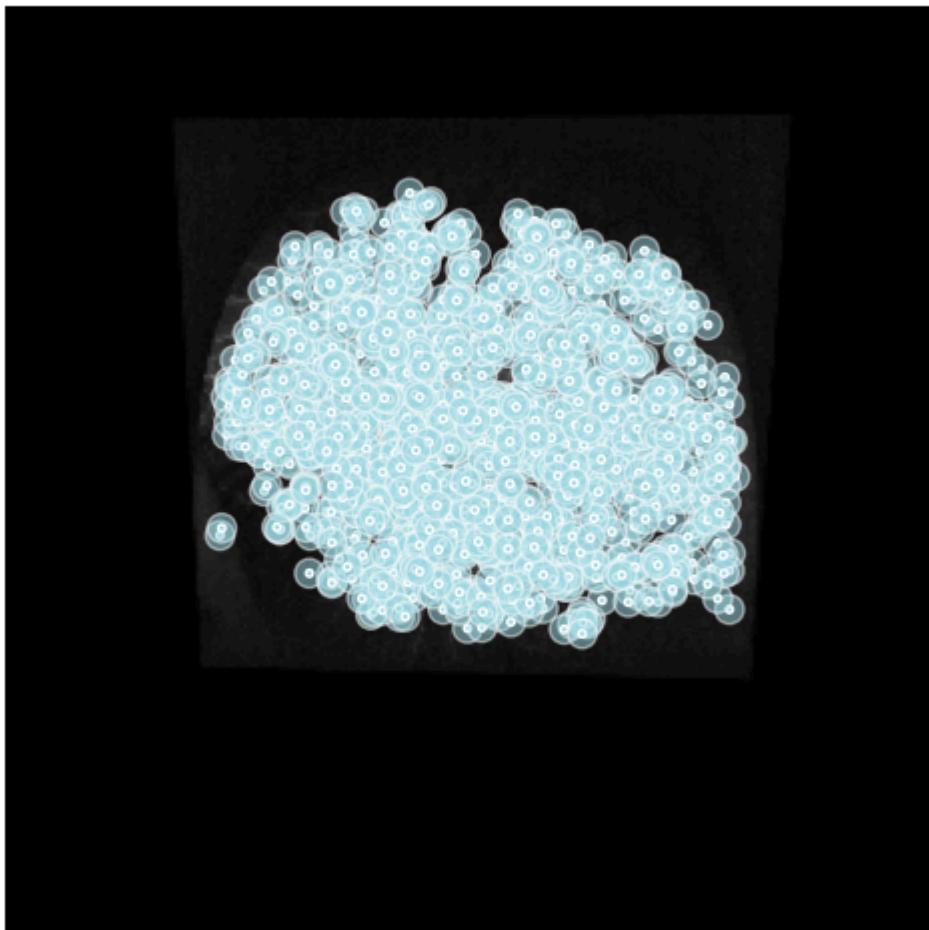
Homography Matrix:

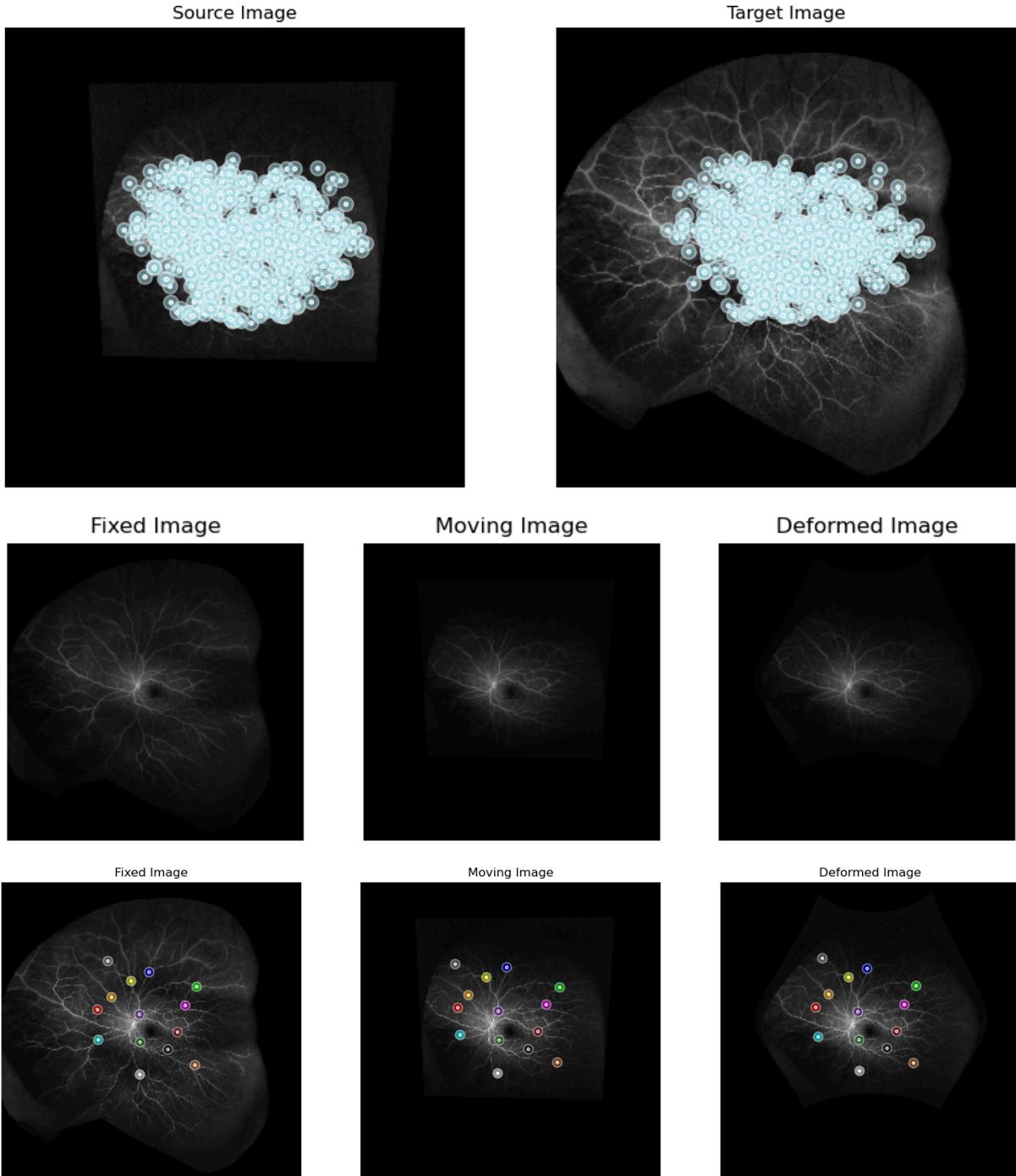
```
[[ 6.39416053e-01  5.71105029e-02  1.85722523e+02]
 [-9.25708648e-03  6.79310184e-01  1.25490572e+02]
 [-3.32240681e-05  1.20027981e-04  1.00000000e+00]]
```



Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
781

Chosen Keypoints



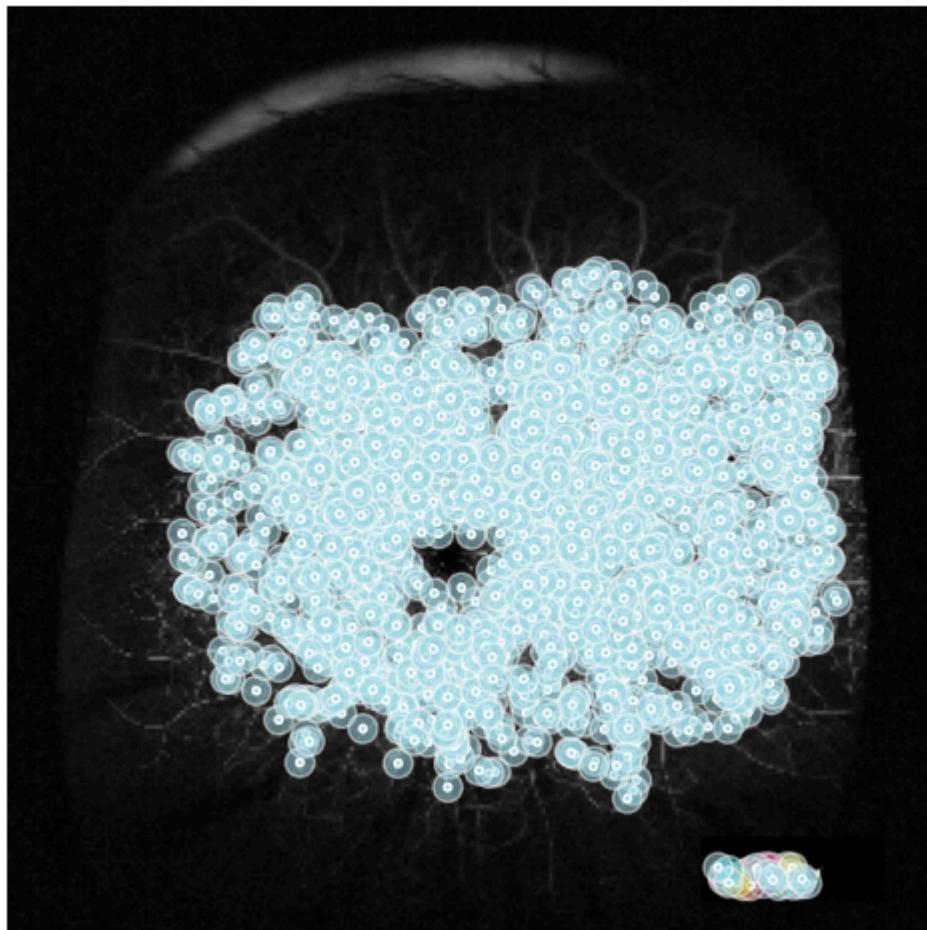


Recorded Landmark Error for Iteration 12 is 39.12664958814495

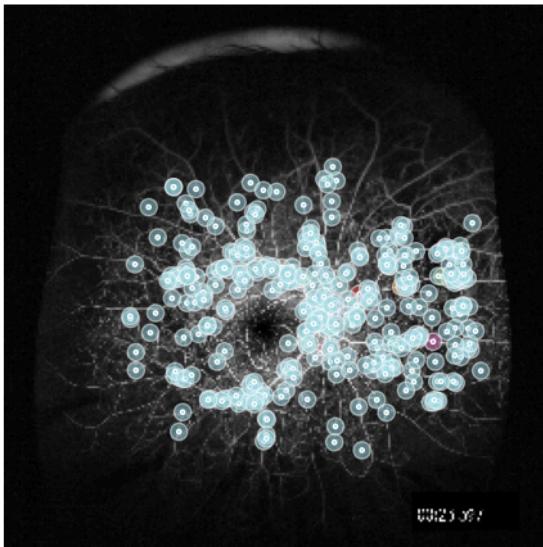
Iteration 13

```
Loading Source Images /blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_5/Montage/Montage_Subject_5.tif ,Target Image/blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_5/FA/Raw_FA_1_Subject_5.tif to the framework
Loading pipeline components...:    0%|          | 0/6 [00:00<?, ?it/s]
350
```

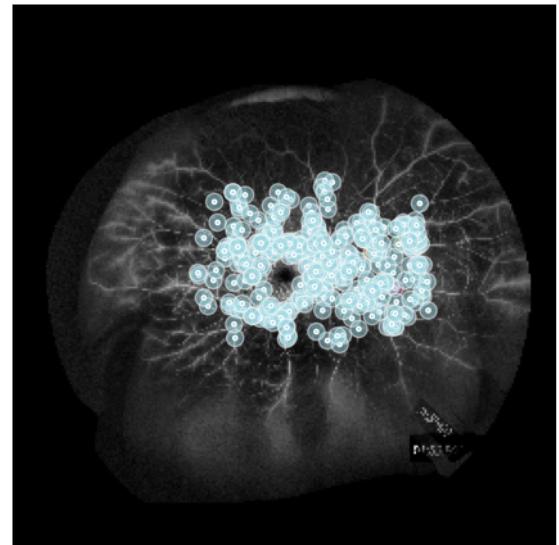
Chosen Keypoints



Source Image

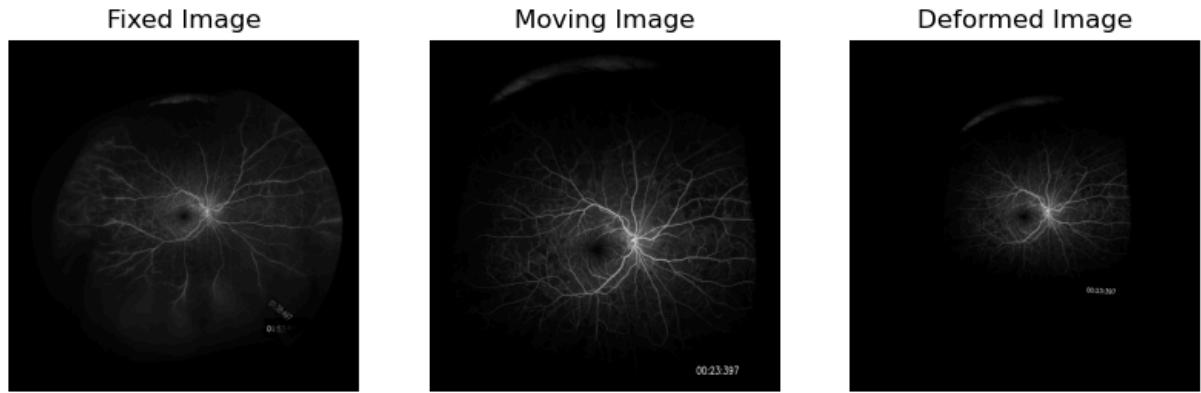


Target Image



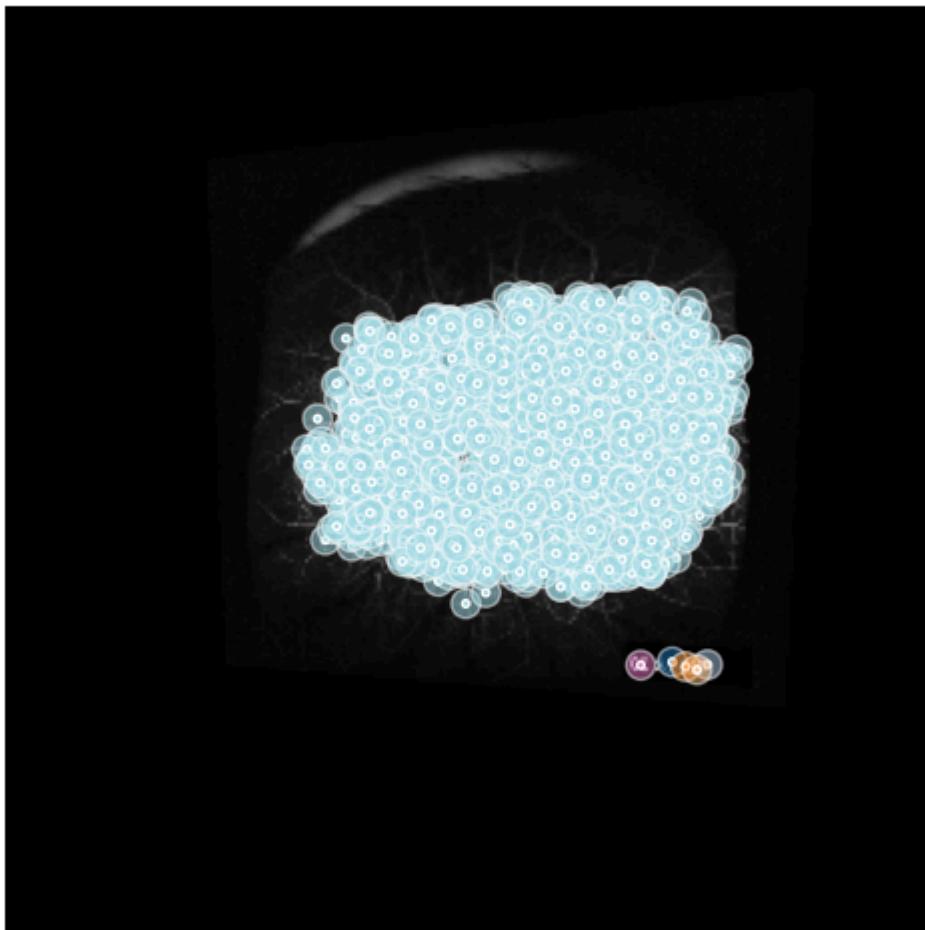
Homography Matrix:

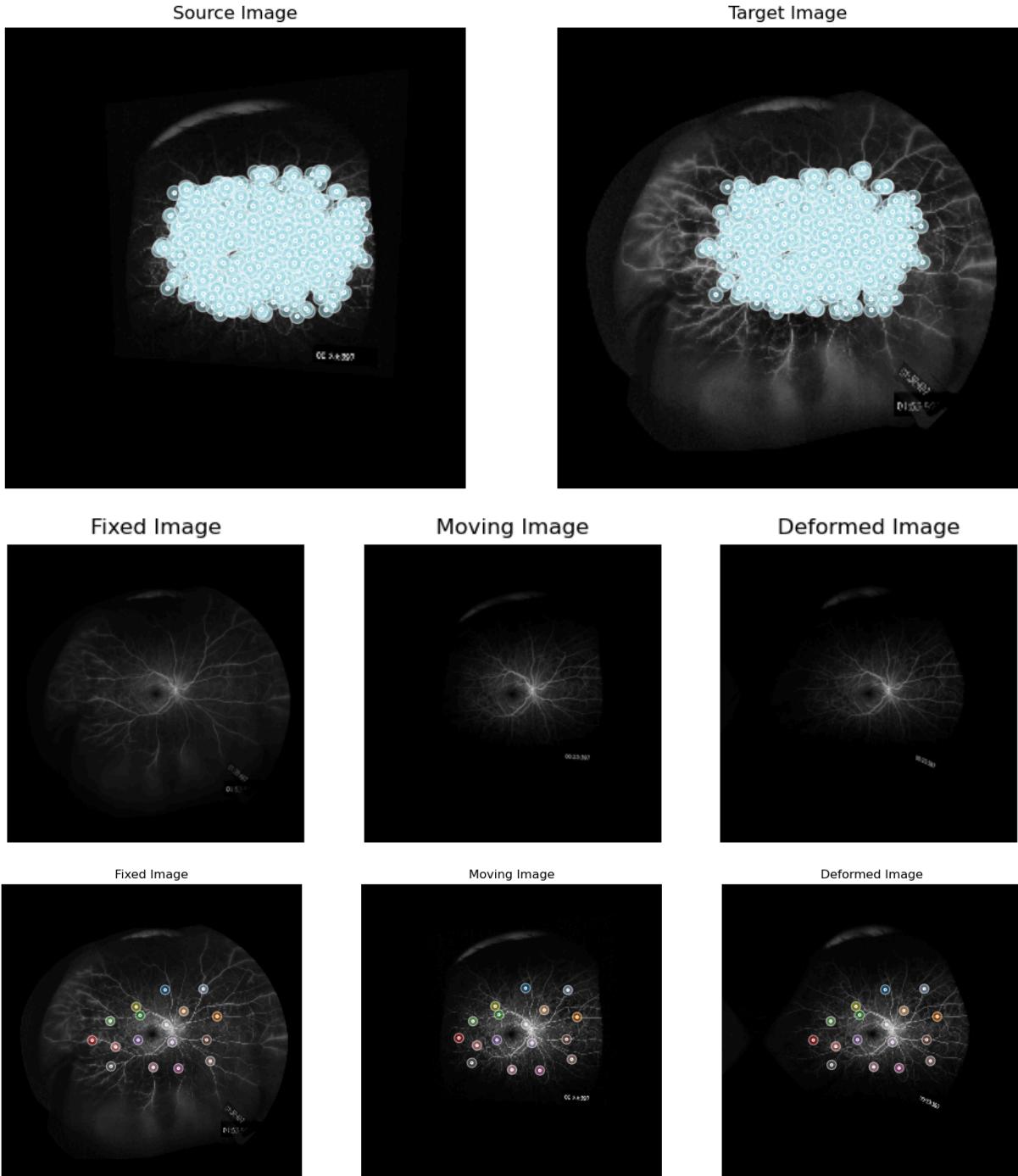
```
[[ 4.92007827e-01  3.92596722e-02  2.23240880e+02]
 [-9.30849915e-02  6.02137103e-01  1.69675224e+02]
 [-1.84995925e-04  7.71913386e-05  1.00000000e+00]]
```



Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
1046

Chosen Keypoints





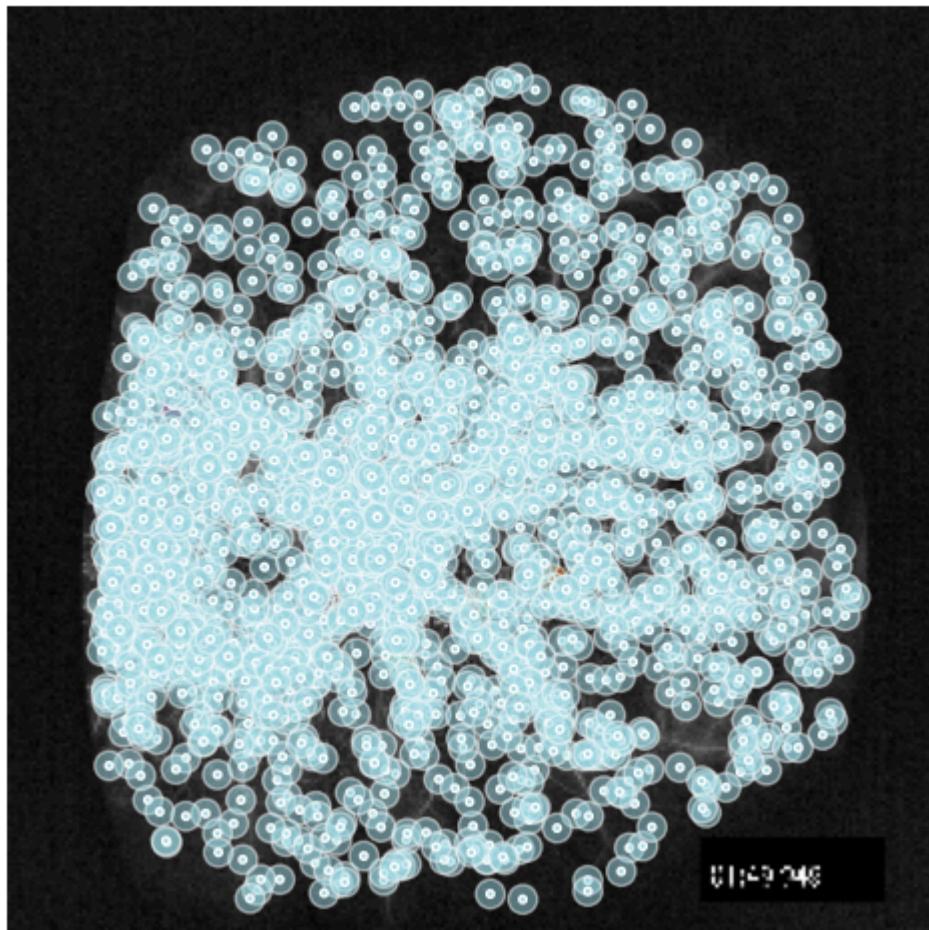
Recorded Landmark Error for Iteration 13 is 9.776384015721703

Iteration 14

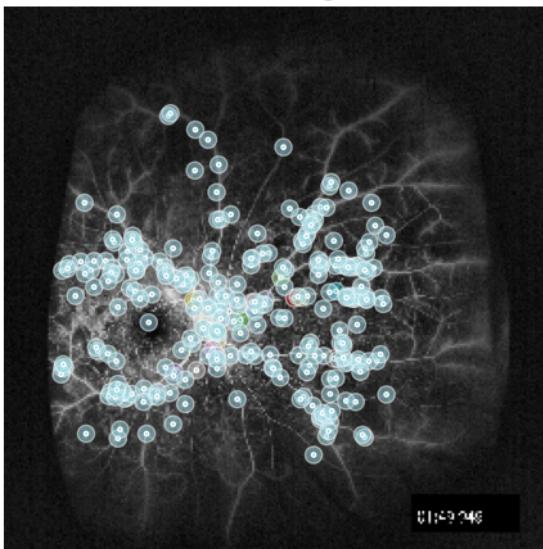
```
Loading Source Images /blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_5/Montage/Montage_Subject_5.tif ,Target Image/blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_5/FA/Raw_FA_2_Subject_5.tif to the framework
Loading pipeline components...: 0%| 0/6 [00:00<?, ?it/s]
```

269

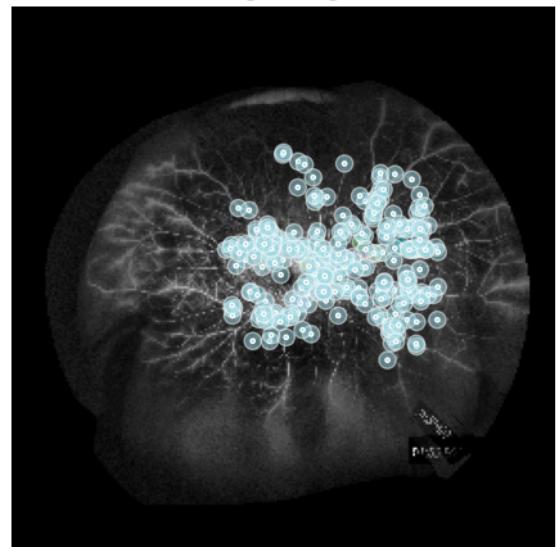
Chosen Keypoints



Source Image

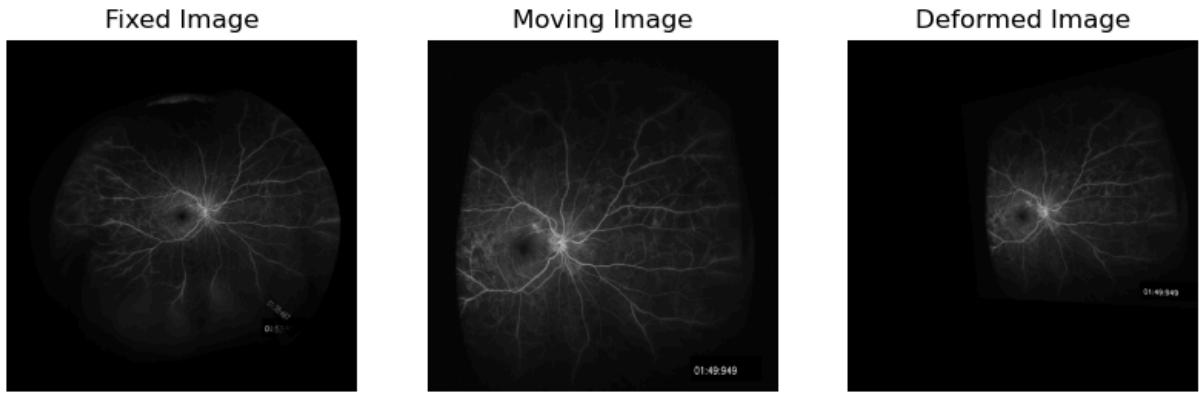


Target Image



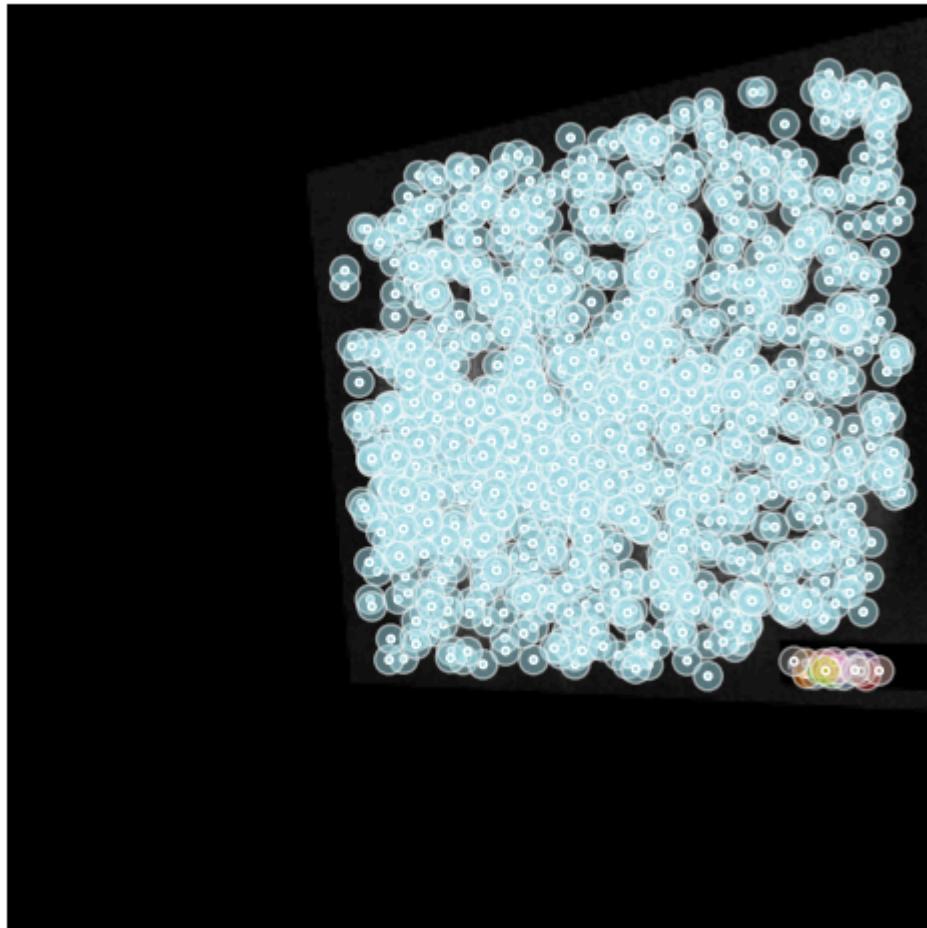
Homography Matrix:

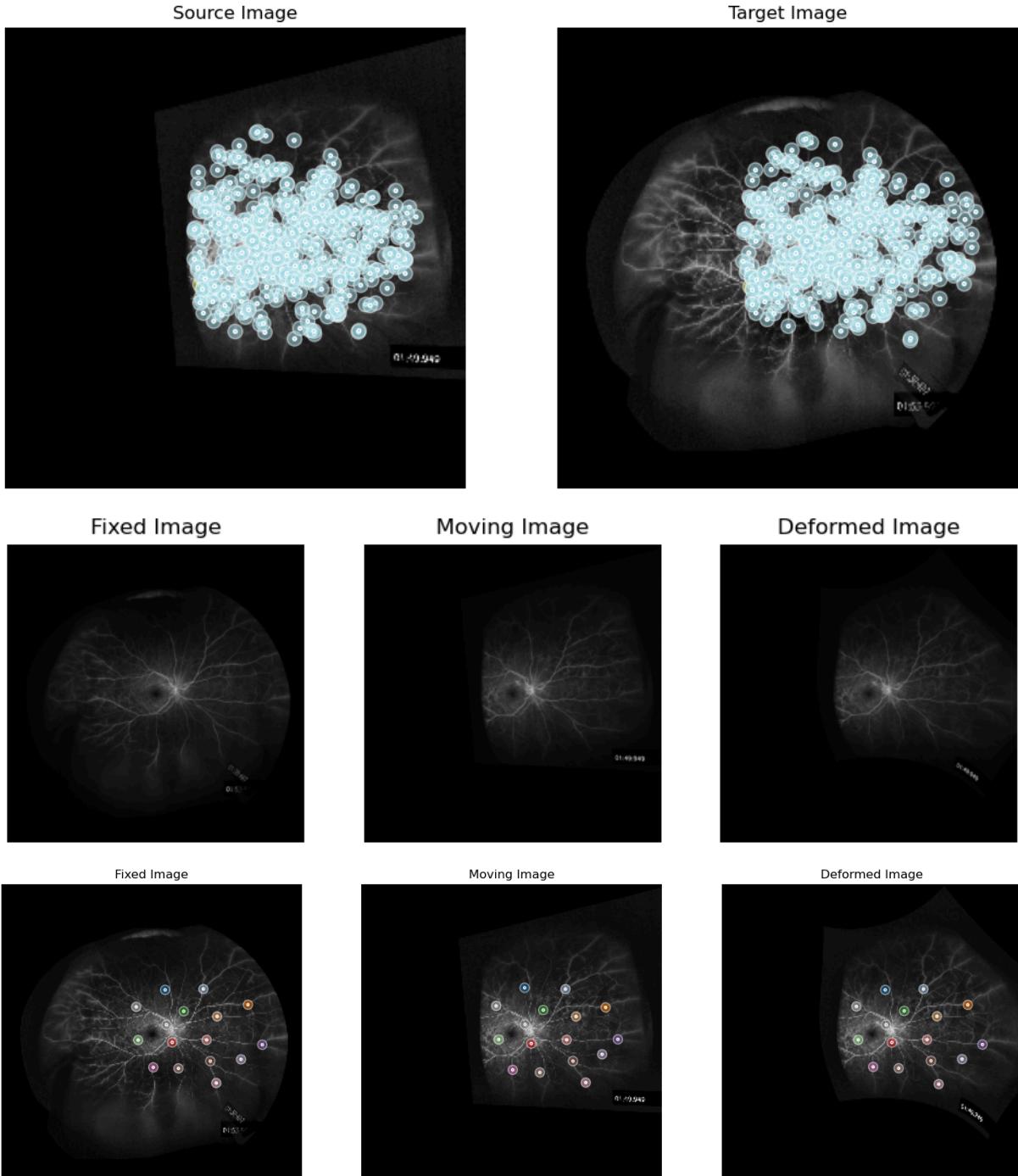
```
[[ 4.07267287e-01  5.50218055e-02  3.31102236e+02]
 [-1.73899897e-01  5.63392649e-01  1.87356513e+02]
 [-2.64131124e-04  1.71498764e-05  1.00000000e+00]]
```



Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
584

Chosen Keypoints





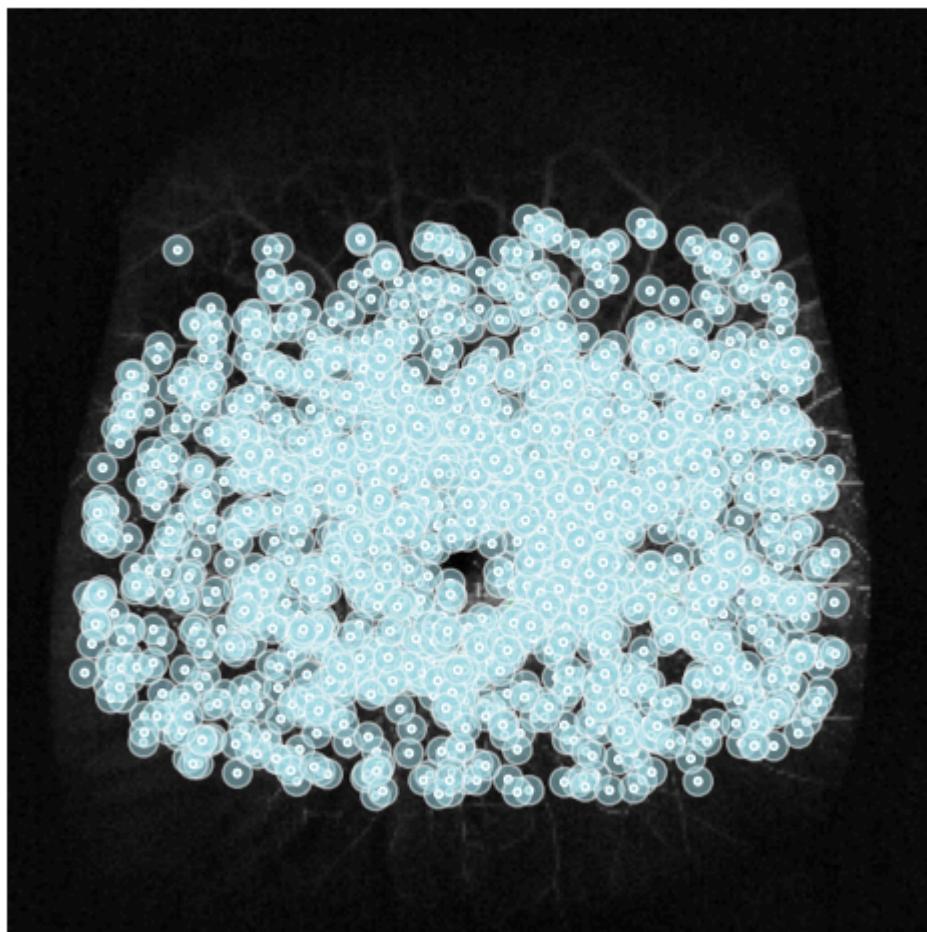
Recorded Landmark Error for Iteration 14 is 10.88296466691726

Iteration 15

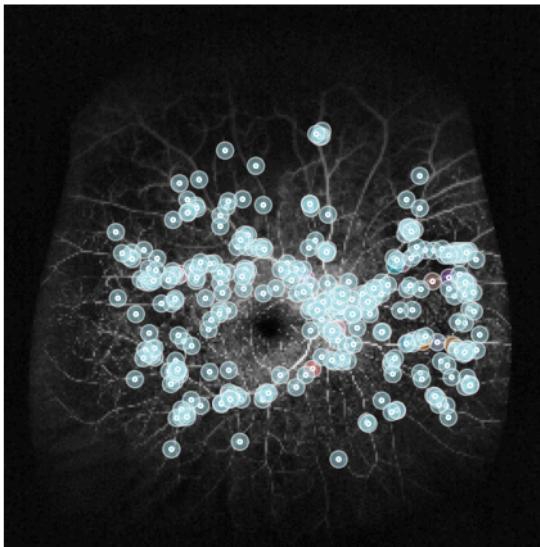
```
Loading Source Images /blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_5/Montage/Montage_Subject_5.tif ,Target Image/blue/weishao/vi.sivaraman/Tasks/T17/2D Registration/FLoRI21_Registration/FLoRI21_DataPort/data/Subject_5/FA/Raw_FA_3_Subject_5.tif to the framework
Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
```

322

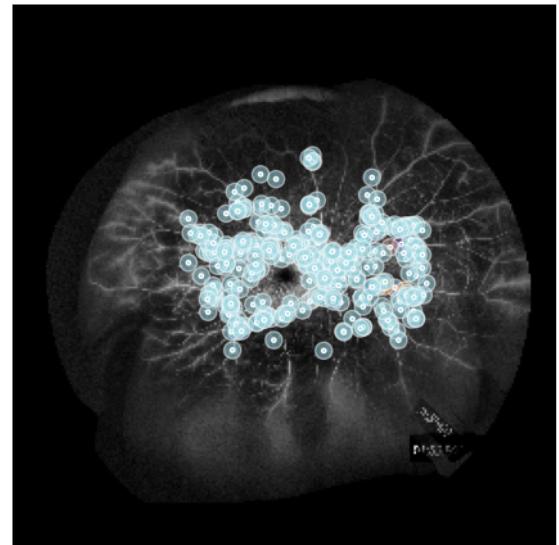
Chosen Keypoints



Source Image



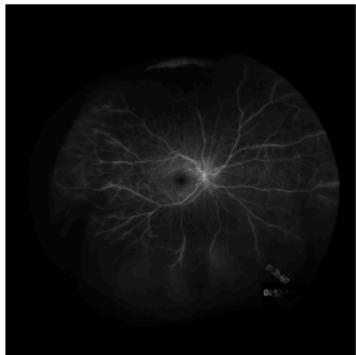
Target Image



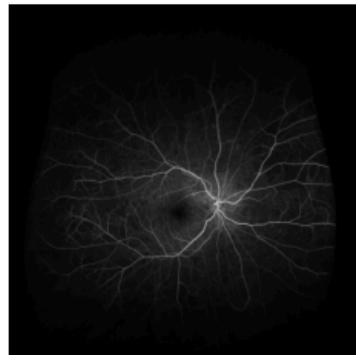
Homography Matrix:

```
[[ 4.99469425e-01  4.36042145e-02  2.12038293e+02]
 [-9.10940554e-02  6.02261021e-01  1.70667994e+02]
 [-1.64585875e-04  5.98574605e-05  1.00000000e+00]]
```

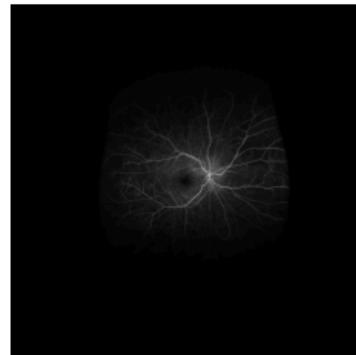
Fixed Image



Moving Image

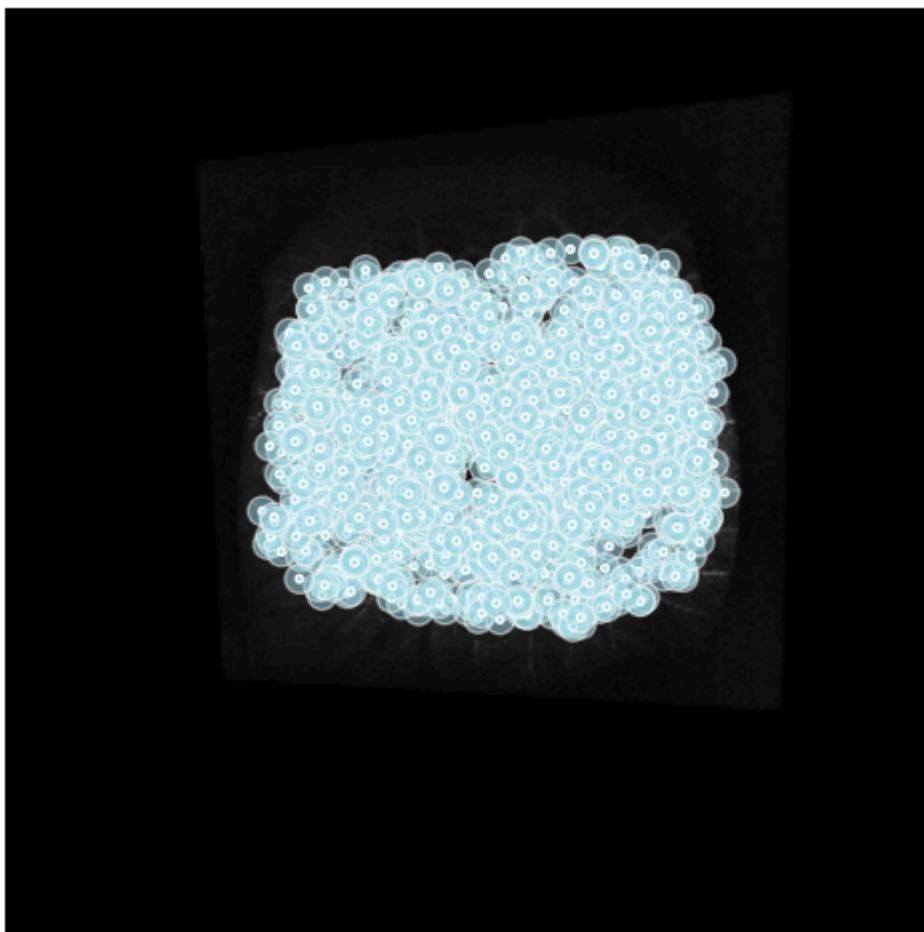


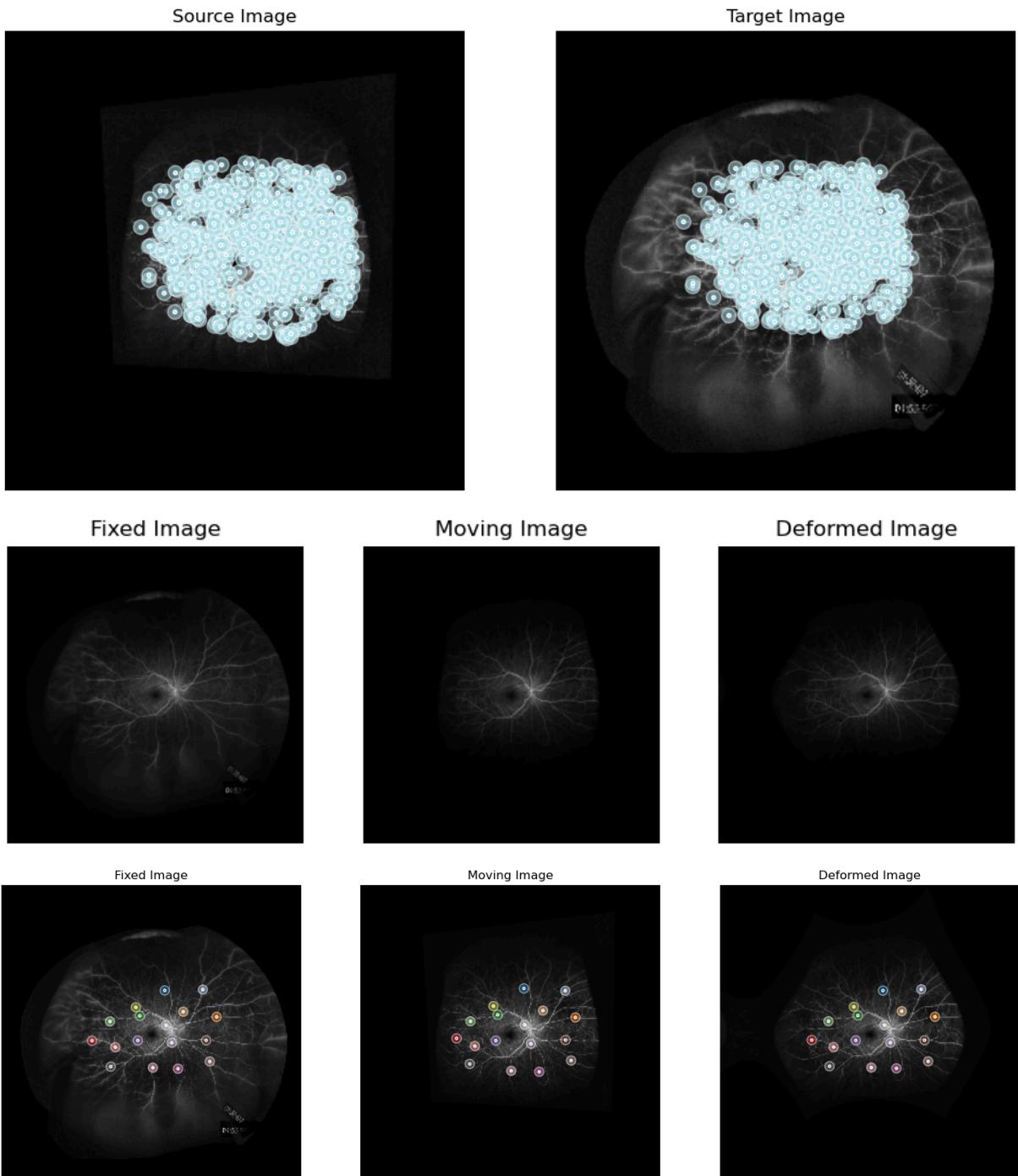
Deformed Image



Loading pipeline components...: 0% | 0/6 [00:00<?, ?it/s]
835

Chosen Keypoints

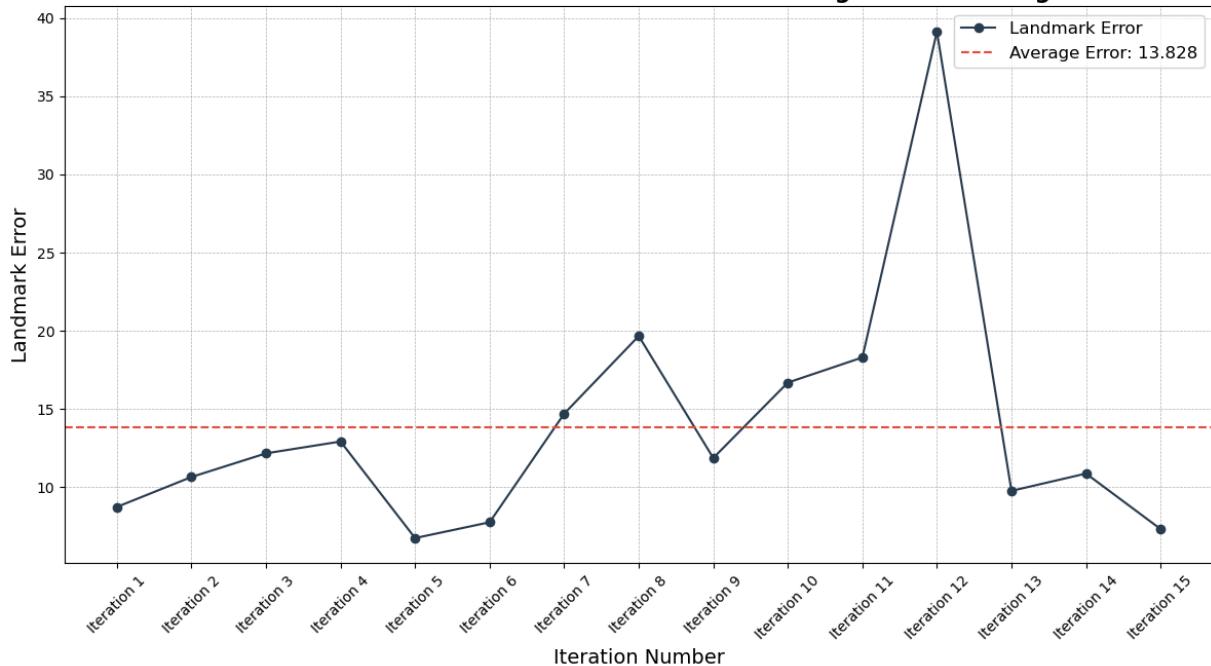




Recorded Landmark Error for Iteration 15 is 7.335814838372301

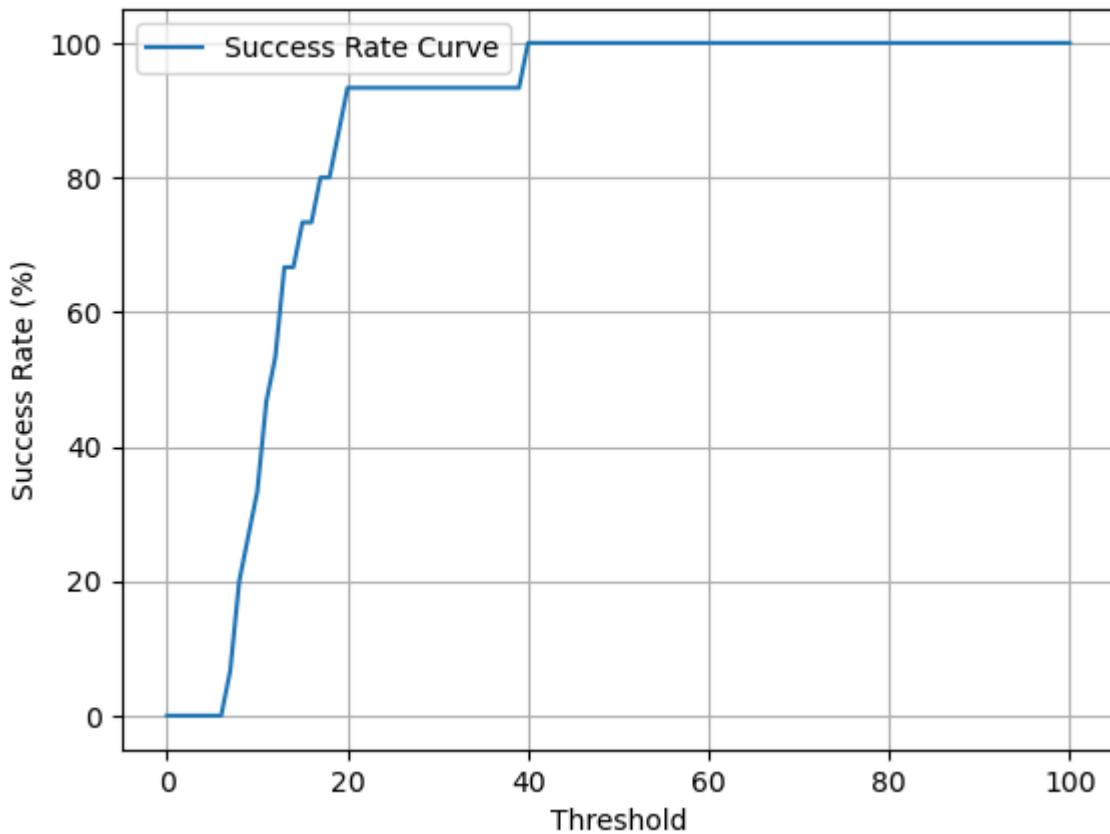
```
In [19]: plot_landmark_errors(landmark_errors,os.path.join(os.getcwd(),'FLoRI21_DataPort_Ima
```

Landmark Error vs. Iteration for Database Housing model All images



```
In [20]: compute_plot_Flori21_AUC(landmark_errors)
```

Success Rate vs. Threshold



AUC: 0.868