ULSAN NATIONAL INSTITUTE OF SCIENCE AND TECHNOLOGY

Assignment #4

Figuera Michal Xiyana Veroska

20225398

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Task 1-1

Explanation

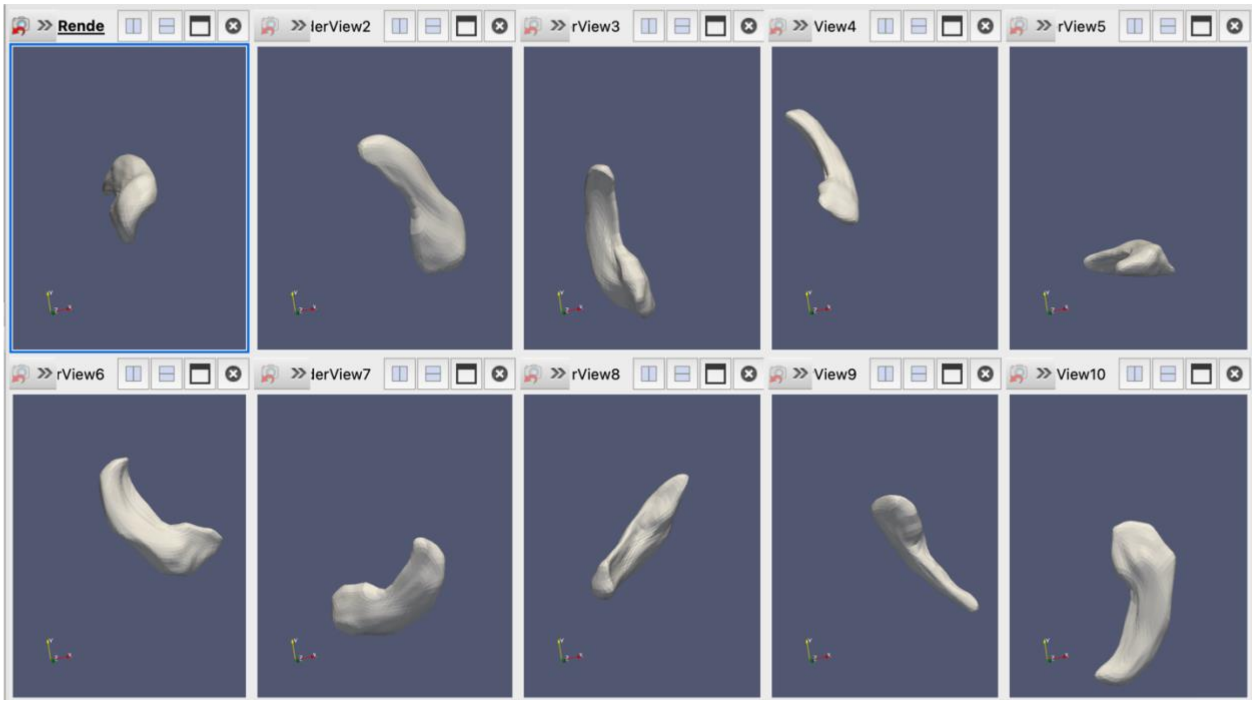
In task 1-1 we visualize hippocampal surfaces already preprocessed by surface registration and re-tessellation. For this we use ParaView and synchronize the viewpoint across all subjects in order to see how the shapes are initially aligned. We use “Link Camera” to sync all windows and enable parallel projection to avoid visual misinterpretation. Also, we compute the average shape and visualize it.

Code

```
%%% Task 1-1

% Declare path
file_path = '/Users/xiyana/Downloads/med-course/homeworks/hw4/hippo/';

% Create celss to store the vertices and faces data
v = cell(10, 1);
f = cell(10, 1);

% Loop to load the hippocampal surfaces
for i = 1:10
    % Construct file name
    file_name = [num2str(i) '.vtk'];

    % Load VTK file
    [v{i}, f{i}] = read_vtk(fullfile(file_path, file_name));
end

% Compute mean of vertices and faces
v_mean = compute_mean(v);
f_mean = compute_mean(f);
write_vtk('/Users/xiyana/Downloads/med-course/homeworks/hw4/results/average_shape.vtk',v_mean, f_mean);


% Function for average
function v_mean = compute_mean(v)

    % Initialize mean variable
    v_mean = zeros(size(v{1}));

    % Compute the sum
    for i = 1:numel(v)
        v_mean = v_mean + v{i};
    end
    % Divide
    v_mean = v_mean / numel(v);
end
```

Result

All subjects (Not aligned)



Average shape

Task 2-1

Explanation

In task 2-1 we want to align the hippocampal surfaces using Procrustes alignment to find the best overlap. We do the following steps:

1) Pick first subject and compute best overlap for each subject via Procrustes alignment.
2) Compute average shape.
3) Compute best overlap for each subject using the average shape
4) Repeat 2 and 3 until the Frobenius norm of the difference between the estimated average shape of the last iteration and current iteration is negligible (< 1e-12)

Code

```
%%% Task 2

% Declare path
file_path = '/Users/xiyana/Downloads/med-course/homeworks/hw4/hippo/';
file_path_output = '/Users/xiyana/Downloads/med-course/homeworks/hw4/results/';

% Create cells to store the data
v = cell(10, 1);
f = cell(10, 1);

% Loop to load hippocampal surfaces
for i = 1:10
    % Construct file name
    file_name = [num2str(i) '.vtk'];

    % Load VTK file
    [v{i}, f{i}] = read_vtk(fullfile(file_path, file_name));
end

% Create cells to store new data
v_new_initial = cell(10, 1);
v_new_initial{1} = v{1};

% Step 1: pick first subject (1.vtk), and compute the best overlap for each subject via the Procrustes alignment.
for i = 2:10
    [~,new_initial] = procrustes(v{1},v{i},'reflection',false,'scaling',false);
    v_new_initial{i} = new_initial;
end
% Step 2: Compute average shape
St_1 = compute_mean(v);   % Raw average
St = compute_mean(v_new_initial); % Procrustes alignment average

difference = St - St_1; % Difference between raw estimated average shape and current iteration

frobenius_norm = norm(difference, 'fro'); % Initialize Frobenius norm

St_1 = St; % Update St_1
```

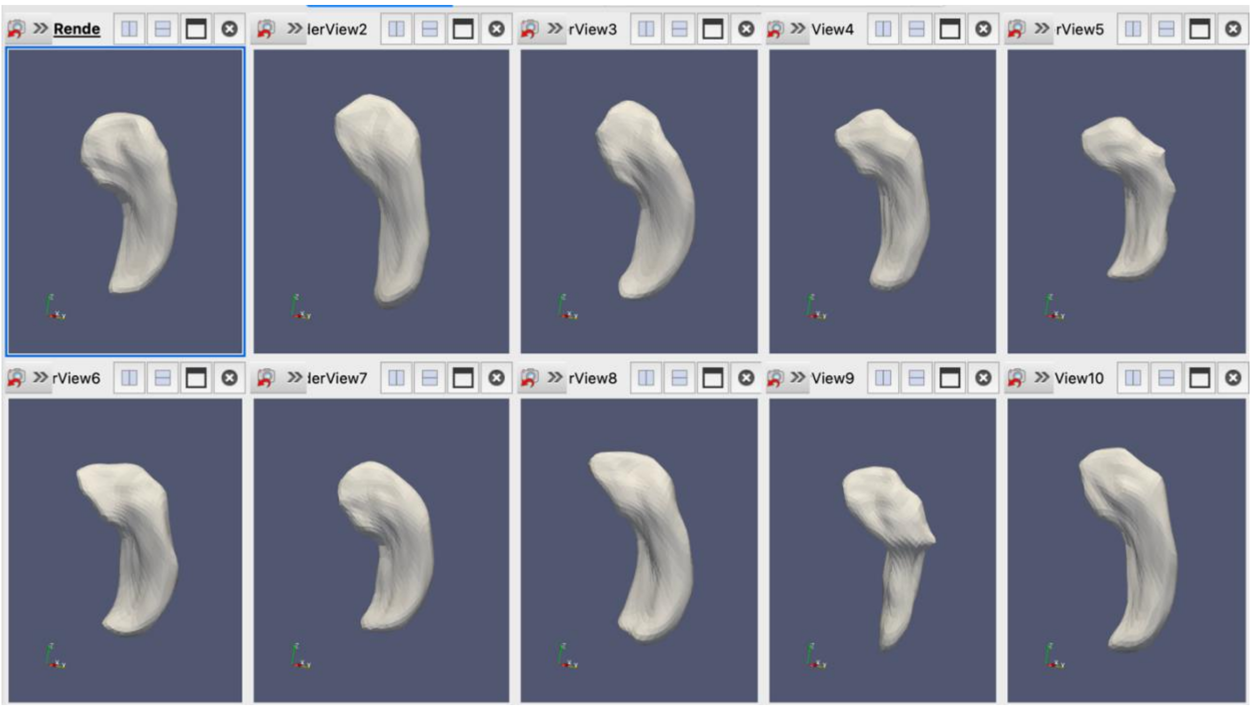
```matlab
% Repeat 2 and 3 until the Frobenius norm of the difference between the estimated average shape of the last iteration
% and current iteration is negligible (< 1e-12)

while frobenius_norm >= 1e-12
    % Declare a cell to store new vertex data
    v_new = cell(10, 1);

    % Step 3: Compute the best overlap for each subject via the Procrustes alignment (with average shape)
    for i = 1:10
        [~,new] = procrustes(St_1,v{i},'reflection',false,'scaling',false);
        v_new{i} = new;
    end

    % Step 2: Compute average shape
    St = compute_mean(v_new);

    % Difference between the estimated average shape of the last iteration and current iteration
    difference = St - St_1;

    % Calculate the Frobenius norm of the difference
    frobenius_norm = norm(difference, 'fro');

    % Update St_1 with the current St for the next iteration
    St_1 = St;

end

f_mean = compute_mean(f);
write_vtk('/Users/xiyana/Downloads/med-course/homeworks/hw4/results/new_average_shape.vtk',St, f_mean);
```

```matlab
% Output VTK files
for i = 1:10
    % Construct the file name
    file_name = [num2str(i) '_new.vtk'];
    file_path_full = fullfile(file_path_output, file_name);
    % Output VTK file
    write_vtk(fullfile(file_path_output, file_name),v_new{i}, f{i});
end

% Function for average
function v_mean = compute_mean(v)
    % Initialize mean variable
    v_mean = zeros(size(v{1}));

    % Compute the sum
    for i = 1:numel(v)
        v_mean = v_mean + v{i};
    end

    % Divide
    v_mean = v_mean / numel(v);
end
```

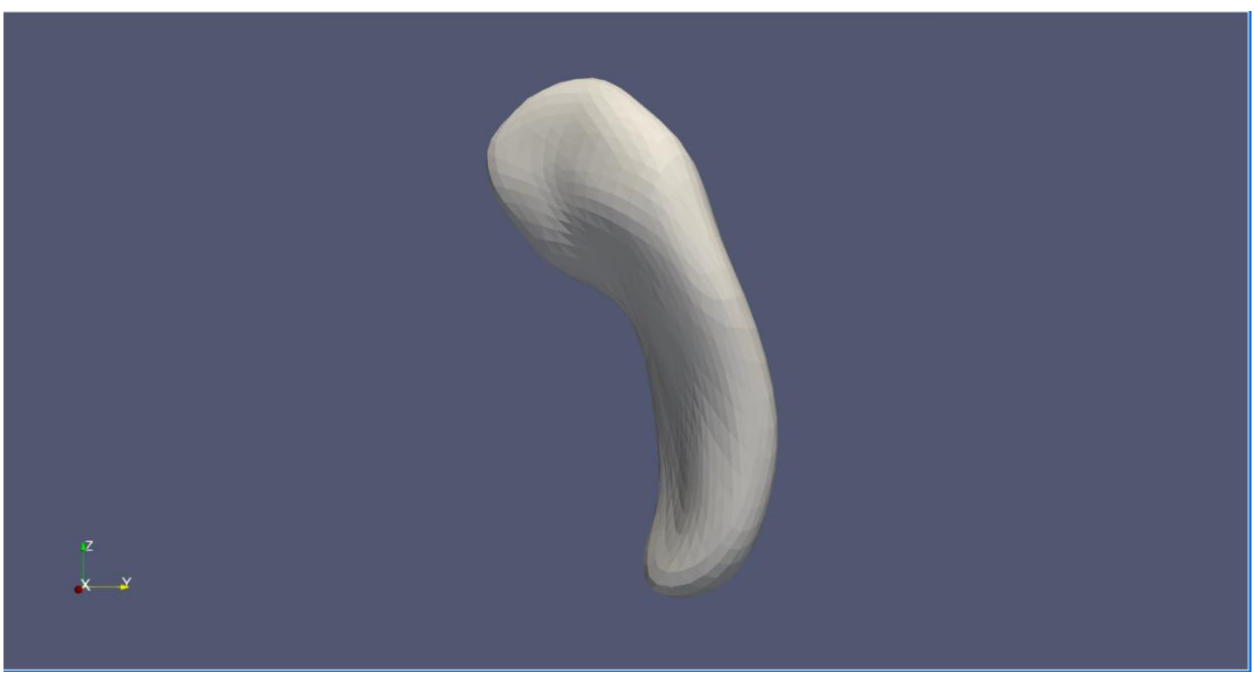
Task 2-2

Result

All subjects (Aligned)



Average shape



Task 3-1

Explanation

In task 3-1 We compute PCA on the aligned data.

Code

```
%%% Task 3-1

% Declare matrix M
M = [];

% Iterate over each subject in the v cell
for i = 1:numel(v)
    % Get a subject
    subject_vector = v{i};
    % Concatenate the subject vector to the matrix M
    M = [M, subject_vector(:)];
end

% Compute PCA
[pc,~,lambda] = pca(M');
```

Task 3-2

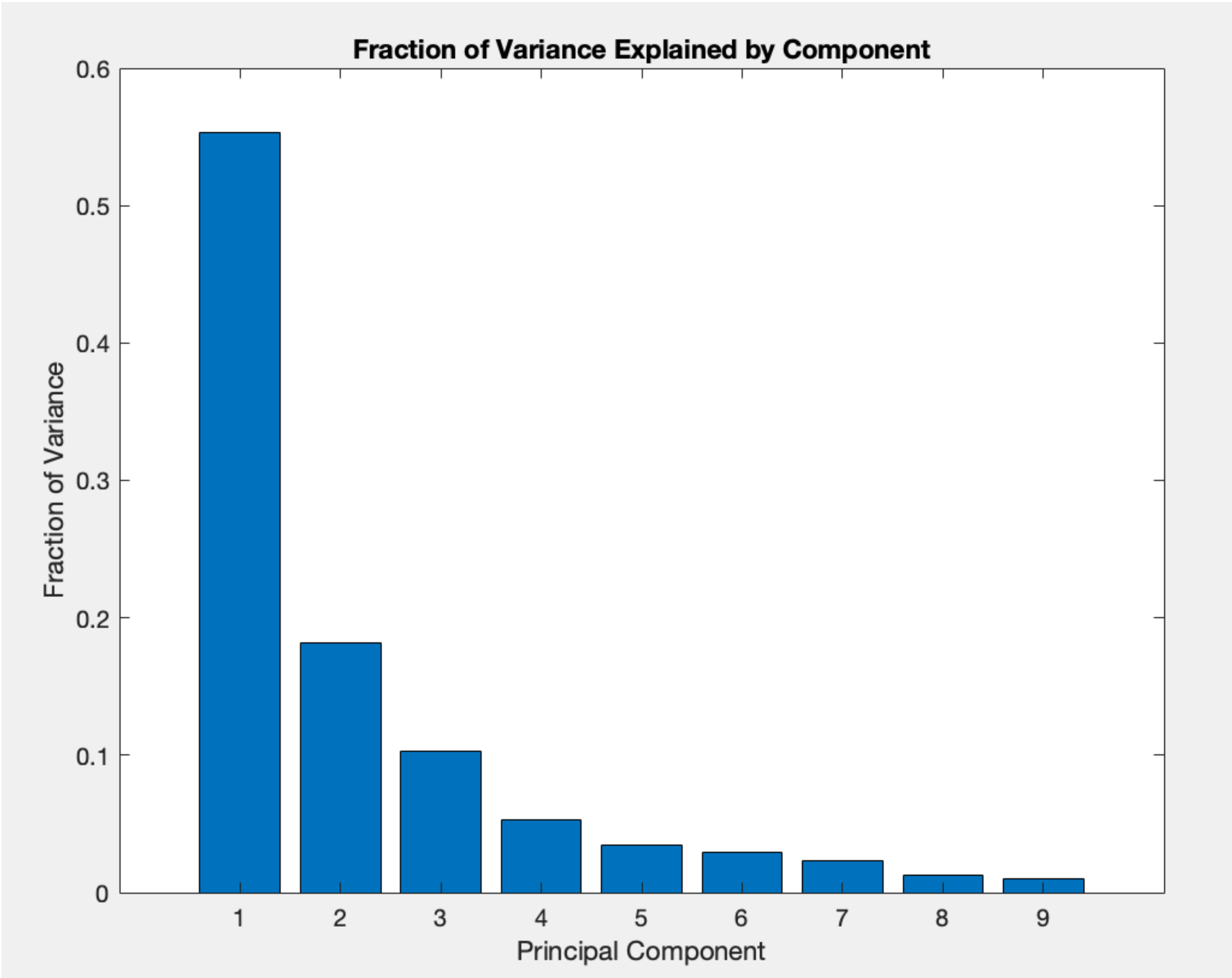
Explanation

In task 3-2 We draw a bar graph of the amount of variation explained by the eigenvalue of each component and compute the variation explained by the first and second largest principal components.

Code

```
%%% Task 3-2

% Compute fraction of variance explained by component
fraction_variance = lambda / sum(lambda);

% Plot a bar graph
figure;
bar(fraction_variance);
xlabel('Principal Component');
ylabel('Fraction of Variance');
title('Fraction of Variance Explained by Component');

% Compute the variation explained by PC 1 and PC 2
var_pc1 = fraction_variance(1);
var_pc2 = fraction_variance(2);

% Print pc1, pc2
fprintf('Variation Explained by PC 1: %.2f%%\n', var_pc1 * 100);
fprintf('Variation Explained by PC 2: %.2f%%\n', var_pc2 * 100);
```

Result




```
Variation Explained by PC 1: 55.31%
Variation Explained by PC 2: 18.14%
```

Task 3-3

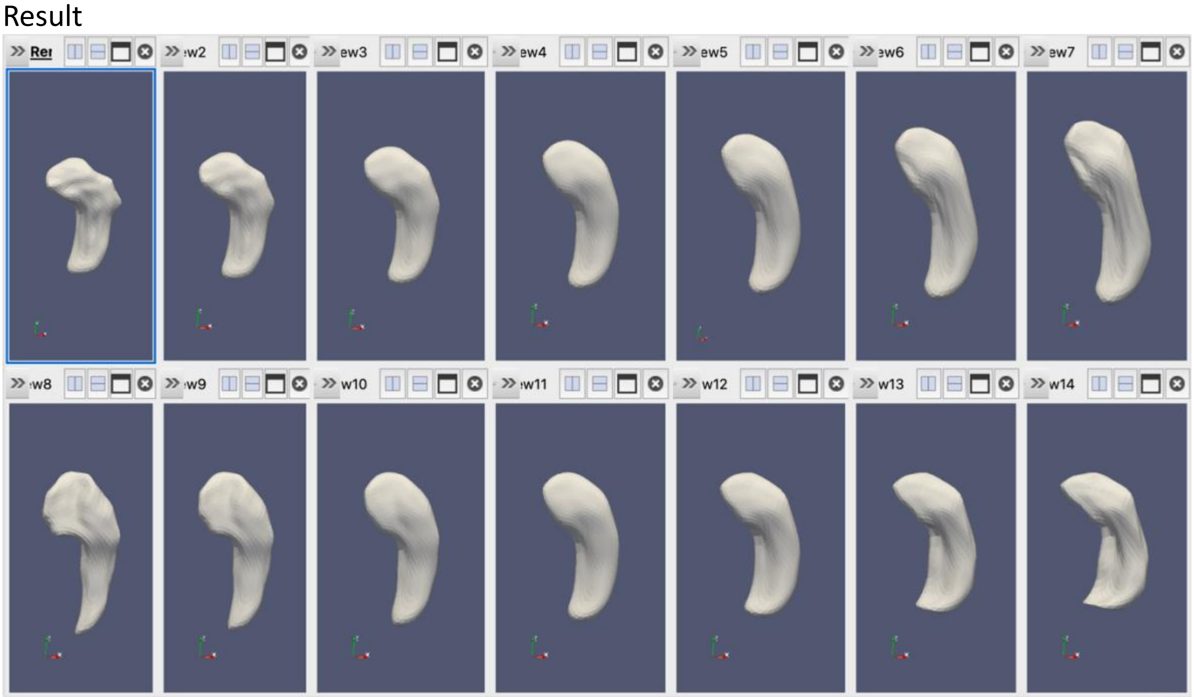
Explanation

In task 3-3 we explore the variation of the two largest principal components.

Code

```
%%% Task 3-3

% Square root of eigen values
sqrt_lambda = sqrt(lambda);

% Load average shape st
[st_v, st_f] = read_vtk('/Users/xiyana/Downloads/med-course/homeworks/hw4/results/new_average_shape.vtk');

% Configurations
elements = [-3, -2, -1, 0, 1, 2, 3];

% For Pc1, Pc2
for i = 1:2

    % Extract (first/second) largest pc
    pc_ = pc(:,i);

    % Reshape pc back to matrix
    pc_matrix = reshape(pc_, [], 3);

    % For configuration
    for j = 1:length(elements)

        st_new = st_v + (elements(j)*sqrt_lambda(i)*pc_matrix);
        file_name = ['pca_' num2str(i) '_' num2str(j) '_pca_new.vtk'];
        file_path_full = fullfile(file_path, file_name);
        write_vtk(fullfile(file_path, file_name),st_new, st_f);

    end
end
```

Result



Discussion

For PC1, the shape has a smaller vertical size than its average when the shape goes further from the mean towards -1, -2 and -3 times PC1 (and standard deviation) while also the features become more visible than for the average. Also, the size becomes bigger in vertical when the shape goes further from the mean towards 1,2 and 3 times PC1 (and standard deviation) while again the features become more apparent.

For PC2, the shape has a slightly bigger vertical size than its average, with horizontal shrinking of the below part and enlarging of the upper part of the shape, when the shape goes further from the mean towards -1, -2 and -3 times PC2 (and standard deviations) while also the features become more visible than for the average. On the other hand the size becomes slightly smaller vertically and bigger horizontally when the shape goes further from the mean towards 1,2 and 3 times PC1 (and standard deviations), with horizontal shrinking of the upper part and enlarging of the below part while again the features become more apparent.

We can notice that PC1 and PC2 do not represent the same variations in shape. PC1 affects prominently in the vertical direction and PC2 affects mainly in the horizontal direction. In both cases we can notice that for other than the average the features become less smoothed.