# Improvement of MRI Phase Contrast Flow Analysis and Imputation Through Temporal Dynamic Image Information

Project Number: 3

**BME 528:** Medical Diagnosis, Therapeutics, and Informatics Applications


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XZ

**Project Lead:** JL

**Abstract**:

Our research enhances cerebral blood flow (CBF) calculation in diabetic patients using phase contrast magnetic resonance imaging (PC-MRI). Using two datasets—one with 3 images taken at intervals of 25-30 minutes and another with 25 images captured milliseconds apart—we developed and evaluated two imputation models. Our study, focusing on vessel identification and flow data extraction, highlights the accuracy of using  interpolation over averaging method. These findings emphasize the significance of precise CBF measurement in understanding cerebral vascular dynamics.

**Introduction**

*Our project* aims to improve CBF calculation using the imputation model. Total cerebral blood flow (CBF) is crucial for assessing brain hemodynamics and perfusion, reflecting the volume of blood delivered to the brain per unit time. CBF is facilitated by four main vessels: the Right and Left Internal Carotid Arteries (ICA) and Right and Left Vertebral Arteries (VA) [1]. This paper will go over the imputation model we built with two data sets one with 3 images and another with 25 images. Dr. Borzage's lab focuses on calculating CBF and identifying vessels for Diabetic patient groups, children under anesthesia, and vessel stiffness effect on CBF. Our project focused on the dataset obtained from the diabetic patient group. The first data set contains 3 images and temporal information as they are taken 25-30 min apart. The second data set contains 25 images and temporal data as it is taken a few milliseconds apart. Calculating this CBF gives us insight into various disease states as low CBF is associated with various medical conditions and also indicates inadequate perfusion to the brain.

*Phase Contrast Magnetic Resonance Imaging (PC-MRI)* visualizes blood flow, measuring velocity and direction by detecting the phase shift of moving blood protons, without invasive procedures or contrast agents. PC-MRI yields quantitative data on blood flow velocity and volume, enabling precise vascular evaluation. It can assess multiple vessels simultaneously but faces challenges like maintaining high resolution, susceptibility to motion artifacts from patient movement, potentially compromising data quality.

Our project involves mastering a phase contrast algorithm that processes MRI images in three forms; phase, magnitude, and complex difference vital for detailed vascular analysis. The algorithm initially identifies vessels and creates masks, which are then refined throughout unaliasing and a watershedding step that uses PC MRI's directional flow data to differentiate closely positioned internal carotid arteries and jugular veins. Subsequently, it identifies vertebral arteries relative to the ICAs. After processing, we manually check and refine the algorithm’s outputs to ensure accuracy. Given that each output requires manual refinement, comprehensive training led by our project leader, J. Liu, is critical. This training is fundamental to properly handle the dataset and develop an imputation model based on these refined outputs.

An imputation model for blood vessels is a computational technique employed in medical imaging to address missing or incomplete data within the images. Dr. Borzage's lab previously utilized a standard least-squares model, which was derived from a study published in Frontier involving PC images from 129 patients [2]. This model primarily focuses on the interrelationships among the four vessels and employs various combinations of ICAs and VAs to estimate missing blood flow values. However, a notable limitation of this approach is its reliance on generalized estimates of cerebral blood flow (CBF) that do not incorporate temporal information from individual subjects. To enhance the model's accuracy, we developed a temporal imputation model that integrates this critical temporal data.

**Developed Imputation Models**

Initially, a dataset consisting of 3 images of a patient, taken 20-30 minutes apart were obtained after running the provided code of vessel identification and manual vessel ID corrections. In this case, all vessels including RICA, LICA, RVA, and LVA on the patients PC MRI were visible, thus none needed to be imputed. However, to be able to develop an imputation model using the provided dataset, one of the vessels was assumed to be missing while the other two image data were used to approximate its value. By applying the same logic to all the vessels, the first method of imputation is developed, which is imputation via averaging. Additionally, the accuracy of the proposed imputation models is analyzed against available actual values.

Applying the averaging method to all the vessels, estimated/imputed vessel IDs are obtained as shown in Table 1. Figure 1 shows a visual representation of the actual vs imputed values for 3 image dataset where averaged values for each vessel, RICA, LICA, LVA, and RVA look to be within the same range. However, the statistical method of regression and residual plots are used to analyze how well the averaging model fits the actual data. On the residual plots, as shown in Figure 2, the vertical axis, the residuals represent the differences between the actual and predicted values from a regression model. Closer the residuals are to 0, less of an error there is and thus the predicted value is more similar, closer to the actual value. Out of all four plots, RVA has the least amount of error in its estimated values as 2 initial residuals are nearly 0, however to mathematically test the observation and see how the residuals fit within the linear model, a linear trendline is added to each plot. The findings are that the ICAs, right and left, have more of a horizontal trendline indicating that the error values are more scattered and there is no relationship between the independent and dependent variables, thus the model for ICAs does not entirely capture variations in the dependent variable. Respectively, $R^2$ values are very low for both RICA and LICA trendlines. On another hand, in terms of VAs, right and left, the linear trendline is more slopped indicating that there is a relationship between the variables and as expected, $R^2$ values are much higher as well. So, the statistical analysis also shows that the averaging method of imputation provides good estimation for VAs, specifically RVA, while there is some error for ICA imputation.

At later stages of the project, the team was provided with other research data, consisting of 25 images of the same patient, taken milliseconds apart. After running the code and manual vessel ID corrections, all images and respective vessel information was obtained. These temporal images provided more data points where two imputation models were considered. Firstly, the averaging method as used for 3 image dataset was applied, where in this case to approximate a missing value 24 other data points were available and used. Table 2 shows imputed values, via the averaging method, for all vessels using the 25 images. In this case since more points were available, regression and residual plot analysis did not provide good information to determine the validity of the averaging method, thus another method of analysis was used which will be discussed later in the report.

Second method of imputation used was imputation via interpolation. Interpolation is a curve-fitting method which utilizes known data points to estimate unknown values. A linear interpolation was used to impute unknown vessel data. Linear interpolation involves calculating the intermediate values along the line based on the proportional distance between the known points and uses the following formula:

$$y = y_1 + \frac{x - x_1}{x_2 - x_1} \times (y_2 - y_1)$$

To apply the linear interpolation model to the 25 image dataset, a MatLab code was developed as shown in Appendix B. The code was run for each vessel where it assigned NaN, vessel missing, value to every image, one at a time, and after imputing it continued onto another until all 25 data points were imputed. Figures 3-6 show results of all imputation models compared to actual values as well as the old imputation model as presented in a published research of 2023. It is apparent from the plots that the interpolation method is better approximation compared to actual than the averaging or old model. In this case, similar to 3 dataset analysis, estimated VA values are more accurate and closer to actual than ICAs. One reason for such observation can be that ICAs are larger vessels with more turbulent blood flow, thus at any given moment blood flow rates vary more drastically than that of VAs.

The old imputation model reveals that while the RICA curve is somewhat shifted, it generally follows the trend as the actual curve. This is attributed to the model's inherent ability to capture the interrelationships among the four vessels [2]. Consequently, fluctuations in the flows of the other three vessels are reflected in the imputation values for RICA, despite the model's lack of temporal data integration. It is important to note, however, that the curves for the other three vessels do not align as closely with the actual data compared to those produced by the interpolation model. This discrepancy arises because the old model does not differentiate between the left and right sides for either the ICAs or the VAs, treating them identically. Our new model addresses this limitation by distinguishing between the sides, which enhances its accuracy and performance over the old model.

The overall curve of cerebral blood flow was considered as well, as seen in Figure 7. In this case, when one point is assumed to be missing that indicates that all 4 vessel IDs on one image are missing. From the plot it can be seen that imputation via averaging provides values that are mostly within the same range and does not behave closely to the actual curve. Imputation via interpolation, however, provides better approximation for individual data points and mimics the actual curve more accurately. Thus, from curve analysis it is concluded that imputation via the interpolation model is a more accurate representation.

**Error Analysis and Improvement**

Table 3 presents the results of our investigation into imputation models for blood vessel imaging, featuring a comparative analysis of Mean Absolute Errors (MAE) for four different vascular identities: RICA, LICA, RVA, and LVA. This analysis encompasses three imputation methodologies: the traditional model previously employed, a newly developed averaging model, and an advanced interpolation model. The results indicate a substantial enhancement in imputation accuracy with the introduction of the new models. Specifically, the interpolation model demonstrates superior performance, achieving the lowest MAE values across all categories—for example, reducing the MAE for RICA from 58.1585 in the traditional model to 5.9092. These findings validate the effectiveness of the interpolation approach in refining the precision of blood flow imputation within vascular imaging, marking a significant advancement over prior techniques.

**Conclusion**

In conclusion, our imputation model that uses interpolation technique showed better accuracy compared to the averaging method. We validated our model with both the data set we received. One of the limitations of our model is it limits point approximation to two data points when using interpolation technique. We would like to explore polynomial interpolation to solve this problem. We would also like to validate our model with a larger data set and look at individual vessels and the total CBF.

**Appendix A (Figures & Tables)**

**Table 1:** *Imputed through averaging model data for 3 image dataset*

| VESSELS | IMPUTED VIA AVERAGING | ACTUAL |
|---|---|---|
| RICA -1 | 315.1865 | 321.4234 |
| RICA -2 | 319.6529 | 312.4906 |
| RICA - 3 | 316.957 | 317.8824 |
| LICA -1 | 251.4072 | 254.622 |
| LICA -2 | 252.2206 | 252.9952 |
| LICA -3 | 253.8086 | 249.8192 |
| RVA -1 | 74.57645 | 69.9884 |
| RVA -2 | 73.67825 | 71.7848 |
| RVA -3 | 70.8866 | 77.3681 |
| LVA -1 | 59.7212 | 57.259 |
| LVA -2 | 59.77205 | 57.1573 |
| LVA -3 | 57.20815 | 62.2851 |

**Table 2:** *Imputed values for all 4 vessels via averaging method*

| | *Avg1* | | *Avg2* | | *Avg3* | | *Avg4* |
|---|---|---|---|---|---|---|---|
| ***RICA -1*** | *244.475* | ***LICA -1*** | *184.016* | ***RVA -1*** | *132.633* | ***LVA-1*** | *46.192* |
| ***RICA -2*** | *245.143* | ***LICA -2*** | *184.615* | ***RVA -2*** | *133.037* | ***LVA-2*** | *46.332* |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| ***RICA -3*** | *244.971* | ***LICA -3*** | *184.341* | ***RVA -3*** | *133.104* | ***LVA-3*** | *46.225* |
| ***RICA -4*** | *245.387* | ***LICA -4*** | *184.385* | ***RVA -4*** | *133.427* | ***LVA-4*** | *46.185* |
| ***RICA -5*** | *244.889* | ***LICA -5*** | *184.082* | ***RVA -5*** | *133.039* | ***LVA-5*** | *46.340* |
| ***RICA -6*** | *244.207* | ***LICA -6*** | *185.150* | ***RVA -6*** | *133.024* | ***LVA-6*** | *46.244* |
| ***RICA -7*** | *243.859* | ***LICA -7*** | *183.853* | ***RVA -7*** | *132.698* | ***LVA-7*** | *46.306* |
| ***RICA -8*** | *243.517* | ***LICA -8*** | *185.751* | ***RVA -8*** | *132.623* | ***LVA-8*** | *46.281* |
| ***RICA -9*** | *244.506* | ***LICA -9*** | *184.172* | ***RVA -9*** | *133.085* | ***LVA-9*** | *46.209* |
| ***RICA -10*** | *244.722* | ***LICA -10*** | *184.442* | ***RVA -10*** | *133.311* | ***LVA-10*** | *46.425* |
| ***RICA -11*** | *244.675* | ***LICA -11*** | *184.191* | ***RVA -11*** | *133.107* | ***LVA-11*** | *46.179* |
| ***RICA -12*** | *244.819* | ***LICA -12*** | *184.372* | ***RVA -12*** | *133.269* | ***LVA-12*** | *46.231* |
| ***RICA -13*** | *243.947* | ***LICA -13*** | *183.896* | ***RVA -13*** | *132.875* | ***LVA-13*** | *46.161* |
| ***RICA -14*** | *243.889* | ***LICA -14*** | *184.040* | ***RVA -14*** | *132.619* | ***LVA-14*** | *46.147* |
| ***RICA -15*** | *244.068* | ***LICA -15*** | *184.244* | ***RVA -15*** | *132.440* | ***LVA-15*** | *46.121* |
| ***RICA -16*** | *244.452* | ***LICA -16*** | *183.898* | ***RVA -16*** | *132.355* | ***LVA-16*** | *45.924* |
| ***RICA -17*** | *244.233* | ***LICA -17*** | *183.649* | ***RVA -17*** | *132.074* | ***LVA-17*** | *45.898* |
| ***RICA -18*** | *243.979* | ***LICA -18*** | *183.379* | ***RVA -18*** | *131.960* | ***LVA-18*** | *45.821* |
| ***RICA -19*** | *244.005* | ***LICA -19*** | *183.593* | ***RVA -19*** | *132.042* | ***LVA-19*** | *46.104* |
| ***RICA -20*** | *244.075* | ***LICA -20*** | *184.095* | ***RVA -20*** | *132.424* | ***LVA-20*** | *46.059* |
| ***RICA -21*** | *243.841* | ***LICA -21*** | *183.775* | ***RVA -21*** | *132.389* | ***LVA-21*** | *46.010* |
| ***RICA -22*** | *243.723* | ***LICA -22*** | *183.863* | ***RVA -22*** | *132.538* | ***LVA-22*** | *46.001* |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| ***RICA -23*** | *243.827* | ***LICA -23*** | *183.916* | ***RVA -23*** | *132.502* | ***LVA-23*** | *45.962* |
| ***RICA -24*** | *244.359* | ***LICA -24*** | *183.891* | ***RVA -24*** | *132.669* | ***LVA-24*** | *45.967* |
| ***RICA -25*** | *243.985* | ***LICA -25*** | *183.242* | ***RVA -25*** | *132.693* | ***LVA-25*** | *46.096* |

**Table 3:** *Comparative Analysis of Mean Absolute Errors (MAE) for Vessel Imputation Models*

| Vessel ID \ Model | **Old Imputation** | **Averaging Model** | **Interpolation Model** |
|---|---|---|---|
| **RICA** | 58.1585 | 10.387 | 5.9092 |
| **LICA** | 54.1024 | 5.5182 | 4.6886 |
| **RVA** | 38.8774 | 8.2937 | 3.5185 |
| **LVA** | 41.6466 | 3.2052 | 1.9748 |

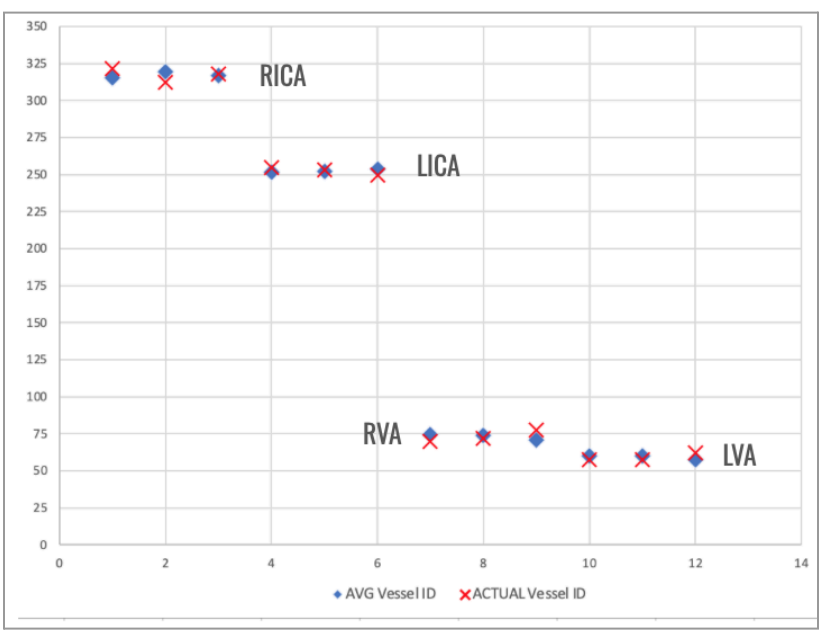


**Figure 1:** *Visual representation of actual vs imputed values of 3 image dataset*

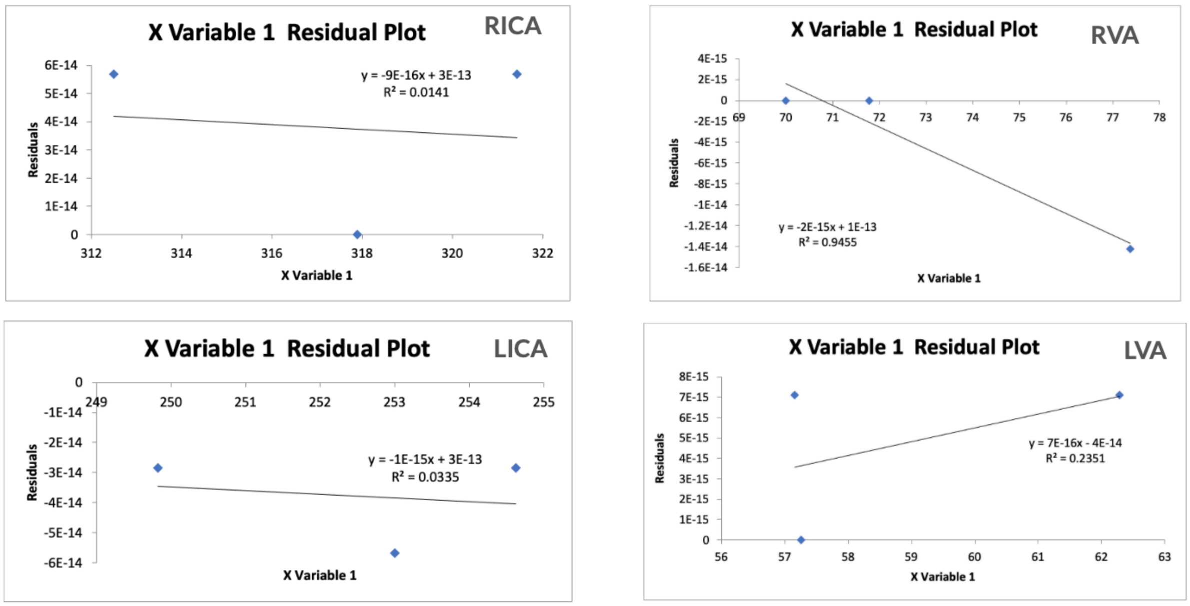


**Figure 2:** *Residual Plots for all imputed vessels with 3 image dataset*

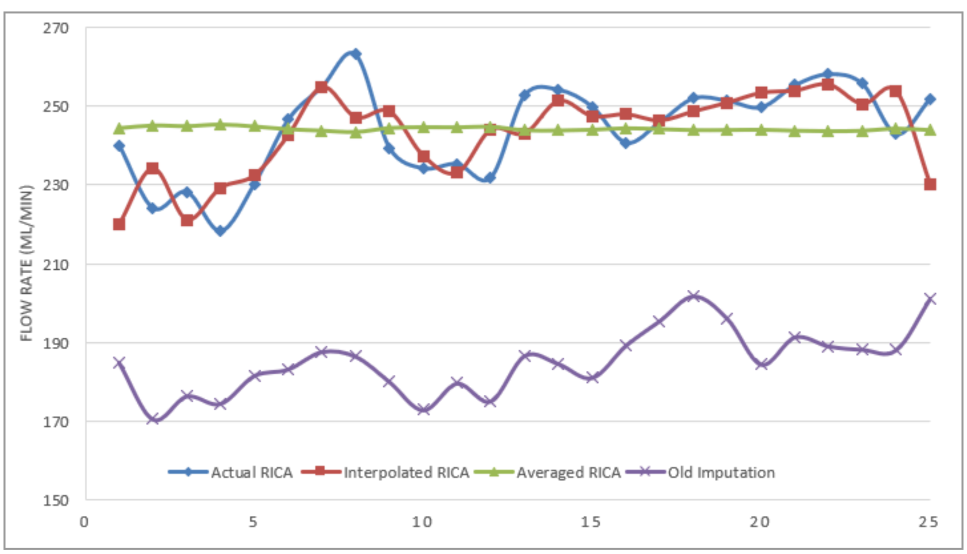


***Figure 3:*** *Imputed flow rates for RICA using averaging, interpolation, old (2023) imputation models against actual*

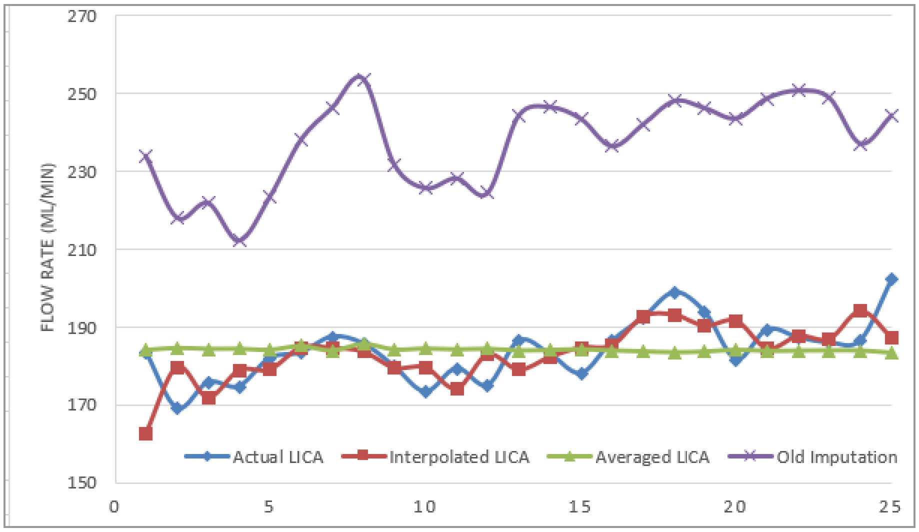


***Figure 4:*** *Imputed flow rates for LICA using averaging, interpolation, old (2023) imputation models against actual*

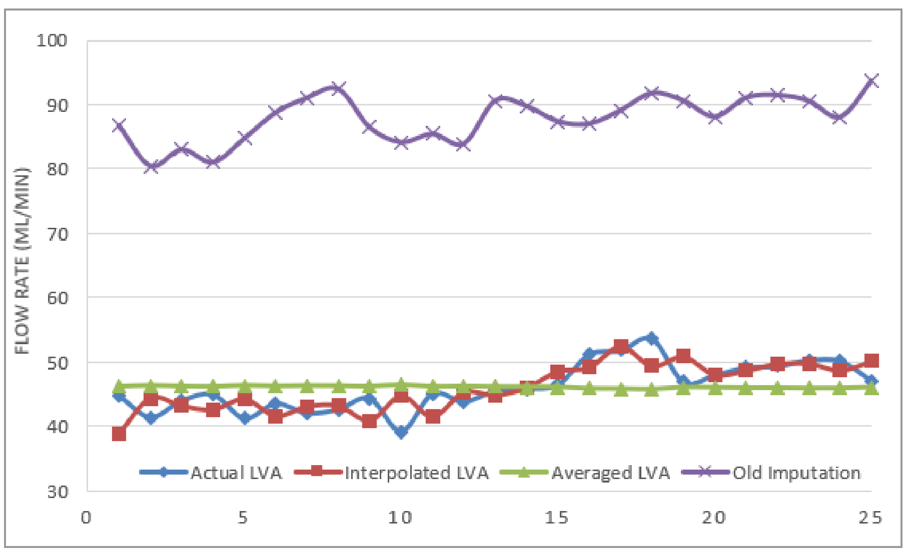


***Figure 5:*** *Imputed flow rates for LVA using averaging, interpolation, old (2023) imputation models against actual*

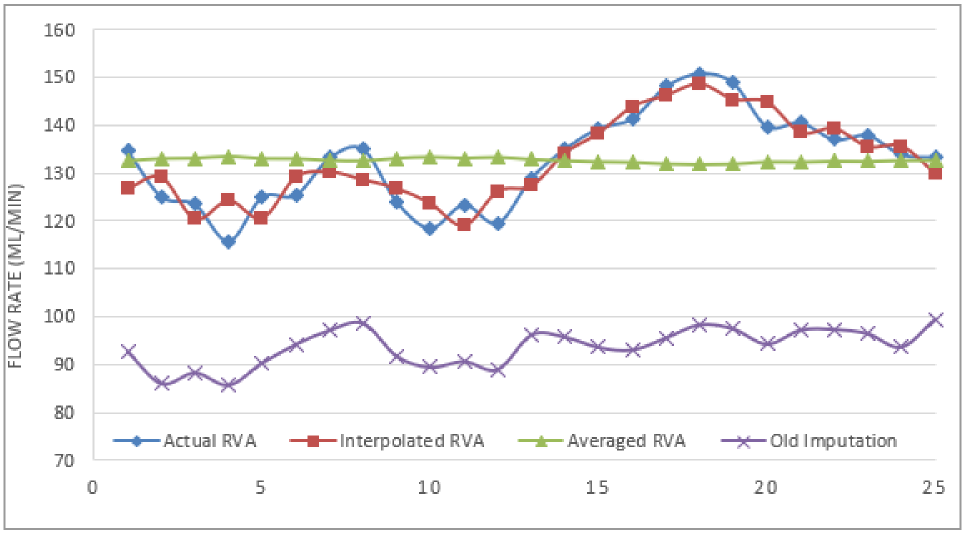


***Figure 6:*** *Imputed flow rates for RVA using averaging, interpolation, old (2023) imputation models against actual*

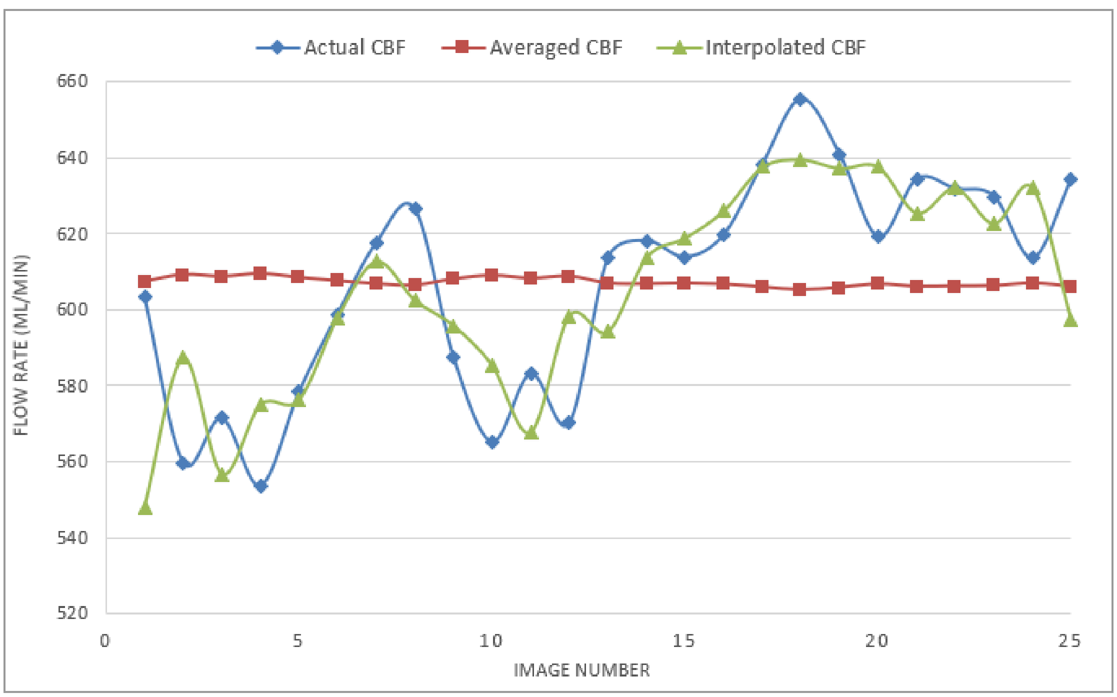


***Figure 7:*** *Imputed flow rates for CBF using averaging & interpolation imputation models against actual*

**Appendix B (MatLab Code)**

```
clc
clear all
%Remove below 2 lines out of comment if want to have 2 unknown values
        %random = randi ([1,25]);
        %Y(random) = NaN;
for j= 1:25
%X Data for images
X = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25];
%Take Y out of comment for whichever vessel want to compute
%RICA
% Y = [240.1432,224.1086,228.242,218.2689,230.213,246.5856, 254.94, 263.155, 239.4188, 234.2248,
235.3426, 231.8853,252.826,254.221, 249.9195,240.7137,245.9703,
252.0551,251.4273,249.7621,255.3782,258.206,255.6948,242.9387,251.912];
%RVA
%Y =
[134.737,125.0554,123.4529,115.6851,124.9964,125.3667,133.1774,134.9946,123.9036,118.4699,123.36
17,119.4751,128.9367,135.0858,139.3676,141.4138,148.1513,150.8896,148.9347,139.7683,140.5982,13
7.0389,137.8885,133.8928,133.2972];
% LVA
%Y =
[44.8146,41.4467,44.0169,43,41.2535,43.5608,42.0727,42.6772,44.3978,39.2145,45.1168,43.8738,45.55
5,45.9002,46.5262,51.2552,51.8633,53.7252,46.9197,47.9946,49.1841,49.3879,50.3252,50.2232,47.1272
];
%LICA
```

```
%Y=
[183.5186,169.1456,175.7204,174.6688,181.9268,183.3577,187.4213,185.647,179.7823,173.288,179.30
83,174.9746,186.4,182.9463,178.0527,186.3553,192.3274,198.7966,193.6563,181.6192,189.2886,187.18
88,185.9046,186.5127,202.0912]
%CBF Values
Y =
[603.2134,559.7563,571.4321,553.6144,578.3897,598.8707,617.6114,626.4738,587.5025,565.1972,583.1
294,570.205,613.7177,618.1533,613.8661,619.738,638.3124,655.4666,640.938,619.1442,634.449,631.82
16,629.8131,613.5674,634.4276];
%one vessel at a time is assumed to be missing in each iteration
Y(j) = NaN;
% Find missing Y-values
missingValue = isnan(Y);
validIndices = find(~isnan(Y));
% Interpolate missing values
for i = find(missingValue)
if i < 2 % if x(1)=NaN
firstValue = interp1(X(validIndices(1:2)), Y(validIndices(1:2)), X(1), 'linear', 'extrap');
Y(1:validIndices(1)-1) = firstValue;
elseif i > 24 % if x(last)=NaN
lastValue = interp1(X(validIndices(end-1:end)), Y(validIndices(end-1:end)), X(end), 'linear', 'extrap');
Y(validIndices(end)+1:end) = lastValue;
else
% Find nearest X-values
leftIndex = find(X < X(i), 1, 'last');
rightIndex = find(X > X(i), 1, 'first');
```

```
% Perform linear interpolation
interpolatedY = interp1([X(leftIndex), X(rightIndex)], [Y(leftIndex), Y(rightIndex)], X(i), 'linear');
% Replace missing Y-value with interpolated value
Y(i) = interpolatedY;
end
Y_interp(j,1) = Y(i);
end
end
disp(Y_interp);
```

## Appendix C (Schedule & Resources)

A screenshot of MS Project used throughout the project for scheduling and assignment of tasks

| | Task Mode | WBS | Task Name | Duration | Start | Finish | Resource Names |
|---|---|---|---|---|---|---|---|
| 1 | | 1 | Initiation | 4 days | Mon 2/12/24 | Thu 2/15/24 | |
| 2 | | 1.1 | Project Introduction & Team Formation | 4 days | Mon 2/12/24 | Thu 2/15/24 | Haochen,Meri,Rutvi |
| 3 | | 2 | Planning | 9 days | Mon 2/12/24 | Wed 2/21/24 | |
| 4 | | 2.1 | Meeting with project manager | 1 day | Mon 2/12/24 | Mon 2/12/24 | Haochen,Meri,Rutvi |
| 5 | | 2.2 | Intro to the project & research | 2 days | Mon 2/12/24 | Tue 2/13/24 | Haochen,Meri,Rutvi |
| 6 | | 2.3 | Team Meeting | 1 day | Sun 2/18/24 | Sun 2/18/24 | Haochen,Meri,Rutvi |
| 7 | | 2.4 | Meeting with PM | 1 day | Wed 2/21/24 | Wed 2/21/24 | Haochen,Rutvi |
| 8 | | 3 | Execution | 51 days? | Fri 2/16/24 | Tue 4/23/24 | |
| 9 | | 3.1 | TASK 1 | 9 days | Fri 2/16/24 | Mon 2/26/24 | |
| 10 | | 3.1.1 | Research MRI & its uses | 3 days | Fri 2/16/24 | Mon 2/19/24 | Rutvi |
| 11 | | 3.1.2 | Research PC MRI and its uses | 3 days | Fri 2/16/24 | Mon 2/19/24 | Meri |
| 12 | | 3.1.3 | Study Coronal Angiogram, Magnitude & Phase Images | 4 days | Fri 2/16/24 | Tue 2/20/24 | Haochen |
| 13 | | 3.1.4 | Meeting with PM | 1 day | Mon 2/26/24 | Mon 2/26/24 | Haochen,Meri,Rutvi |
| 14 | | 3.1.5 | Create Project Timeline | 2 days | Fri 2/16/24 | Sun 2/18/24 | Meri |
| 15 | | 3.1.6 | Team Meeting | 1 day | Sun 2/25/24 | Sun 2/25/24 | Haochen,Meri,Rutvi |
| 16 | | 3.1.7 | Create First Update Presentation | 3 days | Fri 2/16/24 | Mon 2/19/24 | Haochen,Meri,Rutvi |
| 17 | | 3.1.8 | Present to class: First Update | 1 day | Tue 2/20/24 | Tue 2/20/24 | Haochen,Meri,Rutvi |
| 18 | | 3.2 | TASK 2 | 21 days | Tue 2/27/24 | Tue 3/26/24 | |
| 19 | | 3.2.1 | Meeting with PM | 1 day | Tue 2/27/24 | Tue 2/27/24 | Haochen,Meri,Rutvi |
| 20 | | 3.2.2 | Acquire data for cerebral blood flow | 5 days | Tue 2/27/24 | Mon 3/4/24 | Haochen,Meri,Rutvi |
| 21 | | 3.2.3 | Review & study the data: 3 images | 11 days | Tue 3/5/24 | Tue 3/19/24 | Haochen,Meri,Rutvi |
| 22 | | 3.2.4 | Research/Review PC MRI processing algorithm | 11 days | Tue 3/12/24 | Tue 3/26/24 | Haochen,Meri,Rutvi |
| 23 | | 3.2.5 | Team Meeting | 1 day | Mon 3/4/24 | Mon 3/4/24 | Haochen,Meri,Rutvi |
| 24 | | 3.2.6 | Meeting with PM | 1 day | Mon 3/25/24 | Mon 3/25/24 | Haochen,Meri,Rutvi |
| 25 | | 3.2.7 | Create 2nd update presentation | 4 days | Tue 3/5/24 | Fri 3/8/24 | Haochen,Meri,Rutvi |
| 26 | | 3.2.8 | Present to class: Second Update | 1 day | Tue 3/26/24 | Tue 3/26/24 | Haochen,Meri,Rutvi |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 25 | 3.2.7 | Create 2nd update presentation | 4 days | Tue 3/5/24 | Fri 3/8/24 | Haochen,Meri,Rutvi |
| 26 | 3.2.8 | Present to class: Second Update | 1 day | Tue 3/26/24 | Tue 3/26/24 | Haochen,Meri,Rutvi |
| 27 | **3.3** | **TASK 3** | **21 days** | **Wed 3/27/24** | **Tue 4/23/24** | |
| 28 | **3.3.1** | **Study cases of imputed vessels** | **5 days** | **Wed 3/27/24** | **Tue 4/2/24** | **Haochen,Meri,Rutvi** |
| 29 | 3.3.1.1 | Spatial & temporal information of MRI images | 5 days | Wed 3/27/24 | Tue 4/2/24 | Haochen |
| 30 | 3.3.2 | Team Meeting | 1 day | Mon 4/1/24 | Mon 4/1/24 | Haochen,Meri,Rutvi |
| 31 | 3.3.3 | Brainstorm methods to segment, identify & impute vessels | 6 days | Wed 3/27/24 | Wed 4/3/24 | Haochen,Meri,Rutvi |
| 32 | 3.3.4 | Develop averaging method: 3 dataset | 3 days | Thu 4/4/24 | Mon 4/8/24 | Meri |
| 33 | 3.3.5 | Implement averaging method (1) on all vessels: 3 dataset | 3 days | Tue 4/9/24 | Thu 4/11/24 | Rutvi |
| 34 | **3.3.6** | **Meeting with PM** | **1 day** | **Wed 4/10/24** | **Wed 4/10/24** | **Haochen,Meri,Rutvi** |
| 35 | 3.3.7 | Evaluate the performance of the method 1 | 4 days | Tue 4/9/24 | Fri 4/12/24 | Haochen |
| 36 | 3.3.8 | Study received algorithm of 25 images | 2 days | Mon 4/15/24 | Tue 4/16/24 | Haochen,Meri,Rutvi |
| 37 | 3.3.9 | Run code, manually correct, and obtain 25 images | 1 day | Wed 4/17/24 | Wed 4/17/24 | Haochen |
| 38 | 3.3.10 | Apply Method 1 (averaging) to 25 image dataset | 3 days | Thu 4/18/24 | Sun 4/21/24 | Rutvi |
| 39 | **3.3.11** | **Meeting with PM** | **1 day** | **Fri 4/12/24** | **Fri 4/12/24** | **Haochen,Meri,Rutvi** |
| 40 | 3.3.12 | Develop Method 2 - Imputation via interpolation for 25 image dataset | 3 days | Thu 4/18/24 | Sun 4/21/24 | Meri |
| 41 | 3.3.13 | Statistical analysis of methods | 3 days | Sun 4/21/24 | Tue 4/23/24 | Haochen |
| 42 | **3.3.14** | **Meeting with PM** | **1 day** | **Wed 4/17/24** | **Wed 4/17/24** | **Haochen,Meri,Rutvi** |
| 43 | **3.4** | **Close-Out** | **3 days** | **Sat 4/20/24** | **Tue 4/23/24** | |
| 44 | 3.4.1 | Prepare Final Project Presentation | 4 days | Sat 4/20/24 | Tue 4/23/24 | Haochen,Meri,Rutvi |
| 45 | 3.4.2 | Team Meeting | 1 day | Mon 4/22/24 | Mon 4/22/24 | Haochen,Meri,Rutvi |
| 46 | **3.4.3** | **Meeting with PM** | **1 day** | **Mon 4/22/24** | **Mon 4/22/24** | **Haochen,Meri,Rutvi** |
| 47 | 3.4.4 | Present to class: Final Presentation | 1 day | Tue 4/23/24 | Tue 4/23/24 | Haochen,Meri,Rutvi |

**Table 4:** *Number of man hours spent for project 3 from start to finish*

| | Meri Ghazaryan | Rutvi Zalawadia | Haochen Xie |
|---|---|---|---|
| **Average total resource hrs spent (hrs)** | **180** | **180** | **180** |

## Appendix D (Lessons Learned)

- Developed deeper understanding on the subject matter - i.e. how PC-MRI works, how images are obtained and processed, understanding the calculation of CBF and what it entails, functionality and flow of each vessel RICA, LICA, RVA, LVA.

- Learned the existing standard least-squares imputation model adopted by Dr. Borzage's lab.
- Learned and analyzed how the PC-MRI algorithm developed by Dr. Borzage's lab extracted vessel ID and flow information from the images. Additionally, developed understanding of manual vessel ID correction using phase contrast algorithm.
- Developed understanding of challenges to obtain healthcare and research data as well as the steps involved in acquiring clearance to access collaborator data.
- Explored and learned various statistical methods, models, and metrics, including single imputation, least-squares regression, linear interpolation, polynomial interpolation, and residual analysis and mean absolute errors.
- Developed better understanding of how each statistical method can be applied to our project-specific case through trial and error analysis
- Learned to better work in a team and leverage each individual's skill to complete project tasks on time.

## References


1. Zarrinkoob, L., Ambarki, K., Wåhlin, A., Birgander, R., Eklund, A., & Malm, J. (2015, March 31). *Blood flow distribution in cerebral arteries*. Journal of cerebral blood flow and metabolism : official journal of the International Society of Cerebral Blood Flow and Metabolism. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4420884/
2. Shah P, Doyle E, Wood JC and Borzage MT (2023) Imputation models and error analysis for phase contrast MR cerebral blood flow measurements. *Front. Physiol.* 14:1096297. doi: 10.3389/fphys.2023.1096297