

Visualizing Similarities between Volume Datasets by Using Critical Point Graph and Character Recognition Technique

Yasuhiro WATASHIBA¹, Koji SAKAI²,
Koji KOYAMADA², Masanori KANAZAWA³

¹Graduate School of Informatics, Kyoto University

²Center for the Promotion of Excellence in Higher Education, Kyoto University

³Academic Center for Computing and Media Studies, Kyoto University

Abstract

We propose a new technique for visually comparing the similarities between volume data sets by using Critical Point Graph (CPG) and Character Recognition Technique (CRT). Critical Points (CPs) represent feature points inside volume data and, CPG is a graph generated by connecting these points using streamlines based on vector field information. Passing Voxel Method (PVM) is a graph comparison technique which allows the visualization of both similarities and differences between two volume data. However, PVM has some limitations in its ability to judge similarities. Taking into consideration that streamlines of CPG are composed of small straight line segments, we have investigated the use of Directional Element Feature (DEF), usually used in CRT, by extending this technique for use in PVM in order to overcome some of its limitations.

KeyWords: Volume Data, Critical Point Graph, Similarity Judgment, Directional Element Feature

特異点グラフと文字認識技術を利用した ボリュームデータの類似状況の可視化

渡場 康弘¹, 酒井 晃二²,
小山田 耕二², 金澤 正憲³

¹京都大学大学院情報学研究科

²京都大学高等教育研究開発推進センター

³京都大学学術情報メディアセンター

概要

特異点グラフと文字認識技術を利用して、ボリュームデータ間の類似性を視覚的に比較できる手法を提案する。特異点グラフは、ボリュームデータの特徴を三次元空間における曲線という単純な図形で表現したものである。そこで、特異点グラフを比較するために、二次元空間で曲線を比較する手法である文字認識技術を利用した通過ボクセル判定法を考えた。この手法は、文字画像を各ピクセルの値で比較する手法を拡張したもので、ボクセル単位でグラフの通過状況を比較する手法である。そして、ボクセルごとの判定結果に従ってボクセルの色を決めることによって、その類似状況を可視化することが可能である。しかし、この手法にはいくつかの問題点がある。そこで、グラフが細かい線分で構成されていることから、文字認識技術の1つである方向線素特徴ベクトルを利用して、通過ボクセル判定法の問題を解決した。

キーワード: ボリュームデータ, 特異点グラフ, 類似判定, 方向線素特徴

1. Introduction

Nowadays, many large volume data sets have been generated from numerical simulations and digital measurements in various fields. Advances in computer and measurement device technologies have enabled their use in large-scale numerical simulations and high-resolution digital measurements, thus generating volume data which is continuously increasing in size and complexity. As a result, an efficient technique for an automatic classification of and searching for these data sets is highly desired.

Since the target is large volume data sets, the traditional classification method of using simple data comparison is not realistic. Moreover, this problem becomes more challenging since the target is volumetric data sets. So far, there is no well-known, efficient technique for judging the similarity between two volumetric data. Therefore, users who need data classification in order to analyze or measure these kinds of data sets usually need to do it manually. Taking into consideration this situation, we believe that a technique which can quantitatively and objectively classify volume data will be highly valuable.

There is a technique for showing the feature of a given data called Critical Point Graph (CPG) ^{[1], [2]}. A Critical Point (CP) represents a feature inside volume data, and CPG shows the connection between these points based on the information of vector field. Therefore, a general feature layout of a given volume data can be expressed in a simple image from these two elements, thus CPG can be thought of as the simplest layout containing the features of volume data. Taking this into consideration, several CP-based techniques for field analysis have been proposed so far ^{[3] - [7]}.

In this paper, we propose a new technique for visually comparing the similarities between two volume data by using CPG and Directional Element Feature (DEF) which has been efficiently employed in the field of character recognition ^[10]. Some comparative experiments added to [10] are presented in this paper.

2. Generating Critical Point Graph

Critical Points are defined as the positions of zero vectors inside a vector field or where the gradient vectors are zero vectors inside a scalar field. These points can be

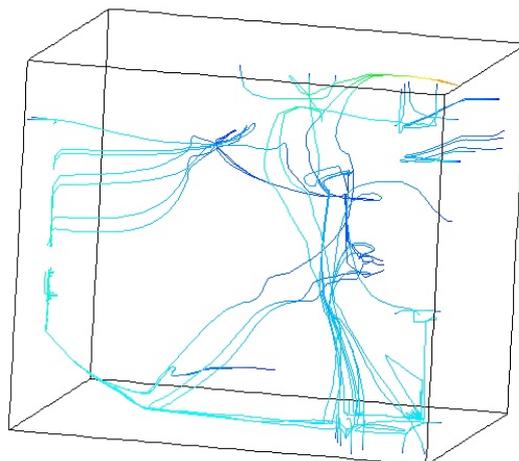


Fig. 1 Critical Point Graph generated from volume data

classified into *maxima*, *minima* or *saddle points* depending on the *eigenvalues* of velocity gradient tensor in each CP.

CPG is generated by connecting the CPs with streamlines starting from the saddle points. However, CPs themselves cannot be used directly as starting points since they are points of zero vectors by definition. Therefore, the streamlines are generated from positions distant from the saddle points in the direction of their eigenvectors. After executing this process from all saddle points the CPG is generated. Fig.1 shows an example of CPG generated from volume data.

3. Passing Voxel Method

We started by performing a similarity judgment by comparing the structures of CPGs. In this case, only the information about the connections between CPs is used while not taking into consideration the information of each CP.

However, the direct comparison of different CPG structures shows a difficult problem because it becomes necessary to compare the curved lines in three dimensional space. Therefore, we focused on a simple similarity judgment method by using voxels for assisting the comparison. The information on whether two different streamlines are passing or not passing together through the voxels is used for the similarity judgment. Each of these voxels is classified into four states. Considering two CPGs, as CPG1 and CPG2, these four states will be:

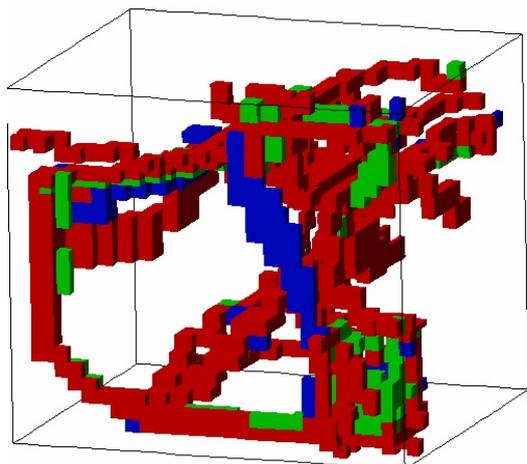


Fig. 2 Visualization result by using Passing Voxel Method

S0: a voxel which includes neither CPG1 nor CPG2.

S1: a voxel which includes only CPG1.

S2: a voxel which includes only CPG2.

S3: a voxel which includes both CPG1 and CPG2.

The similarity is then calculated from the ratio of the numbers of voxels classified as S1, S2 and S3. Considering $N1$, $N2$ and $N3$ as the number of voxels of S1, S2 and S3 respectively, the similarity S can be calculated from the following expression (1):

$$S = \frac{N3}{N1 + N2 - N3} \times 100 (\%) \dots\dots(1)$$

We named this technique as Passing Voxel Method (PVM) and can be considered similar to traditional image comparison techniques. In the case of image comparison, the pixels are compared regarding information such as color. In the case of PVM, the comparison is executed regarding number of voxels belonging to each state.

Therefore, a similar situation of image comparison can be visually obtained by coloring the voxels of each state using different colors. In this work, we used blue for coloring voxels classified as S1, green for voxels classified as S2 and red for voxels classified as S3. Fig.2 shows a visualization result when this technique is applied.

The main advantage of this technique is the ability for easy visual confirmation of similarities. However, we

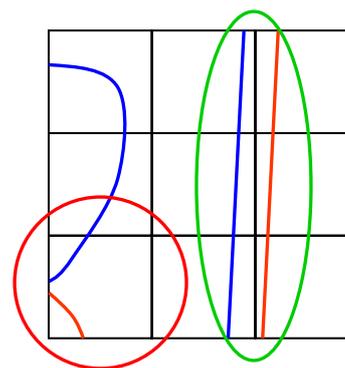


Fig. 3 Some problems found in Passing Voxel Method.

The red circle shows the second problem. The green circle shows the third problem.

can identify three problems in this method. The first is that this method works only when both voxel resolutions are the same. Moreover, this technique cannot handle affine transformations such as rotation or scaling. The second is that this method treats even a voxel having streamlines with different directions passing through this cell as S3. The third is that this method judges similar streamlines passing closer but in different voxels as S0. Fig.3 depicts the second and third problems.

4. Improvement of Passing Voxel Method

In this paper, we mainly focused on the aforementioned second problem. However, possible solutions to the first and third problems are also described. In the following sections, some solutions are presented in order to overcome these three problems by improving the original Passing Voxel Method.

4.1. Solution to the first problem

The first problem is caused because the voxel space used for data generation is directly used as the spatial unit for comparison. As a result, the original PVM was unable to handle volume data with different resolutions. This limitation has made the original PVM not attractive for practical use.

To solve this problem, we applied the normalization and registration methods. The necessary rotation angles and scaling factors are calculated by using the Principal Component Analysis (PCA) to the distribution of CPs [11]. This technique therefore guarantees necessary form

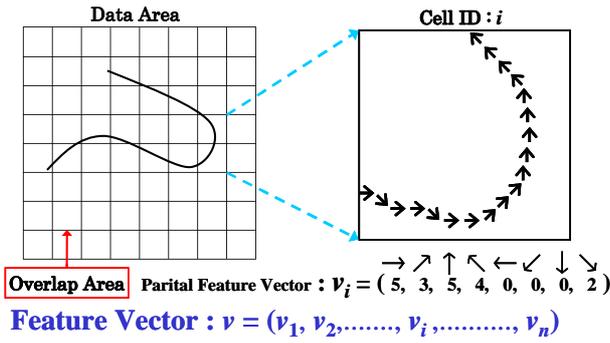


Fig. 4 Generation process of directional element feature vectors. Partial feature vector is generated in each processing area and the elements of the vector show the number of each directional element in the area. Therefore, all elements of the feature vector become nonnegative.

alignment between the CPGs being compared. Since this method processes only the shape information, the comparison area can be repartitioned into rectilinear cells of any arbitrary resolution size, and as a result, enabling the comparison of volume datasets of any size.

4.2. Solution to the second problem

We applied the Character Recognition Technique (CRT) for improving the PVM and solving the second problem. CRT is similar to PVM regarding the comparison of curved lines, although they differ in dimensionality since CRT is a 2D process.

Among the several methods proposed for CRT, we paid special attention to the Directional Element Feature (DEF) [8], [9] because this treats a streamline as a set of small segments with directions. Since CPG can be considered a set of small contiguous segments with directions, DEF appears suitable for application in CPG.

In 2D, DEF is a segment in a domain quantized in any of the eight pre-determined directions. Actually, because the segment is composed of two pixels in the character image, it has only eight directions. Partial feature vector is obtained by grouping together some contiguous segments by storing each direction as an element of the vector. Feature vector is generated by joining these partial vectors of all domains. Fig.4 depicts the DEF and its vectors.

In order to enhance this technique for 3D, we enlarged the quantized directions from 8 to 26 directions. At this time, the segment with the opposite direction is treated as another directional element. Other procedures were

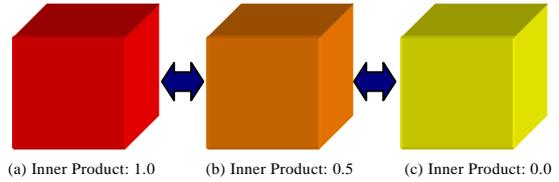


Fig. 5 Change in color of cell in state of S3 according to the value of the inner product of partial feature vectors

retained as in the case of 2D. We applied this enhanced DEF in order to overcome the aforementioned problem of PVM. For this purpose, the partial feature vector was normalized.

Similarity is now calculated by summing the inner product results of the partial feature vectors in each S3 cell instead of the quantity of S3 cells. Designating the value of summing the inner product results as TIP, the equation (1) can be rewritten as equation 2 as follows:

$$S = \frac{TIP}{N1 + N2 - N3} \times 100 (\%) \dots\dots(2)$$

By using this technique, the misjudgments in S3 cells due to the different streamline directions can be solved. Since the partial feature vectors are normalized and the element of the vector is nonnegative because it is composed of the number of corresponding directional element, the inner product result is a value between 0 and 1. Therefore, when streamlines with different directions pass through a cell, the inner product value becomes close to 0 and this cell will not be counted as an S3 cell.

To make this result visible, the color can be assigned proportionately to the value of inner product. In this work, the color changes from red to yellow as the inner product value decreases from 1 to 0. Fig.5 shows the color changing of S3 states according to their values of inner product of partial feature vectors. As a result, it becomes easy to visually distinguish different streamlines passing through the same cell.

4.3. Solution to the third problem

The third problem occurs when two similar streamlines become divided into different neighboring cells. This problem can be solved by changing slightly the resolution of this specific region in order to join these streamlines into the same cells. Therefore, we can handle this problem by comparing these regions in slightly different resolutions during the data comparison.

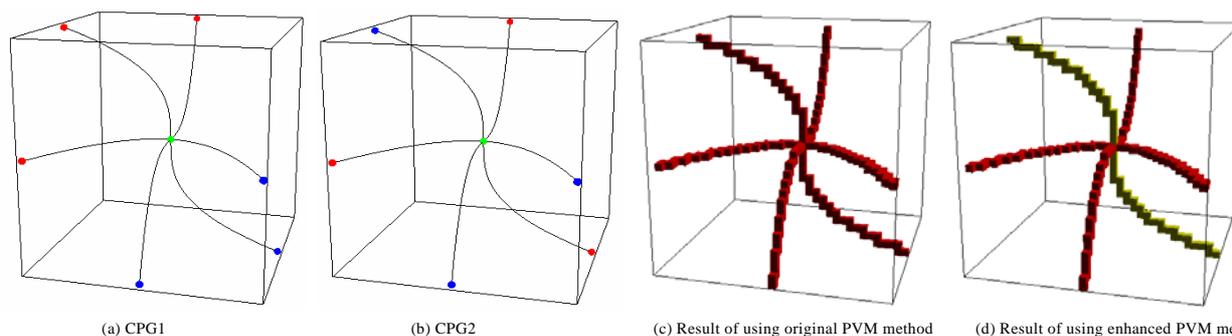


Fig. 6 Comparison of two CPGs having the same shape but different CP types. Although all cells are reds in (c), some cells become yellows in (d) because the inner product values between the normalized partial feature vectors in these cells become smaller than 1.

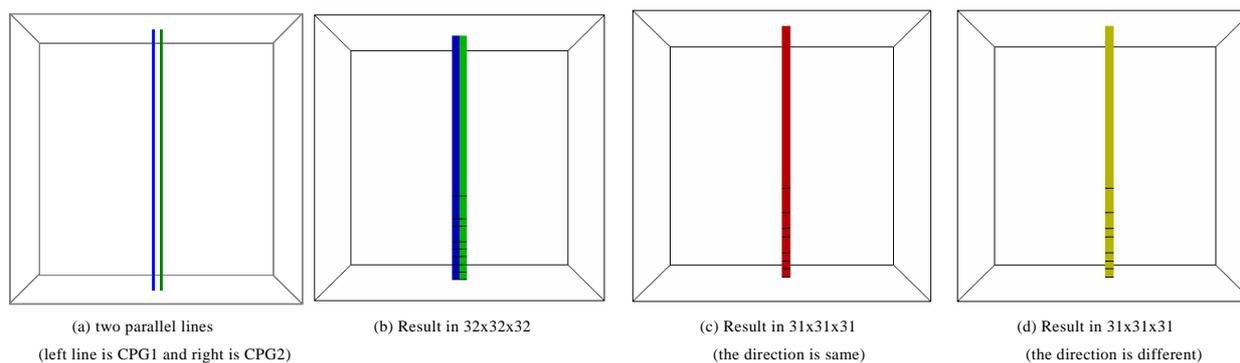


Fig. 7 Comparing two parallel CPG using enhanced PVM in case of changing resolution

5. Experiments

5.1. Regarding the second problem

When CPGs having streamlines in different directions in the same cell, the second problem greatly influences the judgment result. It is worth noting that the normalization method proposed for solving the first problem does not take into consideration the CP types. Therefore, there still remains a high possibility to be influenced by such situation.

We generated a data set which simulates this condition and utilized the original and enhanced PVM for evaluation purposes. Fig.6(a) and Fig.6(b) show the CPGs of these data. In these images, red points correspond to *maxima*, blue points to *minima*, and green points to *saddle points*. The resolution utilized in this experiment was 32x32x32.

From this experiment, we can verify that the obtained similarity between these data was 100% in the original PVM, however 66.7% in the enhanced PVM. From this result, we can verify that the enhanced PVM is able to

correctly distinguish this type of dissimilarity. The visualization results are shown in Fig.6(c) and Fig.6(d), and from the Fig.6(d) we can easily identify this kind of area.

5.2. Regarding the third problem

The third problem occurs when there is a boundary between similar streamlines belonging to different CPGs. Since this boundary moves when the resolution of cell space changes, it is possible to solve this problem by combining the judgment results using different resolutions. For instance, by using the specified resolution and a slightly different resolution.

Two parallel straight lines were utilized in order to evaluate this proposed method (Fig.7(a)). The visualization results when using the enhanced PVM are shown in Fig.7(b)-(d).

The Fig.7(b) shows the comparison result when utilizing the resolution of 32x32x32. At this time, the cell boundary is intentionally placed between these lines, therefore resulting in a disagreement.

The Fig.7(c) and Fig.7(d) show the results when utiliz-

ing the resolution of $31 \times 31 \times 31$. The Fig.7 (c) corresponds to the case when these two lines have the same direction. The Fig.7(d) corresponds to the case when they have opposite directions. Thus, even these cells are considered S3, they should be judged dissimilar. From these figures, we can verify that the enhanced PVM is able to distinguish these cases showing that this method can effectively solve the third problem.

5.3. Real data sets

We verified the results when applying the original and enhanced PVM to real volume data. We used a simulation result of the temperature distribution in a room. The proposed technique enhanced the original PVM in order to judge more precisely. We utilized similar data on both methods to verify the effectiveness of the enhanced PVM compared to the original PVM. For this purpose, the CPGs were generated from the same volume data by using different parameters. The obtained CPGs are shown in Fig.8(a) and Fig.8(b). The CPG of Fig.8(a) was named “CPG1” and of Fig.8(b) as “CPG2”. The similarity between CPG1 and CPG2 was judged by using the original and enhanced PVM.

The obtained similarity was 68.6% when using the original PVM, and 64.2% when using the enhanced PVM. The reason for this similarity decrease is because the cells with different shapes of CPG were judged as S3 cells.

The visualization results are shown in Fig.8(c) and Fig.8(d). The orange circles show the area which occurred this kind of judgment. Although all S3 cells are considered red in Fig.8(c), they change to other colors from red to yellow in Fig.8(d). From these results, we can easily confirm visually that the S3 cells in this area possess CPG of different shapes.

6. Conclusion and Future Work

In this paper, we proposed and evaluated an efficient technique for visually comparing the similarities between volume data by using Critical Point Graph and Directional Element Feature which has been employed in the field of Character Recognition Technique.

We could verify that the enhanced PVM works better than the original PVM since it is able to minimize the

misjudgment of S3 cells. In addition, this also enables the visual confirmation of the degree of similarity.

In the future, we are planning to further improve the visual comparison of volume data. Regarding the third problem, we have described a technique based on resolution changing of comparison areas. However, this method is only effective in the area which is focused on, and this can also generate misjudgment in another area because of the resolution changing. Therefore, it is necessary to consider a technique which extracts the area caused by this problem.

References

- [1] K.Sakai, K.Koyamada, K.Kamisawa, and A.Do, "Classifying Scalar Field by using Critical Point Graph", Proceedings of the 10th International Symposium on Flow Visualization, F326, 2002.
- [2] K.Kamisawa, K.Koyamada, K.Sakai, and A.Do, "A technique for skeletonizing a scalar field using a critical point graph: application to a weather simulation", Proceedings of 4th International Symposium on Computational Technologies for Fluid/Thermal/Chemical Systems with Industrial Applications, PVP-Vol. 448-1, pp. 27-34, 2002.
- [3] J.Helman and L.Hesselink, "Visualizing vector field topology in fluid flows", IEEE Computer Graphics and Applications, Vol.11, No.3, pp36-46, 1991.
- [4] M.Hilaga, Y.Shinagawa, T.Kohmura and T.L.Kunii, "Topology Matching for Fully Automatic Similarity Estimation of 3D Shapes", Proceedings of the ACM SIGGRAPH 2001, pp.203-212, 2001.
- [5] K.Koyamada and T.Itoh, "Finding of Critical Points by Using Tetrahedral Cells", Proceedings of World Congress on Computational Mechanics '94, pp. 454-455, 1994.
- [6] C.L.Bajaj, V.Pascucci, and D. R. Schikore, "Visualization of Scalar Topology for Structural Enhancement", Proceedings of the IEEE Visualization, pp.51-58, 1998.
- [7] K.Sakai, N.Sakamoto and K.Koyamada, "An Analytical Method for the Weather Phenomena with Critical Point Visualization", Proceedings of Visualization, Imaging, and Image Processing 2004, pp.172-177, 2004
- [8] N.Sun, T.Tabara, H.Aso and M.Kimura, "Printed Character Recognition Using Directional Element Feature", Transactions of the Institute of Electronics, Information

and Communication Engineers, J74-D-II, 3, pp.330-339, 1991-3.

- [9] N.Kato, M.Suzuki, S.Omachi, H.Aso, and Y.Nemoto, "A Handwritten Character Recognition System Using Directional Element Feature and Asymmetric Mahalanobis Distance", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol.21, no.3, pp.258-262, March 1999.
- [10] Y.Watashiba, K.Sakai, K.Koyamada and M.Kanazawa, "Similarity Judgment Method of Volume Data by Critical Point Graph Using Directional Element Feature", Pro-

ceedings of NICOGRAPH International 2005, pp.149-153, 2005.

- [11] T.Minami, K.Sakai and K.Koyamada, "A Similarity Evaluation Method for Volume Data Sets by Using Critical Point Graph", Proceedings of International Symposium on High Performance Computing 2005, 2005.

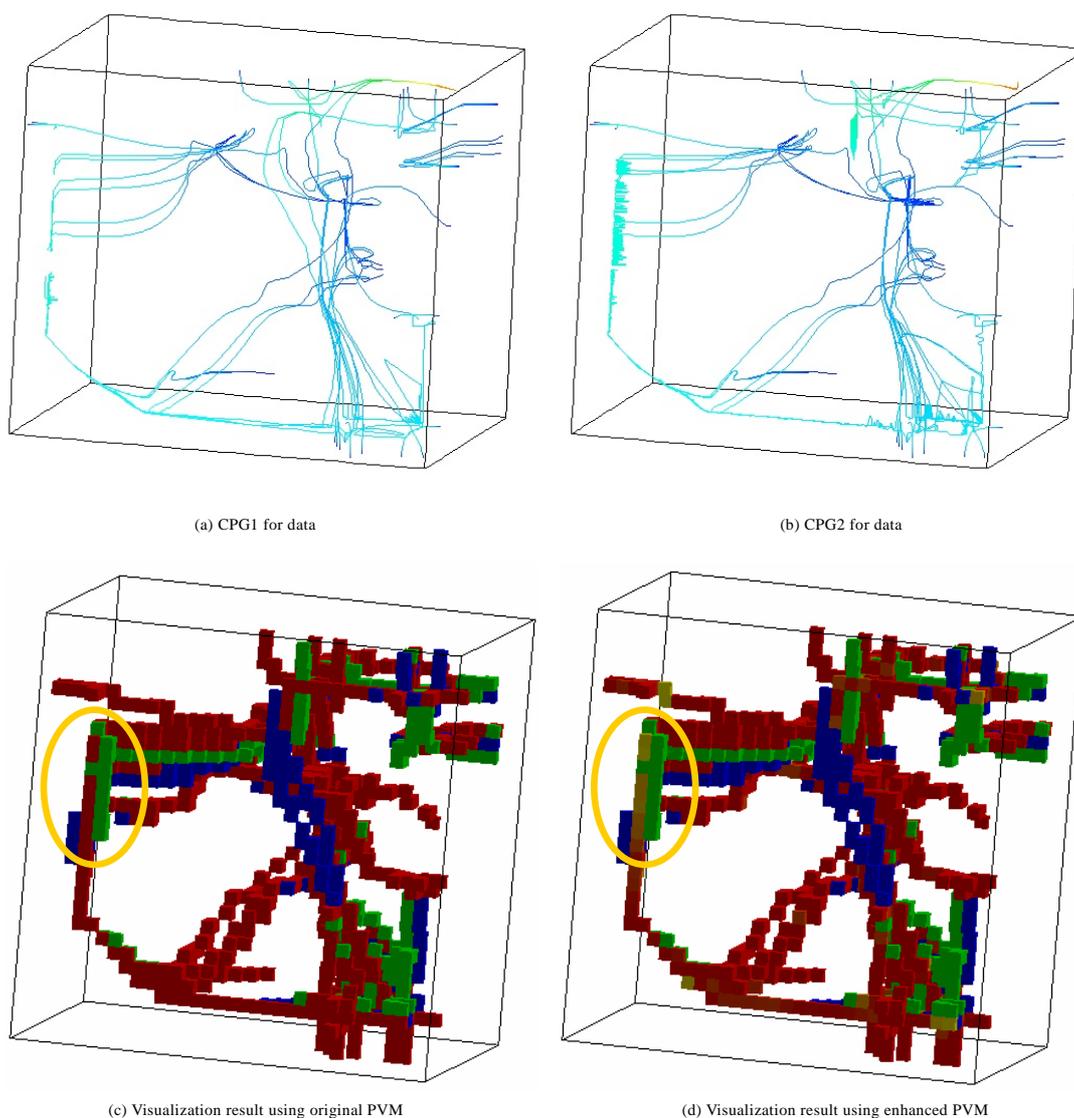


Fig. 8 CPGs to the experiment data and visualization results of comparing these CPGs using original or enhanced PVM.