6-12-2017

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Eurographics Conference on Visualization (EuroVis) 2017
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(Guest Editors)

Short Paper

Intuitive Error Space Exploration of Medical Image Data in Clinical Daily Routine

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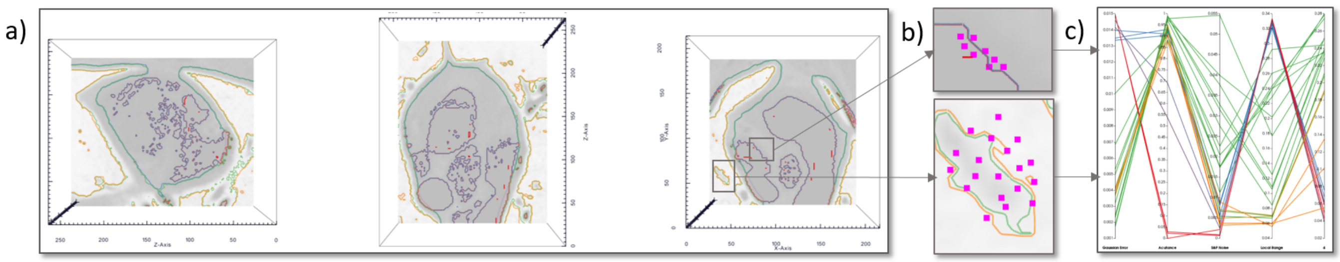

Figure 1: *Intuitive error space exploration of medical image data embedded in the medical workflow. a) Iso-surface visualization of clustered error space embedded in the established slice-by-slice reviewing method utilized in clinical daily routine. b) User selections can be made to inspect interesting pixels. c) Error space of the user selected pixels visualized in a color coded parallel coordinate view.*

Abstract

Medical image data can be affected by several image errors. These errors can lead to uncertain or wrong diagnosis in clinical daily routine. A large variety of image error metrics are available that target different aspects of image quality forming a high-dimensional error space, which cannot be reviewed trivially. To solve this problem, this paper presents a novel error space exploration technique that is suitable for clinical daily routine. Therefore, the clinical workflow for reviewing medical data is extended by error space cluster information, that can be explored by user-defined selections. The presented tool was applied to two real-world datasets to show its effectiveness.

Keywords: Medical Visualization, Multi-variate Visualization, Error Space Exploration

1. Introduction

In clinical daily routine imaging methods such as Computed Tomography (CT) or Magnetic Resonance Imaging (MRI), are a common imaging technique that allow medical doctors to make diagnosis and derive treatment plans. Although the image quality of medical images constantly increased over the past years [Web88], they still contain various image artifacts such as motion, partial volume effects and voxel bleeding [BF].

In many cases it can be hard to determine the health condition of a patient based on images, especially if the medical doctor tries to answer questions such as: do I see a tumor on this scan? How big is the tumor? Is this a problematic tissue change or an image artifact [LATR*16]?

Therefore, various metrics are available, that can be used to estimate the probability, that a voxel is effected by an image error. These metrics target different aspects of a voxel such as the homogeneity of the voxel's neighborhood or the sharpness of an edge between two structures. To understand the quality of an image, the variety of error metrics needs to be examined in its entirety. Unfortunately, an intuitive exploration of this error space suitable for the clinical daily routine was not provided so far 2.

Therefore, this paper presents an intuitive error space exploration technique for medical image data that is embedded in the state of the art slice-by-slice reviewing methods in clinical daily routine 3. The visualization is based on an error space clustering that is visualized by iso-lines in the CT scan visualization. For an intuitive visual

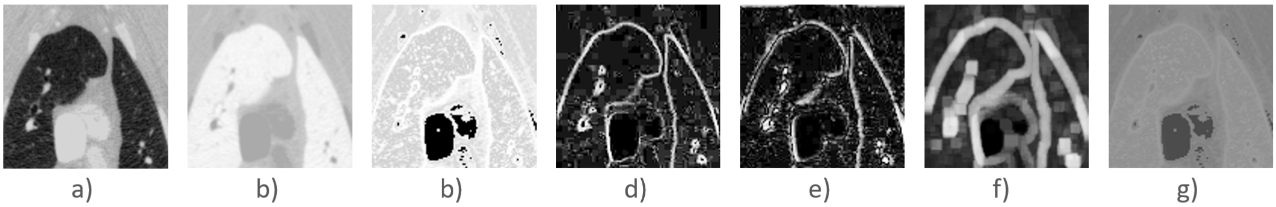

Figure 2: *Image errors. a) Original Image. b) Gaussian Error. c) Local Contrast. d) Acutance. e) Salt and Pepper Noise. f) Local Range. g) Length of error vector.*

exploration of the error space the users can review the composition of the clusters and select specific voxels they want to investigate further in a parallel coordinate plot.

Therefore, this paper contributes:

- Image error visualization in extension to the clinical workflow
- Intuitive error space exploration for medical image data

The effectiveness of the presented approach is shown with an real world example of a brain MRI containing an error with fuzzy borders (Section 4) and a CT scan of a pig thorax. This work is concluded and future directions will be given in Section 5.

2. Related Work

Error and uncertainty visualization [BHJ*14] is a wide topic that is often applied in medical visualization due to the requirement of a high precision in medical image data.

Volume rendering [LLPY07,FMG*16] can be used to encode the degree of trust for different regions in the volume rendered scan. Although this gives a suitable overview of how accurate specific image areas are, these techniques are not able to visualize multiple error measurements. Therefore, the presented technique is able to visualize a multi-variate error space for medical image data.

Multi-variate data visualization [WB97] can be accomplished for all possible kinds of data. Volume rendering [DDC*16, AMCH07, MLM03] utilizing specific transfer functions to visually encode multiple values and their similarities per grid are widely used. Although these techniques offer a suitable volume visualization for multi-variate volume datasets, they are not designed to be used in clinical daily routine. In clinical daily routine, volume rendering is not spread widely. In contrast to that, the presented technique utilizes the available multi-variate visualization techniques and extends them thus they can be embedded into the slice-by-slice reviewing method in clinical daily routine to gain higher user acceptance.

3. Methods

The following Section presents an intuitive visualization to review the error space of CT scans. Therefore, multiple error measures (Section 3.1) are embedded in the standardized medical data visualization (Section 3.2). The visualization is part of a linked view system that allows an intuitive exploration of the image error space (Section 3.3).

3.1. Image Errors

Due to the image reconstruction process of medical image data, the resulting images can contain various errors. Different image error metrics are available to determine the error of an image voxel [TR09]. Unfortunately, most of them solely target one aspect of incorrect image values [MTM12]. Therefore, multiple image errors need to be considered in order to cover the spectrum of image errors as good as possible. In the presented work five metrics, that cover a wide spectrum of image errors, when considering scalar value images such as derived in medical most medical image generation processes, are defined as the error space of a medical image. For an image I, each of its voxels $v$obtains an error vector $v_e = (e_1, e_2, e_3, e_4, e_5)$.

Table 1 shows the considered metrics and their definition:

Entry	Name	Reference	Definition
e_1	Gaussian error	[Fie97]	Distance of pixel value from expected mean
e_2	Local contrast	[LG13]	Pixel value occurrence in the entire image
e_3	Acutance	[Art15]	Length of the pixel gradient
e_4	Salt and pepper noise	[ISRM15]	Degree of affectedness by salt and pepper noise
e_5	Local range	[TXSH04]	Range of pixel values in an image surrounding

Table 1: *Image error space utilized for the presented methods, containing the number, reference and definition of different image errors.*

Figure 2 a) shows the slice of an example CT scan of a pig. b)-f) show the calculated image metrics according to the original image. Figure 2 g) encodes the length of the resulting error vector when assuming each error metric as one dimension. It can be seen, that solely reviewing the length of this error vector does not hold enough information to estimate the error of a pixel or a region. Different combinations of error metric values can lead to the same error length. As error metrics are encoding different aspects, the length of the error vector is not sufficient to explore the error space of medical image data.

3.2. Embedded multi-variate Error Visualization

In contrast to solely reviewing the length of the image error, medical doctors are interested in the composition of the error vector of important regions, e.g. the border of a tumor. Therefore, the goal is to embed this information into the displayed image.

In clinical daily routine a slice-by-slice representation is state of the art and medical doctors are trained to review image data fastly based on this technique. Therefore, the user depicts one coordinate axis and scrolls through the image slices along this axis. The goal of the presented technique is to provide a visualization of the error space embedded in the slice-by-slice visualization technique thus medical doctors can easily use it.

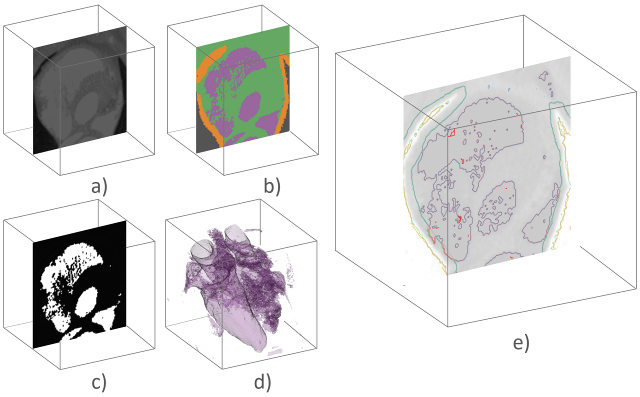

Figure 3: *Computational workflow for the presented approach. a) Original slice of the input volume. b) Resulting Clustering of the error space using k-means clustering ($k = 4$). c) Resulting weights for the first cluster. d) Iso-surface visualization of the first cluster using 0.5 as iso-value. e) Embedding of iso-lines from all cluster into the slice-by-slice reviewing method.*

Error Space Clustering To identify similar behaving areas in an image according to their error space, a clustering of the error space is required. In the presented method, a k-means clustering is used. Although this approach has the drawback, that a suitable k needs to be found this method has a relatively low computational effort. For example, a common CT scan contains about 512x512x512 pixels. Clustering methods that estimate the number of voxels automatically, usually need to compare all data points to each other to find a suitable division into clusters. In the case of the presented error space this would lead to $(512x512x512)^2$ comparisons, which is an unacceptable time consumption for clinical daily routine.

Figure 3 b) shows a slice of the resulting clustering of the image error space for the presented example. Although the presented system requires the user to select a k before the computational pipeline is continued, the system could be easily extended in order to choose k automatically [HE03].

Although this clustering provides a first overview over the behavior of the error space, it would not be sufficient to solely examine this visualization. Medical doctors always require the original dataset. Therefore, the goal is to embed the clustered information in the slice-by-slice reviewing method in clinical daily routine.

Embedded Iso-line Visualization To embed the error space cluster information into the slice-by-slice reviewing method, the presented visualization implements a line-representation of the computed clusters that can added to the original slice-by-slice reviewing method.

To achieve this, it is important to identify areas in the CT-scan, that strongly belong to a cluster and highlight them in the slice by slice-visualization. As the k-means algorithm outputs a cluster center for each cluster it is possible to determine the distance of each error point $d(e)_c$ to each cluster center c. Based on this, it is possible to assign a weight to an error vector for each cluster, that can be computed as follows:

$$\omega(e)_c = \frac{d(e)_c^2}{\sum_c d(e)_c^2} \tag{1}$$

For each voxel, the weights for all clusters sum up to 1. In the case that an error is highly similar to an cluster center its weight will be 1, whereas in contrast if the distance to a center is low its weight will be 0. Figure 3 c) shows the resulting weights for the first cluster.

For all pixels in the image, where the resulting weight of a class is higher than 0.5 it is clear, that this pixel belongs to this cluster. Various algorithms, such as marching cubes can be utilized to generate an iso-suface based on the given weights for each cluster. As Figure 3 shows, the resulting iso-surface for cluster 1 leads to a massive amount of visual clutter. Adding the remaining clusters would lead to an unusable visualization. To solve this problem, the depicted slice of the users works as a stencil that decides the visible iso-line, as shown in Figure 3.

3.3. Error Space Exploration

Although the embedded cluster visualization in the slice-by slice view provides a suitable overview over the error distribution in the observed image it is not able to show how the error vector is composed by the single error components. Therefore, the presented slice-by-slice visualization is part of a linked view system that allows an intuitive error space exploration.

Medical doctors are usually interested in specific image regions in the captured datasets such as the border of brain tumors. Especially these tissues can cause various image artifacts, which makes an error space visualization important. To provide a further investigation of selected areas, the selection view is available. The selection view displays a parallel coordinate visualization containing 5 axes, each representing one of the error metrics. For each selected voxel, the corresponding error vector is displayed in its cluster color.

This provided a focus visualization for selected pixels and areas in the image. The selected pixels are highlighted in purple in the slice-by-slice view. Figure 4 shows an example selection and the resulting parallel coordinate view.

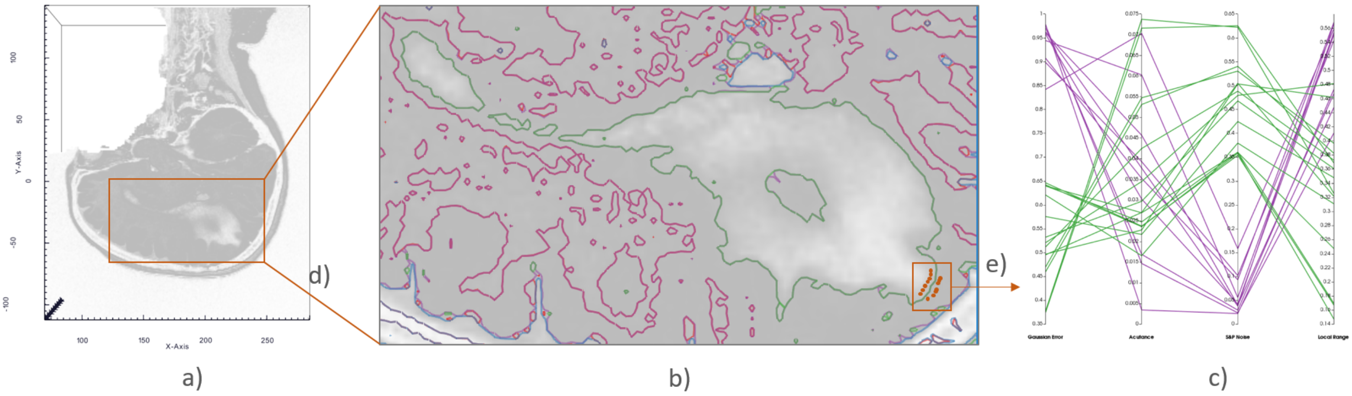

Figure 4: *The presented visualization technique applied to a brain tumor dataset. a) Original dataset in a slice-by-slice visualization common in clinical daily routine. b) Closeup of the tumor with the presented embedded visualization. c) Selection view d) Brain tumor e) User selection at the tumor's border.*

4. Results and Discussion

The presented approach was applied to a tissue inspection scenario as well as a tumor identification scenario. The visualization can be turned on and off if requested.

Tissue inspection Figure 1 shows the presented approach applied to a CT scan of a pig [HCW*02]. In this example, the goal was to explore the dataset in general and review the error space behavior for different tissues. The number of clusters was set to 4. Figure 1 a) shows the embedded cluster information in the slice-by-slice reviewing method. Each axis (x, y and z) can be controlled separately. Two clusters of user selected points are made (shown in Figure 1 b), one in the pig's lung and one on the border of the pig's heart. The resulting parallel coordinates view is shown in 1 c). The different error behavior for different tissues is clearly identifiable.

The design of the error space exploration is intuitive and designed to be used in clinical daily routine, as it is an extension of the widely used slice-by-slice reviewing method. The method is solely depending on one parameter, the number of k, required for the k-means clustering. The example shows, that a small number of k is sufficient to identify different behaving regions in medical image data.

Tumor Boundary Identification Figure 4 shows the application of the presented approach to a real world dataset from the cancer imaging archive [KBK*13]. The example shows a MRT brain dataset that contains a tumor [SMC*16] with the size of 256x215x90 voxels. On the original image, it can be observed, that the border of the tumors can not be identified clearly. In clinical daily routine scenarios this is an important information to determine a suitable treatment plan.

In the presented example, the number of clusters was set to 4. The presented embedded visualization allows the medical doctor to determine different regions in the tumor where error metrics are behaving differently (green line). While solely reviewing, the CT scan, it is hard to determine, where exactly the border of the tumor is located. With the embedded cluster visualization, it is possible to determine two regions in the tumor's border.

For these two regions, the resulting error space behaves differently. By making a selection (see Figure 4 d)) at the tumors border, the user can further explore the composition of the errors in the two clusters. The resulting parallel coordinate plot in Figure 4 shows the single error values of the selected pixels. The plotted lines are colorcoded by green and purple to indicate the cluster, they belong to.

In the example it can be observed, that the selected voxels of the inner (green) cluster holds a small gaussian noise and local range error. Therefore, the medical doctor can declare this region as trustworthy. In contrast to that, the purple area holds a high gaussian noise and a local range, which indicates, that this region is less trustworthy.

5. Conclusions and Future Work

This paper presented a novel error space exploration tool for clinical daily routine. A error space-based clustering was used to indicate areas in medical image data that's errors behave similar and embed these information in the workflow used in medicine. For a further exploration of the error space, a selection view for depicted voxels are provided. The presented example of a brain tumor showed, that this visualization technique can help medical doctors to determine the quality of different regions in medical image data and therefore help them refine their diagnosis.

As a future task, it is planned to perform a clinical study with the presented system to identify further improvements in the error space exploration system. Especially the initial training of users to understand the utilized error metrics and their intuition is targeted. Furthermore, a highlighting that guides users to interesting error configurations is planned.

Acknowledgements

This work was funded by the IRTG 2057 (International Research Training Group) as part of the DFG (German research foundation). We would like to thank Ghassan Kassabs research team for providing the datasets used in this study.

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