A MRI-Guided of Active Raster Exploration of Pixel for Meticulous Neoplasm Segmentation

Abstract—The examplar-based rastering algorithm through investigating the sparsity of natural image patches on brain tumor region. Two novel concepts of sparsity at the patch level are proposed for modeling the patch priority and patch representation, which are two crucial steps for patch propagation in the examplar-based inpainting approach. First, patch structure sparsity is designed to measure the confidence of a patch located at the image structure (e.g., the edge or corner) by the sparseness of its nonzero similarities to the neighboring patches. The patch with larger structure sparsity will be assigned higher priority for further inpainting. Second, it is assumed that the patch to be filled can be represented by the sparse linear combination of candidate patches under the local patch consistency constraint in a framework of sparse representation. Experiments on synthetic and natural images show the advantages of the proposed approach. Experiments demonstrate that the method can successfully achieve segmentation for MR brain images to help pathologists distinguish exactly lesion size and region.

Keywords—: Image Rastering, MRI, Brain Tumor, sparse representation, texture synthesis.

I. INTRODUCTION

In the scientific literature, texture-based applications, providing segmentation and classification tasks on digital images, are widely reported. The basic assumption of such applications is that different local textures can represent different physical characteristics of different objects. Some examples are described in the field of biomedical informatics [1], where texture measurements give information about the presence of masses in mammograms; in oceanography [2], where objects, located on the Mediterranean seabed, are accurately detected and classified; in computer vision [3], where specific elements of natural landscapes are extracted and recognized from images. Medical image analysis typically involves image data that has been generated from heterogeneous underlying physical
processes. Segmenting this data into coherent regions corresponding to different anatomical structures is a core problem with many practical applications.

For example, it is important to automatically detect and classify brain tumors and measure properties such as tumor volume, which is a key indicator of tumor progression [1]. But automatic segmentation of brain tumors is very difficult. Brain tumors are highly varying in size, have a variety of shape and appearance properties, and often deform other nearby structures in the brain [2]. In general, it is impossible to segment tumor by simple thresholding techniques [3].

1.1 Image Rastering

Image rastering provides a means to restore damaged region of an image, such that the image looks complete and natural after the rastering process. Rastering refers to therestoration of cracks and other defects in works of art. A wide variety of materials and techniques are used for rastering. Automatic/Digital rastering are used to restore old photographs to their original condition.

The purpose of image rastering is removal of damaged portions of scratched image, by completing the area with surrounding (neighboring) pixel. The techniques used include the analysis and usage of pixel properties in spatial and frequency domains. Image rastering techniques are also used in object removal (or image completion) in symmetrical images.

Fig 1.1 Micro Array Image Pixel Rastering
Rastering is the process of reconstructing lost or deteriorated parts of images and videos. For instance, in the museum world, in the case of a valuable painting, this task would be carried out by a skilled art conservator or art restorer. In the digital world, rastering (also known as image interpolation or video interpolation) refers to the application of sophisticated algorithms to replace lost or corrupted parts of the image data (mainly small regions or to remove little defects). There are many objectives and applications of this technique. In photography and cinema, it is used for film restoration; to reverse the deterioration (e.g., cracks in photographs or scratches and dust spots in film; see infrared cleaning). It is also used for removing red-eye, the stamped date from photographs and removing objects to creative effect. This technique can be used to replace the lost blocks in the coding and transmission of images, for example, in a streaming video. It can also be used to remove logos in videos.

1.2 Pixel Rastering

Rastering is rooted in the restoration of images. Traditionally, rastering has been done by professional restorers. The underlying methodology of their work is as follows:

- The global picture determines how to fill in the gap. The purpose of rastering is to restore the unity of the work.

- The structure of the gap surroundings is supposed to be continued into the gap. Contour lines that arrive at the gap boundary are prolonged into the gap.

- The different regions inside a gap, as defined by the contour lines, are filled with colors matching for those of its boundary.

- The small details are painted, i.e. “texture” is added.
1.3 Computerized of Image Rasterization

Since the wide applications of digital camera and the digitalization of old photos, rastering has become an automatic process, which is operated on digital images. More than scratch removing, the rastering techniques are also applied to object removal, text removal and other automatic modifications of images and videos. Furthermore, they can also be observed in applications like image compression and super resolution. Mainly three groups of 2D image rastering algorithms can be found in literature. The first one to be noted is structural rastering, the second one is texture rastering and the last one is a combination of these two techniques. All these rastering methods have one thing in common - they use the information of the known or undestroyed image areas in order to fill the gap. Structural inpainting uses geometric approaches for filling in the missing information in the region which should be inpainted. These algorithms focus on the consistency of the geometric structure.

1.4 Combined Structural and Textural Rastering

Combined structural and textural rastering approaches simultaneously try to perform texture and structure filling in regions of missing image information. Most parts of an image consist of texture and structure. The boundaries between image regions accumulate structural information which is a complex phenomenon. This is the result when blending different textures together. That is why, the state of the art rastering method attempts to combine structural and textural rastering. A more traditional method is to use differential equations (such as the Laplace's equation) with Dirichlet boundary conditions for continuity (a seamless fit). This works well if missing information lies within the homogeneous portion of an object area. [1] Other methods follow isophote directions (in an image, a contour of equal luminance), to do the rastering.[2] Model based rastering follows the Bayesian approach for which missing information is best fitted or estimated from the combination of the models of the underlying images as well as the image data actually being observed. In deterministic language, this has led to various variational rastering models. [3] Manual computer methods include using a clone tool or healing tool, to copy existing parts of the image to restore a damaged texture. Texture synthesis may also be used.[4] Exemplar-based image rastering attempts to automate the clone tool process. It fills "holes" in the image by searching for similar patches in a nearby source region of the image, and copying the pixels from the most similar patch into the hole. By performing the fill at the patch level as opposed to the pixel level, the algorithm reduces blurring artifacts caused by prior techniques

1.5 NOISE REDUCTION

Noise reduction is the process of removing noise from a signal. All recording devices, both analogue or digital, have traits which make them susceptible to noise. Noise can be random or white noise with no coherence, or coherent noise introduced by the device's mechanism or processing algorithms. In electronic recording devices, a major form of noise is hiss caused by random electrons that, heavily influenced by heat, stray from their designated path. These stray electrons influence the voltage of the output signal and thus create detectable noise. In the case of photographic film and magnetic tape, noise (both visible and audible) is introduced due to the grain structure of the
medium. In photographic film, the size of the grains in the film determines the film's sensitivity, more sensitive film having larger sized grains. In magnetic tape, the larger the grains of the magnetic particles (usually ferric oxide or magnetite), the more prone the medium is to noise. To compensate for this, larger areas of film or magnetic tape may be used to lower the noise to an acceptable level. Images taken with both digital cameras and conventional film cameras will pick up noise from a variety of sources. Many further uses of these images require that the noise will be (partially) removed - for aesthetic purposes as in artistic work or marketing, or for practical purposes such as computer vision. In salt and pepper noise (sparse light and dark disturbances), pixels in the image are very different in color or intensity from their surrounding pixels; the defining characteristic is that the value of a noisy pixel bears no relation to the color of surrounding pixels. Generally this type of noise will only affect a small number of image pixels. When viewed, the image contains dark and white dots, hence the term salt and pepper noise. Typical sources include flecks of dust inside the camera and overheated or faulty CCD elements. In Gaussian noise, each pixel in the image will be changed from its original value by a (usually) small amount. A histogram, a plot of the amount of distortion of a pixel value against the frequency with which it occurs, shows a normal distribution of noise. While other distributions are possible, the Gaussian (normal) distribution is usually a good model, due to the central limit theorem that says that the sum of different noises tends to approach a Gaussian distribution.

Fig 1.3A single frame from a Real-time MRI movie of a human heart. a) direct reconstruction b) iterative (nonlinear inverse) reconstruction[7]

The advantages of the iterative approach include improved insensitivity to noise and capability of reconstructing an optimal image in the case of incomplete data. The method has been applied in
emission tomography modalities like SPECT and PET, where there is significant attenuation along ray paths and noise statistics are relatively poor.

As another example, it is considered superior when one does not have a large set of projections available, when the projections are not distributed uniformly in angle, or when the projections are sparse or missing at certain orientations. These scenarios may occur in intraoperative CT, in cardiac CT, or when metal artifacts [3] require the exclusion of some portions of the projection data.

In Magnetic Resonance Imaging it can be used to reconstruct images from data acquired with multiple receive coils and with sampling patterns different from the conventional Cartesian grid[4] and allows the use of improved regularization techniques (e.g. total variation)[5] or an extended modeling of physical processes[6] to improve the reconstruction. For example, with iterative algorithms it is possible to reconstruct images from data acquired in a very short time as required for Real-time MRI.[7]

**Convolution Operations**

Convolution is a common image processing technique that changes the intensities of a pixel to reflect the intensities of the surrounding pixels. A common use of convolution is to create image filters. Using convolution, you can get popular image effects like blur, sharpen, and edge detection.

**Convolution Kernels**

Convolution is a series of operations that alter pixel intensities depending on the intensities of neighboring pixels. The kernel provides the actual numbers that are used in those operations. Using kernels to perform convolutions is known as kernel convolution. Convolutions are per-pixel operations—the same arithmetic is repeated for every pixel in the image. Bigger images therefore require more convolution arithmetic than the same operation on a smaller image. A kernel can be thought of as a two-dimensional grid of numbers that passes over each pixel of an image in sequence, performing calculations along the way. Since images can also be thought of as two-dimensional grids of numbers, applying a kernel to an image can be visualized as a small grid (the kernel) moving across a substantially larger grid (the image). The numbers in the kernel represent the amount by which to multiply the number underneath it. The number underneath represents the intensity of the pixel over which the kernel element is hovering. During convolution, the center of the kernel passes over each pixel in the image. The process multiplies each number in the kernel by the pixel intensity value directly underneath it. This should result in as many products as there are numbers in the kernel (per pixel). The final step of the process sums all of the products together, divides them by the amount of numbers in the kernel, and this value becomes the new intensity of the pixel that was directly under the center of the kernel.
Fig 1.4 Convolution kernel modifying a pixel

Even though the kernel overlaps several different pixels (or in some cases, no pixels at all), the only pixel that it ultimately changes is the source pixel underneath the center element of the kernel. The sum of all the multiplications between the kernel and image is called the weighted sum. Since replacing a pixel with the weighted sum of its neighboring pixels can frequently result in much larger pixel intensity (and a brighter overall image), dividing the weighted sum can scale back the intensity of the effect and ensure that the initial brightness of the image is maintained. This procedure is called normalization.

II. LITERATURE SURVEY

Bertalmio et al [2] have introduced a technique for digital rastering of still images that produces very impressive results. Their algorithm, however, usually requires several minutes on current personal computers for the rastering of relatively small areas. Chan and Shen proposed two image-rastering algorithms. The Total Variational [4] (TV) rastering model uses an Euler-Lagrange equation and inside the rastering domain the model simply employs anisotropic diffusion based on the contrast of the isophotes. This model was designed for rastering small regions and while it does a good job in removing noise, it does not connect broken edges. The Curvature-Driven Diffusion (CDD) model [4] extended the TV algorithm to also take into account geometric information of isophotes when defining the “strength” of the diffusion process, thus allowing the rastering to proceed over larger areas. CDD can connect some broken edges, but the resulting interpolated segments usually look blurry. A Telea [4] proposed a fast marching algorithm that can be looked as the PDE based approach without the computational overheads. It is considerably fast and simple to implement than other PDE based methods, this method produces very similar results comparable to other PDE methods. The algorithm propagating estimator that used for image smoothness into image gradient (simplifies computation of flow), the algorithm calculate smoothness of image from a known image neighborhood of the pixel as a weighted average to inpaint, the FMM inpaint the near pixels to the known region first which is similar to the manner in which actual rastering is carried out, and maintains a narrow band pixels which separates known pixels from unknown pixels, and also indicates which pixel will be inpainted next. The limitation of this method is producing blur in the result when the region to be inpainted thicker than 10 pixels.
III. METHODOLOGY

3.1 EXISTING METHOD

The filling-in of missing region in an image, which is called image rastering, is an important topic in the field of computer vision and image processing. Image rastering has been widely investigated in the applications of digital effect (e.g., object removal), image restoration (e.g., scratch or text removal in photograph), image coding and transmission (e.g., recovery of the missing blocks), etc. The most fundamental rastering approach is the diffusion-based approach [1]–[3], in which the missing region is filled by diffusing the image information from the known region into the missing region at the pixel level. Recently, image statistics learned from the natural images are applied to the task of image rastering [6]–[8]. The diffusion-based rastering algorithms have achieved convincingly excellent results for filling the nontextured or relatively smaller missing region. However, they tend to introduce smooth effect in the textured region or larger missing region. The second category of approaches is the examplar-based rastering algorithm. This approach propagates the image information from the known region into the missing region at the patch level. This idea stems from the texture synthesis technique proposed in [9], in which the texture is synthesized by sampling the best match patch from the known region. However, natural images are composed of structures and textures, in which the structures constitute the primal sketches of an image (e.g., the edges, corners, etc.) and the textures are image regions with homogenous patterns or feature statistics (including the flat patterns). Pure texture synthesis technique cannot handle the missing region with composite textures and structures. Bertalmio et al. [10] proposed to decompose the image into structure and texture layers, then inpaint the structure layer using diffusion-based method and texture layer using texture synthesis technique [9]. It overcomes the smooth effect of the diffusion-based rastering algorithm; however, it is still hard to recover larger missing structures. Criminisi et al. [11] designed an examplar-based rastering algorithm by propagating the known patches (i.e., examplars) into the missing patches gradually. To handle the missing region with composite textures and structures, patch priority is defined to encourage the filling-in of patches on the structure. Wu [12] proposed a cross-isophotes examplar-based rastering algorithm, in which a cross-isophotes patch priority term was designed based on the analysis of anisotropic diffusion. Wong [13] proposed a nonlocal means approach for the examplar-based rastering algorithm. The image patch is inferred by the nonlocal means of a set of candidate patches in the known region instead of a single best match patch. More examplar-based rastering algorithms [14]–[16] were also proposed for image completion. Compared with the diffusion-based rastering algorithm, the examplar-based rastering algorithms have performed plausible results for rastering the large missing region.

3.2 DISADVANTAGES

The aforementioned overview shows in recently, image sparse representation is also introduced to the rastering problem [17]–[21]. The basic idea of this approach is to represent image by sparse combination of an overcomplete set of transforms (e.g., wavelet, contourlet, DCT, etc.), then the missing pixels are inferred by adaptively updating this sparse representation. Guleryuz et al. [18]–
[20] proposed an image rastering algorithm using adaptive sparse representation of image. Elad et al. [17] improved this approach by separating the image into cartoon and texture layers, and sparsely represented these two layers by two incoherent over-complete transforms. This approach can effectively fill in the region with composite textures and structures, especially in the application of missing block completion. However, similar to the diffusion-based approach, it may fail to recover structure or introduce smooth effect when filling large missing region.

3.3 PROPOSED METHOD

This paper focuses on the examplar-based rastering algorithm through patch propagation. The two basic procedures of patch propagation are patch selection and patch rastering. In the patch selection, a patch on the missing region boundary with the highest priority is selected for further rastering. The priority is defined to encourage the filling-in of patches on structure such that the structures are more quickly filled than the textures, then missing region with composite structures and textures can be better inpainted [11], [22]. Traditionally, the patch priority is defined based on the inner product between isophote direction and the normal direction of the missing region boundary [11], [22]. In the patch rastering, the selected patch is inpainted by the candidate patches (i.e., examplars) in the known region. The approach in [11] and [22] utilizes the best match candidate patch to inpaint the selected patch. The approach in [13] uses a nonlocal means of the candidate patches for robust patch rastering. To better address the problems of patch selection and patch rastering, two novel concepts of patch sparsity of natural image, i.e., patch structure sparsity and patch sparse representation, are proposed and applied to the examplar-based rastering algorithm. First, we define a novel patch priority based on the sparseness of the patch’s nonzero similarities to its neighboring patches. This sparseness is called structure sparsity in this paper. It is based on the observation that a patch on the structure has sparser nonzero similarities with its neighboring patches compared with the patch within a textured region. Compared with the priority defined on isophote, this definition can better distinguish the texture and structure, and be more robust to the orientation of the boundary of missing region.

3.4 ADVANTAGES

The patch sparse representation is inspired by the recent progress on sparse representation [28], which assumes that the image or signal is represented by the sparse linear combination of an over-complete library of bases or transforms under sparseness regularization. This framework has been widely applied to image denoising [29], [30], edge detection, recognition, super-resolution, texture synthesis, etc., and achieved state-of-the-art performance. In this work, the idea of sparse representation is introduced to the examplar-based rastering algorithm under the assumption that the missing patch can be represented by the sparse linear combination of candidate patches. Then a novel constrained optimization model is designed for patch rastering.
IV. RASTERING COMPLETION APPROACH

In the procedure of patch rastering, the selected patch on the fill-front should be filled in. Instead of using a single best match examplar or a certain number of examplars in the known region to infer the missing patch, we assume that the selected patch on the fill-front is the sparse linear combination of the patches in the source region regularized by sparseness prior. In the example shown in Fig. 1(b), the patch on the fill-front is inpainted by the sparse linear combination of candidate patches weighted by coefficients, in which only very sparse nonzero elements exist. The neighboring patches in are also used to constrain the appearance of patch by local patch consistency constraint.

List of Modules

1. Patch Priority Using Structure Sparsity
2. Comparison With the Isophote-Based Priority
3. Patch Rastering Using Patch Sparse Representation
4. Optimization Algorithm

PATCH PRIORITY USING STRUCTURE SPARSITY

The natural images are generally composed of structures and textures. A good definition of patch priority should be able to better distinguish the structures and textures, and also be robust to the orientation of the fill-front. In this paper, a novel definition of patch priority is proposed to meet these requirements. We now introduce the key component of our definition of patch priority, i.e., structure sparsity.

1) Structure Sparsity:

The structure sparsity is defined to measure the confidence of a patch located at structure instead of texture. Structure sparsity is inspired by the following observations: structures are sparsely distributed in the image domain or 0-D points in the 2-D image domain. Nevertheless, the textures are distributed in 2-D sub-regions of the image domain, which are less sparsely distributed. On the other hand, for a certain patch, its neighboring patches with larger similarities are also distributed in the same structure or texture as the patch of interest. Therefore, we can model the confidence of structure for a patch by measuring the sparseness of its nonzero similarities to the neighboring patches. The patch with more sparsely distributed nonzero similarities are prone to be located at structure due to the high sparseness of structures. Suppose is a patch on the fill-front, its neighboring patch is defined as the patch that is in the known region and with the center in the neighborhood of pixel, i.e., belongs to the set , e.g., the edges and corners are distributed as 1-D curves

be larger than the size of patch. Suppose is a matrix to extract the missing pixels of, and extracts the already known pixels. This theorem tells us that the structure sparsity achieves its maximum and
minimum values when the patch similarities are distributed in the sparsest and smoothest fashion respectively, and the structure sparsity increases with respect to the sparseness of patch’s nonzero similarities to its neighboring patches. We now investigate how the structure sparsity measures the structure confidence for different types of patches in the natural images. For the patch on the 0-D corners it is saliently distributed within the local region; therefore, it has the highest structure sparsity. Due to the sparsity of image edges, the patch on 1-D edge [e.g., Fig. 2(b)] has similar patches sparsely distributed along the same edge; therefore, they have higher structure sparsity. However, for the texture patches [e.g., Fig. 2(c) and (d)], they have similar patches in the 2-D local regions; therefore, they have smaller structure sparsity values. Under the guidance of structure sparsity, the patches located at structures (e.g., edges and corners) have higher priority for patch rastering compared with the patches in texture regions.

![Sparsity Measure for the Distributed Image](image)

**Fig 4.1: Sparsity Measure for the distributed image**

**COMPARISON WITH THE ISOPHOTE-BASED PRIORITY**

Now we show that structure sparsity based priority is more robust to identify the structure than the isophote-based definition [11], [22], which uses the inner product of isophote direction and the normal direction of the fill-front. Fig. 3 presents an example of rastering for an image with composite textures and illusory edge. Fig. 3(a) shows the process of rastering using isophote-based priority, and Fig. 3(b) shows the process of rastering using structure sparsity based priority. The texture synthesis technique in [11] and [22] is incorporated for both cases. Using isophote-based priority, the patch at the top-right part of missing region has the larger priority because the isophote direction is nearly same to the orthogonal direction of the fill-front at its central pixel. For example, the patch in the texture region of the first image in Fig. 3(a) is with the highest priority, and the illusory edge is failed to be accurately recovered in the final result. However, structure sparsity based priority is able to robustly identify the structure regardless of the shape of fill-front. For example, the patch in Fig. 3(b)
along structure is with the highest priority using structure sparsity based priority, and the missing region is inpainted perfectly in the final result.

**PATCH RASTERING USING PATCH SPARSE REPRESENTATION**

The patch on the fill-front with the highest patch priority is selected to be filled firstly. In the traditional examplar-based rastering technique [11], [22], is filled by sampling the best match patch from the known region. Recently, a nonlocal means approach [13] is proposed to fill in patch by the nonlocal means of several top similar patches instead of a single best match patch. Due to multiple samples are utilized, it can more robustly estimate the missing information and produce better result. However, it tends to introduce smooth effect in the recovered image. In this work, we propose a novel model to inpaint patch by the sparse combination of multiple examplars in the framework of sparse representation. This method achieves sharp rastering result by sparseness prior on the combination coefficients, and achieves consistent rastering results with the surrounding textures by the constraints on the patch appearance in local neighborhood. Given the patch to be inpainted, a set of candidate patches are sampled from the image source region, where is the number of candidate patches for . Similar to the previous work [13], [36], the candidate patches are selected as the top most similar patches, and the selection of will be discussed. Denote as a matrix to extract the unknown pixels in patch . Basically, is approximated as the linear combination of , i.e.,

\[ \hat{\Psi}_p = \sum_{q=1}^{N} \alpha_q \Psi_{q*} \]

The combination coefficients are inferred by minimizing a constrained optimization problem in the framework of sparse representation. Since we have assumed that the patch is the sparsest linear combination of , the objective of this constrained optimization problem is to minimize the norm of , i.e., the number of nonzero elements in vector . Next we will introduce the constraints for the linear combination. We now introduce the first type of constraint on the appearance of , which is called local patch consistency constraint. Firstly, we constrain that the estimated patch should approximate the target patch over the already known pixels, i.e.,

\[ \beta \left\| P\hat{\Psi}_p - P \sum_{p_j \in N_s(p)} w_{p,p_j} \Psi_{p_j} \right\|^2 < \epsilon \]

**OPTIMIZATION ALGORITHM**

Generally, the -norm regularized reconstruction model is hard to be solved due to its combinatorial nature. Matching pursuit (MP) or orthogonal matching pursuit (OMP) [38], [39] algorithm and basis pursuit (BP) [40] algorithm can efficiently retrieve the sparse representation and approximate the optimal solution in a greedy fashion. Another method for optimizing the -norm regularized model is to convexify the problem by -norm regularization. The -norm regularized reconstruction model is the
well-known Lasso [41] in the statistical literatures. In applications, due to the simplicity of OMP algorithm, it is widely used in image sparse representation, and applied to image denoising [29], [30], coding [42], edge detection [32], audio source separation [43], and so on. For this optimization problem in (10), we propose a novel algorithm to derive the sparse linear combination coefficients in a greedy fashion. Similar to the Matching Pursuit Algorithm, we gradually select nonzero elements from the candidate set of patches step by step. Suppose we have selected nonzero candidate patches in the step (denoted as t), so the sparse representation

\[
\min_{\alpha} \left\{ \left\| \sum_{j=1}^{m} \alpha_j \cdot D\Psi_{j} + \alpha_{m+1} \cdot D\Psi_{t} - \Psi_{t} \right\|^2 \right\}
\]

s.t. \[ \sum_{j=1}^{m+1} \alpha_j = 1. \]

This optimization problem (14) is well studied in the literature of Locally Linear Embedding (LLE) [37] in manifold learning. We define the Gram matrix value of increases. In summary, the algorithm for filling in the missing pixels in patch using patch sparse representation is listed in Fig. 4. The final rastering algorithm based on patch sparsity is listed in Fig. 5. Fig. 6 presents three examples in which the top corner region of pyramid, the crossing structure of window frame and the curved missing structures are removed. As shown in Fig. 6(b)–(d), the missing regions are gradually completed by the proposed method, and Fig. 6(d) are the rastering results of our method, in which the removed structures are successfully filled in. In Fig. 6(e), we also present the results of the most related algorithm in [22]. The structures in rectangles are not perfectly recovered compared with our results. The keys to the success of our method in completing the complex structures are that, first, the sparsity-based priority better controls the filling order of patches.

**V. EXPERIMENT RESULT**

We identified requirements for and implemented a simple, yet effective, image annotation tool based on the annotation methodology. The tool was designed to be simple to use, to utilize vector-based annotations, and represent annotation groupings. These requirements created the need for a standardized methodology to effectively communicate visual annotations in a consistent and congruent manner while preserving images for reuse. Therefore, the focus of this report is to present the annotation methodology. We also define the schema for development of a software implementation for multispecialty visual annotation of digital images. The software implementation also facilitates visual annotation interactivity and context-appropriate viewing of the visually annotated images. The annotation implementation was developed specifically for clinicians, medical educators, and basic scientists who required the ability to annotate images with visual expert knowledge for viewing in an interactive, context-appropriate, digital environment. The pointer for the annotation is partially defined by the author and partially computed based on where the author initially places it. For example, the author selects where the tail of the pointer should appear, and an algorithm calculates the closest point on the ROI to place the pointer tip. This dual mechanism for anchoring the pointer allows the author to make choices about the layout of visual information on the image without relying on a totally automated and potentially unpredictable layout algorithm.
Fig 5.1 Axial, Coronal and Sagittal View of Tumor Identification in CAD

Fig 5.2 Tumor Iterated by Rasterizing Algorithm
CONCLUSION

6.1 CONCLUSION

This paper proposed a novel patch propagation based Rastering algorithm for tumor segmentation and scientific visualization. It has major novelty of this work is that two types of patch sparsity were proposed and introduced into the examplar-based rastering algorithm. This was inspired from the recent progress of the research in the fields of image sparse representation and natural image statistics. Structure sparsity was designed by measuring the sparseness of the patch similarities in the...
local neighborhood. The patch with larger structure sparsity, which is generally located at the structure, tends to be selected for further rastering with higher priority. On the other hand, the patch sparse representation was proposed to synthesize the selected patch by the sparsest linear combination of candidate patches under the local consistency constraint. Experiments and comparisons showed that the proposed examplar-based patch propagation algorithm can better infer the structures and textures of the missing region, and produce sharp rastering results consistent with the surrounding textures.

### 6.2 FUTURE WORKS

Furthermore, in the future, we will further investigate the sparsity of natural images at multiple scales and orientations, and apply it to the image rastering, super-resolution and texture synthesis. We are also interested in incorporating the human-labeled structures into our framework in order to recover the totally removed structures.

### REFERENCE


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Murugan is an outward Professor in several of the Engineering Institutions in and around Tamil Nadu and he currently working as Associate Professor in ManonmaniamSundaranar University, India and he immensely dedicated his whole life to developing education towards engineering students in the Society. He completed his Bachelor of Engineering academic studies in the Department of Electrical Communication & Engineering in Government College of Engineering with high profile knowledge and later, he finished Master of Engineering in Computer Science & Engineering in Kalasalingam College of Engineering and fosters his proficiency in various multidisciplinary fields. He finished his Ph.D. (Computer Science) in Digital Image Processing from ManonmaniamSundaranar University, Tirunelveli, India. He is a reviewer of series of International Serial Journals and become esteemed Life Member in Indian Society for Technical Education for his outstanding work done in a specified area of Engineering and Technology. Due to his constant enthusiastic and innovation towards research, he qualified for Commonwealth Split-site Scholarships, which provided by the Department for International Development, United Kingdom in 2007.Under his supervision for Ph.D. in Computer Science, many students awarded Ph.D. Degree in Computer Science & Engineering on the research related to Neural Network, Pattern Recognition and Medical Image processing. He published his research paper in many International Journals. His contribution regarding IST ACT peer reviewed international Journal emerging and prospering paves a new way for research publications. He gauges his research interest in applying artificial neural
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