Data Hiding in Medical Images

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Abstract— **This paper presents an efficient technique to hide text information in 3D medical images such as MRI and PET. It embeds text information only in the non-anatomical pixels. It ensures that no anatomical part of the 3D medical image gets contaminated. It makes the retrieval of 100% data. The technique has been tested on several MRI and PET images.**

Index Terms— **MRI, PET, Segmentation, Region Growing, Data Hiding**

I. Introduction

Image is one of the most preferred multimedia which can be used to carry overt information between communicating entities. There exist considerably good number of techniques to hide data within an image. They have been developed based on the specific needs over time. Aim of hiding techniques is to provide the least change in the cover image with the best possible quality of the hidden data. For example, in medical domain, there is often a requirement by physicians to discuss among themselves about the status of the patient's health. Consider the following situation where a doctor who has a brain MRI image of a patient wants to send it to the patient to see his MRI scan and also to communicate his observations to an expert for consultation. There is a necessity of secretly embedding text data in a medical image which can be accessed only by the intended recipient.

This paper presents a new technique of information hiding in the field of medical imaging. The proposed technique is different from watermarking and steganography because in this present work data can not be embedded by distorting region of interest of cover work. In medical domain, distortion of medical images is not permissible due to legal and technical reasons. Hence, embedding in medical images should not distort region of interest in any way. The paper is organized as follows: Section II briefly reviews some well known segmentation algorithms. In Section III, a new information hiding algorithm has been presented. The simulation results are analyzed in the next section. Conclusions are given in Section V.

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II. Related Works

In the context of medical images, segmentation is required for distinguishing organs by different textures in medical images. There exist several segmentation techniques for medical images which can be classified into four categories. First one is based on Region Growing [1]. It is an effective approach for segmenting a diverse class of images. A region growing algorithm generally starts from a seed region (which is typically one or more pixels) which is considered to be within the region of the object to be segmented in the image. Pixels of the neighboring region are tested to decide whether they should also be considered as a part of the region or not. If so, the pixels are added to the region and the process is continued until no more new pixels can be included in the region. Techniques of this kind mainly differ depending on the factors used to decide the possibility to include a pixel in a region, the connectivity used to determine neighbors, or the method of visiting the neighboring pixels.

The second category of segmentation techniques is based on Watersheds [1] which classify pixels into regions by virtue of gradient descent on image features and analysis of weak points along region boundaries. It is based on the principle of water raining onto a landscape and flowing due to gravity towards lower basins. Size of those basins grows with increasing amount of water until water gets spilled into one another resulting in smaller basins merging into bigger ones. Regions are formed using local geometric shapes to relate pixels in image domain with local extrema in some feature measurement. This technique is less affected by user-defined threshold unlike any region-growing method. The watershed techniques are also flexible in terms of not producing a single segmentation but a hierarchy of segmentation as described in [2], [3]. The drawback of this approach is that it produces too many regions by over segmenting the image with redundancy in regions.

Level Set Segmentation [1] is another category which detects evolution of contours and surfaces on the image. The main advantage of using level sets in segmentation

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is that arbitrarily complex shapes can be modeled and topological changes can be handled implicitly. These techniques can be used for segmentation by using image based features such as mean intensity, gradient and edges in the governing differential equation by which the level set function is evolved. In this technique, a contour is initialized by the user to evolve until it finds a perfect fit of an anatomical structure. An overview of this category of segmentation is given in [4]. Techniques under this category are found to be computationally expensive.

Hybrid Segmentation [5], [6] is another category that integrates boundary-based and region-based segmentation methods. This kind of techniques is used when the category of problem is too exceptional to achieve proper segmentation by using any of the above techniques. These techniques are appropriate only when a highly customized solution is required for the segmentation of images.

III. The Proposed Scheme

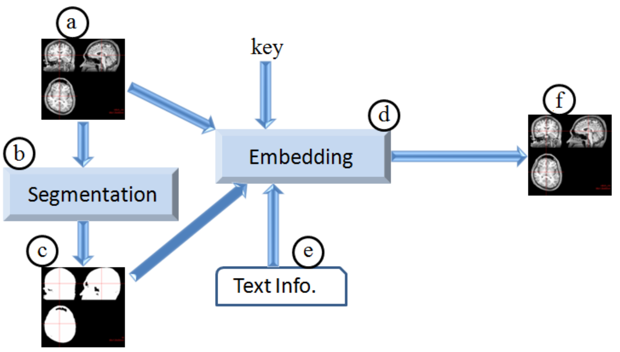


Figure 1. Data Flow diagram for embedding text data into 3D medical brain image (a) Source Image (b) Segmentation unit (c) Mask to distinguish brain area (d) Embedding unit (e) Text data to be embedded (f) Text embedded brain image.

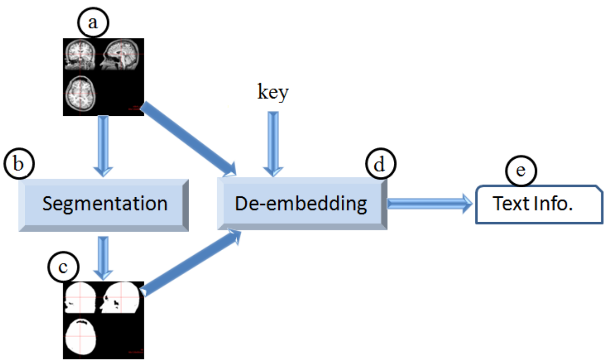


Figure 2. Data Flow diagram for retrieving text data from 3D medical brain image (a) Image with embedded text (b) Segmentation unit (c) Mask to distinguish brain area (d) De-embedding unit (e) Retrieved text data.

This section presents an efficient technique to hide text information inside 3D medical images. It consists of two modules; segmentation of non-anatomical part from brain image followed by embedding secret information. Figure 1 depicts the flow diagram of the technique. The 3D image is segmented to crop out the anatomical region and to form a mask which marks the volumetric pixels (voxels) of the anatomical region so that anatomical and non-anatomical voxels can be distinguished. The text information is embedded in the non-anatomical part of the image with help of the mask. Similarly, at the retrieval stage, the text embedded medical image is segmented into the anatomical and non-anatomical parts and the text information is retrieved from the non-anatomical part. Figure 2 shows the retrieving mechanism.

Medical images are 3D and of gray-scale type with values ranging from 0 to infinite; however, typically the highest gray-scale value of any voxel in an image is found to be 2000. Unlike the 2D images (carrying no sensitive data), the 3D medical images generally carry sensitive patient information and under no circumstance the voxel intensity (in the anatomical regions) can be changed. Hence, the anatomical region should be kept isolated from the embedding process. One might come up with the trivial idea of simply distinguishing the voxel with value 0 or lesser than some threshold as the non-anatomical region of the image; but it can be noted that certain images may contain noise and even non-anatomical region can be considered as anatomical region with this approach. As a result, the embedding capacity becomes considerably low. Figure 3 shows an example of such an image.

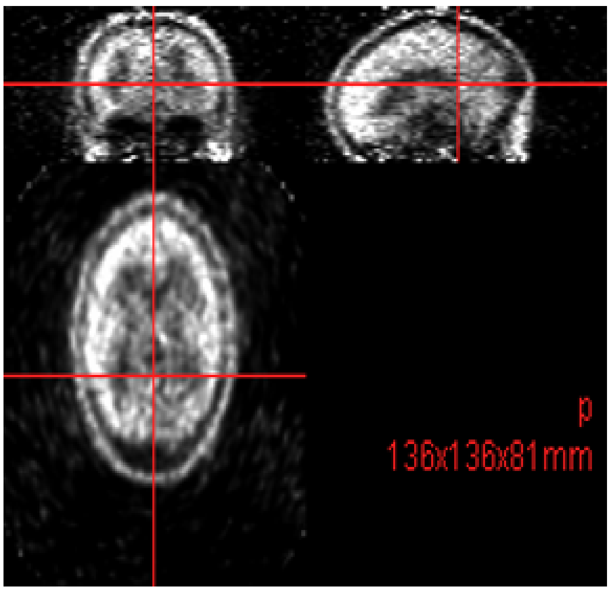


Figure 3. Brain image of PET modality having a lot of noise surrounding the brain.

The anatomical region cannot be found by ruling out the voxels below some threshold since a noisy voxel outside the anatomical region can always have value equal to the value of a voxel in the anatomical region. The technique should be able to exploit the non-anatomical region of the image optimally to achieve the maximum embedding capacity. More the embedding capacity, more text information can be stored.

The proposed segmentation technique is shown in Algorithm 1. It belongs to a region-growing category. It starts from a voxel (which has to be one of the voxels of the anatomical region) and it goes on checking for its neighbors that whether they fall between a lower and upper threshold so that one can include them in the region. In a 3-dimensional space, every voxel has 28 neighbors and hence for each voxel, all its neighbors are checked for candidacy. If it is found to satisfy the criteria, the process is recursively called for each such neighbor. The algorithm traverses the connected neighbors starting from a seed coordinate to detect the anatomical region. The time complexity (worst case) of the technique is equal to the total number of voxels in the image. The initial parameters play an important role in the functioning of the technique. The seed coordinate, upper threshold (β) and lower threshold (α) values are provided to segment out the desired region.

Algorithm 1 : Segmentation

Require: A 3D matrix M representing the voxel values of the medical image of size $(m \times n \times p)$
Seed coordinate $S = (x, y, z)$ denoting the starting point for the algorithm
Lower Threshold α, a real value denoting the minimum allowable value for anatomical voxels.
Upper Threshold β, a real value denoting the maximum allowable value for anatomical voxel

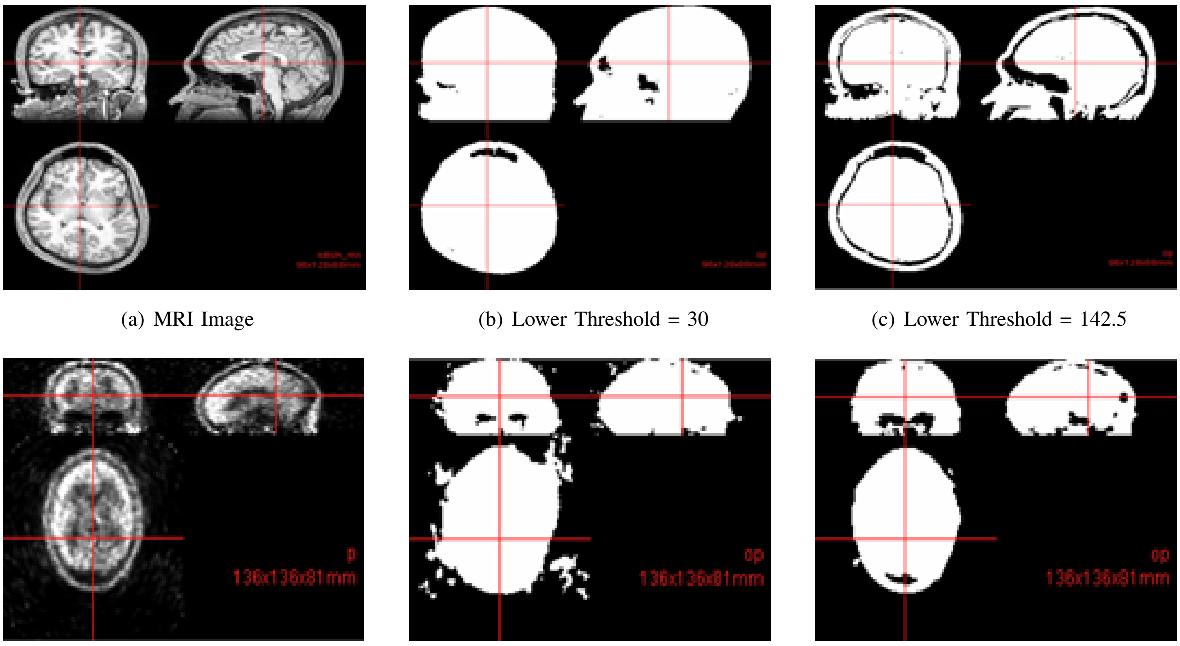
Ensure: A 3D matrix M' with values 0 or 1 representing the mask image for anatomical region of M

$Visited(S) \leftarrow True$
if $Intensity(S) \geq \alpha \wedge Intensity(S) \leq \beta$ **then**
  $M'_{x,y,z} \leftarrow 1$
  for all neighbor N of S **do**
    if $Visited(N) = False$ **then**
      Segmentation(N, α, β)
    end if
  end for
else
  $M'_{x,y,z} \leftarrow 0$
end if
return M'

1) **Seed Coordinate**: It cannot be trivially designated by choosing the mid-voxel viz. the voxel $(m/2, n/2, p/2)$ of an image of dimension $(m \times n \times p)$. This is because such a voxel may not be in an anatomical region but a in hollow part of the anatomical region which might turn out to be of gray-scale value of zero. On the other hand, one might have the intuition to select the voxel with the highest gray-scale value as the seed coordinate. But that may not necessarily succeed since there can be cases where the image might have noise surrounding the anatomical region and coincidentally one of the noisy voxels (totally disconnected from the anatomical region) may have the highest gray-scale value which may be mistakenly taken as the seed-coordinate. In the medical images of any modality, it is seen that the anatomical component certainly occupies the central 20% of the image and because of this, the seed-coordinate can be found in the central 20% of the image. Hence, exploiting this property, the voxel with the highest gray-scale value is found in the central 20% of the image and is used as the seed coordinate for the segmentation technique.
2) **Upper/Lower Threshold**: Ranges of intensity values of different modalities are generally found to be different. Also, two images of the same modality may have different gray-scale ranges. Hence, a constant lower/upper threshold may not provide good result. Threshold values (specific to the input image) are to be selected dynamically from the images. The upper threshold can be determined from the highest gray-scale value of the image. But the selection of the lower threshold value is not trivial. Certain observations can be made from Figure 4. The lower threshold value is very much image specific and thus to be computed dynamically. Also it can be observed that lesser the lower threshold value, more the extraneous voxels selected as the anatomical region. Hence, it is more conservative in terms of flagging a voxel as a non-anatomical voxel. More the conservative segmentation, lesser the embedding capacity and lesser the conservative segmentations, more the chances of contaminating the anatomical region in the image. Through experiments on a considerable number of medical images of different modalities, it is inferred that the lower threshold is nearly equal to $\frac{1}{18}^{th}$ of the value of the upper threshold. By such upper and lower threshold values, it is found to segment the anatomical region completely without inclusion of extraneous voxels.

A. Data Embedding

The embedding process computes mask using segmentation and embeds text in the least significant bits of non-anatomical voxels. Seed coordinate, upper (β) and lower (α) thresholds are computed to segment input medical image M. Segmentation of M is done through the Algorithm 1. This segmented image S is used to compute mask of the image to differentiate between anatomical and non-anatomical part of any medical image. With the mask S for the medical image, embedding of data can be done in the non-anatomical region. Size of secret message is computed and is appended at the beginning of the secret message to form the augmented message as shown in Figure 5. Initial twenty bits of the augmented message are reserved for storing message size. After this, the mask S and medical image M are randomly permuted through key p to get S' and M'. The key k is used to distribute message randomly over the image so that only the intended recipient can extract the secret text. Each of



(a) MRI Image (b) Lower Threshold = 30 (c) Lower Threshold = 142.5

(d) PET Image (e) Lower Threshold = 30 (f) Lower Threshold = 69.11

Figure 4. Brain image Segmentation with various Lower Threshold values.

8 bits of the text character is stored in least significant bit (LSB) of eight contiguous permuted non-anatomical voxels in the M'. Finally, the permuted image M' is rearranged to get the resultant image M''. Algorithm 2 delineates the technique.

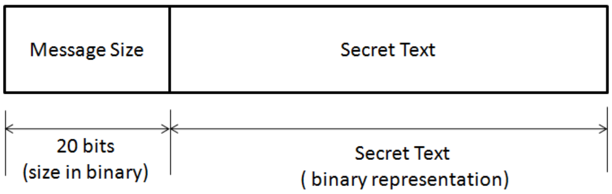


Figure 5. Secret message format.

Algorithm 2 : Embedding3D

Require: A 3D matrix M representing the voxel values of the medical image of size $(m \times n \times p)$
Text to be embedded T
key p

Ensure: M with text T and key p embedded in non-anatomical region

Let Seed coordinate (x, y, z) be the voxel with the highest gray-scale value in central 20% of input image M
Let β (Upper Threshold) be the maximum voxel value in M
Let α (Lower Threshold) be $\frac{\beta}{18}$;
Let Embedding Mask S be the result of Segmentation(M , (x, y, z) , α , β)
Let msg_size be the size of Text to be embedded;
Let T' be the augmented text (size and text)to be embedded;
Let $M' \leftarrow$ permute(M,p); {Permutated Image}
Let $S' \leftarrow$ permute(S,p); {Permutated Mask}
for all character c in T' **do**
  for $i = 1$ **to** 8 **do**
    $(x, y, z) \leftarrow$ next voxel coordinate in S' with value 0; {Embedding Text}
    $M'_{(x,y,z)} \leftarrow c_i$; $\{c_i$ is i^{th} bit of character $c\}$
  end for
end for
$M'' \leftarrow permute(M', p)$; {Re-arranging Image}
return M''

B. Data Extracting

Data extraction is a process to retrieve the embedded message from a image. Steps of extraction are similar to embedding process. Seed coordinate, upper (β) and and lower (α) thresholds are computed to segment the input image M. Segmented image S is used as mask to distinguish the non-anatomical voxels. Image and mask are permutated using same key p to get M' and S'. Twenty bits of message length are extracted to get the size of message (msg_size). Depending upon the message size all remaining bits of the augmented message are retrieved from the LSB of every non-anatomical voxels to form the output text (T). The technique is given in Algorithm 3.

IV. Performance Evaluation

The proposed technique to embed text information in 3D brain images has been tested on 3D images of brain

Algorithm 3 : DataExtracting3D

Require: A 3D matrix M representing the voxel values of the medical image of size $(m \times n \times p)$
key p

Ensure: Text T retrieved from non-anatomical region in M

Let Seed coordinate (x, y, z) be the voxel with the highest gray-scale value in central 20% of input image M
Let β (Upper Threshold) be the maximum voxel value in M
Let α (Lower Threshold) be $\frac{\beta}{18}$;
Let Embedding Mask S be the result of Segmentation(M , (x, y, z) , α , β)
Let $M' \leftarrow$ permute(M,p); {Permutated Image}
Let $S' \leftarrow$ permute(S,p); {Permutated Mask}
let msg_size be the message size retrieved from consecutive voxels in S' with value 0
for $j = 21$ **to** $msg\_size + 20$ **do**
  $Message_j \leftarrow$ LSB of M'_{X_j} {Retrieving Message}
end for
$T \leftarrow$ Message;
return T

of 44 subjects. Out of these images, there are 14 MRI images and remaining are PET images. Each MRI image is of size 192*256*176 while the size of PET images is 128*128*47. A slice of MRI image and a PET image of a brain are shown in Figure 6 and Figure 7. Segmentation and embedding text in the segmented image are done in such a way that there is no contamination or loss of information in the brain image. Thus, the embedding capacity is much lesser than the actual capacity. Maximum size of message that can be embedded in a image is known as embedding capacity. If an image of dimension $(m \times n \times p)$ has x non-anatomical voxels, then its embedding capacity (in terms of number of bits) is be given by

$$EmbeddingCapacity = \frac{x}{m \times n \times p} \quad (1)$$

where $\frac{x}{8} - 2$ is the maximum number of characters that can be embedded.The capacity, however, is considerably large to fit a large amount of text data into 3D images. Each image is segmented to detect the brain region and the embedding capacity is calculated to be 18% or 1,038,666 characters. The mask for the brain region is shown in Figure 8 and corresponding MRI image with embedded text is shown in Figure 9. The proposed technique successfully embedded text information for all the test cases in non-anatomical voxels of a medical image.

V. CONCLUSIONS

This paper has proposed an efficient technique to hide data in 3D medical brain image. It is novel due to the fact that there has been no prior attempt to exploit the non-anatomical voxels of a medical image to embed data for esoteric communication. The conventional way of storing information in image header is accessible to anyone and hence, any data hiding technique of this type certainly helps to maintain secrecy of information within users viz. doctors and patients. On the other hand, the proposed segmentation technique proposed can be further extended to segment different organs of the brain viz. cerebrum, medulla, etc. Further, it can be used as a tool

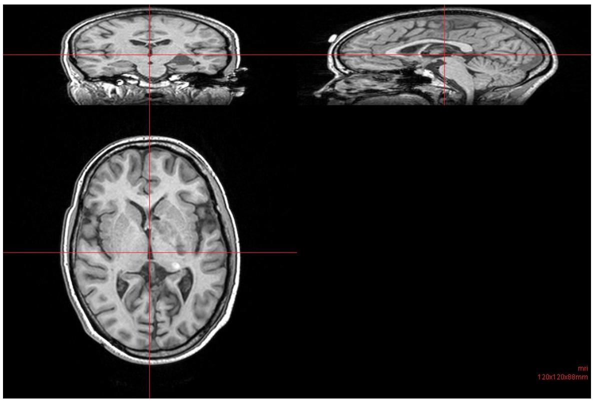


Figure 6. MRI Image with he Text to be Embedded.

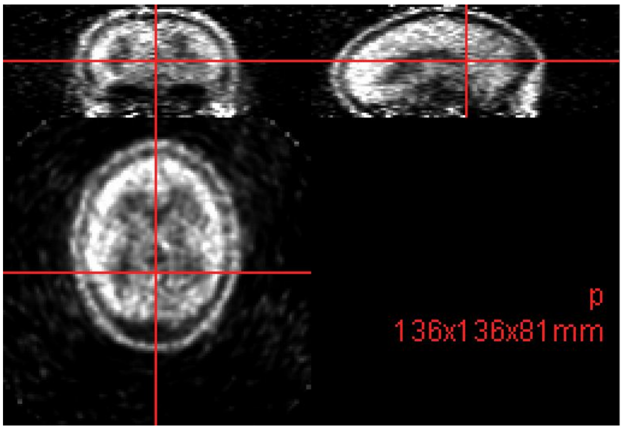


Figure 7. PET Image of Dimension $(128 \times 128 \times 47)$ and size 1.47 MB.

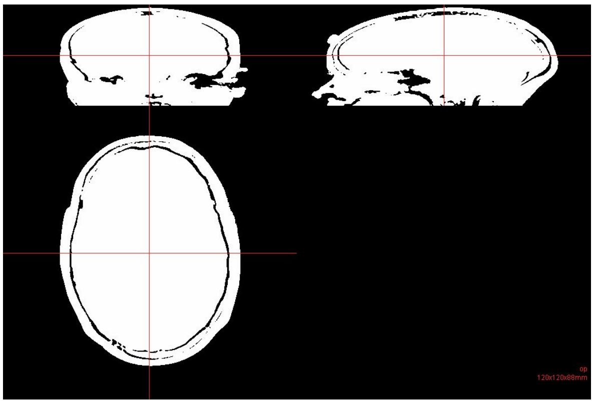


Figure 8. MRI Image Mask for Brain Region.

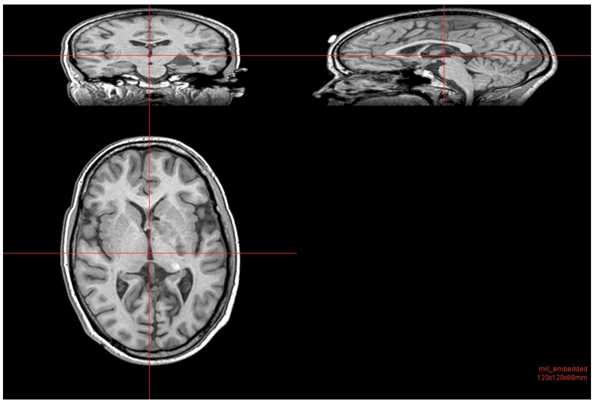


Figure 9. MRI Image Embedded with Text Data.

to remove noise from a medical images. It can be done simply by embedding continuous sequence of characters with ASCII 0 i.e. all pixels which do not belong to the anatomical region can be set to a value zero. This technique can also be used to embed information in other anatomical images like lungs, limbs, etc. In that case, the segmentation algorithm may be customized and properly tuned for desirable results.

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REFERENCES

[1] L. Ibanez, W. Schroeder, L. Ng, J. Cates, and T. I. S. Consortium, *The Insight Tool Kit Software Guide*, 2nd ed. Insight Tool Kit, 2005.

[2] T. Yoo, U. Neumann, H. Fuchs, S. Pizer, T. Cullip, J. Rhoades, and R. Whitaker, "Direct visualization of volume data," *IEEE Journal on Computer Graphics and Applications*, vol. 12, no. 4, pp. 63 –71, 1992.

[3] T. S. Yoo, U. Neumann, H. Fuchs, S. M. Pizer, T. Cullip, J. Rhoades, and R. Whitaker, "Achieving direct volume visualization with interactive semantic region selection," in *Proceedings of the 2nd conference on Visualization(VIS '91)*. Los Alamitos, CA, USA: IEEE Computer Society Press, 1991, pp. 58–65. [Online]. Available: http://dl.acm.org/citation.cfm?id=949607.949617

[4] A. M. Andrew, "Level set methods and fast marching methods: Evolving interfaces in computational geometry, fluid mechanics, computer vision, and materials science," *Robotica*, vol. 18, no. 1, pp. 89–92, 2000. [Online]. Available: http://dl.acm.org/citation.cfm?id=980371.980382

[5] C. Imielinska, P. D, D. Metaxas, P. D, J. Udupa, P. D, Y. Jin, and T. Cheng, "Hybrid segmentation of the visible human data," in *Proceedings of the Third Visible Human Project Conference, Bethesda, MD*, 2000.

[6] C. Imielinska, D. N. Metaxas, J. K. Udupa, Y. Jin, and T. Chen, "Hybrid segmentation of anatomical data," in *Proceedings of the 4th International Conference on Medical Image Computing and Computer-Assisted Intervention(MICCAI '01)*. London, UK: Springer-Verlag, 2001, pp. 1048–1057. [Online]. Available: http://dl.acm.org/citation.cfm?id=646924.709334

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