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GPU acceleration of liver enhancement for tumor segmentation

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ABSTRACT

Background and objective: Medical image segmentation plays a vital role in medical image analysis. There are many algorithms developed for medical image segmentation which are based on edge or region characteristics. These are dependent on the quality of the image. The contrast of a CT or MRI image plays an important role in identifying region of interest i.e. lesion(s). In order to enhance the contrast of image, clinicians generally use manual histogram adjustment technique which is based on 1D histogram specification. This is time consuming and results in poor distribution of pixels over the image. Cross modality based contrast enhancement is 2D histogram specification technique. This is robust and provides a more uniform distribution of pixels over CT image by exploiting the inner structure information from MRI image. This helps in increasing the sensitivity and accuracy of lesion segmentation from enhanced CT image. The sequential implementation of cross modality based contrast enhancement is slow. Hence we propose GPU acceleration of cross modality based contrast enhancement for tumor segmentation.

Methods: The aim of this study is fast parallel cross modality based contrast enhancement for CT liver images. This includes pairwise 2D histogram, histogram equalization and histogram matching. The sequential implementation of the cross modality based contrast enhancement is computationally expensive and hence time consuming. We propose persistence and grid-stride loop based fast parallel contrast enhancement for CT liver images. We use enhanced CT liver image for the lesion or tumor segmentation. We implement the fast parallel gradient based dynamic seeded region growing for lesion segmentation.

Results: The proposed parallel approach is 104.416 (± 5.166) times faster compared to the sequential implementation and increases the sensitivity and specificity of tumor segmentation.

Conclusion: The cross modality approach is inspired by 2D histogram specification which incorporates spatial information existing in both guidance and input images for remapping the input image intensity values. The cross modality based liver contrast enhancement improves the quality of tumor segmentation.

1. Introduction

Computed tomography (CT) images of abdomen often possess low contrast [1,2]. Radiologists often manually delineate lesions during segmentation of medical images, which can be difficult, time-consuming and prone to observer variability [3]. Some segmentation algorithms do not perform well when applied on the CT images and are time consuming [4,5]. However, their performance can be made better once the CT images are preprocessed [6,7]. Therefore, preprocessed CT images help in refining the lesions. One possible preprocessing step is image enhancement for the better visualization of tumors in undertaking surgical procedures [8–10].

Efficient preprocessing can certainly help to attain accurate segmentation of the critical structures in medical images [7,11]. High sensitivity and specificity indicates the improved quality of the segmentation [5,12]. The liver images obtained from the CT scans are sometimes noisy, low in contrast and contains high amounts of details. We consider contrast as the important feature. If the image is high contrast then it becomes easier to identify and segment the

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object of interest [2,13]. In our case, lesion is necessary to be segmented.

There are many methods proposed to improve the contrast of the image. Histogram equalization, histogram specification and histogram matching are some of the ways to improve the contrast in the image as discussed by [1,14,15]. We apply 2D histogram matching where CT liver is the target image and the magnetic resonance imaging (MRI) liver slice is the guided image [16,17]. Cross modality based contrast enhancement exploits 2D histogram matching for liver enhancement. Once the image is enhanced then the task is to segment tumor from enhanced image. Seeded region growing for tumor segmentation is an easy and effective process. But the task of cross modality based liver enhancement is computationally expensive and time consuming [18]. Hence it becomes necessary to use GPU for real time performance of liver contrast enhancement and tumor segmentation. We propose accelerated cross modality guided liver enhancement scheme in this paper and demonstrate that our technique improves tumor segmentation on enhanced image.

The aim of this study is cross modality based liver enhancement to improve the contrast of CT liver image for tumor segmentation. We propose parallel implementation of liver contrast enhancement. This is accomplished by 2D histogram matching using CT and MRI liver images. We propose dynamic region of interest (RoI) based seeded region growing (SRG) for tumor segmentation from enhanced CT image. The overall average speedup obtained by parallel implementation is 104.416 ± 5.166 times compared to the sequential CPU implementation of the contrast enhancement and tumor segmentation. The enhanced liver image improves the sensitivity and specificity of the lesion segmentation. This is the first work targeted towards the high performance multi-modality guided liver enhancement for tumor segmentation to the best of our knowledge.

The rest of the paper is organized as follows. Section 2 briefs the related works, background and motivation with respect to the liver image enhancement. Section 3 explains the proposed methodology for liver contrast enhancement and its parallel implementation on the GPU. Further, we discuss dynamic RoI based fast parallel SRG for tumor segmentation in Section 4. Performance results and comparison of contrast enhancement and seeded region growing for tumor segmentation are mentioned in the Section 5. Section 6 concludes summarizing the main results related to the cross modality based contrast enhancement and tumor segmentation.

2. Background and motivation

Segmentation of lesions is a challenging problem in medical images because of the similar intensity values of structures of interest and the nearby regions in image. Research works are targeting various methods for the segmentation [19–21]. The results of the segmentation are subsequently used in patient specific model for diagnostics, surgery planning and navigation. One such approach using gradient based SRG has been presented to segment the aorta and rib bones in thorax images by Rai and Nair [21]. Inspired by this idea, we propose parallel SRG to segment tumors from CT liver images.

Image enhancement is regarded as a precursor to the accurate segmentation. CT scans are commonly used due to the availability and quicker imaging time compared to MRI. CT scans often suffer from low contrast which limit their utility [1,2]. In this work, we show through our experiments that corresponding MR image can be employed to improve the contrast of CT. The idea to enhance an image using another cross modal image has been witnessed in the literature for natural images [6–9]. The motivation to use cross modality guided image enhancement is to use the additional information contained in the other image having similar contents in different imaging times or position but better contrast or minimal noise. Ultimately, the details in the enhanced image can be improved from the perceptual perspective. In the context of liver images, tumors can be easily seen in the enhanced CT image.

In this regard, the contrast of photographs was improved using the corresponding near infra red images [6,14]. Histogram specification in combination with wavelet domain processing was used in this work. Yan et. al proposed a variational approach using anisotropic filter to eliminate noise in color images using infrared images [9]. The authors calculated cross correlation between input images and then used joint filtering for denoising in another approach [7,11].

Deep learning is applied to multimodal image denoising recently [8]. A deep learning method consisting of three convolutional neural networks has been applied to denoise natural images. Various deep learning based approaches for CT denoising have been presented in the last few years, however, they do not incorporate the multimodality guidance and use the CT image alone for supervised learning [16,17,22]. Histogram based methods are useful to enhance the global contrast of image [14], however, they introduce bad artifacts in the processed images. Since it does not consider the neighborhood of the pixels while remapping, it does not necessarily gives the desired contrast [2,14,23]. Two dimensional histogram specification is presented recently to improve the 1D histogram specification [18]. It uses 2D cumulative distribution function of the input and target images for remapping intensity values in the original image.

We apply same notion to CT liver images by applying 2D histogram matching based cross modality approach for liver contrast enhancement in the following section.

3. Methodology: liver contrast enhancement

We aim to improve the contrast of CT liver image considering MRI liver image as the guidance image to increase the quality of lesion segmentation. The methodology includes 2D contrast enhancement, gradient of enhanced image and segment the lesion using gradient based SRG. The parallel approach for liver enhancement and lesion segmentation makes the process faster in order to achieve real time implementation. In this section, we discuss parallel implementation of the cross modality based liver enhancement.

The flow of proposed GPU implementation of cross modality based contrast enhancement is shown in Fig. 1. We load CT and MRI images of liver on CPU and transfer it to the GPU. The first step of contrast enhancement of CT liver image is 2D (or pairwise) histogram calculation (Hist_2d). We calculate parallel 2D histogram of both CT (hist_CT) and MRI (hist_MRI) images. A 2D histogram is a plot of pixel and its neighbouring element which allows us to discover, and show, the underlying 2D frequency distribution (shape) of image. This shows how often each set of values (pixel and neighbour) in the image occurs. Instead of just considering the individual pixel values, it considers every possible pixel pair in the input and guidance image and calculate 2D CDF accordingly [18,24].

Further the calculation of cumulative distributive function (CDF_2d) of CT (CDF_CT) and MRI (CDF_MRI) images on GPU creates the input for the next step i.e. histogram equalization. 2D CDF is a function that describes the probability of a possible pixel pair in the input and guidance image. This helps in finding most frequent pairwise intensity values for histogram equalization [18].

Then we perform parallel histogram equalization (HE_2d). This step spreads out the most frequent pairwise intensity values increasing the global contrast of image. Hence it improves lower contrast areas to gain a higher contrast [18,24].

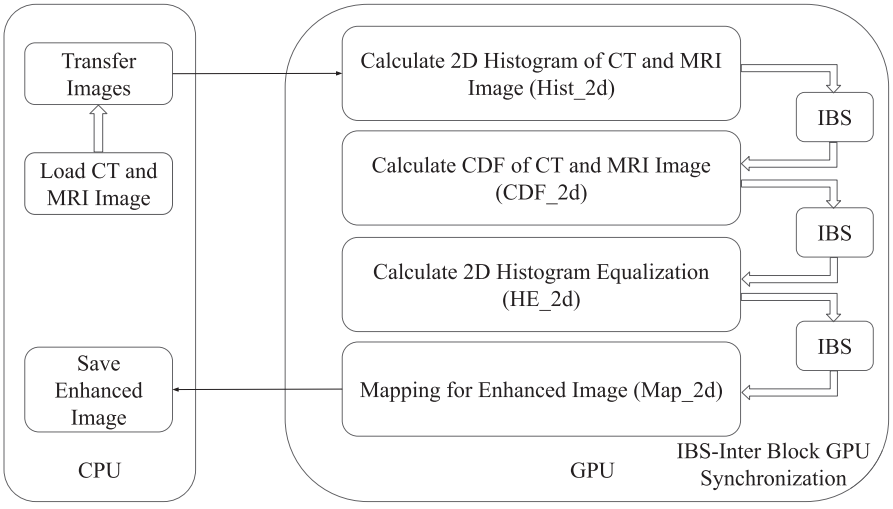


Fig. 1. GPU implementation of the cross modality based contrast enhancement.

The mapping (Map_2d) of histogram equalization onto the CT image gives the enhanced image. It maps the modified intensity values obtained from 2D histogram equalization to the corresponding pixels [18].

Inter block GPU synchronization (IBS) makes sure the updated values are sent to the next modules in GPU computing blocks. These parallel implementations of sub-modules of contrast enhancement are explained in following sections.

3.1. 2D Histogram

In this section, we discuss the 2D histogram implementation on GPU as the first step of the contrast enhancement of CT liver image. The histogram length (HL) is 256. We launch HLxHL parallel threads and find the histogram of neighboring elements in pairs. Hence it is called as pairwise histogram. Pairwise histogram is stored in an array of size HLxHL.

For each thread in parallel, it takes the pixel (x,y) and neighbouring pixel (x+1,y) value. This represents one of the indices in the range of (0-HLxHL-1) in histogram array given by variable temp as shown in Algorithm 1. We increment corresponding value

Algorithm 1: 2D Histogram of CT and MRI Image (Hist_2d).

```
1: HL=256 and launch HL x HL parallel threads
2: ti and tj can be any thread id between 0–255
3: while x<width_of_image do
4:    while y<height_of_image do
5:       if ti == I[x][y] and tj == I[x + 1][y] then
6:          temp=ti*HL+tj;
7:          atomicAdd(histogram[temp], 1);
8:       end if
9:    end while
10: end while
```

in the index position in histogram array as shown in Fig. 2. This function hist_2d for CT and MRI images gives hist_CT and hist_MRI histograms respectively. These 2D histograms are the input to the cumulative distributive function which is the next step of contrast enhancement.

3.2. Cumulative distributive function (CDF)

In this step of contrast enhancement, we calculate CDF of 2D histograms of CT and MRI liver images. The maximum number of

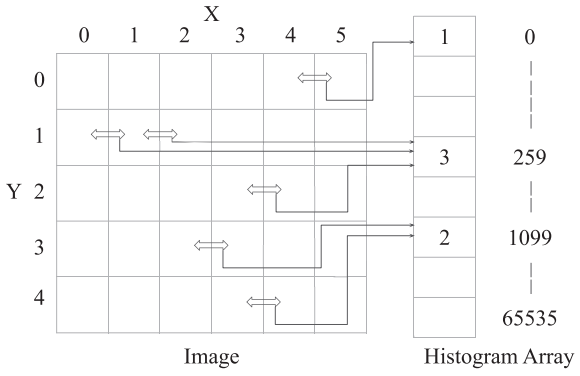


Fig. 2. 2D Histogram.

histogram pairs can be (w−1)×(h) where w and h are width and height of the image.

We launch HL × HL threads in parallel as shown in Algorithm 2. Each thread calculates its CDF from respective 2D histogram values. These CDF values for CT (CDF_CT) and MRI (CDF_MRI) images are the input to the next step of contrast enhancement which is 2D histogram equalization.

Algorithm 2: Calculate CDF of CT and MRI Image (CDF_2d).

```
1: count= (width-1)*height i.e. maximum number of pairs
2: HL=256 and launch HL x HL parallel threads
3: ti and tj can be any thread id between 0–255
4: temp=ti*HL+tj;
5: while temp<HL*HL do
6:    for int j=0; j<=temp; j++ do
7:       cdf[temp]+ = histogram[j]/count;
8:    end for
9: end while
```

3.3. 2D Histogram equalization (HE_2d)

2D Histogram Equalization technique improves the contrast of image. It spreads out the most frequent intensity values. This method increases the global contrast of image. This improves the lower contrast areas to gain higher contrast. The pseudocode for 2D histogram equalization is shown in the Algorithm 3. We launch

Algorithm 3: Calculate 2D Histogram Equalization (HE_2d).

```
HL=256 and launch HL x HL parallel threads
ti and tj can be any thread id between 0–255
index=ti*HL+tj;
for k=0; k<HL; k++ do
   for l=0; l<HL; l++ do
      temp8=k*HL+l;
      temp = cdf1[index]-cdf2[temp8]
      if temp is minimum then
         x = k
      end if
      if multiple minimum values found then
         temp2 = absolute((ti-k) + (tj-l))
         if temp2 is minimum then
            x = k
         end if
         if multiple minimum temp2 are found then
            temp3 = absolute((ti-tj) - (k-l))
            if temp3 is maximum then
               x = k
            end if
         end if
      end if
   end for
end for
HE[index]=x;
```

HLxHL threads in parallel. Each thread calculates the corresponding histogram equalization by taking the minimum difference between two CDFs (cdf1 for CDF_CT and cdf2 for CDF_MRI). It takes into the account the first minimum euclidean distance value between the indices when multiple minimum difference in CDFs are found. Again when multiple solutions are available, it further computes and find out the equalized value saved in array HE. This array is ready to get mapped for enhanced image which is the final step of contrast enhancement.

3.4. Mapping

The mapping of 2D histogram equalization is essential for obtaining enhanced CT image as an output. We launch wxh threads where w and h are width and height of the image respectively. This is reverse process of 2D histogram calculation as explained in the psuedocode given by the Algorithm 4. The index value is

Algorithm 4: Mapping for Enhanced Image (Map_2d).

```
launch (width)*(height) parallel threads
HL=256
tw can be any thread id between 0 to width-1
th can be any thread id between 0 to height-1
temp1 = I[tw][th];
temp2 = I[tw + 1][th];
index = temp1 * HL + temp2;
I[tw][th] = HE[index]; //EnhancedImage
```

generated from the neighbouring pixel values of the CT image. The pixel value in the CT image is changed by the corresponding value in the location (index) given by the 2D histogram equalization array. When all the threads are finished processing corresponding pixels, the enhanced image is sent back to the CPU.

4. Application to the tumor segmentation

Seeded Region Growing is an easy approach to segment the various objects in an image. The result of the region growing relies mainly on the initial seed(s) and the criteria defined to end recursive or iterative region growing process [4,19,25,26]. The parallel implementation of SRG based tumor segmentation is shown in Fig. 3.

We load CT and MRI images and transfer it to the GPU. GPU performs cross modality based contrast enhancement and stores the enhanced CT image in GPU memory. The control comes back to the CPU. This is essential for the selection of seed(s) and to change the number of persistent blocks. These persistent blocks (i.e. number of available computing resources on the GPU) differ depending on the application. The next task is tumor segmentation. GPU computes the gradient of enhanced CT liver image. The gradient of enhanced liver image is communicated through IBS to the next module for tumor segmentation. We apply SRG on the gradient of enhanced liver image. Region grows and new seeds are formed from initial seed(s) based on the threshold criteria. This process is iterative until the threshold criteria is satisfied. The process stops when new seed(s) can not be formed and region can not be grown further.

In this work, we use threshold criteria defined by the homogeneity of region and region aggregation considering the pixel values and their gradient direction and magnitude. The criteria is defined via a cost function that uses few features of the image around seed. Value of the cost function is compared with homogeneity criteria specified to check if the value is smaller than 1. The pixel becomes part of the region if there is a match; otherwise it is excluded from the region. The cost functions for threshold criteria are given by Rai and Nair [21]. They select homogeneity criterion using gradient based cost function which are dependent upon object contrast, texture features like shape and color, intensities values, gradient direction and magnitude. The cost function exploits features of image around the seed.

We apply parallel gradient based SRG algorithm on both enhanced images and original CT liver images. We propose dynamic RoI based parallel SRG.

4.1. Dynamic SRG

Dynamic SRG as the name suggests, it increases the region of interest (RoI) in each iteration of SRG. The initial RoI is decided by number of active computing blocks or persistent blocks that can be launched on GPU. This represents the phenomenon of persistence. In order to communicate valid data in between the blocks, inter block GPU synchronization (IBS) is necessary. Persistence and IBS provide flexibility to exploit parallelism using grid-stride loop through constant increase in RoI. One grid-stride is number of active computing threads that can be launched on GPU device.

Gupta et al. [27] have explored persistent thread based GPU programming. The idea behind this is once the SRG kernel launched from CPU, the control returns from GPU when the region is grown completely. Intermediate data transfers between CPU and GPU are avoided in this approach. SRG kernel on GPU is launched from the host CPU. Region is grown on GPU. Image elements are updated and communicated to the blocks via IBS. The region is grown again on GPU, if new similar neighbouring elements are found. This process continues until no similar neighbouring elements are available. The kernel terminates when the region can not be grown further and control returns to the CPU. Redundant data computations and communications are optimized on GPU using proposed approach. This process is explained in the Fig. 4.

There are four persistent blocks processing grid of blocks using grid-stride loop as shown in Fig. 4a. We map 3D liver on grid of

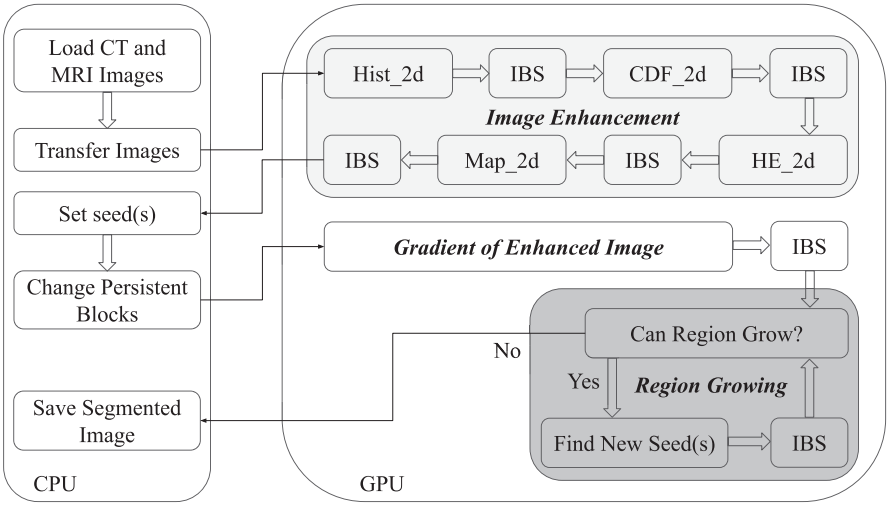
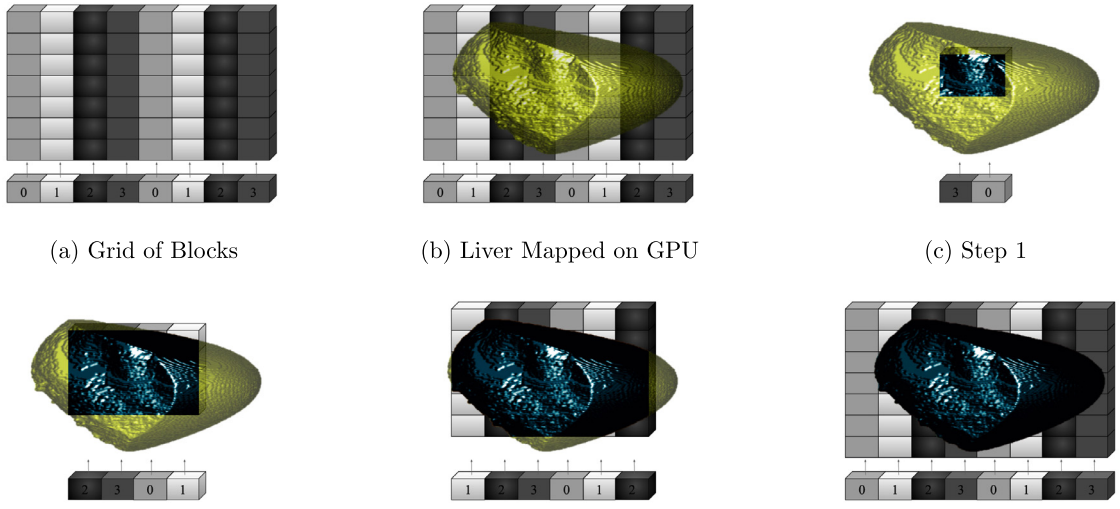


Fig. 3. GPU implementation of SRG based tumor segmentation.



(a) Grid of Blocks (b) Liver Mapped on GPU (c) Step 1

(d) Step 2 (e) Step 3 (f) Step 4

Fig. 4. SRG using dynamic RoI of tiles.

blocks as shown in Fig. 4b and initialize RoI of tiles around the seed as shown in Fig. 4c. Persistent blocks operate within RoI. First step of SRG takes place. Region is grown and RoI is incremented in all directions. This process makes necessary neighbouring voxels available for the second step of SRG as shown in Fig. 4d. New neighbouring voxels perform same function and RoI is incremented again. This flow is repeated until region can not be grown further as shown in Fig. 4e and f. This approach reduces compute and memory operations resulting in the increased performance. It is needed to ensure that the increase in RoI lies within the image dimensions.

Complete process is defined in the Algorithm 5 . RoI should be initialized in such a way that all threads are busy performing SRG. Variable “blockgrow” is essential to check the increase the RoI. Increase RoI of tiles if value of “blockgrow” is "1", otherwise stop SRG as region is grown completely. This variable “blockgrow” along with the variable “unfinished” are updated in the SRG segmentation step. Lower and upper values of RoI (in x, y, and z directions) are calculated when “blockgrow” is “1”. It has to be made sure that the RoI should not increase beyond image dimensions in the successive steps of SRG.

Persistent blocks operate inside the RoI. Kernel SRG is called for the voxels within the RoI. IBS makes sure only updated values are communicated to the persistent blocks in each step of SRG. IBS can be atomic, quasi, lock free or based on cooperative groups from NVIDIA toolkit CUDA 10.1 [28–30]. We use quasi IBS for our approach due to its efficient implementation [28].

5. Results and discussion

We discuss performance analysis of proposed parallel cross modality based liver enhancement for tumor segmentation. The enhanced liver images and segmented tumors are shown and the performance analysis of tumor segmentation is discussed based on quality assessment. We use Intel(R) Core(TM) i7-7700HQ CPU @ 2.80GHz RAM 24 GB, NVIDIA GPU GeForce GTX 1050 (RAM 4GB), and CUDA Toolkit 10.1 to compare the proposed parallel GPU approach with CPU implementation.

Algorithm 5: Grid-stride Loop through Dynamic RoI.

```
blockgrow=1;
while blockgrow==1 do
    blockgrow=0;
    unfinished=1;
    Increase RoI of Tiles;
    To Increase RoI of Tiles
    w=w+1; h=h+1; d=d+1;
    Ensure RoI within image dimensions;
    while unfinished==1 do
        unfinished=0;
        for int i=blockIdx.x;i<=w/blockDim.x;i+=gridDim.x do
            for int j=blockIdx.y;j<=h/blockDim.y;j+=gridDim.y do
                for int k=blockIdx.z;k<=d/blockDim.z;k+=gridDim.z
                do
                    Region_Growing(arguments, unfinished,
                    blockgrow);
                end for
            end for
        end for
        Inter_Block_GPU_Sync();
    end while
end while
```

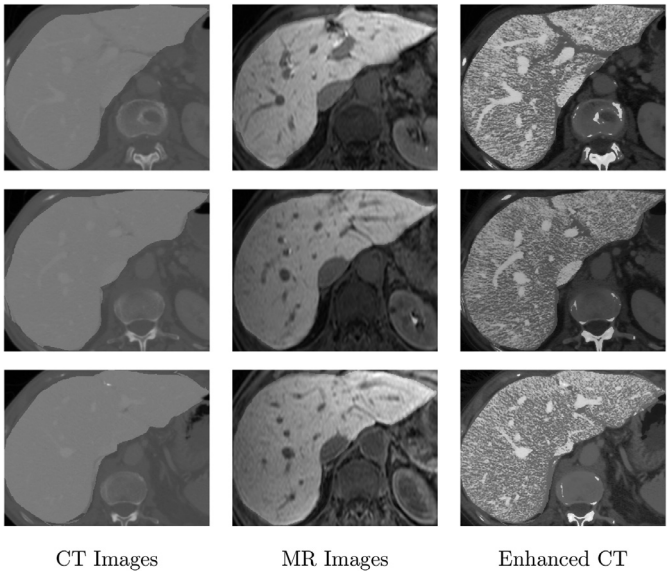


Fig. 5. CT, MR and enhanced CT images.

5.1. Liver enhancement

We propose fast parallel cross modality based contrast enhancement. 2D histogram of CT image is mapped to 2D histogram of guidance or MR image to get a better contrast image.

Fig. 5 shows input CT, MRI and enhanced CT liver images without any tumors. Fig. 6 shows enhanced CT liver images with tumors. Figures show the contrast is enhanced significantly to observe tumors clearly. Enhanced image is further processed for tumor segmentation using SRG. Average time taken by NVIDIA GPU GeForce GTX 1050 is 1.976 s ± 0.43 s providing the average speedup of 104.416 ± 5.166 times over CPU implementation (208.082s ± 55.799s) for tumor segmentation using 2D cross modality based contrast enhancement.

In order to enhance the contrast in CT images, we investigate quality improvements by fusing the information that is available in one modality (e.g. liver inner structures in MRI) to guide the adaptive enhancement in other image modality (e.g. CT in our case). This provides better control over the enhancement and is more effective and efficient than the state of the art technique used by clinicians. Clinicians generally use manual histogram adjustment technique based on 1D histogram specification on CT or MRI scans. This process does not provide efficient distribution of pixels for contrast enhancement of CT or MRI image. There are more chances of artifacts in 1D enhancement as it results in random histogram and is also a time consuming process.

However, 2D histogram specification incorporates spatial information while calculating 2D CDFs of both the guidance and input

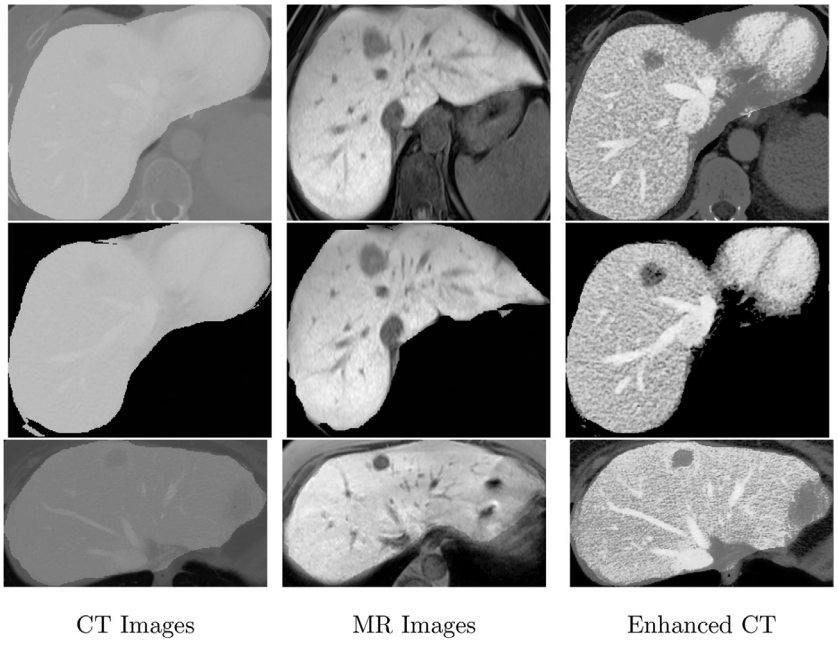
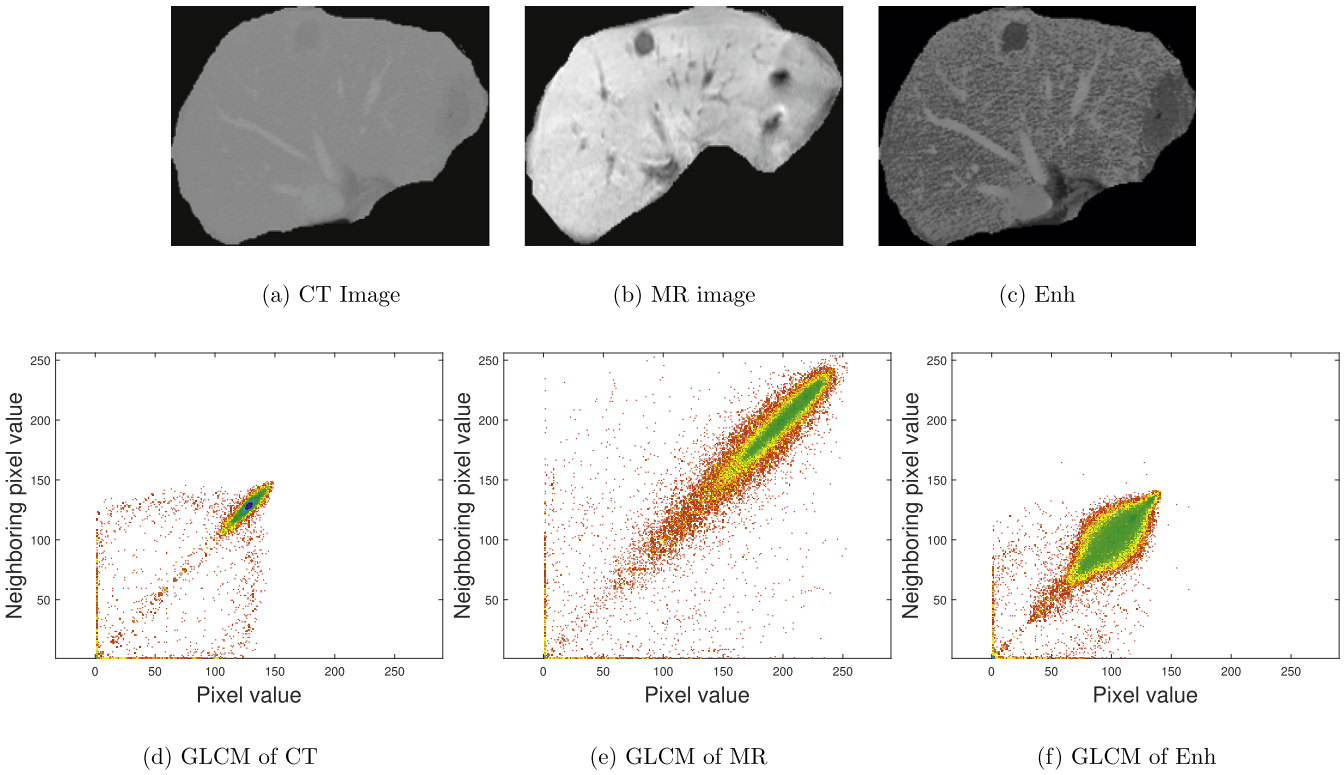


Fig. 6. CT, MR and enhanced CT images showing tumors.



(a) CT Image (b) MR image (c) Enh

(d) GLCM of CT (e) GLCM of MR (f) GLCM of Enh

Fig. 7. CT, MR and enhanced CT (Enh) with GLCM plots.

images and for remapping the input image intensity values. Instead of just considering the individual pixel values, it considers every possible pixel pair in the input and guidance image and calculate 2D CDF accordingly. Looking at the Gray Level Co-Occurrence Matrix (GLCM) plots in Fig. 7, it can be observed that the distribution of pixel pairs in GLCM plot of the resulting enhanced image (Fig. 7f) is expanded but concentrated along the diagonal in comparison to GLCM plots of CT and MR image (Fig. 7d and e), which means it does not introduce artificial artifacts unlike 1D histogram specification or histogram equalization.

We provide the histogram comparison of images using 1D and proposed 2D technique as shown in Fig. 8. The proposed 2D cross modality approach provides a proper distribution of pixel elements using guided MRI compared to 1D approach applied on CT or MRI image. 1D approach introduces unpleasant effects in the enhanced image. The histogram of enhanced CT using cross modality approach is similar to guided MRI image. There are more chances of artifacts in enhanced image using 1D approach as clinicians use manual adjustment which may result in any random histogram of the enhanced image. In the next section, we discuss the impact of cross modality based contrast enhancement for tumor segmentation.

5.2. Tumor segmentation

We propose fast parallel gradient based dynamic SRG for tumor segmentation. Our proposed parallel SRG is implemented on GPU. It does not involve transfer of data between CPU and GPU. The data for the research work have been acquired from The Intervention Center, University of Oslo, Norway [31]. The ground truths for tumor segmentation are provided by the clinician. We present the visual comparison of tumor segmentation on both enhanced and original CT liver images. The results in Figs. 9–11 show the tumor segmentation from original and enhanced liver images. Fig. 9a1 represents the original CT liver image. The gradient of input CT image is shown in Fig. 9a2. The tumor segmentation (Seg) and the ground truth (GT) for the original CT liver slice are shown in Fig. 9a3 and a4 respectively.

We enhance original CT liver image (Fig. 9a1) using cross modality based liver enhancement and the enhanced image (Enh_CT) is shown in Fig. 9b3. The tumor segmentation is performed on the enhanced CT liver image (Fig. 9b3) and segmented tumor from enhanced CT image is shown in Fig. 9b5. The quality of tumor segmentation is validated in our clinical validation section using Table 1. Tumor segmentation for other CT liver slices are shown in Figs. 10, and 11 and the segmentation quality is improved when the image is enhanced. Hence the cross modality based contrast enhancement on CT liver images improves the quality of tumor segmentation and it is faster. The proposed fast parallel liver enhancement based tumor segmentation is 104.416 $\pm$ 5.166 times faster compared to the sequential implementation. We include Table 2 showing experimental evaluation on 10 different datasets (including 107 tumor slices) obtained from The Intervention Centre, Oslo University Hospital, Oslo, Norway. It can be observed from the table that the cross modality based liver enhancement helps in improving the sensitivity, specificity (denoted by 'Sensi' and 'Speci' respectively in Table 2) and accuracy of tumor segmentation and GPU implementation of proposed approach is around 100 times faster compared to the CPU implementation. *P* value from ANOVA (analysis of variance) for the ten datasets is 3.31×10^{-14} which is less than 0.05. We reject the null hypothesis and conclude that not all means are equal which confirms the means are statistically significant for the concerned experiments.

5.3. Clinical validation

Tables 1 and 2 show the analysis of tumor segmentation before and after enhancement of CT liver images. Table 1 includes 5 liver slices with tumors from different datasets and Table 2 shows performance evaluation on 10 different datasets including 107 tumor

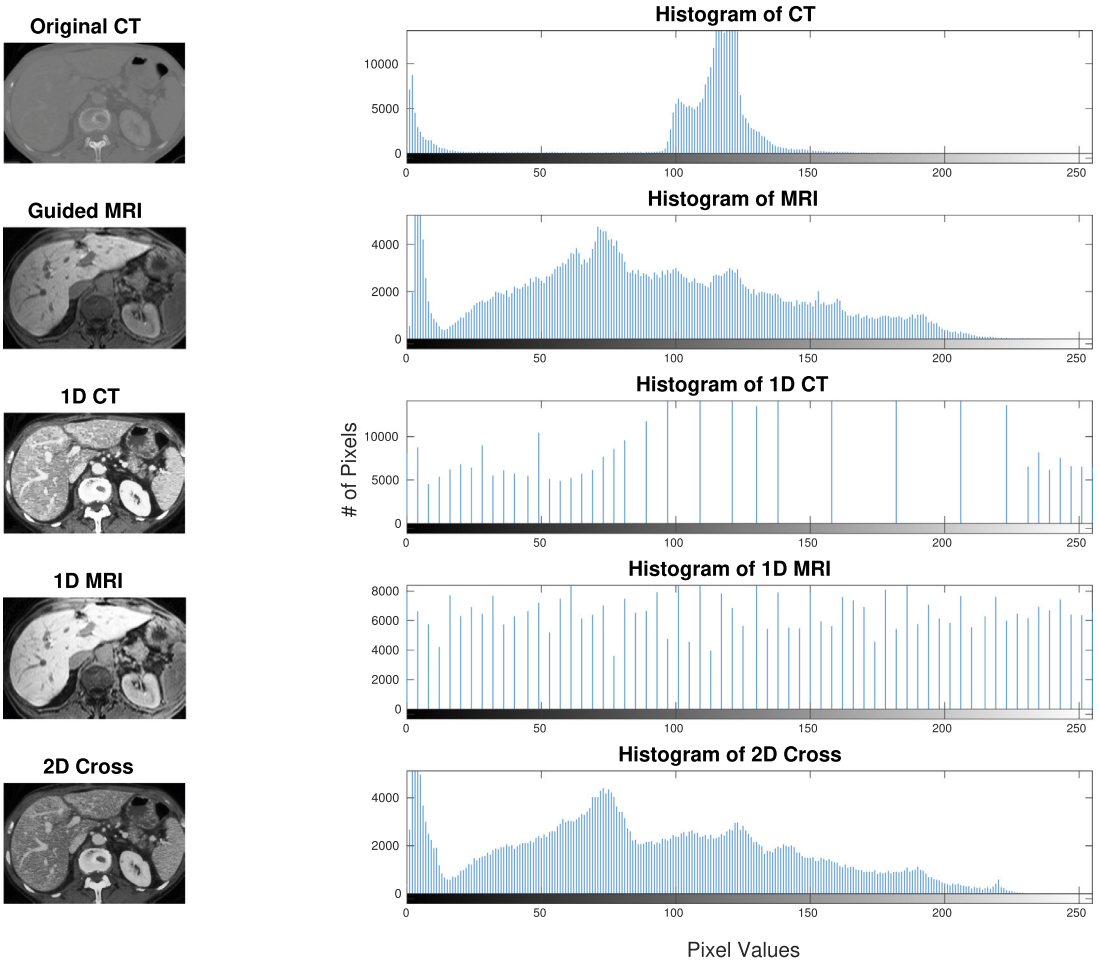
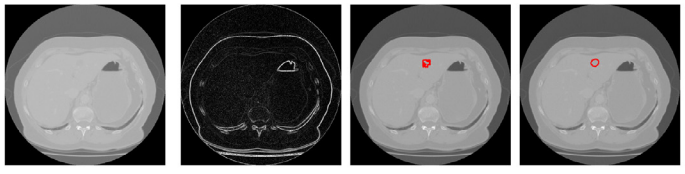
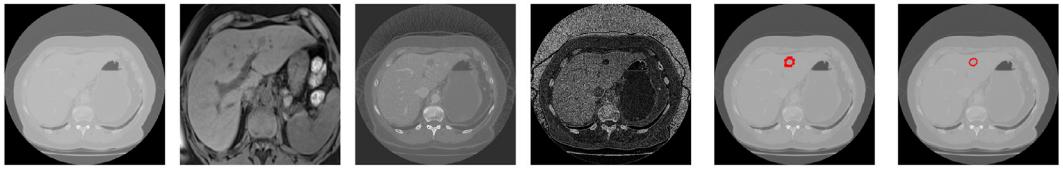


Fig. 8. Comparison between 2D cross modality and 1D histogram approach.



(a1) CT Image (a2) Gradient (a3) Seg (a4) GT

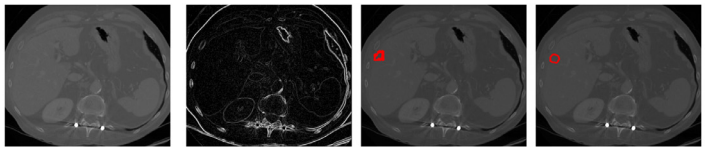
(a) Original Liver Image 1



(b1) CT Image (b2) MR (b3) Enh_CT (b4) Gradient (b5) Seg (b6) GT

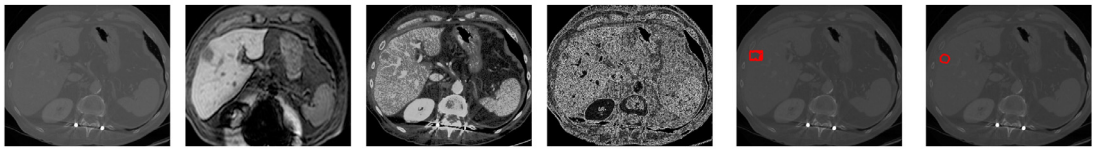
(b) Liver Enhancement and Tumor Segmentation from Enhanced CT Image 1

Fig. 9. Tumor segmentation from original and enhanced CT image 1.



(a1) CT Image (a2) Gradient (a3) Seg (a4) GT

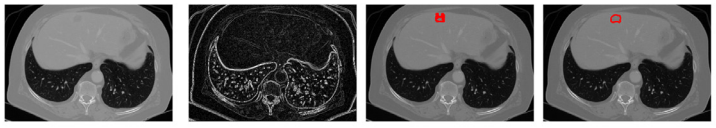
(a) Original Liver Image 2



(b1) CT Image (b2) MR (b3) Enh_CT (b4) Gradient (b5) Seg (b6) GT

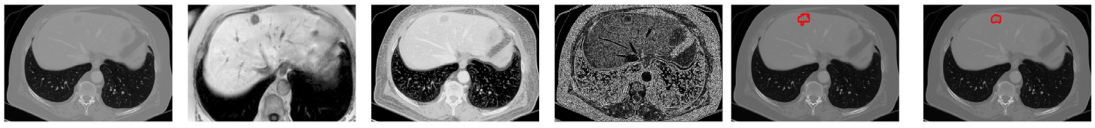
(b) Liver Enhancement and Tumor Segmentation from Enhanced CT Image 2

Fig. 10. Tumor segmentation original and enhanced CT image 2.



(a1) CT Image (a2) Gradient (a3) Seg (a4) GT

(a) Original Liver Image 3



(b1) CT Image (b2) MR (b3) Enh_CT (b4) Gradient (b5) Seg (b6) GT

(b) Liver Enhancement and Tumor Segmentation from Enhanced CT Image 3

Fig. 11. Tumor segmentation from original and enhanced CT image 3.

Table 1
Tumor segmentation analysis on five slices.

Tumor	Without any Enhancement		With Enhancement		Time-Enh+SRG(s)		Speedup
Slice #	Sensitivity, Specificity	Accuracy	Sensitivity, Specificity	Accuracy	CPU	GPU	
1	0.55	0.99899	0.82	0.99906	272.07	2.48	109.706
2	0.38	0.99918	0.81	0.99898	265.98	2.41	110.365
3	0.47	0.99769	0.58	0.9968	167.81	1.68	99.887
4	0.83	0.87091	0.50	0.99765	162.03	1.61	100.64
5	0.47	0.99786	0.74	0.99823	172.52	1.70	101.482
Average	0.54	0.973	0.69	0.998	208.082s	1.976s	104.416
Std. Dev.	0.173	0.057	0.143	0.001	55.799s	0.43s	5.166

slices. We chose sensitivity (true positive rate or recall) and specificity (true negative rate) as performance metrics for the evaluation of tumor segmentation [5,12]. It is observed that, the sensitivity and specificity are increased when the accuracy is nearly 1 on the enhanced image. This implies that when the tumor is actually present, then it is predicted more accurately when the image is enhanced.

5.4. Discussion

In this paper, we propose fast parallel cross modality based contrast enhancement for CT liver images. Further GPU performs dynamic RoI based tumor segmentation on enhanced CT liver image. These fast parallel implementations are based on persistence, grid-stride loop and IBS. The process of cross modality based contrast

Table 2
Tumor segmentation analysis on ten different datasets.

Dataset #	Size of each Slice (wxh)	Total # of Slices	# of Tumor Slices	Without any Enh (Average)		With Enh - Average (Avg.)		Enh+SRG Avg. Time (s)		Avg. Speedup
				Sensi, Speci	Model accuracy	Sensi, Speci	Model accuracy	CPU	GPU	
1	406 × 299	73	10	0.28	0.99132	0.36	0.99517	141.07	1.41	100.054
2	512 × 512	139	7	0.41	0.99213	0.52	0.99796	252.22	2.29	109.901
3	381 × 304	67	10	0.48	0.99412	0.65	0.99689	131.89	1.32	99.916
4	405 × 346	87	8	0.39	0.99325	0.47	0.99717	158.56	1.56	101.641
5	462 × 321	59	14	0.32	0.99173	0.50	0.99823	167.01	1.63	102.460
6	380 × 512	58	9	0.49	0.99112	0.64	0.99421	202.02	1.89	106.89
7	443 × 437	63	6	0.51	0.99201	0.71	0.99501	193.17	1.83	105.55
8	361 × 249	63	7	0.37	0.99312	0.57	0.99427	126.60	1.26	100.47
9	483 × 386	80	6	0.31	0.99415	0.59	0.99612	185.78	1.80	103.21
10	456 × 400	216	30	0.42	0.99178	0.62	0.99324	189.93	1.82	104.35

enhancement is computationally expensive and hence time consuming. This involves 2D histogram calculation, equalization and histogram matching [22]. They require several light weight tasks. The performance on GPU is improved compared to the CPU by dividing the tasks on several active threads.

The second part of the process is tumor segmentation. We propose gradient and dynamic RoI based SRG inspired from the works of Rai and Nair [21]. Initially, the process needs small part of the region to be accessed instead of whole image (as implemented previously on GPU). As soon as region grows, RoI should be increased to access more neighbouring elements. GPU implementation of SRG involves kernel termination and relaunch continuously from CPU. This is time consuming. We avoid this by using persistence and grid-stride loop and obtain the significant speedup i.e. 104.416 ± 5.166 times compared to the sequential implementation of liver enhancement and tumor segmentation.

6. Conclusion

In this paper, we discuss cross modality based contrast enhancement for CT liver images, application to tumor segmentation and their fast parallel implementation on GPU. Cross modality based liver enhancement includes CT liver image as an input and MRI liver image as a guided image. Pairwise 2D histogram implementation and histogram equalization spreads the intensity values across the image producing contrast enhanced CT image. We propose persistence and grid-stride loop based fast parallel implementation on GPU. The enhanced image then used for segmentation of tumors from enhanced CT liver images effectively. We propose gradient and dynamic RoI based seeded region growing for tumor segmentation. The parallel approach for liver enhancement and tumor segmentation is 104.416 ± 5.166 times faster compared to the CPU implementation.

Declaration of Competing Interest

We, the undersigned, confirm that the manuscript represents our own work, is original and has not been copyrighted, published, submitted, or accepted for publication elsewhere. We further confirm that we all have fully read the manuscript and give consent to be co-authors of the manuscript.

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