PARALLEL APPROACH TO EXPEDITE MORPHOLOGICAL FEATURE EXTRACTION OF REMOTE SENSING IMAGES FOR CBIR SYSTEM

Sandeep Kumar, Swati Jain

Institute of Technology,Nirma University
Computer Science and Engineering Department
Ahmedabad,India

Tanish Zaveri

Institute of Technology,Nirma University
Eletrical Engineering Department
Ahmedabad,India

ABSTRACT

In this paper, we have proposed a parallel approach to the morphological feature extraction process and demonstrated a good computational speedup. Remote sensing images have a typical property of incrementing constantly and each image being very large. Since the images are acquired constantly and hence added into the database regularly in good numbers, hence there is a need to make the feature extraction work more efficient. Moreover morphological features are good texture descriptors and are extremely compute-intensive as well. It is hence attempted to utilize the power of multi-core architecture and expedite the process of feature extraction. These feature descriptors are tested on UC Merced Land Use Land Cover Data set. Experimentation shows that with the use of parallel programming and architecture speed up of as good as 20X is obtained for CCH and RIT feature sets.

***Index Terms*—** CBIR,CCH,RIT, Parallel Approach,Remote Sensing

1. INTRODUCTION

Remote sensing centers across the world are the storehouses of images and act as decimation centers of these images for those who want to use them. Most of these centers are managing the images using its meta data. Users specify the requirements which are mapped in meta data information which is usually less precise. Need of defining and managing the image data set based on its content has been very well understood and established in the field of remote sensing. Most of the Content Based Image retrieval (CBIR) systems have at least two modules feature extraction and feature matching. People have explored various local features, and have tried to represent the images as holistic as possible[1]. Going a step ahead to bridge the gap of users perspective. Some of the authors have proposed relevance feedback for bridging the semantic gap[2, 3].

Feature extraction, being an offline process the features from the image data are extracted once and typically stored in a database. When a query image is fired the feature set of the query image is compared to the feature set of the data base images using an appropriate similarity matching algorithm to serve users with relevant images after ranking them in the order of their similarity. The correctness of relevant images retrieved lies in how appropriately and exhaustively the feature set defines the image. Recently introduced, texture descriptors are circular covariance histograms(CCH) and rotation invariant point triplets(RIT), on content based remote sensing image retrieval. Author Erchan Aptoula has exhaustively performed a survey and is optimistic with the use of mathematical morphology in this domain[4]. The paper proposes the use of morphological operators as it is inherently good in exploiting the relation between the pixels which exactly is the texture and hence this makes it apt for using texture description.

The inherent challenges of CBIR system for remote sensing Images are 1. Large number of images 2. Huge size of images 3. Constantly increasing dataset 4. Huge amount of information, as each pixel is represented in various bands.

2. MORPHOLOGICAL TEXTURE DESCRIPTORS

2.1. CCH

Texture can be defined as a relationship between the neighborhood pixels that is generated by a common function. The author has discussed about morphological covariance[4]. As per his definition morphological covariance k is defined as the volume of the image eroded by pair of points at a distance. Various characteristics of co-variance with varying distance represented the texture properties like width,size and thinness of the pattern.Very soon the limitations were also established such as the features being variant to rotation and illumination. Mainly they were due to the structuring element, morphological operator used and the evaluation method.

To overcome the above limitation a symmetric SE was proposed and hence shape of SE was identified as circular which makes it invariant to rotation and illumination.The various combination of dilation and erosion of a given set of pixel value is suggested as morphological operator. Later CCH which is circular covariance histogram was introduced.

2.2. RITs

RIT is a different way of implementing circular SE. The circular SE is broken into point triplets at different orientation and hence considering all the directions but one at a time. Given an image f and circular SE as in CCH B_i at different radii $i \in$ [1,n] , the RIT structuring elements are obtained by decomposing the circular SE into 4×i point triplets where i is the radius of the circular SE. Thus the new SE is $B_{i,j}$,$j \in$ [1, 4×i]. The image is then processed using a morphological operator and SE $\{B_{i,j}\}_{1\leq i\leq n, 1\leq j\leq 4\times i}$, of points triplets.

3. GPU ARCHICTECTURE AND CUDA

The GPU device being used is Nvidia Geforce GTX 480 having a memory of 1.5 GB. CUDA offers a data parallel programming model that is supported on NVIDIA GPUs.

In this model, the host program launches a sequence of kernels. A kernel is organized as a hierarchy of threads. Threads are grouped into blocks, and blocks are grouped into a grid. Each thread has a unique local index in its block, and each block has a unique index in the grid. Kernels can use these indices to compute array subscripts, for instance.

The dilation and erosion are independent operations. So these can executed be done in parallel on GPU on per pixel basis. This technique comes under the category of SIMD(single Instruction Multiple Data) as the same set of operation is being executed on multiple data in parallel.

4. IMPLEMNTATION

We have used the UC Merced LULC data set, which is the largest of its kind[5]. In particular, it consists of images categorized into 21 classes, with a pixel resolution of 30 cm. Each class contains 100 RGB color samples of size 256 × 256 pixels,. For feature extraction, we aim to compare serial and parallel approaches. Moreover, all data have been processed in grey level, with the conversion having been conducted through Grey = 0.299 × R + 0.587 × G + 0.114 × B.

4.1. CCH

CCH has been implemented using two operations i.e. dilations and erosions for ten different radii of SE. The radii vary from 3 pixels to 21 pixels at a step size of 2. Thus for 2 operation and 10 radii, total number of features in the feature vector is 2*10=20.

10 Structuring element of different radius are generated and saved in an array.

Serial approach

```
input  : IN, filter
output: OUT
INIT Max to -1;
  foreach element in IN do in parallel
      foreach row in filter do
        foreach column in filter do
           if filter(row,column) is 1 then
              SET L to IN(row,column);
              if L is greater than Max then
                 SET Max to L;
              end
           end
        end
      end
      SET OUT to Max;
  end
```

Algorithm 1: dilation using parallel approach

1. Dilation is performed on database images with the stored Structuring Element iteratively. The resultant matrices for 10 different matrix are stored as I1 to I10.
2. Now the images I1 to I10 are subtracted from the original image and divided by the number of ones in the corresponding Structuring Element. The corresponding radius, for which the result is maximum is saved.
3. The result is a matrix of same size as that of the database image but values ranging from 1 to 10.
4. Now histogram of matrix is calculated which gives 10 values which are used as feature descriptor of the image

After that, above operation is repeated once again for erosion. So now an image is represented using 20 descriptors.

Parallel approach

The Algorithm 1 performs dilation on image **IN**, the structring element **filter** is operated, **Max** represents the Maximum value within SE to generate the output image **OUT**.

For dilation maximum value out the 45*45 filter is taken after convolution. Similarly erosion is done in parallel but for that minimum value is found after convolution.

After the dilation and erosion results are obtained, another Algorithm 2 is invoked which computes the value of radius for which the difference between the corresponding radius and original image is maximum. **INR[ ]** represents the result of dilation with different radii from Algorithm 1 and **Pos** represents the radius value for which diffrence is maximum.

Thus resultant image of same no. of pixels as original image with values ranging between 1 and 10 is obtained. Now histogram of the resultant image is generated which is the feature descriptor for the given image of size 20.

```
input  : IN, INR[ ]
output: OUT
INIT Max to -1;
INIT Pos to 0;
  foreach element in IN do in parallel
      foreach column in INR do
        SET D to column*16+9 ;
        SET L to (IN-inr(column))/D ;
        if L is greater than Max then
            SET Max to L;
            SET Pos to column;
        end
      end
      SET OUT to Pos;
  end
```

Algorithm 2: maxradius for CCH

4.2. RITs

The SEs obtained in CCH section is used to generate triplets. Triplets could be generated easily by taking only 2 points at a time which are exactly opposite to each other and the third point is the center point which is common to all. So for SE with radius i, 4*i triplets are obtained and saved in matrix.

```
input  : IN,FilterPos
output: OUT
  foreach element in IN do in parallel
      //x,y are pixel position of required erosion value
      foreach row k in FilterPos do
        SET L to 0;
        SET Min to 255;
        SET x to FilterPos(row,1);
        SET y to FilterPos(row,2);
        for i ← 1 to rowsize(FilterPos) do
            SET P to FilterPos(i,1)+x;
            SET Q to FilterPos(i,2)+y;
            SET L to IN(P,Q);
            if L is less than Min then
                SET Min to L;
            end
        end
        SET arry(k) to Min;
      end
      SET OUT to maximumof(arry);
  end
```

Algorithm 3: opening using parallel approach

Serial Approach

1. Opening is performed on database images with the stored structuring element iteratively. The resultant matrixes for different triplets are stored as It1 to It84.
2. For each pixel all the images from It1 to It84 is scanned to find the maximum value and it is stored in images I1 to I10.
3. Now the images I1 to I10 are scanned to the maximum value for each pixel. The corresponding radius, for which the result is the maximum, is saved.
4. So the result is matrix of same size as of the database image but values ranging from 1 to 10.
5. Now histogram of matrix is calculated which gives 10 values which are used as feature descriptor of the image

After that, above operation is repeated once again for closing. So now an image is represented using 20 descriptors.

Parallel Approach

In serial approach the SE consist of matrix of size 45*45 with only 3 points set as ones remaining all are zeros. So to compact the representation we save the coordinate value of only these 3 points and neglect the remaining points.

In RIT, there are two level of merging

1. Merging results obtained from different orientation for one SE.
2. Merging results for 10 different radii to obtain one labeled image

The Algorithm 3 performs first level of merging where **FilterPos** stores the coordinate values of filter whose value is 1, **Min** stores the minimum pixel value out of the three neighboring pixels, **x,y** represents the x and y coordinate on which erosion operation is to be performed **P,Q** represents the coordinate of left and right neighbouring pixel

The next level of merging is to obtain a labeled image. This is done by combining all the F_i by maximizing on F_i value for the corresponding pixel. This is again done pixel per thread hence many on images parallely.

5. RESULT

Comparison of the time taken for computation of 20 features for parallel and serial implementation is shown in Figure 1 for CCH and Figure 2 for RIT. The graph is drawn with number of images in x axis and time taken in seconds in y axis.

As can be seen from the Figure 1 and Figure 2 the time taken for serial approach in both the cases increases almost linearly with increasing number of images,where as the time taken in parallel approach increases slowly.The speedup is calculated by following computation

$$\mu_{speedup} = \frac{\Sigma_{i=1}^{G} \frac{T_{is}}{T_{ip}}}{G} \tag{1}$$

where $\mu_{speedup}$ is the average speedup
T_{is}=time taken by i images in serial approach
T_{ip}=time taken by i images in parallel approach

For CCH

$$\mu_{speedup} = \frac{155.62}{10} = 15.56 \tag{2}$$

For RIT

$$\mu_{speedup} = \frac{200.64}{10} = 20.06 \tag{3}$$

The data from Figure 3 is used for calculating the $\mu_{speedup}$ for CCH and RIT. Hence the speedup obtained in the case of CCH parallel implementation in against serial implementation is 15 times and in case of RIT it is 20 times. The number of images that are to be added in remote sensing database is in thousands and hence this speedup will give a good performance boost for the feature extraction process.

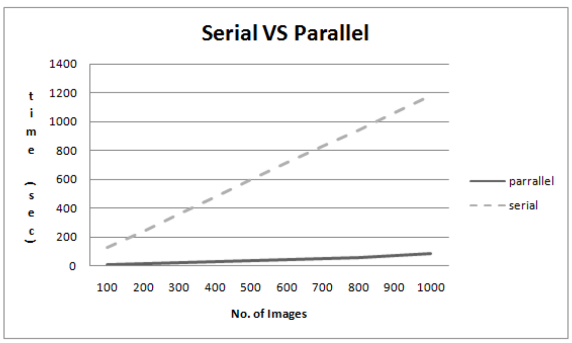

Fig. 1. Computation time for CCH

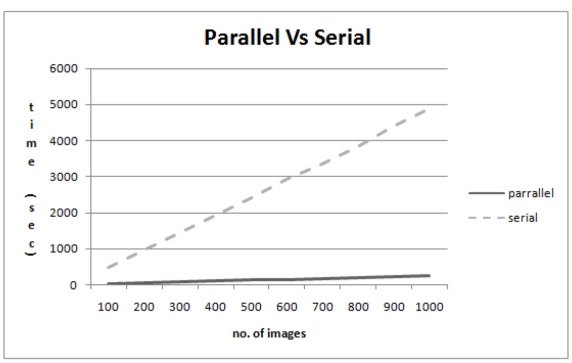

Fig. 2. Computation time for RIT

6. CONCLUSIONS

Morphological operator are computationally complex and also good descriptor for texture representation. Texture feature is inevitable feature set in case of remote sensing images,

Image Count	Computation Time (sec)					
	CCH			RIT		
	serial	parallel	speedup	serial	parallel	speedup
100	123.62	7.50	16.47	493.50	24.03	20.52
200	235.57	15.13	15.56	971.12	48.01	20.22
300	353.13	22.49	15.69	1447.4	72.10	20.07
400	476.52	29.99	15.88	1929.3	95.64	20.17
500	595.70	37.26	15.98	2413.2	120.23	20.07
600	713.00	44.77	15.92	2925.1	143.06	20.44
700	828.87	52.21	15.87	3341.5	168.62	19.81
800	943.93	59.46	15.87	3838.8	193.17	19.87
900	1060.1	71.71	14.78	4296.5	217.57	19.74
1000	1182.3	87.18	13.56	4775.2	242.45	19.69
speedup sum			155.62			200.64

Fig. 3. Serial Vs Parallel time computation

the parallel approach to the CCH and RIT feature extraction is proposed to expedite the performance for feature extraction for CBIR system. The characteristic of remote sensing images of constantly incremental is being identified and tried to address. The performance gain obtained is as good as 20 times when done in parallel which is a substantial gain for the number of images added in the remote sensing data set regularly. Mentioned algorithm is tested for 1000 images in parallel, due to memory constraints in the mentioned hardware. However, we are optimistic about working of this algorithm for much more images in better configuration GPU's.

7. REFERENCES

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