International Journal of Mechatronics, Electrical and Computer Technology

Vol. 4(12), Jul, 2014, pp. 1041-1056, **ISSN**: 2305-0543

Available online at: http://www.aeuso.org

Seabed Image texture Clustering Using Parallel Computing

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Abstract

Seabed image clustering is the one of the most important applications in sonar imaging. Due to textured appearance of sonar images, texture analysis methods are a common choice for seabed acoustic images. The subsampled contourlet transform is a new version of the contourlet transform that allows analysis of images in square-size coefficients with various resolution levels and directions. This paper uses subsampled contourlet transform for clustering seabed image texture. Due to complexity of clustering algorithm and the need of some sonar applications to run algorithm faster, this paper presents the implementation of seabed image clustering using parallel computing. In this paper seabed image clustering algorithm is done using multi core programming to improve efficiency. In this paper results are executed on single core and multiple core of CPU on different sets of seabed image texture and the performance analysis shows improvement in terms of speedup and execution time.

Keywords: Contourlet transform, Sonar, Image Clustering, Parallel computing, Multi core computing.

1. Introduction

Today, sonar (Sound Navigation and Ranging) systems are commonly used in underwater cognizance and provide underwater seabed images [1], [2]. One of the most important applications in sonar imaging is seabed image clustering. Clustering seabed images can be useful in recognizing different geo-acoustic regions. Clustering of seabed

Vol. 4(12), Jul, 2014, pp. 1041-1056, ISSN: 2305-0543
Available online at: http://www.aeuso.org

sonar images aims to categorize the acoustic image into clusters of similar images with respect to certain physical properties or geological characteristics. The goal of the clustering task is to assign these different geo-acoustic regions to seabed types as sand, pebbles, rocksand etc [3]. Analysis of image texture can help to categorize them into clusters. One of the popular analysis methods is contourlet transform. Contourlet transform is a new extension of the two-dimensional wavelet transform using multi scale and directional filter banks. Subsampled contourlet transform is a new version of contourlet transform that is proposed by Javidan[1].Subsampled contourlet transform helps analysis of images in square-size coefficients with various resolution levels and directions. In this paper subsampled contourlet transform is used to analyze seabed image texture. In some sonar applications, it is necessary to cluster seabed images in real time. Usually, image clustering algorithms are more complex and take long time to run. Parallel computing techniques such multicore programming can help to improve efficiency of image clustering algorithm. This paper uses multicore programming method to execute the proposed seabed image texture clustering algorithm faster and improve the efficiency of algorithm. The rest of this paper is organized as follow. In Section 2, we discuss some of the previous related works. Then we present the proposed image clustering algorithm in detail in Section 3. After that, we evaluate the performance of the proposed algorithm in Section 4. Finally we give our conclusions in section 5.

2. Related Works

In recent years, for the purpose of automatic seabed classification, special kinds of sonar systems, i.e., automatic acoustic ground discrimination systems, such as RoxAnn, QTC-View and EchoPlus have been developed [4]. However, various classification methods produce different results for the same region. Some of these systems are also susceptible to noise, ship speed, and motion. In a large extent, the quality of classification results depends

Vol. 4(12), Jul, 2014, pp. 1041-1056, ISSN: 2305-0543
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on the human skills and experiences and the intended use of the system. In addition, sometimes sea bottoms labeled identical acoustic signatures by a particular classification system may not necessarily be geologically similar. Therefore, most of the current acoustic seabed classification systems are essentially empirical devices, that are more or less application oriented, and require intensive calibration (ground truth) when are used to discriminate different seabed types [5]. Therefore developing new acoustic ground discrimination systems is still the current interest of researchers [6]. Image texture clustering and analysis is still considered an interesting but challenging problem in computer vision. In the past, several methods have been proposed for image texture analysis [7]. Recently, researchers have focused on multiresolution space/scale texture models such as Gabor filters and wavelet transform [8]-[10]. The output of Gabor filter banks are not mutually orthogonal, thus they may result in significant correlation between texture features. Moreover, these transformations are usually not completely reversible, which limits their capability for texture synthesis. In addition, Gabor filters require proper tuning of filter parameters at different scales [11]. On the other hand; one major advantage of wavelet analysis [12] is its localization property, which reveals various aspects of data like trends, breakdown points, discontinuities at higher derivatives, and self-similarities.

There are several methods have been specially presented for sonar image analysis. Methods based on Hierarchical MRF modeling [13], Markovian multigrid algorithm [14], self-organizing map and a noise model estimation [15], Markov Random Field and Fuzzy Logic Modeling [16], and wavelet packet transform and Fourier transform [17] are good examples of such proposed methods. Even all the above methods work effectively in many cases; however the common drawback of these algorithms is the complexity of calculations that may produce difficulties for real time processing. In addition, some of them are susceptible to noise and ship speed and sometimes are not very accurate. The author in [6],

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Available online at: http://www.aeuso.org

[7] presented a new method based on standard wavelet transform and fuzzy logic as an effort to overcome these drawbacks.

As a matter of fact, seabed images like more natural images contain intrinsic geometrical structures, with a significant role in image analysis, including feature extraction and classification. A major drawback of two-dimensional wavelet transform is its limited capability in capturing directional information. To overcome this deficiency, researchers have recently come up with a new family of wavelet methods that can capture the intrinsic geometrical structures such as smooth contours in natural images [18]. Some examples include, complex wavelets [19], ridgelet transform [20], curvelet transform [21], and contourlet transform [22].

Curvelets are very successful in detecting image activities along curves, while analyzing images at multiple scales, locations, and orientations. While wavelet decomposition captures point discontinuities, directional decomposition links point discontinuities into linear structures.

Contourlet transform overcomes directionality lack of 2-D wavelets by geometrically representing smoothness of contours. Contourlet transform allows having different and flexible number of directions at each scale, which makes it a suitable tool for seabed image analysis. In addition, the contourlet transform uses iterated filter banks with computational efficiency. Specifically, it requires operations for an n-pixel image. Finally, unlike other continuous approaches such as curvelets, contourlet transform starts with discrete-domain construction and then studies its convergence in the continuous domain. Nonsubsampled contourlet transform [23] is a redundant version of standard contourlet transform.Subsampledcontourlet transform [1] is like nonsubsampled contourlet transform, except that it avoids coefficient redundancy at various resolution levels. Unlike standard contourlet transform which does not have square shape coefficients, the subsampled contourlet transform allows practical processing on square-size directional sub-bands that

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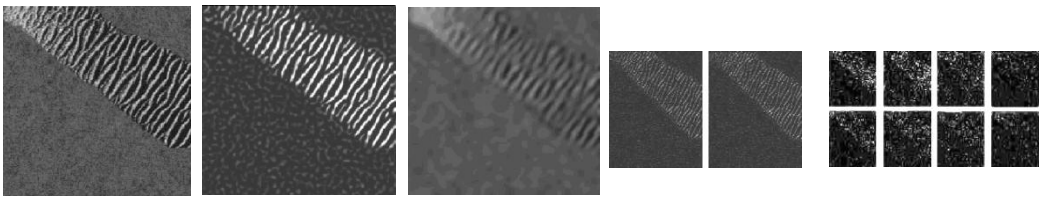
brings more flexibility, simplicity and accuracy for feature calculation. In addition, its multiresolution approach provides capability of using single-sensor system instead of multi-sensor system to distinguish different seabed types which texturally may be very similar but are composed from different sediments. Figure 1 shows an example of a real seabed image and its corresponding three levels pyramidal subsampled contourlet transform with 12 directional bandpass sub-bands.



(a) (b) (c) (d) (e)

Figure1: (a) Original real seabed image. The result of three-level subsampled contourlet transform with 12 directional bandpass sub-bands: (b) S_1 **. (c)** S_0**. (d)** S_{21}, S_{22}**. (e)** $S_{31} \ldots S_{38}$ **. [1]**

3. The Propose Image Clustering Algorithm

The task of seabed image texture clustering is to cluster each image texture to each category of image textures in image texture database, accurately and efficiently. Figure 2 demonstrates block Diagram of proposed method. According to Figure 2, three level subsampled contourlet transform [1] with 12 directional sub bands is performed to the original image texture. The contourlet transform coefficients in different sub bands are used for calculating energy value to construct feature vector of the original image texture .Euclidean distance is used to cluster each image texture. Following the block diagram of Figure 2, the seabed image texture is first transformed into subsampled contourlet domain and 12 sub bands are created. Contourlet transform is performed using three pyramid decomposition levels and 9-7 filters with 12 directional sub bands using dmaxflat7 filters.

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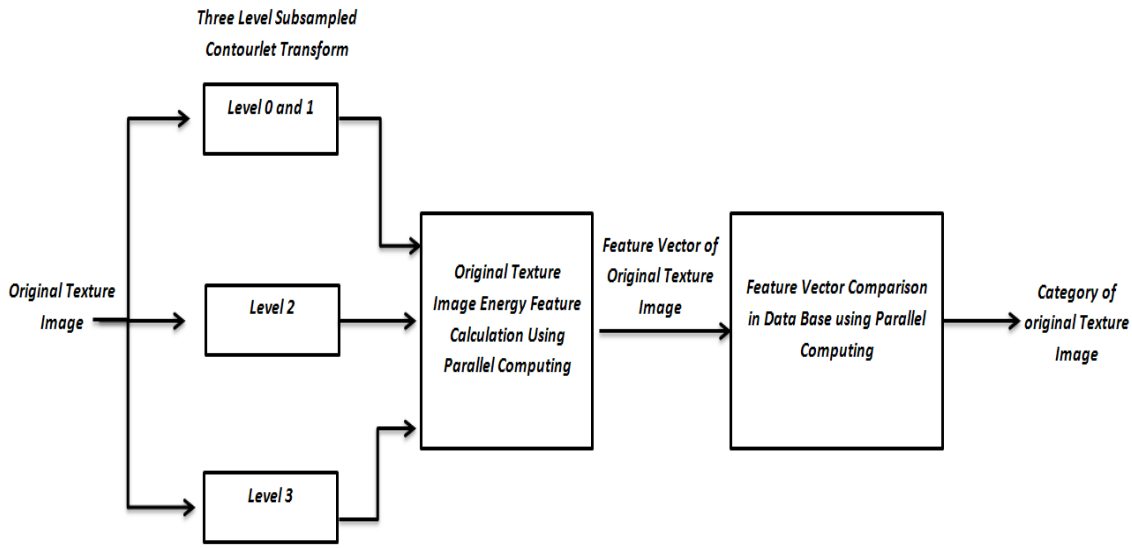

Figure 2: Block diagram of the proposed seabed image texture clustering algorithm

Using the above parameters and based on Figure 1, 12 directional sub bands (8 at level 3, 2 at level 2, 1 at level 1 and 1 at level 0) are obtained. Let S0,0 be the lowpass sub band and S1,1, S2,1-S2,2 and S3,1…S3,8 be bandpass directional sub bands at the first, second and third decomposition levels, respectively. Our experiments showed that local energies of the subsampled contourlet coefficients provide separated feature space accurately. Since the energy of natural image textures is mainly concentrated in the mid frequencies, subsampled contourlet transform can preserve most of the original signal energy and can provide reliable description of the texture. This can also be observed from the compression property of the subsampled contourlet transform, where the transform of a given image texture consists of a small number of large coefficients (high energy) and a small number of coefficients (low energy). Then, the distribution of energy can be selected as a valuable feature. Figure 3 shows such distribution where the histograms of a given image texture and its three level subsampled contourlet transform coefficients are shown.

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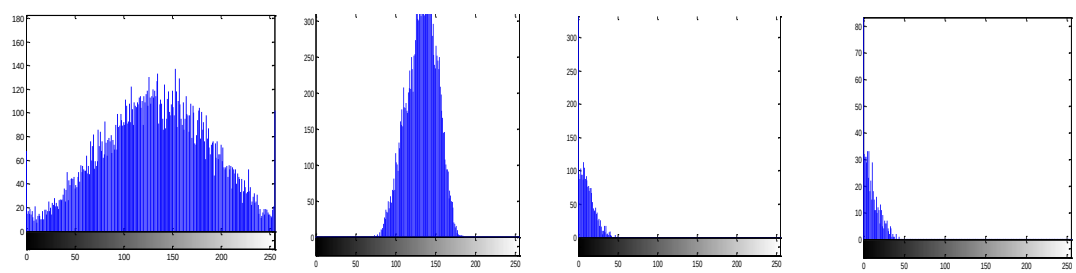
Squared root of average energy of the subsampled contourlet coefficients of the original image texture on each sub band with size N*M is calculated as:

$$E_s = \sqrt{\frac{\sum_{i=1}^{N}\sum_{j=1}^{M} S^2(i,j)}{NM}} \quad (1)$$

The process begins from top left corner of each sub band of each level and continuing in raster scan manner to form the feature vector. For three level decomposition, the resulting subsampled contourlet feature vector FV which consists of 12 energy feature vector is given as:

$$FV = [E_{S1}, E_{S2}, E_{S3}, \dots\dots\dots\dots, E_{S12}] \quad (2)$$



(a) (b) (c) (d)

Figure 3: A comparison between histogram distribution of original image and its three-level subsampled contourlet transform coefficients.Original image histogram. Subsampled contourlet transform coefficient for (b) S_0 (c) S_{21} and (d) S_{31}, respectively.[1]

Following feature calculating, Euclidean distance is used for clustering original image texture. If FVOimage is the feature vector of original image texture and FVDbimage is the feature vector of a image texture in feature vector database, the Euclidean distance between them is given by:

$$D(FV_{oimage}, FV_{Dbimage}) = \sqrt{\frac{\sum_{i=1}^{12}(FV_{oimage} - FV_{Dbimage})^2}{12}} \quad (3)$$

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According to Figure 2, for saving time and improving performance of clustering algorithm in terms of execution time, energy values of each sub bands calculation and feature vector construction and feature vector based on Euclidean distance comparison are performed using parallel computing.Parallel computing to improve efficiency, utilizes multithread programming on multicore processor. Clustering algorithm divides each operation into multiple independent parts and then assigns each part to a thread. Each thread executes on the independent processor core. Performance can be increased depending on number of threads or cores on processor. Figure 4 shows thepseudo code of the proposed clustering algorithm. Highlighted parts are done parallel.

4. Experimental Results

Author's Name(s) is/are to be centered beneath the page title and printed in Times New Roman 11-point and affiliations are in Times New Roman 10-point.

Although the proposed method can be used on any type of seabed image texture; however in this paper to validate proposed method Brodatz album [24] images are used. The configuration of the system on which experimental results are shown in Table 1.

Table 1: Configuration of the system

Processor	**Intel Core i7-3770K @ 3.50GHz, 8MB cache, 4 cores, 8 threads.**
Memory Ram	4GB
Programming language	Java (NetBeans), Matlab 2010a

In this paper speed up factor defined as follows:

$$\text{Speed Up} = \frac{T_1}{T_n}$$

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Where T1 is the execution time of clustering algorithm taken by the single core and Tn is the execution time of clustering algorithm taken by the multi core.

```
Procedure Prallel_Image_Clustering(Image I)
Begin
    Compute _Contourlet(I);
    S=[S0,0 ,S1,1 ,...S3,8];
    For each sub-band of Contourlet
                        Ei=Calculate_Energy(Si);
    End For
Feature_Vector=[E1,E2,...,E12];
For each cluster in Image DataBase
        Cluster=Find_Minimum_Euclidean_Distance( Feature_Vectorimage, Feature_VectorDB_image);
End For
Return Cluster;
End
```

Figure 4 . Pseudo code of the proposed clustering algorithm

According to the Figure 4, subsampled contourlet transform of each given image texture are calculated separately using Matlab software.The result of this step are 12 directional sub bands which are given to parallel clustering program. Then parallel clusteringprogram clusters the given image texture.

In the first run image texture with different size are used. In this run the size of image texture energy vector database is 50000 records. Each record indicates to energy vector of a image texture. Table 2 shows the execution times in milliseconds of various numbers of threads for different given image texture sizes in parallel clusteringprogram for clustering. Table 3 shows the execuion times in seconds of subsampled contourlet transform for generating 12 directional sub bands in Matlab.All the results are obtained from the average of 10 runs. Table 2 show that execution time decreases for various image texture sizes as the number of threads increases. Also table 2 indicates that execution time of clustering

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algorithm increases as the size of image texturesize decreases. Table 3 show that execution time of subsampled contourlet transfrom considerably decreases as the size of image texture decreases.

Figure 5 illustrates speed up factor for various numbers of threads which execute the clustering algorithm on different sizes of image texture. As seen in the Figure 5, speedup factor for differnet size of image texture increases as the number of threads increases.

Table 2: execution time of clustering algorithm based on thread numbers and image texture size

Texture Image Size	8 thread	7 thread	6 thread	5 thread	4 thread	3 thread	2 thread	1 thread
1024*1024	1502	1669	1854	2457	2836	4516	9828	38975
512*512	1293	1524	1812	2355	2931	4478	9789	38984
256*256	1299	1528	1859	2335	3098	4492	9801	38920
128*128	1282	1489	1811	2272	3065	4475	9781	38920

Table 3: execution time of subsampled contourlet transform for given image texture

Matlab Execution Time	Seconds
1024*1024	431.31665
512*512	96.753881
256*256	23.487567
128*128	5.805937

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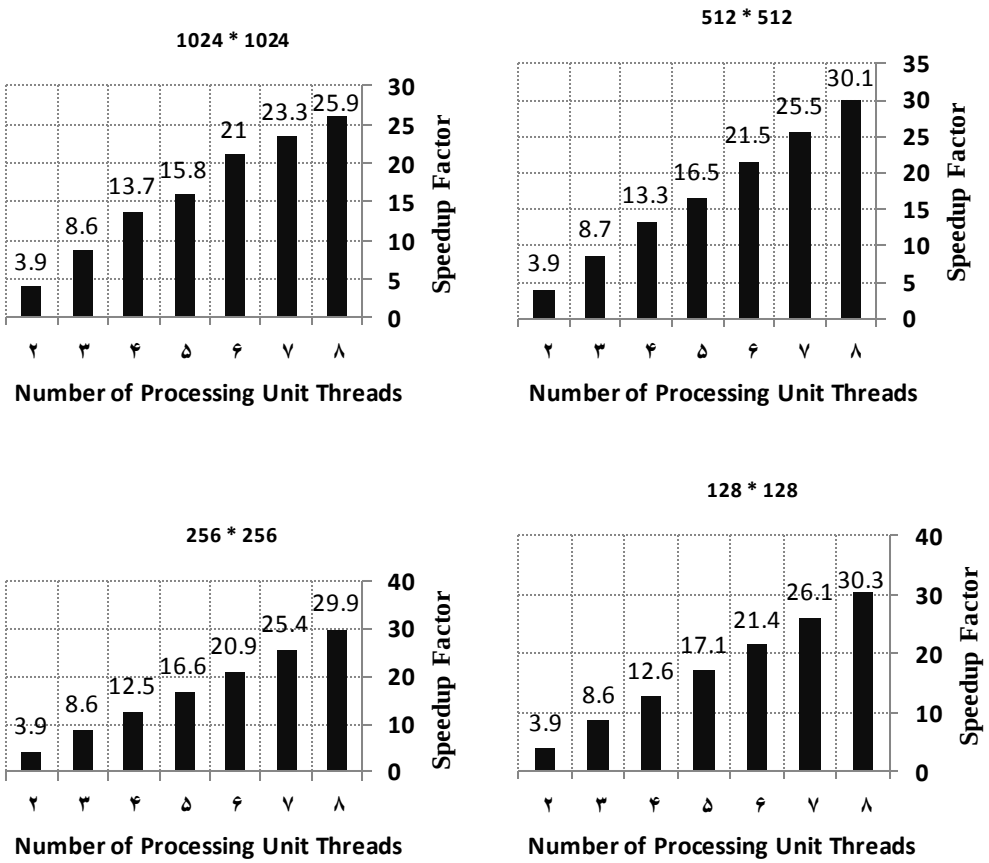

Figure 5: speed up factor for various numbers of threads and different image texture sizes

It can be concluded from Table 2 and Figure 5 that image texture clustering algorithm can be run faster in multi core or multi thread architecture. Speedup considerably grows as the number of threads or cores increases. Therefore in real time sonar imaging applications, using multicore processing unit is very useful. In the second run a image texture with size 256*256 is considered to find in databases with different sizes.In this run as mentioned above, subsampled contourlet transform is done and then 12 directinal sub bands are given to parallel clustering program. The parallel clustering program computes energy vector and

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then searches database for clustering the given image texture. According to the Table 3, execution time of subsampled contourlet transform for given image texture with size 256*256 is23.487567seconds.Table 4 shows the execution times in milliseconds of various sizes of image texture energy vector databases for a image texture with size 256*256. All the results are obtained from the average of 10 runs. In Table 4 number of records (energy vector of image textures) varies from 30000 to 60000.

Table 4: execution times in milliseconds of various sizes of image texture energy vector databases

DataBase size(records)	8 thread	7 thread	6 thread	5 thread	4 thread	3 thread	2 thread	1 thread
30000	500	610	680	862	1074	1581	3513	13996
40000	867	970	1177	1485	1862	2848	6265	24939
50000	1290	1541	1825	2319	3067	4481	9799	38998
60000	1826	2168	2583	3325	4208	6474	14133	56127

As seen in Table 4, execution time decreases as number of threads increases. Moreover execution time increases as the size of database increases. Figure 6 illustrates speed up factor for various sizes of threads which execute the clustering algorithm on different number of records inimage texture energy vector databases. As illustrated in Figure 6, speedup factor of clustering algorithm on different database sizes considerably increases as the number of threads increase. Moreover Figure 6 shows that in the case of large size databases, speedup factor of multi core architecture considerably increases. It can be concluded from Table 4 and Figure 6 that performance of clustering algorithm can be improved by using multi core technique. In some sonar imaging applications it is possible

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that the size of image texture database is large and real time clustering is needed. In such cases applying multi core technique can be improved performance of seabed image clustering and will lead to better results.

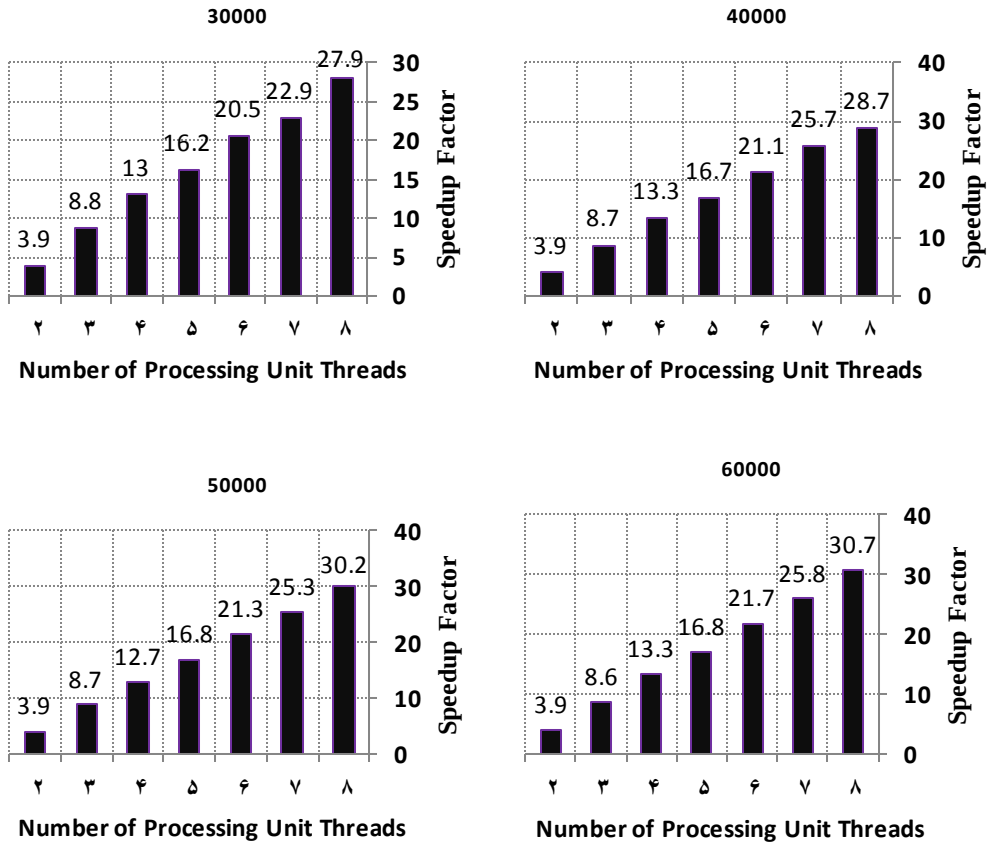

Figure 6: speed up factor for various numbers of threads and different image texture database sizes

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Conclusions

In this paper a new seabed image texture clustering using parallel computing technique is presented. The subsampled contourlet transform presented in this paper to be a useful method to perform this goal, because it gives analysis of image textures not only at many directions, but at various resolution levels. In this paper as shown that subsampled contourlet transform derived energy features are effective for image texture clustering. To overcome time complexity of clustering algorithm parallel computing technique which based on multicore processing was presented. In this paper speedup factor of clustering algorithm was calculated on different image texture sizes and different image texture database sizes using multicore processing method. Experimental results show that multicore processing can be considerably improved performance of the clustering algorithm. This performance improvement is a useful parameter in sonar imaging systems that require real time image clustering.

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