Seafloor Sidescan Sonar Image Segmentation


2. Assistant of Islamic azad university Mahshahr branch, Iran.

e-mail: sadegh_1999@yahoo.com

3. Assistant professor and member faculty of Islamic azad university, central Tehran branch, Iran.

Email: jvd2205@yahoo.com

Abstract

Segmentation and automatic classification of sub-sea areas is one of the most important applications of sonar systems. The proposed method in this paper is an unsupervised algorithm for sidescan sonar images of the seafloor segmentation using Contourlet transform. Firstly, a multi-resolution representation of the input image is created using Contourlet transform. Then an 8-dimensional feature vector is extracted for each pixel. Dimensions of the final feature vector have been decreased by using Principal Component Analysis (PSA). Finally, feature vectors are classified using the Cummins classification. The proposed algorithm works similar for almost sub-bands with more than 8 and parse levels more than 3. Using the 8-fold sub-bands unlike the usual wavelet which only are extracted in three direction of coefficients, help us to detect the image's directional details more better, and also enhance the details which extracted in different sub-bands according to the same direction, and take advantage of the correlation of sub-bands. The proposed method does not have the problem of overlapping area that is resulted in active contour method and so it can detect inside zones of large areas. In general, the proposed algorithm improved the overall performance 6% compared to the active contour and, 1% more than in compared to the two-dimensional feature extract method of wavelet transforms.

Key words

Segmentation, Sonar image, Sidescan, Contourlet, Inseparable multi-resolution transform

1-Introduction

Nowadays many researchers studied on sidescan sonar image and have achieved much success in segmentation of sidescan sonar image such as Markov random field, neural networks, spectral clustering, etc. The present preprocessing methods had not satisfactory result for removal the shadow based on histogram equalization or gray threshold transform. In recent years, the image segmentation method based on level set was proposed by successful applying of partial differential equations in image processing, that its reason is the priority of solving the problems with curve topology structure transform to the parametric methods. The importance of this study is clear in machines, computer graphics, image processing and target tracking fields. Next investigations recover the previous major drawbacks and reduces the computational complexity strongly. Thus, It has more worth for research.

Active contour and level set methods have been used for segmentation of seafloor-like areas [1]. In this mode, the overall texture characteristics of a sidescan image were extracted including two limited areas. A "Haralyk"
feature set based on co-occurrence matrix was considered, and it leaded to a high-quality segmentation of the sea floor.

A Markovian segmentation algorithm was used for segmentation of three classes of sonar image by Mignotte and Collet [2]. Later they extended a hierarchical markov random field model for segmentation of two classes of sonar images. Although the results were satisfactory, but the procedures of process were quite complicated and in terms of computational were so costly. A statistical spiral method was implemented for extracting contours of mine-like objects by [3].

In the sonar image segmentation based on GMRF and level set, Chang et al. firstly extract the local texture characteristics of sonar images based on Gaussian-Markov random field (GMRF) model, and then add it in the energy level set functions, and then evaluation function of level set was obtained by minimizing energy [4]. One of the advantages of this model is that this model with the same parameters set can fairly be operate for a wide range of different images. It means that the different sonar images can be segmented using the same model automatically. By applying two-phase model proposed by Chang et al., almost no noise was evident in the results and the level set converged by about the 200 iterations in the synthetic sonar and with 2000 times in real sonar. While the Chan-vese model requires more number of iteration for convergence and it contains more noise in the segmentation results.

The proposed model consists of local-texture feature based on GMRF image. Although the chen-vese two-phase model is also including of both edge and local-texture information of the objects. Local texture make more limited the overall image spatial interactions of sonar image noise. To reduce the number of iterations, the level set function is initialized as some small circles, that the result of minimizing the overall energy has been observed in less iterations from the single circle method. Furthermore, the shadow boundary extracted successfully using the proposed two-phase model.

The proposed multi-phase segmentation results of Chung et al. are robust and it converges after 3000 iterations. While the multi-phase Chan-vese method required more number of iterations.

Experiments showed that the proposed model of chung et al. obtains almost strong accuracy and results for different sonar images without clear boundaries of objects in wide range of noise levels.

In 2011, Reza Javidan et al. from the University of Shiraz proposed the novel algorithm of division and merge based on Contourlet transform without sub-sampling for automatic segmentation and classification of the sea floor images [5]. The proposed method provides a rapid tool with enough accuracy that can be implementing in a parallel structure for real-time processing.

Multi-resolution methods of Space/Scale can be use like the wavelet transform in texture parse. A major drawback for the two-dimensional wavelet is its limited ability in obtaining of direction information. The Contourlet transform has overcomed to the lack of orientation of two-dimensional wavelet by using smooth lines graph. Contourlet transform allows to have the different and flexible number of directions at each scale that makes it a suitable tool for parsing of seafloor image. No sub-sampling contourlet transform, is another
version of the contourlet transform, which is invariable in terms of the shift and obtains the flexibility, simplicity and more accuracy for feature calculation.

Obtained segmentation results in Contourlet domain is more accurate in compared with wavelet domain using the same feature set and the metric distance.

By studying paper about the new method for sidescan sonar image segmentation [6] we found that texture parse techniques are a common choice for segmentation of sonar images of the sea floor due to the appearance of sonar image excellent texture. This indicates that the multi-resolution scale-space methods such as wavelet transform are usable for texture parse. In this paper, a low-cost but effective computational algorithm was used for the unsupervised segmentation of seafloor in sidescan sonar images for reducing the previous problems that this algorithm is lossless discrete wavelet transform for multi-resolution parse.

The lossless discrete wavelet transform is used instead of discrete wavelet transform due to the following properties:

1. The lack of reduction sampling and jagging.

2. Is shift-Invariant, it means that if the original image be transformed before parse, the parse of image energy remain invariant between the multi-scale parse levels. This algorithm improved the performance 5.42% than the active contour.

In general, the active contour and the lossless discrete wavelet transform algorithm provide a proper segmentation. However, the lossless discrete wavelets transform work better than active contour in representation and extraction of the significance environment. In addition, the lossless discrete wavelets transform algorithm work 150 times faster than the active contour on average.

2- Proposed Method

Unlike optical images, sidescan sonar images have very noise and some parts of sidescan sonar images have a lot of information, while the other parts are without any feature or pointless. In some images, accurate changes in texture are the only distinct characteristics. Therefore all of the above unsupervised seafloor segmentation algorithms requires the learning of the process automation step or computational costly mathematic modules for sidescan sonar images segmentation in some predefined regions. Such needs make these algorithms inappropriate for the all-purpose applications, which prepared already the nature of input sidescan sonar images. The texture parse techniques are common choices for segmentation of acoustic images of seabed due to the appearance of sonar image excellent texture. This indicated that the multi-resolution scale-space methods are applicable like wavelet transform for the texture parse [1] [7].

The contourlet transform is a insepratable directional two-dimensional transform that use to describe curves and fine details in images. Unlike common wavelet transformation which applys only in horizontal, vertical and diagonal directions, this transform is parsed to $2^l$ directional sub-bands at each step of the parse. Contourlet expansion was formed of the base functions which tend to the different directions with different scales and shapes (anisotropy). With this set of rich basis functions, the Contourlet transform describes efficiency smooth
contours that are the basic and important components in natural images. By relying on these properties, feature extraction of contourlet sub-bands definitely has more information and can describe better the texture of the seafloor. Feature extraction of multi-scale sub-bands should be in such way that the logical connection preserve between each sub-band. After feature extraction, feature vector size will be definitely too high due to the volume of image and extracted feature. However, by considering that a large part of the seafloor image have the same and repeated texture, after the representation to the feature space, this texture will display by a certain number of coefficients and many of transform coefficients will have very low range domain. To reduce the number of features, we can eliminate the coefficients with low value, which have de-noising property and also the size of data that should be classified, will decrease. To retain maximum detail of properties, the process of reducing the number of features will perform by principal component analysis. Both methods have been implemented concurrently for determining the effect of sampling in Contourlet and comparison. Figure 1 shows the implemented algorithms.

Figure 1: Implementation steps of two proposed methods

Let us consider the brightness of a sidescan sonar image as:

\[ X = \{x(i,j)\}_{1 \leq i \leq H, 1 \leq j \leq W} \]  

With size of HxW pixel. Suppose that when the segmentation algorithm is applied for the input image, it generates a label matrix, segmentation map (SM):

\[ SM = \{L(i,j)\}_{1 \leq i \leq H, 1 \leq j \leq W} \]  

SM components are belong to a finite set of M labels, ie,
\[ L(i, j) \in \{l_1, l_2, \ldots, l_M \} \]  \hspace{1cm} (3)

It is belonged to the labels of image area, which are generated by segmentation algorithms.

All segmentation problems can be formulated as an estimation of the number of regions (M) and extraction of significant regions M in the input image.

The proposed algorithm consists of four main steps. (Figure 1)

1) Obtaining a multi-resolution presentation of the input image using contourlet transform with and without loss

2) Creation of feature vector space using both inter-data resolution and in-data resolution

3) Reducing the feature vector dimensions using principal component analysis

4) Generation of segmentation map by feature vector space clustering by using Cummins algorithm

2.1 - Obtaining multi-resolution presentation based on contourlet

Effective parameter of the directional bank filter that is usable in contourlet level, is parse tree (L). The number of generator directions of sub-bands is specified through L parameter. The number of parse tree sub-bands in each level is equal to \(2^L\). The main construction of a directional bank filter was shown in figure (2) [8].

![Diagram](image)

Figure (2). Procedure of generating sub-bands in Contourlet transform in 8 different directions.
The sampling matrix at each step is according to the following formula:

\[
S_k^{(l)} = \begin{cases} 
\text{diag}(2^{l-1}, 2) & \text{for } 0 \leq k < 2^{l-1}, \\
\text{diag}(2, 2^{l-1}) & \text{for } 2^{l-1} \leq k < 2^l, 
\end{cases}
\]  

(4)

and following formula is used again for reconstruction state:

\[
\left\{ D_k^{(l)} (m - S_k^{(l)} m) \right\}_{0 \leq k < 2^l, \ m \in \mathbb{Z}^2},
\]  

(5)

In which \(D_k^{(l)}\) is reconstruction filter and \(E_k^{(l)}\) is contourlet decomposition basic filters.

Now, multi-scale analysis can be created by combining the directional bank filter and Laplacian pyramid.

Since the directional bank filter has been designed for taking high-frequency, the low frequency contents of the input image is computed weaker. Therefore, it is better before applying the directional filter and losing of low-frequency components, at first low-frequency components be separated using Laplacian pyramid and dimensions also be reduced and in each stage, directional filter be applied to high-frequency components and the rests go to the next stage after subsampling and this process is repeated. Figure (3) shows the procedure of generating contourlet bank filter. In this figure, the input image figure is transferred to a multi-scale space. Also the number of directions of applying filter increases depending of the value \(L\) unlike wavelet that is horizontal, vertical and diagonal.

Figure (3). Procedure of generating bank filter with help of contourlet

Laplacian pyramid does not apply to non-sampling contourlet, but at the beginning, different frequency components are separated by applying frequency filters and each of them are separated by decomposition directional filter. Procedure of ideal decomposition and segmentation of frequency space has been shown in figure (4).
2-2 extraction of feature vector

The first step output of the algorithm is \( X_M = \{X^0, X^1, \ldots, X^S\} \) in which Indices \( s \) indicates the number of resolution and \( s \) the maximum number of resolution. Zero-resolution is related to the input sonar image, in form of \( X^0 = X \). A multi-resolution representation is used to reduce the effect of noise which exists inherently in the sonar image. In particular, the obtained images are affected severely with a small amount of noise \( s \), and are described with very high geometric details. Whereas the obtained image with a high amount of \( s \) represents a significant reduction in noise, but has little geometric details. For example, providing of multi-resolution of sonar image has been presented with \( S=4 \) which was shown in figure (5).

Figure (5). Contourlet transform without wasting for the four-step parse.

A feature vector is generated for each pixel at space location \((i, j)\) and is created by sampling of dataset \( X_M \). Different types of samples can be used; According to the masks of figure (7), the white pixels are utilized in sampling of local data around the pixel \((i, j)\). \( n_{i,j} \) is Neighborhood of a pixels \((i, j)\) of a sampling scheme which was shown in figure (7). We use of \( n_{i,j} = \{n_{i,j}^{(1)}, n_{i,j}^{(2)}, \ldots, n_{i,j}^{(N)}\} \) for simplicity in demarcation that is
the total number of pixels in scheme. The internal resolution feature vector \(X^s\) is defined as follows:

\[
(6) \quad V^s_{i,j} = \left[ X^s \left( \eta^{(2)}_{i,j} \right), ..., X^s \left( \eta^{(L)}_{i,j} \right) \right]
\]

A feature vector is generated between resolution \(V_{i,j}\) of dimension \(1 \times D = NS\) for each pixel with combination of extracted intra-resolution feature vector of \(X^s, s = 0, ..., S\). It means that in \(V_{i,j} = \left[ v^0_{i,j}, v^1_{i,j}, ..., v^S_{i,j} \right]\) for simplicity of mathematical demarcation, \(V^p\) is used for determining of vector \(V_{i,j}\) in which \(p\) is indicated a indices with \(1 \leq p \leq P = HW\).

![Figure 6](image6.png)

Figure (6). The procedure of feature extraction for pixel neighborhood wavelet transform (i, j) [].

Regarding the development of directional number in created bank filter by contourlet, it is be better to consider this property for extracting feature in feature extraction, so the feature extraction for contourlet has been proposed as shown in figure (7). With this 8 features can be covered each extracted eight angles.

![Figure 7](image7.png)

Figure (7). Procedure of feature extraction for contourlet transform around pixel neighborhood (i, j).

In wavelet transform for each 2 pixels and in contourlet transform for each 8 pixels is extracted a feature that it will lead to higher features, therefore the number of features should be reduced for reducing the classification time that this is described in the next section.

2-3 Reducing the dimension of feature vector
The dimension of each feature vector is decreased from D to K for taking advantage of low cost computation by using principal component analysis. The vector set \( V^{(p)} \) use principle components analysis for creating a special vector space.

Mean vector set is defined as follows:

\[
\Psi = \frac{1}{p} \sum_{p=1}^{P} \Psi^{(p)}
\]

Each feature vector is subtracted from the mean vector \( \Delta^{(p)} = \Psi^{(p)} - \Psi \), with principal component analysis vector of a set D seeks orthogonal vector \( e_k \), K=1,2,....D and scalars vector \( \lambda_k \) related to them are the best descriptions of the used data distribution in feature vector set \( \Delta^{(p)} \). The related vectors \( e_k \) and scalars \( \lambda_k \) are eigenvectors and eigenvalues of Covariance matrix, respectively.

\[
C = \frac{1}{P} \sum_{p=1}^{P} \Delta^{(p)}^T \Delta^{(p)}
\]

Where T is transpose operator.

Matrix \( C \in \mathbb{R}^{(D \times D)} \) specifies the eigenvalues and eigenvectors. Assume that the created vectors \( C \) in descending order of their eigenvalue, means \( \lambda_k \geq \lambda_{k+1} \) dimensions of feature vector space, then with scheme of each feature vector \( V^{(p)} \) in definite vector space with the largest eigenvector K of equation (5) decrease. It means that the feature vector \( V^{(p)} \) of a member of \( \mathbb{R}^D \), transforms to \( \check{V}^{(p)} \in \mathbb{R}^K \) in form of

\[
\check{V}^{(p)} = (V^{(p)} - \Psi) E \quad \text{where} \quad E = \{e_1, e_2, ..., e_K\} \in \mathbb{R}^{D \times K}
\]

is a specific value matrix. Value K is estimated automatically using the eigenvalue as follows:

\[
K = \arg \min_{k=1,\ldots,m} \frac{\lambda_k}{\lambda_1} \leq 0.1
\]

Where \( \lambda_1 \) is the largest specific value and K for each proportion of \( \lambda_k \), as the minimum value of k is chosen smaller than 0.1. The value 0.1 is selected from observation of few images.

It should be noted that the feature vectors are normalized before applying the pca, it means that the total mean vector is subtracted of each elements.

### 2-4 Classification of the reduced feature vector

The final step of the proposed algorithm is to generate discrete M-class with clustering of feature vector space v using Cummins clustering algorithm that K = M and assigning each feature vector to an appropriate class using Euclidean distance. Let \( \check{V}_{Wx} \) be mean feature vector of luster for \( Wx \). Segmentation map
\[ SM = \{sm(i,j) | 1 \leq i \leq H, 1 \leq j \leq W\} \] generates using \( \theta_{wk} \). \( sm(i,j) \in \{w_1, w_2, ..., w_M\} \) means:

\[
sm(i,j) = \arg\min_{w_k \in \{w_1, w_2, ..., w_M\}} \| \theta(i,j) - \theta_{wk} \|_2
\]

Which \( \| \|_2 \) is called Euclidean distance.

3-Results

Measurement criteria \( \rho \) is computed for comparing the computed segmentation map \( SM \) with the actual ground-truth segmentation map \( SM_{GT} \).

\[
\rho = 1 - \frac{\sum_{i=1}^{H} \sum_{j=1}^{W} \theta(SM_{GT}(i,j), sm(i,j))}{HW}
\]

Which \( \theta(a, b) = 1 \) when \( a = b \) and we have \( \theta(a, b) = 0 \), when \( a \neq b \). When \( SM_{GT} \) and \( SM \) are same then \( \rho \) is “1”, and \( \rho \) will tend to zero when no similarity between them increases; hence higher value of \( \rho \) is better for segmentation. All implementations have been done on MATLAB version 2010. A computer i5 with 6 GB of RAM has been used for implementing the program. Reference [6] has been used for tested images that it has 3 different images with dimension 256 x 256 pixels and for each of them correct segmentation map has been specified.
3-1-Marking the selection of decomposition level and the number of contourlet angles

The number of subbands of parse tree in each level is equal to $2^L$. So here, we have two variables which must be studied: first the number of decomposition level and second, the number of subband at each level of decomposition that must be studied for different states. To do this, the number of levels is selected from 2 to 5 and the number of subbands equal to (2, 4, 8 and 10) and L equal to 1 to 4. The experiments are conducted on the first image and the amount of criteria $\rho$ and test run is recorded in each test. Purpose is to select the maximum criteria $\rho$ and minimum run time. The obtained results have been shown in Table 1. No significant difference is seen between the number of subbands 8 and 16, but run time of subband 16 is more than subband 8; therefore the value of number of subband 8 is selected. On the other hand, no difference is seen between results in composition levels three and four, and then the value of decomposition level 3 is selected.

Table 1: Obtained results for different values of level decomposition and different subbands.

<table>
<thead>
<tr>
<th>Decomposition level</th>
<th>Number Of Subband</th>
<th>Run time (second)</th>
<th>Criteria $\rho$ percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>2</td>
<td>7.3</td>
<td>62.02</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>13.7</td>
<td>67.81</td>
</tr>
<tr>
<td>2</td>
<td>8</td>
<td>18.6</td>
<td>79.72</td>
</tr>
<tr>
<td>2</td>
<td>16</td>
<td>25.3</td>
<td>85.04</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>14.5</td>
<td>68.11</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>17.9</td>
<td>87.45</td>
</tr>
<tr>
<td>3</td>
<td>8</td>
<td>21.5</td>
<td>99.13</td>
</tr>
<tr>
<td>3</td>
<td>16</td>
<td>42.8</td>
<td>99.14</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>13.4</td>
<td>78.56</td>
</tr>
<tr>
<td>4</td>
<td>4</td>
<td>18.3</td>
<td>87.32</td>
</tr>
<tr>
<td>4</td>
<td>8</td>
<td>36.7</td>
<td>99.14</td>
</tr>
<tr>
<td>4</td>
<td>16</td>
<td>58.6</td>
<td>99.14</td>
</tr>
</tbody>
</table>

3-2 - Comparison of the proposed method with other methods

In this section, the proposed method has been compared with active contourlet algorithms [9] and wavelet coefficients clustering [6] for comparing it with other common segmentation methods which have been used for seafloor images. The obtained results have been shown for three images in figures (9) to (11). Also, the overall results have been summarized in table 2.
Figure 9. Comparison of the proposed method with active contour method and wavelet coefficients classification method for original image.

Figure 10. Comparison of the proposed method with active contour method and wavelet coefficients classification method for the second image.

Figure 11. Comparison of the proposed method with active contour method and wavelet coefficients classification method for the third image.
Table 2: Comparison of the obtained results for the proposed method with active contours algorithm [9] and wavelet coefficients clustering [6] on the three different images.

<table>
<thead>
<tr>
<th>Method</th>
<th>Number Of image</th>
<th>Run time (second)</th>
<th>Criteria (percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>The proposed method With Contourlet without sampling</td>
<td>1</td>
<td>20.36</td>
<td>98.63</td>
</tr>
<tr>
<td>The proposed method With contourlet with sampling</td>
<td>1</td>
<td>13.22</td>
<td>97.34</td>
</tr>
<tr>
<td>Wavelet coefficient clustering [6]</td>
<td>1</td>
<td>2.15</td>
<td>97.93</td>
</tr>
<tr>
<td>Active method [9]</td>
<td>1</td>
<td>309</td>
<td>97.78</td>
</tr>
<tr>
<td>The proposed method With Contourlet without sampling</td>
<td>2</td>
<td>19.78</td>
<td>93.50</td>
</tr>
<tr>
<td>The proposed method With contourlet with sampling</td>
<td>2</td>
<td>12.56</td>
<td>86.17</td>
</tr>
<tr>
<td>Wavelet coefficient clustering [9]</td>
<td>2</td>
<td>2.33</td>
<td>92.62</td>
</tr>
<tr>
<td>Active method [6]</td>
<td>2</td>
<td>288</td>
<td>88.06</td>
</tr>
<tr>
<td>The method proposed With Contourlet without sampling</td>
<td>3</td>
<td>18.65</td>
<td>93.50</td>
</tr>
<tr>
<td>The method proposed With contourlet without sampling</td>
<td>3</td>
<td>12.45</td>
<td>91.98</td>
</tr>
<tr>
<td>Wavelet coefficient clustering [9]</td>
<td>3</td>
<td>2.22</td>
<td>92.25</td>
</tr>
<tr>
<td>Active method [6]</td>
<td>3</td>
<td>322</td>
<td>85.22</td>
</tr>
</tbody>
</table>

In figure (9) to (11), in addition to the actual image, the related ground-truth segmentation maps have been also shown. In figure (9), active contour algorithm has not succeeded to extract small area inside the lower tissue, but the proposed method was able to detect it and also improve the segmentation accuracy.

In figure (10) that is a sonar image of fish aggregation, an aerial overlap has been emerged that is resultant of active contours, in fact unlike the active contour, fish colony and background with the proposed algorithm and wavelet are sufficiently separated. The proposed method improved the performance about 6% in compared with active contour, also it has been improved the process about 42% in compared with wavelet method. Figure 11 shows an image of sinking ship in seafloor. The fracture part of ship can be easily recognized from seafloor.
according to the texture difference and intensities. When the segmentation results are considered, it is clear that
the proposed algorithm detects sufficiently the drowned floating part with details, in fact active contours were
not successful by producing area overlapping. Furthermore, the performance of the proposed algorithm has
improved about 10% than the active contour. Also it has been improved the process 1.25% that wavelet method.

4-Conclusion

In this thesis, we proposed a multi-scale unsupervised seafloor segmentation algorithm for sidescan sonar
images. A multi-resolution display of input sonar image was sampled using inter-data and in-data scales for
creating a set of feature vectors. Dimensions of eigenvectors were reduced using principal component analysis
for obtaining faster computations. Feature vectors were separated using Cummins algorithm in discrete sets for
obtaining the final segmentation.

The obtained segmentation results illustrate the relationship between keeping spatial details and noise reduction
using different values for the maximum number of decomposition level and also subband. Furthermore, the
proposed algorithm almost operates the same for subbands more than 8 and decomposition level more than 3.

The use of 8-fold subbands help us to identify more about the directional details of image, unlike the
conventional wavelet which are extracted only in three directions of coefficients. Also, the use of eight
directional features for each pixel is caused that the extracted details in different subbands be strengthened
according to the same direction and to be taken maximum use from the correlation of subbands.

In comparison between the use of contourlet with sampling and non-sampling, non-Sampling method has been
quite successful. This success may be for this reason that downsampling and aliasing problems do not exist. It is
also Shift-Invariant, it means that image energy decomposition does not change between multi-scale
decomposition levels. The last reason is that in the feature extraction process in different levels does not need to
change the scale. In other words, we damage the information during decomposition with sampling of image, but
we must again make the scales of coefficients equal to higher coefficients for feature extraction, that to do this,
noise will be added unwanted and then, quality of the segmentation is reduced.

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