Hierarchical Clustering Linkage for Region Merging in Interactive Image Segmentation on Dental Cone Beam CT

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***Abstract*— Interactive image segmentation has better result than the automatic and manual image segmentation because user can help the image segmentation algorithm by marking the sample of background and object in the image. The algorithm will merge the regions in the image based on this user marking result. In interactive image segmentation, the calculation of distance between regions and the sequence of merging process are important to obtain an accurate segmentation result. In this paper we proposed a new region merging strategy using hierarchical clustering based on varian inter-class and intra-class region for each region and neighboorhood relationship. This research aims to improve the region merging strategy and it is expected to result better than the previous research that did not implement the hierarchical clustering. The process to segment an image concludes splitting the image into several region, user marking to mark the sample of background and object, merging the region that is not marked by user using the hierarchical clustering until the image fully segmented.**

***Keywords*—Interactive image segmentation; hierarchical clustering; Inter-class; Intra-class.**

I. INTRODUCTION

The process to separate a digital image into some segments or a set of pixels is called image segmentation. Image segementation process will result in some segments covering the entire image collectively or countours that was extracted from the image. This process aims to represent the image to be something that is easy to analyze and meaningful. Image segmentation is usually become the first step in image analysis. This process is usually used to split the object and its background.

Image segmentation is an important and challenging part in image processing, especially in clinical application [1] [2]. In clinical application, the image segmentation process can help to determine the accurate information that was contained in the image. Incorrect segmentation of object and background will affect to the inaccurate information that is provided by the image. And this will cause the fatal identification in clinical application.

In general, there are three type of image segmentation e.g., manual, semi-automatic, and automatic [3]. The automatic image segmentation uses texture, shape, or color features provided by image. For some segmentation process, the certain parameters or weight will be added to those features. Different optimal value of parametes has to be defined by the user. This parameter uses to achieve the satisfying result in segmentation process, especially in case of low contrast image and natural images [4].

Medical images such as dental panoramic radiographs, echocardiographic, dental cone beam CT (CBCT) scans data etc, usually contaminated with some speckles or multiplicative noise from the X-Ray imaging process. This medical image also has low contrast. This will make the automatic image segmentation difficult. To solve this, we can use filter to reduce the speckle noise that contaminates the image. There are NLM filter, Weiner filter, Kuan filter, or Lee filter that can be used for this. Meanwhile, more feature informations that is provided by user can be integrated to improve the performance of image segmentation [5].

To solve this problem, some semi-automatic image segmentation techniques have been developed. This methods combines manual and automatic segmentation by providing some information added by user. This information will help the system in segmentation process to extract the object from the background. This methodology can help the low contrast image to be segmented accurately. Semi-automatic image segmentation is also called interactive image segmentation.

An image can be composed of some objects and backgrounds. In image segmentation process, the image may be splitted into more than two objetcs and background. The correct result of image segmentation is considered by calculating the distance. Based on Arifin, et. al [6], there are two variants that affect to the distance calculation, those are inter-class and intra-class variance. The inter-class varianceis used to calculate the distance between object and background, and the intra-class is the distance between the same object or the same background. From Agus, et. al [7], it is said that the calculation of inter-class variants is adequate to know the differences between objects and backgrounds. However, the intra-class variance is also important, because it calculates the neighborhood region in the same clusters (object or background). Moreover, in Arifin, et. al [7], the region merging process is done by calculates and compares the distance between all of the non-marked regions with the regions in object and background cluster, iteratively.

This will affect to a less efficient computation strategy. Whereas, the neighboring region of an object region may have a high probability of being in the same cluster of the object region. In interactive image segmentation, the calculation of distance between regions and the sequence of merging process are important to obtain an accurate segmentation result.

In this paper we proposed a new region merging strategy using hierarchical clustering based on the calculation of intra-class and inter-class variance. Hierarchical cluster analysis (HCA) [6] is methodology that build a hierarchical cluster which is presented using dendogram. Hierarchical clustering classify data based on the distance measurement and the sequence of data. This research aims to improve the region merging strategy to be more accurate and efficient by incorporating intra-class analysis to calculate the distance between regions and using hierachical clustering for the region merging process.

II. RELATED WORK

A. Research Trend in Image Segmentation

The most important process in image processing is image segmentation that aims to divide an image into some parts, called segments. The existing technique in image segmentation can be classified into three categories [8] [9]: structural, stochastic, and hybrid segmentation. The structural segmentation techniques is technique that depend on the information structure of required portion of the image, i.e. the required region to be segmented. Stochastic segmentation technique works on the discrete pixels values of the image instead of the structural information of region. Hybrid techniques uses the concepts of both above techniques.
From those techniques the most popular technique in the image segmentation are: threshold method, edge detection based, region based, clustering, watershed techniques, partial differential equation based and ANN (artificial neural network) based technique.

Zohrizadehet, et. al [10] using the spare subset selection in image segmentation. This research adopts the local spectral histogram features that is used to encode the visual information from the small segments and convert it into high dimensional vectors that is called super pixel features. This proposes method is very efficient in running time and computation. This method can also implement the parallel method and it can be easily extended to other application such as application to summarize video, dimensionality reduction, etc. Besides, this method is not restricted to solve any certain problem in image segmentation.

Elshazlyet, et. al [11] implements the image stegabgraphy algorithm that uses the modification direction of generalized exploiting and the strategy of pixel segmentation. The result shows the high embedding rate, high embedding payload capacity, less computational complexity and it also can keep the high stego image quality that is comparable to previous work.

Pratondo, et. al [12] integrates the machine learning with region -based active contour models in medical image segmentation. This method can effectively segment the image with poor boundaries defined. But this method often fail when it is implemented in image that has homogeneity. The k-nearest neighbor and SVM (support vector machine) with the Chan Vese method is integrated in this research. The result is compared with the traditional methods. The comparison result shows that the proposed methods can give the better accuracy and it is less sensitive in parameter tuning.

Chakraborty, et. al [13] integrates an approach for automated image segmentation in biomedical. This research uses the fuzzy clustering method to configure the controlling parameter needed automatically. The fuzzy clustering method is used to control the parameter of level set method. This method can increase the efficiency of the level set method.

B. The Semi-Automatic Image Segmentation

The automatic image segmentation has consistent result. This automatic image segmentation is depend on the optimal value of variable defined. The manual image segmentation has inconsistent result. To solve this problem, it has been developed the semi-automatic image segmentation that is also known as interactive image segmentation. The quality of interactive image segmentation is influenced by the human factors. The user will help to determine objects in the image, then the system will process to split the image based on the input provided by user.

Yongjun and Jiying [14] implements the Quantum-m inspired Ant Colony Algorithm in automatic tomato image segmentation. This proposes algorithm increase the search space so it can result better diversity of population than the traditional Ant Colony Algorithm and it also can overcome the premature stagnation phenomenon effectively in the optimization process.

The segmentation accuracy in interactive image segmentation is affected by the quantity of input that is provided by user. Park, et. al [15] proposes a seed growing method that expand the quantity of a seed. This aims to reduce bias in the given seed and improve the accuracy in segmentation process. This research used the support vector machine (SVM) classifier and the geodesic distance features is used to grow the given seed. The promising result shows the improvement of segmentation accuracy from the existing segmentation methods using the dataset from public benchmark.

In medical image segmentation, some researches implement the interactive image segmentation. Karasevet, et. al [16] model an approach that aims to enables the analysis of control-theoretic and design for synthetic image segmentation. This method is effective to solve the problem in challenging segmentation of a patellar tendon in magnetic resonance and shattered femur in computed tomography.

Alansary, et. al [17] presents a novel method to correct the motion artifacts. These motion artifacts are presented in fetal MRI (magnetic resonance image) scans of the whole uterus. The proposed method, results the successful application of PVR motion compensation. This research use the whole uterus, placenta, and fetal body to test the proposed method.

C. Hierarchical Clustering

Hierarchical clustering that is also known as hierarchical cluster analysis or HCA, is methodology to partitioning object into optimal homogenous groups on the basis of empirical measures of similarity among those [18].The hierarchical clustering has two types i.e., agglomerative and divisive. The agglomerative HCA starts to cluster its own cluster and continue to the pairs of cluster that will be merged as one. These pairs of cluster will be moved up to the hierarchy. The divisive HCA is known as "top down" approach. This technique starts from one cluster and recursively split as one moves down the hierarchy. The hierarchical clustering result is usually presented in dendrogram. This research uses the agglomerative hierarchical clustering.

Fachrurrozi, et. al [19] implement the Agglomerative Hierarchical Clustering (AHC) to group face images automatically. The face images is grouped to help the improvement of speed in searching the CBIR based face recognition system. The face image vector feature is gotten from the feature extraction process. This research use the AHC and it also implements the single linkage, average, and complete. The Cophenetic Correlation Coefficient (CCC) value is used to validate the test. The result show the higher value of CCC than the other methods. The result also shows the face recognition system that implement pre-processing cluster has faster and better performance than the face recognition system that does not implement the pre-processing clustering.

III. METHOD

Image segmentation is process to split image into some objects and backgrounds. This research improves the previous research from Agus et.al. [7] and proposes the new approach in region merging strategy of image segmentation process. In the region merging strategy, we propose to merge the neighborhood region with the same cluster using hierarchical clustering that is based on the calculation of intra-class variance and inter-class variance. Figure 1 shows the process of this image segmentation. The process start with the input image. Then, the system will process the region splitting. This research uses the mean-shift by Edison System to split the region.

The region merging measurement will begin after the representative sample region selected by user. The respresentative sample will mark the region into some objects and background. Image will be splitted into some clusters of region based on the user marking. Then, there are three cluster generated i.e. object cluster, background cluster, and non-marked cluster.. An object marked will clasify to object cluster (*O*), the region marked will clasify to the background cluster (*B*). The non-marked region will remain in the non-marked cluster (*C*). This non-marked cluster will be processed based on hierarchical clustering based on intra-class variance and inter-class variance method. The non-marked cluster will be move to either object or background cluster. Region in both object cluster and background cluster is notated in equation 1 and 2.

$$O = \{O_i\}_{i=1,\dots,n} \quad (1)$$

$$B = \{B_i\}_{i=1,\dots,m} \quad (2)$$

where *n* represents the region number in the object cluster and *m* represents the region number in the background cluster. Because the image is splitted into some region object, background and non-marked cluster, we can conclude that the input image consists three clusters i.e., non-marked cluster (C), object cluster (O), and background cluster (B). This can be described in the equation 3.

$$I = \{C, O, B\} \quad (3)$$

After the sample region of object and background cluster is defined, system will measure the characteristic difference between the non-marked region to each object and background region. This process is known as distance measurement and it will be used in merging process. This research proposes the distance measurement using the inter-class and intra-class variance. The distance of non-marked region will be calculated. The non-marked region will be moved to the smallest distance from object or background.

The inter-class variance uses to calculate varian between the region image. The input image is divided into K regions. The pixels number in *k* region is notated by n_k.
$N = n_1 + n_2 + \dots + n_k$ denotes the total pixels number in the input image. The varian between *k* region in n_k pixels and the image with *N* pixels is denoted by ω_k, then:

$$\omega_k = \frac{n_k}{N} \quad (4)$$

L_k levels $[1, 2, \dots, L_k]$ presents the value of pixel in region *k* and x_i denotes the pixels number in region k at level *i*. Then the number of pixels in region *k* is:

$$n_k = x_1 + x_2 + \dots + x_{l_k} \quad (5)$$

μ_k is the main value of pixels in the region *k*, then:

$$\mu_k = \frac{\sum_{i=1}^{L_k} x_i}{n_k} \quad (6)$$

Suppose that we devide the pixels into two classes C1 and C2 (background and objects, or vice versa) by using the thresholds at level *k*; probabities mean level of each class given by equation 7 and 8.

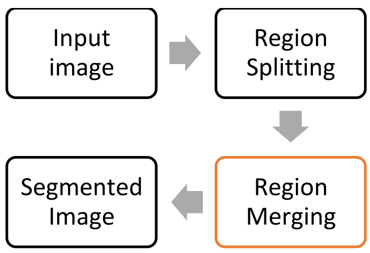

Figure 1. The Image Segmentation Process

$$\mu_0 = \mu(k)\Big/\omega(k) \quad (7)$$

$$\mu_1 = \frac{\mu_T - \mu(k)}{1-\omega(k)} \quad (8)$$

In addition to the mean level of each class, it is necessary to calculate the probabilities of occurrence of the class given by equation 9-11. Equation 11 is used because ω is an opportunity and the sum of the opportunities must be value 1.

$$\omega_1 = \omega_k \quad (9)$$

$$\omega_2 = 1 - \omega_k \quad (10)$$

$$\omega_1 + \omega_2 = 1 \quad (11)$$

The inter-class variance σI between two clusters is the sum of square distance between means of two clusters and the total mean of both clusters μT. Equation 12 can be simplified by omitting the value of μT at equation 13 and equation 11. So the simple formula of interclass search be obtained in equation 14.

$$\sigma_I{}^2 = \omega_1(\mu_1 - \mu_T)^2 + \omega_2(\mu_2 - \mu_T)^2 \quad (12)$$

$$\omega_1\mu_1 + \omega_2\mu_2 = \mu_T \quad (13)$$

$$\sigma_I{}^2 = \omega_1\omega_2(\mu_2 - \mu_1)^2 \quad (14)$$

The cluster you want to share can consist of many objects and backgrounds so that variance needs to be generalized so that it can be used for n clusters. Interclass variants for n clusters can be seen in equation 15.

$$\sigma_I{}^2 = \sum_{i=1}^{n}\sum_{j=i+1}^{n}\omega_i\omega_j(\mu_i - \mu_j)^2 \quad (15)$$

In addition to counting inter-class variants, this paper also considers intra-class variants. Intra-class variants are variants among regions in the same cluster.. To calculate the intra-class variant, it is necessary to look for variants of each cluster as in equation 16 and 17. So that the intra-class search formula can be seen in equation 18. For n clusters, intra-class variants can be seen in equation 19.

$$\sigma_1^2 = \sum_{i=1}^{k}(i - \mu_0)^2\Big/\omega_1 \quad (16)$$

$$\sigma_2^2 = \sum_{i=k+1}^{L}(i - \mu_1)^2\Big/\omega_2 \quad (17)$$

$$\sigma_A^2 = \omega_1\sigma_1^2 + \omega_2\sigma_2^2 \quad (18)$$

$$\sigma_A^2 = \sum_i^n \omega_i\sigma_i^2 \quad (19)$$

IV. Result and Analysis

In this paper, we used dental cone beam CT scans data that contain tooth. The result of our proposed method method will be compared with the previous research that has been done by Arifin, et. al [7]. Evaluation for experiment used in this paper is Misclassification Error (ME) dan Relative Foreground Area Error (RAE). Evaluation ME is used to measure objects and backgrounds of objects on ground truth that are misclassified. While RAE is used to measure the difference of area between object in ground truth and segmentation result.

$$ME = 1 - \frac{|O_g \cap O_r| + |B_g \cap B_r|}{|O_g \cap B_g|} \quad (20)$$

Equation 20 is ME with O_g is object from the ground truth image, O_r is object from the segmentation result, B_g is background from the ground truth image, B_r is background from the segmentation result. The small number of ME shows the good segmentation result. This can describe that the segmentation result is similar with the ground truth image.

$$RAE = \begin{cases} \frac{A_g - A_r}{A_g} & if\, A_r < A_g \\ \frac{A_r - A_g}{A_r} & if\, A_r \geq A_g \end{cases} \quad (21)$$

Equation 21 is RAE with A_g is area of ground truth image, A_r is area of segmentation result. RAE is like ME. The small number of RAE will result the better image segmentation and it will be more similar with the ground truth. Table 1 shows the ME and RAE for the segmentation result of the proposed method. The average computation time, ME, and RAE value of the proposed method are 1.58 second, 2.66%, and 14.92%, respectively. The average computation time, ME, and RAE value of the previous research are 47.14 second, 2.41%, and 15.68%, respectively.

Table 1.The ME and RAE for Image Segmentation Result

No	Proposed Method			Previous Research		
	Time (s)	**ME (%)**	**RAE (%)**	**Time (s)**	**ME (%)**	**RAE (%)**
1	2.81	2.26	9.49	137.12	2.15	17.17
2	3.19	3.75	25.70	109.70	3.57	28.89
3	0.31	1.02	21.84	1.40	1.07	16.49
4	2.64	4.43	26.85	83.70	4.49	31.21
5	1.42	3.32	1.67	36.90	2.97	6.68
6	0.70	1.57	20.25	5.06	2.97	6.36
7	0.46	1.14	3.88	2.23	1.15	6.20
8	1.81	3.85	17.11	39.72	3.81	20.08
9	0.85	2.56	7.48	8.44	2.49	8.07
Mean	**1.58**	**2.66**	**14.92**	**47.14**	**2.41**	**15.68**

From Table 1, it can be seen that the proposed method have much faster computation time than the method from Arifin, et al [7]. While the accuracy of the proposed method and the method from previous research is similar. For further analysis, the input images and its ground truth that were used in this experiment is shown in Figure 2 and Figure 3, respectively. The user marking result is shown in Figure 4, in which the red line represents the sample of object cluster and the blue line represents the sampel of background cluster.

Figure 5 shows the segmentation result of the proposed method, while Figure 6 shows the segmentation result of the previous research. It can be seen that both methods produce similar segmentation results. However, the proposed method tends to misclassified small background regions as the object. This is because the regions in the object cluster tend to have small size, hence integrating intra-class variance in the distance measurement process will resulting in small distance value between small non-marked regions and the object cluster.

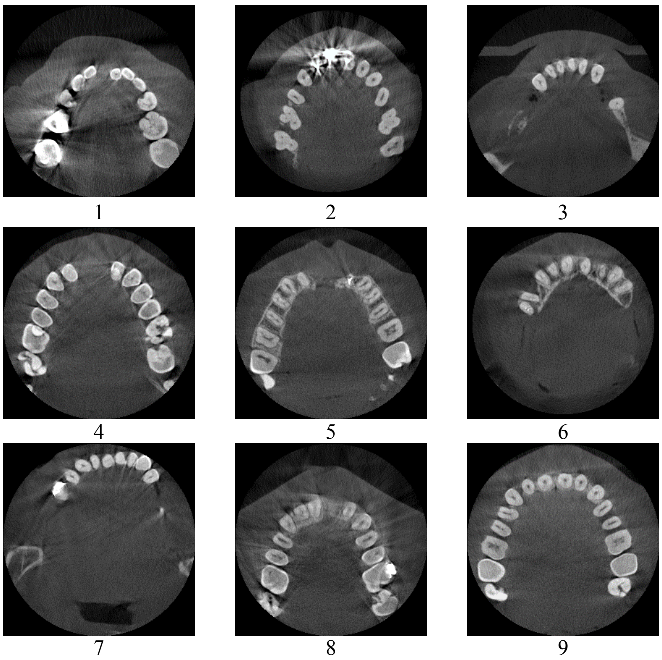

Figure 2. The Input Image

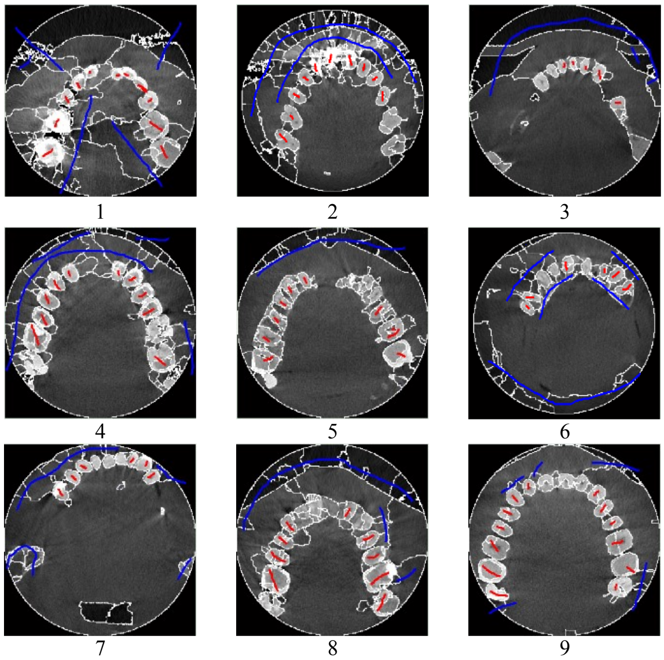

Figure 4. The Markers from User

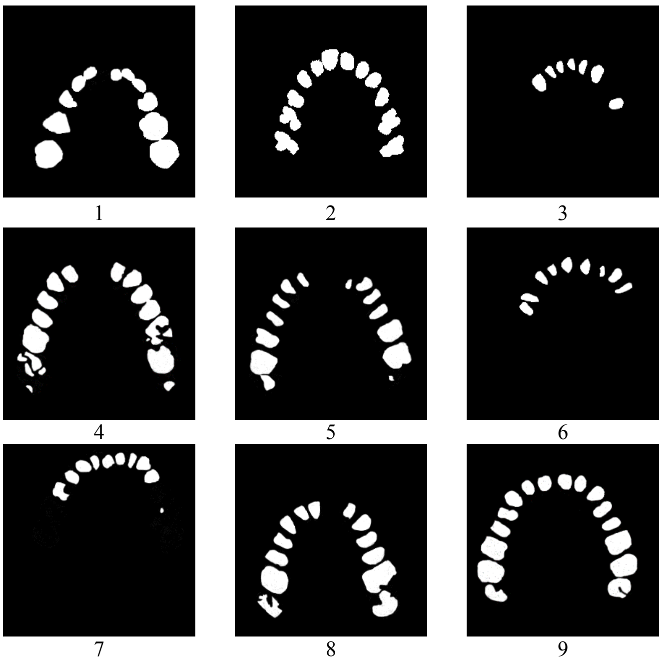

Figure 3. The Ground Truth Image

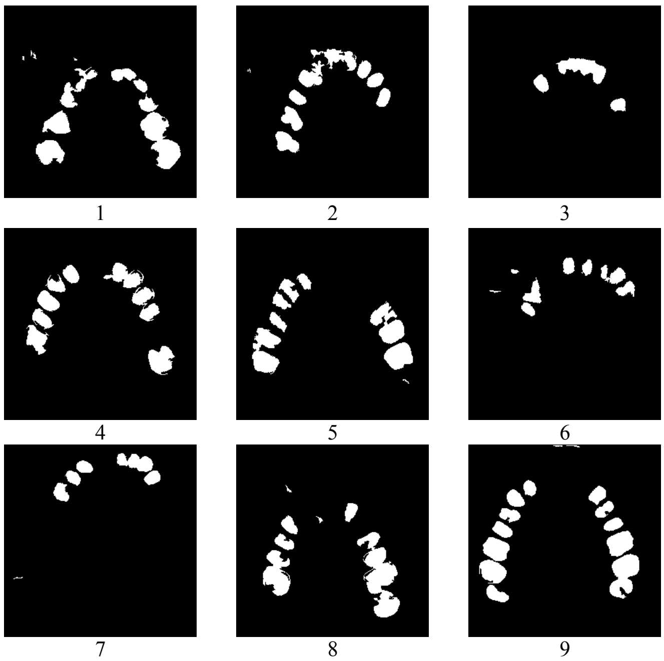

Figure 5. The Result of Proposed Image Segmentation Method

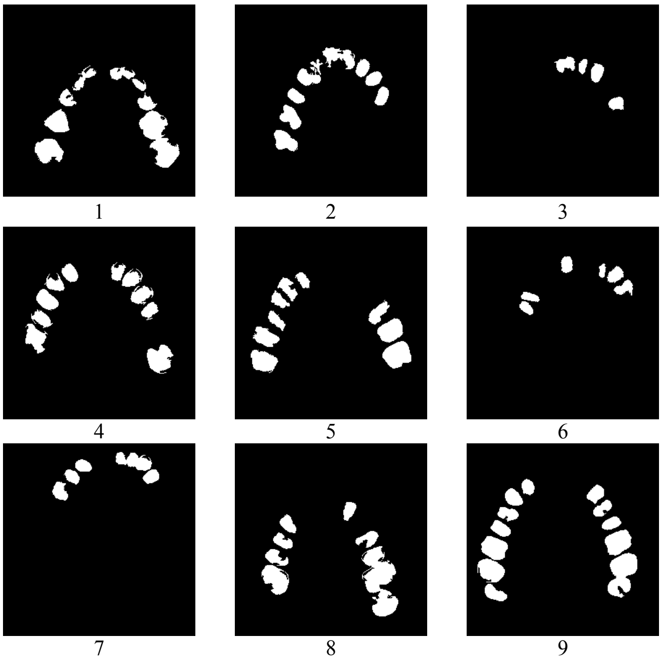

Figure 6. The Result of Previous Image Segmentation Method

Because the method in the previous research did not include intra-class variance in the distance measurement process, it did not suffer from the problem of small regions. However, even though the segmentation results of the proposed method and the previous research are quite similar, the method from the previous research is exposed to more severe under-segmentation problem than the proposed method. This can be observed on image 4 and image 6 where the proposed method can detect other tooth object that have not been marked by the user. It can be concluded that the use hierarchical clustering can make the region merging process much more efficient. While the use of intra-class variance in the distance measurement process make the segmentation not severely affected by under-segmentation problem. However, the distance measurement algorithm should be developed therefore it can be more accurately classify the small regions in the image.

V. CONCLUSION

This research proposes regional merging method using hierarchical clustering by changing distance using observed variants between clusters (inter-class) and variants among data in one cluster (intra-class), to improve the region merging strategy and it is expected to result better than the previous research that did not implement the intra-class. The proposed method can give more effective and efficient result in the segmentation process. The average computation time, ME, and RAE value of the proposed method are 1.58 second, 2.66%, and 14.92%, respectively.For future work of this research, it can be implemented various clustering algorithm for the region merging process to improve the efficiency of the merging process.

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