Effective Computer-Assisted Automatic Cervical Vertebrae Extraction with Rehabilitative Ultrasound Imaging by using K-means Clustering

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ABSTRACT

Neck pain is one of most common musculoskeletal condition resulting in significant clinical, social and economic costs. Muscles around cervical spine including deep neck flexors play a key role to support and control its stability, thus monitoring such muscles near cervical vertebrae is important. In this paper, we propose a fully automated computer assisted method to detect cervical vertebrae with K-means pixel clustering from ultrasonography. The method also applies a series of image processing algorithms to remove unnecessary organs and noises in the process. The experiment verifies that our approach is consistent with human medical experts' decision to locate key measuring point for muscle analysis and successful in detecting cervical vertebrae accurately – successful in 48 out of 50 test cases (96%).

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1. INTRODUCTION

Neck pain is very common complaint affecting up to 70% of individuals at some point of their lives [1]. Clinical neck pain is associated with impairment of muscle performance and the functional impairments associated with neck pain and the cause-effect relationships between neck pain and motor control are well investigated [2]. Antevertebral deep cervical flexor (DCF) muscles such as longus coli and longus capitis do key role to stabilize cervical articulations and to preserve the lordotic curvature of the spine [3] and sternocleidomastoid muscle (SCM) is related with the rotation of the neck [4]. Strengthening of these muscles is important to treat the patients with neck pain provoked by various pathologies of cervical spine [5].

Using ultrasound image in muscle analysis is appropriate for its non-invasive, inexpensive, real time responses [6]. However, its limitations are often pointed out that sonographic images are dependent on the qualities of equipment and skills of expertise thus the diagnosis often misleads to subjective judgment [7]. Thus, we need an automatic image segmentation and identification tool for anatomical landmarks that can eliminate such subjectivity in the image analysis [8].

Unfortunately, there is almost no directly related research for such an automatic neck pain related muscle extractor/analyzer by computer vision yet. A recent study tried to give an automatic segmentation of cervical vertebrae from X-rays [9] but not related to muscles of our interests. Our concern is to detect and extract muscles such as sternocleidomastoid and longus capitis/colli in conjunction with cervical vertebrae automatically from ultrasonography and measuring the thickness for further medical analysis [10-11]. All three vision based approaches aim to locate measuring key point accurately to avoid manual subjective key point setting for muscle analysis.

In our previous study [10], we applied fuzzy sigma binarization to overcome low brightness contrast by its adaptive thresholding characteristic. However, it does not consider the average brightness nor morphological characteristics of cervical vertebrae thus its performance is not stable especially when it forms the thickness measuring key points.

In this paper, we propose a K-means pixel clustering [11] approach to find the key points accurately in detecting cervical vertebrae. With such a clustering approach and subsequent smearing technology to restore lost information, our software is more consistent with human medical experts' opinions in detecting cervical vertebrae and locating key points.

2. PROCEDURE FOR AUTOMATIC CERVICAL VERTEBRAE EXTRACTION

Obtained digital image follows DICOM (Digital imaging and Communications in medicine) standard format. In the main region of interest (ROI) part of the image as shown in Figure 1, there will be a blood vessel in between two important muscles - the sternocleidomastoid (SCM) and the deep cervical flexors (DCF). Its lower part has irregular curve due to the border line of cervical vertebrae.

The cervical vertebrae area in the ultrasonography is shown as bright region under DCF since the area has high density. In order to detect cervical vertebrae, however, we need to remove other organ such as cartilage and subcutaneous fat area as noise that also have relatively high brightness. Thus, we need brightness enhancement procedure and subsequent noise removal/ image restoration process.

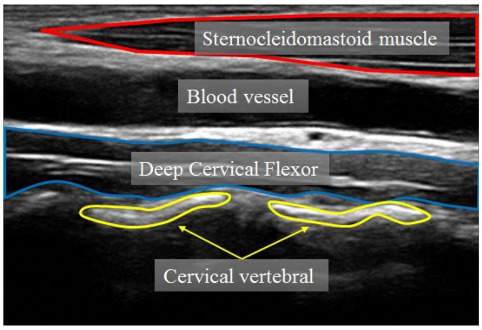


Figure 1. ROI of Ultrasound Image

3. CERVICAL VERTEBRAE DETECTION WITH K-MEANS PIXEL CLUSTERING

In order to extract the cervical vertebrae object from the ultrasound image, we should find the lower bound of DCF area that is the upper bound of the cervical vertebrae existence. Once the range of target object existence is decided, we cluster pixels with K-means algorithm to form the cervical vertebrae object with respect to the morphological limitations such as long oval shaping. During such image processing steps, there can be some information loss which might cause undesired disconnections of the objects formed by K-means clustering. Thus, we apply image restoration process by Smearing algorithm to finalize the extraction of cervical vertebrae.

3.1. Locating the Cervical Vertebrae Candidate Object

From this ROI image that contains only muscles, fasciae and spines, we try to extract candidate DCF by applying a series of image processing algorithms. The first step is a normalization process known as the Ends-in Stretching to the image processing community [12]. That stretching enhances the intensity contrast to differentiate the target and the background area more clearly. Formula (1) explains Ends-in search stretching.

$$C(x,y)=\begin{cases} 0 & P(x,y)\le Min \\ 255\times\dfrac{P(x,y)-Min}{Max-Min} & Min<P(x,y)<Max \\ 255 & P(x,y)\ge Max \end{cases} \tag{1}$$

where *Min* and *Max* denote the maximum and minimum intensity value of the given image and $P(x, y)$ is the intensity value of the pixel at (x, y) coordinates in the original image and $C(x, y)$ is the resultant intensity value after Ends-in search stretching. Such normalization process is necessary to minimize the information loss since there might be a blurring due to the scattering effect of ultrasound technique.

From that contrast-enhanced image, we apply average binarization and Blob algorithm [13] to remove unnecessary noise in detecting DCF muscle area. The Blob algorithm we adopted can be summarized as follows;

```
Given Binary Image
Let the initial Color[k]=0

Step 1
Scan the original image from left to right and top to bottom (raster Scan) using L-
Shape template

For k=Image Size
    if Image[C]=255 then
        if Image[U]=255 and Image[L]=0 then
        Color[C]=Color[U]
        if Image[U]=0 and Image[L]=255 then
            Color[C]=Color[L]
        if Image[U]=0 and Image[L]=0 then
            Color[C]=K++, new Color
        if Image[U]=255 and Image[L]=255 then
            if Color[U] is not equal Color[L] then
                ReColoring Table Color[C]=Color[L]
repeat

Step 2
For count=k
    Color[count]=ReColoring[Color[count]]
repeat

where U, C, L denote Up, Center, Left in respectively.
```

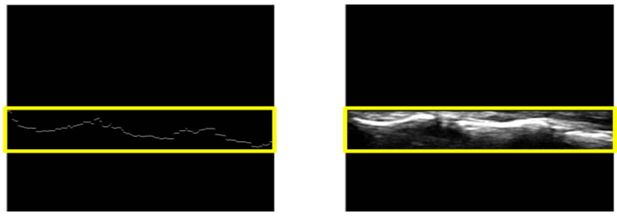
A blob is a region of an image in which some properties are constant or approximately constant. The pixels in a blob have the same quantized color although they may have different colors in the original image. Thus, using this algorithm, we can form a similarly colored object regions and then remove unnecessary objects from our interest. For example, we know that our target DCF is sufficiently long in the original image thus the area of formed object is too small or the length is less than the half of the image width, that object is unnecessary in our image analysis thus remove such objects. The effect of this Blob application can be shown as Figure 3(b) from the contrast enhanced image shown as Figure 2(a).

(a) Ends-in Search Stretching (b) Average Binaization & Blob Removing (c) Extracting Blood Vessel (d) DCF Candidate

Figure 2. Process for Locating DCF Candidate

Then extracting the blood vessel is easy since that has relatively low intensity and a significant but almost uniform thickness as shown in Figure 2(c). Then we know that the DCF area is located below the blood vessel as shown in Figure 2(d).

Then, our target object, cervical vertebrae, is below the lower fascia boundary lines and has a long curved shape. Thus, we try to find the rough range of target object’s existence by searching an object of significant size from the bottom and from the top after removing blood vessel and DCF object from the image. Then the range of Cervical vertebrae’s existence is given as Figure 3(b).



(a) Lower boundary of DCF (b) Range search

Figure 3. Range of Cervical Vertebrae Candidate Existence

3.2. Pixel Clustering by K-means with Morphological Information

Within the range of target object existence, we try to apply pixel clustering. K-means clustering is a well-known unsupervised learning algorithm that has many variants with respect to the application and we follow a speed up version of it [11].

Begin Initialize n, k, $\mu_1, \mu_2, \ldots, \mu_k$
Do classify n samples according to nearest μ_i
recompute μ_i
Until no change in μ_i
Return $\mu_1, \mu_2, \ldots, \mu_k$
End

The principle of K-means is as simple as above description. From arbitrarily given k sets, the algorithm iteratively re-assigns the data sets according to the center point and re-computes center points at every iteration until there is no significant change. In our experiment k is given as 6. And the effect of K-means can be shown as Figure 4.

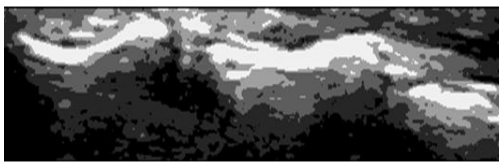


Figure 4. The Effect of K-Means Pixel Clustering

The next step is to extract meaningful objects by local region labeling procedure. Since the cervical vertebrae area is relatively bright, we apply the labeling to only highly bright clusters. The result of this labeling procedure is shown as Figure 5.

In Figure 5, the extracted objects contain noises such as cartilage and subcutaneous fat. In order to remove such noise objects, we test the circle rate and extension rate of objects in consideration. Formula (2) explains such shape parameters. The shape of cervical vertebrae is long curve with relatively consistent form while other noises have irregular shapes thus such morphological characteristics can discriminate target objects from noises with measurements explained in formula (2).

Figure 5. After Labeling Procedure

$$C = \frac{P^2}{4\pi A}, \quad E = \frac{|Width - Height|}{Height} \qquad (2)$$

As shown in formula (2), the circle rate C is defined as 1 if the object is a perfect circle and it becomes more than 1 if the object is complex since the circumference (P) becomes larger. A is the area of the region in this formula. The extension rate (E) denotes the rate of the difference between the width and the height divided by the height for the minimum quadrangle that includes the object. E becomes 0 when the quadrangle is a square (or a circle of course). Any non-zero E represents the direction and the degree of unbalance of the object thus it helps to figure out the noise to be removed.

The effect of noise removal is shown as Figure 6.

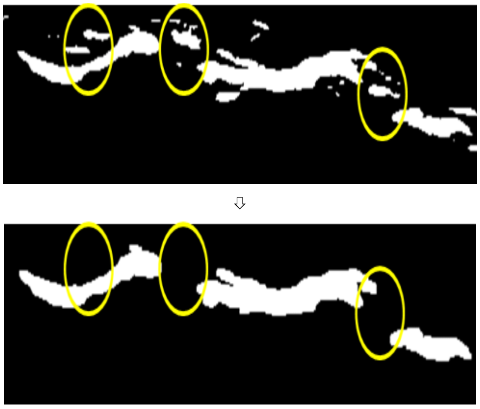
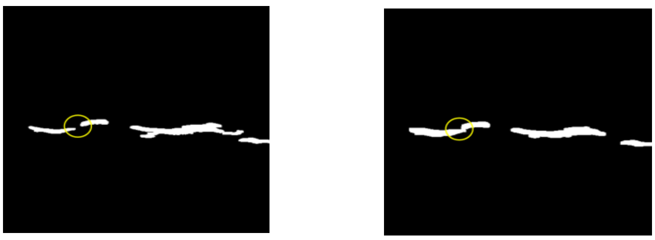


Figure 6. Noise Removed

3.3. Cervical Vertebrae Object Restoration by Smearing

The resultant image may have lost information during the noise removal process so that the labelled objects are very close but disconnected. The horizontal smearing process [13] is applied to compensate such information loss to obtain the final output image for extracting cervical vertebrae with reconnecting procedure. In the process morphological operators [13] are applied for image smoothing and restoration and the result can be shown as Figure 7.



(a) Disconnected Cervical Vertebrae (b) Image Restoration

Figure 7. Cervical Vertebrae Image Restoration

4. EXPERIMENT

The proposed method is implemented with C++ under Microsoft Visual Studio 2010 on the IBM-compatible PC with Intel(R) Core(TM) T-4200 CPU @ 3.40GHz and 2GB RAM. The experiment uses fifty two 800x600 size DICOM format linear ultrasound images

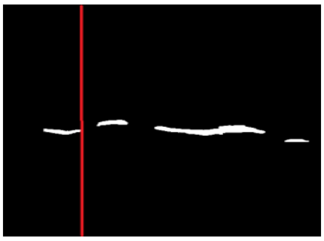
The accuracy of the method or the utility of the automatic vision based cervical vertebrae analyzer can be measured by the agreement rate of locating DCF muscle thickness measuring key points with human experts – physical therapists. In order to avoid human subjectivity, our ground truths of measuring points are obtained by two physical therapists' agreements. Extracting cervical vertebrae which is the theme of this paper is required in order to analyze those important muscles (DCF and SCM) for neck pain management. As described in Table 1, the proposed system showed 96% agreement rate with multiple human experts' agreements.

Table 1. Muscle Thickness Measuring Key Points Extraction

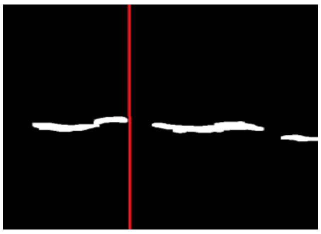
	Proposed Method
Key Points	48/50 (96 %)

In our proposed method, key point is set to be the lowest point of the first cervical vertebrae object and the range of measurement is within 1 cm left and right of that key point. The thickness of the DCF muscle is then computed as the average length of vertical lines within that measuring range.

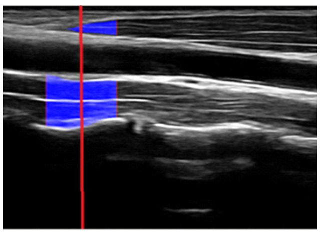
In our previous attempt [10], we used fuzzy sigma binarization to control low brightness contrast by its adaptive thresholding characteristic instead of K-means pixel clustering that the proposed method offers. However, the previous approach does not consider the average brightness nor morphological characteristics of cervical vertebrae thus its performance is not stable especially when it forms the thickness measuring key points. Thus, the proposed method utilizes morphological information of cervical vertebrae in noise removal process. Figure 8 shows the difference of the proposed method and previous attempt [10] in detecting measuring key points.



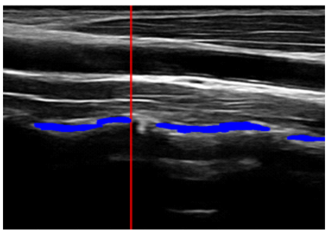
(a) Extracting Cervical Vertebrae [10]



(b) Extracting Cervical Vertebrae (Proposed)



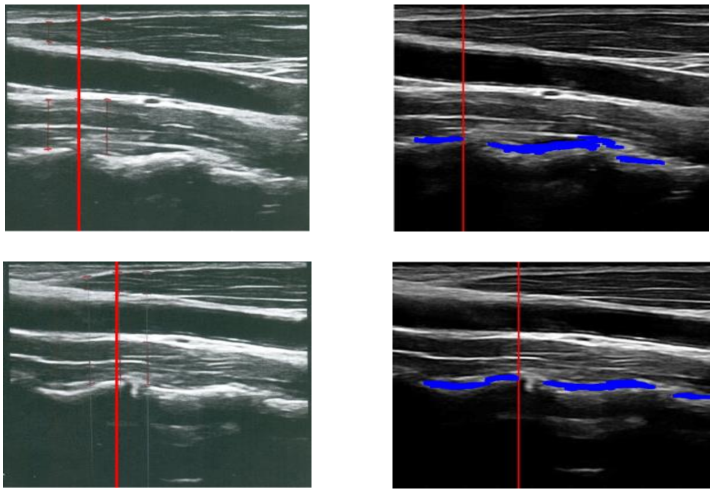
(a) Key Points [10]



(b) Key Point (Proposed)

Figure 8. Performance Comparison

As shown in Figure 9, the results from the proposed method is consistent with those of human experts.



(a) Manual Key Point Detection (b) Proposed Method

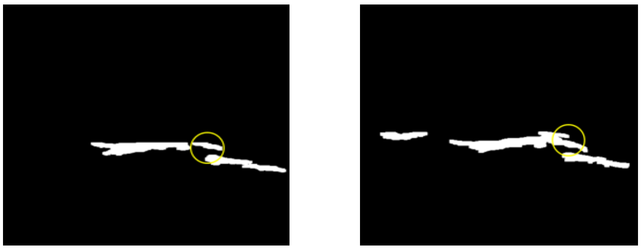
Figure 9. Performance comparison 2: Human experts vs Proposed method

5. CONCLUSION

In this paper, we propose a method to extract cervical vertebrae automatically by using various image processing techniques and K-means pixel clustering to form the target cervical vertebrae object from ultrasonography. For technical concerns, our method consists of three parts in this automatic extraction. Firstly, we should find the lower bound of DCF area that is the upper bound of the cervical vertebrae existence. In this part, we apply average binarization and Blob algorithm from intensity enhanced image to remove unnecessary part and locate only the region that the target object can appear. Once the range of target object existence is decided, we cluster pixels with K-means algorithm to form the cervical vertebrae object with respect to the morphological limitations such as long oval shaping. Lastly, we apply image restoration process by Smearing algorithm to compensate possible object disconnection or other information loss that was caused from previous image processing steps.

The performance of the proposed method is evaluated by the agreement rate with human experts in locating measuring key points for related muscle analysis. The proposed method was successful in 48 out if 50 test cases.

However, as shown in Figure 10, two cases are failed due to imperfect noise removal.



(a) Noise Removal Failed (b) Overlapped Objects

Figure 10. Failed Cervical Vertebrae Extraction

In case Figure 10(a), the false positive noise was not removed since it has significant size and in Figure 10(b), cervical vertebrae objects are not separated due to incorrect removal of related cartilage and subcutaneous fat explained in section 3.2. In order to overcome such imperfection, we may need more complex learning procedure to delimitate unnecessary objects from target object. Otherwise, the proposed method is effective and stable with respect to manual detection of measuring key points for related muscles.

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