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Automated Extraction of Cranial Landmarks from Computed Tomography Data using a Combined Method of Knowledge and Pattern Based Approaches

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Abstract
Accurate identification of anatomical structures from medical imaging data is a significant and critical function in the medical domain. Past studies in this context have mainly utilized two main approaches, the knowledge and learning methodologies based methods. Further, most of previous reported studies have focused on identification of landmarks from lateral X-ray Computed Tomography (CT) data, particularly in the field of orthodontics. However, this study focused on extracting cranial landmarks from large sets of cross sectional CT slices using a combined method of the two aforementioned approaches. The proposed method of this study is centered mainly on template data sets, which were created using the actual contour patterns extracted from CT cases for each of the landmarks in consideration. Firstly, these templates were used to devise rules which are a characteristic of the knowledge based method. Secondly, the same template sets were employed to perform template matching related to the learning methodologies approach. The proposed method was tested on two landmarks, the Dorsum sellae and the Pterygoid plate, using CT cases of 5 subjects. The results indicate that, out of the 10 tests, the output images were within the expected range (desired accuracy) in 7 instances and acceptable range (near accuracy) for 2 instances, thus verifying the effectiveness of the combined template sets centric approach proposed in this study.

Keywords: Computed Tomography (CT); Pattern recognition; Contour Template matching; OpenCV

Introduction

From a number of medical applications, branching into various other fields, identification of anatomical structures from cross sectional medical image slices plays a vital role. Thus, accurate identification of such landmarks from medical imaging data such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) is important in many ways. Automated extraction and identification of craniometric structures related to the human skull from CT data is the focus of this study. Most previous reported studies in this context have focused on the analysis of cephalograms, where researchers have attempted to identify landmarks from lateral X-ray CTs to be mostly utilized in treatment planning and evaluation in the field of orthodontics and other areas of oral and maxillofacial surgical operations. The intention of these previous studies was to identify landmarks from a single or limited number of lateral CT images. However, the focus of the current study is the automated identification of craniometric landmarks or brain objects from large sets of cross sectional CT slices.

In the current context in most instances, such identification of anatomical structures or craniometric landmarks from the aforementioned data sets, is done manually by medical personnel (in a medical setting). However, this procedure, to be completed in a repeated manner to a large data set is a tedious and time-consuming process. Further, for a non-medical person such identification is quite challenging, thus prone to errors. Our project team encountered such an instance where 30 anatomical landmark locations were needed to be identified from large CT data sets to measure the tissue thickness values of the same locations (Figure 1). These tissue thickness data were intended to be used for a novel forensic facial reconstruction study where the accuracy of the outputs were solely depended on this data set [1,2]. Thus, it was of paramount importance to identify these landmarks accurately from the large sets of CT data. Initially, a medical officer carried out this process manually, but it was soon apparent that this was not practical once the data set was gaining data (new cases) substantially. Therefore, it was necessary to resort to an automated technique for the aforementioned process.

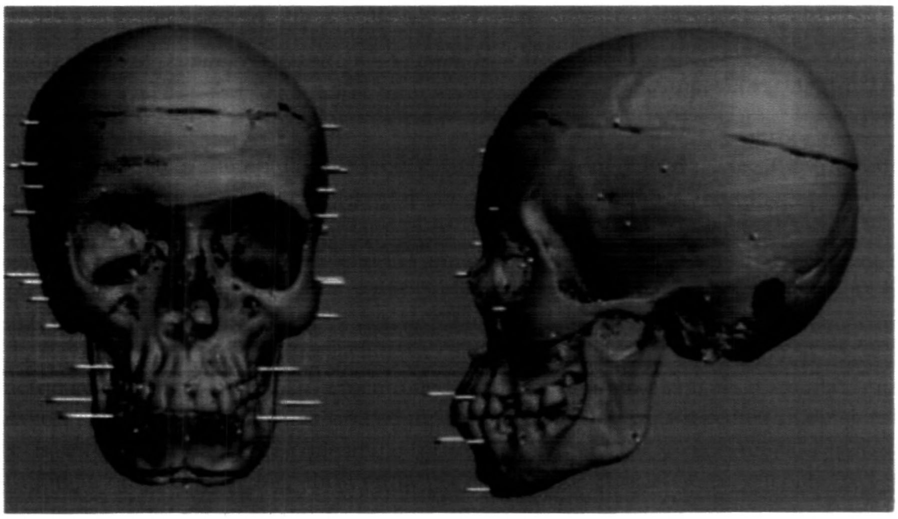

Figure 1. Skull landmarks used in the forensic reconstruction project, FaceID: A 3D Computer Graphic Application for Forensic Medicine [2]

Whilst there are previous studies that have explored the possibility of automating identification and extraction of craniometric landmarks from medical imaging data, complete automation has proved to be difficult due to the nature and complexity of the task. This is due to the reason that there is a substantial variation of the anatomical features of a given skeletal landmark among human subjects. Whilst it is possible for a medical personnel trained for this specific task to identify landmarks from these images, due to the aforementioned variation the following difficulties arise in relation to completely automating this process.

1. The general pattern and shapes of the interested feature varies substantially across cases [3]
2. Indistinct boundaries between adjacent features [4]
3. Difficulty to encode positive shape constraints for features which may differ significantly from slice to slice [5]
4. Distortions due to old age, diseases, and injuries to the skull [6]

Research related to the analysis of cephalograms can be considered as studies in close relation to the problem addressed by this paper. The analyses of anatomical landmarks in these studies are used by orthodontists in what is referred to as cephalometric evaluations [7]. Even though in most of these earlier studies, the focus is on identifying landmarks from lateral X-ray CTs (as opposed to cross sectional CTs which are focused in this study), concepts devised by such studies have been utilized in the current study as they were readily applicable.

The past research that have attempted to automate the identification of landmarks from cephalograms, can be classified into the following three categories [8]:

1. Knowledge based methodologies
   This method uses knowledge of the cranial structure in image processing techniques to identify landmarks. (E.g. via devising rules that encode anatomical knowledge)
2. Learning methodologies
   These include studies where artificial intelligence, genetic programming, and pattern matching techniques have been used.
3. Combined approaches
   This category includes studies where a combination of the two aforementioned approaches has been utilized.

Most current studies state that the former two approaches have substantial drawbacks. Studies indicate that the knowledge based methods rely on rigid rules, are unreliable specifically in face of image anomalies, and variable image quality [9,10], can only be applied to a small number of images conforming to the shape parameters encoded in the rules [8] and poses difficulties to the user when adding new landmarks [11,12]. Pertaining to the learning methodologies approach, it is stated that this method is limited by its dependence on the reproducibility of the image appearance around each landmark across all images [9]. Limitations of these two techniques give the motivation to study the combined approach [13,14].

Hence, this paper proposes an automated method based on a combined approach of the two main existing paradigms, and aims to mirror the judgment of the manual identification process by medical personnel. Further, it aims to utilize the research findings of cephalometric analysis studies adopting the combined approach, in the context of identification of landmarks from large sets of cross sectional CT slices.

Subsequent to the discussions with specialists in radiology, it was established that they train themselves to recall not only the general pattern pertaining to each of the landmarks but also the variations in size and shape detail among different individuals. Therefore, in this study, one of the main aims was to establish whether the encoding of the general pattern and its variation using a template data set via contour matching techniques, would pave the way to a successful automated identification method. Then it was further attempted to increase the accuracy and efficiency of the above learning methodologies based approach by combining it with a rule based filtering stage. By combining these techniques, the main goal of the study was to devise an anatomical landmark independent methodology for automated identification of brain or skull objects from data related to one of the most used imaging modalities, X-ray Computed Tomography.

Method and Implementation

At the initial stage of the study, the focus was on selecting anatomical landmarks to test the proposed methodology of this study. A consultant radiologist selected the two landmarks presented in Figure 2 for this purpose.

These points were selected considering an easier landmark (Dorsum sellae) and a comparatively difficult landmark (Pterygoid plate) to be automatically identified, depending on their relevant contour patterns. It should also be noted that, for most of any given cranial landmark, the relevant 2D representation exits across multiple slices. Generally the inter-slice distance between two CT scan images ranges from 1-10mm [15]. Thus, when the dimensions of a brain/skull object exceed that range, it appears in more than 1 CT slice.

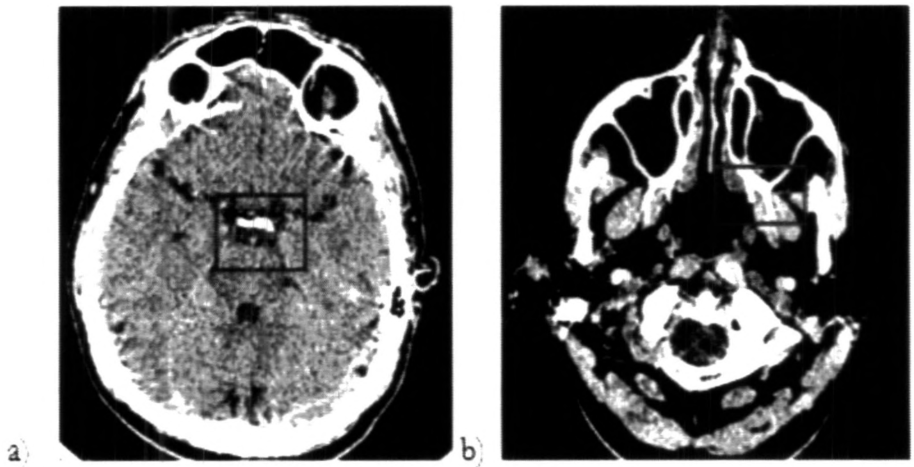

Figure 2. a: Dorsum sellae skeletal landmark; **b**: Pterygoid plate

A template data set was used firstly in devising the parameters for the rules related to the knowledge-based approach. Subsequently the same templates were utilized for the next stage, where a contour based template-matching function, in relation to the learning methodologies paradigm was performed (Figure 3).

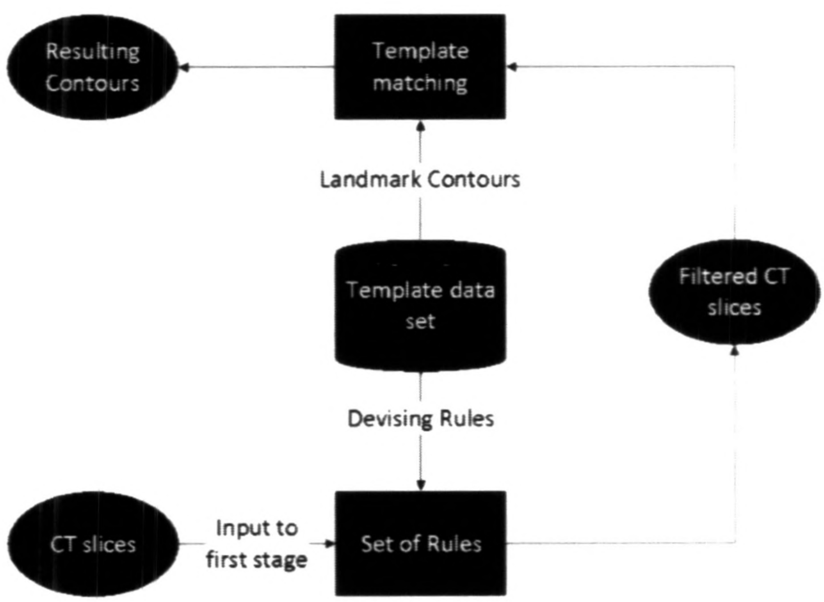

Figure 3. The Template data set centric process flow adopted in the study

Our proposed template set centric structure satisfies two requirements. Primarily, it enables us to formulate a method, which mirrors the manual identification process by medical personnel in similar domains. After consulting a radiologist and forensic specialist in this regard, it was understood that they recall a general pattern, related characteristics (e.g. placement, size, and area), and the possible variations of that pattern in relation to each of the anatomical landmarks. In this study, the general pattern and its variations related to two landmarks were captured via two template data sets, which consist of the actual landmark contours obtained from CT data sets from a sample group. In addition, in the main search function similarity was compared by matching these actual contour patterns with the contours obtained from the CT data sets. Secondly, the same template data sets were employed to create rules for the initial filtering stage, where the parameters of those rules were devised using the sample template images.

According to the proposed structure, it is apparent that the template data set is of high importance to the success of the study. Hence, these images were chosen by a consultant radiologist to minimize potential errors. Eleven sample images for the Dorsum sellae landmark (Figure 4) and 9 images for the Pterygoid plate landmark were chosen for the initial template data sets.

Figure 4. 5 Sample images/contours in the template data set of the Dorsum sellae

After the sample template data sets were established, the following steps were followed to carry out the automated extraction task.

Image Acquisition

The CT images were acquired through two government hospitals in Colombo, Sri Lanka. 16 slice CT scanners were functioning at both hospitals (Toshiba Aquilion 16 slice CT scanner: at the Colombo South Teaching Hospital, a Philips Brilliance 16 slice scanner: at the Sri Jayawardenapura General Hospital). As per the ethical clearance agreement that was acquired by the project team for the study, personal identification data were removed from the CT scans. CT data sets without abnormalities such as fractures or facial injuries were chosen for the study.

Pre-processing

In this stage, the DICOM source images of the CT data sets were converted to the more accessible JPEG format. MATLAB was used to batch convert the data sets selected at the first step of the process.

Subsequently the requirement was to extract the contour sets of the CT images. Thus edge detection techniques were explored in order to select the most appropriate method for the current study. The canny edge detection algorithm was used at this stage due to its all-round suitability to this research. This edge detection operator was utilized via OpenCV to detect the edges of the converted JPEG image sets (Figure 5). Suited threshold values (100, 300-400) were decided based on trial and error runs so that the grey matter details were reduced but the important contour patterns, which would be the main search target, would not decrease.

Further processing was done depending on the nature of the CT images. For instance, skewed and out of scale images were rectified using MATLABs image registration technique.

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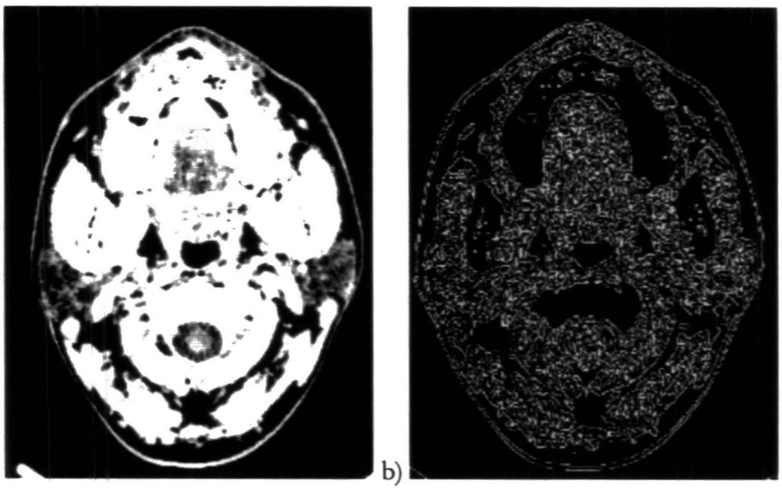

a) b)

Figure 5. a) Converted JPEG image of a DICOM slice; **b)** Output image after applying canny edge detection to the converted JPEG images

Segmentation

The user is then required to choose a Region of interest (ROI) with regard to the landmark location in consideration. At this point, the user has the option to select a generic region of interest, where the landmark generally appears in the reference slice provided in the interface developed for this project. For instance in relation to the first landmark, Dorsum sellae, the user has to select the general vicinity in which it appears in the reference image as shown in Figure 6. This was done as it minimizes the run time of the program and more importantly, reduces the error substantially by targeting a specific area to search the landmark contour pattern in all images of the data set. The user has to be mindful to not select a very limited ROI based on the reference image, so that the relevant contour patterns of CT slices fall outside the selected area. If in any case that the search returns no results, the user is allowed to edit the previously selected ROI.

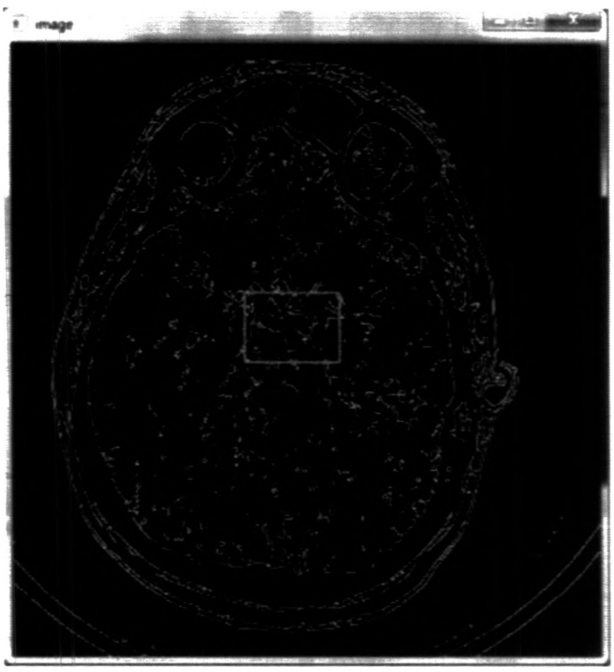

Figure 6. Selecting the region of interest for Dorsum sellae

Representation

The implementation of this stage is twofold. Firstly, a typical implementation of the knowledge based approach was applied for the contours detected from the ROI, where contours belonging to certain rules were only selected to the next processing stage. For the current study, the following two parameters were considered to devise the rules.

1. Contour area in relation to skull area
2. Contour perimeter in relation to skull perimeter

Value sets for the two parameters were obtained for both landmarks from their respective template data sets. Then a range was formulated for each of the 2 parameters from the minimum and maximum values of the data sets (Table 1). The values devised for the Dorsum sellae and Pterygoid process landmark are as follows. (All values are presented in pixels and the image resolution was similar (96dpi) in all images considered.)

Table 1. Parameter ranges for the rules

Dorsum sellae	Minimum /pixels	Maximum /pixels	Pterygoid plate	Minimum /pixels	Maximum /pixels
Contour area	235	585	Contour area	47.5	134.0
Contour perimeter	106.56	116.08	Contour perimeter	292.14	524.61

Only contours conforming to these rules (within the range) were filtered and passed to the next stage of the process, where the learning methods based approach was applied. Here, the resulting contours of the above step were then matched for similarity using a template/shape matching technique with the contours of the sample images of the relevant template data set. Due to the diverse nature of the shape contours of the landmark locations, a scale and rotation independent shape matching function in OpenCV was utilized in this regard.

Each of the contours in the ROI were assigned a match rate, hereinafter called "similarity value" (I), by means of the OpenCV matchShapes function (Equation 1), where the ROI contours were matched with the contours of all the sample images of the relevant template data set. This function returns a value corresponding to the similitude of the two contours, ranging from 0.0 for perfect match and a higher value for non-matching contours (the smaller the returned value, the more similar the contours) [16]. As the contours of the template data set were devised from images chosen by an expert, a close similarity value with images of the template set will possibly represent a positive match. The similarity values (I) were then added to an array (C) for the last step of the process.

A = {contour in the ROI}

B = {contour in the sample template set}

$$I_1(A,B) = \sum_{i=1\ldots7} \left|\frac{1}{m_i^A} - \frac{1}{m_i^B}\right| \qquad (1)$$

where, $m_i^A = sign(h_i^A) \cdot \log h_i^A, m_i^B = sign(h_i^B) \cdot \log h_i^B$ [16]

and, h_i^A, h_i^B are the Hu moments of A and B

C= {Array of the resulting similarity values}

n= Number of contours in the ROI × Number of contours in the template dataset

$$C = (I1\ \ I2\ \ I3 \text{ -- } In) \qquad (2)$$

Recognition

In this stage, the values resulting from Equation (2) were sorted and the contours conforming to the minimum values of this array (closest matching contours to the template set) were selected as the results of the search. The user is presented with the image conforming to the most similar contour (lowest value), devised from this step (Figure 7). Further, the extracted contour pattern that reflected the best similarity value (I) from that resulting image is also presented.

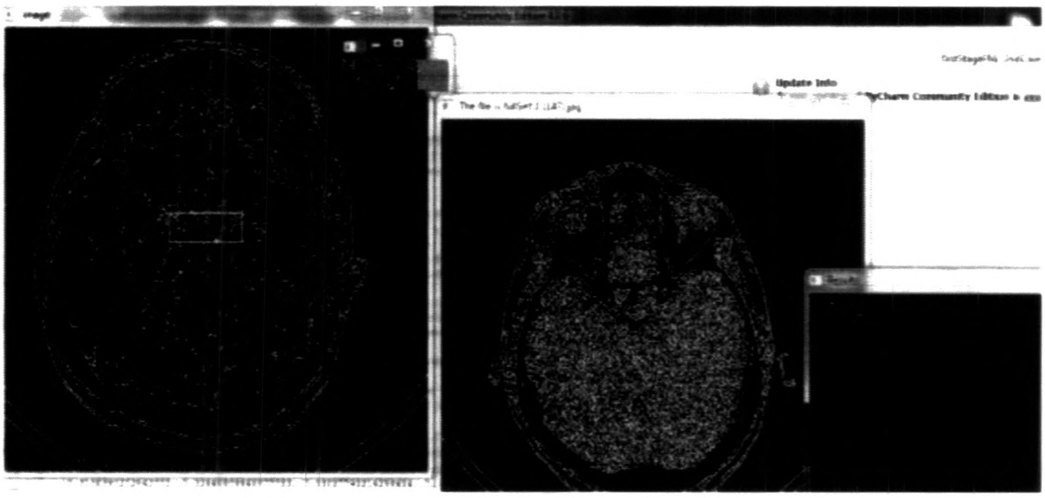

Figure 7. Results of the process adopted in this study for a Dorsum sellae case

Accuracy Assessment

5 cases (10 tests) were used to assess the accuracy of the method devised in this study. The accuracy levels of the resulting image were assessed as follows.

- Desired accuracy: The resulting image was within range expected.
- Near accuracy: The resulting image was not within range, but the error was less than 2%
- Invalid result: The resulting image was not within range and the error was greater than 2%

The cut off mark between near and invalid accuracy levels was decided after extensive discussions with the consultant radiologists, as no similar mechanism was available in the literature. In determining this value special consideration was given on how a landmark is spread across the cross sectional slices and on what would constitute as an invalid result.

Further to assess the effect of using a rule based filtering stage (knowledge-based paradigm) on this process, it was decided to run the same 10 tests using only the pattern based approach.

Results and Discussion

Table 2 presents the test results obtained for the two aforementioned landmark locations with regard to 5 cases (C01-C05).

Table 2. Results of the 5 cases for the two landmark locations

Test ID	Landmark	Number of Images	Range expected	Resulting image	Accuracy level
1	Dorsum sellae	124 (C01)	74-79	76	Desired accuracy
2	Dorsum sellae	411 (C02)	261-265	265	Desired accuracy
3	Dorsum sellae	425 (C03)	317-326	323	Desired accuracy
4	Dorsum sellae	374 (C04)	280-287	282	Desired accuracy
5	Dorsum sellae	505 (C05)	270-278	269	Near accuracy
6	Pterygoid plate	124 (C01)	108-112	112	Desired accuracy
7	Pterygoid plate	411 (C02)	361-371	369	Desired accuracy
8	Pterygoid plate	425 (C03)	394-406	386	Near accuracy
9	Pterygoid plate	374 (C04)	353-364	360	Desired accuracy
10	Pterygoid plate	505 (C05)	360-371	384	Invalid result

As mentioned in the earlier sections, a range of slices (range expected) is existent in the tests due to the landmarks in consideration being present in more than one of the slices in each of the cases. Further, it should be noted that the area of focus or scan type (e.g brain, sinus, full head scan) was different between cases. Therefore, a variation exists in the total number of images and expected range among cases.

According to the Table 2 it is apparent that the desired accuracy has been achieved for the tests 1-4, 6, 7 and 9. Tests 5 and 8 resulted in near accuracy levels. Only test no. 10 resulted in an invalid outcome. Accordingly, it can be noted that for the Dorsum sellae, positive results were obtained for all tests. With regard to the Pterygoid plate, positive results were obtained for 4 out of 5 tests.

Regarding the tests which were performed without the rule based filtering stage, out of the 10 test cases, 4 returned invalid results (Table 2). Further for all cases the time taken to run the program increased substantially. Table 3presents the summary of the results obtained in this study.

Table 3. Summary of the results obtained using the 3 main methodologies considered in this research

Methodology used for the process	Invalid results	Near and Desired accuracy results
Pattern recognition (template matching) only	4	6
Rule based filtering only	Not applicable since this method was used only to filter the contour set to a reduced size for later pattern based analysis	
Combination of both aforementioned methods	1	9

As mentioned above, this study adopts a combined approach of the existing two main approaches. A pattern matching technique based on the learning methods approach was utilized as the main search mechanism of this study. It was mentioned in the literature that the knowledge-based methods had a number of drawbacks in the current context. Thus, the rule-based technique of this approach was only utilized initially to filter the data set for later pattern recognition based analysis. When these two techniqus were combined, only 1 test case out of the 10 cases resulted in an invalid outcome.

On the tests conducted without this filtering stage, it was mentioned (Table 3) that 4 cases returned invalid results. This is due to the reason that without the rule based filtering process, all contours of all the images are now being compared for similarity measurement (as opposed to the filtered contours). Therefore, it can be noted that even though the rule based method has drawbacks, it can be used effectively as a filtering mechanism in this context. Hence, it can be postulated that by combining these two approaches, greater accuracy could be reached as compared with the accuracy level of each of the techniques used individually.

Initially the authors considered generalization of landmarks via averaging the contour patterns. Yet it was found out that by doing so, the resulting contour pattern loses similarity to either of the initial contours which were used for the generalization. It was only then, a sample template data set that contained the contours of the skeletal landmarks in its actual state was considered. Further, once the number of sample images of the template set increased, the accuracy of the search also improved marginally. Whilst this is expected, in the current study 11 and 9 sample images were used respectively for the Dorsum sellae and Pterygoid plate landmarks to obtain a fair level of accuracy.

Additionally the same tests were carried out with varying scales and rotations of the sample images of the template data set. The same results were obtained. This is due to the reason that the OpenCV functions utilized in this study was scale and rotation invariant [16]. This was quite important for a study of this nature as CT scans of varying scales and rotations of subjects were present in the data collected from the medical institutes.

Due to the above mentioned reasons it can be presumed that, the method used in this study can be extended to any other landmark, given that an appropriate template data set is constructed. As this project is related to the facial reconstruction project mentioned before, the project team is currently extending the template data sets to reflect the other required landmarks as well. A proper mechanism of including the successful search results into the sample data sets is also planned, so that future tests will result in outcomes that are more accurate.

As limitations of the current study, as a contour based methodology is used, open contours and contours with a certain level of noise (other irrelevant contours attached) in landmark locations caused inaccuracies (Figure 8).

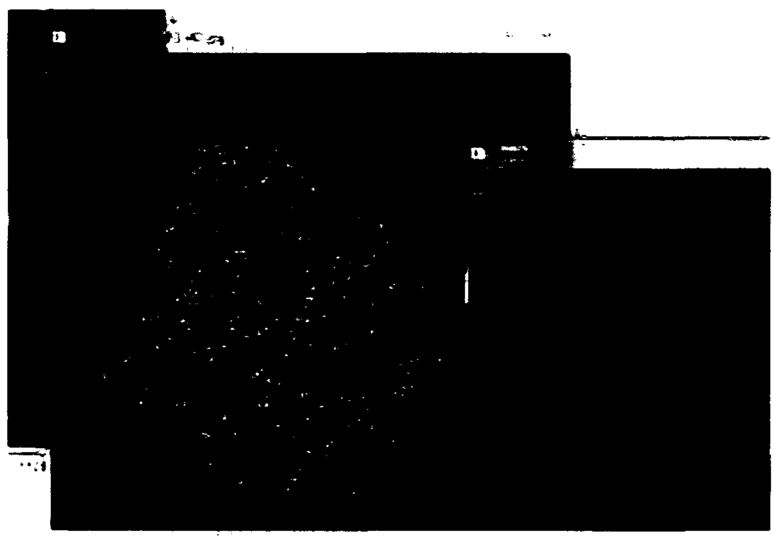

Figure 8. Contours with other irrelevant contours attached: Pterygoid plate landmark

This was particularly true for the 10th test case of the Pterygoid plate landmark. Therefore, in future studies, it is planned to further utilize edge detection methods to overcome this problem. More research is warranted particularly in terms of devising more rules for the filtering stage, which would result in greater accuracy, but does not overly limit the range for the 2nd stage of the search. Currently only two rules are applied for this study.

Conclusions

Whilst complete automation of identification of anatomical landmarks from neuroimaging data has been proven challenging, this study presents a successfully evaluated template set centric approach. The tests conducted using the proposed method resulted in desired/expected range (7 instances) to near accuracy range outcomes (2 instances) in relation to two landmarks, Dorsum sellae and Pterygoid plate. Out of the 10 tests carried out for these two landmarks, only one test resulted in an invalid outcome. While further research is needed to raise the accuracy particularly in relation to the more difficult landmarks, the methodology presented in the study can be extended to any other landmark, if a considerable template data set can be acquired. Further, it can be noted that even though a number of studies have been done in the analysis of cephalograms, predominantly related to the field of orthodontics, where automated identification of landmarks has been attempted, similar efforts were rare with regard to the extraction of anatomical landmarks from large cross sectional CT data sets. Although this study was conducted only on CT data, the same methods can be used for landmark identification from other types of medical imaging technologies (e.g MRI) as well. In addition, as the conclusion it can be noted that by combining the existing knowledge and pattern based approaches with template matching techniques, superior methods of automated craniometric identification can be devised.

Conflict of Interest

The authors declare that they have no conflict of interest.

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References

1. Rajapakse RN, Madugalla AK, Amarasinghe IU, Padmathilake VH, Dharmaratne AT, Sandaruwan KD, et al. Facial Muscle Anatomy Based Approach for Forensic Facial Reconstruction in Sri Lanka. International Conference on Advances in ICT for Emerging Regions (ICTer). 2012. p. 27–35.
2. Madugalla AK, Rajapakse RN, Amarasinghe IU, Padmathilake VH, Dharmaratne AT, Sandaruwan D, et al. FaceID: A 3D Computer Graphic Application for Forensic Medicine. International Conference on Computer Medical Applications, Sousse-Tunisia. 2013. p. 1–6.
3. Ciesielski V, Innes A, John S, Mamutil J. Genetic Programming for Landmark Detection in Cephalometric Radiology Images. Int J Knowledge-Based Intell Eng Syst. 2003;7(3):164–71.
4. Golodetz S, Voiculescu I, Cameron S. Region analysis of abdominal CT scans using image partition forests. CSTST '08 Proceedings of the 5th international conference on Soft computing as transdisciplinary science and technology. 2008, p. 432–7.
5. Golodetz S, Voiculescu I, Cameron S. Automatic spine identification in abdominal CT slices using image partition forests. 2009 Proc 6th Int Symp Image Signal Process Anal. 2009;
6. Cheng Y, Kheng Leow W, Chye Lim T. Automatic identification of Frankfurt plane and mid-sagittal plane of skull. Proc IEEE Work Appl Comput Vis. 2012;233–8.
7. Cardillo J, Sid-Ahmed M a. An image processing system for locating craniofacial landmarks. IEEE Trans Med Imaging [Internet]. 1994;13(2):275–89. Available from: http://www.ncbi.nlm.nih.gov/pubmed/18218504
8. Douglas TS. Image processing for craniofacial landmark identification and measurement: a review of photogrammetry and cephalometry. Comput Med Imaging Graph [Internet]. 2004;28(7):401–9. Available from: http://www.ncbi.nlm.nih.gov/pubmed/15464879
9. Hutton TJ, Cunningham S, Hammond P. An evaluation of active shape models for the automatic identification of cephalometric landmarks. Eur J Orthod. 2000;22(5):499–508.
10. Vasamsetti S, Sardana V, Kumar P, Kharbanda OP, Sardana HK. Automatic Landmark Identification in Lateral Cephalometric Images Using Optimized Template Matching. J Med Imaging Heal Informatics [Internet]. 2015;5(3):458–70. Available from: http://openurl.ingenta.com/content/xref?genre=article&issn=2156-7018&volume=5&issue=3&spage=458
11. Grau V, Alcañiz M, Juan M., Monserrat C, Knoll C. Automatic Localization of Cephalometric Landmarks. J Biomed Inform [Internet]. 2001;34:146–56. Available from: http://linkinghub.elsevier.com/retrieve/pii/S1532046401910147
12. Kaur A, Singh C. Automatic cephalometric landmark detection using Zernike moments and template matching. Signal, Image Video Process. 2013;9(1):1–16.
13. El-Feghi I, Sid-Ahmed M a., Ahmadi M. Automatic localization of craniofacial landmarks for assisted cephalometry. Proc 2003 Int Symp Circuits Syst 2003 ISCAS '03 [Internet]. 2004;37:609–21.
Available from: http://linkinghub.elsevier.com/retrieve/pii/S0031320303003200
14. Shahidi S, Oshagh M, Gozin F, Salehi P, Danaei S. Accuracy of computerized automatic identification of cephalometric landmarks by a designed software. Dentomaxillofacial Radiol. 2013;42.
15. drs.dk. General principles associated with good imaging technique: technical, clinical and physical parameters [Internet]. [cited 2015 Jul 16]. p. 004. Available from: http://www.drs.dk/guidelines/ct/quality/Page004.htm

16. Opencv.org. Structural Analysis and Shape Descriptors [Internet]. 2015 [cited 2015 Aug 12]. Available from: http://docs.opencv.org/modules/imgproc/doc/structural_analysis_and_shape_descriptors.html#matchshapes