Semi-automatic Detection of Fracture in Wrist bones using Graph-based Grammar Approach

P.Divya
SSN College of Engineering
divprab@gmail.com

R.Geetha Priya
SSN College of Engineering
rujgpriya@gmail.com

S.Kavitha
SSN College of Engineering
kavithas@ssn.edu.in

Abstract

Medical image analysis is systematic evaluation which is similar to expert knowledge of radiologists and other clinical specialists. To perform this, cognitive recognition facilitates the semantic analysis and understanding of the images. In this paper, the X-ray images of wrist bones are analyzed for fracture identification in metacarpal region, using graph based grammar approach. For a normal wrist X-ray image, graph is constructed by considering the ulna of the wrist bone as the starting node and the graph is traversed through each bone which are assumed as node and the path is ended when it reaches the phalanges. From the constructed graph, the production rules are generated from the ulna(start symbol). For the test image using the grammar rules, input strings are generated and validated using the parser. If a valid strings(normal X-ray) are given, it reaches the final state, else it reaches an invalid state(fractured image). Based on the state it reaches, the type of the fracture that exist in the wrist X-ray image is identified. Any kind of fracture in the wrist bone can be easily detected by extending or adding the production rules without modifying the system is an important aspect of image understanding.

Keywords : Cognitive recognition, Semantic analysis, X-ray image, Ulna, Phalanges.

1. INTRODUCTION

Medical imaging is the technique and process used to create images of the human body parts for clinical purposes or medical science that includes the study of normal anatomy and physiology. Since the number of images is growing enormously in this information era there is a need for automatic analysis of the medical images because manual analysis is a tedious job.

In automated analysis i.e. CAD(Computer Aided Disease Diagnosis) has been constructed for different kinds of modalities like X-ray [6], Magnetic Resonance Imaging (MRI) [7], Computed Tomography (CT) [8], Positron Emission Tomography (PET), Single-Positron Emission Tomography Tomography (SPECT),etc.

Currently most of the work is based on syntactic approach that deals with the shape, color, size, contour etc whereas semantic interpretation deals with the understanding of images. Cognitive data analysis is on of the semantic techniques discussed in [1 ,2], analyzes the lesions in the foot bones using grammar rules [3].

The cognitive categorization systems described in [4] explains the interpretation and analyzes about image-type data and reasoning based on it. The various types of fracture like fissure, traverse, spiral, displaced fractures,etc are identified using set of production rules defined for various types of bone fractures.

Semantic approach is preferred in automatic analysis, since the meaning of the image is required. In this paper X-ray was chosen as the modality because,

i. It shows the anatomy of the bone structure and easily acquirable.
ii. Cost of acquiring is cheap.

In this paper, a linguistic formalism based on graph-based grammar approach is discussed for wrist bone X-ray images.

2. SYSTEM DESIGN

The system design is shown in Fig. 1. The input is an X-ray image of the wrist. The image is pre-processed using sequence of steps. After pre-processing, graph is constructed for a normal palm X-ray. From the graph, attribute grammar rules are generated. For a test image, angles of deviations are calculated and depending on the angles, strings are generated and given as input to the parser. Based on the final state of the parser fracture is detected.

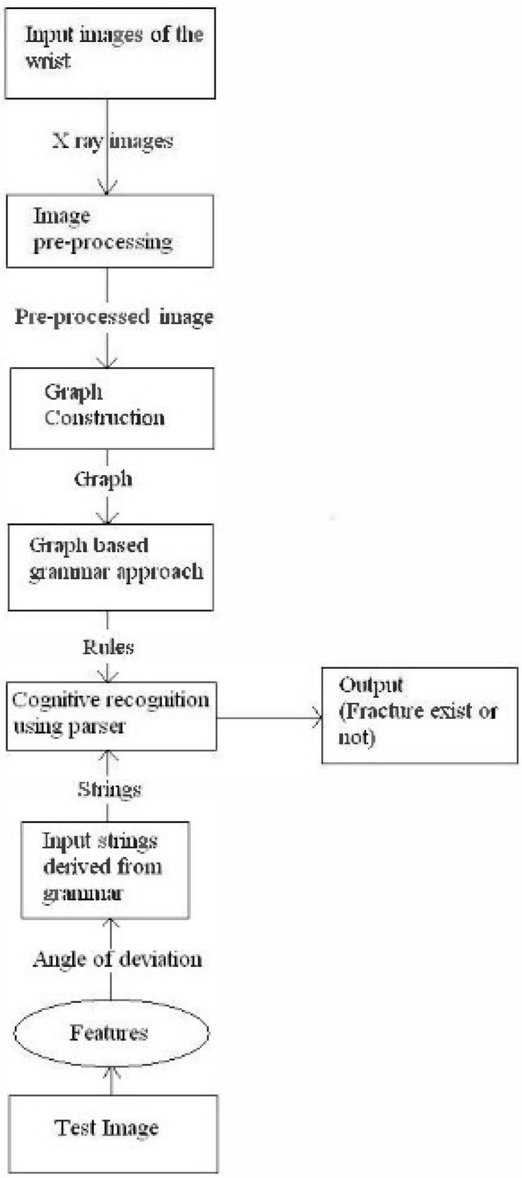

Fig. 1. Semantic interpretation of wrist bones for fracture identification

The features extracted from the image is the angle of deviations, which are compared with the terminal constraints in the attribute grammar. Using this comparison, set of strings are given as input to the parser which identifies the presence or absence of a metacarpal fracture.

2.1 Data Collection and Analysis

The data set used in the system has been collected from the Radiology department of Geneva University Hospital, Switzerland contains a database of 51 different collections of medical image[9]. The main reason for selecting this data set is that the visible parts are numbered and makes the interpretation easier [4]. For the test data X-ray images of wrist bone with or without fracture are acquired from the hospitals.

The normal image data set is collected from the IRMA (Image Retrieval in Medical Applications) data set [10]. This data set has large number of wrist bone images acquired using X-ray.

2.2 Image Pre-processing

The X-ray images are down-scaled to have uniform size, histogram equalized for a better contrast and edges are detected using canny edge detection algorithm.

2.3 Graph Construction

The semantic analysis of palm bones X-rays, is based on the mechanisms of the linguistic perception and understanding of data defined in the form of a formal grammar. The key in introducing the right definition of the formal grammar is to adopt names of bones found within the palm. Fig. 2 shows the bone structure of the palm. Each number in the figure represents a node name as follows :

- ulna (S)
- scaphoid (1)
- lunate (2)
- triquetrum (3)
- pisiform (4)
- trapezium (5)
- trapezoid (6)
- capitate (7)
- hamate (8)
- metacarpal (9,10,11,12,13)
- proximal phalanx of finger (14)
- middle phalanx of finger (15)
- distal phalanx (16)

From the bone structure of the wrist, graph is constructed as shown in Fig.3.

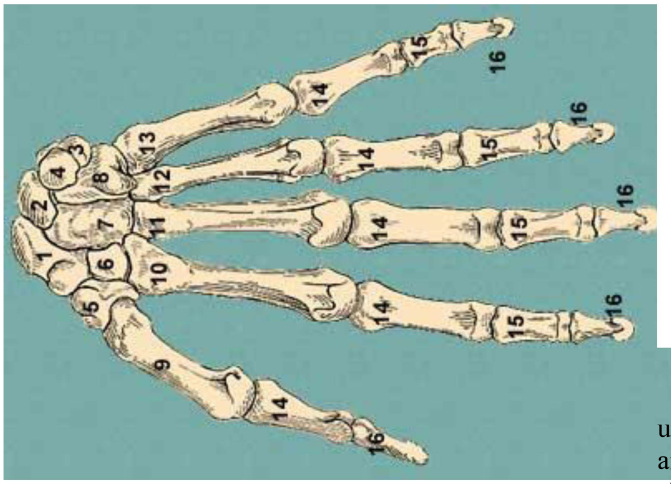

Fig. 2. Bone structure with numbered bones used for graph generation

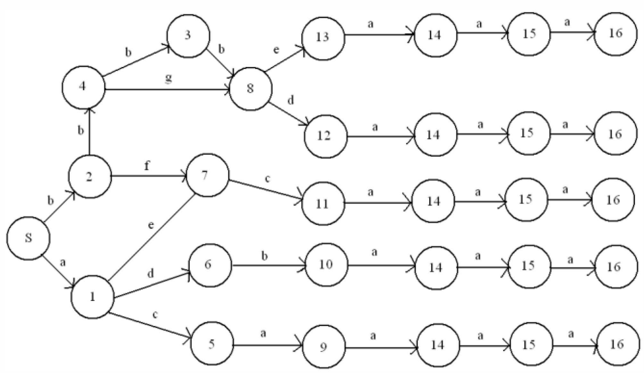

Fig. 3. Constructed graph from Fig. 2

S is the Ulna bone and considered as the starting point for construction of the graph. 1 and 2 are the bones that are in contact with ulna, so edges are drawn between S and 1, S and 2. Similarly it is carried out for other nodes also.

2.4 Attribute Grammar Rule Generation

From Fig. 3, attribute grammar rules are generated. A rule is obtained from a particular node with the input symbol and a set of terminals or non-terminals. Attribute grammar G is defined as :

G = (N, T, S, P)

N ---> denotes the set of non-terminal symbols,

T ---> denotes the set of terminal symbols,

S ---> denotes the start symbol

P ---> finite number of production rules.

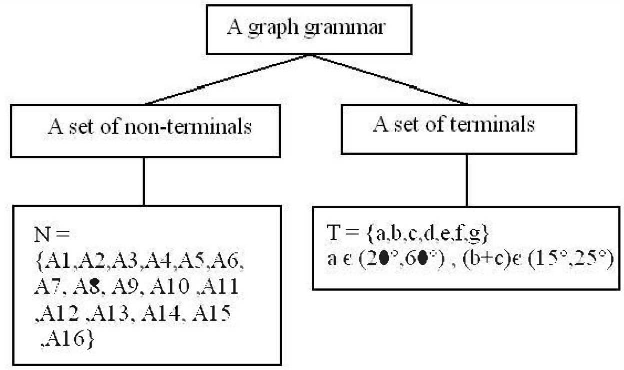

Fig. 4. Representation of terminals and non-terminals

Fig. 4 represents the set of terminals and non-terminals used in the constructed graph grammar. The terminals d,e,f and g correspond to phalanges, there is no angle constraint since only metacarpal fractures are defined in this paper.

N = {A1,A2,A3,A4,A5,A6, A7, A8, A9, A10 ,A11 ,A12 ,A13, A14, A15, A16}

T = {a,b,c,d,e,f,g} where a ϵ (20°,60°) , (b+c)ϵ (15°,25°)

S = {S}

P ={ S → bA2 | aA1

A1 → cA5 | dA6 | eA7

A2 → bA4 | fA7

A5 → aA9

A6 → bA10

A7 → cA11

A3 → bA8

A4 → bA3 | gA8

A8 → dA12 | eA13

A9 → aA14

A10 → aA14

A11 → aA14

A12 → aA14

A13 → aA14

A14 → aA15

A15 → aA16 }

The rules are written for a normal X-ray image shown in Fig. 6a.From the start symbol S, when the input is 'b'- the state change is to A2, if it is 'a' – the state change is to A1, and for any other input it will be invalid . Similarly other rules are written according to the input symbol.

The production rules are validated based on the input image and the present state of the parser. When the production rule, A5 → aA9 is violated, the type of fracture is identified as Bennett fracture. In case of Boxer's fracture the rules A6 → bA10 or A7 → cA11 is violated. If the rule A8 → dA12 | eA13 is violated then it is detected as Bar room fracture.

2.5 Fracture Identification

The metacarpal bones of the wrist are identified semi-automatically and the angle of deviation between two adjacent metacarpals are calculated. Depending on the obtained angles of deviation for all the normal X-rays , the presence of fracture is detected using the parser.

i. The starting and the ending of each metacarpal is identified.

ii. The coordinates of the starting and ending of each metacarpal bone is saved in a file.

iii. The coordinates are retrieved in another program and the slopes of each of the metacarpal is calculated.

iv. Using the slopes, angle of deviations are calculated.

v. The range of angle between first and second metacarpal is (20°,60°) and the summation of the angles between second – third and third – fourth is obtained to be(15°,25°).

vi. Using the range of each angle of deviations, set of strings are derived and given as input to the parser.

vii. The type of fracture is identified depending on the final state reached by the parser.

3. RESULTS

This section explains the results obtained at sequence of stages of implementation. The screen-shots of various stages of the implementation is given along with explanation.

3.1 Data set

Fig. 5 describes the number of images used in the analysis of the system.

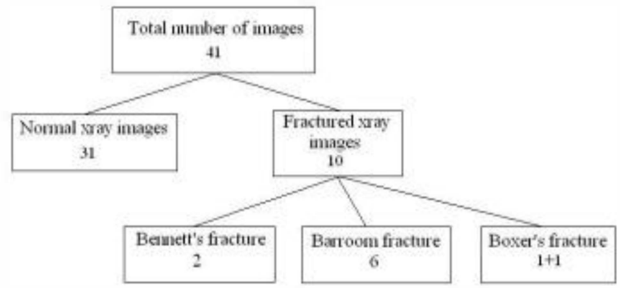

Fig. 5. Data set

Fig. 6. a)Normal X-ray image b)Bennett fracture

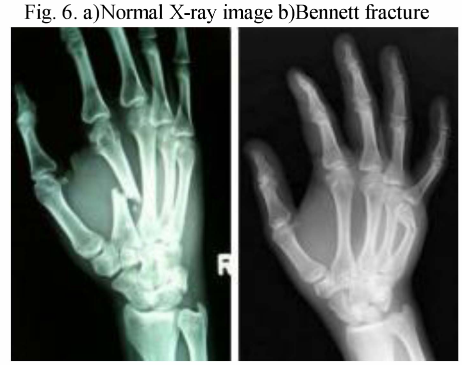

Fig. 6. c)Boxer's fracture d)Bar room fracture

Fig. 6a shows is a normal X-ray image from the IRMA [10] data-set. The various types of wrist fractures that the system analyzed are

- Bennett's fracture (Fig. 6b)- Is a fracture of the base of the first metacarpal bone which extends into the carpometacarpal (CMC) joint
- Boxer's fracture (Fig. 6c)- Is the second and/or third metacarpal transverse neck fracture that is more likely to occur from a straight punch.
- Bar room fracture (Fig. 6.d)- Is a transverse fracture of the fourth and/or fifth metacarpal neck.

The system cannot detect hair line fractures and ligament damages because the canny edge algorithm detects only the contour and it cannot be used to find very fine deviations. The system will not be efficient for wrist X-ray images of children, since the metacarpals would not have been fully grown.

3.2 Pre-processing

Pre-processing is carried out to enhance the required features using a sequence of steps: down-scaling, histogram equalization and canny edge detection.

3.2.1 Down-scaling

Since the mode of acquisition of the images are different, the images need to be re-sized. The given X-ray image is down-scaled to an uniform size of 300X500. In case of images where only the metacarpal region is used as 275X185.

3.2.2 Histogram equalization

This method increases the global contrast of medical images. This is applied to gain a higher contrast. The input for histogram equalization is the re-sized image.

3.2.3 Canny edge detection

Edges in the images are the areas with strong intensity contrast. Detecting edges significantly reduces the amount of data and filters out unwanted information while preserving the important structural properties which is required for fracture detection.

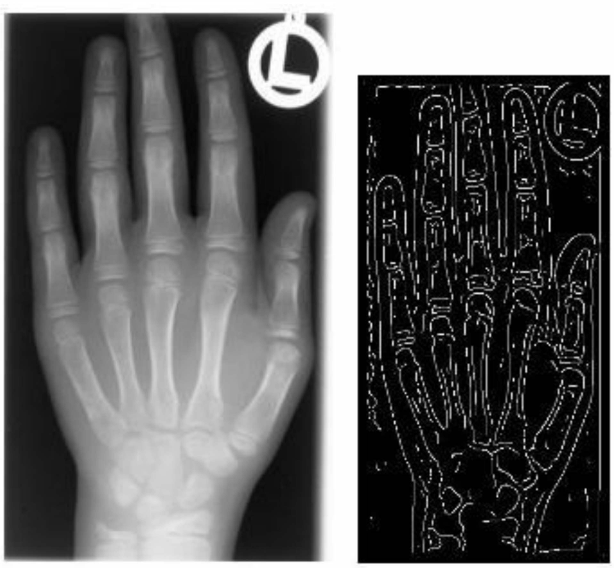

Fig. 7. a)Input wrist X-ray image b)Pre-processed image.

Fig. 7a is the input for pre-processing and Fig. 7b is the down-scaled, histogram equalized, canny edge detected image.

3.3 Fracture detection using parser

The metacarpals are semi-automatically detected and the coordinates of the midpoints of start and end of each metacarpals is determined. Based on each pair of coordinates the slope of each metacarpal is calculated. The angle of deviations between two adjacent metacarpals are calculated using the formula in Eq (1).

$$\tan \Phi = (m2-m1)/(1+m1*m2) \quad (1)$$

where Φ - angle of deviation

m1- slope of first metacarpal

m2- slope of second metacarpal

The screen-shot for angle of deviations is shown in Fig. 8. Depending on the angles, and the normal attribute grammar rules, set of strings are derived and given as input to the parser. The strings are validated and the output is as shown in Fig. 9.

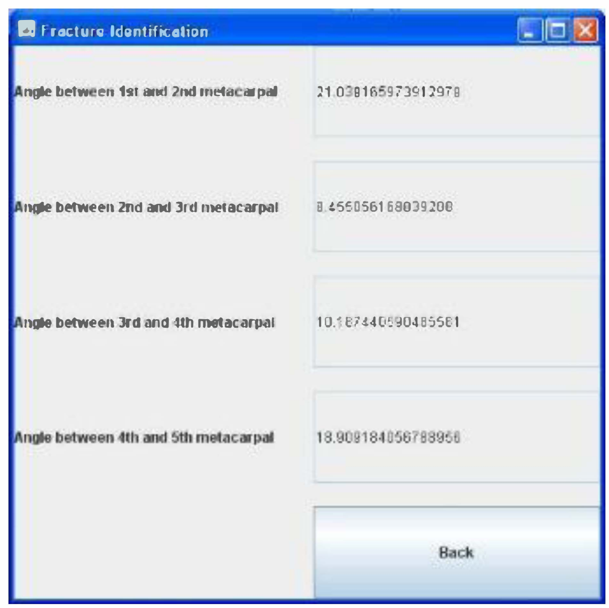

Fig. 8. Screen-shot for angle of deviations for normal X-ray image-type

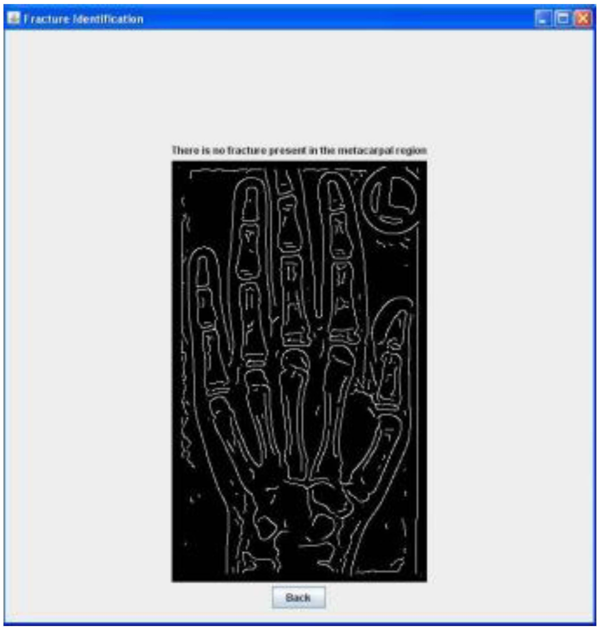

Fig. 9. Screen-shot for fracture identification of normal X-ray image.

Fig. 10 shows the angles of deviation for a bennette fractured image. Since the angle between first and second metacarpal does not match with the terminal rule constraint, while parsing the final state reached by the parser is A15. Therefore the fracture is identified as shown in Fig. 11.

Fig. 10. Screen-shot for angle of deviation for fractured X-ray

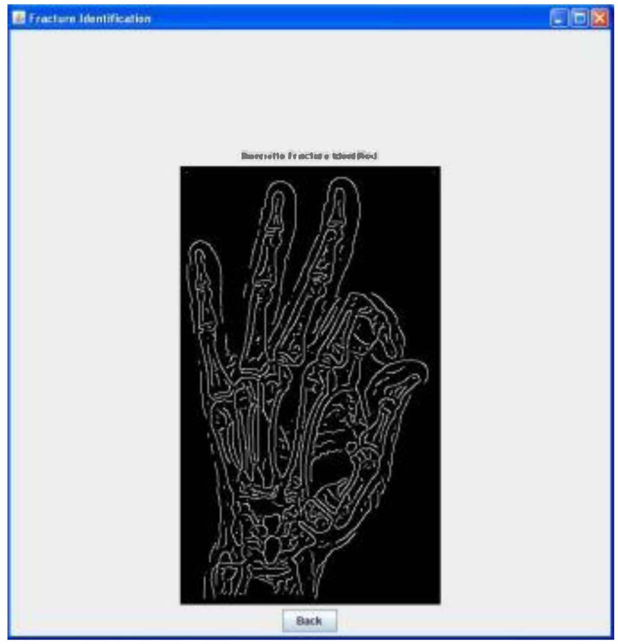

Fig. 11. Screen-shot for fracture identification.

4. DISCUSSION AND FUTURE WORK

The system is implemented using mat lab and java. For a normal X-ray wrist bone image graph and attribute grammar are constructed with rules. From this, the angle of deviation was found out for all the existing normal wrist bone X-ray images and a range of values were identified. When there are deviations in the range of angles(in a test image), the strings that are generated differ from the set of strings for normal wrist X-ray image. Hence it wont reach the final state and correspondingly fracture type is identified. Unlike classification,where only similar images can be classified, this system will work for any input X-ray image of the palm. This system can be used in any real time system as a part of whole body X-ray medical image analysis.

The system can be upgraded to detect multiple fractures in the palm. New rules can be added and this system can be extended to fractures in the other regions of the hand also. Using pavildis skinning algorithm[4] the carpal bones of the wrist can be outlined and the whole system can be advanced to a whole palm fracture detection system. There will be irregularities like an extra bone or an abnormal growth those can also be detected by doing improvisation in this system.

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