COMPUTER ASSISTED DIAGNOSIS
OF CERVICAL SPINE FRACTURES IN
COMPUTED TOMOGRAPHY SCANS
OF TRAUMA PATIENTS

A review of current literature
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Abstract

Diagnosing cervical spine fractures is a time critical problem - with delays in diagnosis causing disastrous consequences such as lifetime quadriplegia. This review is written in preparation for a thesis detailing the creation and utility of what will be the world's first computer assisted diagnosis algorithm for computed tomography images of the cervical spine in trauma patients. This algorithm will be able to augment the speed of radiological interpretation by aiding radiologists in performing time consuming measurements, as well as acting as second reader system and triage system to identify problematic scans for urgent interpretation. This review is written in two parts, the first examining the medical need for such an algorithm, as well as different radiological signs that may be utilized by the algorithm. The second part is a narrative approach to the state of the art in computer diagnosis concerning spinal fractures and discusses potential computer vision techniques that may be applicable in this context. This review concludes that such an algorithm would be possible within the limits of current day technologies and should be able to run in near real time on consumer level hardware, and would likely be a great asset to the Emergency Radiology department.

Definitions

CT – Computed Tomography

C1-7 – First to seventh cervical vertebra

CT – Computed Tomography

ICU – Intensive Care Unit

MRI – Magnetic Resonance Imaging

NEXUS – National Emergency X-Radiography Utilization Study

RANSAC – Random Sample Consensus

Detection – The process of finding approximate locations of regions of interest within an image.

Segmentation – The process of delineating exactly regions of interest within an image

Recognition – The process of identifying uniquely different regions of interest within an image

Googol – One with a hundred zeroes behind it, namesake of Google Inc.
1 INTRODUCTION

Cervical spine trauma is a common injury in blunt trauma patients, and can be found in 2-6% of these patients. (Schoenwaelder et al. 2009) The most common mechanism of injury to the cervical spine is reported to be accidental falls, with motor vehicle accidents coming second. This experience may vary between centres.

Cervical spine trauma has many varying degrees, and can range from minor ligamentous injuries to frank cervical instability with cord injury. Minor cervical injuries may not require any treatment, and yet the consequences of untreated unstable cervical spine trauma can be disastrous, and delays in diagnosis can increase the risk of neurological deficit by 10-fold. (Reid et al. 1987)

Hence it is important to exclude cervical spine trauma rapidly in most trauma patients – a process known as clearing the cervical spine. Practically speaking, the cervical spine can be cleared either clinically or radiologically. Different sets of clinical criteria can be applied to clear the cervical spine, including the National Emergency X Radiography Utilization Study (NEXUS) low-risk criteria and the Canadian C-Spine rule. While each have their own merits, it is not within the scope of this review to analyse them. Both criteria are detailed in Table 1 and Figure 1.

However, prior to the clearance of the cervical spine, suspected injuries are usually immobilized with a cervical collar, which is not without its risks. One study found that leaving a cervical collar in situ significantly increased intracranial pressure, although the clinical significance of this was undetermined. (Hunt et al. 2001a) Other studies found a significant association between the length of time in a collar and the formation of decubitus ulcers, as well as other (Intensive Care Unit) ICU related complications such as aspiration and hypoxia. (Dunham et al. 2008a; Ackland et al. 2007)

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**Figure 1:** Canadian C-spine Rule, Adapted from (Stiell et al., 2003, fig. 1)

**Nexus Low-Risk Criteria (All criteria must be met)**

| **No posterior midline cervical spine tenderness** |
| **No evidence of intoxication** |
| **A normal level of alertness** |
| **No focal neurological deficit** |
| **No painful distracting injury** |

**Table 1:** NEXUS Low risk criteria, Adapted from (Stiell et al., 2003, Table 1)

In view of the urgency of this critical task, this project aims to support clinicians by developing an assistive computer program that can identify radiological signs on computed tomography (CT) scans of the cervical spine. Secondary aims of this project include validating the program’s accuracy as well as the sensitivity and specificity of selected radiological signs. This project will
be the first to produce a fully automated program that can interpret cervical CT scans.

This literature review of cervical spine trauma will encompass its epidemiology, consequences, management, and compare different radiographic modalities. This review will also cover different radiological signs used commonly in the diagnosis of cervical spine trauma. Furthermore, this review will examine the state of the art in computer assisted diagnosis, and introduce some of the common mathematical and computer science techniques that will be employed in the program.

2 CERVICAL SPINE ANATOMY

The cervical spine is a complex mechanical system comprising of bony vertebrae as well as disco-ligamentous structures. Due to the unique anatomy of the second (C2) and first (C1) cervical vertebra, the cervical spine is divided into the upper and lower cervical spine. The upper cervical spine spans the base of the occipital condyle to the inferior end-plate of C2. The lower cervical spine spans the superior end-plate of C3 till the inferior end-plate of C7.

The first cervical vertebra is also known as the atlas and contains several important features. Bony landmarks on C1 include the anterior and posterior arch, with the anterior arch replacing the normal vertebral body found in other vertebrae. There are two lateral masses which contain the superior articular facets which articulate with the occipital condyle, and the inferior articular facets which articulate with C2. The anterior arch also has a smooth depression on its inner surface, known as the fovea dentis, which articulates with the odontoid process of C2. The anatomy of the first cervical vertebra is demonstrated in Figure 2.

![Figure 2. Atlas, Adapted from (Donovan & Schweitzer, 2012, fig. 3.1a)](image)

The second cervical vertebra, also known as the dens, has several unique features. The most significant bony landmark of the dens is the odontoid process, which articulates with C1. The transverse ligament of C1 helps to maintain this articulation and is disrupted in atlanto-axial dislocation. The anatomy of the second cervical vertebra is demonstrated in Figure 3.

![Figure 3: Axis, Adapted from (Donovan & Schweitzer, 2012, fig. 3.1b)](image)

The remainder of the cervical vertebrae are similar and have the following features: a vertebral body forming the anterior section, and a posterior section comprising of the transverse processes, pedicles, superior and inferior articular facets, laminae, and a bifid spinous process. These features are demonstrated in Figure 4.
Each cervical vertebra articulates with the vertebrae above and below via the articular facets, with intervertebral discs separating the respective endplates of the vertebral bodies. The anatomy of the cervical vertebral column is demonstrated in Figure 5.

Fractures to C1 comprised mainly of anterior or posterior arch injuries (68.6%) with injuries to the lateral mass and facets only in 21.0% of C1 fractures. The remaining subaxial vertebrae were most likely to be fractured at the body or the spinous process, with these comprising of 30% and 20% of all subaxial fractures respectively. The most common dislocation or subluxation occurred however in the lower cervical spine at the C5-C6 level. (Goldberg et al. 2001) Table 3 and Table 4 show the total distributions of fractures, dislocations and subluxations by spinal level.

The need for urgency in clearing the cervical spine, or otherwise immobilizing the spine prior to clearance, is demonstrated by the resultant consequences. One study demonstrated that 10.5% of patients with delayed diagnoses of cervical spine fractures developed a subsequent secondary neurological injury, as compared to 1.4% of those who had their fractures identified on
A more recent study described neurological complications in 8 out of 11 patients with delayed diagnoses, ranging from motor and sensory deficits to complete quadriplegia. (Platzer et al. 2006)

<table>
<thead>
<tr>
<th></th>
<th>No. of fractures</th>
<th>% of all fractures</th>
</tr>
</thead>
<tbody>
<tr>
<td>Occipital condyle</td>
<td>20</td>
<td>1.67</td>
</tr>
<tr>
<td>C1</td>
<td>105</td>
<td>8.79</td>
</tr>
<tr>
<td>C2</td>
<td>286</td>
<td>23.93</td>
</tr>
<tr>
<td>C3</td>
<td>51</td>
<td>4.27</td>
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<td>C4</td>
<td>84</td>
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<tr>
<td>C5</td>
<td>179</td>
<td>14.98</td>
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<td>C6</td>
<td>242</td>
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<tr>
<td>C7</td>
<td>228</td>
<td>19.08</td>
</tr>
<tr>
<td>Total</td>
<td>1195</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Table 3: Distribution of fractures, Adapted from (Goldberg et al., 2001)

<table>
<thead>
<tr>
<th></th>
<th>No. of injuries</th>
<th>% of injuries</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlanto-occipital</td>
<td>5</td>
<td>2.16</td>
</tr>
<tr>
<td>C1-C2</td>
<td>23</td>
<td>9.96</td>
</tr>
<tr>
<td>C2-C3</td>
<td>21</td>
<td>9.09</td>
</tr>
<tr>
<td>C3-C4</td>
<td>23</td>
<td>9.96</td>
</tr>
<tr>
<td>C4-C5</td>
<td>38</td>
<td>16.45</td>
</tr>
<tr>
<td>C5-C6</td>
<td>58</td>
<td>25.11</td>
</tr>
<tr>
<td>C6-C7</td>
<td>51</td>
<td>23.37</td>
</tr>
<tr>
<td>C7-T1</td>
<td>9</td>
<td>3.90</td>
</tr>
<tr>
<td>Total</td>
<td>231</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Table 4: Distribution of dislocations and subluxations, Adapted from (Goldberg et al., 2001)

Prolonged cervical spinal immobilization of the patient can also lead to undesired consequences, such as increased intracranial pressure (Hunt et al. 2001b), ICU-related complications (Dunham et al. 2008b; Stelfox et al. 2007), thrombosis as well as pressure sores and decubitus ulcers (Cooper & Ackland 2005). A mean rise of 4.6 mmHg was demonstrated in patients with traumatic head injury with a rigid cervical collar, which was a significant rise from the baseline intracranial pressure. The authors postulated that venous congestion might be the aetiology behind this, and while there were no clinically significant outcomes followed in the study, prompt clearance of the spine would likely help in the management of patients with prior intracranial hypertension. (Hunt et al. 2001b)

ICU related complications such as delirium and ventilator associated pneumonia were also increased with prolonged cervical collar use. A prospective trial identified that patients who underwent MRI scanning as opposed to CT only experienced on average 4 days more of spinal immobilization, which led to an absolute risk increase of 22% and 14% of delirium and ventilator associated pneumonia respectively. (Stelfox et al. 2007)

A retrospective review done at the National Trauma Research Institute in Melbourne, Australia identified that the major risk factor for collar-related ulceration was time to clearance, and for every extra day, the risk of collar related ulceration increased by 66%

Hence, in view of the consequences of prolonged spinal immobilization and delayed diagnoses of cervical spine fractures, there is a strong imperative for clearing the cervical spine as quickly as possible, clinically or radiologically.

4 Radiological modalities

4.1 X-rays

Prior to the development of CT and MRI scans, 3 – 5 view cervical spine X-ray series were used to radiologically clear the cervical spine. With the
publication of the NEXUS clinical criteria in 2000, this practice became commonplace in many institutions. (Bailitz et al. 2009) However, with recent studies showing the lack of sensitivity of even 5-view cervical X-ray series, many centres have begun shifting to CTs as a primary screening modality. (Griffen et al. 2003; Diaz et al. 2003; Mathen et al. 2007; Holmes & Akkinepalli 2005)

While the original NEXUS study reported a sensitivity of 89% with combined clinical and X-ray clearance, subsequent studies have reported sensitivities of between 44%-74% as compared to CT scans, and hence most high risk populations are now screened using CT rather than cervical spine X-ray.

4.2 COMPUTED TOMOGRAPHY (CT)

The superiority of CT scanning over radiographs has been established since 1985 (Mace 1985), and limited CT examination when radiographs cannot adequately demonstrate the entire cervical spine has been suggested since 1987 (Acheson et al. 1987). However, cost and radiation dose concerns limited its use until recently when prospective studies established its superiority as a routine screening modality over cervical spine X-ray. (Ajani et al. 1998)

In patients who fail clinical clearance but are not obtunded, many studies have demonstrated that CT cervical spine has a sensitivity of between 95-100% for significant cervical spine injury. (Como et al. 2009; Holmes & Akkinepalli 2005; Daffner & Hackney 2007; Mathen et al. 2007; Berne et al. 1999)

However, in unconscious patients, there are conflicting views as to whether CT alone is sufficient or if routine Magnetic Resonance Imaging (MRI) is required. Several studies have demonstrated that even in obtunded patients CT scanning does not miss any clinically significant injuries. (Tomycz et al. 2008; Panczykowski et al. 2011; Schuster et al. 2005; Schoenwaelder et al. 2009)

On the other hand, several studies have demonstrated that routine MRI scanning can reveal injuries which were not detected on CT scans. (Fisher et al. 2013; Menaker et al. 2008; Sarani et al. 2007) However, most of these injuries are ligamentous, and it appears that the major difference between these studies is the consideration of which injuries are clinically significant. A common definition adopted in most retrospective studies is the need for further intervention – however this is also subject to local practice variation.

Most studies which show that CT scanning is sufficient, adopt the Denis classification for unstable spine injuries, and require two adjacent spinal columns to be disrupted for an injury to be considered unstable. (Schoenwaelder et al. 2009)

However, studies which favour MRI scanning add on other criteria, and consider single ligamentous injuries as significant and requiring intervention. (Hoffman et al. 2000). One study did find two out of 254 patients with multicolumn ligamentous injuries that were undetected on CT, but also considered cord injury, fracture, disc herniation dislocation, and single column ligamentous injuries to be significant, and included these other injuries in their analysis. (Sarani et al. 2007)

Other considerations in using routine CT scanning to radiologically clear the cervical spine include the slice thickness and resolution. One study managed to
demonstrate that 3mm slice axial images were non inferior to 1mm slice images when multiplanar reformats were provided. (Phal et al. 2008) This is encouraging as data with 0.3mm thick slices are not kept at the hospital that this project will be performed at, and performing this project on finely sliced data would require the collection of prospective data. The non-inferiority of 3mm slice axial images allows for the use of retrospective data which will vastly increase the available sample size as scans can be retrieved from over the last 15 years.

4.3 Magnetic Resonance Imaging (MRI)

As mentioned before, routine MRI has been proposed for the clearance of cervical spine in high risk, obtunded patients. While MRI scanning may detect ligamentous injuries that CT may not, the significance of these injuries are debatable. A study comparing MRI positive ligamentous injuries to results from subsequent dynamic flexion-extension X-rays found that all 70 MRI positive injuries in that study that were not detected on CT were stable, even after 23 of them had undergone flexion-extension X-ray. (Horn et al. 2004)

Furthermore, one study which examined patients who underwent MRI clearance protocol versus a CT clearance protocol identified that MRI patients on average spent 6 days in a collar as opposed to 2 days, required 4 days of mechanical ventilation instead of 3, and spent 6 days in the ICU as opposed to 4. (Stelfox et al. 2007)

Another study found that aspiration during MRI scanning occurred in 20.6% of high risk patients, including patients with hypotension, increased ICP, hypoxia or early ventilated associated pneumonia. The risk of secondary brain injury during transportation for MRI was also increased, with 14.6% of patients experiencing some form of secondary brain injury. (Dunham et al. 2008b)

In light of the good sensitivities of CT and the uncertainty about using routine MRI for screening cervical spine injuries, this literature review concludes that the most appropriate modality of choice to apply a computer assisted diagnosis algorithm to, would be CT scans with a slice thickness of 3mm or less. This modality would enable the algorithm to have the highest clinical utility due to its high sensitivities and specificities, as well as the widespread utilization of this modality in trauma settings.
5  **RADILOGICAL SIGNS AND MEASUREMENTS ON CT RELATING TO CERVICAL SPINE INJURY**

Many different radiological signs and measurements have been developed to aid the radiologist in identifying cervical spine pathology. These measurements are not routinely taken by radiologists as there are many different types and it would be time consuming to take them all. While most of these measurements were performed on X-rays, it is the intent of this project to take these measurements on CT scans to identify their respective utilities. This literature review will not identify all the different radiological signs and measurements, but rather discuss some of them which would be easier to implement in a computer assisted diagnosis algorithm.

5.1  **UPPER CERVICAL SPINE**

In the upper cervical spine, atlanto-occipital dislocation or occipitocervical dissociation is measured by multiple methods, including the Power’s Ratio (Powers et al. 1979), basion-dens interval and basion axial interval (Harris et al. 1994), condylar-C1 interval (Pang et al. 2007), Lee’s X lines (Lee et al. 1986) and Wackenheim’s line (Wackenheim 1974).

5.1.1  **Powers’ Ratio**

Powers’ ratio is the ratio between the line BD / AC as depicted in Figure 6 where A is the anterior arch of C1, B the basion, C the opisthion and D the posterior arch of C1. The original study by Powers described the mean value as 0.77±0.09, and that a ratio greater than 1.0 would be indicative of atlanto-occipital dislocation. (Powers et al. 1979) However, the original work was performed on X-rays rather than CTs, and may have differing normal ranges on CTs.

![Figure 6: Power’s Ratio](image)

5.1.2  **Basion-dens interval and basion-axial interval.**

The distance between the basion and the rostral tip of the dens is defined as the basion-dens interval. The posterior axial line as shown in Figure 7 as the line CD, is the rostral extension of the posterior cortex of the dens. The shortest distance BC from the basion to the posterior axial line is the basion-axial interval. The original study by Harris measured these intervals in normal subjects and concluded that the basion-axial interval did not exceed 12mm in 98% of subjects and that the basion-dens interval was within 12mm for 95% of subjects, and concluded that a basion-dens interval or basion-axial interval larger than 12mm is abnormal. However, the original work was also performed on X-rays rather than CTs, and may have differing normal ranges on CTs.
5.1.3 Condylar-C1 interval

The condylar-C1 gap is measured from the average of 4 equidistant points in the condylar-C1 joint interval. This can be measured on a sagittal or coronal reformat. A condylar-C1 interval larger than 4mm is considered to be abnormal. This method of measurement is detailed in Figure 8. According to the original study, which was performed on CT scans, this measurement is 100% sensitive and specific, although their population was small, with 16 positive cases and 10 negative cases.

5.1.4 Lee’s X lines

Lee’s X lines consists of two lines, as shown in Figure 9, between the basion and the anterior aspect of the posterior ring of C2 (BD) and between the posteroinferior edge of the body of C2 and the opisthion (AC). The first line BD should pass across the posterosuperior aspect of the dens and the second line should pass just anterior to the posterior ring of C1. If both lines are displaced from their reference positions, atlanto-occipital dislocation is considered to be present. The original study concluded that this method had a sensitivity of 75%, which was superior to the Powers’ ratio and basion-dens interval in their cohort which had sensitivities of 50% and 33% respectively. (Lee et al. 1986) However, like many previous measurements, the original work was performed on X-rays rather than CTs, and may have differing sensitivities on CTs.

5.1.5 Wackenheim’s line

Wackenheim’s line is simply a line tangential to the clivus which should tangentially intersect the posterosuperior aspect of the dens, as demonstrated in Figure 10. (Wackenheim 1974) Although not in the trauma patient, one study reported the sensitivity of Wackenheim’s line in detecting atlanto-occipital
dislocation as 88% in rheumatoid patients. (Riew et al. 2001)

5.1.6 Atlanto-dens instability

Another common measurement in the upper cervical spine is the atlanto-dens interval. The anterior atlanto-dens interval is the shortest distance between anterior arch of C1 and C2 on a sagittal reformat, as demonstrated by line AB in Figure 11. The posterior atlanto-dens interval is the distance between the posterior arch of C1 and C2, as demonstrated by line CD. An anterior atlanto-dens interval of larger than 3mm is considered abnormal. The posterior atlanto-dens interval has been examined in rheumatoid patients as a prognosticator but not in trauma patients. (Bono et al. 2007; Torretti & Sengupta 2007)

5.2 LOWER CERVICAL SPINE

In the lower cervical spine, pathology can be classified in various ways but this review will use the Allen and Ferguson classification, dividing injuries by their ‘injury vectors’, which can be thought of as the direction of force applied to cause the injury. (Allen et al. 1982)

5.2.1 Vertebral Height

One type of injury resulting from the vertical compression injury vector is the vertebral compression fracture. One study proposed that anterior vertebral height as a ratio of vertebral width might be useful for the detection of vertebral compression fractures, and calculated a set of reference ranges from lateral radiographs of 100 females and 36 male adults. (Frobin et al. 2002a) The measurement used in this study can be seen as the length of the line AB divided by the average of line AC and BD in Figure 12. The reference ranges calculated in this study can be seen in Table 5. However, as these reference ranges are calculated from lateral radiographs, measurements may differ in the sagittal CT reformats, which may necessitate recalculation of new reference ranges.
Vertebral body height, Female (SD in parentheses) | Vertebral body height, Male (SD in parentheses)
--- | ---
C3 | 0.935 (0.114) | 0.911 (0.093)
C4 | 0.883 (0.094) | 0.844 (0.079)
C5 | 0.845 (0.093) | 0.812 (0.074)
C6 | 0.834 (0.088) | 0.846 (0.085)
C7 | 0.909 (0.104) | 0.923 (0.073)

Table 5: Reference ranges for vertebral height, Adapted from (Frobin et al. 2002)

5.2.2 Disc space widening

Another injury in the Allen and Ferguson classification is the disruption of the anterior longitudinal ligament and disc from distractive extension, resulting in the widening of the disc space. (Allen et al. 1982) The previous study also measured normal anterior disc heights by measuring the corrected anterior disc height and dividing it by the mean depth of the caudal vertebra. (Frobin et al. 2002b) Angle correction was undertaken to account for different postures of the cervical spine, and was performed via the formula below:

\[
\text{Disc Height}_{\text{corrected}} = \frac{\text{Anterior Disc Height}_{\text{uncorrected}}}{S(\alpha - \alpha_{\text{standard}})}
\]

Where S and \(\alpha_{\text{standard}}\) are empirically determined values. \(\text{Anterior Disc Height}_{\text{uncorrected}}\) was measured by the ratio of the disc height to the depth of the caudal vertebra, as described by lines EF and FG respectively in Figure 13. S is the slope of disc height vs. sagittal plane angle \(\alpha\), as that study determined that disc height varied linearly with \(\alpha\). \(\alpha\) is measured as the angle between two adjacent vertebral mid-planes, as demonstrated by the angle between lines AB and CD on Figure 13.

\[
\alpha_{\text{standard}} \text{ is the average of the sagittal plane angles in the normal population. For each vertebral level, S and } \alpha_{\text{standard}} \text{ are recalculated. The reference ranges for } \alpha_{\text{standard}} \text{ and S are detailed in Table 6 and Table 7 respectively.}
\]

<table>
<thead>
<tr>
<th>Angle (°), Female (SD in parentheses)</th>
<th>Angle (°), Male (SD in parentheses)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C2/C3</td>
<td>9.5 (4.6)</td>
</tr>
<tr>
<td>C3/C4</td>
<td>9.4 (4.4)</td>
</tr>
<tr>
<td>C4/C5</td>
<td>9.4 (4.1)</td>
</tr>
<tr>
<td>C5/C6</td>
<td>10.6 (5.3)</td>
</tr>
<tr>
<td>C6/C7</td>
<td>6.2 (7.4)</td>
</tr>
</tbody>
</table>

Table 6: Sagittal Plane Angles, Adapted from (Frobin et al. 2002)
5.3 OTHER MEASUREMENTS

Studies done on cadaveric samples have also suggested that an anterolisthesis distance of more than 3.5mm or more than 11 degrees of rotational difference between adjacent vertebrae should be considered unstable—a hypothesis which can be tested within the framework of this project. (White et al. 1975)

Another common radiological sign used to identify cervical spine pathology is pre-vertebral thickness. First used in lateral radiographs, it has also been adapted to sagittal CT reformats, although some of the reference values differ. (Rojas et al. 2009) The pre-vertebral thickness at each vertebral level is the shortest distance between the mid anterior point on each vertebral body (excluding C2, which is measured from the mid-anterior point excluding the dens) and the air column. This method is demonstrated in Figure 14.

<table>
<thead>
<tr>
<th></th>
<th>S (deg⁻¹), Female (SD in parentheses)</th>
<th>S (deg⁻¹), Male (SD in parentheses)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C2/C3</td>
<td>0.00971 (0.00307)</td>
<td>0.00955 (0.00218)</td>
</tr>
<tr>
<td>C3/C4</td>
<td>0.00989 (0.00176)</td>
<td>0.00989 (0.00298)</td>
</tr>
<tr>
<td>C4/C5</td>
<td>0.00979 (0.00185)</td>
<td>0.00968 (0.00164)</td>
</tr>
<tr>
<td>C5/C6</td>
<td>0.00983 (0.00166)</td>
<td>0.00969 (0.00190)</td>
</tr>
<tr>
<td>C6/C7</td>
<td>0.00981 (0.00230)</td>
<td>0.00890 (0.00200)</td>
</tr>
</tbody>
</table>

Table 7: S, Adapted from (Frobin et al. 2002)

Figure 14: Pre-vertebral thickness

With this method, one study found that pre-vertebral thickness had a large variability at the C4-5 level. The upper limits of normal for the other levels were calculated as 2 SDs above the mean, the results of which are displayed in Table 8.

<table>
<thead>
<tr>
<th></th>
<th>MEAN PRE-VERTEBRA THICKNESS (MM) (RANGE IN PARENTHESIS)</th>
<th>UPPER LIMITS OF PRE-VERTEBRAL THICKNESS (MM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>4.4 (1.5-11)</td>
<td>8.5</td>
</tr>
<tr>
<td>C2</td>
<td>3.7 (1.5-8.5)</td>
<td>6</td>
</tr>
<tr>
<td>C3</td>
<td>4.2 (2-9.5)</td>
<td>7</td>
</tr>
<tr>
<td>C4</td>
<td>7 (2.5-16)</td>
<td>NA</td>
</tr>
<tr>
<td>C5</td>
<td>12.4 (5-20)</td>
<td>NA</td>
</tr>
<tr>
<td>C6</td>
<td>13 (5.5-24)</td>
<td>18</td>
</tr>
<tr>
<td>C7</td>
<td>11.6 (2.5-21)</td>
<td>18</td>
</tr>
</tbody>
</table>

Table 8: Pre-vertebral thickness, Adapted from (Rojas et al. 2009)
6 CERVICAL SPINE PATHOLOGY COMMANLY MISSED ON CT

While CT is commonly accepted as sufficient for radiologically clearing the cervical spine – several studies, as mentioned earlier, have identified pathologies that were not picked up by CT, but were detected on MRI. The significance of these injuries are debatable, as different trauma centres have different thresholds for treating cervical injuries.

In one study with 8902 total trauma patients, 18 patients, out of 743 patients who had both a cervical spine CT and cervical spine MRI, had abnormal MRI findings, 14 of which required collar interventions, and 2 which required operative intervention. (Menaker et al. 2008) Injuries in this study are detailed in Table 9. Note that each patient may have had more than one ligamentous injury.

<table>
<thead>
<tr>
<th>INJURY TYPE</th>
<th>NUMBER</th>
</tr>
</thead>
<tbody>
<tr>
<td>Posterior longitudinal ligament</td>
<td>2</td>
</tr>
<tr>
<td>strain/rupture</td>
<td></td>
</tr>
<tr>
<td>Anterior longitudinal ligament</td>
<td>2</td>
</tr>
<tr>
<td>strain/rupture</td>
<td></td>
</tr>
<tr>
<td>Ligamentum flavum tear</td>
<td>6</td>
</tr>
<tr>
<td>Interspinous ligament strain</td>
<td>5</td>
</tr>
<tr>
<td>Supraspinous ligament strain</td>
<td>2</td>
</tr>
<tr>
<td>Cord contusion</td>
<td>5</td>
</tr>
<tr>
<td>Prevertebral oedema (injury not</td>
<td>1</td>
</tr>
<tr>
<td>specified)</td>
<td></td>
</tr>
</tbody>
</table>

Table 9: Injuries missed on CT, Adapted from (Menaker et al. 2008b)

In another study, 13 patients out of 277 obtunded blunt trauma patients with both a CT and MRI scan had clinically significant cervical spine injuries that were missed by CT scans – 7 of which required intervention. (Fisher et al. 2013) Some of these patients had multiple injuries detected on MRI. Yet another study found that 42 out of 164 obtunded blunt trauma patients with a normal CT scan had a further injuries, 31 of which had a change in management. (Sarani et al. 2007)

It is interesting to note that most of the injuries are ligamentous or soft tissue in nature, indicating that CT is sensitive for bony injuries, and that a computer assisted diagnosis system should focus on ligamentous injuries, which may augment human interpretation of the CT scan and reduce the rates of missed diagnosis.

7 THE CURRENT STATE-OF-THE-ART

To date, there are no cervical spine specific systems described in the literature, which provide quantitative anatomical measurements or computer assisted diagnosis.

Within the grey literature, there are two grants for two computer-assisted diagnosis systems, one for the interpretation of lateral X-rays and one for flexion-extension X-rays. A recent 2013 grant is for the development of computer assisted diagnosis software in the emergency setting, and is meant to act as a second-reader system. This system is meant to produce alignment curves, helping to focus the clinician on regions of interest that may be problematic. (Slabaugh 2014)

Another grant, given in 2004, concerns the tracking of features such as spinous processes, vertebral corners, and occipital bones on dynamic flexion-extension x-rays. While not specifically focusing on emergency or trauma
patients, this system has now matured as a research tool and has been used for analysing implants as well as generating reference standards in normal patients. (Hipp & Lamp 2004)

Within the computer science literature, several publications have produced completely automated algorithms to partition pixels in 3D or 2D data into segments which represent different objects of interest, such as vertebrae, spinal cord, or other structures. This process is widely referred to as segmentation in the literature.

In 2009, a paper described the use of Haar cascades to detect vertebrae positions as well as approximate bounding boxes on 2D sagittal MRI slices. (Huang et al. 2009) This process is widely referred to as ‘object detection’ in the literature.

The method of Haar cascades, also referred to as the Viola-Jones object detection framework, is a method for the detection of faces by cameras. (Viola & Jones 2001) This method was the first sufficiently accurate and robust method that ran in real time (at fifteen frames per second), on consumer level hardware. It has since been adopted in many other computer vision problems.

The paper then proceeds to describe the use of Random Sample Consensus (RANSAC) to select likely locations of vertebrae while rejecting outliers, by fitting a curve to these locations and dropping outliers from the curve.

To further extract the contours of each vertebrae, a segmentation approach using iterative graph cuts was employed. Graph cuts are a widely employed method in computer vision to solve problems such as separating foreground from background, and rely on the fact that foreground pixels vary in intensity from background pixels.

Using these methods the group was able to detect 98% of vertebrae and segment 96% of them successfully, without any false positives. While this system is not cervical spine specific, they managed to identify 46 out of 47 cervical vertebrae. The specifics of the methods used by these authors will be discussed later in the literature review.

In the same year, another group used a different approach to segment 3D CT data. (Klinder et al. 2009) A generalised 3D Hough Transform was used to locate a seed point within the spinal cord, and a progressive tubelet adaptation was used to segment the spinal cord in 3D. A generalised Hough Transform is a method adapted from the specific Hough Transform which is used for object detection of circles and lines in an image – a generalised Hough Transform is used for more complex objects. Their method was applied to CT scans with varying slice thicknesses, between 0.5-3.0mm.

Using the spinal cord’s curvature, they then reformat the scan such that all the vertebrae are vertically aligned, a technique known as curved planar reformation. A 3D generalised Hough Transform was then used for the detection of vertebrae. Vertebrae are then identified by comparing the appearance of the 3D data block around each proposed vertebrae location to a mean vertebrae model constructed from normal prior data.

Vertebrae segmentation is achieved using a shape-constrained deformable mesh approach – an adaptation of the active shape model segmentation method used in 2D images. This approach works by first
superimposing an initial guess upon the 3D data. The initial guess is a scale and translation adjusted version of the mean vertebra model for that identified vertebra. A feature function derived from the image gradient is evaluated at every point in 3D space – points with a greater change in image intensity from their neighbours have a higher feature response. The initial guess is then iteratively deformed to maximize the total feature response of the 3D contour while minimizing the difference from the original guess.

Multi-object segmentation is also attempted in this paper, an approach which iteratively deforms the mesh model for each vertebra simultaneously, while also penalizing collisions with other meshes. This approach reduces the number of overlapping vertebral mesh models, and especially in patients with degenerative disease and tight intervertebral spaces, and increases the detection rate.

With this method, they successfully detected vertebrae in 59 out of 64 data sets – meaning that for each vertebra in the image they had a candidate location within the 3D vertebral model marked as the ground truth.

However, they did comment that within the head and neck region, especially in patients with calcified intervertebral discs and degenerative disc disease, detection was more unreliable, detecting 15 out of 18 cervical scans.

Their segmentation accuracy was calculated by first finding the shortest distance between each point on their segmented mesh to the ground truth mesh, and subsequently averaging it out over the entire mesh. Their final mean error for the entire system was 1.12 ± 1.04mm across all images.

In 2012, another group utilized a technique known as iterative marginal space learning, using Haar-like features, but applying them in 3D rather than 2D. (Kelm et al. 2012) This method was applied to T1-weighted MRI sequences, as well as CT reformats with a slice thickness of 3.0mm.

Iterative marginal space learning is a heuristic method that reduces the computation time by first ignoring orientation and scale, and only considering position as a possible parameter. After locating possible position candidates of vertebrae, the algorithm considers different orientations for each position, and then different scales for each of those orientations. This is opposed to the exhaustive search method which considers different orientations and scales for every possible position, which is not computationally feasible.

This method is used to identify the position, orientation and scale of the spinal discs. Vertebral positions and scale were estimated from this and accurate segmentation was achieved using the graph cuts framework. Using this method, 98% of spinal discs were detected on CT. An average position error of 3.22mm and an average angular error of 4.47° was obtained. However, their CT dataset did not include cervical spine vertebrae.

While not a complete representation of all spine detection techniques in the computer vision literature, the above is a summary of techniques that the author believes will be relevant to the fully automated segmentation of the cervical spine in CT scans with a slice thickness of 3mm of more.
This survey of the literature indicates that segmentation of the cervical spine is possible within current day technologies and has been achieved at near real-time speeds with consumer level hardware, while retaining precision sufficient for detailed measurements. As none of these systems provide any diagnostic support, this review also indicates the lack of computer aided diagnosis systems in current use for CT scans of the cervical spine.

8 POSSIBLE COMPUTATIONAL APPROACHES

This section of the literature review will now examine in depth some of the techniques used by earlier papers and also introduce new techniques that may be useful in the project.

To start, the different steps in a theoretical framework will be introduced. The first step in any framework is pre-filtering, the pre-processing of images to remove noise or other unwanted artefacts. An example of this step is the conversion of colour images into grayscale images for processing.

This step is followed by object detection, where features or objects of interest are approximately located, possibly along with scale and orientation information. An example of this step is the location of faces in a picture. This step may be followed a filtering step where additional information such as the total number of objects or their position relative to other objects is utilized to remove false positives.

Next is object recognition, where detected objects are assigned a unique value. An example of this step would be to identify the faces in the aforementioned step and assigning names to each face.

Following this is object segmentation, where the exact region of interest or contours are drawn and extracted.

Analysis of the extracted regions of interest is the next step, where more advanced techniques such as machine learning techniques can be utilized to classify regions of interest into abnormal or normal. Analysis also includes the relations between each region of interest, for instance the measurement of distances between separate vertebrae. Figure 15 shows each step and its resultant effects on each image.

![Figure 15: Block diagram of framework](image)

8.1 PRE-FILTERING

8.1.1 Thresholding

A common pre-filtering operation is thresholding. Thresholding is the simple operation of setting all pixels in an image below a cut-off value to 0, and any above that threshold to the maximum value, which is traditionally 255 on an 8-bit image.
Other forms of thresholding include threshold-to-zero, where pixels below the threshold are set to 0 and pixels above that threshold are kept as they are. The following equations describe the respective mathematical operations for binary thresholding and threshold-to-zero.

**Binary thresholding:**

\[
T_{i,j} = \begin{cases} 
M & \text{if } I_{i,j} > \alpha \\
0 & \text{if } I_{i,j} \leq \alpha 
\end{cases}
\]

**Threshold - to - zero:**

\[
T_{i,j} = \begin{cases} 
I_{i,j} & \text{if } I_{i,j} > \alpha \\
0 & \text{if } I_{i,j} \leq \alpha 
\end{cases}
\]

Where \(T_{i,j}\) is the thresholded pixel value at coordinates \(i,j\), \(M\) the maximum value supported by the image format, \(I_{i,j}\) the original pixel value at coordinates \(i,j\), and \(\alpha\) the cut-off value.

The idea of thresholding is particularly suited for the removal of soft-tissue and lower densities on a multi-detector CT scan – as the radiodensity of a particular tissue type as measured in Hounsfield units remains constant across different positions in the image, unlike in a cone beam CT scan. By removing all pixels lower than a Hounsfield unit of 500 or so, we can isolate bone pixels which are of interest in this project. (Brooks 1977)

### 8.1.2 Morphological operations

Morphological operations are a class of functions that operate on multidimensional arrays. The most basic morphological operations are dilation and erosion.

An easy way to understand dilation is to imagine text. Applying a dilation operator to written text makes the image look as if it was written with a thicker pen-tip.

To perform dilation and erosion, one must first define a structuring element. This structuring element can be any shape but is most often a cross, circle or a square.

Dilation can be understood as the union of all the pixels covered by the structuring element as the centre of the structuring element moves around the foreground of the image. Erosion is the locus of the centres of all possible locations of the structuring element while the structuring element is still contained entirely within the foreground.

In Figure 16, the left red rounded square represents the dilation of the grey square by the structuring element defined by the red circle. The right blue square represents the erosion of the grey square.

**Figure 16:Dilation and erosion**

These mathematical operators can be defined as:

**Erosion:**

\[
A \ominus B = \{ z \in E \mid B_z \subseteq A \}
\]

**Dilation:**

\[
A \oplus B = \bigcup_{b \in B} A_b
\]

Where \(A\) is a binary image defined on a 2D space \(E\) and \(B\) is the structuring element. \(z\) and \(b\) are 2D coordinates that are used as variables in the calculations.

These operators are used to construct other operators such as opening and closing. Opening is defined as an erosion operation followed by a dilation operation, as defined by:

\[
A \circ B = (A \ominus B) \oplus B
\]

Closing is defined by dilation followed by erosion:

\[
A \cdot B = (A \oplus B) \ominus B
\]
These operators are useful for removing noise. The results of opening and closing are shown in Figure 17 and Figure 18 respectively.

Figure 17: Opening, adapted from (Bradski 2014)

Figure 18: Closing, adapted from (Bradski 2014)

8.2 OBJECT DETECTION

8.2.1 Template matching

The simplest object detection method is template matching. Template matching simply compares a template of the image to every location on the image, and attempts to detect the locations which are most similar. Template matching works well for rigid objects that only undergo translation (for instance finding printed letters on a page), but is less successful in finding objects that undergo other transformations such as stretching, rotation, or deformation.

There are many methods used to compare the template to the target image, but this literature review will only discuss one of the simplest and most commonly used methods, the Sum of Absolute Differences (SAD).

\[
S_{x,y} = \sum_{i}^{T_{rows}} \sum_{j}^{T_{columns}} |T_{i,j} - I_{x+i,y+j}|
\]

Where \(S_{x,y}\) represents the similarity of the target image to the template at coordinate \(x,y\), \(T_{i,j}\) represents the intensity of pixel \(i,j\) on the template \(T\), and \(I_{x,y}\) represents the intensity of pixel \(x,y\) on the image \(I\).

An example of this operation can be seen in Figure 20 where this method is applied to Figure 19, with the template in the top left corner.

Figure 19: Example image with template of C2

Figure 20: Similarity map

As evident in Figure 20, the brightest point in the similarity map corresponds to the expected location of the C2 vertebrae on the sagittal reformat as an averaged version of C2 is used as the template.
8.2.2 Viola Jones object detection framework

A more robust framework for the detection of objects is the Viola-Jones object detection framework, first proposed for face detection. (Viola & Jones 2001)

Now commonplace in cameras and smartphones, this algorithm evaluates 2D images by calculating the value of Haar-like features in the image. The four basic Haar-like features used in the Viola-Jones framework are described in Figure 21:

![Figure 21: Haar-like features, Adapted from (Viola & Jones 2001)](image)

These features can be stretched horizontally or vertically, and can be repositioned to any pixel in the image. The value of any given feature is calculated by the sum of the pixels in the shaded area minus the sum of the pixels in the unshaded area.

As no single feature has enough discriminative power to identify the presence or absence of an object in a window, the Viola-Jones object detection framework employs a meta-algorithm known as Adaptive Boosting to select the best features.

This meta-algorithm is utilized as exhaustively searching the feature space is computationally impractical – a single 24 by 24 pixel image has over 162336 features, constructing a cascade of 20 features would mean evaluating 162336^{20} = 1.6 \times 10^{104} or over 16000 googol (1 with a hundred trailing zeroes) combinations.

In this meta-algorithm, a set of positive samples containing the target object and a set of negative samples from the expected environment around the target object are supplied. The steps for the meta-algorithm are as follows:

Given that \((x_i, y_i)\) where \(x\) is an image

and \(y_i = \begin{cases} 1 & \text{if positive sample} \\ 0 & \text{if negative sample} \end{cases}\)

1. Initialize weights \(w_{1,i} = \begin{cases} \frac{1}{2m} & \text{if } y_i = 0 \\ \frac{1}{2l} & \text{if } y_i = 1 \end{cases}\)

Where \(m\) and \(l\) are the number of negative and positive samples respectively

For \(t = 1 \ldots T\) where \(T\) is the maximum number of stages

2. Normalize \(w_{t,i} \leftarrow \frac{w_{t,i}}{\sum_{j=1}^{m+l} w_{t,j}}\)

3. For each feature \(j\), find a classifier \(h\), where \(h_j(x) = \begin{cases} 1 & \text{if } p_j(x) < p_j \theta_j \\ 0 & \text{otherwise} \end{cases}\) by finding \(p_j\) from the set \(\{0, 1\}\) and \(\theta_j\) from the set \(\mathbb{R}\) such that \(e_j = \sum_i w_i|h_j(x_i) - y_i|\) is minimized

4. Choose a classifier \(h_t\) for stage \(t\) with the lowest \(e_t\)

5. Update weights \(w_{t+1,i} = w_{t,i} \beta_t^{1-e_t}\) where \(e_t = \begin{cases} 0 & \text{if } x_i \text{ is classified correctly} \\ 1 & \text{if otherwise} \end{cases}\)

and \(\beta_t = \frac{e_t}{1 - e_t}\)

After \(T\) stages the final classifier is:
With a sufficiently large, well-chosen training set, this detector should perform well upon sagittal CT reformats in detecting C3-C7 vertebral bodies. While it may take a while to train the final classifier, once trained, this classifier should be able to work in real time at rates of 15 frames per second.

8.3 OBJECT CONFIRMATION AND RECOGNITION

8.3.1 Random Sample Consensus

Random Sample Consensus or RANSAC is a method used for fitting a line stochastically to data, by randomly selecting subsets of data points. RANSAC works as follows:

1. Assume a line described by parameters $x_i$ can be fitted from $N$ points e.g. for a cubic polynomial $N \geq 4$
2. Select $N$ data points at random
3. Estimate parameters $x_i$
4. Calculate total number of inlier data points given a user – defined threshold If sufficient points are inliers, exit
5. Repeat 1.4 * $L$ times
   
   where $L = \frac{\log p_{\text{fail}}}{\log (1 - (p_g)^N)}$,
   
   $p_{\text{fail}}$ is the user – defined accepted probability of the algorithm failing and $p_g$ the signal to noise ratio

Equations adapted from (Fischler & Bolles 1981)

This method is useful for identifying lines in noisy images as it ignores outliers and runs within a reasonable time limit given a high enough signal to noise ratio. Hence, this method can be used to exclude outlying suggested vertebra locations to decrease the number of false positives.

Figure 22 demonstrates an example of using RANSAC to fit a polynomial of degree 1 (a line) to some noisy data. This produces the red line which ignores outliers, unlike linear regression (green line), which is deflected by these outliers.

8.3.2 Principal component analysis

Principal component analysis is a method of representing a vector of values as a linear combination of basis vectors, otherwise known as principal components, and was first described by Pearson in 1901. (Pearson 1901)

While it is not within the scope of this review to cover all the different methods of calculating principal components, this review will cover the basic principles

$$ h(x) = \begin{cases} 
1 & \text{if } \sum_{t=1}^{T} \log \frac{1}{\beta_t} h_t(x) \geq \frac{1}{2} \sum_{t}^{T} \log \frac{1}{\beta_t} \\
0 & \text{if otherwise}
\end{cases} $$

Equations adapted from (Viola & Jones 2001)
and applications of principal component analysis to object recognition.

Assume a matrix \( X \)
where each row represents an image
and each column represents a pixel on that image.

The first principal component \( w_1 \)
is the unit vector \( w \) that maximizes:

\[
\sum_i \left( x_i \cdot w \right)^2
\]

The \( k^{th} \) component is \( w_k \) which maximizes:

\[
\sum_i \left( X_{k-1} \cdot w_k \right)^2
\]

where \( X_{k-1} = X - \sum_{i=1}^{k-1} X w_i w_i^T \)

With these components, we can find out how much of an image is composed by each component by projecting the image onto each component. An example from the face recognition literature is as such:

Given a set of faces in Figure 23:

![Figure 23: Face set, Adapted from (Vision Lab 2012)](image)

We can calculate the principal components:

![Figure 24: Principal components, Adapted from (Vision Lab 2012)](image)

These components can be used to identify a face:

![Figure 25: Projection, Adapted from (Vision Lab 2012)](image)

These components can also calculate the distance in ‘face space’ between two faces, which is simply the normalized difference of the coefficients of each principal component of each face. This distance effectively tells us how similar one face is to another.

Using this technique, we can identify vertebrae by calculating how similar they are to other vertebrae at different cervical levels.

8.4 SEGMENTATION

8.4.1 Graph cuts

Graph cuts are a method used to segment pixels into foreground and background pixels, given some prior knowledge. In this project, foreground pixels are pixels that are part of vertebrae or bone, and background pixels are other tissues. In prior work, graph cuts have been used to separate pixels indicating bone from soft-tissue or air densities accurately.
In this method, individual pixels are modelled as nodes in a graph, and each pixel is further connected to a foreground and a background node, depending on the \textit{a priori} estimate of how likely a pixel is to be foreground or background. Figure 26 demonstrates how these pixels are connected, with foreground pixels connected to the foreground node below and the background pixels to the background node above.

![Figure 26: Pixels as nodes on graph](image)

Each connection between the nodes are also weighted according to how similar each node is to its neighbours, as well as the background and foreground node. A cut through the graph is defined as the set of all the connections that have to be broken such that all pixels are either connected to the foreground or the background, but not both.

Assuming that the observed image is a distortion of an underlying ‘correct’ image with added noise, a core result in graph theory is that the cut that contains the smallest total weights in this configuration is the \textit{maximum a posteriori} estimate – or the most likely underlying image that would generate the observed image. (D Greig 1989)

The GrabCut method, is an adaptation of the graph cuts method using normalized cuts, where larger foreground and background segments are favoured. Furthermore, GrabCut automates the estimation of \textit{a priori} foreground and background probabilities. A bounding box is employed where every pixel outside the box is assigned a higher probability of being background, while pixels within the box are assigned a higher probability of being foreground. (Rother et al. 2004)

9 \hspace{1cm} \textbf{CONCLUSIONS}

This review of the current literature highlights the critical nature of cervical spine injuries and the urgency of clearing the cervical spine, with both over and under treatment of cervical spine injuries having possibly disastrous consequences.

As well as the controversies in the choice of screening modality used to exclude cervical spine injuries. Considering the relative strengths and differences of each modality, this review suggests that CT as a modality would be most suitable for computer assisted diagnosis due to its high sensitivities and specificities, as well as its status as a screening modality in high risk trauma centres.

Radiological signs and measurements that are feasible for a computer to interpret were discussed, along with their respective accuracies. As pathologies that were commonly missed upon CT were also mostly disco-
ligamentous, this review concluded that measurements between bony landmarks would be a useful starting point for computer assisted diagnosis. This system will also have the benefit of being able to calculate sensitivities and specificities for each measurement, which can be taken objectively.

Hence, given the state of the art and the success of various segmentation strategies used by different authors on both CT and MRI datasets, this review concludes that computer assisted diagnosis would be feasible within current day technologies, and would likely be able to contribute to the current radiological workflow by acting as a second reader and early triage system.

Word Count: 8090
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