TraumaSCAN: Assessing Penetrating Trauma with Geometric and Probabilistic Reasoning

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This paper presents TraumaSCAN, a prototype computer system for assessing the effects of penetrating trauma to the chest and abdomen. TraumaSCAN combines geometric reasoning about potentially injured anatomic structures with (probabilistic) diagnostic reasoning about the consequences of these injuries. We also present results obtained from testing TraumaSCAN retrospectively on 26 actual gunshot wound cases.

INTRODUCTION

Assessment of penetrating trauma requires knowledge of the relationships among human anatomy, physiology, and physical manifestations of injury. In medical practice, situations sometimes arise in treating penetrating trauma patients in which spatial relationships between different anatomical structures is not clearly understood, as the following case description illustrates [3]:

> A patient presented to the Emergency Center with a knife embedded in the right lower paraspinal chest and no other abnormal physical findings on examination. Anterior-posterior and lateral roentgenograms of the chest showed the tip of the knife just anterior to the seventh thoracic vertebra with the blade just to the right of the vertebra. The physicians caring for patient recognized that the descending aorta was anatomically too far to the left of the vertebral column to be injured, but were concerned enough about anatomical proximity to the esophagus to consider a contrast study of the esophagus. The availability of an atlas of cross sectional anatomy of the thorax at the T-7 level showed that the esophagus was also too far to the left at this level to be injured and the contrast study was not done based on this information. The knife was removed in the operating room and the patient was observed. He was treated for a delayed pneumothorax and recovered without further consequences.

The case description shows that an unnecessary diagnostic test was going to be ordered as a result of the physicians' uncertainty about the spatial relationships among vital anatomical structures. This uncertainty was cleared up by the *immediate* availability of an atlas of cross-sectional anatomy. However, the depth information that is missing from 2D images may render them insufficient for conveying information about how objects in the 2D images are spatially related in 3D space. Rosse has suggested that the anatomical reasoning skills of health care providers may be enhanced by the use of 3D computer-based spatial models of the human body [13]. Computer simulations of penetrating injury using such 3D models could thus serve as training tools and/or diagnostic aids.

TraumaSCAN [10] is a computer-based system that provides a means of simulating and evaluating the consequences of penetrating injury to the chest and abdomen. A fundamental requirement of the system is the ability to reason about the consequences of injury in the face of uncertainty. One source of uncertainty is that it may not be possible to accurately measure the extent of damage associated with a particular mechanism of injury. Another source of uncertainty is variability in the amount of information available about patient signs, symptoms, and test results. The TraumaSCAN approach integrates knowledge about anatomy, physiology, and patient findings (signs, symptoms, and test results). To assess the effects of penetrating trauma, the system combines geometric/spatial reasoning about potentially injured anatomic structures (using 3D models of the human anatomy) with probabilistic reasoning about consequent diseases.

TraumaSCAN consists of the following components (see Fig. 1):

1. PpathSCAN [7, 8, 9], an interactive, graphical user interface in which penetrating injuries may be simulated, and a 3D geometric reasoner coupled to this interface,
2. a diagnostic reasoner based on Bayesian networks which assesses patient injuries given probabilities

of injury to particular anatomic structures and, if available, information about patient findings,

3. methods for communicating between the geometric reasoner and diagnostic reasoner.

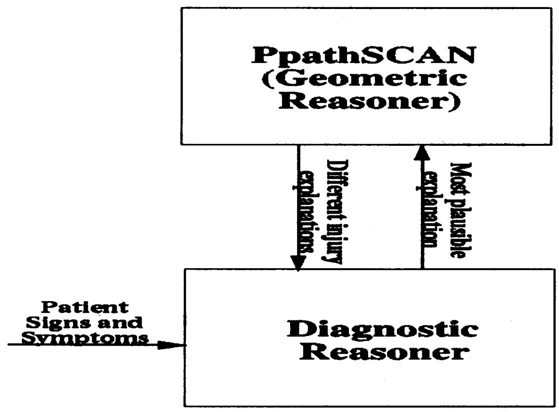

Figure 1: TraumaSCAN components and their interactions

TraumaSCAN's geometric and diagnostic reasoners are coupled bi-directionally. Given surface wound or bullet location information for a particular penetrating trauma case, the geometric reasoner computes the probabilities that different anatomic structures are injured and passes these probabilities on to the diagnostic reasoner. The diagnostic reasoner uses these probabilities as well as any information about patient findings to determine the most likely diseases present. Feedback from the diagnostic reasoner helps the geometric reasoner refine its reasoning about anatomic structure injury. The sections that follow give describe the different components that comprise the TraumaSCAN system.

GEOMETRIC REASONING

PpathSCAN makes use of a rotatable 3D torso model which includes 3D models of internal anatomic structures. It is based on *Jack*®[1], a system for displaying and animating three-dimensional figures given their polygonal surface representations. A user can enter external wounds onto the torso model and place bullets within the torso model. To assess a particular penetrating trauma case, the geometric reasoner takes as input the provided surface wound and bullet location information, and constructs a 3D model of the damage that corresponds to the mechanism of injury. Potentially injured anatomic structures are identified by determining whether their 3D representations intersect with the 3D models of damage constructed. Once the set of anatomic structures that may have been injured is identified, the probability of injury to each structure is calculated (as described in [9, 10]).

If a penetrating trauma case involves multiple gunshot wounds, the reasoner also identifies different injury hypotheses that are plausible for the given set of wounds. For example, consider a patient presenting with two anterior entry wounds and two bullets lodged in the body. If one wound and bullet are in the left chest area, and the other wound and bullet are in the right chest area, there are two possible hypotheses* for the paths that the bullets may have taken:

1. The bullet on the left entered through the left chest and the bullet on the right side entered through the right chest (i.e., the paths of damage are parallel from anterior to posterior – Figure 2(a))
2. The bullet on the left entered through the right chest and the bullet on the right side entered through the left chest (i.e., the paths of damage cross – Figure 2(b))

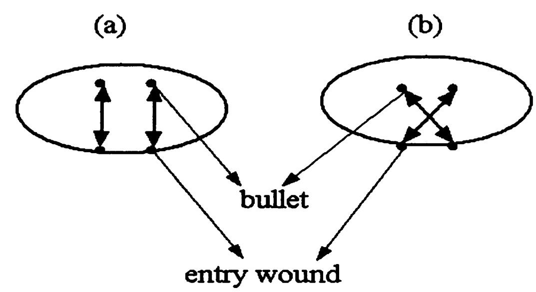

Figure 2: Two penetration path hypotheses for the same set of wounds and bullets

These two hypotheses could yield markedly different potential consequences for a patient. The task of determining the most likely hypothesis for a situation involving multiple gunshot wounds is performed by the diagnostic reasoner.

PROBABILISTIC REASONING

TraumaSCAN's diagnostic reasoning system is based on Bayesian networks [2, 4, 6, 11]. A Bayesian network is a directed acyclic graph comprising a set of nodes which correspond to random variables, and directed edges between the nodes which represent probabilistic relationships among the random variables. Bayesian networks allow the dependence and independence relationships among events in a domain to be explicitly modeled, and enable inferences to be made

*TraumaSCAN does not model projectile ricochet because it is difficult to predict when and how it occurs.

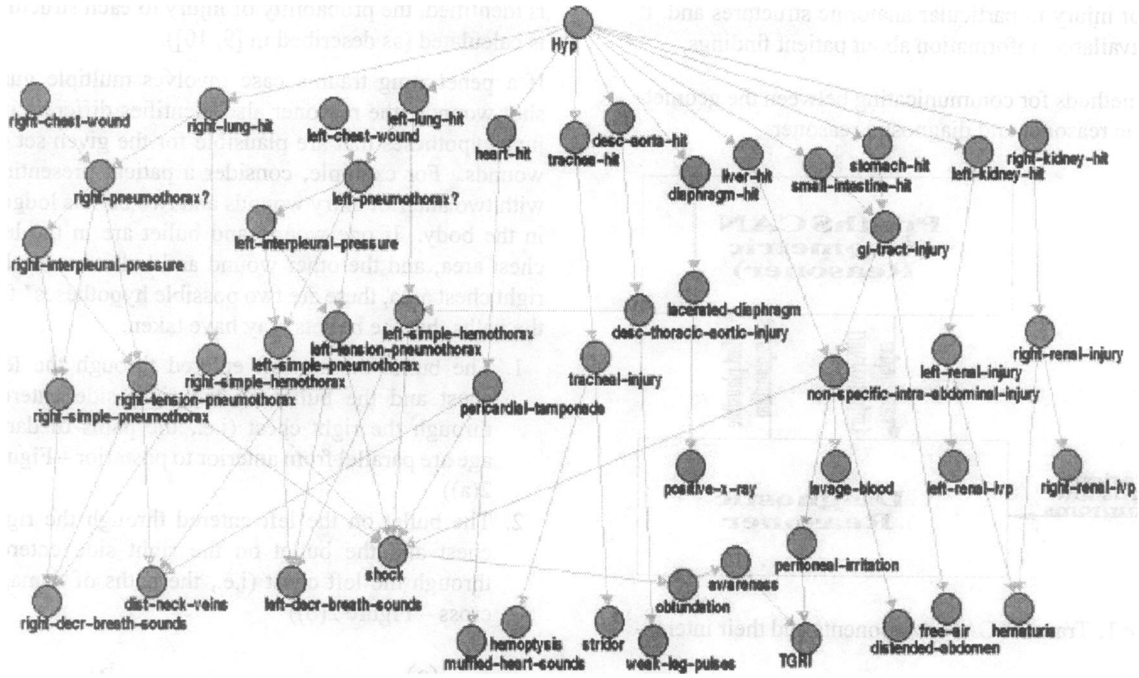

Figure 3: Bayesian network model for TraumaSCAN

even when there is only partial knowledge available about the domain. They are thus well-suited to the task of diagnostic reasoning under conditions of uncertainty.

The Bayesian network software used by TraumaSCAN is JavaBayes (developed by Fabio Cozman at Carnegie Mellon University). TraumaSCAN's network model covers the most common subset of chest and abdominal diseases and consists of 51 variables (Figure 3). The network model was created by identifying causal and associational relationships among anatomic structure injury, diseases, and patient findings in the domain of chest and abdominal trauma. These were identified from the rule base of TraumAID [14, 15], and by consulting with a trauma surgery expert (Dr. John Clarke).

The root node for the network (Hyp) has as its values the different hypotheses identified by the geometric reasoner, as well as the value "other" which represents the fact that the geometric reasoner may not capture all injury possibilities. The hypotheses from the geometric reasoner are considered to be equally likely, while "other" is considered less likely and has a fixed prior probability of 1%. The network has nodes that represent injury to the lungs, heart, trachea, descending thoracic aorta, diaphragm, liver, intestine, stomach, and kidneys. Two nodes (right-chest-wound and left-chest wound) are used to model the fact that a pneumothorax can occur as a result of a chest wound (without a lung being hit). This fact can be directly observed and is not based on the output of the geometric reasoner. Diseases represented as nodes in the network are: right and left simple pneumothoraces, right and left tension pneumothoraces, pericardial tamponade, tracheal injury, decsending thoracic aortic injury, lacerated diaphragm, non-specific intra-abdominal injury, gi-tract injury, and left and right renal injury. Findings represented as nodes are right and left decreased breath sounds, distended neck veins, shock, muffled heart sounds, weak leg pulses, hemoptysis, stridor, lavage blood results, obtundation, awareness, peritoneal irritation, free air, distended abdomen, tenderness, guarding, rebound-tenderness, and ileus (TGRI), positive x-ray for lacerated diaphragm, right and left renal ivp results, and hematuria.

Data was not readily available for estimating the conditional probabilities of disease given anatomic structure injury, and symptoms given disease, so these probabilities were elicited from the trauma surgery expert. Over 400 probabilities had to be obtained in this manner. Although studies have shown that expert estimates may not be optimal for diagnosis [5, 12, 16], methods exist for augmenting the estimates of experts with empirical data as it becomes available over time [6].

Diagnostic reasoning for a trauma case is performed after the geometric reasoner calculates the probabilities of injury to anatomic structures for that case and writes these probabilities to a database using the XML Bayesian Interchange Format (XMLBIF). The database already contains the expert's estimates for the conditional probabilities of different diseases given anatomic structure injury and of different symptoms given diseases. The diagnostic reasoner reads in these probabilities and can then compute the posterior probabilities of disease and anatomic structure injury. Observations about patient findings can be made prior to computing the posterior probabilities, but the computations can be performed in the absence of such observations.

BI-DIRECTIONAL COMMUNICATION

Communication between the diagnostic and geometric reasoners is based on updating databases of anatomic structure injury probabilities. As described above, PpathSCAN updates a database that provides the initial probabilities required by the diagnostic reasoner. Once the diagnostic reasoner computes the posterior probabilities for the network nodes, and identifies the most plausible hypothesis for a trauma case, it in turn updates a database that is read by PpathSCAN. PpathSCAN then displays the posterior probabilities of anatomic structure injury and the posterior probabilities for each disease represented in the Bayesian network. It also alters the colors of those anatomic structures in the 3D torso model that have nodes representing their state of injury in the Bayesian network as follows:

- Anatomic structures with a posterior probability of injury that is in the range $[0, 0.25)$ are shaded green.
- Anatomic structures with a posterior probability of injury that is in the range $[0.25, 0.50)$ are shaded yellow.
- Anatomic structures with a posterior probability of injury that is in the range $[0.50, 0.75)$ are shaded orange.
- Anatomic structures with a posterior probability of injury that is in the range $[0.75, 1.0]$ are shaded fuchsia.

These colors were selected in such a way that there is no correspondence between them and the normal colors of any anatomic structure in the torso model. They are intended to provide visual cues as to the suspected severity of injury to a structure.

TEST RESULTS

TraumaSCAN was tested on 26 gunshot wound cases obtained from MCP-Hahnemann University for which the correct disease diagnoses were known. Each case included a written set of findings observed by the trauma team at the time the patient was cared for and the set of injuries or diseases diagnosed. Information about external wound locations for each case was marked (by a physician or research assistant) on paper diagrams, each depicting anterior, posterior, left lateral and right lateral views of a torso. Information about bullet locations, if any, were also indicated based on radiology reports. These wound and bullet locations were transcribed onto TraumaSCAN's 3D torso model to determine the system's assessment of the cases.

Table 1 gives TraumaSCAN's true positive rate, true negative rate, false positive rate, and likelihood ratio at different thresholds for the presence of disease for the 26 gunshot wound cases. These results are for assessments performed by the system using information about surface wound and bullet locations *before patient findings are entered into the Bayesian network* (i.e., the Bayesian network reasoned with incomplete information). The corresponding area under the receiver-operator characteristic (ROC) curve is 0.8647. An interesting implication if this trend holds on a larger set of cases is that physicians may not have to enter large amounts of data on the patient's state to obtain a good diagnostic outcome.

Threshold (%)	TPR (%)	TNR (%)	FPR (%)	LR
0	100.00	0.00	100.00	1
10	80.00	93.69	6.31	12.69
20	66.67	94.59	5.41	12.33
30	64.44	94.59	5.41	11.92
40	64.44	94.59	5.41	11.92
50	64.44	94.59	5.41	11.92
60	57.78	95.50	4.50	12.83
70	46.67	95.50	4.50	10.36
80	22.22	97.30	2.70	8.22
90	6.67	99.10	0.90	7.40
100	0.00	100.00	0.00	

Table 1: Pre-finding diagnostic accuracy results at different thresholds

Evaluation of the system after patient findings were entered produced a higher true positive rate overall, but also a slightly higher false positive rate (Table 2). The area under the ROC curve in this case was 0.8801. Some of the findings recorded by health care providers and used in TraumaSCAN turned out to be erroneous

Thresh-old (%)	TPR (%)	TNR (%)	FPR (%)	LR
0	100.00	0.00	100.00	1
10	91.11	87.39	12.61	7.22
20	82.22	87.39	12.61	6.52
30	80.00	87.39	12.61	6.34
40	80.00	90.09	9.91	8.07
50	75.56	90.09	9.91	7.62
60	73.33	90.99	9.01	8.14
70	71.11	93.69	6.31	11.28
80	62.22	95.50	4.50	13.81
90	24.44	98.20	1.80	13.57
100	0.00	100.00	0.00	

Table 2: Post-finding diagnostic accuracy results at different thresholds

and this accounts in part for some of the false positives. However, in the case of descending thoracic aortic injury, analysis suggests that the model for this disease in the Bayesian network may have been too simplistic. An arc connecting this node to a node representing the presence or absence of weak arm pulses is needed in addition to the arc connecting it to weak leg pulses.

CONCLUSION

We have presented TraumaSCAN, a system for assessing penetrating trauma in the face of limited information about patient findings, and uncertainty about the extent of injury. Initial results suggest that the system holds promise as a diagnostic tool. However, a significantly larger number of cases would have to be evaluated in order to fully assess TraumaSCAN's diagnostic abilities. A unique feature of TraumaSCAN is that it brings together two qualitatively different forms of reasoning, geometric and probabilistic reasoning, and uses the strengths of each reasoning method to reinforce the other.

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