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Identifying Scapholunate Ligamentous Injury

Frederick W. Werner¹, Haoyu Wang², Walter H. Short¹, Levi G. Sutton¹, and Paula F. Rosenbaum³

¹Department of Orthopedic Surgery, SUNY Upstate Medical University, 3214 Institute for Human Performance, 505 Irving Avenue, Syracuse, NY 13210

²Bowling Green State University, Bowling Green, Ohio

³Department of Medicine, SUNY Upstate Medical University, Syracuse, New York

Abstract

The first purpose of this study was to develop a noninvasive clinical tool that could predict whether the scapholunate interosseous ligament and other secondary stabilizing ligaments are injured in the presence of suspected scapholunate instability. The second purpose of this study was to determine which of those ligaments or ligament groups have been injured. Kinematic and three-dimensional (3D) measurements from 62 cadaver wrists moved in a wrist joint motion simulator were used to develop various neural network predictive models. One group of models was based on angular changes in scaphoid and lunate motion before and after ligament sectioning (representing scapholunate instability). A second group of models was based on changes in the minimum distance between the scaphoid and lunate as well as other 3D gap measurements. The models, based on the scaphoid and lunate angular data, could predict with a 93% accuracy rate whether the wrist ligaments were intact. These models could also predict whether it was the dorsal ligaments or the volar ligaments that were sectioned 84% of the time. The models worked best using data with the wrist in 10 to 30 degrees of wrist flexion. The viability of a CT-based predictive model has been demonstrated by obtaining high prediction rates, sensitivity, specificity, and kappa statistic values.

Keywords

scapholunate instability; neural networks model

Scapholunate instability is the most common type of carpal instability, and typically is the result of a fall onto an outstretched hand. Frequently, the scapholunate interosseous ligament (SLIL), as well as secondary stabilizing ligaments, are partially or fully torn, resulting in changes in the ways the scaphoid and lunate move.^{1–3} The instability pattern between the scaphoid and lunate may cause pain and the inability to grasp tools or lift objects.⁴ As noted by Garcia-Elias et al.,⁵ the adverse effects of the ligament tears are underestimated, and the injury is frequently untreated or poorly managed. Numerous surgical treatments have been

developed with varying success.⁶ Early treatment is preferable; this, however, requires accurate and early detection of scapholunate instability.

In some stages of scapholunate instability such as stage 3, described by Watson et al.⁷ as static instability, the instability can be detected from plain radiographs. However, in earlier stages such as predynamic or dynamic, this may not be possible. Invasive wrist arthroscopy remains the gold standard to determine the integrity of the wrist ligaments.⁸ Some minimally invasive methods requiring injection of dye with MRI or CT scans are showing promise.⁹ However, a completely noninvasive technique would not only be safer but also more cost effective. To quantifiably and noninvasively detect scapholunate instability, specific parameters, such as changes in scaphoid and lunate position have to be measured and evaluated using some predictive method. One predictive method used to classify or predict various outcomes is based on a mathematical method known as neural networks. This method has been used in orthopedics in topics ranging from predicting total hip replacement success,¹⁰ trabecular bone structure,¹¹ and estimation of Cobb angles.¹²

The first goal of this study was to develop a non-invasive clinical tool to determine whether the SLIL and associated secondary stabilizing ligaments are intact or injured in suspected scapholunate instability. The second goal of this study, after determining that some scapholunate stabilizers have been injured, is to identify which wrist ligaments or groups of ligaments have been injured in conjunction with the SLIL. If successful, this tool would allow the surgeon to more accurately select an appropriate surgical repair and allow for earlier treatment.

MATERIALS AND METHODS

Data from 62 fresh-frozen cadaver wrists previously tested in a wrist joint motion simulator¹³ were used in developing this mathematical model. These arms had been previously tested to determine the relative importance of the various wrist ligaments in stabilizing the wrist.¹⁻³ Each wrist had been moved through cyclic wrist flexion-extension and cyclic radioulnar deviation motions under physiological tendon loading. The flexion-extension cycle ranged from 30 degrees of wrist extension to 50 degrees of wrist flexion. The radioulnar deviation motion ranged from 10 degrees of radial deviation to 20 degrees of ulnar deviation. Electromagnetic motion sensors (Fastrak, Polhemus, Colchester, VT) were mounted indirectly to the scaphoid and lunate to track each bone's motion relative to electromagnetic sources mounted to the ulna. During each cycle of wrist motion, 273 samples of kinematic data were collected for each of the 62 intact arms.

In 31 of the arms, kinematic data were also collected after the dorsal, proximal, and palmar components of the SLIL were sectioned, as well as two volar wrist ligaments: the scaphotrapezial and the radioscaphocapitate. In the remaining 31 arms, kinematic data were also collected after sectioning the SLIL and two dorsal wrist ligaments: the dorsal radiocarpal and the dorsal intercarpal. When sectioned, the dorsal intercarpal ligament was lifted off of its attachment to the scaphoid, trapezium, and trapezoid. The first group of 31 arms was named the volar group, the later group of 31 arms was named the dorsal group.

Each wrist was dissected at the conclusion of the experiment to verify the appropriate ligaments were completely sectioned.

Nine kinematic measurements were computed: first in the intact arm and then after the three ligaments had been sectioned. From the continuously sampled data, these kinematic measurements were extracted at each 10 degree increment of flexion-extension or radioulnar deviation. Thus, during the flexion-extension motion, data were tabulated at 30, 20, and 10 degrees of wrist extension, and at 0, 10, 20, 30, 40, and 50 degrees of wrist flexion.

Of the nine measurements, the first four kinematic measurements were the scaphoid flexion-extension angle, scaphoid radioulnar deviation angle, lunate flexion-extension angle, and lunate radioulnar deviation angle and were determined for all 62 arms. These angles were extracted from the electromagnetic sensor data which were “zeroed” with the wrist in a static neutral flexion-extension position. These four angular measurements were called the angle measurements and used in the “angle model.”

The latter five measurements, termed the gap measurements, were the minimum distance between the scaphoid and lunate,¹⁴ the dorsal and volar gap openings between the scaphoid and lunate (Fig. 1), and the proximal and distal gap openings between the scaphoid and lunate. These gap or distance measurements were extracted from computer-aided design (CAD) models that were created at each of the 273 increments of motion during a cycle of wrist motion. As previously described,¹⁴ CT scans of the distal radius, distal ulna, scaphoid, and lunate were performed on each of the 62 arms. However, due to technical problems with the CT scanning and arm preparation process for the CT scan, accurate scans were available for only 36 of the arms. Animations of each motion were created using the experimentally collected kinematic data for each motion of each arm. These animations were exported into CAD software where these five gap measurements could be computed. The use of these five gap measurements is based on the assumption that the separation between the scaphoid and lunate might be uneven, depending upon which ligaments have been torn. For example, the scaphoid and lunate might have a greater dorsal gap increase than a volar gap increase if only the dorsal ligaments have been injured.

The data from these nine kinematic measurements were used as input variables in several predictive models to determine if certain wrist ligaments were sectioned. Our challenge was to find a suitable method to diagnose the levels of injury based on the limited wrist bone geometry information received from CT scans. Mathematically, we needed a function that maps independent variables (kinematic measurements) to dependent variables (levels of injury) that have a highly nonlinear relationship. We chose to primarily use neural networks because they are highly regarded for their ability to model very complex nonlinear relationships and are easy to apply. We used nonlinear probabilistic neural network models developed using Matlab’s Neural Network Toolbox (Math-Works, Natick, MA). Probabilistic neural networks are a radial basis network suitable for classification problems because they are supervised neural networks that are fast to train and have one parameter (a spread variable) to tune. Using data from the four angular measurements, one group of models was developed and called the angle models. These models were based on 62 arms. Using data from the five gap measurements another group of models was developed and

called the gap models. Because these models were based on the CT scans and animations, they were based on 36 arms.

A new model was created at each 10 degree increment of wrist motion. The structure of the model was always the same, but data for each increment of motion were used in the model to test how well the model worked with data from various wrist positions.

One set of models was asked to predict whether the wrist ligaments were intact or had been sectioned (representing ligamentous injury). Another set was asked to predict whether the dorsal ligaments (as well as the SLIL) or the volar ligaments (along with the SLIL) had been sectioned. For the models used to predict if the dorsal or the volar ligaments had been sectioned, there was one group of models based on the absolute carpal bone angles or gaps, while another group was based on the relative change in the angle or gap from the intact case. Thus, there were a total of six sets of models as shown in Table 1.

Each neural network model was trained by using data with known input parameters and known outcomes. The resultant model can then be tested using additional known input data to predict an outcome and then determine whether that predicted outcome matches the known outcome. To maximize the training base of arms, we used a method known as “leave one out.” Leave one out is a subset of crossvalidation, whereby the set is broken into k groups, and then trained k times using all but one of the groups. Thus, here, the data from all but one of the arms were used for training the model and the data from the remaining arm was used to test the model. Also, instead of examining k groups where each group is removed once, we used 1000 random cases where for each case, one group was randomly removed. In each model a range of spread variables from 0.2 to 4.0 were used. Models were made at spread value increments of 0.2 in that range. A larger spread variable generalizes the model to allow it to work better with input data that is not represented by the training data. However, this can potentially cause the model to less accurately predict the known training data.

For the first angle model, which was used to determine if the ligaments were intact or not and was based on 62 arms, there were a total of 124 cases (each arm had an intact case and a cut case). For each of the 1000 random combinations of arms used in the model, 123 of the cases were used for training the model and 1 used to test the model. By using 1000 random combinations, a number of duplicate cases were considered. In the second angle model, used to determine if the dorsal or volar ligaments were cut, there were a total of 62 arms and a total of 62 cases because a case could be only either volar or dorsal cut. Thus, 61 cases were used for training and 1 used to test the model. The number of cases used for each model is shown in Table 1.

For each type of model and at each increment of wrist motion, the correct prediction rate as a percentage was determined as the number of times the model correctly predicted the results for the 1000 combinations of training and test arms. By knowing the number of true positives, false positives, true negatives, and false negatives the sensitivity, specificity, and kappa statistic values were calculated. For the models predicting if the ligaments were intact or not, a true positive was the case when the models correctly predicted that a wrist with

intact ligaments had intact ligaments. For the models predicting if the volar or the dorsal ligaments were cut, true positives were the cases when the model correctly predicted the wrists with sectioned volar ligaments as being cut volarly. Kappa, as described by Fleiss et al.¹⁵ is a measure of agreement with desirable properties. Kappa statistic values that are greater than 0.75 are considered to represent excellent agreement beyond chance, and a value between 0.4 and 0.75 may be taken to represent fair to good agreement beyond chance.¹⁵

In addition to using the neural network's toolbox available in MatLab, we examined a subset of the data using Weka Neural Network software (developed by Little and Frank¹⁶) and Logistic Regression in SPSS (SPSS, Chicago, IL) software. We used a subset of 34 arms in which we included all nine input variables. Only 34 arms were used, instead of 36, because this analysis was started before all the data was extracted from the rest of the arms. One benefit of the Matlab toolbox is that it allowed initial normalization of the input variables so that at least initially one variable would not outweigh the other variables. This was done by using the "prestd" function in Matlab's neural network toolbox so that the input data have means of zero and standard deviations of 1. The Weka software allowed for "boosting" of the data using the Adaboost algorithm.¹⁷ Adaboost is an algorithm designed to construct a strong classifier from a linear combination of weaker classifiers. To consider a nonneural network method, we used Logistic Regression. This method allows for the use of continuous or categorical input variables to produce a dichotomous outcome. Due to the relatively small sample size, only the angular changes in scaphoid flexion were used as inputs in the Logistic Regression method. The purpose of this comparison was to determine if other methods might have the potential to also serve as predictive models.

RESULTS

The neural networks models that were based on the scaphoid and lunate angular measurements were best at predicting the integrity of the wrist ligaments (Table 1). Up to a 93% correct prediction rate was achieved using data at 30 degrees of wrist flexion and a spread variable of 0.2. The angle model could also predict whether the dorsal or volar ligaments were cut with an 84% correct prediction rate based on the relative change in the angles from the intact case. The neural network models that were based on the gap measurements between the scaphoid and lunate were able to predict at a 78 to 81% correct prediction rate if the ligaments were intact or if the dorsal or the volar ligaments had been sectioned. High kappa statistic values were obtained especially with the angle models (Table 1).

The models were best at predicting the integrity of the ligaments (intact or sectioned) with the wrist in flexion (Fig. 2). The models were relatively less effective in predicting the integrity of the ligaments with the wrist in extension. This corresponds to our visual observations during the experiment, that any gap and instability in cadaver forearms was observed least in wrist extension. Of interest, during the wrist flexion-extension motion, data extracted with the wrist in 10 to 30 degrees flexion produces better predictive results than at 50 degrees of wrist flexion. Using data extracted during the wrist radioulnar deviation motions, the models worked best using data at neutral radioulnar deviation (Fig. 3).

Most models were best at predicting whether the dorsal or volar ligament groups had been sectioned using data with the wrist in 10 to 20 degrees of wrist flexion during the wrist flexion-extension motion, or with the wrist in 0 or 10 degrees of ulnar deviation during the radioulnar deviation motion.

Each model was evaluated using a range of spread variables. In the case of the angle model, when it was used to predict the integrity of the ligaments, based on data extracted with the wrist at 30 degrees of flexion (Fig. 4), an increase in the spread variable beyond 1 had minimal effect on the percent correct, sensitivity, or specificity of the model. Yet for this model, using spread values larger than 1, the model still was able to correctly predict the integrity of the ligaments in 85% of the cases.

Using a subset of data, the three different methods, using MatLab, Weka or Logistic Regression produced high correction prediction rates of greater than 80% (Table 2). High kappa statistic values were also found.

DISCUSSION

The goal of this study, to develop a model that could predict the integrity of wrist ligaments that are suspected to be torn, was achieved. The viability of the model is demonstrated by obtaining up to a 93% correct prediction rate with a sufficiently high kappa statistic value to indicate that the prediction can be considered to be excellent beyond chance. The models were most effective in predicting the integrity of the wrist ligaments using data with the wrist in slight flexion. Additionally, the models were reasonably good in differentiating as to whether the dorsal or the volar structures had been sectioned.

A future goal is to use this neural networks modeling method in a clinical setting. Ideally, if one can detect ligamentous damage early, patients can be seen by a hand surgeon sooner and potentially obtain a better clinical result by having an early repair of an acute injury. Although in this study the model based on angular changes in the scaphoid and lunate produced better predictive results than the gap model, clinical implementation of the angle model may prove difficult because one would need to quantify these clinical angular positions with a precision that may not be currently possible. Alternatively, the gap model might be more appropriate to use because these measurements can be readily obtained from 3D models of the scaphoid and lunate that can be easily generated from CT scans.

A potential concern in the development of this clinical tool was that ligamentous sectioning of the scapholunate stabilizers caused the equivalent of a chronic, static, scapholunate dissociation that would normally be easily detected on plain radiographs. However, 16 of the 62 arms exhibited little or no gap between the scaphoid and lunate following ligamentous sectioning and no instability. In an additional 18 arms, a slight gap was evident, but again, there was no clunking of the scaphoid back into the radioscapoid fossa. Clinically it would be difficult to assert that these arms have scapholunate instability from only plain radiographs.

A challenge with neural networks is that typically a large number (e.g., 1000) of specimens or samples are needed to develop adequate models. By using the accepted method of “leave

one out” we were able to maximize our training base of arms. This method worked well with the carefully controlled injury patterns created in this experiment, but only a clinical trial will show if it will work with the variety of injury patterns that occur clinically.

As shown in Figure 4, smaller spread values gave better results. However, below 0.2 the angle model predicting the integrity of the ligaments has a lower sensitivity and lower percent correct. In fact, with a spread value of 0, the models gave only a 50% correct prediction rate. When the spread value was increased up to 0.15 or 0.2, the correct prediction rate increased dramatically because the model was better able to respond to data that was not used for training. Assuming 0.2 gives us the best prediction, or classification result, spread values larger than 0.2 allows the model to be more generalized and makes it possible to predict correctly samples it has never seen before. Spread values less than 0.2 could cause the model to have perfect or 100% correct prediction rates for the training data, but then the model could have poorer performance when tested with samples which are not in the training set. From Figure 4, there appears to be no benefit to use a spread value greater than 1.0.

The primary emphasis of this study was to determine if we could develop a mathematical model that has the potential to predict scapholunate instability and to identify which ligaments have been torn. We did most of the work using Matlab’s neural network toolbox but wanted to also see if Weka neural network models and Logistic Regression models had potential. Although Matlab’s neural network toolbox is quite versatile, Weka is open source software that has many machine learning models that are not available in Matlab. At the time when we were first working on the models, the Weka software included a feature called adaboost that better compares two outcomes such as intact versus sectioned. Matlab did not have that feature.

Examination of Table 2 shows that for this data set, Logistic Regression produces a higher correct prediction rate and kappa value than with the two neural network methods. This would suggest that the Logistic Regression method would be a better technique to use. However, the Logistic Regression method requires large sample sizes for the model to converge and provide unbiased parameter estimates because calculations are made using maximum likelihood estimation. Logistic Regression modeling also requires approximately 10 positive events or cases for each parameter in the model; consequently, we were only able to enter one variable in the model as we had a total sample of 34 arms (17 positive and 17 negative events). To fully explore the potential of Logistic Regression prediction, many more wrists would have to be tested. Using a much larger data set, Logistic Regression could very well produce equivalent or better results than with using Neural Networks.

In this study we chose to make identifying scapholunate ligamentous injury a two-step process. First, we wanted to detect if any ligaments were torn, and then second determine which one or which group was torn. This was done to take advantage of certain neural network features that can be applied to a binary outcome. Early models having three outcomes (intact, dorsal structures cut, volar structures cut) had lower correct prediction rates.

A limitation to this study is that we have only been able to differentiate between the dorsal and volar ligamentous structures. A much larger sample size of specimens would be needed to study the integrity of individual ligaments.

Most of these results are based on the absolute measured angles or gaps for the scaphoid and lunate. The rest were based on relative changes in the angle or gaps from the intact wrist case. Based on our results, determining the integrity of the ligaments may be best determined using the absolute angles measurements. Clinical determination of whether the tear is dorsal or volar may be best aided by looking at relative changes in the angle or gap values from the presumed intact contralateral wrist.

This study has demonstrated the viability of using a neural network model based on plain CT scans without any dye injection or other invasive methods to detect ligamentous integrity and to differentiate between ligament groups. It warrants the effort to improve on this method by adding more arms to the data base, by examining additional neural network feature selection methods to determine the optimal predictive parameters, and by the potential inclusion of additional kinematic measurements. This method will continue to be refined to eventually provide presurgical information that may help the clinician diagnose and treat scapholunate instability.

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Dorsal and Volar Gap Openings Between the Bones

Figure 1.

Two of the gap measurements used in the gap neural network model: dorsal and volar gap openings between the scaphoid and lunate.

Figure 2.

Effect of the wrist flexion-extension position on the neural network model's ability to predict the integrity of wrist ligaments. Here the angle model has the highest correct prediction rate at 10 or 30 degrees of wrist flexion. For this model, the spread value was 0.2.

Figure 3.

Effect of the wrist radioulnar deviation position on the neural network model's ability to predict the integrity of wrist ligaments. Here the angle model has the highest correct prediction rate at 0 degrees of wrist radioulnar deviation. For this model, the spread value was 0.4.

Figure 4. Effect of the neural network spread variable on tuning the model, with the wrist at 30 degrees of flexion. Shown are the results for the angle model when trying to predict the integrity of the wrist ligaments.

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Table 1

Best Neural Network Predictive Results

Type of Model	Angle Models Based on 62 Arms			Gap Models Based on 36 Arms		
	Intact vs. Cut Ligaments	Dorsal vs. Volar Ligaments Cut	Relative	Intact vs. Cut Ligaments	Dorsal vs. Volar Ligaments Cut	Relative
Outcome to predict						
Based on absolute or relative change in angles or gaps						
Number of cases in each model	124	62	62	72	36	36
% correctly predicted	93%	79%	84%	81%	78%	80%
Sensitivity	0.98	0.80	0.88	0.86	0.72	0.81
Specificity	0.89	0.78	0.79	0.77	0.85	0.79
Kappa statistic	0.86	0.58	0.67	0.63	0.57	0.60

Table 2

Comparison of Three Predictive Methods, Each Using a Subset of 34 Arms, Using Data Extracted at 30 Degrees of Wrist Flexion, to Predict the Integrity of the Wrist Ligaments

Predictive Model	Matlab (Using a Neural Network model)	Weka (Using a Neural Network Model)	Logistic Regression
Percent correct	88.1%	82.4%	94.1%
Sensitivity	0.93	0.79	0.94
Specificity	0.82	0.85	0.94
Kappa statistic	0.76	0.65	0.88