Aggregation Operators Enhance the Classification of ACL-Ruptured Knees Using Arthrometric Data

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Article info:
Received: November 12 2013
Accepted: February 26 2014

Keywords:
Anterior Cruciate Ligament,
Knee Arthrometer,
Classification,
ANFIS,
MLP,
Aggregation Operators.

ABSTRACT

Many people suffer from the anterior cruciate ligament (ACL) injury, which can lead to knee instability associated with damage to other knee structures

Purpose: In this study we present a classification method based on aggregation operators, using Adaptive Network-based Fuzzy Inference System (ANFIS) and Multilayer Perceptron (MLP) neural network to differentiate between arthrometric data of normal and ACL-ruptured knees.

Methods: The data involves 132 samples consisting of 59 patients with injured knee and 73 normal subjects. ANFIS hybrid training algorithm is implemented using Fuzzy C-Means (FCM) and subtractive data clustering. The Levenberg–Marquardt (LM) training algorithm is used for MLP neural network. The results of ANFIS and MLP are then combined using aggregation operators.

Results: The best accuracy (96%) is obtained by applying Choquet integral to the outputs of ANFIS classifier with the antecedent parameters selected using FCM algorithm.

Conclusion: The experimental results show that aggregation operators enhance the outcomes of ANFIS and MLP classifiers in discriminating between ACL raptured knees and normal subjects.

1. Introduction

Knee joints bear large forces. For example in running and jumping, double and quadruple an individual's body weight apply to the knee joint. Therefore, the knee joint is more likely to be injured than any other joint in the body. In fact the knee injury is very common in sporting activities. A serious injury among athletes and other people is tearing of the Anterior Cruciate Ligament (ACL). These injuries occur at an expected prevalence of 100,000 per year in the US [1-3]. Miyasaka et al. reported that 40% of all injuries in knee are related to ligament injuries [2]. Bollen et al. reported that about 50% of the knee ligament injuries are ACL injuries. ACL ruptures often lead to decreased functionality [1].

Although the knee joint appears simple, it is one of the most complex joint types. The knee joint is the largest joint in the body which is made up of four main bones namely femur, tibia, fibula and patella. It also contains an extensive network of ligaments, capsule, articular cartilage, menisci and muscles [4, 5].

Ligaments cause stability of the knee. They consist of Medial Collateral Ligament (MCL), ACL, Posterior Cruciate Ligament (PCL) and Lateral Collateral Liga-

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ment (LCL). Particular function of each one plays a role in maintaining optimal knee stability at different positions. ACL has the most important role in movement and joint stability. The ACL-deficient knee results in a bigger antero-posterior translation of the tibia with regard to the femur (AP laxity). Some techniques are used to evaluate AP laxity [6, 7]. They are divided into two main groups, namely clinical examinations and instrumental tests. Clinical diagnosis methods such as Lachman, Pivot, and Anterior Drawer tests are subjective [7]. On the other hand, instrumental tests are objective methods [8-11]. Many devices such as KT 1000, KT 2000, GNRB, Kneelax and Rolimeter arthrometer have been developed to diagnose injured knees. KT1000 and KT2000 are reliable and commercialized devices. Knee evaluations performed by these devices are clinically accurate, valuable and helpful in diagnosing ACL instability.

Over the past two decades, several researchers investigated the validity and reliability of the clinical and instrumental ACL tests [8, 9, 12-15]. In the clinical test group, Lachman test is considered reliable, having the greatest validity and highest diagnostic accuracy with 85% sensitivity [9, 16]. For anterior drawer and the pivot shift tests, best results for sensitivity are 55% and 24% while the specificities are 92% and 98% respectively [16]. Because of low sensitivity in clinical tests, the use of instrumental tests to assist the physician is necessary. The reliability and validity of instrumental technique is proved in [16, 17] but they suggest that it should be used with caution. When the examination is limited to only one knee, the stiffness can be used to help discriminate the ACL injury. Heydari et al. used ANFIS to classify normal and ACL ruptured knees [17]. They reported 96% accuracy. The purpose of this research is to combine classification outputs at diverse force values using aggregation operators to achieve better results in diagnosing ACL-ruptured from normal cases.

2. Materials and Methods

2.1. Materials

Seventy three normal cases and fifty nine patients with the clinical diagnosis of anterior cruciate ligament injury were examined at approximately 25 degree of knee flexion. The cases were examined by an expert physician and the ACL rapture of patients was confirmed in the ACL reconstruction surgery conducted after the measurements. The arthrometer had a design similar to the KT 2000 system and was equipped with an S-Beam load cell (DBBP series, Bongishin, China), a rectilinear displacement transducer (PY3, Gerfran, Italy), and a data acquisition card (6024E, National Instruments, USA). In a previous study, the reliability of the arthrometer was examined [18]. In the 90% confidence limit, it shows a variability of less than 1.6 mm at 150N force. The resulting force-displacement curve was captured by a PC. To make force-displacement data more comparable, each curve is resampled to get 300 equidistance points, leading to an overall data size of 396000 points. We use examinations that are carried only on one knee.

2.2. Methods

Artificial Neural Networks (ANNs) simulate the biological nervous system. In general, they are designed to perform a nonlinear mapping from a set of inputs to a set of outputs. ANNs learn from experiences, presented to them in the form of examples. The multilayer perceptron network (MLP) is the most popular supervised network, consisting of highly interconnected processing elements (neurons). The most common way to train this network is via back-propagation in which network's weights are modified in proportion to their contribution to the observed error in the output unit. In this study, the Levenberg-Marquardt (LM) training algorithm is used [19, 20].

Fuzzy logic could be used to represent uncertain and imprecise knowledge describing complicated systems. A Fuzzy Inference System (FIS) consists of (1) a rule base, containing fuzzy if-then rules, (2) a database, defining the Membership Functions (MF) and (3) an inference system that combines the fuzzy rules and observed facts to produce the final results [21, 22].

Neural networks cannot always explain why they have arrived at a particular solution. In addition, they cannot always assure an absolutely certain result, ending up with the same solution again using the same input data, or guarantee the best result. On the other hand, a major problem with fuzzy logic is that there are no efficient techniques to define the membership function parameters [21-23].

A combination of fuzzy logic and neural net techniques can decrease the problems related to each one. ANN has the ability to learn from input and output samples. The learned knowledge can be used to generate fuzzy logic rules and membership functions.

Adaptive Network-based Fuzzy Inference System (ANFIS), having a Sugeno fuzzy system structure, was first introduced by Jang in 1993 [24]. ANFIS is a multilayer feed forward network where each layer performs a particular function on incoming signals. The ANFIS architecture consists of a fuzzification layer, a product layer, a normalization layer, a defuzzification layer, and a summation layer as shown in Figure 1.

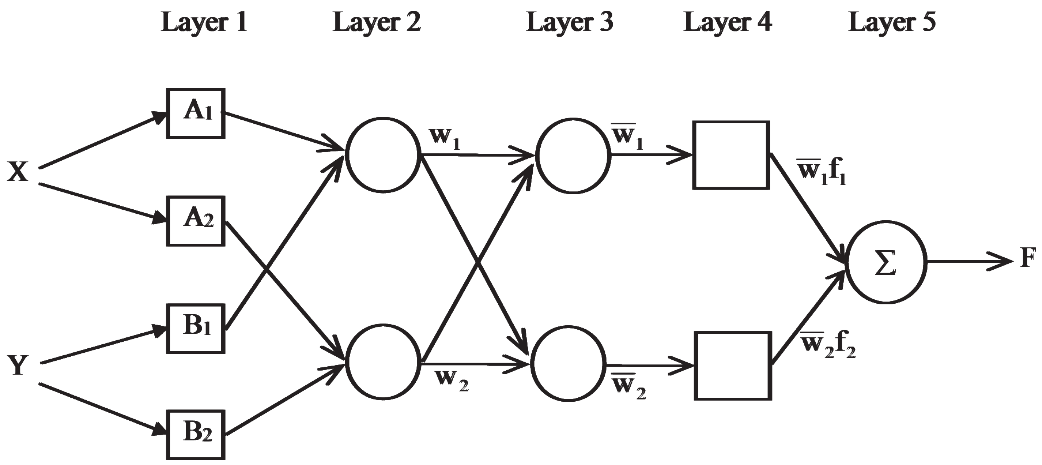


Figure 1. Adaptive Network-based Fuzzy Inference System structure.

ANFIS learns the antecedent and consequent parameters of the rules using a hybrid training algorithm proposed by Jang, Sun and Mizutani [23, 24]. The learning algorithm uses a two pass combination of steepest descent and Least Squares Estimation (LSE) methods. In the forward pass, consequent parameters are computed using LSE algorithm, while premise parameters are calculated in the backward pass using gradient descent. By clustering the input data, an optimal number of rules and fuzzy sets could be obtained. If there is no clear idea of how many clusters should be for a given set of data, subtractive clustering should be applied. By adjusting influence range, squash factor, and accept and reject ratios; the number of clusters could be changed. Fuzzy c-means (FCM) is another data clustering technique that could be used to decide on the number of membership functions and, hence, the rules [23].

Information fusion is a broad area that studies methods of combining data or information. Aggregation operators simultaneously use pieces of information provided by multiple sources to come to a conclusion or a decision [17]. Main properties and kinds of aggregation operators are mentioned in [25-28]. In this article we use minimum, maximum, mean, majority, Ordered Weighted Average (OWA) and Choquet integral operators.

Two main groups of aggregation operators are classical aggregation operators (minimum, maximum, mean and OWA) and fuzzy aggregation operators. Mean is the most common operator. The ordered weighted averaging aggregation operator (OWA), was proposed in 1988 by Yager and is defined as

$$OWA(x_1, x_2, \dots, x_n) = \sum_{i=1}^{n} w_i x_{\sigma i} \tag{1}$$

where σ is a permutation that orders the elements such that

$$x_{\sigma(1)} \leq x_{\sigma(2)} \leq \cdots \leq x_{\sigma(n)} \tag{2}$$

The weights are all non-negative ($w_i \geq 0$) and $\sum_{i=1}^{n} w_i = 1$.

The main weakness of classical additive aggregations is that they do not consider redundancy and synergy in their model [29]. Fuzzy aggregation operators, on the other hand, directly model the interaction (synergy) between variables or information sources. However, there still remains the question of how to determine the fuzzy measures that provide the weights for representing the synergies [30, 31].

Consider a finite universe $X=\{x_1,x_2,\dots,x_n\}$. A fuzzy measure $\mu:P(X)\rightarrow[0,1]$ is a set function satisfying

$$1)\ \mu(0) = 0,\ \mu(X) = 1, \tag{3}$$

$$2)\ A \subseteq B \Rightarrow \mu(A) \leq \mu(B) \tag{4}$$

where $P(X)$ is the power set of X, the set of all subsets of X. With X having n members, the fuzzy measure requires 2^n coefficients, namely the measures of the 2^n subsets of X. The Choquet integral of a function f:$X \to R^+$ with respect to the measure μ is defined as

$$C_\mu(f(x_1), f(x_2), \dots, f(x_n)) \triangleq \sum_{i=1}^{n} (f(x_{(i)}) - f(x_{(i-1)})\mu(A_{(I)}) \quad (5)$$

where $\cdot_{(i)}$ indicates that the indices have been permuted such that

$$(f(x_{(0)}) = 0) \leq f(x_{(1)}) \leq \dots \leq f(x_{(n)}) \leq 1 \quad (6)$$

and

$$A_{(I)} \triangleq \{x_{(i)}, \dots, x_{(n)}\}. \quad (7)$$

In this research we apply the algorithm introduced in [32] to compute the fuzzy measure.

3. Results

Mean, standard deviation and ranges of displacement within normal and injured populations are shown in Table 1 for different force values. Force-displacement curves for all normal and injured subjects are presented in Figure 2. As can be seen, it is difficult to discriminate between some of the data belonging to different classes, because they are marginal and have close force-displacement curves.

Different ANN and ANFIS classifiers were trained and tested in a 4-fold cross validation framework. Final results were then calculated by aggregating classifier outputs using various operators.

Table 1. Mean, standard deviation and range of displacement within normal and injured populations.

Force (N)	30	50	70	90	110	130
Injured knee displacement (mm)	3.17±2.1 [0.57-8.9]	5.25±2.34 [1.06-11.2]	7.2±2.51 [1.32-14.2]	8.81±2.58 [2.1-15.8]	10±2.61 [3.23-17.61]	10.81±2.7 [4.3-18.8]
Normal knee displacement (mm)	1.75±1.4 [0.04-4.84]	2.45±1.19 [0.04-5.31]	3.04±1.29 [0.46-5.81]	3.42±1.22 [1.12-6.12]	3.91±1.26 [1.44-6.46]	4.33±1.27 [1.71-6.69]

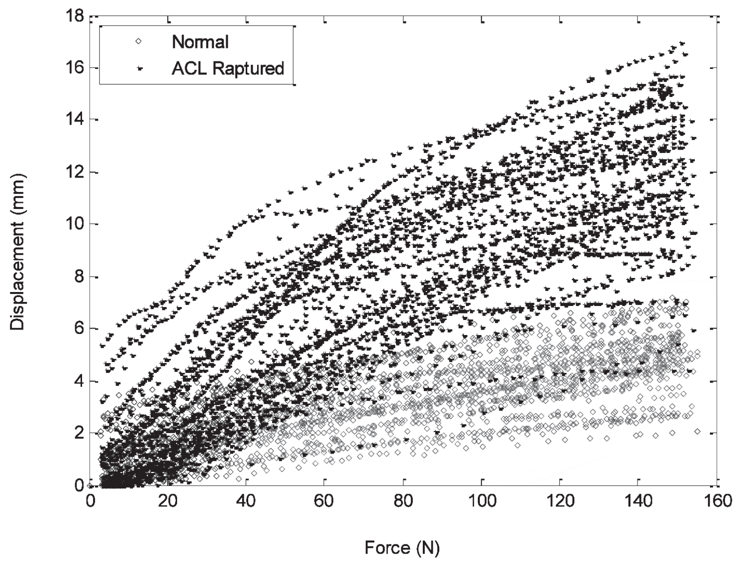
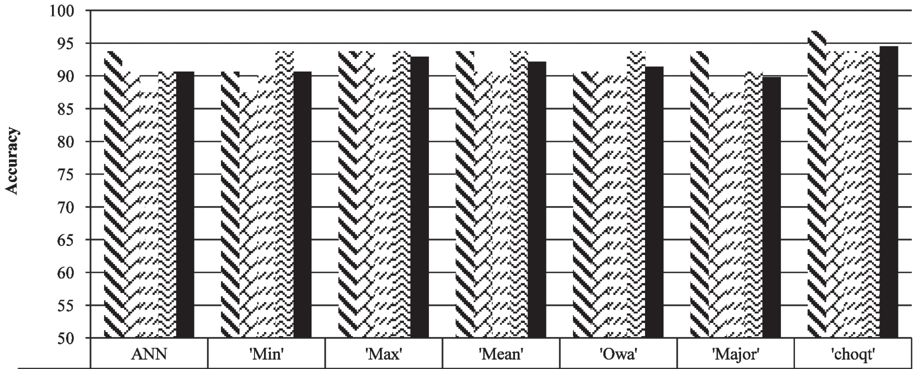


Figure 2. The arthrometric data points for 132 subjects.

In the ANN classifier the force and displacement values of each arthrometric data point were used as inputs. The network had one hidden layer and one neuron in the output which produces a value between 0 and 1 to depict the diagnosis situation. Simulation studies showed that the network having 10 sigmoid hidden neurons and a linear output neuron produced the best results. Balanced 75% of data were used for network training, while the remaining 25% were used to test the classifier. In each fold, mean performances of five runs were reported as the final result for that fold. Figure 3 shows the accuracy results for each fold and the mean value calculated over all folds.

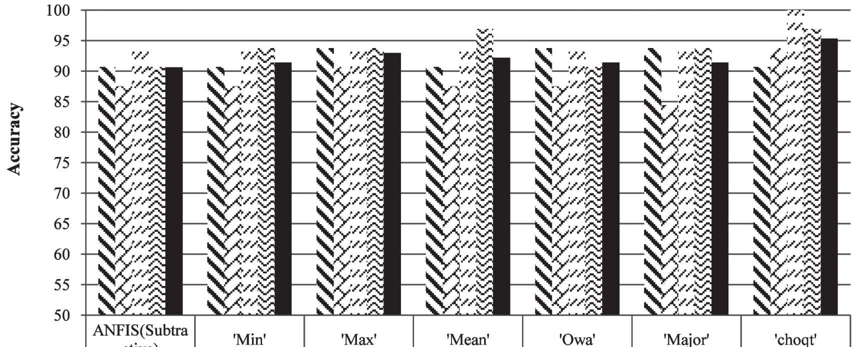
Implementing Choquet integral to fuse 300 classification results obtained from each person's data points is very costly and time consuming. Therefore, a two-step aggregation process was used. The results were first down sampled to 25 decisions for every person which were divided to 5 groups, each containing 5 samples. Then, the results were aggregated in each group to obtain 5 decisions. Finally, these outputs were aggregated again to produce the overall diagnosis.

The ANFIS classifier was also tested as a diagnostic tool to help physicians in the classification of normal and ACL ruptured knees. ANFIS needs clustering of input data using subtractive or fuzzy c-means (FCM) methods. The results of using these two methods in ANFIS classifier design are shown in Figures 4 and 5, respectively. For subtractive clustering, the influence range, squash factor, and accept and reject ratios were set to 0.4, 1.15, 0.5 and 1.15, respectively.



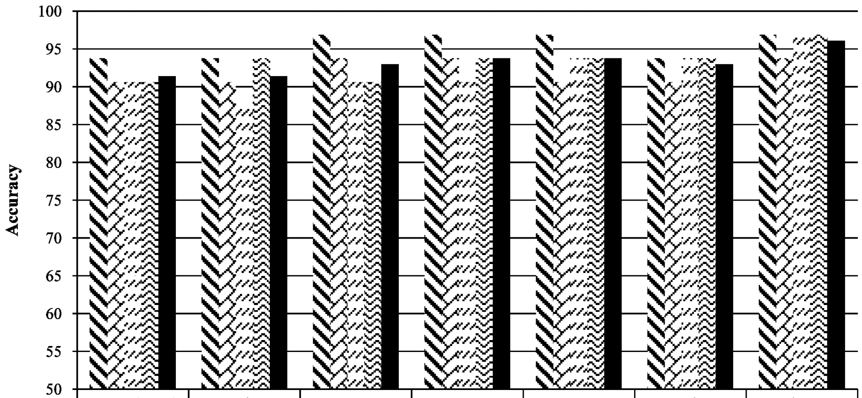
	ANN	'Min'	'Max'	'Mean'	'Owa'	'Major'	'choqt'
1	93.75	90.62	93.75	93.75	90.62	93.75	96.87
2	90.62	87.5	93.75	90.62	90.62	87.5	93.75
3	87.5	90.62	90.62	90.62	90.62	87.5	93.75
4	90.62	93.75	93.75	93.75	93.75	90.62	93.75
MEAN	90.62	90.62	92.96	92.18	91.4	89.84	94.53

Figure 3. Accuracy of classification with ANN and aggregation operators using test data.



	ANFIS(Subtractive)	'Min'	'Max'	'Mean'	'Owa'	'Major'	'choqt'
1	90.62	90.62	93.75	90.62	93.75	93.75	90.62
2	87.5	87.5	90.62	87.5	87.5	84.37	93.75
3	93.75	93.75	93.75	93.75	93.75	93.75	100
4	90.62	93.75	93.75	96.87	90.62	93.75	96.87
MEAN	90.62	91.4	92.96	92.18	91.4	91.4	95.31

Figure 4. Accuracy of classification with ANFIS (Subtractive clustering) and aggregation operators using test data.



	ANFIS(FCM)	'Min'	'Max'	'Mean'	'Owa'	'Major'	'choqt'
1	93.75	93.75	96.87	96.87	96.87	93.75	96.87
2	90.62	90.62	93.75	93.75	90.62	90.62	93.75
3	90.62	87.5	90.62	90.62	93.75	93.75	96.87
4	90.62	93.75	90.62	93.75	93.75	93.75	96.87
MEAN	91.4	91.4	92.97	93.74	93.74	92.96	96.09

Figure 5. Accuracy of classification with ANFIS (FCM) and aggregation operators using test data.

4. Discussion

As can be seen in Figure 1 and Table 1, the normal and ACL raptured data have a partial overlap especially at low force-displacements. It makes the classification task difficult and raises the need for considering the whole range of forces and their resulting displacements rather than just one or two points as the current routines suggest.

As we expected, training the neural network with different initial conditions resulted in diverse results. To minimize the effect of initialization conditions on the classifier results, an average of 5 independent runs in each fold is used. This reduced the variation of results and increased the repeatability considerably.

A comparison of Figures 3, 4 and 5 shows that ANFIS classifier outperforms ANN classifier. It is mainly because ANFIS is a hybrid network and combines the strengths of both artificial neural networks and fuzzy logic.

Fuzzy clustering partitions data more appropriately. Therefore, the results of ANFIS with FCM are better than the classifier using subtractive clustering in the training phase.

Although the 3rd classifier performs well, it can be seen that almost all kinds of aggregation operators enhance the results. This justifies the idea of using aggregation operators in such circumstances where relying on just one decision may be misleading because of inconsistent or opposing local evidences.

The effectiveness of aggregation varies with the operator. Choquet integral, a fuzzy aggregation operator, performs better than the other operators in all three cases. In fact, it evaluates all contributing decisions based on the presented samples and adjusts their role in the derivation of the final decision.

The best result is 96% and belongs to the Choquet integral applied to the ANFIS network with FCM clustering. We can infer that both enhancing the classifier and aggregating the results can improve the classification performance.

Despite the success of aggregation techniques, especially fuzzy integrals, the practical use of fuzzy measures could be difficult. For an n criteria decision problem, one has to identify 2^n coefficients in order to define a fuzzy measure. So the increased computational cost is the main drawback. We converted the problem to a hierarchy of multiple sub-problems to overcome this difficulty.

The best accuracy is 96%, obtained by applying Choquet integral to 132 complicated overlapping cases. Heydari, et al. reported 95.5%, and 100% for sensitivity and specificity respectively, using more distinct data consisting of 80 cases from the above mentioned dataset [17].

5. Conclusion

In this study, a diagnosis system based on ANN, ANFIS and aggregation operators for the classification of normal and ACL-ruptured knees was presented. The

ANN and ANFIS classifiers were trained using force-displacement values of arthrometric data points as inputs. Generalized bell shaped membership functions were used in the antecedent of the fuzzy rules.

The study shows that the classifier performance can be improved by using aggregation operators. The best result is obtained by applying Choquet integral to aggregate outputs of the ANFIS system trained using FCM method. The 96% accuracy is promising and encourages one to consider this method for the diagnosis.

Acknowledgment

This work is partly supported by the research center for science and technology in medicine (RCSTIM), Tehran University of Medical Sciences, Tehran, Iran.

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