Neural network-based shoulder instability diagnosis modelling for robot-assisted rehabilitation systems

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Many researchers are anticipating that robotic systems will contribute to compensating for the shortage of providing therapy for age-related injuries. Therefore, any prospective approach to robot-assisted therapy has to offer systems that can practically and objectively evaluate a patient’s physical functions and apply evidence-based rehabilitation protocols. One of the most common disorders, among the general population particularly seniors, 40–60 years of age, is the frozen shoulder. Clinically, frozen shoulder can be diagnosed based on two shoulder functions: instability and cooperativeness of the shoulder joint. The purpose of the present study is to introduce a shoulder instability diagnosis model using artificial neural networks (ANN), which can be applicable using robotic systems. Training, validation, and testing of the neural network were achieved using the force exerted by a subject measured during predesigned clinical examinations. The proposed method has the ability to produce shoulder joint instability evaluations equivalent to those clinically obtained by therapists.

Keywords: robotic-assisted therapy; neural networks; rehabilitation; evaluation models; age-related injuries; shoulder joint instability

Introduction

With age, one is more vulnerable to contracting diseases and suffering from disabilities, as ageing negatively affecting the body basics, i.e., muscles, joints, and bones. According to the World Health Organization, senior citizens, at least 65 years of age, will increase in number by 88% in the coming years (Morales et al., 2010). Consequently, the incidence of age-related diagnoses, such as shoulder injuries, will increase. Rehabilitation services become a pressing necessity with an ageing population. In many cases and due to various causes such as medical service reforms, patients may be forced to leave the hospital before sufficiently recovering. This situation creates both a need and an opportunity to deploy technologies such as robotics and robotic therapy to assist recovery. Generally, rehabilitation programs are suggested based on the observation and evaluation of each patient’s case. Consequently, introducing an efficient rehabilitation process requires quantitative and objective assessment of the physical function (Sato et al., 2013). Evaluation of physical functions through conventional methods depends on a therapist’s clinical experience and skills (Kikuchi et al. 2007; Mochizumi, 2007). Therefore, there is a necessity to introduce evaluation methods and systems that have the capability to quantitatively evaluate physical functions.

In the last decade, interest in robotic therapy research has exponentially increased. Robot therapy systems have been developed worldwide for the rehabilitation of both upper and lower extremities. For example, the design and characterization of a robotic-assisted rehabilitation system for patients with upper limb disability was introduced by the third author of this study (Maeda et al., 2003). As the shoulder is one of the most complex joints in the human body, the correct diagnosis in shoulder injuries normally requires a thorough history and examination by an experienced professional. Robot-assisted rehabilitation attempted to offer therapeutic systems for the shoulder joint (Noritsugu, Tanaka, & Yamanaka, 1997; Ozawa et al., 2010; Yamaji, Yoshii, Wada, Tanaka, & Tsukamoto, 2001); however, most of the research focused on designing devices that support rehabilitation training, and do not address the quantitative evaluation of human joint functions. Few studies have been conducted on extrapolating quantitative methods for the evaluation of rehabilitative therapies. Sato et al. (2013) developed a quantitative evaluation of shoulder joint functions, which are the flexibility/stability and the cooperativeness. For the flexibility/stability shoulder joint functions, they focused on the ratios between the maximum isometric forces exerted by the patient’s left and right arms, and reproduced the clinical test results using
Figure 1. 3D robotic-assisted therapy system.

A regression equation. For the cooperativeness evaluation, they derived threshold values of the upper arm rotation angle and the exerted force. These are optimum values for determining the continuity of the exerted force. Kamada et al. (2014) proposed a screening test robot for the prevention and early detection of the functional decline of the shoulder joint.

This study aims to introduce a robotic-assisted therapy system, which provides a quantitative and objective assessment of the upper extremity physical function, shown in Figure 1, in order to improve upper extremity function and reduce pain in patients with shoulder problems. This robotic-assisted therapy system is a three-dimensional reaction force display robot (3D robot). The design and characterization of this robot was introduced by the third author at Nagoya Institute of Technology. This robot has potential as an evaluation tool for therapeutic effect (Maeda et al., 2003). Morita, Akagawa, Yamamoto, Ukai, and Matsui (2002) proposed a method to enable movement in subjects’ upper arms by providing impedance control. Yasukita et al. (2012) introduced a method that allows the robot to replace the therapist to provide load resistance training. Abdelhameed, Kamada, Sato, and Morita (2015) proposed a control algorithm for robotic-assisted isotonic training through circular trajectory.

To the best of our knowledge, quantitative evaluation of shoulder joint functions cannot be performed by any existing device. In this study, the clinical diagnoses obtained by the therapist are defined as correct diagnoses. The proposed evaluation method can be applied to the 3D robot and reproduces diagnoses equivalent to those obtained by therapists. Kamada et al. (2014), in a screening test of flexibility/stability, used the 3D robot to measure the maximum isometric force exerted on the brace of the 3D robot by a subject. In the screening test for functional decline in cooperativeness, the 3D robot was used to measure the maximum isokinetic force exerted by the subject as well as the rotational angle of the upper limb. Sato et al. (2013) proposed a linear regression algorithm, multiple regression analysis (MRA), using Statistical Package for Social Sciences to diagnose shoulder instability. When the MRA algorithm was applied for diagnosing new subjects, the predictive accuracy was 70%. In this study, in order to improve the predictive accuracy of the shoulder instability diagnosis, obtained by Sato et al. (2013), the authors proposed a predictive algorithm with specific attributes. These attributes can be summarized as follows. Firstly, a nonlinear regression algorithm (a neural network-based algorithm) is proposed instead of the MPA algorithm to extract a nonlinear model from the data, as the shoulder mechanism is a complicated model and a nonlinear behaviour is expected. Secondly, the direct measured data of both right and left arms are used as a database for the diagnosis model, whereas the resulting ratio of left to right arm data was used by Sato et al. (2013). Finally, to improve the generalization ability of the proposed model, the database has been divided into three data sets to train, validate, and test the proposed model. This is in contrast to the previous reference wherein the entire database was used to estimate the parameters of their diagnosis model. Consequently, the final objective of this article is to propose a neural network-based evaluation method to reproduce the diagnosis of shoulder joint instability that is obtained clinically by a therapist.

Clinical shoulder joint instability diagnosis

In this section, a representation of shoulder joint anatomy has been introduced, followed by an explanation of the pathogenic mechanism of scapulohumeral periarthritis.
Finally, the clinical examination method conducted by a therapist for shoulder instability, a scapulohumeral periarthritis-related shoulder joint physical function, is given.

Anatomy of shoulder joint
The shoulder joint plays a major role in most of daily life activities, as it is the most mobile joint in the body. The flexibility of the shoulder joint allows the shoulder’s range of motion. Figure 2, which is reproduced and modified by Price and Beaty (2003), illustrates that the shoulder (a ball-and-socket joint) is made up of three bones: the humerus, the scapula, and the clavicle, which are the upper arm bone, the shoulder blade, and the collarbone, respectively. The head of the humerus fits into a shallow socket in the shoulder blade. The joint is surrounded by shoulder capsule which is a strong connective tissue. Synovial fluid lubricates the shoulder capsule and the joint to facilitate shoulder movement. The muscles and tendons of the rotator cuff provide the stability of the shoulder joint and allow the shoulder to rotate. The muscles in the rotator cuff include four muscles: teres minor, infraspinatus, supraspinatus, and subscapularis. Each muscle of the rotator cuff inserts at the scapula, and has a tendon that attaches to the humerus. Together, the tendons and other tissues form a cuff around the humerus. The tendons of these muscles surround and support the humerus while the contraction of the muscles rotates, adducts, or abducts the humerus. Due to its flexibility, the shoulder is not particularly stable which may easily lead to injury.

Frozen shoulder injury
A frozen shoulder, which is also called adhesive capsulitis, is a shoulder joint that has lost a substantial amount of its range of motion due to scarring around the joint. The frozen shoulder range of motion is limited in both active and in passive motion. The active range of motion is the moving of a shoulder joint through its range of motion when the patient attempts motion and exerts forces, while the passive range of motion is conducted without the patient exerting any force. The latter is usually conducted by a therapist who attempts to move the joint while the patient relaxes.

The frozen shoulder is a common condition, especially senior citizens. It has an incidence of 3–5% in the general population (Manske & Prohaska, 2008). Manual labourers such as construction workers and house painters are among those with a higher risk. Frozen shoulder occurs more prevalently in women, as mothers are subject to years of stress on their shoulders. In addition, shoulder muscles are affected by ageing, that is, a reduction in muscle force and an abnormality in muscle force balance. This can result in the head of the humerus becoming dislocated and the subacromial bursa and the rotator cuff becoming sandwiched between the acromion and the greater tubercle, resulting in a chance of bones collision. The authors in this study focus on one of the important shoulder functions, that is, the flexibility and stability function. This function is an index indicating whether the head of the humerus is stabilized at its proper position.

The shoulder joint has the following normal ranges of movement (basic motions): external rotation, flexion, extension, horizontal abduction, and abduction, as illustrated in Figure 3. In this research, the motion of external rotation adopted at clinical sites is a horizontal rotation of the upper arm from front to side, with the elbow bent at 90°, in contact with the trunk of the body. As noted, one’s dominant extremity is often more susceptible to injury than the non-dominant side. Additionally, the complex series of articulations of the shoulder allows for a wide range of motion. Consequently, to determine the patient’s normal range of motion, the affected extremity should be compared with the unaffected one. In this study, ranges of the shoulder joint basic motions have been specified based on a therapist’s opinion, as shown in Table 1.

There are various clinical examinations of shoulder stability. The test developed by Sato et al. (2013) has been used to get the clinical evaluations of the shoulder joint instability for this study. The physical examination included inspection and palpation, as well as assessing
Table 1. Specifications of basic motions.

| No. | Motion              | Range of motion [°] |
|-----|---------------------|---------------------|
| 1   | External rotation   | 0–45                |
| 2   | Flexion             | 0–60                |
| 3   | Extension           | 5–45                |
| 4   | Horizontal abduction| 0–75                |
| 5   | Abduction           | 0–65                |

the range of motion for possible impingement syndrome and shoulder joint instability. In the instability test, the patient is sitting down and the therapist checks, by touching the patient’s shoulder joint, if the head of the humerus is in a proper position with respect to the glenoid cavity of the scapula. More than 90% of patients improve with relatively simple treatments to control pain and improve range of motion (American Academy of Orthopaedic Surgeons, n.d.). Restoring shoulder joint mobility and function can be achieved by continued exercise of the shoulder. Robot-assisted therapy can play a part by providing exercises targeting the improvement of shoulder joint range of motion in addition to evaluating its physical functions.

Shoulder joint instability diagnosis method using neural network

In this research, artificial neural network (ANN) has been used to assist the shoulder instability diagnosis by means of iterative training of data obtained from designed clinical examinations. ANNs are a learning system based on a computational technique that can simulate the neurological processing ability of the human brain, and they can be applied to handle nonlinear problems. They were successfully applied to solve a variety of classification problems, including scientific and medical applications (Kamruzzaman, Hasan, Siddiquee, & Mazumder, 2004; Kamruzzaman & Islam, 2006). Landi, Piaggi, Laurino, and Menicucci (2010) stated that, even though the linear regression algorithms are common for statistically analyzing the data, their capability of extracting data only from linear models limits their applicability to real problems. In order to improve their linear model prediction using the same selected variables, they used ANNs to benefit from their nonlinear modelling capability. Whereas Srivastava and Tripathi (2012) noted that ANNs are being widely used for nonlinear regression and classification applications because of their advantages in data analysis and prediction.

Generally, during the ANN modelling process, the following proceedings are common: collecting ANN training data (database of the studied problem), creating the network structure, training the network, and finally simulating the network response to new inputs.

Database of shoulder joint stability function

The database of the shoulder instability diagnosis using ANN can be classified into two groups of data. The first group is input data for training ANN, which is collected from the clinical examinations conducted by the therapist, as shown in Figure 4(a)–(c), that is, the patient’s maximum exerted isometric forces during the basic motions of both right and left shoulder joints. The second group is the ANN targets, which are produced by a therapist through a diagnostic test of the shoulder instability, as shown in Figure 4(d), that is, the clinical test identifies the infected shoulder as a positive result, and the non-infected one as a negative result.

In this study, the maximum exerted isometric force during external rotation, abduction, and horizontal abduction motions is assumed, and used as the explanatory variables. These three motions were adopted as medical findings, which indicate that functions of the inner muscle of the shoulder joint are closely related to scapulo-humeral periarthritis and the inner muscle of the shoulder joint contributes to these motions. The clinical examination of external rotation, abduction, and horizontal abduction motions is shown in Figure 4(a)–(c), respectively. During this examination, the subject carries out the basic motions with maximum effort against the therapist’s resistance. The therapist holds the patient’s shoulder with one of his hands.

Figure 4. Clinical examination for ANN database collection.
Table 2. Binary equivalents for shoulder instability test and ANN outputs representations.

| Clinical instability examination results | Binary equivalents of the results | Equivalent binary number | ANN output representations |
|-----------------------------------------|----------------------------------|--------------------------|----------------------------|
| Left shoulder                           | Right shoulder                   |                          |                            |
| 1 Negative                              | Negative                         | 0                        | 0                          |
| 2 Negative                              | Positive                         | 0                        | 1                          |
| 3 Positive                              | Negative                         | 1                        | 0                          |
| 4 Positive                              | Positive                         | 1                        | 1                          |

To keep the shoulder from moving. With the therapist's other hand, a resistance is applied to the subject's upper arm in order to keep it from moving at the initial position of basic motion. A force sensor is sandwiched between the therapist's hand and the subject's arm to measure the forces exerted by the subject. The clinical instability examination results by the therapist were described by 1 for the shoulder, which is evaluated as positive, and 0 for that evaluated as negative. Because shoulder instability mainly affects the dominant extremity of a person, the following strategy has been proposed to diagnose it: the maximum exerted isometric forces during the selected three basic motions of both right and left shoulders (six variables per subject) were collected to be used as the input data of the ANN model. The diagnostic test results of both the left and right shoulders are expressed as binary numbers, that is, the equivalent digits of the right and left shoulders are considered as the units and twos digits of the resultant binary number, respectively. The binary equivalents for these descriptions and their representations as ANN outputs (their decimal equivalents) are illustrated in Table 2.

Finally, the previously collected data are applied to train and test a neural network model to produce results equivalent to those produced by the therapist. A total of 16 data sets (from 16 subjects) were used in this research. The collected data sets are divided into 3 groups: 60% of the collected data were used to train the ANN model, 20% were used to cross-validate the relationships established during training process, and the remaining 20% were used to test the ANN model to evaluate its prediction accuracy through final analysis. These three sets of data, the measured isometric forces, and the instability examination results by the therapist, are shown in Figures 5–9. In the figures, ‘Abd.’, ‘Ext. Rot.’, and ‘Horiz. Abd.’ are abbreviations for abduction, external rotation, and horizontal abduction, respectively.

**Neural network structure**

For mapping the selecting input and output data, an ANN consisting of a series of layers was selected. One common ANN algorithm is a feed-forward back-propagation neural network (FFBPNN). These networks have the ability to map their inputs and outputs through a training procedure.
The input layer consists of six neurons, which is equal to the number of input data points. As the number of collected data points is limited, and with a view to avoid network over-fitting by minimizing the number of the network’s parameters, the number of neurons in the first hidden layer was chosen to be one. The second hidden layer consists of three neurons (chosen by trial and error), and according to the number of output data points, the number of the output layer neurons has been chosen to be only one, as shown in Figure 10. The total number of network’s parameters is 17, which can be described as follows: the weights of the input layer, $w_{i1} \sim w_{i6}$; the weights of the first hidden layer, $w_{h11} \sim w_{h13}$; the weights of the second hidden layer, $w_{h21} \sim w_{h23}$; the bias of the first hidden layer, $b_1$; a three element vector representing the biases of the second hidden layer, $b_2$; and the bias of the output layer, $b_o$.

Typically, in order to scale the output of the neural network into proper ranges, the ANN pass the output of their layers through activation or transfer functions. Because the proposed shoulder instability diagnosis model is a nonlinear model, the activation functions of the ANN have to be nonlinear to express its nonlinearity. Hyperbolic tangent and sigmoid functions are common nonlinear activation functions. In order to allow the output layer to receive only positive values, the activation functions of the second hidden layer were chosen as sigmoid functions, whereas the hyperbolic tangent functions were chosen by trial and error for the first hidden layer. Finally, the output layer was selected as a linear transfer function. These activation functions are expressed in Equations (1)–(3), where $u$ is the output of a neuron in the previous layer, which is calculated as the sum of the weighted inputs and the bias of that neuron. The general structure of the proposed ANN is illustrated in Figure 10.

Hyperbolic tangent function: $f(u) = \frac{e^{2u} - 1}{e^{2u} + 1}$, (1)

Sigmoid function: $f(u) = \frac{1}{1 + e^{-u}}$, (2)

Linear function: $f(u) = u$, (3)

Neural network training

The FFBPNN training process involves adjusting network parameter values, weights, and biases, to improve network performance. This adjustment occurs through a performance function. The mean square error (MSE) function, which is the average squared error between the network outputs and the ANN target, is selected in this study. The MSE is defined by the following equation:

$$
\text{MSE} = \frac{1}{N_t} \sum_{i=1}^{N_t} (e_i)^2, \quad (4)
$$
where $e_i$ is the error between the $i$th network output and its related target, and $N_t$ is the number of training data points. Arbitrarily, the optimization techniques attempted to minimize this performance function. The back-propagation learning algorithm is based on the minimization of the MSE of the training data, which is known as least mean squares method. The basic idea is to adjust the network parameters in order to minimize the MSE of the input data through an optimization function. The Levenberg–Marquardt numerical optimization algorithm has been used to optimize the performance function during FFBPNN training. This optimization method uses the Jacobian of the network errors with respect to the weights. During the training process, the back-propagation algorithm is used to search for network parameter values that generate neural network outputs that closely correlate to the targeted data. Training with back-propagation is an iterative process.

In order to improve the ANN generalization, a technique called early stopping is used. In this technique, the error in the validation set is calculated during the training process to give an indication for training improvement; that is, if the validation error decreases during the initial phase of training, as the error of the training set does, this indicates normal training. However, when the error on the validation set typically begins to rise, this indicates that the network is beginning to overfit the data (MathWorks Company, 1994–2015). Moreover, a stopping criterion has been evaluated by the optimization algorithm as it calculates the reciprocal of the MSE from the neural network during training. The training process stops occurring for one of the following reasons: performance goal is reached (i.e. the MSE term drops below $10^{-6}$), maximum number of epochs to train is reached (i.e. after 1000 iterations), the validation error for 10 iterations is increased (in this case, the parameters at minimum validation error are returned).

However, in order to test the generalization ability of the ANN model, the training process is followed by a testing process, which does not affect the ANN training. The test set error is calculated during the training process to indicate the quality of the division of the data set; that is, if the error in the test set reaches a minimum at a significantly different iteration number than the validation set error, this might indicate a poor division of the data set (MathWorks Company, 1994–2015). Training, validation, and test errors are indicated in Figure 11 as blue, green, and red lines, respectively. The figure indicates good training of the ANN model. The best validation performance is $5.5821 \times 10^{-4}$ which was achieved at epoch 11.

**Evaluation of the trained neural network**

A FFBPNN is implemented for shoulder instability diagnosis. Once ANN training is complete, the weights and biases are specified and the trained ANN model can be used to generate outputs for new inputs. As an additional quality check of the generalization ability of the ANN model, the prediction accuracy is calculated. The ability of the trained ANN for shoulder instability diagnosis is estimated based on the absolute prediction error (APE) of all data sets,
which is defined by the following equation:

$$APE_i = |y_i - \hat{y}_i|,$$

where APE\(_i\) is the APE for the \(i\)th network output \(\hat{y}_i\), and its related target \(y_i\). Figure 12 shows the APE for the ANN model using the training, validation, and test data sets. The maximum prediction errors are \(7.657 \times 10^{-6}\), \(4.2 \times 10^{-2}\), and \(10.2 \times 10^{-2}\) for the training, validation, and test data sets, respectively, which are within the acceptable limit.

Furthermore, the mean absolute percentage error (MAPE) for the training, validation, and test data sets (defined by Equation (6)) are \(1.677 \times 10^{-6}\), \(1.4603 \times 10^{-2}\), and \(3.975 \times 10^{-2}\), respectively, where \(N_s\) is the number of data points in each set. The MAPE is considered to be a ‘robust’ measure of predictive accuracy, as it is based on the absolute value of the error. In addition, it is evident that the trained ANN model has a good generalization capability; that is, ANN has good performance on unseen data.

$$\text{MAPE} = \frac{1}{N_s} \sum_{i=1}^{N_s} \text{APE}_i.$$

The high performance of the proposed ANN model is confirmed by a high correlation coefficient \(R\) between the clinical shoulder instability diagnosis and those obtained from the ANN model, as indicated by the \(R\) value in the regression plots shown in Figure 13. These plots have been created for the training, validation, and test subsets as shown in Figure 13(a)–(c), respectively. In the regression figure, dashed lines in each plot represent the ideal result, whereas the solid lines represent the best fit linear regression line between ANN outputs and its targets. As shown in Figure 13, the training, validation, and test results indicate high correlation, \(R > 0.99\).

The proposed ANN model was applied in shoulder instability diagnosis. The targeted data and ANN outputs from the training data set are illustrated in Figure 14, while those of the validation and test data sets are shown in Figure 15(a) and 15(b), respectively. The final diagnosis of shoulder instability can be obtained from the ANN output through two steps: the first step is the approximation of the output to the nearest integer, the second step is converting the approximated value to its binary equivalent. The digit in the units place is related to the right extremity diagnosis, while the digit in the twos place is related to the left side. If the digit value is 1, the shoulder is identified as a positive case, and if it is 0, the shoulder is identified as a negative case.

To conclude, the predictive accuracy for patients’ diagnosis is 100%, in contrast to the 70% achieved using the MRA algorithm. As mentioned previously, the hidden layer number, number of neurons in the second hidden layer, and the first hidden layer activation function have been chosen by trial and error. The best results were achieved from the nominated ANN structure, whereas other trials resulted in poor models. When using a sigmoid activation function for all the hidden layers, the predictive accuracy of the test data set was 33.3%, indicating poor generalization of the ANN model. In addition, when using more than three neurons for the second hidden layer, the total number of network parameters was increased dramatically compared to the available
Conclusions

In order to evaluate the shoulder joint instability function, this research has proposed an evaluation method that is applied to a 3D robot in the third author’s laboratory. This evaluation method reproduces test results equivalent to those clinically produced by a therapist. For a shoulder joint instability diagnosis based on ANN, the maximum exerted isometric forces of the three basic motions (external rotation, abduction, and horizontal abduction) are used as explanatory variables for the network. The clinical evaluations were used as network targets. An ANN model was simulated and succeeded in generating outputs equivalent to those obtained clinically. As a future work, in order to verify the generality of the proposed ANN diagnosis algorithm, it will be applied for a greater number of subjects. In addition, an evaluation of shoulder cooperativeness based on an artificial technique will be attempted. Consequently, after verifying the reliability of the evaluation techniques of the shoulder stability and its cooperativeness, the proposed methods can be applied to our robot.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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