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Applying a computational intelligence method to predict the rehabilitation treatment for females with lateral patellar displacement

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ABSTRACT

A lateral positioned patella has long been regarded as a major contributing factor in the development of patella femoral pain (PFP). Despite extensive research, there is still little consensus as to the most effective treatment strategy for the management of patients with lateral patellar displacement (LPD). Computational intelligence methods are proving useful aids to physicians and other medical staff, improving objectivity when making diagnostic and treatment decisions and reducing the time to make decisions. This study describes an adaptive network-based fuzzy inference system (ANFIS) used to build a model for the indirect prediction of rehabilitation treatment outcomes for females with LPD from only demographic and clinical characteristics. The prediction abilities offered using two ANFIS models (ANFIS-subtractive clustering method and ANFIS-fuzzy c-means clustering method) are presented using data from 48 female patients referred to rehabilitation clinics of Isfahan Ayatollah Kashani and Al Zahra hospitals, Iran. The results indicate that the ANFIS model has strong potential to improve indirect prediction of rehabilitation treatment for females with LPD with a high degree of accuracy and robustness.

1. Introduction

A lateral positioned patella has long been regarded as a major contributing factor in the development of patella femoral pain (PFP) (Grelsamer, 2000; Shellock, Mullin, Stone, Coleman, & Crues, 2000; Wilson, 2007). It is hypothesized that this lateral patellar displacement (LPD) potentially puts uneven stress on both the patella itself and the peripatellar tissues, leading to articular cartilage degeneration and subsequent pain (Ota, Ward, Chen, Tsai, & Powers, 2006; Smith, Davies, & Donell, 2009; Wilson, 2007). Patients with LPD suffer pain in the anterior knee, which may occur during functional activities such as squatting and descending stairs (Lai, Levinger, Begg, Gilleard, & Palaniswami, 2009; Shellock, 2000; Song, Lin, Jan, & Lin, 2011). Deficiency of patellar stabilizers including tightness of the lateral patellar structures and laxity or weakness of the medial structures is the main cause of this displacement (Fredericson & Yoon, 2006; White, Dolphin, & Dixon, 2009).

Many different operative and non-operative treatments have been suggested to manage patients with LPD (Callaghan, Bagley, Selfe, & Oldham, 2002; Shellock et al., 2000; Shellock, 2000). Initially, non-operative treatments are used to treat these patients, with the three most common treatments being therapeutic exercise, bracing and therapeutic exercise with bracing. Different studies show that the degrees of improvement with these treatments are varied, and no one specific treatment has been found to be useful for every patient. For example, Balci et al. (2008) found that exercise was useful in reducing pain, improving functional activities and increasing the independence of these patients. Douciette and Goble (1992) report an exercise program that improved tracking of the patella, ameliorated the nutrition of the joint, decreased contact forces of patella femoral joint, and reduced oedema. Shellock et al. (2000) found that use of the brace improved the abnormal positions of the patella in most of the patients studied. Powers et al. (2004) reported that the utilization of a brace did not decrease loads on the patella femoral joint structures during stair ambulation in patients with PFP. Mohammadi et al. (2008) reported that long term application of knee sleeves needed to be done in conjunction with exercises or risk weakening muscles. Choi et al. (2011) confirmed that the brace could be effective in the short term, but long terms use of a brace weakened the vastus medialis oblique (VMO). As a consequence, a program of selective muscular strengthening for the VMO should be emphasized.

However, Martin (2001) reported the use of functional braces, knee sleeves, and postoperative braces had been accepted clinically on the basis of subjective performance. If used, knee braces should supplement, rather than replace, rehabilitation program

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and surgery. Lun et al. (2005) compared the effect of patellar bracing on four treatment groups: (1) home exercise program, (2) patellar bracing, (3) home exercise program with patellar bracing, and (4) home exercise program with knee sleeve. They found that there was a significant improvement in knee function and pain within all groups over 12 weeks and no significant difference between groups. Despite this body of research, there is still little consensus as to the most effective treatment strategy for the management of patients with LPD.

Computational intelligence methods using artificial neural networks (ANNs), fuzzy logic (FL), support vector machine (SVM), or machine learning algorithms have been developed to aid physicians and other medical staff in making medical decisions (Hastie, Tibshirani, & Friedman, 2011; Hawamdeh et al., 2012). These methods have shown great promise as the basis for models aimed at supporting clinical diagnosis and prediction (Gil, Johnsson, Chamizo, Paya, & Fernandez, 2009; Green et al., 2006; Peled, 2005; Shanthi, Sahoo, & Saravanan, 2009), as well as clinical management (Frize, Ennett, Stevenson, & Trigg, 2001; Papageorgiou, 2009). Such computational models also improve the potential to overcome traditional diagnostic and clinical management techniques, which can be subjective and time-consuming (Yoo, Kim, Choi, Kim, & Kim, 2013). As a result, using computational intelligence methods can lead to time and cost savings, as well as increased accuracy of treatment recommendations by physicians (Hawamdeh et al., 2012).

A range of studies show that computational intelligence methods are widely used in medical applications. For example, Lai et al. (2007) reported that the SVM was able to effectively recognize gait patterns that were affected due to patella femoral pain syndrome (PFPS) condition from a combination of selected gait features with 89% accuracy. Watt and Bui (2008) found that use of Bayesian Belief Networks (BBNs) could effectively predict the symptoms commonly associated with the presence of knee osteoarthritis (OA). Hawamdeh et al. (2012) developed an ANN-based decision support system that was able to accurately predict the treatment prescribed by the physician for 87% of the patients with knee osteoarthritis. Tam et al. (2004) found that a prediction model developed using ANN was useful when deciding which treatment regime best suited a patient with knee OA. Lai et al. (2009) found that the SVM was equally able to detect gait changes in patients with PFPS. This result was encouraging for the future application of SVMs in gait diagnostics as well as in the evaluation of treatment interventions, especially in the PFPS population. Yoo et al. (2013) reported that the SVM method could contribute to the advancement of clinical decision-making tools and to a better understanding of risk factors associated with knee OA progression. Gil et al. (2009) found that an ANN model was able to distinguish and classify between healthy patients and patients with urological dysfunctions. Cho et al. (2013) reported that there was merit in making use of a trained ANN as an additional tool for classification of trochlear dysplasia. Al-Shayea et al. (2013) reported that ANN had powerful pattern classification and prediction capabilities for medical diagnosis.

Although computational intelligence methods have been used in the diagnosis, progression and treatment of various dysfunctions, there are limited studies in the rehabilitation domain. Our work looks to inform this domain with a model aimed at predicting the best rehabilitation for the treatment of LPD. This study employed an adaptive network-based fuzzy inference system (ANFIS) to design and test a model to predict rehabilitation treatment for females with LPD using only their clinical and demographic characteristics. ANFIS hybrid systems combine the advantages of fuzzy systems, which deal with explicit knowledge which can be explained and understood, and ANNs, which deal with implicit knowledge which can be acquired by learning. ANN learning provides a good way to adjust an expert decision maker's knowledge and automatically generate additional membership functions (MFs) and fuzzy rules, to meet certain specifications and reduce costs and design time (Fattahi, 2016). In this study, two ANFIS models were implemented by subtractive clustering method (SCM) (Chiu, 1994) and fuzzy c-means clustering method (FCM) (Bezdek, 1973) for prediction of rehabilitation treatment for females with LPD.

2. Materials and methods

2.1. The methodology of adaptive network-based fuzzy inference system

A fuzzy inference system can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. ANN are information-processing programs inspired by mammalian brain processes. ANN are composed of a number of interconnected processing elements analogous to neurons. The training algorithm inputs to the ANN a set of input data and checks the ANN output desired result. Combining ANN with FL has been shown to emulate the human process of expert decision-making reasonably well. In traditional ANN, only weight values change during learning, thus the learning ability of ANN is combined with the inference mechanism of the FL for a neuro-fuzzy decision-making system (Lin & Lee, 1991).

Jang (1993) proposed an ANFIS algorithm based on the Sugeno fuzzy inference model. The ANFIS can construct an input–output mapping based on both the fuzzy if–then rules and the stipulated input–output data pairs. The if-then rules of Sugeno fuzzy inference model are often applied for obtaining the inference of an imprecise model used to make a conclusion in the indefinite system, which can be better than human decision making. These if–then rules are based on stipulated input–output training data pairs and appropriate MFs produced. The ANFIS employs the neural training process to adjust the MF and the associated parameter that approaches desired data sets (Wu, Hsu, & Wu, 2009). To better understanding ANFIS, an example with two inputs (x and y) and one output (f) is presented in Fig. 1.

As can be seen in Fig. 1, generally, the ANFIS system includes five layers, excluding the input layer.

Layer 0: is the input layer. It has n nodes where n is the number of inputs to the ANFIS system.

Layer 1: is the fuzzification layer. In this layer MFs of input variables are used. Each node i in this layer generates a membership grades of a linguistic label. For instance, the node function of the i^{th} node that is defined as follows:,

$$Q_i^1 = \mu_{Ai}(x) = \frac{1}{1 + \left[\left(\frac{x - v_i}{\sigma_i}\right)^2\right]^{b_i}} \tag{1}$$

where, x is the input to node i, and Ai is the linguistic label associated with this node; and $\left\{\sigma_i, V_i, b_i\right\}$, is the parameter set that changes the shapes of the MF.

Layer 2: each node in this layer calculates the 'firing strength' of each rule via multiplication (Eq. (2)).

$$Q_i^2 = W_i = \mu_{Ai}(x).\mu_{Bi}(y)_, \ i = 1, 2 \tag{2}$$

Layer 3: is the normalization layer. Nodes are fixed in this layer and are labeled with N, indicating that they play a normalization role. This layer normalizes the strength of all rules according to the equation

$$Q_i^3 = \bar{W}_i = \frac{w_i}{\sum_{j=1}^{2} w_j}, \ i = 1, 2 \tag{3}$$