Application of Neural Networks in Assessing Changes around Implant after Total Hip Arthroplasty

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Abstract. Bone and joint diseases afflict more and more younger people. This is due to the work habits, quality and intensity of life, diet and individual factors. Hip arthroplasty is a surgery to remove the pain and to allow the patient to return to normal functioning in society. Endoprosthesoplasty brings the desired effect, but the life span of contemporary endoprosthesis is still not satisfactory. Clinical studies have shown that the introduction of the implant to the bone causes a number of changes within the bone – implant contact. The correct prediction of changes around the implant allows to plan the surgery and to identify hazardous areas where bone decalcification and loss of primary stability in implant can occur.

1 Introduction

The demand for a variety of prostheses, resulting from increasingly higher number of injuries and osteoarticular pathologies which are a consequence of ageing society, stimulates the necessity for improvement of materials used for implants [5]. Reconstruction surgery allows for repairing the tissues damaged as a result of an injury or pathological changes, which makes it possible to regain the lost functions [13]. An essential problem is proper diagnosing of tissue structure and identification of functional deficiency. Achievement of these aims necessitates the use of proper diagnostic methods, precision and experience of the surgeons [15]. Due to its functions, hip joint is one of the most frequently used load–bearing joint [2], which leads to occurrence of degenerative

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changes [8]. Human race has always sought methods of reconstruction of damaged tissues and organs and the scientists have focused on these activities for over a hundred years. The only method of treatment in the case of serious problems was to remove the damaged organ. However, it improved life comfort only to an insignificant degree. The situation changed when progress in both medical science and material engineering allowed for collection and transplantation of living tissues and implantation of synthetic or natural biomaterials in order to restore the functions of defected or even removed organs [14].

We use neural networks which are one of methods constituting the soft computing concept. There are other soft computing methods [4][7][9][10][11][12][16] but neural networks are the best choice for nonlinear regression problem as we deal with in the paper. Some methods [6] have inherent ability to handle missing data but in our case we had complete vectors with patient evaluation data.

2 Research Method

Retrospective control examination of patients with implanted stem was carried out among 109 women and men. The oldest woman at the moment of surgery was 86 years old, whereas the youngest one was 43 (age average 71 years). Among women, the most frequent hip joint replacement concerned the right leg (61.1% of the cases with 38.9% cases for the left leg). In the case of two women, two-sided hip joint replacement was carried out. In the group of men, average age of the patients on the day of operation was 68 years (the oldest men was 83 years old whereas the youngest one was 47 years old). In the studied group of males, right hip joint replacement was carried out in 64.5% of the cases: hip joint replacement for the left leg was carried out in 35.5% cases. In one patient, the surgery was carried out in both legs.

Average age of the patients was 70 years. Indications for hip joint replacement in the analysed group of patients are presented in chart 1. In the case of 134 persons, side surgical access was used, whereas 19 cases concerned rear surgical access. In order

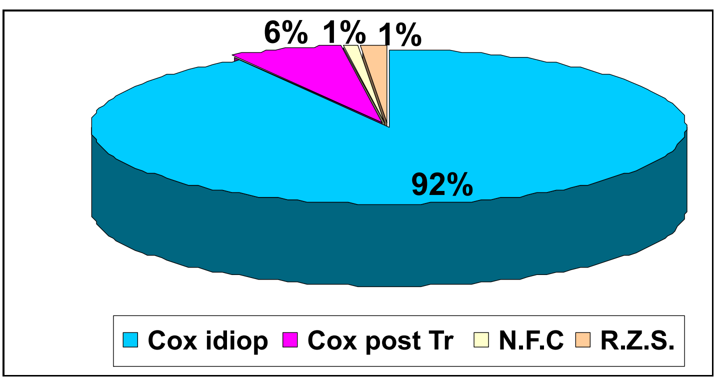

Fig. 1. Dysfunction of hip joint as a reason for hip joint replacement

to determine the effect of implantation of stem on femur remodelling, a representative group of 153 persons after implantation of stems with observation period from 12 to 66 months (average observation time of 58 months) was selected.

Based on RTG images the assessment of heterotopic ossifications and determination of bone decalcification which proves occurrence of bone defects. Patchy ossification in soft tissues, qualified under classification of Broker as I0 was observed in 18% of the patients (example RTG image see Fig. 1a). Exostosis (calcifications) from proximal part of femur or pelvis, not connected with the opposite side, a break over 1 [cm] was confirmed in 7% of person after 2hip joint replacement (example RTG image see Fig. 1b).

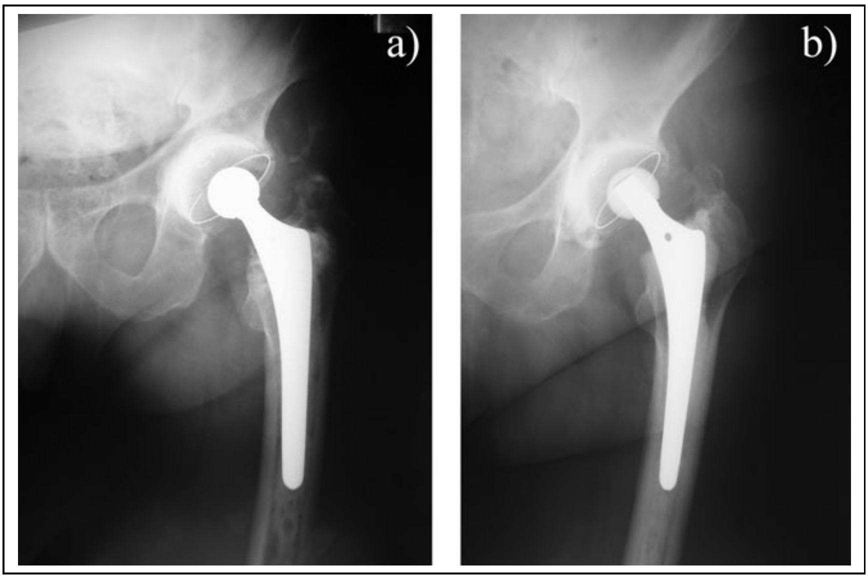

Fig. 2. Assessment of heterotopic ossification according to Broker. 2a - Patchy ossification in soft tissue, 2b - Exostosis (calcifications) from proximal part of femur.

Based on RTG images of the bone with implanted stem, the zones of bone decalcification were defined. Figure 2 present radiograms of hip joint with implanted stem. In the case of Fig. 2a and 2b, visible decalcifications of the bone in Gruen zone VI and VII can be observed. The RTG image presented in Fig. 2a presents decalcification in the acetabula in the area of De Lee zone III (central part of pelvis). Radiogram 2c presents the bone with decalcifications in the area of Gruen zone I and VII. Changes in the whole area of acetabulum can also be observed (De Lee zone I, II and III). Bone calcification which can be observed in RTG images might confirm that implantation of the stem causes changes in loading of femur, particularly in the area of contact of bone–implant (bone – cement – implant), where bone stiffness occurs. It should be emphasized that changes are insignificant in the adopted period of time, which makes prediction for stem life in the body satisfactory.

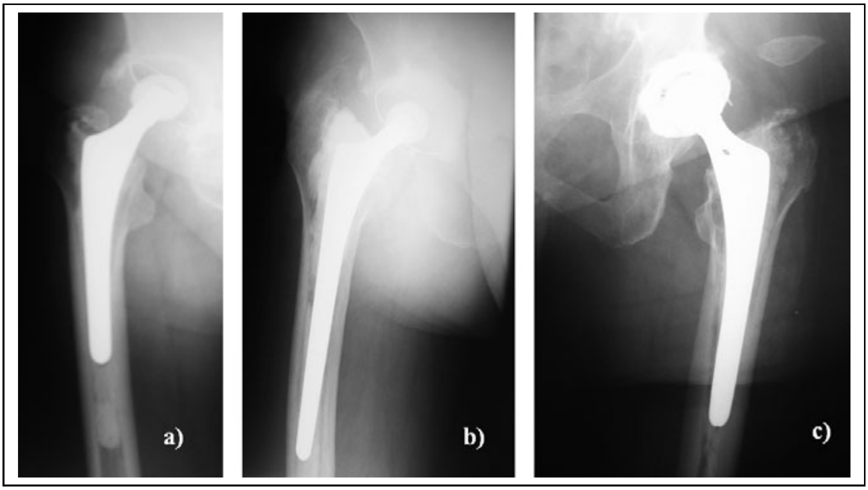

Fig. 3. RTG images of the bone with implanted stem, 2 a)b) decalcifications of the bone in Gruen zone VI and VII, 2c) decalcifications in the area of Gruen zone I and VII

3 Experimental Results

The presented results reveal that hip joint replacement brings desirable effects in a considerable majority of the cases. This is confirmed by the results obtained during analysis and assessment of the data according to the set criteria.

To learn a neural network to forecast and assess changes in bone around the implant, 153 patients histories from Orthopedics and Traumatic Surgery Department of NMP Voivodship Specialist Hospital in Częstochowa were used. Rated factors affecting bone strength parameters such as age and sex of patients, the cause of qualifications for arthroplasty (traumatic and degenerative) together with an indication for implantation of the waiting period (illness behavior) and the life of the prosthesis by the patient. Additionally, analyzed the factors that may affect the state of the bone around the implant after the implant prosthesis. These factors were introduced in three groups: The first group - motility of patients - the functionality of the limb during gait, her mobility with regard to physical activity. The second group - the biomechanical parameters affecting the load arm during basic activities such as limb length, the stability of the prosthesis in the bone, the shape of bones, etc. The data in the third group were obtained after evaluation of X-ray images of the type of implanted prosthesis and method of attachment in bone. X-ray studies allowed us to determine the changes around the implant (Gruen zones) characteristic for the type of prosthesis and ossification outside the bones (Brook's classification). The above data allowed to teach the neural network forecasting changes in the femur in various stages of use of selected types of prosthetics and evaluation of the bone in the area of contact around the stem. We used the LevenbergMarquardt algorithm [3] to train multilayer nonlinear feedforward artificial neural network [1]. The network had five neurons in the first hidden layer, five neurons in the second hidden layer and one neuron in the output layer. The network had several dozens inputs and one output denoting artificial hip assessment from 1 to 10. We obtained 100% accuracy. The neural network was able to reflect accurately the assessment made by orthopaedists.

4 Conclusions

We used a multilayer perceptron trained to assess changes around changes around implant after total hip arthroplasty. We used several dozens inputs and one output to numerically determine level of changes in femur. The neural network was trained by the Levenberg–Marquardt algorithm. The algorithm is able to find a local minimum of a nonlinear function over a space of parameters of the function. In the case of neural networks the parameters are weights which store the knowledge obtained during learning. During learning the weights are changed to fit the network to the learning data. Using moderately sized neural network we achieved maximal accuracy, thus the artificial neural network was able to imitate the assessments made by orthopaedists.

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