Forecasting Wear of Head and Acetabulum in Hip Joint Implant

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Abstract. Total hip joint replacement is a multi-aspect issue, where life span of the implant system in human body depends on numerous factors. One of the main reasons for having a hip replacement is loosening or wear of the associated components in artificial joint. The rate of wear depends mainly on the type of materials working together in the artificial joint, the burden resulting from the patient's body weight, intensity of use, limb functionality, age of the patient's and individual factors. The analysis of all factors leading to the joint wear and articulation expensiveness will allow for the appropriate selection of an head–acetabulum system which provide long-lasting and trouble-free operation. We use neuro–fuzzy systems to machine–learn the data to predict automatically the wear of elements in the artificial hip joint.

1 Introduction

Restoration of the pathologically changed or damaged in an accident, apart from removing hip pain, should ensure normal mobility and functionality of the hip joint. The human hip joint carries a large load and its mobility should allow the patient normal activities resulting from the daily duties [10]. Low friction occurring in human joints burdened with the normal and tangential force can be explained by the creation of a lubricant wedge formed by the synovial fluid that fully separates the contacting surfaces of bones, covered with elastic tissue of femoral cartilage [11]. Hip replacement

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is accompanied by a change of elements working in an artificial joint. Originally elements working together in the hip joint were made of metal, but due to rapid wear more new materials are being introduced to improve the life of the friction node[3]. Currently in the reconstruction of the hip joint, we can distinguish many kinds of friction pairs, differing in both strength parameters, tribological parameters as well as energy absorption. The main factor determining the type of head–acetabular system, apart from its life span, is the price of artificial joint components [9]. Reconstruction of the bone around the friction node should provide strong fixation of the acetabulum with pelvic bone, however, the resulting ossification should not restrict joint mobility [8]. Proper selection of artificial joint components should guarantee full comfort of the patient, maximally long life of elements in the body and the minimal cost of articulation. In addition, the wear of the elements should be small enough so they do not transfer wear products into the patient.

2 Materials and Methods

Prediction of the head and acetabulum wear in artificial hip joints was carried out on the base of the disease history of the 220 patients of Orthopedics and Traumatic Surgery Department of NMP Voivodship Specialist Hospital in Czestochowa. The criterion for selection of artificial joint components has been structured in three groups. In the first group, the pelvic bone changes seen on X-Ray (DeLee zone) were rated. The parameters evaluated in this criterion were determined in the way of mounting acetabulum in the bone. The first method (press fit) is pocketing the acetabulum with a larger size than prepared bone lodge (oversized component). The second method (exact fit) is equivalent to fitting the acetabulum of the size of milled box (on-line fit). The initial stabilization of the acetabulum takes place by micromechanical anchoring by the elastic and plastic deformations of trabeculae. Evaluation of clinical material helped to systematize the mechanism of late loosening of bearings such as the resorption process starting from the edge of the acetabulum, or the formation of the intermediate connective membrane at the border of cement - bone. On the basis of radiographic evaluation, we obtained also patches ossification in the soft tissues and bone decalcification were defined, showing the formation of bone defects. Second factor affecting the intensity of the friction is the set of parameters such as age, sex, body weight of patients, and the functionality of the limb: the possibility of walking and physical activity. In addition, range of mobility was analyzed by assessing the joint angular values: flexion, abduction, external rotation in extension, adduction, and straightening the limb. In the third group the type material of the head and the acetabulum, their respective configurations, their life-span and friction were analyzed. To predict the wear intensity we used common in orthopedics configurations of the following materials:

1. head
    - CoCr – standard finish
    - CoCr – increased smoothness (also for metal / metal),
    - Aumina + zircon.

2. inserts
   - plain UHMWPE,
   - partially cross–linked UHMWPE,
   - HXLPE highly crosslinked,
   - HXLPE + Vit E,
   - Metal / metal,
   - Alumina + zirconia,

All diagnostic procedures and measurements were carried out in accordance with the criteria commonly used in medicine [1][2][5][6]. The above data allowed to teach the neural network prediction of changes in the tribological parameters of the various stages of use of selected elements of the head and the acetabulum. In addition, evaluated changes of the factors of the bone–tissue in the pelvic area (DeLee zone) and ossification in the soft tissue and joint mobility allow for precise prediction and adaptation of the selected type of articulation to individual patient needs.

3 Numerical Simulations

We used Mamdani-type neuro-fuzzy systems [4][7][12] to learn obtained data described in the previous section. At the beginning of this section we describe the neuro fuzzy systems. We consider multi-input-single-output fuzzy system mapping $\mathbf{X} \to Y$, where $\mathbf{X} \subset R^n$ and $Y \subset R$. Theoretically, the system is composed of a fuzzifier, a fuzzy rule base, a fuzzy inference engine and a defuzzifier. The fuzzifier performs a mapping from the observed crisp input space $\mathbf{X} \subset R^n$ to a fuzzy set defined in X. The most commonly used fuzzifier is the singleton fuzzifier which maps $\bar{\mathbf{x}} = [\bar{x}_1, \ldots, \bar{x}_n] \in X$ into a fuzzy set $A' \subseteq X$ characterized by the membership function

$$\mu_{A'}(x) = \begin{cases} 1 \text{ if } x = \bar{x} \\ 0 \text{ if } x \neq \bar{x} \end{cases} \tag{1}$$

Equation (1) means that, in fact, we get rid of the fuzzifier. The knowledge of the system is stored in the fuzzy rule base which consists of a collection of N fuzzy IF-THEN rules in the form

$$R^{(k)} : \begin{cases} \text{IF} \quad x_1 \ is \ A_1^k \ AND \\ \qquad x_2 \ is \ A_2^k \ AND \ldots \\ \qquad x_n \ is \ A_n^k \\ THEN \ \ y \ \ is \ B^k \end{cases} \tag{2}$$

or

$$R^{(k)}\text{: IF } \mathbf{x} \text{ is } A^k \text{ THEN } y \text{ is } B^k \tag{3}$$

where $\mathbf{x} = [x_1, \ldots, x_n] \in \mathbf{X}$, $y \in Y$, $A^k = A_1^k \times A_2^k \times \ldots \times A_n^k$, $A_1^k, A_2^k, \ldots, A_n^k$ are fuzzy sets characterized by membership functions $\mu_{A_i^k}(x_i)$, $i = 1, \ldots, n$, $k = 1, \ldots, N$, whereas B^k are fuzzy sets characterized by membership functions $\mu_{B^k}(y)$, $k = 1, \ldots, N$. The firing strength of the k-th rule, $k = 1, \ldots, N$, is defined by

$$\tau_k(\bar{\mathbf{x}}) = \mathop{T}_{i=1}^{n} \left\{ \mu_{A_i^k}(\bar{x}_i) \right\} = \mu_{A^k}(\bar{\mathbf{x}}) \tag{4}$$

The defuzzification is realized by the following formula

$$\overline{y} = \frac{\sum_{r=1}^{N} \overline{y}^r \cdot \mu_{\overline{B}^r}(\overline{y}^r)}{\sum_{r=1}^{N} \mu_{\overline{B}^r}(\overline{y}^r)}. \tag{5}$$

The membership functions of fuzzy sets $\overline{B}^r$, $r = 1, 2, \ldots, N$, are defined using the following formula:

$$\mu_{\overline{B}^r}(y) = \sup_{\mathbf{x} \in \mathbf{X}} \left\{ \mu_{A^r}(\mathbf{x}) \overset{T}{*} \mu_{A^r \to B^r}(\mathbf{x}, y) \right\}. \tag{6}$$

With singleton type fuzzification, the formula takes the form

$$\mu_{\overline{B}^r}(y) = \mu_{A^r \to B^r}(\overline{\mathbf{x}}, y) = T\left(\mu_{A^r}(\overline{\mathbf{x}}), \mu_{B^r}(y)\right). \tag{7}$$

Since

$$\mu_{A^r}(\overline{\mathbf{x}}) = \mathop{T}_{i=1}^{n} \left(\mu_{A_i^r}(\overline{x}_i)\right), \tag{8}$$

we have

$$\mu_{\overline{B}^r}(y) = \mu_{A^r \to B^r}(\overline{\mathbf{x}}, y) = T\left[\mathop{T}_{i=1}^{n} \left(\mu_{A_i^r}(\overline{x}_i)\right), \mu_{B^r}(y)\right], \tag{9}$$

where T is any t-norm. Because

$$\mu_{B^r}(\overline{y}^r) = 1 \tag{10}$$

and

$$T(a, 1) = a, \tag{11}$$

we obtain the following formula

$$\mu_{\overline{B}^r}(\overline{y}^r) = \mathop{T}_{i=1}^{n} \left(\mu_{A_i^r}(\overline{x}_i)\right). \tag{12}$$

Finally we obtain

$$\overline{y} = \frac{\sum_{r=1}^{N} \overline{y}^r \cdot T_{i=1}^{n} \left(\mu_{A_i^r}(\overline{x}_i)\right)}{\sum_{r=1}^{N} T_{i=1}^{n} \left(\mu_{A_i^r}(\overline{x}_i)\right)}. \tag{13}$$

Input linguistic variables are described by means of Gaussian membership functions, that is

$$\mu_{A_i^r}(x_i) = \exp\left[-\left(\frac{x_i - \overline{x}_i^r}{\sigma_i^r}\right)^2\right], \tag{14}$$

If we apply the Larsen (product) rule of inference, we will get the following formula

$$\overline{y} = \frac{\sum_{r=1}^{N} \overline{y}^r \left(\prod_{i=1}^{n} \exp\left[-\left(\frac{\overline{x}_i - \overline{x}_i^r}{\sigma_i^r}\right)^2\right]\right)}{\sum_{r=1}^{N} \left(\prod_{i=1}^{n} \exp\left[-\left(\frac{\overline{x}_i - \overline{x}_i^r}{\sigma_i^r}\right)^2\right]\right)}. \tag{15}$$

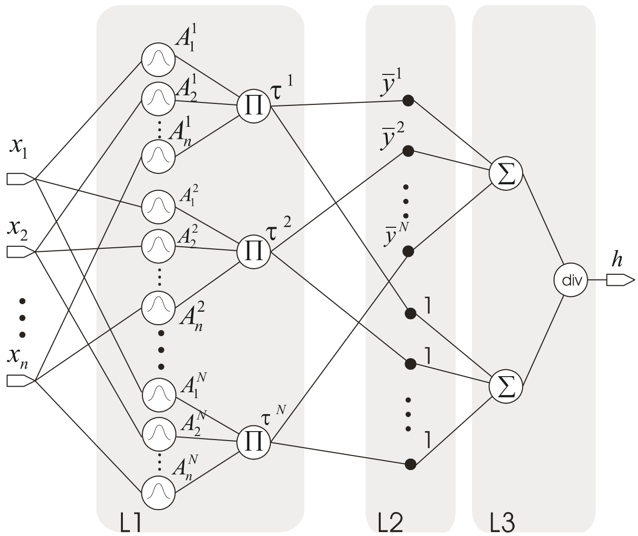

Fig. 1. Single Mamdani neuro-fuzzy system

The output of the single Mamdani neuro-fuzzy system, shown in Fig. 1, is defined

$$h = \frac{\sum_{r=1}^{N} \bar{y}^r \cdot \tau^r}{\sum_{r=1}^{N} \tau^r}, \tag{16}$$

where $\tau^r = \mathop{T}\limits_{i=1}^{n} \left(\mu_{A_i^r} \left(\bar{x}_i \right) \right)$ is the activity level of the rule $r = 1, ..., N$. Structure depicted by (16) is shown in Fig. 1. We used several dozen inputs and one output. The system was trained by the backpropagation gradient learning. The neuro–fuzzy system achieved 96% accuracy.

4 Conclusions

Total hip joint replacement is a multi-aspect issue, where life span of the implant system in human body depends on numerous factors. The rate of wear depends mainly on the type of materials working together in the artificial joint, the burden resulting from the patient's body weight, intensity of use, limb functionality, age of the patient's and individual factors. The analysis of all factors leading to the joint wear and articulation expensiveness will allow for the appropriate selection of an head–acetabulum system which provide long-lasting and trouble-free operation. We used neuro–fuzzy systems to machine–learn the data to predict automatically the wear of elements in the artificial hip joint. All system parameters were determined by the backpropagation algorithm.

Thanks to neuro-fuzzy systems, apart from purely data-driven designing, we can use some expert knowledge in the form of fuzzy rules. The system was able to predict accurately the wear of the artificial hip joint.

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