TKA WEAR SCAR PREDICTION USING ARTIFICIAL NEURAL NETWORKS

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Introduction: Wear in total knee arthroplasty (TKA) is highly variable. From retrieved specimens inconsistent wear patterns have been reported [1]. The type of activity [2], as well as the patient specific gait [3] are factors influencing those wear patterns. In order to evaluate and predict the longevity of new prosthetic materials, knee wear simulation is common practice and required by many regulatory bodies. However, according to current standards, only one testing protocol is pursued (being either load or motion controlled) [4]. The testing procedure itself relies on the application of a normal walking cycle with 5 million repetitions. Time constraints – a test lasts typically up to 3 months – prohibit the analysis of other activities and/or gait patterns, even though their relative importance for the overall wear outcome is mostly unknown. Therefore, in this study, an Artificial Neural Network (ANN) approach has been conducted to model the relationship between simulator input parameters and the generated wear scars.

Materials and Methods: A backpropagation neural network (BP) was chosen because of its proven capabilities to generalize any solution for multidimensional and non-linear problems. Such a model consists of a multi-layer network (with at least one hidden layer) in which the network connections are trained (i.e. adjusted) to create an input-to-output relationship. For each network interaction an error value is computed and back-propagated to the hidden layers. This allows adjustment of the connections ('weights') to minimize the error.

For network training, testing and cross-validation 124 short-term tests were conducted using a four-station Endolab® knee simulator in load control mode (Tab.1). Implants were of single design (MG II, Zimmer Inc.) and coated with a tracer material allowing the rapid identification of the wear scar boundaries [5] Each test was run up to 5,000 cycles in a bovine serum lubricant (30g/L protein content).

Axial force (N)	Flexion (deg.)	Ant/Post force (N)	Int/Ext Moment
ISO, 0.5*ISO and 2*ISO	ISO, 0.5*ISO and 2*ISO	ISO, 0.5*ISO and 2*ISO	ISO, 0.5*ISO and 2*ISO
Const. (500, 1000, 1500, 200)	Sinus (0 – 30, 50, 70)	Sinus (±50, ±100, ±150, ±300)	Sinus (±2, ±4, ±6)

Table 1: A total of 124 tests were conducted taking combinations of the above matrix. Each test resulted in a medial and lateral wear scar

After each test, the generated wear scars on the tibial plateaus were manually digitized by means of a video based measuring system (SmartScope®). Data points of the wear scar contour were then plotted and transferred into 46x36 black and white bitmap images for computer analysis. These images formed the output data set of the backpropagation neural network (BP).

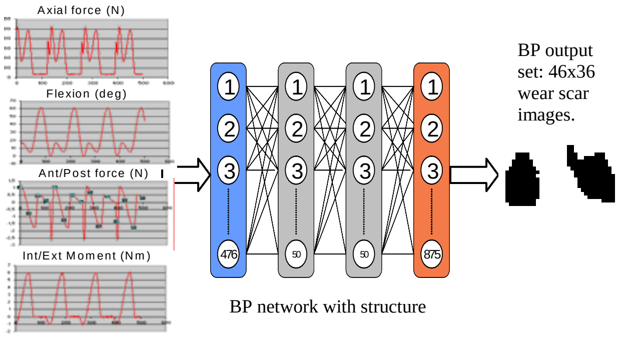

Figure 1: The two-hidden-layers backpropagation network designed in this study.

The BP input data set was based on *measured* simulator input variables, (flexion/extension angle, internal/external rotation, anterior/posterior and axial forces) allowing an optimal representation of the knee simulator input-to-output relationship. While the number of neurons per input and output layer was determined by the dimensionality of the input and output data sets, the number of hidden layers as well as their neurons were assigned through the specific model algorithm. A sensitivity analysis was conducted to determine the best network configuration. The resultant network structure was a two-hidden-layer backpropagation network (50 neurons per hidden layer) with 476 neurons in the input layer and 875 neurons in the output layer. The transfer function for the input and hidden layers was sigmoid, while the output layer had a linear transfer function (Fig. 1).

Training of the multi-layer network was conducted with the Backpropagation learning algorithm developed by Rumelhart *et al* [6]. 80% of the total scenarios were randomly assigned for neural network training, 10% for testing and 10% for cross-validation. The wear scars of the samples for cross-validation did not enter the model.

Results: Neural network training resulted in 80% accuracy of the input-to-output relationship as found using the 12 testing samples. Cross-validation reached 72% predictive capability generating the correct wear scar. Examples are shown in Figure 2.

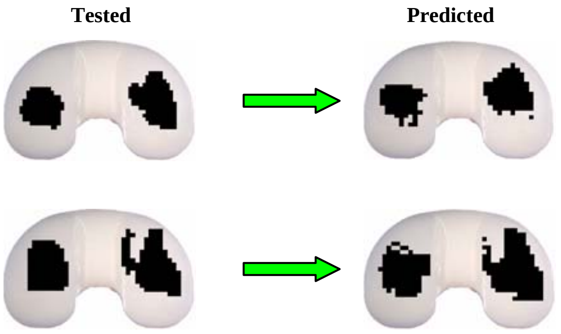

Figure 2: Predicted wear scars from scenarios the BP network was not trained with (cross-validation set)

Discussion: The artificial neural network could be sufficiently trained to predict the wear scar generation at the tibial plateau. Based on observation the predicted wear scars were highly similar to those generated by the wear simulator, similar not only in shape, but also in the area and the location on the tibial plateaus. Most likely, the predictive capabilities of the BP network can be further enhanced by utilizing a modification of the BP learning algorithm, such that the backpropagation with adaptive learning rate or with momentum. Thus, in the future it may be possible to predict patient specific wear patterns based on activity profile and patient gait. Further investigations are necessary to confirm the findings for various prosthetic designs.

References: [1] Wimmer MA, *Trans ORS, 20:1204, 2005*; [2] Benson L, *Proc Inst Mech Eng, 216(6):409-18, 2002*; [3] Schwenke T, *Trans ORS, 29:0295*; [4] ISO 14243-1, 3; [5] Schwenke T, *Relationship between Input Data and Wear in Knee Joint Simulation, Proc Biomechanica 2005, Hamburg, Germany, 2005.* [6] Rumelhart DE *et al*, Parallel Distributed Processing: Exploration in the Microstructure in Cognition, MIT Press Cambridge, MA; 318-362, 1986.

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