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ORIGINAL ARTICLES

Total knee arthroplasty radiographic evaluation via a Bayesian belief network. A pilot study

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Abstract: *In an attempt to standardize the X-ray analysis and to create relevant correlations between it and the functional results, we present a pilot model of an artificial neural network based on a Bayesian belief network (BNN) designed for the automatic analysis of anteroposterior X-ray of the knee following total knee arthroplasty and more precisely the analysis of the tibial component.*

A prospective analysis was conducted in which 30 patients were analyzed and two groups resulted: the first was made up of 12 cases considered "normal" by the examiners (optimal positioning and cementation) and the second one, which was considered "pathological" (incorrect positioning or cementation) and included 16 cases.

Based on 22 points established on the tibial component several geometric sizes (calculated parameters) were computed. Several parameters were compared and the results were up to 75% accuracy, 81.25% sensitivity, and 66.7% specificity.

BBNs can be a solution for X-ray evaluation of total knee arthroplasty and can improve the understanding of its evolution. It needs confirmation in time, its accuracy rising with the number of patients introduced in the analysis algorithm.

Keywords: *TKA; Bayesian method; ANN; X-ray analysis*

INTRODUCTION

Artificial Neural Networking (ANN) are computer systems that create connections, similar to those existing in the biological neural network [1]. Such systems are programmed to learn based on examples, without being programmed in advance to identify specific tasks [2]. For example, artificial neural imaging systems can identify an area of osteolysis, the area that has been previously set as osteolysis using a yes/no algorithm on other images. They can perform this task without having the ability to understand what an osteolysis area means.

ANN is made up of a mass of nodes connected by artificial neurons just like the component of a biological brain. Artificial neurons are interconnected by synapses and can send information between them.

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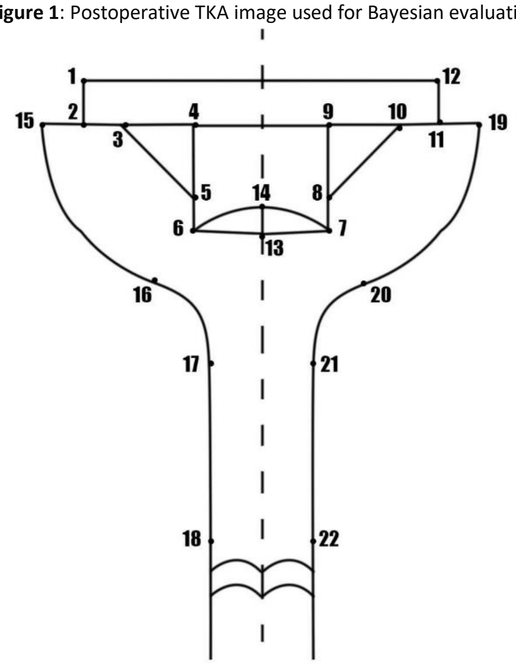
The initial purpose of these artificial neural networks was to create a replica of the human brain and the latter to be able to make decisions similar to those made by a human. Following their application in different fields, the initial purpose was forgotten. They are currently used for verbal recognition, translation, social networks, but most importantly in the medical diagnosis, such as total knee arthroplasty (TKA) [3, 4, 5, 6].

Thus, for patients with diseased knee or hip joints, total knee or hip arthroplasty (TKA/THA) is considered as one of the most effective procedures for relieving pain and improving joint function [7]. Improvements in joint arthroplasty procedures will routinely witness rapid recovery, faster functional recovery, lower postoperative discomfort, and higher patient satisfaction, which is a win-win for patients and surgeons [8].

The importance of the restoration of the biomechanical axis of the pelvic limb is emphasized in current studies [9]. Proper prosthetic positioning, mobility restoration, and pain disappearance are factors predicting the long-term survival of the prosthesis as well as the postoperative patient satisfaction [10].

Figure 1: Postoperative TKA image used for Bayesian evaluation



Radiological postoperative evaluation following total knee arthroplasty is essential to improve the quality of the surgical act. The standard procedure implies that two postoperative X-rays are performed, one anteroposterior, and one profile X-ray. They analyze the mechanical alignment of the knee, bone coverage by the prosthesis, femoral anterior and posterior offset, femoral flexion and extension, tibial slope (Figure 1).

Also, during the initial postoperative evaluation, any deficiencies in the cementation technique are identified. Ideally, it is sought to obtain a uniform cement coat for thickness and distribution.

In an attempt to standardize the X-ray analysis and to create relevant correlations between it and the functional results, we present a pilot model of an artificial neural network based on a Bayesian belief network (BNN) designed for the automatic analysis of anteroposterior X-ray of the knee following total knee arthroplasty and more precisely the analysis of the tibial component.

BNNs are frequently used in medicine, they provide the probability of an outcome based on creating intuitively relations between variables [11-15].

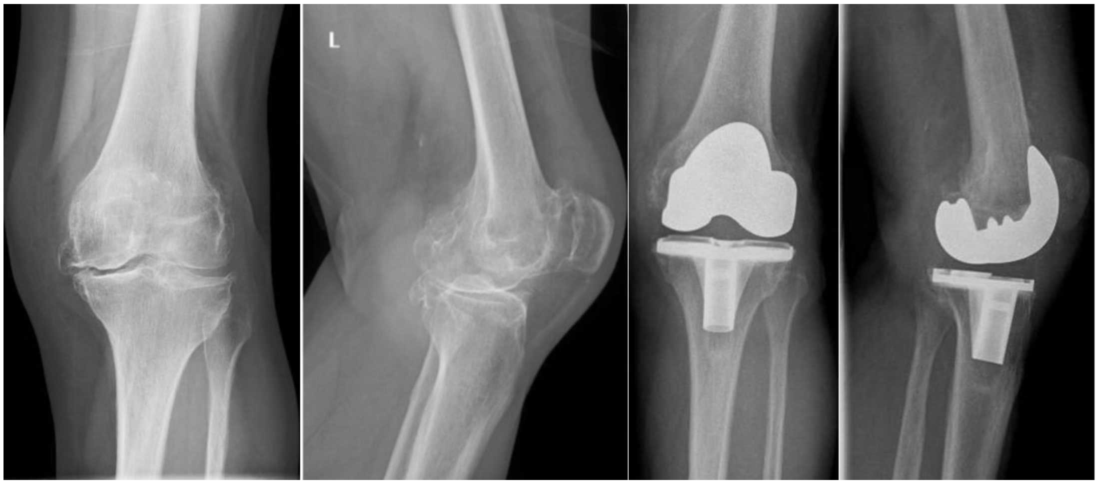
MATERIALS AND METHODS

A prospective study in which two lots of patients were used. In both, patients with gonarthrosis were included, who were subjected to total knee arthroplasty, which was performed in the same center by the same surgical team. The inclusion criteria were patients over 65 years old, who were subjected to TKA, with underlying gonarthrosis disease. Exclusion criteria included inflammatory arthritis, post-traumatic gonarthrosis with major deformities, unicompartmental arthroplasty.

The two lots of patients were conceived following the X-ray analysis on day 0 postoperatively by an independent team of orthopedists. Standing AP, profile, and full leg X-rays of 30 patients were analyzed and two groups resulted: the first was made up of 12 cases considered “normal” by the examiners (optimal positioning and cementation) and the second one, which was considered “pathological” (incorrect positioning or cementation) and included 16 cases. 2 patients were excluded following the appearance of postoperative complications. The same patient groups were followed up at 1 month, 6 months, and 1 year postoperatively. The same set of X-rays was performed at each visit.

Following the constitution of the two groups of patients, it was decided to start the computer analysis of the postoperative X-rays from 6 months and 1 year. To test the validity/relevance of the automatic analysis, we decided that the initial analysis should be performed at the tibia level, on front-loading X-ray. 22 control points were established at the level of the tibial component (Figure 2) that corresponds to the placement of the prosthesis and the tibial bone, as shown in the schematic picture, 14 points on the contour of the prosthesis and 8 points on the tibia.

Figure 2: 22 control points at the level of the tibial component



Using the identified points, several geometric sizes (calculated parameters) were computed:

1. The left-right rotation of the X-ray image, determined by the difference of the areas associated with the triangles determined by points 3 – 4 – 5 and 8 – 9 – 10 on the prosthesis.
2. Up-down rotation of the X-ray view, determined by the area associated with the ellipse determined by points 6 – 7 – 13 – 14 on the prosthesis.
3. The angle of vertical offset between the axis of the prosthesis (calculated as bisector of the angle formed by sides 4 – 5 – 6 and 7 – 8 – 9) and the axis of the bone, calculated as bisector of the angle formed by sides 17 – 18 and 21 – 22.
4. Horizontal offset angle between the base of the prosthesis (2 – 3 – 4 – 9 – 10 – 11) and the cut of the bone 15 – 19.
5. Percentage of coverage to the left of the prosthesis, determined by the part of the head bone not covered by the prosthesis at level 15 – 2.
6. Percentage of coverage to the right of the prosthesis, determined by the part of the head bone not covered by the prosthesis at level 11 – 19.
7. Variation of previously calculated parameters between postoperative images at 1 month and 6 months.

RESULTS

Following the schematic of the calculated parameters, a Bayes statistical model was applied.

DECISION 1: Normal-pathological differentiation tests at the level of individual X-rays

Of the many variants tested to make the decision, the best results were obtained based on measure 5 (percentage of coverage left of the prosthesis), with a threshold of 0.82 for differentiation (pathological > 0.82). Taking into account these conditions, the normal/ pathological decision correctly identified: 11 images from normal patients (out of the 24) and 26 images from pathological patients (out of the 32).

This led to the following sizes: 66.1% accuracy, 81.25% sensitivity, and 45.8% specificity.

DECISION 2: Normal-pathological differentiation tests at the level of the pair of individual postoperative X-rays at 1-6 months

Of the many variants tested to make the decision, the best results were obtained based on combined measures:

A. The decision according to a single parameter: the sum of parameter 1 (left-right rotation of the X-ray view) at 1 and 6 months, with a decision threshold of 0.47; pathological > 0.47). Taking into account these conditions, the normal/ pathological decision correctly identified: 9 pairs of images from normal patients (out of the 12) and 9 pairs of images from pathological patients (out of 16).

This led to the following sizes: 64.3% accuracy, 56.25% sensitivity, and 75% specificity.

B. The decision according to several parameters: the sum of parameter 1 (left-right rotation of the X-ray view) at 1 month and 6 months, with a decision threshold of 0.47, pathological > 0.47, or difference of parameter 3 (vertical offset angle between the axis of the prosthesis) at 1 month and 6 months, with a decision threshold of 0.75, pathological < 0.75 and difference of parameter 4 (horizontal offset angle between the axis of the prosthesis) at 1 month and 6 months, with a decision threshold of 1.8, pathological < 1.8.

Taking into account these conditions, the normal/ pathological decision correctly identified: 8 pairs of images from normal patients (out of 12) and 13 pairs of images from pathological patients (out of 16). This led to the following sizes: 75% accuracy, 81.25% sensitivity, and 66.7% specificity.

DISCUSSION

Artificial neural networks are increasingly present in classifications, group creation, pattern recognition, and prediction in many disciplines, medicine being among them. The huge potential is represented by speed, volume, and accuracy of data analysis.

The Bayesian system developed by us can recognize immediately and accurately any deficient positioning of the tibial prosthetic component. It can integrate this assessment into the clinical context and provide answers to a series of questions of patients with low satisfaction. It may be an optimal way of evaluating the series X-ray with results that are superimposed over those obtained by a CT scan.

Our model of X-ray analysis by BBN has several limitations. The number of patients is not large enough to obtain sufficiently conclusive results. X-ray analysis is performed only for the tibial component at present, a comprehensive X-ray analysis that also includes the femoral component is required. The registered data do not contain patient information: age, weight, degree of osteoarthritis, preoperative and postoperative mobility, pain scores, and so on.

CONCLUSIONS

BBNs can be a solution for X-ray evaluation of total knee arthroplasty and can improve the understanding of its evolution.

It needs confirmation in time, its accuracy rising with the number of patients introduced in the analysis algorithm.

It may provide an answer for low satisfaction rates of certain patients in whom the prosthetic components are optimally positioned and have no other postoperative complications.

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