Design of an Intelligent Controller for Above Knee Prostheses based on an Adaptive Neuro-Fuzzy Inference System

D A Kadhim¹, M N Raheema¹, J S Hussein¹

¹Engineering College, University of Kerbala, Kerbala, Iraq.

Abstract. The number of Above Knee (AK) amputees has increased in recent years and this has led to a need for urgent work on the design of proper lower limb prostheses. Lower limb prosthetics can be divided into active and passive devices. However, passive prosthetics cannot fully provide the natural motion of a healthy leg, and the technologies used in active prosthetics with knee joints are often far too expensive for amputees in developing countries such as Iraq. In this paper, an active lower limb prosthesis with an efficient knee joint is thus designed. Two strategies were used to collect data for gait cycle analysis of the leg in the sagittal plane: the first was based on the use of a force platform device to obtain the ground force according to the foot position (x, y), while the second utilised a video-camera based system to examine knee joint angles. The obtained data were all sent to an intelligent controller that uses an Adaptive Neuro-based Fuzzy Inference System (ANFIS). The ANFIS controller determines the ground force, mimicking the moment of the active knee with a DC motor and flexion-extension angle values. The experimental data for the motion of the knee joint were collected in the Gait Laboratory, then transformed to joint angles using the ANFIS controller. The results show excellent response in the proposed ANFIS controllers in terms of determining angle and moment values of the knee joint with a very low RMS error of 0.006.

Key Words: Above Knee, lower limb prosthesis, knee joint, gait cycle, Adaptive Neuro-based Fuzzy Inference System, ANFIS.

1. Introduction
The major reasons for amputations are wars, diabetes, and cars accidents, and in recent decades, the number of persons with amputations has considerably increased in Iraq [1]. Classification of prostheses for above-knee amputations may be intelligent (controlled by microprocessor) or passive (non-microprocessor). Traditional inactive devices are not adaptive to gait motion and do not need exterior power sources. Knee joints with electro hydraulically motors were one of the earlier forms of powered lower limb prosthetics for above knee amputees, and Schwirtlich and Popovic used dynamic programming to build up an DC motorized active knee that used optimal gait control based on position tracking [2]. Intelligent prostheses have, in contrast, been greatly improved by modern progress in biomedical engineering, and they can provide highly natural gaits by using recent explicit algorithms and programs to control the limb based on information from the embedded sensors [3, 4]. These intelligent prostheses are, however, very expensive due to the advanced technologies and improved components used in them [5].
Many developments in prosthetics have recently occurred due to improvements in knowledge of the mechanics of ambulation and enhanced use of technology [6]. Russell et al. introduced a bioinspired bicondylar with a minimised actuator dimensions in the knee joint. It was based on a mechanism that reproduced the sliding, rolling, and elastic parts of the human knee, and thus reduced the peak force of the actuator on stair climbing [7]. Maqbool et al. introduced a method based a wireless gyroscope connected to the shank of the lower limb of the amputee for recognition of a coincident gait on ramps and level ground. They showed that the Toe Off (TO) and Initial Contact (IC) events were recognised more quickly in the transtibial amputee compared with in the transfemoral amputee [8]. Awad et al. proposed a knee with both passive and active forms for a transfemoral amputee. Their semi-active device used only the energy necessary through the gait cycle for different daily behaviours [9]. No-Sang Kwak et al. presented a control system a lower limb exoskeleton using a brain–machine asynchronous interface, with canonical correlation analysis and k-nearest neighbour methods used to classify electroencephalography signals [10]. Rodriguez et al. presented three controllers for reconfigurable exoskeletons: Proportional Derivative (PD), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Model Predictive Control (MPC). Their results showed that MPC and ANFIS controllers were capable of learning from environment turbulence and could reduce performance error through increased torque/traction control [11].

Recently Expert and Intelligent control systems such as Artificial Neural Networks (ANN), fuzzy logic, and hybrid networks have been documented as significant methods to improve the performance of Prosthetics and Orthotics. Combinations of these adaptive intelligent systems are the subject of hopeful exploration in the realistic execution of Lower Limb prostheses. The design and achievement of smart limbs is generally based on mathematical models of the knee. However, the design of such systems is very costly and not easy to obtain, due to the need for expert input and skilled operators of automatic control systems [12]. In this situation, ANN, together with fuzzy logic, plays a very significant function in developing modern controllers. A standard mathematical model of the system may not be easy to develop or even viable. Various identification techniques must thus be used to obtain an appropriate model. Furthermore, the tuning of a conformist controller may add additional complexity and will decrease its reliability due to increases in the realisation costs of the control system. Hybrid neuro-fuzzy techniques can be used to overcome these challenges, and thus, in recent years, there has been a large upswing in control systems based on fuzzy logic in engineering requests [13]. Yashuhiko et al. established a prognostic controller for systems with AC drives using neuro-fuzzy controllers to reduce the noise in the controlled plant [14], while Zie et al. presented a model identification technique using a Takagi–Sugeno Fuzzy system to offer a neuro-fuzzy network that could recognise variation of multiple factors in the controlled system [15].

This work proposes a new design and implementation of an intelligent and low cost prosthesis with an active knee joint for use by amputees in Iraq and similar developing countries.

2. Materials and Methods

Biomechanical analysis was used to design the active knee prosthesis and its range of motion. The mathematical model of a lower limb prosthesis consists of the kinematics and kinetic analysis of the joint using a set of ordinary differential equations.

2.1 Knee biomechanics during gait cycle

Five events associated with the gait cycle were used to illustrate knee biomechanics during walking on level ground. These gait periods are shown in Figure 1 [16]:

1. A gait cycle is a period beginning when the heel of the foot initially contacts the ground, at which point, the knee starts to flex to 17°. This is the support phase for the knee and the heel foot contact with the ground represents about 60% of the total gait cycle, a stance called knee flexion.
II. When the extreme flexion point of the support phase is reached, the knee joint starts to extend for about 17% up to 47% of the gait cycle, in a stance called knee extension.

III. When the swing phase starts, the knee of the supporting leg starts a quick flexion phase in preparation for the swing phase.

IV. When the foot leaves the ground, the knee stays flexed, and the hip is also flexed.

V. When the maximum knee flexion angle is reached, the knee starts to extend forward.

Figure 1. Gait Cycle Phases: a) Normal gait cycle; b) Gait cycle with prosthesis [17].

2.2 Adaptive Neuro-Fuzzy Inference System

ANN plays a central role in multiple modern engineering and scientific applications such as signal and image processing, classification and pattern recognition, robots, and adaptive control. ANNs have the ability to learn from set parameters, and they can approximate many non-linear and complex functions at any preferred level of precision. Furthermore, ANNs work with fault tolerance properties and parallel computation processes, allowing investigation of powered electronics applications for AC and DC drives due to accurate estimation of force and speed [18]. Another successful tool for real-time control applications is fuzzy logic. In fuzzy logic, a fuzzy set is created where input variables are represented as linguistic parameters (e.g. small or large) rather than numerical values. This conversion is performed in a fuzzification process, and the resulting linguistic variables are used in a set of conditional IF-THEN statements to implement fuzzy rules that control the signals in a fuzzy logic controller. A defuzzification process is used to reconvert the output information into a better-defined form. Centre of gravity and Maximum value are the most common methods of defuzzification. To obtain even better results, fuzzy logic can be merged with ANNs. The knowledge representation of fuzzy and the learning properties of the ANNs can lead to improved hybrid methods known as neuro-fuzzy techniques [18]. One of the most common networks of this type is the Adaptive Neuro-Fuzzy Inference System (ANFIS). Its general structure features fuzzy components with five ANN layers:

- Layer 1: Membership Functions (MFs) for the input variables.
- Layer 2: The fuzzy sets with the weights for each MF.
- Layer 3: The activation level (pre-condition matching) for fuzzy rules.
- Layer 4: Provides output values from the inference system.
Layer 5: Converts the fuzzy results (linguistic classification types) into numerical (crisp) values in a defuzzification process. Back-propagation algorithms and least-squares estimation are usually used to tune ANFIS networks.

3. Mathematical Models of the Proposed Mechanism

Simple models for the kinematics and dynamics of lower limb prosthesis motion were used to simulate the model to derive the leg prosthesis model for the ANFIS controller.

3.1 Kinematic Model

The kinematic prosthesis leg model, in a sagittal plane passing from anterior to posterior dividing the body into its right and left halves, is shown in Figure 2. The leg is defined as a system of three parts, thigh, shank, and foot. To obtain kinematic parameters, the following assumptions are proposed:

- The leg base is located at the hip joint $H(x_H, y_H)$, with the knee joint at $K(x_K, y_K)$, the ankle joint at $A(x_A, y_A)$ and the foot at $F(x_F, y_F)$.
- Lengths of links are based on anthropometric data [19] such that thigh length $l_t = 0.4165m$, shank $l_s = 0.4182m$, and length from ankle to metatarsal $l_f = 0.0981m$.
- All joints are revolute types and the limitations of angles for hip, knee, and foot ($\theta_h, \theta_k, \theta_a$) are known;
- The initial values for $\theta_h, \theta_k, \theta_a$ are known.
- The coordinates of the goal are available.

![Forward Kinematics Model](image)

**Figure 2.** Left: Leg Prosthesis in a Sagittal Plane with Actuated Knee joint. Right: Free body diagrams of shank and thigh segments for the derivation of inverse kinematic and dynamic equations of motion.

3.1.1 Forward kinematics model

By using forward kinematics, it is possible to determine the orientation and the position of the foot prosthesis. Several techniques have been proposed to resolve this, from the geometrical to the analytical;
here, Denavit-Hartenberg’s process and homogeneous matrices are used to represent the transformation in the reference systems [20]. The kinematic model of the leg in the sagittal plane is thus

\[
\begin{align*}
x_F &= l_t \cos \theta_h + l_s \cos(\theta_h - \theta_k) - l_f \sin(\theta_h - \theta_k) - \theta_a \\
y_F &= l_t \sin \theta_h + l_s \sin(\theta_h - \theta_k) + l_f \cos(\theta_h - \theta_k) - \theta_a
\end{align*}
\]

\[d = (x_F^2 + y_F^2)^{1/2}, \quad d_1 = \left(l_t^2 + l_s^2 + 2l_t l_s \cos \theta_k \right)^{1/2}, \quad d_2 = \left(l_s^2 + l_f^2 + 2l_s l_f \cos \theta_a \right)^{1/2}
\]

\[
\begin{align*}
\theta_k &= \beta_s - \alpha_s, \quad \theta_a = \gamma_s - \alpha_s - 2^{-1} \pi, \quad \theta_f = \pi - \gamma_s
\end{align*}
\]

3.1.2 Inverse kinematics model

Here, the set of joint angles that produce a specific foot prosthesis position are determined. If the orientation is known (foot angle \( \theta_f \)) along with the final position, it is possible to obtain analytical solutions by using these formulae:

\[
\begin{align*}
\theta_k &= \arccos\left(\frac{(x_F - l_f \sin \theta_f)^2 + (y_F - l_f \cos \theta_f)^2 - l_t^2 - l_s^2}{2l_t l_s}\right) \\
\theta_h &= \arctan\left[\frac{(y_F - l_f \cos \theta_f)(x_F - l_f \sin \theta_f)^{-1}}{l_f \cos \theta_f}\right] + \arccos\left(l_t^2 - l_s^2 + (x_F - l_f \sin \theta_f)^2 + (y_F - l_f \cos \theta_f)^2\right)^{1/2} \\
\theta_a &= \theta_h - \theta_k - \theta_f + 2^{-1} \pi
\end{align*}
\]

3.2 Dynamic model with actuated knee joint

The proposed dynamic equations of motion are derived from Newton’s Second Law and verified with Lagrangian mechanics. All measures and masses are based on anthropometric data [21].

The dynamics of leg motion can be modelled as a double inverted pendulum. Figure 2.b shows the residual leg and the prosthesis represented by two segments. A knee joint is modelled as hinge joint connecting the two segments, and the lower segment, i.e. the prosthesis, rotates around a pivot point on the ground, which defines the origin of the world coordinate system. The Lagrangian of every system can thus be represented as the difference between the potential and kinetic energies [21]:

\[L = T - P\]

By using the Lagrange theory for preservation of energy, the Lagrange equation of movement is thus derived as

\[
\frac{d}{dt} \left( \frac{\partial L}{\partial \dot{q}_i} \right) - \left( \frac{\partial L}{\partial q_i} \right) = \dot{Q}_i
\]

more easily represented in a matrix arrangement as

\[M(q) \ddot{q} + C(q, \dot{q}) \dot{q} + G(q) = Q\]

3.3 Design of the proposed above-knee prosthesis

The prototype of the proposed above knee prosthesis was implemented at the Robotics Laboratory at the Engineering College of Kerbala University, Iraq, as in shown in Figure 3. Its structure includes a dynamic prosthetic foot connected with the shank by a zero Degree of Freedom (DoF) ankle joint, an active knee joint, and a socket. The above-the-knee knee joint has a simple mechanism that offers accurate control of the system and provides high damper force and less elasticity aloe the prosthesis to map human natural gaits well. The Active Knee Prosthesis is driven by one DC rotary motor with a planetary gear connected to the knee joint structure to provide rotary motion of the knee joint during the swing phase.
The ground reaction force data is detected and measured by using a force plate with four-axis force sensors. The Active Knee Prosthesis mechanical design has the following advantages:

i) Effective prosthesis at low cost.

ii) The limb can completely power the knee joint through ambulation, decreasing the energy expenses of amputees.

The proposed gearing drop enlarges the torque created by the motor for the Active Knee Prosthesis. Thus, the proposed design of the above knee prosthesis overcomes the common difficulty of many active prosthetic legs, which is the inadequate torque generated throughout the stance phase.

4. Experimental setup

4.1 Video-Camera Strategy

A 51-year old male patient with transfemoral amputation (above knee) participated in this case study. Reflective markers were attached to knee to allow motion analysis, as shown in Figure 4. A single video-camera was used to subsequently record the marker positions of the amputee’s side as the participant walked. This experimental procedure then used the obtained kinematic knee data for gait cycle analysis.
Figure 4. Marker placement: contralateral knee of patient with transfemoral amputation for gait cycle analysis.

4.2 Force Plate Strategy
The force platform has pressure sensors used to capture the ground reaction forces’ distribution associated with the planar position under the feet while the participant was standing and walking, allowing the calculation of optimal stride length based on a model gait cycle. Figure 5 shows the procedure of data collection based on the force plate strategy.

Figure 5. Collection Data using a Force Plate Device: a) Force Plate description with the ground force, foot, and the latter’s position, b) Peak pressure analysis to identify and quantify peak pressure areas, c) XY coordinates of the gait cycle
Figure 6 shows the overall block diagram of experimental setup for the collection data system. It consists of two main parts: the sensing system (force plate and video camera) and the control implemented by the intelligent controller based on ANFIS.

![Block diagram of Experimental Data for AKIP](image)

**4.3 ANFIS Controller Design**

An ANFIS controller is proposed to control the force of the DC motor for the designed knee. It contains several fuzzy processes: knowledge base, fuzzification, inference, and defuzzification, in addition to the NN training algorithm used to tune the membership functions of the fuzzy inference system with Sugeno-type input-output training data.

In this work, the input-output training data is the "XY Coordinates-Force" dataset. This refers to the input to the ANFIS network, while the force operates as the system output, as shown in Figure 7. In the fuzzification process, the crisp XY data values are represented as linguistic variables (-B, -M, -S, Z, +S, +M, and +B), where: -: Negative, Z: Zero, +: Positive, B: Big, M: Middle, and S: Small. These parameters are given to the rule based process as inputs to produce set of 7×7=49 IF-THEN rules, as shown in Table 1. The proper rules are selected through the training process by using the back propagation algorithm to generate the desired output force signal, as shown in Figure 8. The inference process is used to generate the control decisions, based on Table 1.

| X | Y |
|---|---|
| -B | -B |
| -M | -B |
| -S | -M |
| Z | -S |
| +S | Z |
| +M | +S |
| +B | +M |

**Table 1:** Rules matrix of the fuzzy parameters
Figure 7. Structure of ANFIS  

Figure 8. Fuzzy IF-THEN rules

The defuzzification process receives the linguistic output, then converts it into crisp values that represent the force data. Centre of gravity defuzzification and Gaussian membership functions are used in this work, as shown in Figure 9.

Figure 9. Membership functions of Left) X-axis. Right) Y-axis

5. Results

In this study, the force plate was activated using foot pressure as input data for all experiments. The rigidity and hampering parameters of the revolute ankle joint were represented by translation in the x and y axes.

Figure 10 shows the XY data points generated by rotation of the amputee on the Force Plate Device, and the measured force values. Figure 10 left represents the translation trajectory of the ankle joint in the X and Y axes. The ground reaction forces applied by the force plate on the foot control the ankle translational trajectory and ground reaction forces. Figure 10 right shows the simulated ground reaction forces of the heel foot segment.

Figure 11 shows the experimental measurements of the Moment and Angle of the Knee. From Figure 11 left, it is clear that the APK joint moment reached maximum value at flexion stance, later decreasing to zero (19% of gait cycle). During the extension of the knee at stance phase, the magnitude moment was negative, and the behaviour of the APK moment at swing phase was repeated, though the value of moment in the positive-negative regions was less than in stance phase.

Figure 11 right represents the flexion and extension of the prosthetic knee angle over the gait cycle; as the foot heel contacts the ground at the stance phase, the knee starts to flex from 0 to maximum flexion of 19°. The AKP angle after maximum flexion begins to decrease as result of extension of the knee.
During stance phase, the knee angle of the prosthesis reached a maximum value of 57° at flexion, then the AKP angle started to decrease or extend forward during the swing phase. The results of the moments and angle knees were acceptable in comparison to previous work such as [19]. ANFIS controllers were developed for the force, knee moment, and angle estimation using a DC motor with a gear box. MATLAB 2014a was used to simulate the performance of the system and to train the three initial ANFIS networks with the experimental XY Coordinates-Force, XY Coordinates-Moment and XY Coordinates-Angle. The initial model for the ANFIS network consisted of two input neurons, four hidden layers, and one output neuron, as shown in Figure 12. The operations of the four hidden layers represented the input membership function, IF-THEN rules, output membership function, and the inference process sequentially. The system was trained using a back-propagation learning algorithm. Figure 13 provide a graphical depiction of rules status, showing all 49 rules and an applied example, represented by the red line for input data, and its result. Figure 14 shows the surface plot for the X and Y forces, as it is important to monitor the force values for the XY districts.

The performance of the trained ANFIS was observed by generating an individual plot of the output signal, as shown in Figure 15. This figure also contains a plot of the experimental performance of the force values as seen in Figure 10 right. It is clear from Figure 15 that the designed ANFIS successfully predicted the required force value for each predetermined XY coordinate. This prediction can be considered a very good result across the work data. Figure 16 shows the results of the second ANFIS controller, designed for moment values; the RMS error between the predicted moment value and the experimental value of this second controller is 0.3006. Figure 17 shows the results of the third ANFIS controller, designed for angle values, and the error between the predicted angle value and the experimental value. The RMS error of this third controller is 0.006. Figure 18 shows the relationship between the moment and the angle of the designed knee during the testing process. The curve consists of two phases: stance and swing phase: at the stance phase, it shows that the moment knee joint reaches maximum value and then, with any increase the value of the angle, the moment of the knee joint decreases.

Figure 10. Left) Experimental XY coordinate data points, Right) Measured Force values.
Figure 11. Experimental measurements of the moment and angle of the knee.

Figure 12. Five layers of ANFIS architecture
Figure 13. Graphical display of the fuzzy rules

Figure 14. Output force surface plot
Figure 15 Left up) Comparison between ANFIS predicted and experimental values for force. Others) Zoom regions for exploration

Figure 16 Left) Comparison between values of moment from the experimental work and as simulated by the ANFIS predictor. Right) Error between the experimental and the ANFIS predicted values of moment
6. Conclusions

This work presents the design and experimental testing of a lower prosthesis with an active intelligent knee that imitates the human gait. A proper mechanism was formed by replicating human knee movement in the designed active knee. The model of the designed knee prosthesis reduced the complexity of the anatomical knee from six DOF to a single DOF, and stimulation of the proposed intelligent prosthesis was subject to an ANFIS controller. In this paper, a methodology to realise force, moment, and angle control for a DC motor driven by ANFIS was investigated and found to offer good stabilisation and increased dynamic operation. The results from the experimental tests with a patient showed that the designed prosthesis can imitate the biomechanics of a normal knee in an amputee during walking on a flat surface. The ANFIS network optimised in this work offers a successful controller because of its simplicity, high accuracy, and low cost of implementation. It can be implemented easily by using different interface cards such as a Field Programmable Gate Array (FPGA), allowing use in real-time prosthetic applications.
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