Using Neural Networks for Modelling Piezoelectric Energy Harvesting Systems in a Prosthetic Leg

P. Manoonpong[1,*], F. Wörgötter[1], K. Pechrach[2], K. Tungpimolrut[3], N. Hatti[3], J. Phontip[4], K. Komoljindakul[4]

[1] Bernstein Center for Computational Neuroscience, University of Göttingen, Germany
[2] Ronsek Ltd, Bishops Stortford, UK
[3] The National Electronics and Computer Technology Center (NECTEC), Thailand
[4] Department of Electrical Engineering, Kasetsart University, Bangkok, Thailand
[*] Corresponding author, Email: poramate@physik3.gwdg.de

Abstract

In this paper, we present energy harvesting systems in a prosthetic leg using piezoceramic Macro Fiber Composites (MFCs) and their models using artificial neural networks. The piezoceramic MFCs are implemented at the sole and heel of the leg and transform impact forces into electrical power during walking. The neural model of the energy harvesting system installed at the sole is developed on the basis of a standard feedforward backpropagation neural network. On the other hand, the neural model of the energy harvesting system installed at the heel is manually synthesized from different neural modules (networks). Experimental results show that these neural models can appropriately transform the impact forces detected by force sensing resistors (FSRs) into the electrical responses of the piezoceramic MFCs. The models will be used to study and analyze dynamical behaviors of the piezoelectric materials with respect to walking.

Introduction

The idea of energy harvesting has become popular over the past few decades due to high energy consumption all over the world. Piezoelectric power generation is one of the alternative energy sources. It can transform kinetic energy (i.e., ambient vibrations or impact forces) into electrical energy that can be stored and later used to drive electrical devices, like sensors and actuators. From this point of view, a significant amount of research has been devoted to develop and understand power harvesting systems. Umeda et al. [1] investigated the power generated when a free-falling steel ball impacted a plate with a piezoceramic wafer attached to its underside. Sodano et al. [2] developed a mathematical model of piezoelectric power harvesting beam based on energy methods. The model can predict the amount of power capable of being generated through the vibration of a cantilever beam with attached PZT elements. Kymissis et al. [3] examined using a piezofilm and a Thunder actuator to charge a capacitor and supply a radio frequency identification (RFID) transmitter from the energy lost to the shoe during walking. Elvin et al. [4] built a self-powered damage detection unit that used the polyvinylidene fluoride film (PVDF) for energy generation and a capacitor to store the energy. Jian-Hui et al. [5] presented theoretical and experimental analyses of vibration-based piezoelectric power generator in discontinuous operation mode.

In contrast to these published studies, the central goal of our study is to develop modular and compact electrical energy harvesting systems using piezoelectric materials for self power generation in advanced prosthetic legs (e.g., variable-damper prosthesis [6]) during walking. Based on our goal this paper concentrates on developing models of the energy harvesting systems using piezoceramic Macro Fiber Composites (MFCs) implemented at the sole and heel of a prosthetic leg. We employ artificial neural networks to develop the models. One network is a standard feedforward backpropagation neural network which was trained to transform the force at the sole into the response of the piezoceramic MFC. In contrast, another network is manually synthesized from different neural modules to transform the force at the heel into the response of the piezoceramic MFC. These developed models will be used to study and analyze dynamical behaviors of the piezoelectric materials with respect to walking. Besides this, we also show that the artificial neural networks can be a powerful technique for modelling such nonlinear dynamic systems.

Piezoelectric Energy Harvesting Systems in a Prosthetic Leg

Here, we use the piezoceramic MFCs to harvest energy in a prosthetic leg during walking. This type of piezoceramics is selected because it is flexibly adaptable to the structure's surface being suitable to install at the sole and heel of the leg. We implement the piezoceramic MFCs together with force sensing resistors (FSRs) at the sole and heel (see Fig. 1). The FSRs serve as force detection during walking.

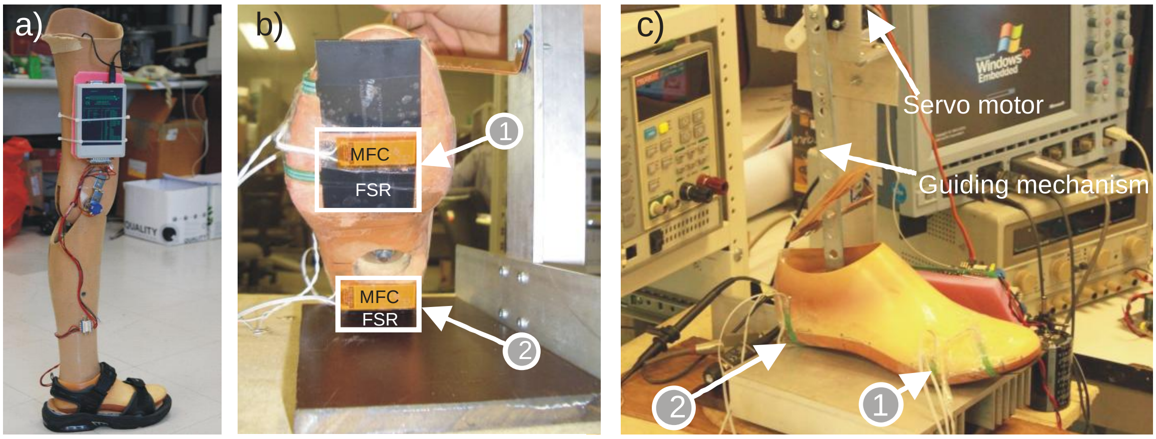

Fig. 1. a) Prosthetic leg donated by Rehabilitation Research Institute (RRI). We install the sensors and the piezoelectric materials for our experiments. b) Installation of the piezoceramic MFCs and FSRs at the sole (1) and heel (2) of the leg. c) Experimental setup to simulate walking behavior.

To simulate walking behavior in a simple but effective way, we disconnect the foot from the leg (see Fig. 1a) and reattach it to a servo motor with a guiding mechanism (see Figs. 1b and c). The servo motor is controlled via a servo-controller board in which a step waveform is programmed with a frequency of 0.5 Hz. This frequency is set according to normal walking frequency. Using this experimental setup, the foot can be naturally moved in vertical and slightly horizontal directions. During walking, the FSR signals and electrical power generated by the piezoceramic MFCs are recorded via an oscilloscope with a sampling frequency of 10 kHz. These data are filtered and then used to develop the models using artificial neural networks.

Neural Models of the Piezoelectric Energy Harvesting Systems

The models of the piezoelectric energy harvesting systems at the sole and heel were developed using artificial neural networks. They basically transform a force sensory input (i.e., impact forces detected by force sensing resistors (FSRs)) into the electrical response of the piezoceramic MFC. We designed the neural model of the energy harvesting system at the sole (see position 1 in Fig. 1b) as a simple four-layer feedforward neural network (see Fig. 2a). Input and output layers have one neuron while two hidden layers have four neurons. In addition, a bias neuron is given at the input and hidden layers each. All neurons of the networks are configured as a discrete-time non-spiking neuron. The output of each neuron is governed by:

$$y(\vec{x}) = g\left(\sum_{i=0}^{n} w_i x_i\right). \qquad (1)$$

The neuron has n input 'dendrites' ($x_0 ... x_n$) and one output 'axon' $y(\vec{x})$. The weights ($w_0 ... w_n$) determine, how much the inputs are transmitted, and the activation function g does a transformation of the output. The bias neurons receive no input and emit a constant output of 1.0. The activation function of the input and output neurons is linear, while the hidden layer neurons have a symmetrical sigmoid activation function $g(x) = \tanh(x)$. We use a standard backpropagation algorithm [7], where the weights are updated after each training pattern. As a result, after 10000 epochs learning converges where the network gives a good performance of output prediction with a small mean square error of about 0.00037.

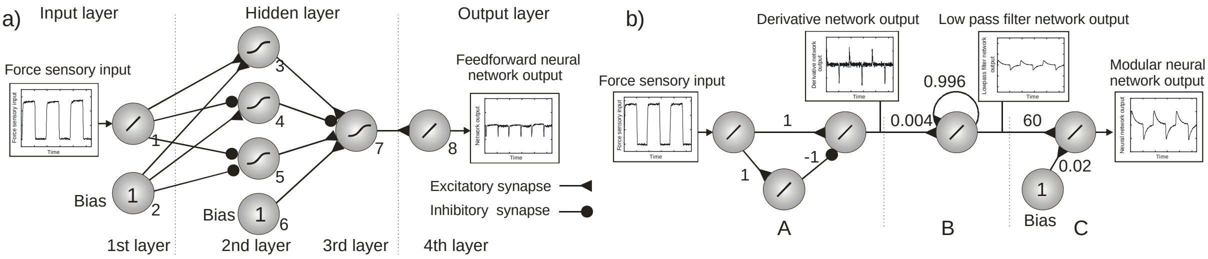

Fig. 2. a) Feedforward neural network with linear activation functions for input and output neurons and symmetric sigmoid activation functions (i.e., tanh*) for hidden neurons. The weights (w from neuron j to neuron i) were trained by a backpropagation algorithm. The resulting weights are w_{31} = 0.142, w_{32} = 0.062, w_{41} = -0.679, w_{42} = 0.221, w_{51} = -1.012, w_{52} = -0.493, w_{73} = 0.049, w_{74} = -0.360, w_{75} = 0.422, w_{76} = 0.143, w_{87} = 4.0. b) Modular neural network with a liner activation function of all neurons. It consists of three modules: (A), (B), and (C). All synaptic weights indicated by the small numbers were manually tuned.*

To develop the neural model of the energy harvesting system at the heel (see position 2 in Fig. 1b) having different input-output patterns from the ones at the sole, we apply a modular neural network technique [8] using linear neurons. The network is basically synthesized by observing signal transformations. The network consists of three neural modules (Fig. 2b). The module (A) performs as a derivative network while the modules (B) and (C) perform as low-pass filter [9] and signal scaling networks, respectively. All neurons of the networks are configured as a discrete-time non-spiking neuron similar to the network shown above. The output of each neuron is defined by Eq. 1 with a liner activation function. In this case, the synaptic weights were manually tuned. As a result, the network can perfectly transform the force sensory input into the response of the piezoceramic MFC at the heel with a small mean square error of about 0.00028.

Experimental Results

In this section, we show the performance of our developed neural models of the energy harvesting systems. The models were implemented on a PC using C++ programming. We recorded data from ten simulated walking steps at a frequency of 0.5 Hz. Figure 3 shows recorded data and the performance of the neural models. It can be seen that the neural models can generate the outputs (see Figs. 3b and f) from the given force sensory inputs (see Figs. 3a and e) where their outputs show patterns close to the desired outputs (i.e., the responses of the piezoceramic MFCs (see Figs. 3d and h)). In general, the developed neural models function as nonlinear mapping of these dynamic systems (see Figs. 3c and g).

These experimental results show that the used methods are able to deal with a non-linear relationship between the force sensory signal and the electrical response of the piezoceramic MFC. We feel that conventional methods could probably still do the tasks here. However, they would require carefully design where the neural network can learn to find the solution without efforts (see Fig. 2a) or it can be synthesized based on a modular technique (see Fig. 2b).

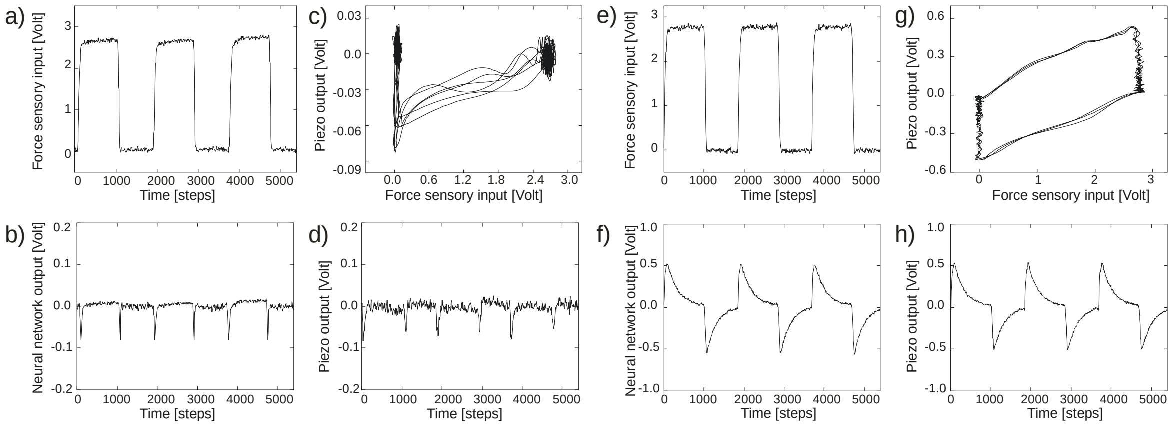

Fig. 3. a) Force sensory input from the FSR at the sole during simulated walking driven by the setup shown in Fig. 1c. It is used as an input of the neural model. b) The output of the neural model which was trained to obtain a desired response of the piezoceramic MFC at the sole. c) Nonlinear relation between the force sensory input and the response of the piezoceramic MFC at the sole. d) The response of the piezoceramic MFC at the sole during simulated walking. e) Force sensory input from the FSR at the heel during simulated walking. It is used as an input of the modular neural model of the piezoelectric energy harvesting system. f) The output of the modular neural model which shows a similar pattern to the response of the piezoceramic MFC at the heel. g) Nonlinear relation between the force sensory input and the response of the piezoceramic MFC at the heel. h) The response of the piezoceramic MFC at the heel during simulated walking. All filtered signals are recorded at a sampling rate of 10 kHz.

Conclusion

In this paper we present energy harvesting systems at the sole and heel of a prosthetic leg and their neural models. Two different structures of the neural models were developed. As a result, using the force sensory input, each neural model can predict the response of the piezoceramic MFC during simulated walking at the approximate normal walking frequency. For future research, more demanding tasks will be related to the use of these models to study and analyze dynamical behaviors of the piezoelectric materials from the strength and pattern of the force sensory input according to different walking behaviors. We will also use these neural methods to develop models of different types of piezoelectric materials, like PZT implemented at other parts of the leg.

Acknowledgments

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