ABSTRACT

Objective of this thesis work is analyzing and comparing two different types of adaptive systems. In particular, we focus our attention on behaviour of the Echo-State Network (ESN) and the Least Mean-Square algorithm (LMS). The former is a new born kind of Recurrent Neural Network while the latter represents the most used technique concerning adaptive filtering.

Our purpose is designing a filter for prediction using such as algorithms. After introducing motivations for using adaptive systems, we will explain theories related to ESN and LMS. Afterwards, we will show how to predict a signal with these two techniques and then their performance. Finally, we will illustrate basic differences between the algorithms and that LMS presents advantages both in performance and in computational time with respect to ESN.

CHAPTER 1: INTRODUCTION

The term adaptation is mainly used in biological field to indicate a living beings able to modify themselves in order to survive in a changing environment. Adaptations enable living organisms to cope with environmental stresses and pressures. They refer to any alteration in the structure or function of an organism or any of its parts that results from natural selection and by which the organism becomes better fitted to live and multiply in its own environment.

Such definition can be easily extended to the engineering world, where a mathematical system is nothing but a model of a physical system. Interest in studying adaptive systems originates from its attractive feature to be able to adapt its behaviour according to changes in its environment or in parts of the system itself. A human being, for instance, is certainly an adaptive system; so are organizations and families. Some engineering systems can be adaptive as well; for instance, control systems utilize feedback loops in order to sense conditions in their environment and adapt accordingly.

Particular kinds of adaptive systems are *adaptive filters* and *neural networks*.

An *adaptive filter* is defined as a filter whose characteristics can be modified to achieve some end or objective, and is usually assumed to accomplish this modification automatically, without the need for substantial intervention by the user. Lacking the knowledge about the input signals for which the filter is designed, the designer turns to an adaptive filter, which can learn the signal characteristics when first turned on and thereafter can track slow changes in these characteristics.

Adaptive filters can be implemented in a variety of ways, allowing an ever wider variety of practical problems to be solved. Their feature is to have some or all of the following characteristics:

- They can automatically adapt (self-optimize) in the face of changing (non-stationary) environments and changing system requirements.
- They can be trained to perform specific filtering and decision-making tasks. Synthesis of systems having these capabilities can be accomplished automatically through training. In a sense, adaptive systems can be programmed by a training process.
- Because of the above, adaptive systems do not require the elaborate synthesis procedure usually needed for non-adaptive systems. Instead, they tend to be self-designing.
- They can extrapolate a model of behaviour to deal with new situations after having been trained on a finite and often small number of training signals or patterns.
- To a limited extent, they can repair themselves; that is, they can adapt around certain kinds of internal defects.
- They can usually be described as nonlinear systems with time-varying parameters.

- Usually, they are more complex and difficult to analyze than non-adaptive systems, but they offer the possibility of substantially increased system performance when input signal characteristics are unknown or time varying.

Neural Networks represent a technology used in many disciplines: neurosciences, mathematics, statistics, physics, computer science, and engineering. Neural Networks find applications in such diverse fields as modelling, time series analysis, pattern recognition, signal processing, and control by virtue of an important property: the ability to *learn* from input data with or without a teacher. Work on neural networks has been motivated from recognizing that the human brain computes in an entirely different way from the conventional digital computer. The brain is highly complex, nonlinear, and parallel computer. It has the capability to organize its structural constituents, know as *neurons*, in order to perform certain computations many times faster than the fastest digital computer in existence today. Furthermore, the brain has the ability to build up its own rules through what we usually refer to *experience*., that is to say, the property of *plasticity*. Plasticity permits the developing nervous system to *adapt* to its surrounding environment. Just as plasticity appears to be essential to the functioning of neurons as information-processing units in the human brain, so it is with neural networks made up of *artificial* neurons. In its most general form, a neural network is a machine that is designed to *model* the way in which the brain perform a particular task; the network is usually implemented by using electronic components or is simulated in software on a digital computer. To achieve good performance, neural networks employ a massive interconnection of simple computing cells called *neurons*. A wide class of neural networks perform useful computation after a process of *learning*, the equivalent of the human experience. This process involves a *learning algorithm* at the end of which the synaptic weights of the networks are modified in order to obtain a desired objective. Such an approach is the closest to *linear adaptive filter* theory. A neural network derives its computing power through its parallel distributed structure and its ability to learn and therefore *generalize*. It main properties and capabilities are:

- *Nonlinearity.* An artificial neuron can be linear or nonlinear. A neural network, made up of an interconnection of nonlinear neurons, it itself nonlinear. Nonlinearity is a very important property, particularly if the physical mechanism responsible for generation of the input signal (e.g., speech signal) is nonlinear.
- *Adaptivity.* Neural networks have the capability to *adapt* their synaptic weights to changes in the surrounding environment. In particular, a neural network trained to operate in a specific environment can be easily *retrained* to deal with minor changes in the operating environmental conditions. Moreover, when it is operating in a nonstationary environment (i.e., one where statistics change with time), a neural network can be designed to change its synaptic weights in real time.
- *Contextual Information.* Knowledge is represented by the whole structure an activation state of a neural network. Every neuron in the

network is potentially affected by the global activity of all neurons in the network.

- *Fault Tolerance.* A neural network, implemented in hardware form, has the potential to be fault tolerant, or capable of robust computation, in the sense that its performance degrades gracefully under adverse operating conditions.
- *Neurobiological Analogy.* The design of a neural network is motivated by analogy with the brain, which is a living proof that fault tolerant parallel processing is not only physically possible but also fast and powerful. Neurobiologists look to artificial neural networks as a research tool for interpretation of neurobiological phenomena. On the other hand, engineers look to neurobiology for new ideas to solve problems more complex than those based on conventional hard-wired design techniques.

Progress in microcircuit design and production has resulted in very compact, economical, and reliable signal processors that rival biological nervous systems in size and are clearly superior to biological systems in speed. The result has been a very fast-growing field of applications for all types of digital processing, including adaptive processing. Current applications for adaptive systems are in such fields as image processing, speech recognition, radar, sonar, seismology, mechanical design, navigation systems, front-end signal processors and biomedical instrumentation.