Neural Network-Based Hardware Architecture multi-sensor for Monitoring Forest fires in Wireless Sensors Network

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Abstract—In this paper, we present and evaluate multi-sensor hardware architecture for monitoring forest fires using wireless sensors network (WSN). In the proposed architecture, each node is equipped with various sensors for temperature and carbon monoxide in order to improve accuracy detection. A method of neural network is applied to the data processing detected by the different sensors. This hardware multi-sensor architecture was assed for monitoring forest fires, especially designed to enable low power and higher precision in WSN. In this paper we show that neural network is a powerful and accurate mechanism which can successfully be applied not only to fire detection but to any event detection sensor network application. Compared to using crisp values, neural network maintains a high accuracy level despite fluctuations in the sensor values. This helps to decrease the number of false detection, while still providing accurate event detection. The proposed hardware architecture is planned to reach high performance running in FPGAs circuit. Synthesis results and relevant performance comparisons with related works are presented.

Keywords - Wireless sensor network; multi-sensor systems; Neural network; MultiLayer Perceptron; forest fire detection; FPGA.

I. INTRODUCTION

Forest fires are one of the most important and widespread kinds of disasters through their effect on the environment. In recent years, the frequency of forest fires has increased considerably due to climate change and human activities [22], their has become a global concern for organizations involved in forest fires. Techniques of detection of forest fires are mainly observation watchtowers [4, 10], satellite monitoring [8,20], and lately the wireless sensor networks [1,9]. Although the observation watchtower is feasible, it requires a lot of financial and material resources as well as the limited coverage area. Detection satellite is also limited by a number of factors [23]. Because of the disadvantages in the detection systems based on satellite, the wireless sensor network technology might be used to detect forest fires.

In WSN, nodes were deployed in a surveillance zone and all sorts of information about the target environment were collected by nodes of cooperation. For forest fire detection, nodes deployed in the forest to gather information changes dynamically as the fire temperature, humidity, and atmospheric pressure. Weather events are complex, ambiguous and vague in nature [21]. The majority of research in WSN is to improve and increase the lifetime of the network by offering new technique for detecting high energy efficiency. Much work is also done in the data aggregation technique to increase the battery lifetime of the node thus improving the sensor network life.

In [14], a fire detection system based on multi-sensor technology and neural networks was provided. Sensor nodes detect the values of ambient temperature, smoke density, and the carbon monoxide density. This model requires a large number of samples before applying a neural network technique. Furthermore, we assumed that the possible fire detection events must be learned in advance by the neural network. Thus, for shooting an invisible event, the entire structure must be re-neurons formed.

An algorithm had been made for multi-sensor data fusion in WSN[12] using fuzzy logic for the application of event detection. In this method [15], each sensor node is provided with various sensors (temperature, light from moisture, and carbon monoxide). The use of more than one sensor provides additional information on the state of the environment. Processing and fusion of these signals are made based on a fuzzy system. All signals from the various sensors are collected at the head of the cluster and then merged. This method reduces the energy efficiency of the system.

A system for monitoring wildfire using WSN which collects temperature, humidity, and barometric pressure had been previously described [16]. Sensor nodes communicate with a base station that collects the sensed data. Systems based on infrared (IR) technology were used for the detection of fires [17, 18]. However, these systems use a single sensor field that makes them vulnerable to false alarms. In a WSN platform
which has a fuzzy nature and different parameters are involved in its behavior, neural networks can help through dimensionality reduction, obtained simply from the outputs of the neural-networks detection architecture algorithms, leads to higher precision detection and energy savings.

Neural network provides a suitable tool for modeling imprecise data [5]. In addition, this intelligent tool can process large raw data and extracts a small amount of useful information for the final decision. Therefore, it can be said that neural network might be suitable for forest fire announcement. The neural network takes as input the measured data to produce index, which measures the likelihood of a fire detection. The neural network has been applied to a large number of applications [13], in the last two decades, including the detection of forest fires, Classifier for Face Detection, intelligent analysis [6,2,19].

Since the neural network affects the accuracy and speed of detection in the WSN [5,6,2], a contribution in this field aims to present a hardware multi-sensor architecture for monitoring forest fires, especially designed to enable low power and higher precision in WSN. The proposed architecture is based on neural network approach to satisfy the constraints’ requirement of sensors (power consumption, execution time, operating frequency and resources occupancy). The proposed solution is planned to reach high performance running in FPGAs circuit.

Our approach to enhance this solution is based on the introduction of artificial intelligence techniques in the WSNs: expert systems, artificial neural networks, fuzzy logic and genetic algorithms [5]. However, vision sensors are applied to corroborate the detection process. Moreover, the proposed processes of fusion data multi sensor, management assistance reduce the false alarm rate while satisfying the requirement for early fire detection. Our method proposed neural network is a new type of treatment operation. Such operation extracts information from raw data. Thus, it is more effective than other treatment approaches in certain scenarios.

II. ARCHITECTURE FOR FOREST FIRE DETECTION

In the literature, there are several techniques geared towards improving the performance of approaches for detecting of Forest Fire. Generally, these approaches have focused on the variation metrics (energy consumption, reliability, range of detection, Quality of Service (QoS), ...) to optimize parameters (battery level of a node, collision, congestion) to determine a best detections and a good quality of service, to increase the lifetime of the network at the same time, reduce the number of packets to be transmitted and minimize the time from beginning to end.

In this context, the use of artificial intelligence algorithms (neural network) to optimize the metric adopted is a promising technique since it allows to combine and evaluate various parameters effectively [5, 11, 21]. The objective of our work is to develop an intelligent multi-sensor architecture based on artificial intelligence algorithms (neural network) for the detection of forest fires from classic architecture to fully satisfy the constraints Application of WMSNs: limited resources (memory and computing power) and at the end to improve performance (detection range, energy ...) of the entire network.

This will reduce the processing time and energy consumption and thereby extend the life of the network.

The proposed architecture of the sensor network is composed of two types of node, scalar and multimedia node. All nodes are deployed in a sensing field in three dimensions to form cluster with one as Cluster-Head (CH). For our application, multimedia nodes are the CH and the member nodes are scalar nodes in a clustering algorithm for WSNs, as shown in Figure 1.

![Figure 1. Scenario of WMSN in forest fire application](image)

The operation of the proposed architecture is spread over two phases: detection and monitoring. The sensing phases are executed by the scalar sensors and the phase control is realized by the visual sensor.

During the detection phase, sensors detect the values of the temperature and quantity of carbon monoxide (CO), and the variation of the temperature and that of the quantity of carbon monoxide calculate the probability of detection using a system of neural network and transmit its value to CH. After the detection, CH receives the probability detection values by these members. If these values exceed a threshold, CH triggers the visual sensor to take a picture and then send information to the sink. The use of neural network, the technique of multi-sensor and the visual sensor, might improve the detection accuracy of the proposed architecture.

III. IMPLEMENTATION OF THE ARCHITECTURE

A. Neural Networks

Multi-layer perception (MLP) is a particular neural network MLP consists of several layers: input layer, hidden layer and an output layer [5]. These layers are based on processing units (Figure 2) which are interconnected by means of bonds reflected in the forward reaction. All units perform the same operation. The neuron computes the sum of its inputs; then this value passes through the activation function to produce its output.
The general model of an artificial neuron is shown in Figure 2. Where \( x_{(i)} \) is the input value and \( w_{(ij)} \) is the corresponding weight value, \( O_{(j)} \) is the output of the neuron, and \( \text{tanh} \) is the activation function. The activation function is chosen by the designer for specific training algorithm, and then the weights will be adjusted by some learning rule so that the neuron input/output relationship meet some specific goal.

The structure of the MLP is represented in Figure 3. The input layer is a vector consisting of four neurons (temperature, variation in temperature, quantity of carbon monoxide (CO), and variation of CO). The hidden layer neuron includes 3 and the output layer is a single neuron. An MLP is a parallel array of single units and distributed non-linear processing. Parallelism, scalability and dynamic adaptation are the three characteristics of computation usually associated with MLP. Many of these characteristics are either inherent or desirable for WSNs.

B. FPGA-based implementation of MLP

In this section, we describe the implementation of artificial neural networks on FPGA [2] and the different block of a MLP.

1) Storage unit of the weights and bias (ROM): In the function neuron, the weights are saved in a ROM memory and the size of this memory will be defined according to the position of the neuron in the network (i layer), and the number of inputs.

2) Multiplier-Accumulator (MAC): The MAC is the processing step and can be designed [3]. It uses a single multiplier and one accumulator. It is to multiply an input by its equivalent weight and the result is then added to that previously accumulated. The battery performs the addition of the weighted sum of the individual outputs by the multiplier calculating already. Figure 4 represents a MAC.

![Multiplicateur-acumulateur (MAC)](image)

The simulation was performed using the software ModelSim. Figure 5 illustrates the simulation of MAC module using three inputs \( x = 2, y = 4, z = 8 \). MAC starts by acquiring the Z then the polarization multiplication. The output in Figure 5 a represents \( a = 8 \times 2 \times 4 = 8+8=16 \).

![The timing diagram of the MAC](image)

3) Activation function (AF): This function takes as input and any output value and belongs to a well-defined interval. Function sigmoid activation is commonly used in MLP. The implementation of this function is very difficult because it consists of an infinite power series. In order to simplify function expression, it was linearized on several intervals \([C_i, C_{i+1}]\) and its value is evaluated using two constants \((a_i \text{ and } b_i)\) corresponding to this interval [2].

\[
F(x_i) = \begin{cases} 
a_i x_i + b_i & \text{for } x_i \in [C_i, C_{i+1}] \\
1 & \text{for } x > 3
\end{cases}
\]

4) Neuron model: The structure of the artificial neuron consist in one memory block, one MAC unit and an activation unit. The structural description of a neuron with VHDL allows during the compiling step to specify generically some characteristics like the input numbers and the data size. The
neuron computes the product of its inputs, with the corresponding synaptic weights, which are memorized in an ROM, and then the results are added. The result is presented to a comparison unit designed to represent an appropriate sigmoid function. Figure 6 represents a neuron model [2].

![Neuron model](image1)

**Figure 6. Example of neuron model**

The simulation is realized with the software ModelSim. Figure 7 illustrates the simulation using the three neuron inputs \( x_1 = 2, x_2 = 4, x_3 = 8 \) and the weight \( W_1 = 2, W_2 = 3, W_3 = 2 \). Begins with the neuron of the acquisition polarization \( b = 8 \) and then multiplying by the finite application of the activation function. The output represents \( s = AF(8 + 2 \times 2 + 3 \times 4 + 2 \times 8) = 39 \) (Figure 7).

![Timing diagram neuron](image2)

**Figure 7. The timing diagram of the neuron**

5) **Controller:** A multiplexing module (MUX controller) was used to provide a neuron output at each clock cycle to the next step. The controller is like a state machine, which connects the calculation step needed. It consists of a management module and a control signal generation module selection signals through the data multiplexer.

6) **Hardware architecture of the MLP:** The internal architecture of the proposed circuit was designed as a set of synchronous blocks interaction via internal signals [2]. This is a single ring of the chip, which contains various processing modules. Different circuit blocks designed was defined as a set of states finites Extended Machine (EFSMs) in the RTL level. Four input had been defined in MLP; an output value representing the probability of detection parameters will return. The block diagram of the hardware architecture proposed is shown in Figure 8. The design consists of three layers: the input layer neurons to four, three neuron hidden layer, and an output layer having a single neuron and two multiplier and a controller for the synchronization signals. Our architecture requires a reduction of physically in the MLP structure and involves a high execution time satisfied by the constraints of WSN. Figure 8 represents the architecture of the MLP.

![MLP architecture](image3)

**Figure 8. Global architecture of the neural network.**

![Timing diagram MLP](image4)

**Figure 9. The timing diagram of the MLP.**

C. **Simulation results**

The goal of the hardware implementation is to achieve very short time and low power event detecting. The proposed architecture is implemented using Xilinx ISE Design Suite 13.1. FPGA platform for Spartan3 type “xc3s2000” family is used for synthesis process. The MLP is modeled using Very High Description Language (VHDL) programming. This design can be implemented on a prototyping platform based on FPGA.

1) **Simulation:** Sensors are generally believed to be unreliable and imprecise. therefore, to increase our confidence in the presence of an event somewhere in the monitored area, we often need readings from multiple sensors and/or readings over some period of time. Consider for example two fire detection scenario. the first is based only on the temperature and carbone monoxide readings for a particular moment, the second is based not only on the temperature and carbone
monoxide readings for a particular moment, but also on the change of both the temperature and CO levels. MLP architecture of the first scenario takes two variable (temperature, co). else MLP architecture of the second scenario takes four variable (T, ΔT, CO, ΔCO) Table I shows the result of the simulation of the first and the second scenario.

In Table I we present some simulation results based on scenarios proposed. From the first row of the table, it can be seen that temperature is low (T = 30), temperature change is low (ΔT = 2), carbone monoxide is low (CO = 45) and CO change is low (ΔCO = 5) then fire probability is medium (53%) for scenario 1 and low (21%) for scenario 2. From the result of this table it can be concluded that the use of the change of the environmental parameter is a technique can improve the reliability and accuracy of detection.

Table 1 shows that the probability precision is greatly improved in the scenario 2 related to scenario 1. First, with the parameter values presented in the first row of the table indicating a low risk of having a fire; our architecture seems more effective with probability value equal to 0.21 compared to an equal to 0.57 at the scenario 2. Second, the values of the parameters contained in the fifth row of the table indicating an elevated risk of having a fire, our architecture seems more effective with a probability value equal to 0.76 compared to an equal to 0.6 at the scenario 2.

2) Synthesis for FPGA circuits: The FPGA circuit solution is, nowadays, considered as one of the most used prototyping environments. In fact, with the increase of the available programmable cells in these circuits, it is being possible to implement a wide range of sophisticated algorithms. Furthermore, with their adaptability to the re-use concept [1], the FPGA solutions are considered more than a validation step of research approach.

Table II presents a summary of results for the proposed architecture. The hardware resource occupancy (logic cells), the power consumption, and the used memory are pointed out. The maximum operating frequency of the designed circuit is 176.653 MHz.

This table shows efficiency of our implementation on FPGA device, in fact, we used only 2% of the total number of slices, 6 MULT18X18s with use of 15% of the total number of multiplexers and 1,165 mW of total power that shows the effectiveness of our architecture.

Also, an implementation of neural network on FPGA has been proposed in Ref. [7]. It contains 2 millions of logic gates and occupation of logic in terms of CLB (registers, LUTs) which is 59%; 17 616 is the number of slices. We can see that our solution provides best results in terms of occupied area and operating frequency.

IV. CONCLUSION AND FUTURE WORKS

In this paper, multi-sensor hardware architecture for monitoring forest fires is proposed, it is especially designed to enable low power and higher precision in WSN. The proposed architecture is based on neural network approach to improve the mapping between the requirements quality of service for detection process and material resources available in WSN nodes.

The simulation results show that the use of MLP in the detection of forest fires is promising approach. The built up neural network is effectively managing uncertainty and imprecision in the data environment. A detection method of given events improves its accuracy by data processing of several sensors and its variation. Our approach shows that WSN is a promising system for detection of events with low false alarm rate. For future work, we plan to perform experiments on a sensor testbed. This will allow us to more evaluate how using neural network (MLP) influences the accuracy and speed of event detection when neural decision is run on sensor node.

REFERENCES


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TABLE I. THE RESULTS OF SIMULATION

<table>
<thead>
<tr>
<th>Input parameter</th>
<th>Fire Probability</th>
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<tbody>
<tr>
<td>T °C</td>
<td>∆T (°C)</td>
</tr>
<tr>
<td>1</td>
<td>30</td>
</tr>
<tr>
<td>2</td>
<td>38</td>
</tr>
<tr>
<td>3</td>
<td>20</td>
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<tr>
<td>4</td>
<td>30</td>
</tr>
<tr>
<td>5</td>
<td>80</td>
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TABLE II. SUMMARY OF RESULTS

<table>
<thead>
<tr>
<th>Results Synthesis Spartan3</th>
<th>Used</th>
<th>Total</th>
<th>Percentage (%)</th>
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<tbody>
<tr>
<td>Number of slices</td>
<td>447</td>
<td>20480</td>
<td>2%</td>
</tr>
<tr>
<td>Number of slice flip flops</td>
<td>90</td>
<td>40960</td>
<td>0%</td>
</tr>
<tr>
<td>Number of MULT18X18s</td>
<td>6</td>
<td>40</td>
<td>15%</td>
</tr>
<tr>
<td>Number of 4 input LUTs</td>
<td>828</td>
<td>40960</td>
<td>2%</td>
</tr>
<tr>
<td>Number of bonded IOBs</td>
<td>172</td>
<td>333</td>
<td>51%</td>
</tr>
<tr>
<td>Number of GCL.Ks</td>
<td>2</td>
<td>8</td>
<td>25%</td>
</tr>
<tr>
<td>Total power (mW)</td>
<td>1165</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>


