A Pattern Recognition Framework for Embedded Sensor Electronics

Himanshu Mazumdar, Agnel Amodia

Abstract*: The recent developments in the area of high speed micro-electronics and computational intelligence has opened new opportunities in smart sensor design. In this paper a generic pattern recognition framework is presented for integrated sensor based system design. Two case studies are described for Rock-Image Classification and Pulse Shape Identification. Both applications use same framework that consist of pre-processing of sensor data, wavelet based data compression, feature extraction and neural net based feature classification. The rock identification combines multi-parameter analysis to improve the accuracy. The proposed system is tested using above two case studies for real time application. The average accuracy observed for pulse shape and rock type identification is 96% and 95% respectively. The system is applicable for similar sensor based embedded systems. The application is developed under a Planetary Exploration Technology Research project.

Index Terms*: feature extraction, neural net based classification, Pulse Shape Identification, Rock-Image Classification, wavelet based data compression.

I. INTRODUCTION

With availability of high end embedded devices like ASIC and FPGAs it has become possible to analyze the sensor data in real time for interactive applications. Some such applications are face location in modern cameras, blood pressure monitoring wrist watches etc. Many such applications share similar building blocks (modules) as shown in Fig.1. Each application uses different types of sensor devices. Most of these sensors come with integrated electronic data acquisition system consist of transducer, sample and hold digitizer, buffer and data read out circuits. Each of these outputs though standardized but needs format conversion, files management, buffering etc. While reading these data from file or buffer it needs further processing for display devices or interactive environment. There are several algorithms and methods available which are used to analyze such data for actual implementation. For example consider a classical approach to hand written character analysis, where hands written text is scanned or electronically generated to create image file. Image file is further processed to separate lines and characters. The characters are analyzed to extract features which in turn are classified to recognize the alphabet [1], [2]. In most publications considerable amount of processing resources are used in encoding, decoding, buffering and file systems. In contrast to above in real time system like a modern mobile phone the raw data from sensor is directly processed while being acquired using dedicated processing hardware adjacent to the sensor. This has the advantage of reduced processing overhead and processing time. It also allows interactive control, feedback and intelligent operations. For example in camera application image post-processing may help automate focusing; aperture control and motion blur correction.

The concept is illustrated using two case studies. In first application we demonstrate and integrated particle counter with pulse shape pattern identifier as shown in fig. 2 [5]. This is to count a weak radiation source that produces few counts per second to few counts per day. Counting is often polluted by noise. The noise could be manmade or natural in the environment. Such measurement heavily depends on signal to noise ratio. However, often a human experimenter can identify a good pulse from noise burst by visually examining the pulse shape. Existing detection techniques often fails to distinguish noise from genuine counts. In the proposed method, each signal and noise event is analyzed to classify signal and noise signatures using supervised learning of pulse shape features. This is achieved using techniques like wavelet transform and neural network.

In the second example we classify different rocks using multi-sensor pattern recognition algorithms as shown in fig.3. It provides a simple but efficient technique in Planetary Exploration Technology Research programs. Three different parameters of each rock sample are measured and classified for rock identification. These parameters are color, texture and grain which are acquired using same imaging sensors used at different magnifications. These parameters are important indicators of rocks chemical and structural properties. Each of these parameters is used for pattern classification.

Manuscript published on 30 April 2012.
***** Correspondence Author (s)
Parveen Dabur*, Department of Electrical Engineering, HCE, Sonipat (Haryana), India. E-mail: parveen.eng11@gmail.com
Gurdeepinder Singh, Department of Electrical Engineering, H.I.T, Sonipat (Haryana), India. E-mail: gi_singh143@yahoo.co.in
Naresh Kumar Yadav, Department of Electrical Engineering, DCRUST, Sonipat (Haryana), India. E-mail: nkyadav76@gmail.com

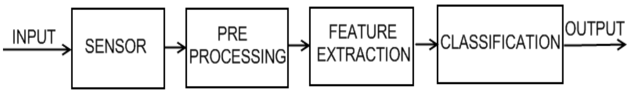

Fig.1. General purpose block diagram of integrated sensor with pattern recognition firmware.

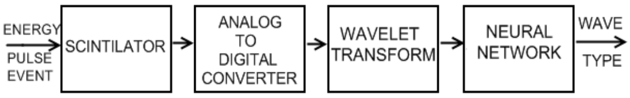

Fig. 2. Block diagram of a intelligent radiation counter.

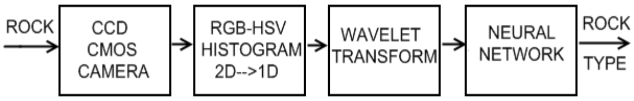

Fig. 3. Block diagram of a rock image classification system.

The combined analysis of these results increases the accuracy and reliability of prediction of rock type. The project started with earth rocks identification. Sixty different earth rock samples are collected from different river bed and cataloged in image gallery. Six microscopic grain images with magnification of 50 are taken of each rock sample. These 360 grain sample images are used for classification of 60 rock types [4]. Fig.6 shows 5 rock samples with grain images.

Fig. 4. Experimental setup for intelligent radiation counter.

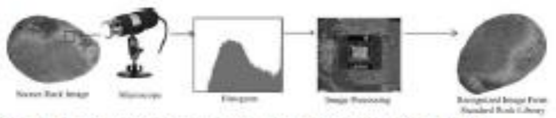

Fig. 5. Experimental setup for Rock Image Classification system.

Fig. 6. Top row shows the five rock images out of 60 rock samples used for the experiment. The bottom row shows grain images of corresponding rocks with magnification 50x. For each rock six grain samples are collected one of each grain sample shown here.

II. PROPOSED METHOD

As described above in Fig.1 the following processes are common in many such embedded sensor systems.

1. Sensor data acquisition
2. Sensor signal pre-processing
3. Data compression and feature extraction
4. Classification and pattern recognition

Two different types of sensors are described in the introduction. In both the applications digitized sensor signal is acquired in the memory buffer and pre-processed to convert to a common format.

This helps standardizing the post-processing hardware like FPGA or micro-controller with standard firm ware. Such post processing device is reusable for range of applications.

In case of pulse shape recognition example we consider radiation counters. Most particle or photon counters receive signal in scintilator or photon-detector sensor respectively. These sensors consist of integrated pulse amplifier and pulse shaping electronics. Each energy-burst has a well recognizable shape, whereas the noise is an unpredictable component with wide variety of energy distributions profiles. These counters often use pulse height threshold to detect genuine counts which detects some noise bursts of high amplitude. In this paper a method is described to model signal pulse shape that is more consistent unlike noise. A very small component of noise may have correlation with signal, but it is expected to be orders of magnitude less. It is assumed that signal is weak and of low pulse repeating frequency (PRF). Our experiment consists of 6 bit high speed ADC followed by high speed hardwired wavelet transform to analyze the energy distribution profile of incoming events. This data is further classified by a hardwired pre-trained Neural Net that filters out the undesired noise. The whole process is implemented using Altera FPGA hardware module with interface of high speed ADC, DAC.

In second application of Rock-Image classification, sensor data are images of rocks at different magnifications using a MOS camera interface. The image data needs to be converted to common format for further processing using the FPGA based firmware module developed for pulse shape identification.

A fixed number of pixels are randomly selected for analysis of color parameter. Texture and grain data is collected by taking a randomly selected pairs of pixels around randomly selected location. The texture pixel pair is selected within average radius of 60 pixels and grain pixel pair is collected within average radius of 6 pixels. Each of the RGB pixels is converted to HSV format. Only hue value is used for further analysis. A histogram of color data is computed for 360 levels of hue values. The histogram is normalized and used as input to the FPGA processing module for color analysis. The histograms for texture and grain are having 129600 (360x360) possible pixel pairs. Only top high frequency 360 values are selected for analysis of texture and grain. The further processing in FPGA module consist of wavelet transform and neural network classification as described in section 2.1 and 2.2 below.

III. WAVELET TRANSFORM

Wavelet transform is a convolution tool with strong application in signal processing, data compression, noise filtering and feature extraction [7-9]. It is similar to Fourier transform with certain advantages [11]. Unlike Fourier transform Wavelet basis functions are arbitrary chosen orthogonal functions depending on the application [3]. We use here Daubechies D4 scaling and wavelet functions. The equations for the scaling and wavelet inner products are shown in equation (1) and (2) respectively.

The scaling and wavelet values a_i and c_i are calculated by taking the inner product of the h_j and g_j.

$$a_i = h_0 s_{2i} + h_1 s_{2i+1} + h_2 s_{2i+2} + h_3 s_{2i+3} \quad (1)$$

Where $h0 = (1+\sqrt{3})/4\sqrt{2}$, $h_1 = (3+\sqrt{3})/4\sqrt{2}$, $h_2 = (3-\sqrt{3})/4\sqrt{2}$ and $h_3 = (1-\sqrt{3})/4\sqrt{2}$. $c_i = g_0 s_{2i} + g_1 s_{2i+1} + g_2 s_{2i+2} + g_3 s_{2i+3}$ (2)

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

Where $g_0=h_3$, $g_1=-h_2$, $g_2=h_1$ and $g_3=-h_0$
The above algorithm is also simulated in C# .net environment to generate training data. The wavelet output is filtered to remove high frequency components. In case of wave shape identification first 37.5% of transformed outputs are retained for classification. Similarly in case of Rock Image classification first 50% values are retained for classification. The filter profile is selected iteratively to optimize the accuracy and speed.

IV. NEURAL NETWORK ARCHITECTURE

The filtered and normalized values of wavelet transform are used as input to a multilayer neural network. The network consists of binary outputs. Each output corresponds to a desired identification types. Multilayer Perceptron (MLP) used here is widely used type of artificial neural networks that uses supervised learning technique. It is used for classification, generalization and non-linear mapping abilities [10]. A MLP network consists of an input layer, one or more hidden layers and an output layer.
In a network of fully connected MLP every neuron in a layer is connected to every neuron of next upper layer by weighted links. Such a network is shown in Fig.6 [6]. In our network, input layer is connected to the feature vectors of wavelet output which need to be classified in desired groups. Each neuron in the hidden and output layers includes a nonlinear activation function of sigmoid type.

$$Y_i = 1 / (1 + e^{X_i}) \quad (3)$$

Input to each neuron is weighted sum of neuron outputs of previous layer or inputs as shown below.

$$X_j = \sum (W_{ij} * Y_i) \quad (4)$$

Where i, j are the layers in the network.

The neurons in the first layer receive external inputs as shown in Fig. 6 which provides the starting point for the network. The outputs of the neurons in the last layer are considered the network outputs. The hidden neurons are responsible for extracting meaningful features from the input vectors. Learning rule used here is back propagation algorithm for modifying weights and biases of a network.
Training of weights and biases of the network are performed by computing output error. The error is calculated as the difference between the desired output and the network output. The training goal is to find the global minima of the average of square of the sum of these errors. The weights of the trained network are ported to the FPGA firmware for real time analysis.

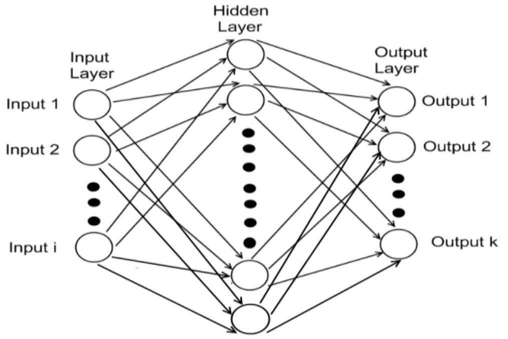

Fig.6. A multilayer neural network for pattern recognition. Input i is from wavelet transform and binary outputs k are the pattern nodes.

V. EXPERIMENTAL RESULTS

Following are the test results of both the identification systems. It is observed that the pulse shape identification accuracy depends on number of samples per wave form as shown in Table.1. The accuracy increases at the cost of the processing time.

Table1. Pulse Shape Identification accuracy of different waveform samples per experiment.

Samples per waveform	1000 Trials	10000 Trials	20000 Trials
32	86.70%	86.08%	86.30%
64	94.70%	95.17%	95.36%
128	98.50%	98.51%	98.49%
256	99.20%	99.13%	99.03%
512	99.70%	99.33%	99.38%
1024	98.90%	99.03%	99.00%

The result of Rock Image Classification is shown in Table 2. The individual feature identification achieves 80% accuracy while overlapping the accuracy of all the three features achieves average of 95% identification in 1000 trials.

Table 2. Rock Image Classification accuracy as average of 360 Rock image samples per experiment. These samples are not used in training.

Feature	Color	Texture	Grain	Combined
Experiment-1 (1000 Trials)	80%	80%	80%	94%
Experiment-2 (1000 Trials)	80%	80%	80%	96%

VI. CONCLUSION

A generic pattern recognition framework is described in this paper for integrated sensor based system design. Two real time applications are presented. Both the applications use similar computational firmware adapted to two different front ends. The same approach could be used as a building block for other smart sensors applications. Through this development we show the concept of using reusable firmware module which will reduce the cost and time of the online application development.

ACKNOWLEDGMENT

This work is carried out under the project "Planetary Exploration Technology Research", funded by PLANEX program of Physical Research Laboratory, ISRO, Government of India.

REFERENCES

1. Himanshu S. Mazumdar., "Hand Written Character Recognition using Neural Network " CSI Communication, p.16-18 (Feb. 1998)
2. A Multistage Handwritten Marathi Compound Character Recognition Scheme using Neural Networks and Wavelet Features in International Journal of Signal Processing, Image Processing and Pattern Recognition International Recognition Vol. 4, No. 1, March 2011
3. Discrete Wavelet Transforms and Artificial Neural Networks for Speech Emotion Recognition International Journal of Computer Theory and Engineering, Vol. 2, No. 3, June, 2010 1793-8201.

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

4. Himashu Mazumdar, Agnel Amodia, Pratik Patel "Rock Image Classification" in Conference on Planetary Science and Exploration, physical research laboratory, December 2011, pp. 61-62 .
5. Himashu Mazumdar, Agnel Amodia, Himanshu Purohit "Pulse Shape Recognition using Wavelet and Neural Network" in Conference on Planetary Science and Exploration, physical research laboratory, December 2011, pp. 63-64.
6. Himanshu S. Mazumdar & Leena P. Rawal, "A Neural Network Tool Box using C++", in CSI Communications, April, pp. 22-25, 1995.
7. Inan Gulera, Elif Derya Ubeylib. "ECG beat classifier designed by combined neural network model", Pattern Recognition 38 (2005) 199 – 208
8. Shahshahani "Data compression by Wavelet Transform".
9. J. Brailean, R. Kleihorst, S. Efstratiadis, A. Katsaggelos, and A. Lagendijk, "Noise reduction filters for dynamic image sequences: A review," Proceedings of the IEEE 83(9), pp. 1272–1292, 1995.
10. B.Lerner, H.Guterman, M.Aladjem and I.Dinstein, (1996) "Feature extraction by neural network nonlinear mapping for pattern classification", Proc. of the 13th Int. Conf. on Pattern Recognition, Vienna, August, 25-30, Vol.IV, IEEE Computer Society Press, 320-324.
11. Amara Graps "An Introduction to Wavelets" p. 5-6

AUTHOR PROFILE

Himanshu S Mazumdar (Senior Member, IEEE) received the Bachelor degree in Electronics and Telecommunication engineering from the Jadavpur University of, Calcutta, India. in 1968, and the Ph.D. degree in "Application of Neural Network for Problem Solving" from the Dharmsinh Desai University, Nadiad, India in 2004 . Currently working as Professor Electronics and Communication and Head of Research and Development Center at Dharmsinh Desai University. He started his carrier with Physical Research Laboratory Ahmedabad, Gujarat, India and has been the Head of Electronic and Computer Science Lab of PRL and served as Senior Instrumentation Engineer of Planetary Exploration Program (PLANEX) developing Remote Sensing Payloads for Indian moon missions. He was also invited to work with the University of London and UKIR telescope at Hawaii, USA. He has been former Director Research and Development, Defense Training & Technologies, Champaign, IL. He also served Volition-Inc, THQ-Inc, Champaign, IL, USA, working as Senior Programmer on world's number 1, Real World Game development project using Xbox360 and MS .Net technology. He has also been the Director Research and Development, Axiom Technologies International, Woodland Hills, CA. Chairman Computational Services, Physical Research Laboratory. His major area of researches includes image processing, Neural Network, Fuzzy Logic, Genetic Algorithm, Assembly Language Programming. Analog and Digital system design, Power Electronics, Micro controller and PC based System design, parallel processing, Networking, VHF communication, Instrumentation, Process Control and Fuzzy controller design, Space payload design.

Agnel Amodia received the Bachelor degree in Computer engineering from the Dharmsinh Desai University of, Nadiad, Gujrat, India in 2008. In 2008 he joined the Research and Development Center, at Dharmsinh Desai University, Gujarat, India where he is currently working as an Senior System Engineer on project of Planetary Exploration Technology Research of Physical Research Laboratory. His research interests include implementation of Image Processing algorithms, Neural Networks, Wavelet Transforms.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)