

Systems for Health Monitoring

Zbigniew Kalbarczyk

(in collaboration with: M. Saleheen, H. Alemzadeh, A. Cheriyan,
A. Jarvi, R. Iyer, K. Watkin)

Center for Reliable and High Performance Computing and
Center for Health, Aging and Disability
University of Illinois, Urbana-Champaign

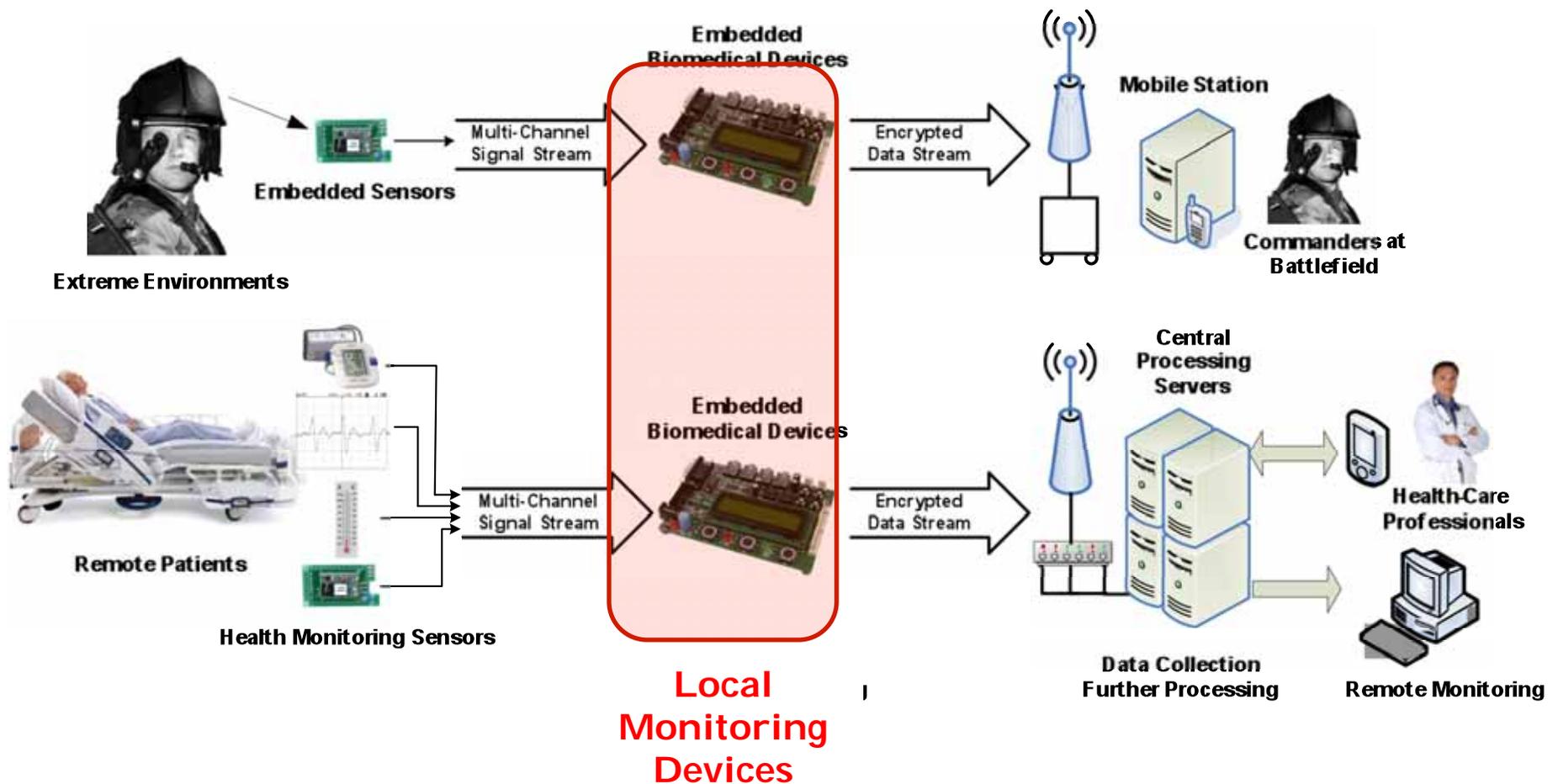
Motivation and Goals

- Advances in computing technology enable deployment of robust, cost-effective embedded devices with increased processing power
- Support biomedical applications, which require
 - real-time processing of a large amount of physiological data
 - rapid detection/identification of abnormalities in measured signals
 - notification of medical personal in remote sites
- Create a hardware system for robust, secure, and non-invasive health monitoring and diagnosis
 - demonstrate a prototype device in detecting conditions such as epileptic seizure
 - **Long term goal** – develop an adaptive system on a chip

Challenges

- System architecture
 - Small footprint, reconfigurable, low power solution
 - Enable rapid adaptation to application specifics
 - Support application-specific trust
 - Reliability and security in data processing and transmission
- Data processing
 - Accuracy of monitoring and diagnosis depends on the quality of the sensor data and the algorithm used to process the data
 - Adaptability and extendibility to different sensing elements and data processing algorithms

Remote Health Monitoring *Application Scenario*



Approach

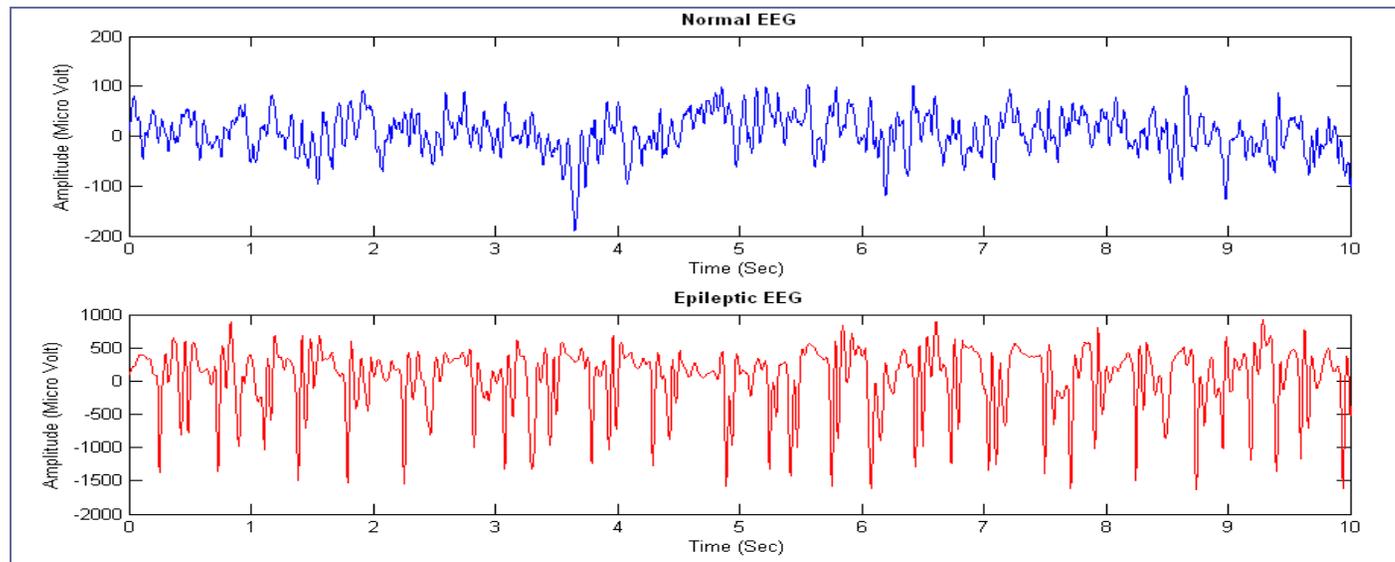
- Use smart bio-sensors for continuous and autonomous monitoring of human physiological signals
 - ability to collect EEG, oxygen saturation, and heart rate in real time
 - detect abnormalities in the data
 - alert the user and a remote logging base station
- Use COTS (Components Off the Shelf) power-efficient device (e.g., microcontroller) to deploy the embedded monitoring system
 - Provide adaptability to different application scenarios which involve different sensors and data

High Accuracy Detection of Epileptic Seizures

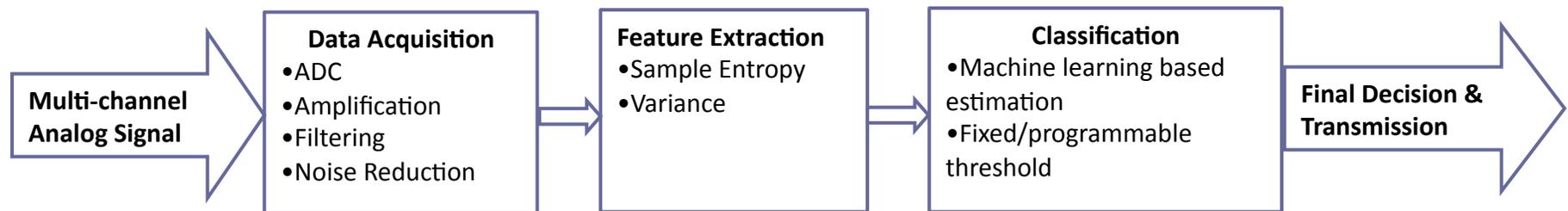


Overview

- Epileptic seizure
 - unusual recurrent electrical discharges in neurons, observed in EEG (electroencephalogram)
 - ~50 million suffer from seizure worldwide
 - Need prolonged inspection before treatment/surgery, can be done at home
- Automated seizure detection
 - Embedded HW, high accuracy, low area and power



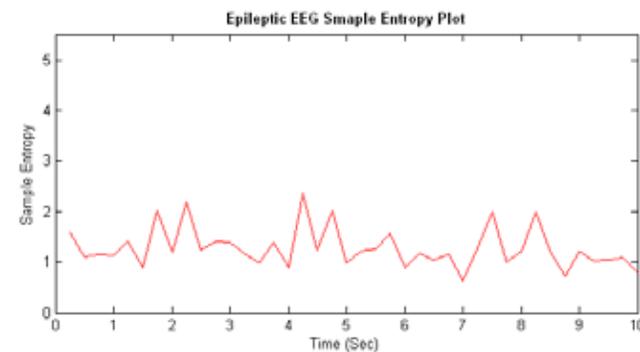
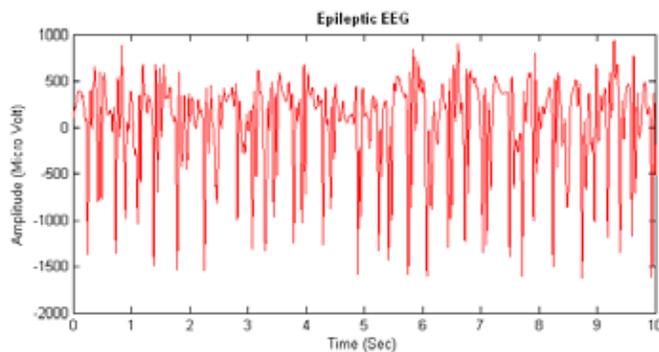
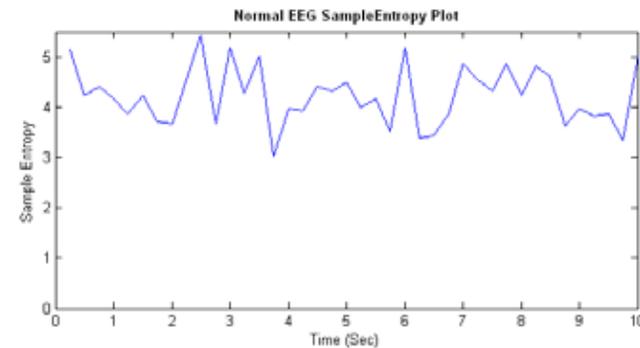
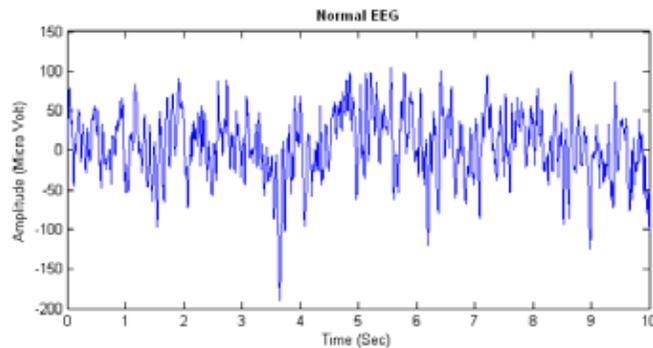
Automated Seizure Detection Flow



- Digital EEG Database – University of Bonn
 - 100 sets of Healthy EEG
 - 100 sets of Seizure EEG

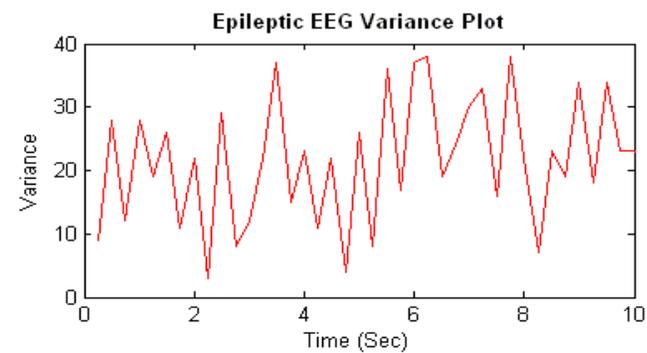
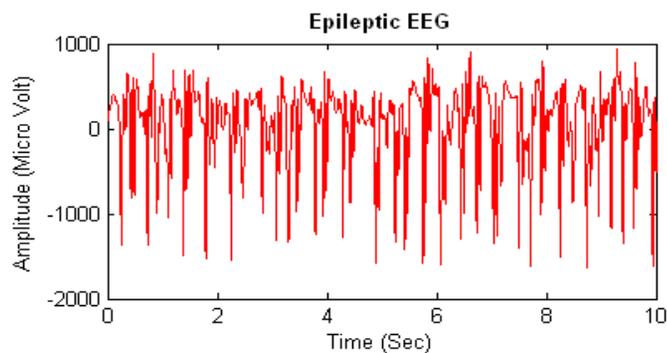
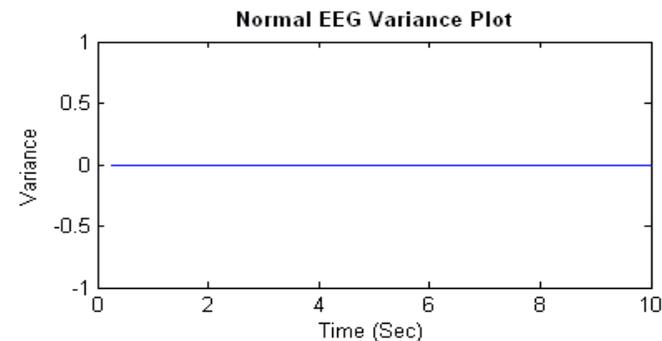
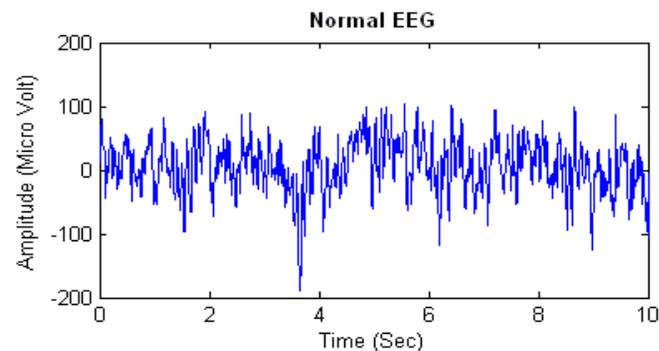
Feature Extraction: Sample Entropy

- Measures complexity/randomness in time series
 - Richman & Moorman (2000)
- Large value of Sample Entropy
 - > More complexity/randomness -> Normal Brain Activity
- Small value of Sample Entropy
 - > Less complexity/randomness -> Seizure

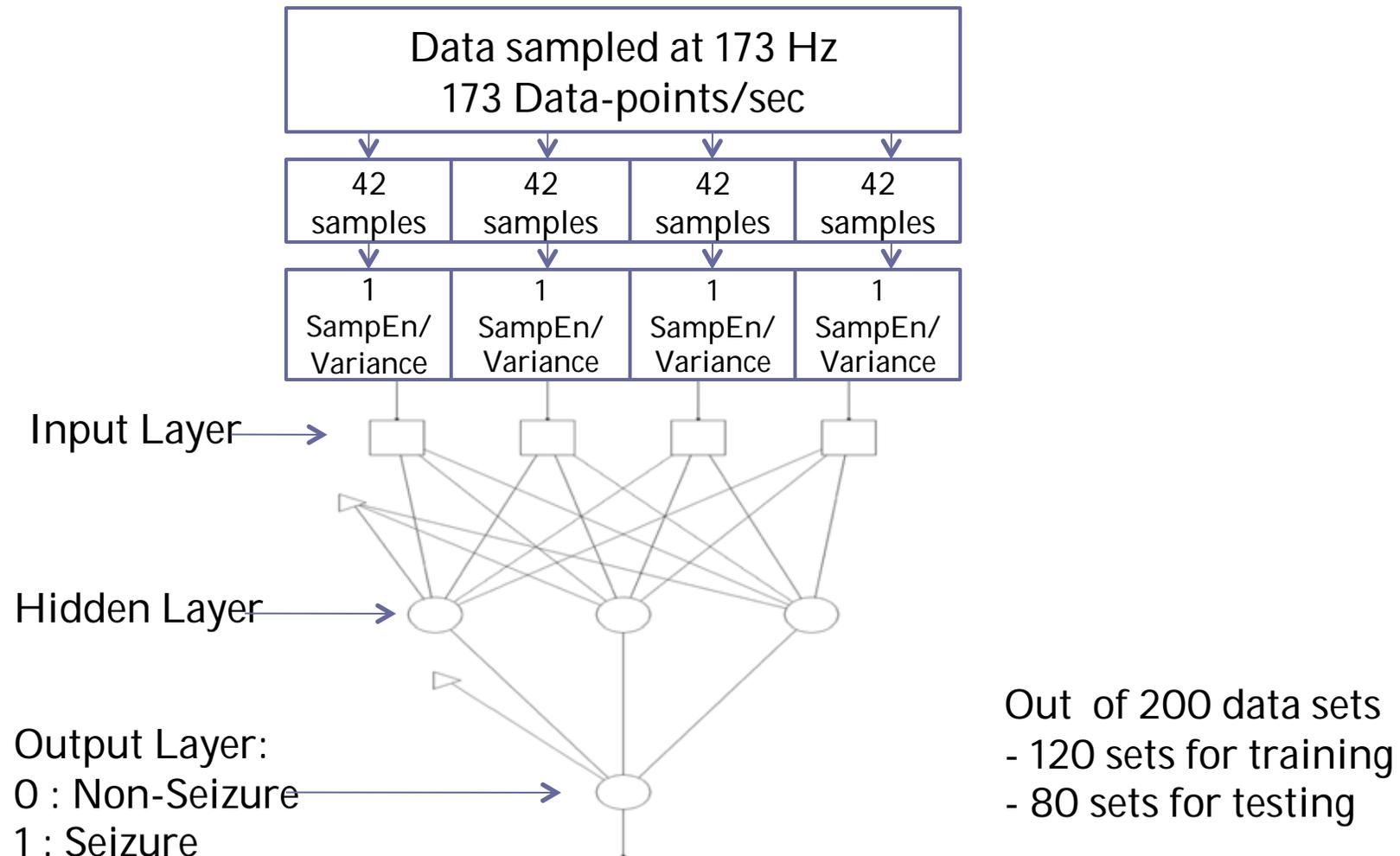


Feature Extraction: Variance

- measure of the variation of the data set from its mean.
 - Normal EEG -> smaller spikes -> low variance
 - Seizure EEG -> larger spikes -> high variance



Classification: Neural Network



Performance and HW Footprint

- Configurations (feature extraction + classification):
 - (1) Sample Entropy + ANN
 - (2) Variance + ANN
 - (3) Variance + Predetermined Threshold

Detection Performance

<i>Measurement</i>	<i>SampEn + ANN (%)</i>	<i>Variance + Threshold (%)</i>	<i>Variance + ANN (%)</i>
Overall Accuracy	99.73	98.52	99.18
Sensitivity	99.46	99.47	98.60
Specificity	100.00	97.61	99.78

FPGA Footprint

<i>SampEn + ANN</i>			<i>Variance + ANN</i>		
Module	ALUT Usage	Percentage	Module	ALUT Usage	Percentage
SampEn	36964	76.44	Variance	2490	5.15
ANN	15432	31.91	ANN	18683	38.64
Total	52396	108.35	Total	21173	43.79

Optimization: Reduced Precision

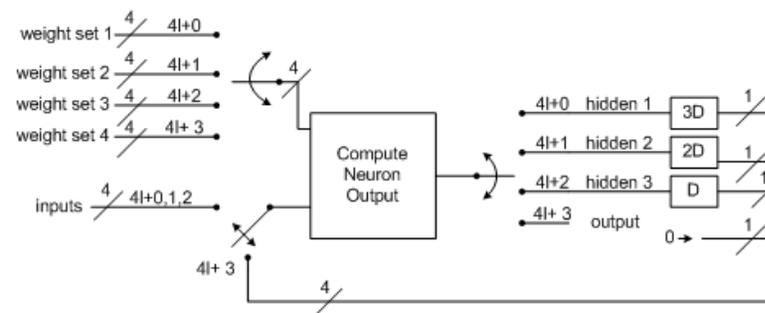
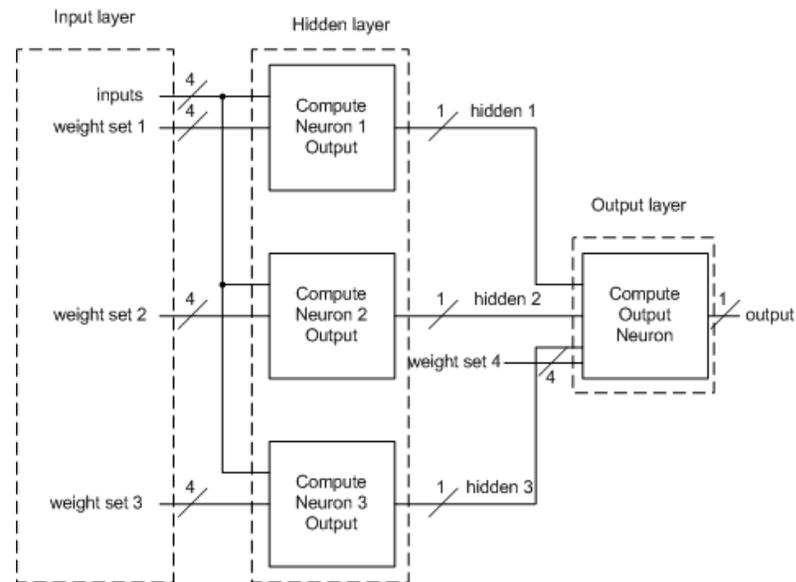
- Initial implementation: 32 bits words
 - Format: sign bit + integer bits + fraction/precision bits = word
 - Experiment with reduced precision and word-length

Precision and Performance

<i>Precision (bits)</i>	<i>Total Word- Length (bits)</i>	<i>Overall Accuracy (%)</i>	<i>Sensitivity (%)</i>	<i>Specificity (%)</i>
1	11	47.45	100.00	48.75
2	12	84.02	68.04	100.00
3	13	92.23	86.45	100.00
4	14	96.47	93.49	99.88
5	15	99.08	99.24	98.92

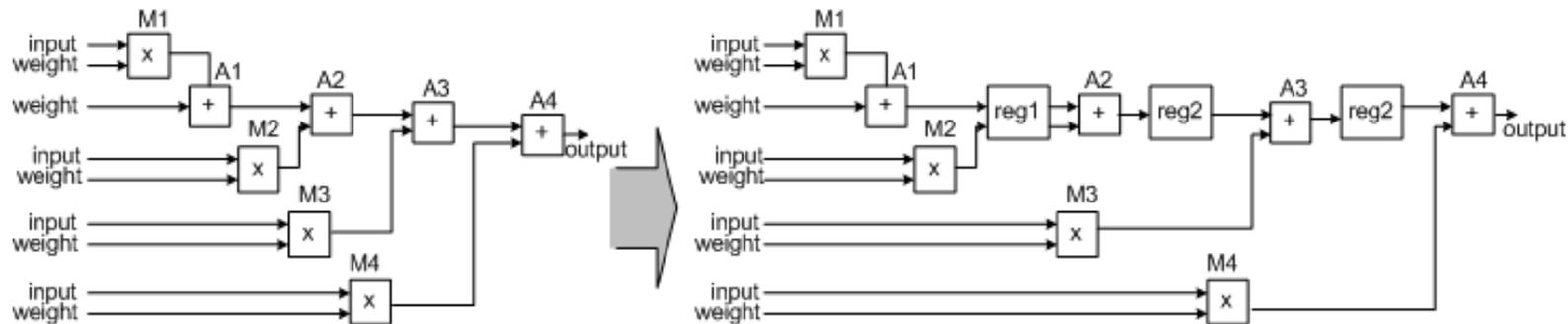
Optimization: Folding

- Re-use component by time-multiplexing redundant section
- Need control circuitry For scheduling



Optimization: Pipelining

- Introduce registers in intermediate stages
- Smaller signal propagation path = lower power consumption
- Extra memory for intermediate states



Area and Power Consumption

- 78% reduction in resource, 62% reduction in power

Area and Power Usage with Optimizations

<i>Architecture/ Optimization</i>	<i>Resource Usage (ALUTs + Registers)</i>	<i>Resource Usage Decrease (%)</i>	<i>Dynamic power (mW)</i>	<i>Power Saving (%)</i>
Un-optimized	21472	--	4.3	--
Reduced precision	6828	68.20	2.85	33.72
Red. prec. + Folding	4902	77.17	1.62	62.33
Red. prec.+ Fold.+ Pipeline	5022	76.61	1.63	62.09

Findings

- Variance with ANN allows high accuracy (99.18%) with moderate HW usage (44%).
- Algorithmic and architectural optimizations allow 4.4X reduction of HW usage and 2.7X reduction of power
- Embedded seizure detection implementation with:
 - High accuracy
 - Real-time detection
 - Simple design
 - Power efficient
 - Small HW foot-print

Reconfigurable Hardware Design for Health Monitoring



Reliability Aware Computing

Trusted ILLIAC Approach

Automated Derivation & Synthesis of Checks

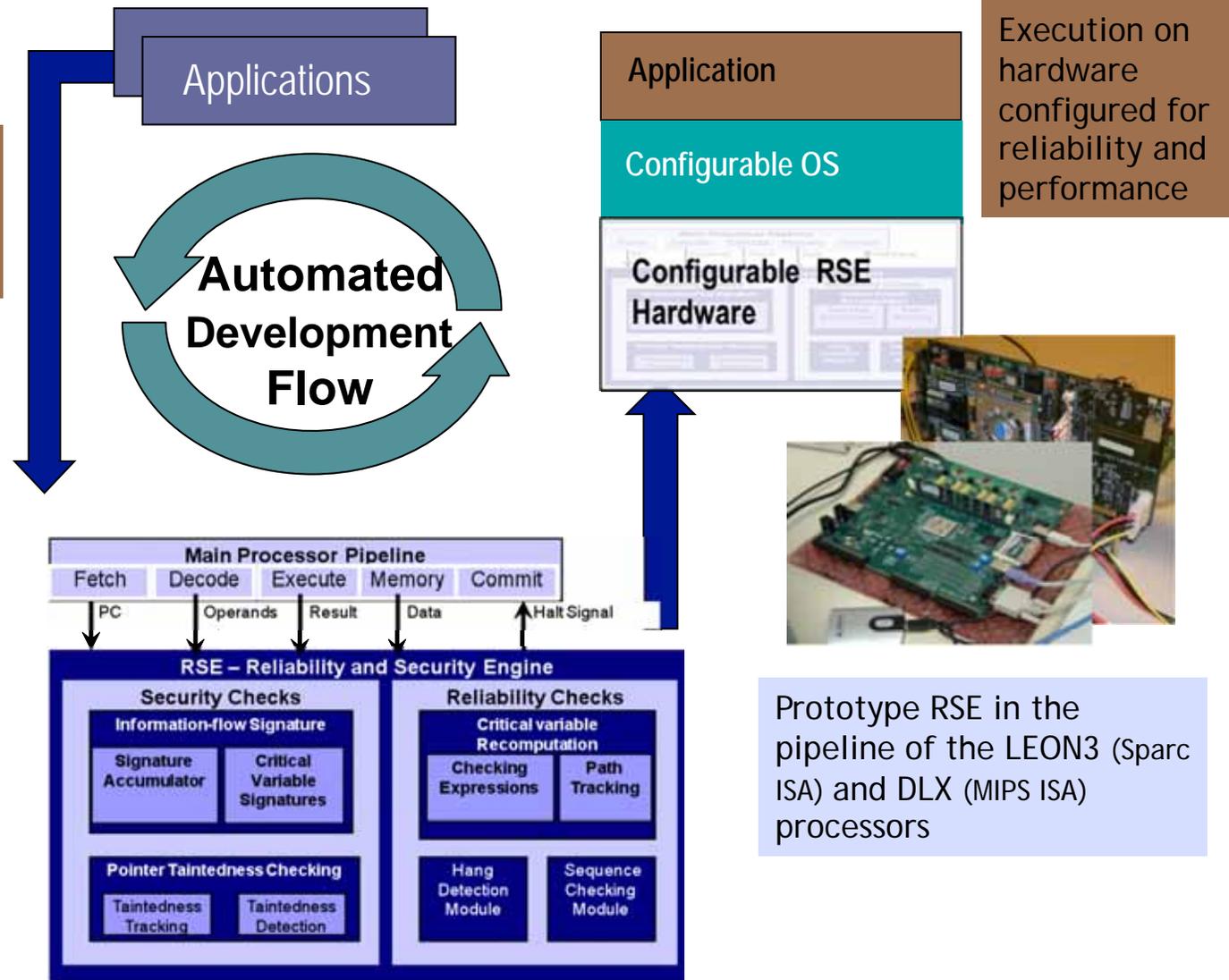
Extract application reliability and security properties (critical variables or application segments)

Compiler assisted generation of hardware for

- Critical application segments
- Error detectors

Reliability and Security Engine (RSE)

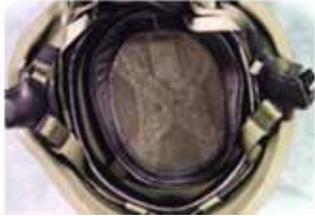
- processor-level hardware framework to embed modules needed by application



Execution on hardware configured for reliability and performance

Prototype RSE in the pipeline of the LEON3 (Sparc ISA) and DLX (MIPS ISA) processors

Evolution of RSE for Health Monitoring: Helmet Project

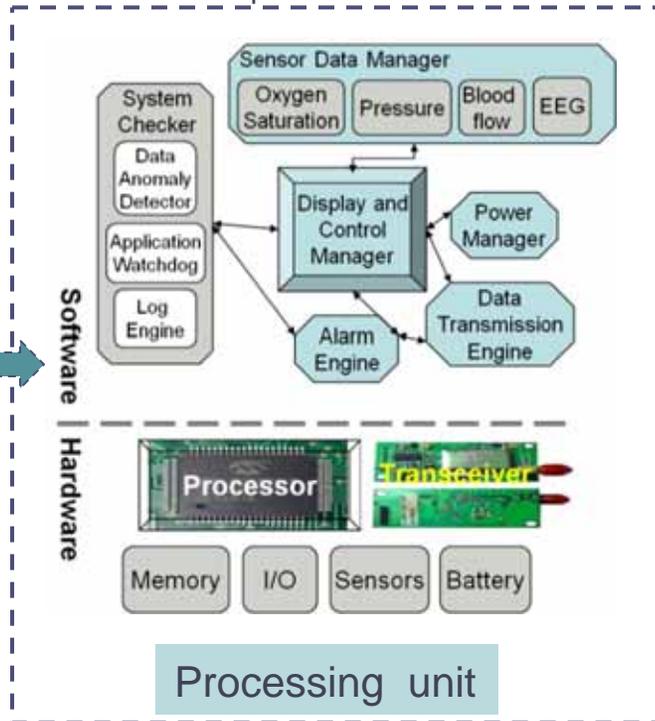
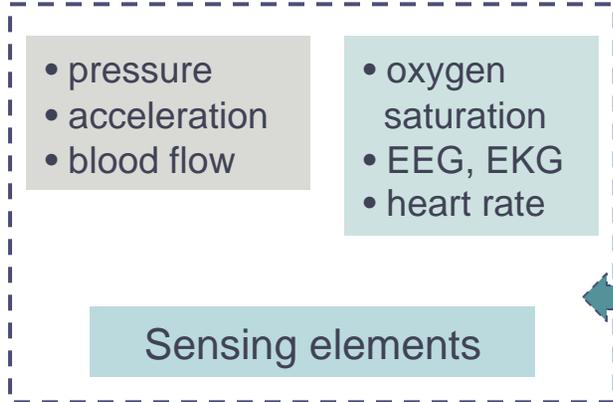


- Small footprint, light-weight, low power consumption, real time data monitoring and diagnostics
- Wireless or satellite data uplinking

Embedded within chin-neck pad

Embedded within headband

Embedded within neck pad



Server

- Data Collection
- Multiple Sources
- Multi-level and longitudinal analysis



Analysis Software

- Local data processing
- Real-time feedback
- Data forwarding to the remote serve

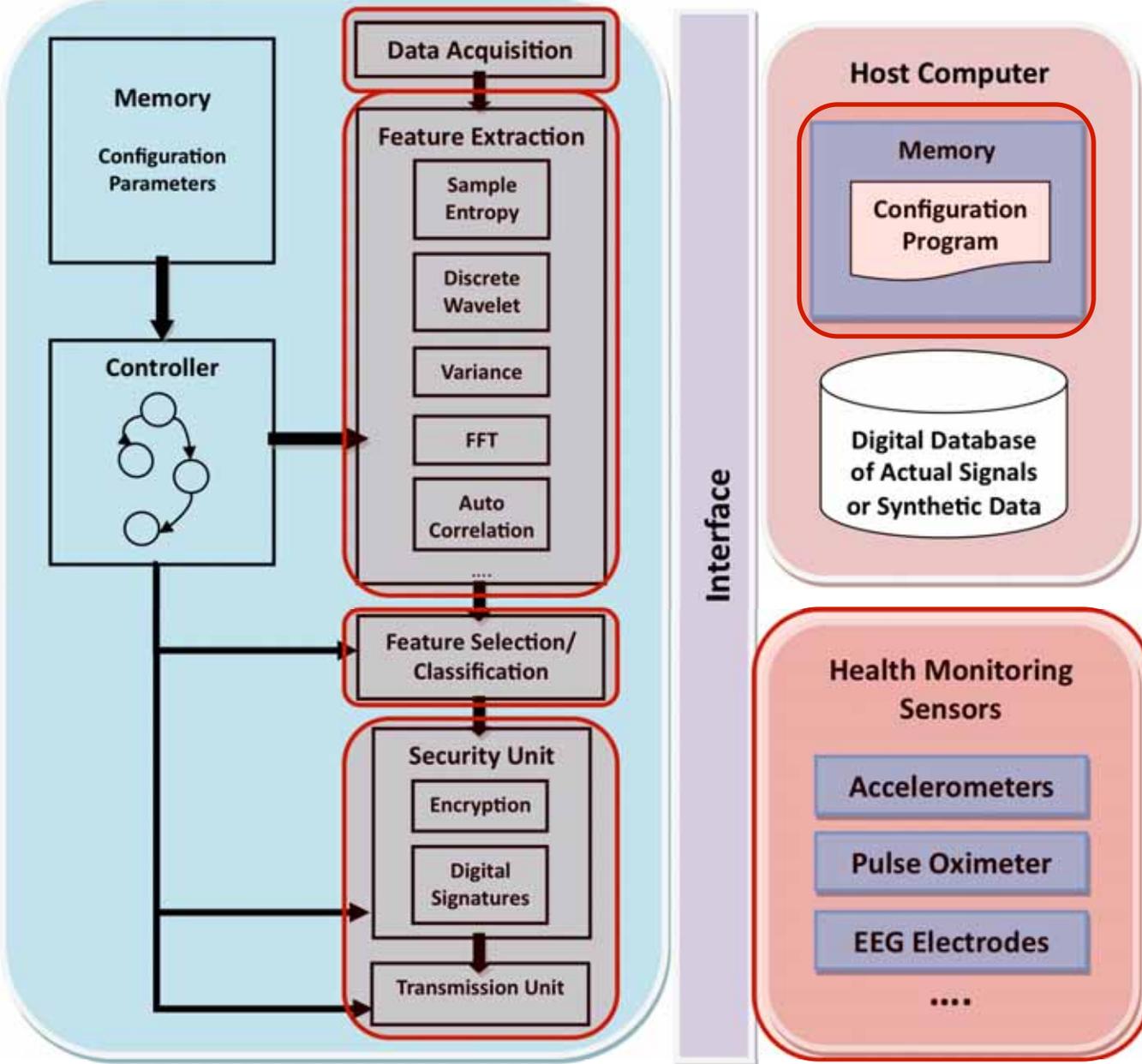


Reconfigurable Hardware Platform

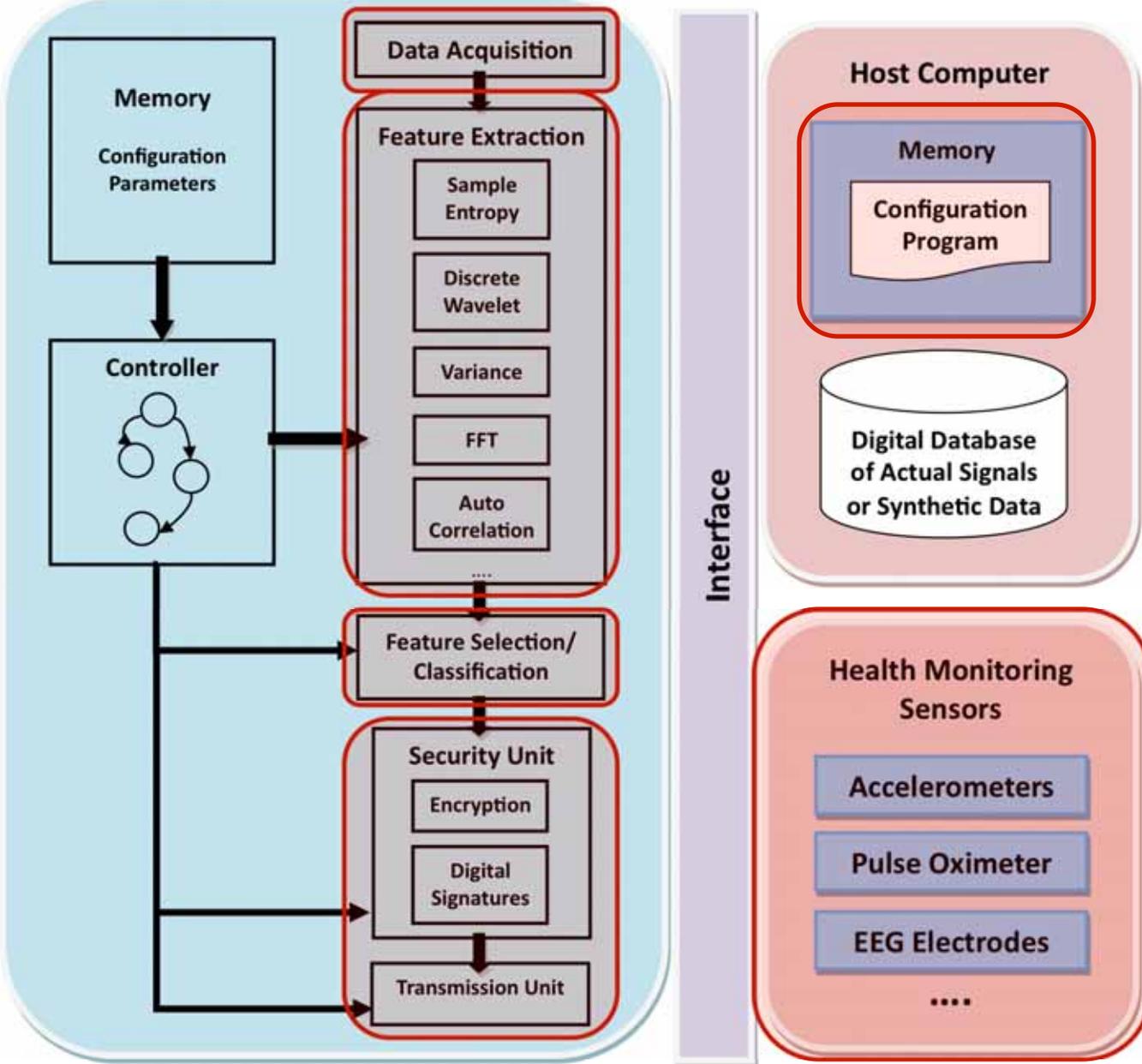
Biomedical Engines

- Main Goal:
 - Analysis of a variety of physiological signals
 - Configuration of built-in biomedical detection engines
 - Anomaly detection
 - Correlation of the extracted features from detection engines
- Plan:
 - Design and integration of basic signal processing blocks for extracting different features
 - Programming interface for configuration of biomedical detection engines and correlating their results
- Limiting Factors:
 - High computational complexity (Arithmetic/FP calculations)
 - Concurrent analysis & correlation/Accurate processing
 - Battery life
 - Wearable devices

Reconfigurable Architecture for Biomedical Processing



Reconfigurable Architecture for Biomedical Processing





Sensing elements

EEG

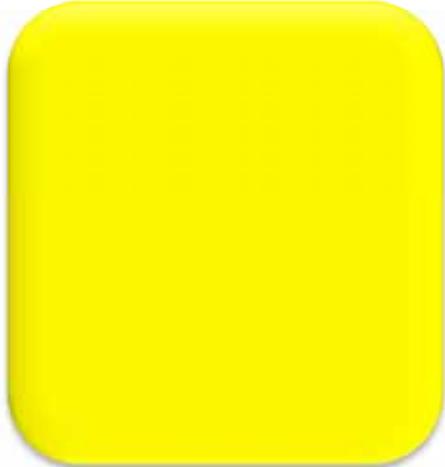
ECG

Oxygen saturation

Acceleration

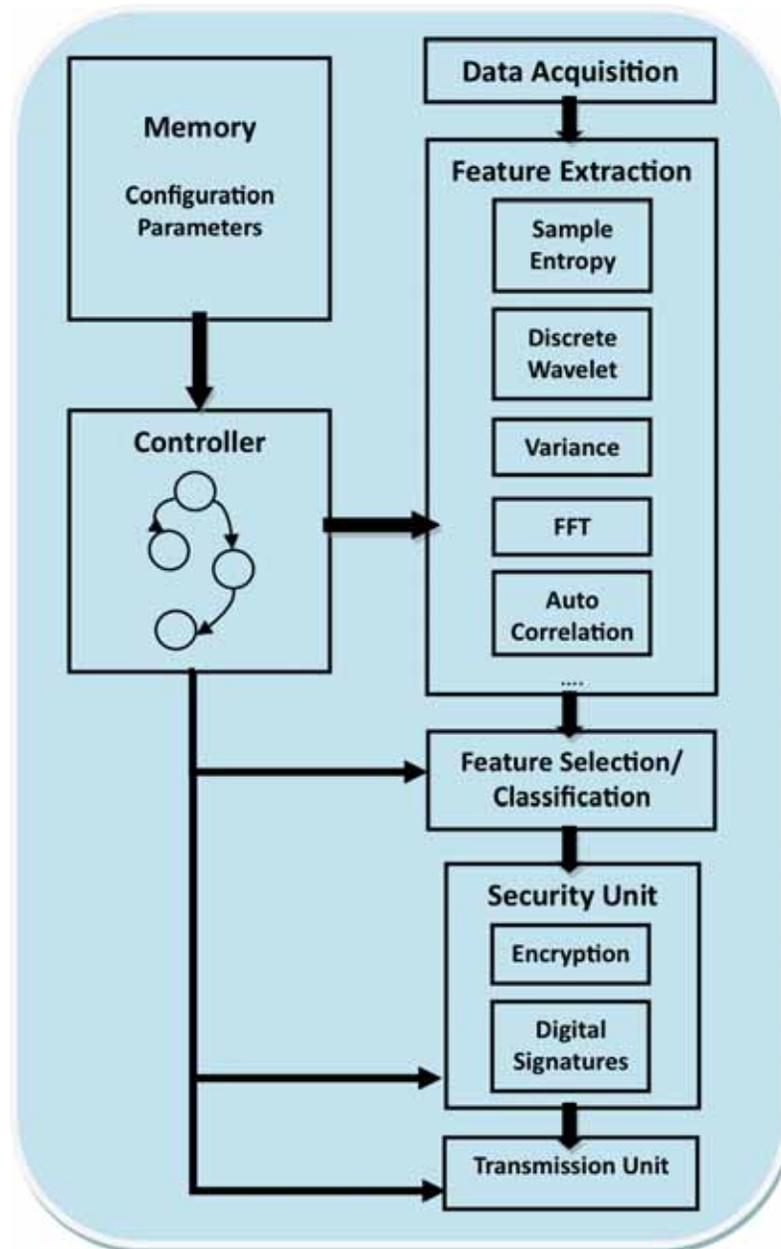
Database

Actual or
synthetically
generated signals

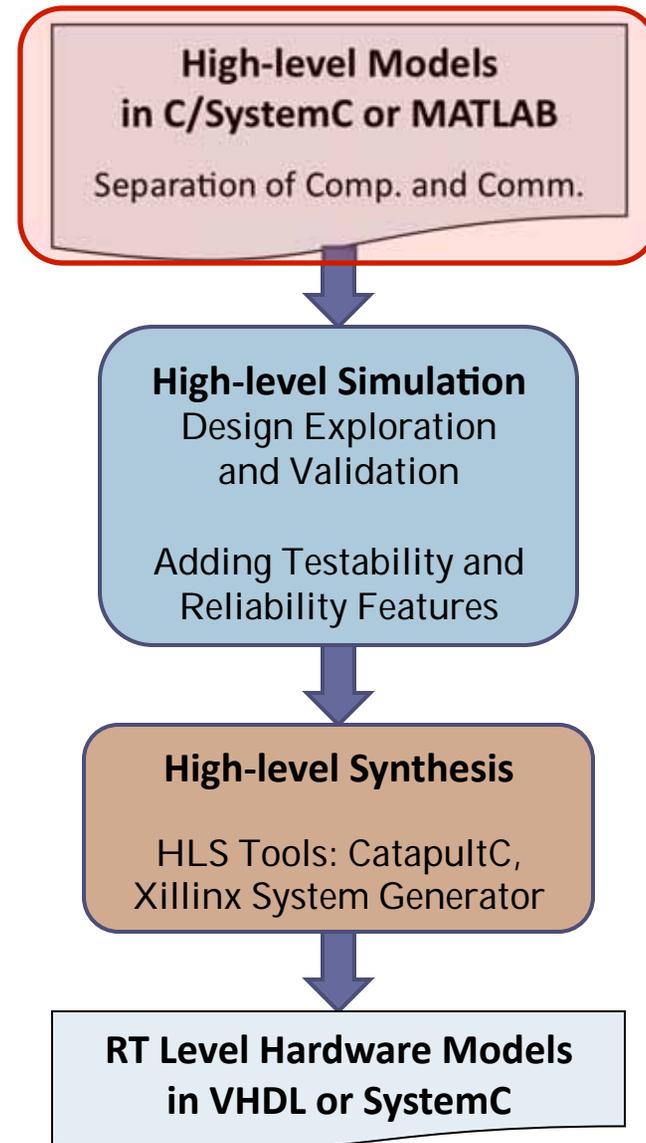


**Configuration
Program**

Reconfigurable Architecture for Biomedical Processing



Design Flow



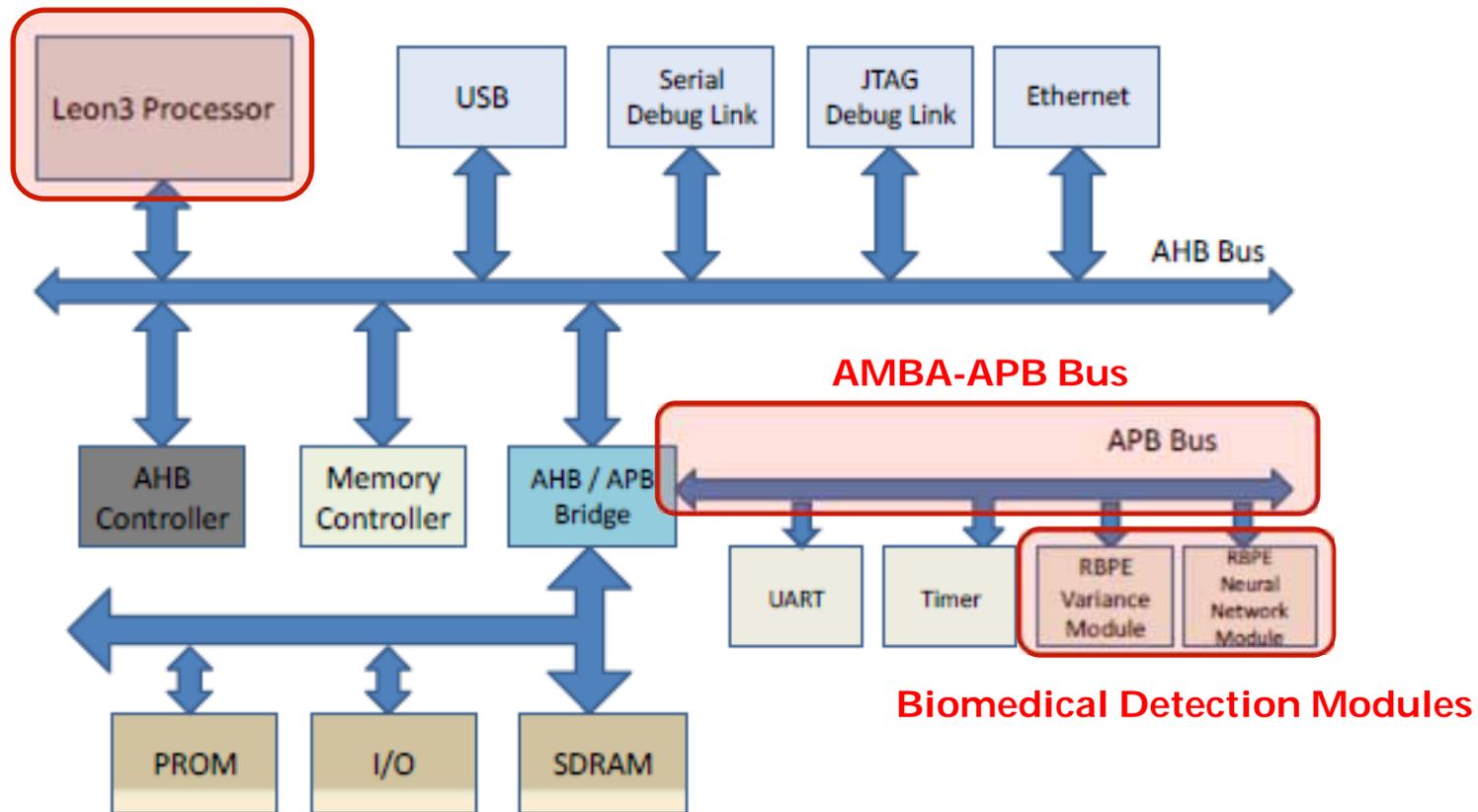
Biomedical Detection Engines

Seizure Detection Example

- Epileptic Seizure Detection
 - Transient & unexpected electrical disturbance of brain
 - Epilepsy detection:
 - Recording Electroencephalogram (EEG)
 - Visual scanning for spikes and seizures
- Feature Extraction
 - Local Variance:
 - Simplest statistics for investigating dynamics of EEG
 - Calculated in consecutive non-overlapping windows and compared with a constant threshold
- Feature Selection/Classification
 - Artificial Neural Network (ANN)

Initial Prototype on FPGA

Integration with Leon3 Processor



Summary

Conclusions and Future Work

- Reconfigurable Hardware Platform
 - Biomedical detection engines
 - Understanding the nature of signals (EEG, ECG, ABP, etc)
 - Different features to be extracted
 - Correlation of features for detection
 - Signal analysis and processing cores
 - Reconfigurability
 - Reconfigurable Classification
 - ANN or SVM
 - Dependability Requirements
 - Integration of security engines
 - High level evaluation of dependability features
 - Reliability and Security

Questions



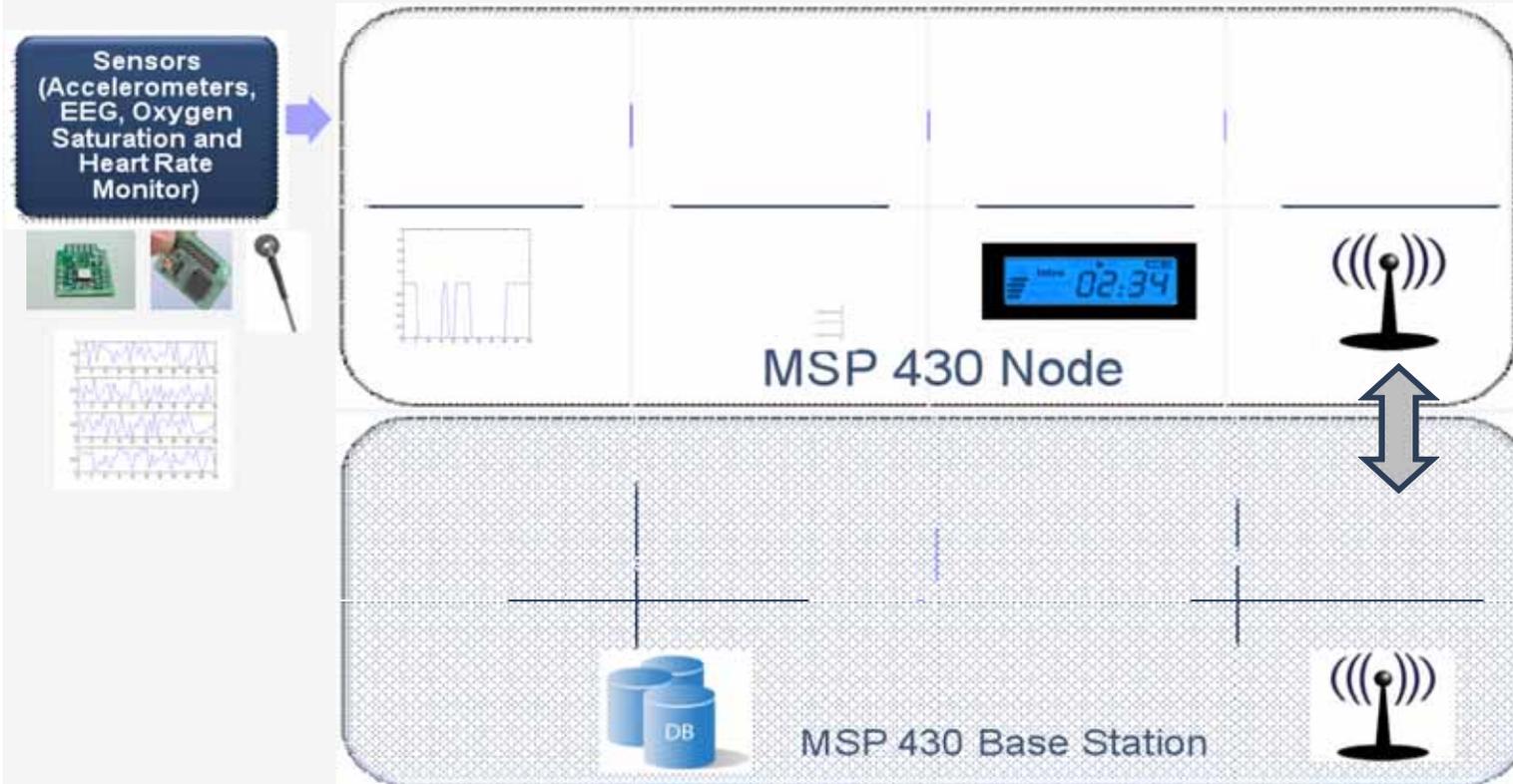
Pervasive Real-Time Biomedical Monitoring System

A. Cheriyan, A. Jarvi, Z. Kalbarczyk, R. Iyer, K. Watkin

Center for Reliable and High Performance Computing
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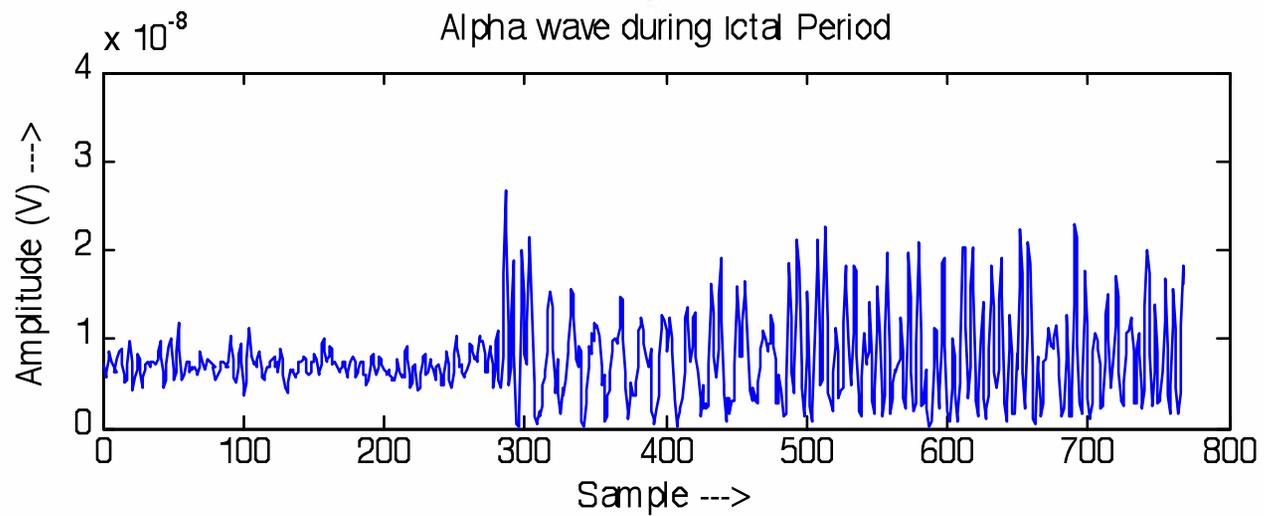
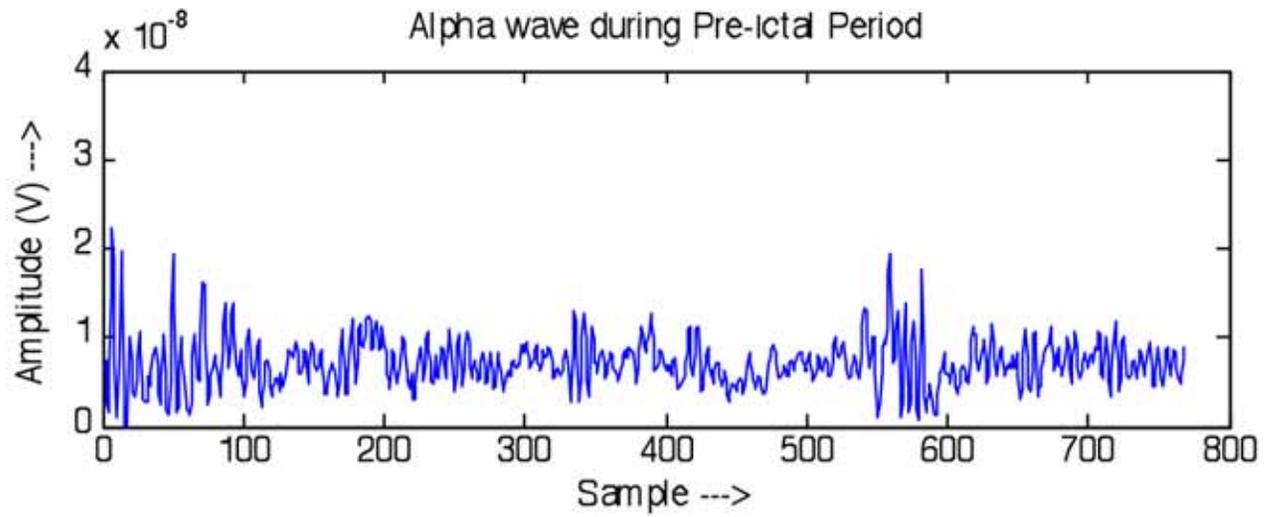
Prototype System Architecture



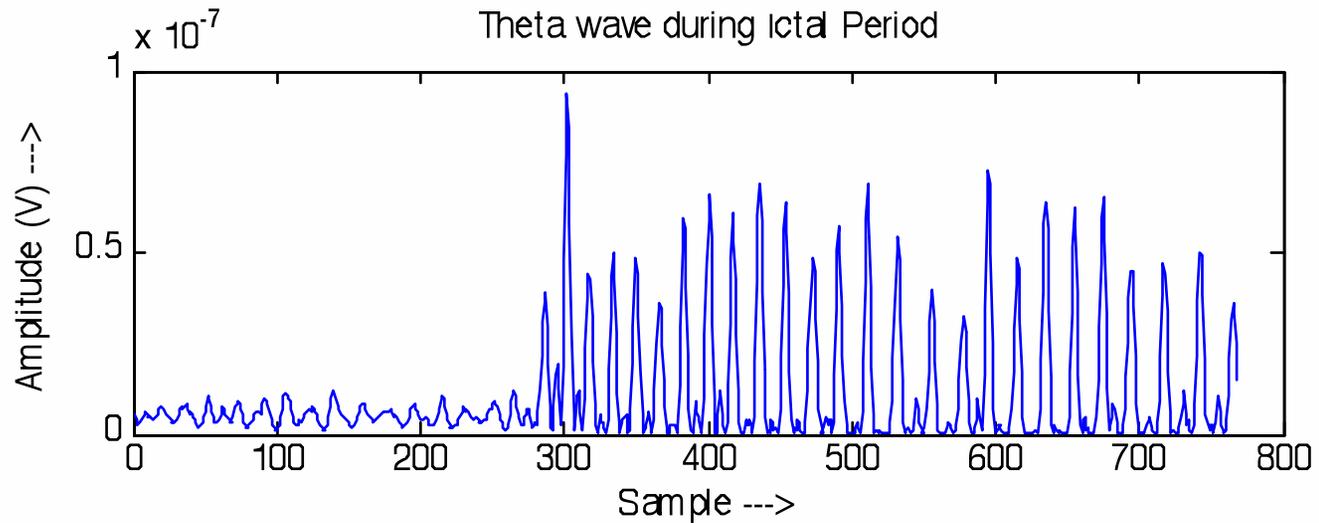
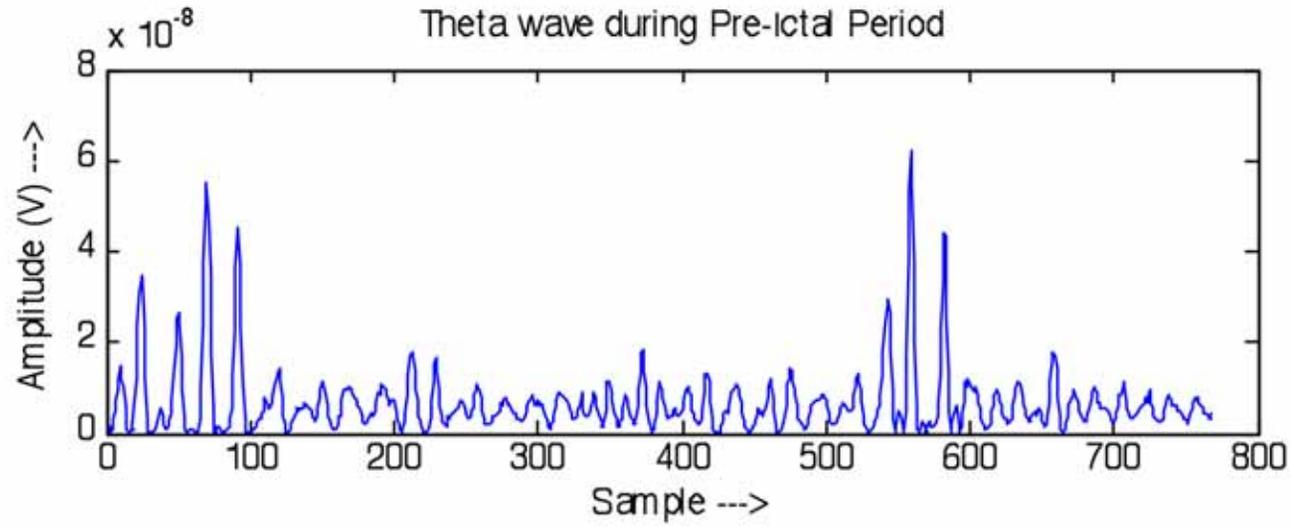
Data Gathering

- EEG signals are sampled at 64 Hz
- Two frequency bands are of primary interest
 - Alpha Band – 8 - 12 Hz
 - Alpha levels are noted to attenuate under mental exertion
 - Theta Band – 4 - 7 Hz
 - Theta levels typically indicate abnormalities, e.g., significantly increase for seizure
- Data measured over a time window of 12s is used to compute metrics, which enable diagnosis
 - Tradeoff between accuracy and the limited memory space provided by the system

Mε



Me.



Metrics

- EEG Signal
 - Primary indicator is the *alpha/theta* ratio (i.e., ratio of power contained in each frequency band as computed over the measurement window)
- Oxygen Saturation and Heart Rate
 - Absolute values for the two are used

Property Measured	Metric Name	Normal Value	Abnormal Value
EEG	Critical EEG	Above 50 %	Less than 50 %
Oxygen Saturation	Critical Oxygen	Above 70 %	Less than 70 %
Heart Rate	Critical Heart Rate	Above 75 %	Less than 75 %

Criticality Factor Value	Inference
0	Individual is healthy
1	Abnormality
2	Possible Injury / Seizure
3	Seek immediate medical care

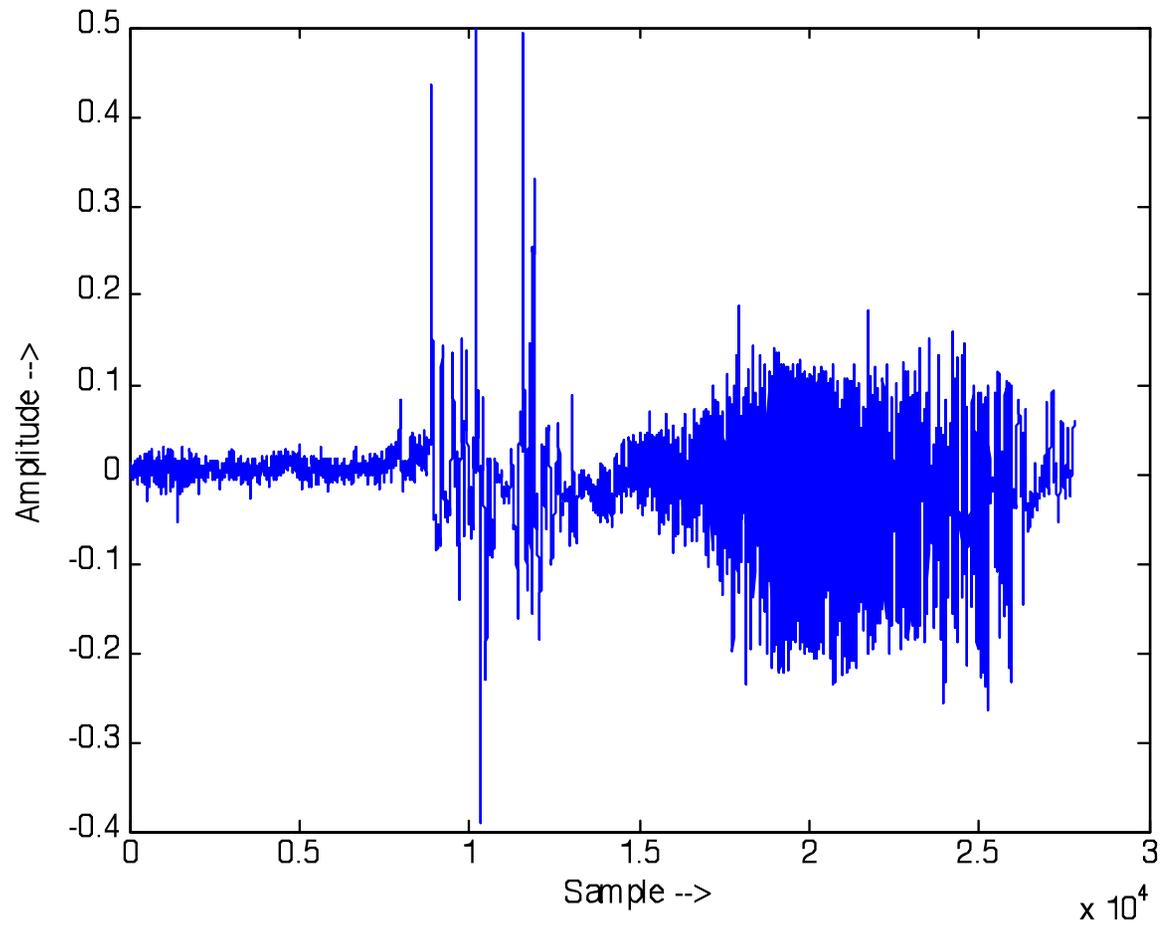
Validation of Metrics

- Need to characterize detection coverage of *alpha/theta ratio* metric
- Use larger EEG data sample to characterize
 - *alpha/theta ratio* metric
 - accuracy of the data processing algorithm
- Use EEG Database at Albert- Ludwigs University, Freiburg, Germany
 - Data recorded during an invasive pre-surgical epilepsy monitoring with 24 hours of EEG

Validation Results (sample)

Patient Information	Seizure Number	Baseline Alpha/Theta Ratio	Seizure Alpha/Theta Ratio
15 year old female	1	0.7804	0.4575
	2	0.7804	0.54
	3	0.7804	0.76
14 year old male	1	0.9296	0.2560
	2	0.9296	0.1828
32 year old female	1	1.3943	0.2786
	2	1.3943	1.0228
	3	1.3943	0.9208

Seiz

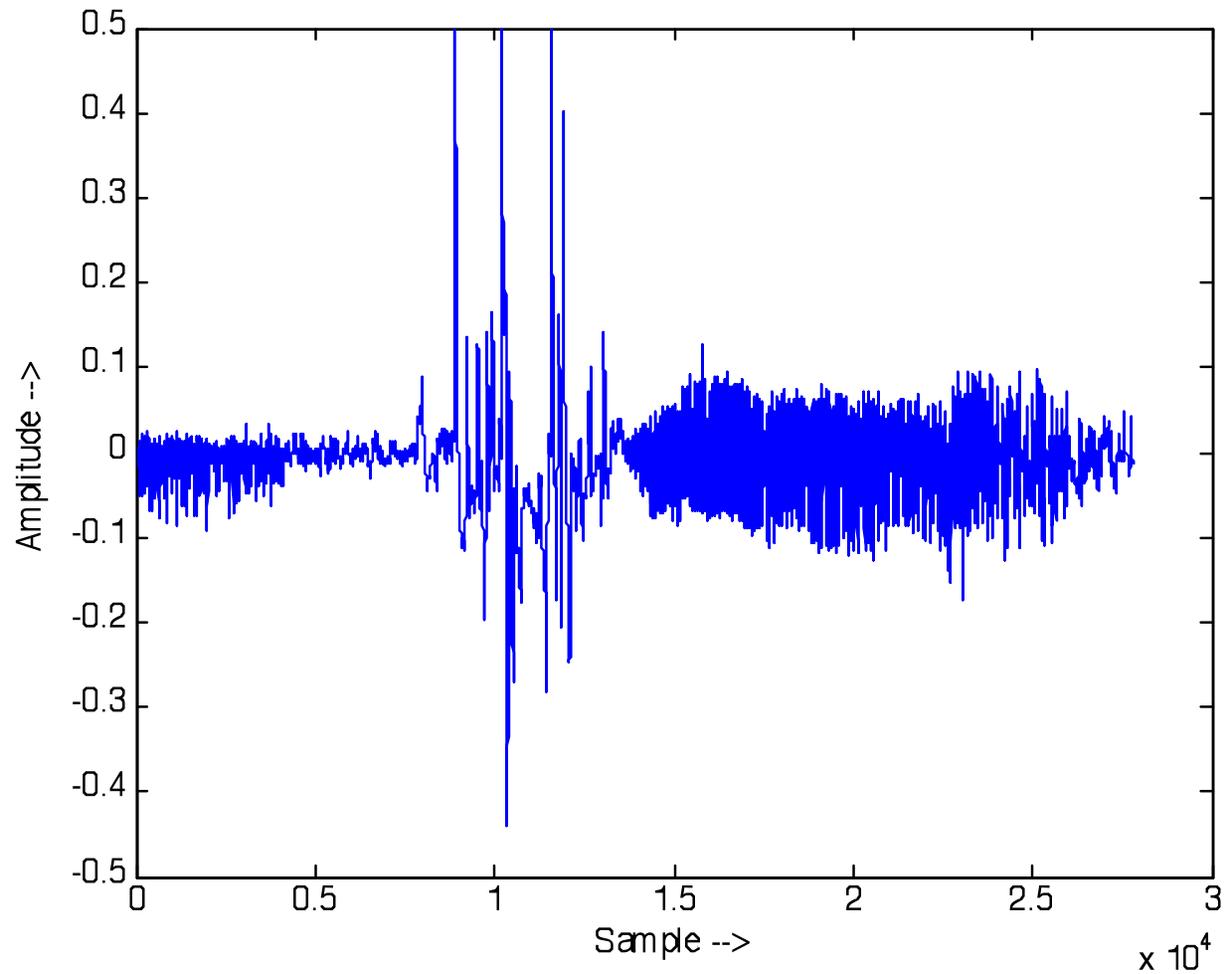


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Alpha/Theta Ratio = 0.2560

Seizure Pattern 2 - 15 yr old

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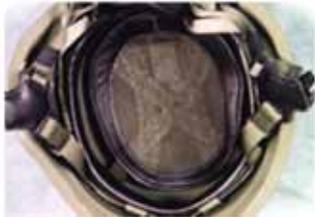


Alpha/Theta Ratio = 0.4575

Application: Monitoring Traumatic Brain Injuries (Blast Exposure to Battlefield Personnel)



Embedded within chin-neck pad



Embedded within headband



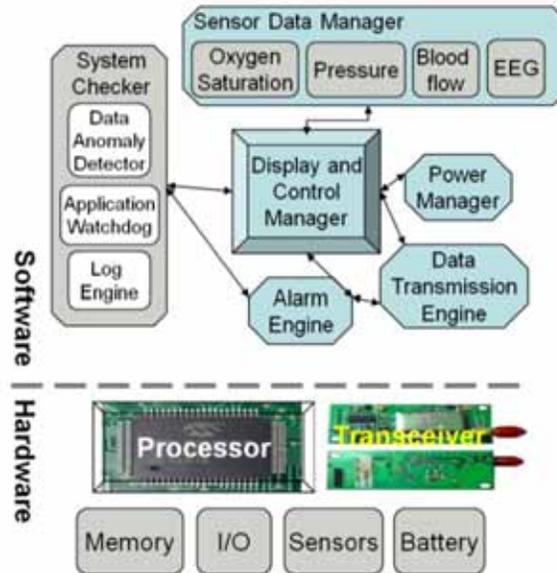
Embedded within neck pad

- Small footprint, light-weight, low power consumption, real time data monitoring and diagnostics
- Wireless or satellite data up-linking

- pressure
- acceleration
- blood flow

- oxygen saturation
- EEG, EKG
- heart rate

Sensing elements



Processing unit

Server
 - Data Collection
 - Multiple Sources
 - Multi-level and longitudinal analysis



Analysis Software
 - Local data processing
 - Real-time feedback
 - Data forwarding to the remote serve



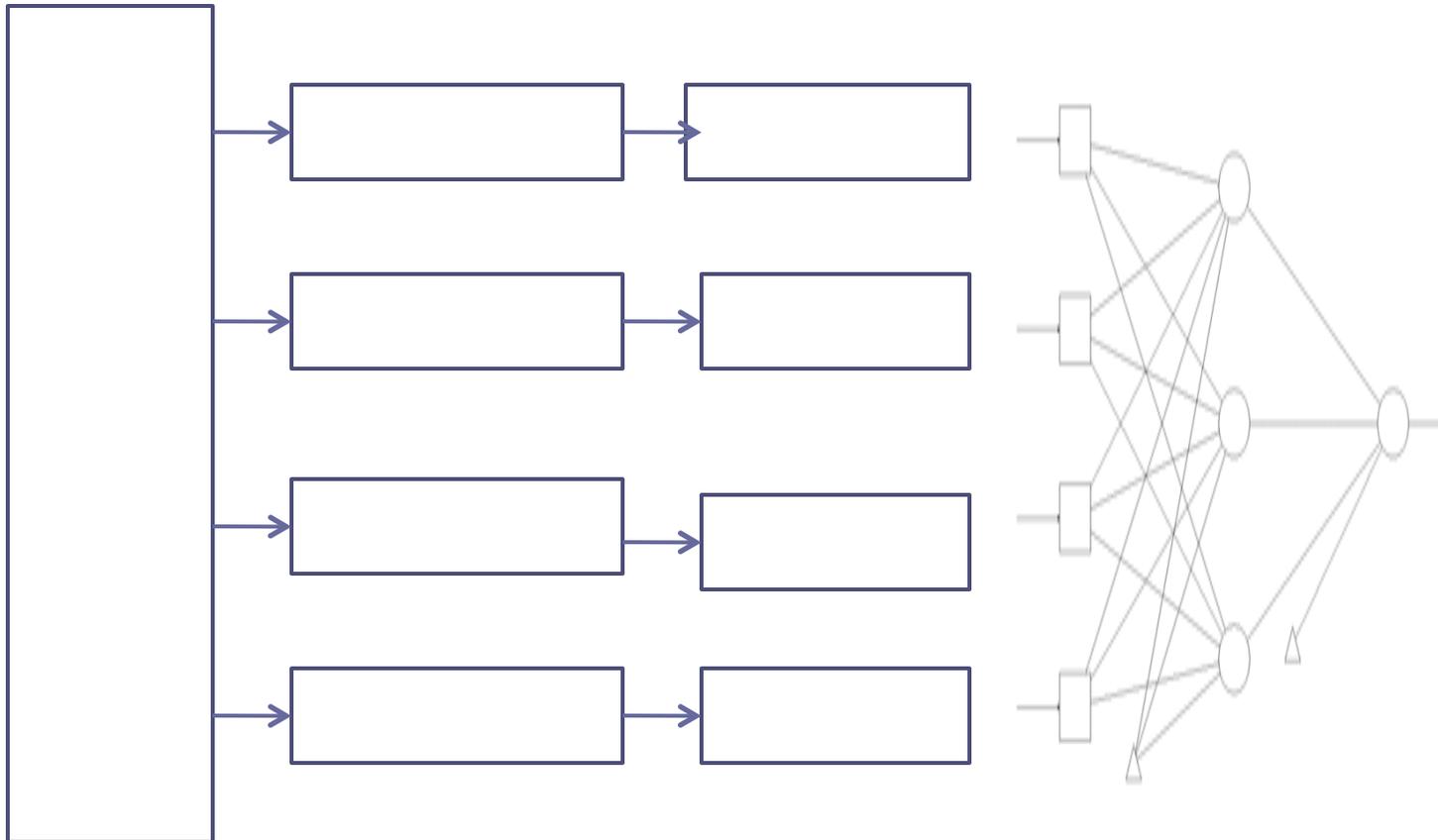
Pros and Cons of Proposed System

- Pros
 - COTS components used to design low-cost system capable of robust real-time data gathering, processing, and communication
 - Accurately detecting (certain) seizure patterns
 - Non-invasive sensors
- Cons
 - Cannot detect all seizure cases
 - good for detecting the most common epileptic seizures
 - Limited hardware capabilities limit the processing power
 - Need for more “precise” data analysis, sophisticated algorithms, and metrics more sensitive to anomalies in measured signals

Case for Reconfigurable Hardware Platform

- Rectify some of the disadvantages of the COTS implementation
- Fast and accurate detection using more sophisticated algorithms
 - Complex data processing algorithms can be directly embedded in hardware
- Enable/disable features at run-time
- Multi-feature detection
 - e.g., EEG detection , ECG arrhythmia , stroke detection

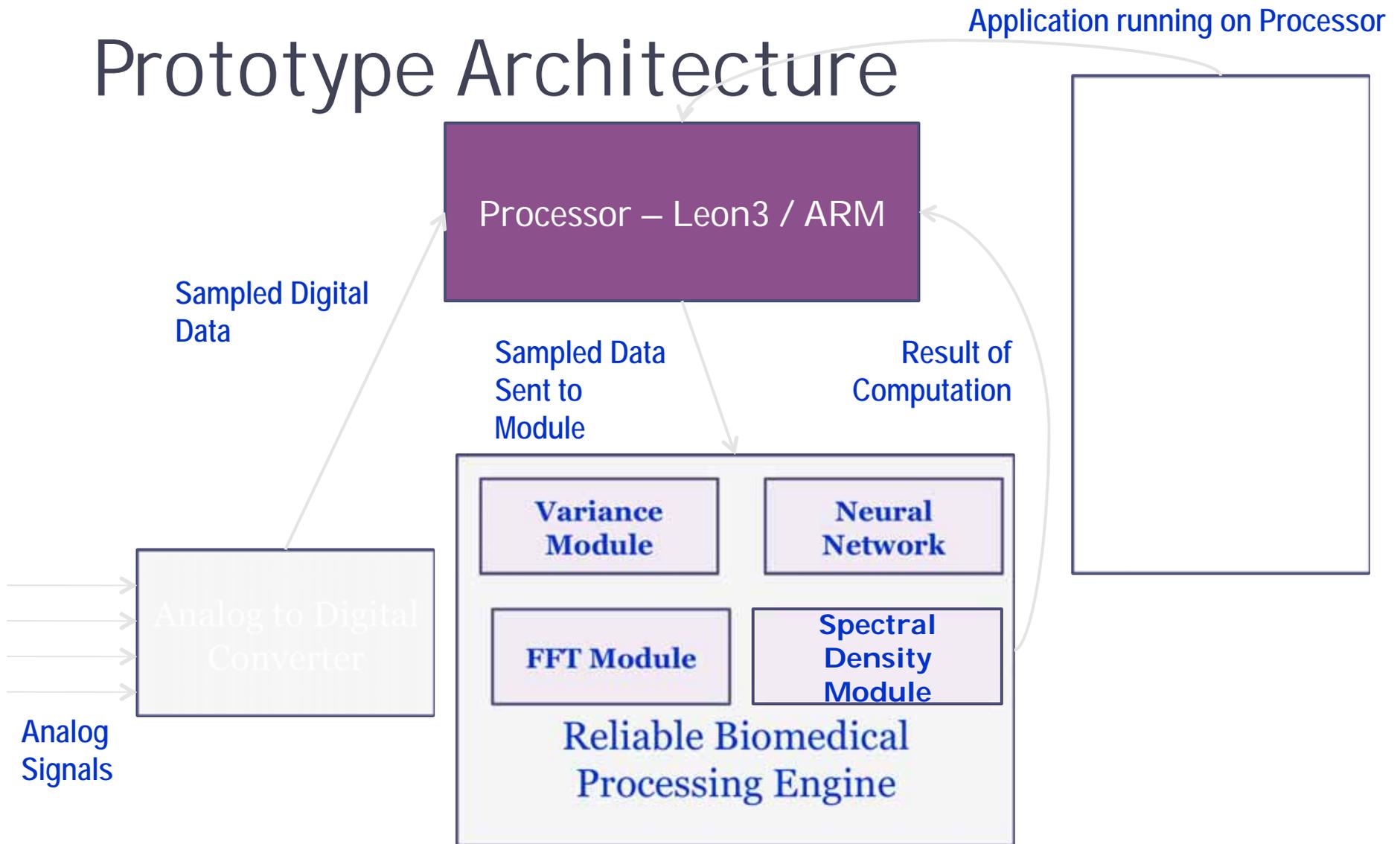
Prototype System: Principle of Operation



Data preprocessing by computing *Variance* in the sampled signal

Detection using a Neural Network which is trained to reduce the mean squared error

Prototype Architecture





Prototype FPGA Implementation

- Data sets from a study conducted at the University of Bonn used to train and test the implementation
 - 200 sets with 100 seizure sets, 100 normal sets
 - 60 sets of normal and seizure used to train the Neural Network
 - 40 sets used for the detection phase.
- 99.97 % detection accuracy
- Very low logic utilization on Altera Stratix II FPGA platform



Future Work

- Focus on detection algorithms for various abnormalities, e.g., seizures, arrhythmia, or stroke
- Explore other non-invasive sensors and measurements which can be used for multi-facet detection scheme
- Support for reliable and secure operation in presence of accidental failures and malicious tapping with the system
- Design Reliable Biomedical Engine on FPGA platforms and eventually SoC implementation



BACKUPS

System Components: Sensors

- Accelerometers
 - Detect motion of a person or an object
 - *Used: Biaxial Accelerometers from MEMSIC*
- EEG sensor
 - Detect the person's EEG
 - Trauma can be detected by monitoring the *delta* and *theta* frequencies in EEG signal
 - *Used: EEG Simulator : gives a 60s EEG sample of a seizure patient*
- Oxygen saturation and heart beat sensor
 - Detect the amount of oxygen in the person's blood
 - Measurement based on light absorption properties of hemoglobin
 - Use to compute person's heart beat
 - *Used: Sensor from NONIN*



System Components: Processing Elements

- Central processing element is Texas Instruments MSP430 microcontroller
 - Integrated ADC
 - Serial communication interface
- Wireless Communication
 - TI ChipCon CC 2500 transceivers