Algorithm Characterization and Implementation for Large Volume, High Resolution, Multichannel Electroencephalography Data in Seizure Detection

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Objectives

- Personalized health care depends crucially on continuous monitoring and processing of large volumes of data about individuals and populations.
- As the number of people and the amount of data being produced grows, the challenges become:
  - How to extract useful information for identifying health states
  - How to integrate complex large data processing algorithms into a low power wearable device.
- Embedded real-time processing is a must
  - Perform signal processing and classification right at the sensor instead of transmitting the raw data and therefore significantly saving communication power and storage requirement
- Increasing energy-efficiency (i.e. ↑GOPS/W, ↓pJ/op) , accuracy and reliability requires innovations in algorithms, programming models, processor architectures, and circuit design
  - Study methods to represent large volumes of medical time series so that the information they carry about health state is exposed
  - Study the algorithms are best to extract that information and can be implemented efficiently
  - Explore classification accuracy, computational complexity and memory requirements
  - Study the implementation of the algorithms on different hardware approaches e.g FPGAs GPUs, and ASIC.

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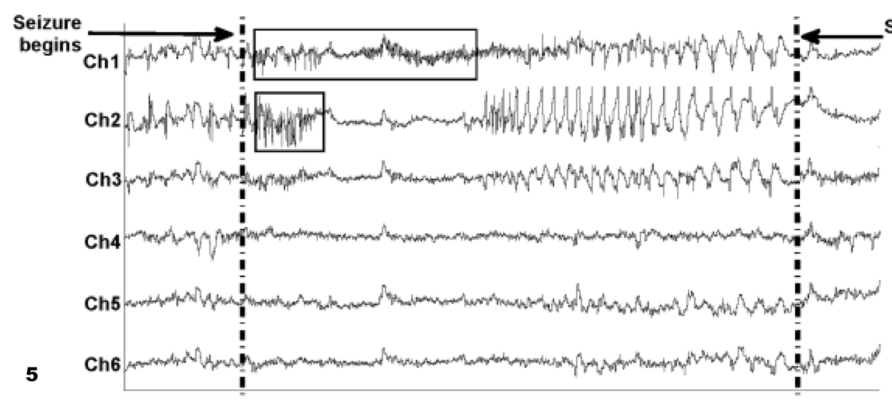
Wearable EEG Seizure Detection

- Electrical signals can be detected by EEG signals before or just at the start of clinical symptoms
  - The ability to detect can be used to warn the patient or caregiver
  - Implementation must be able to detect seizure and warn the patient or caregiver within one to two seconds after the electrical onset
- Each signal represents one channel from an electrode
  - Ch1 and Ch2 detect seizure
  - Complex algorithms and multichannel detection is necessary to remove false positives



Chandler et al BioCass 2011

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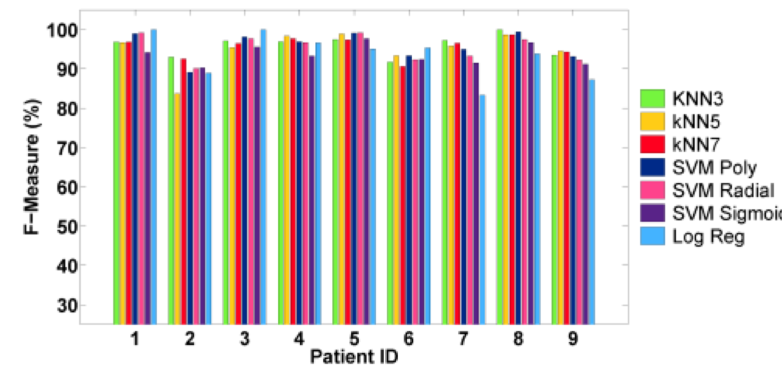
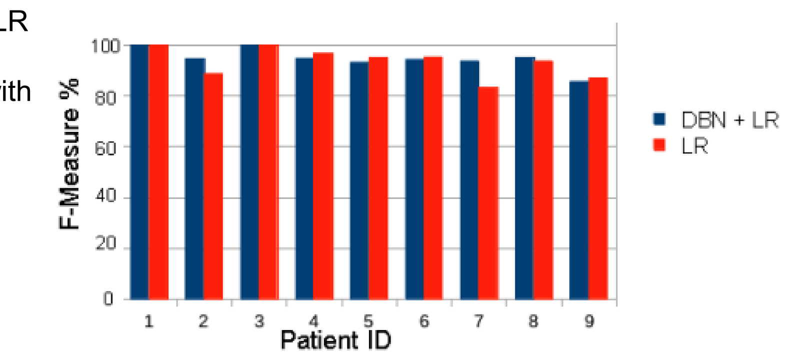
Detection accuracy comparison

- Comparison of different classifiers detection accuracy (F1 score) when single patient data is used for training and test



- Comparison of DBN+LR and LR detection accuracy (F1 score) with single Patient Testing.



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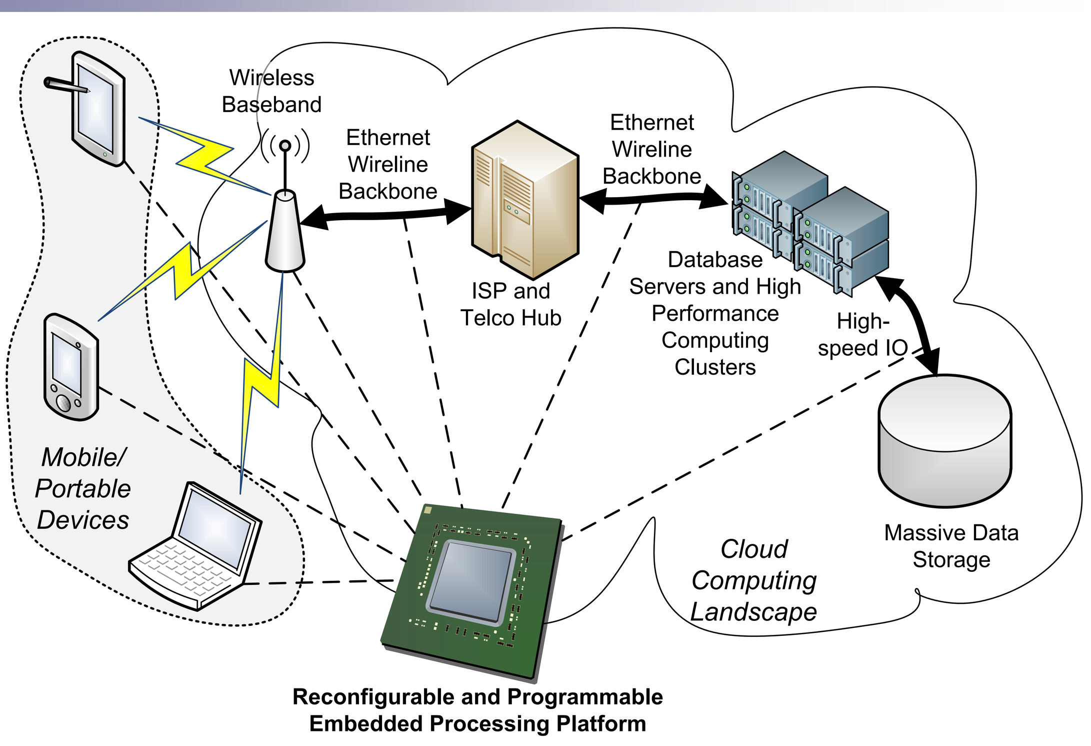
Embedded Processors in the Big Data Infrastructure



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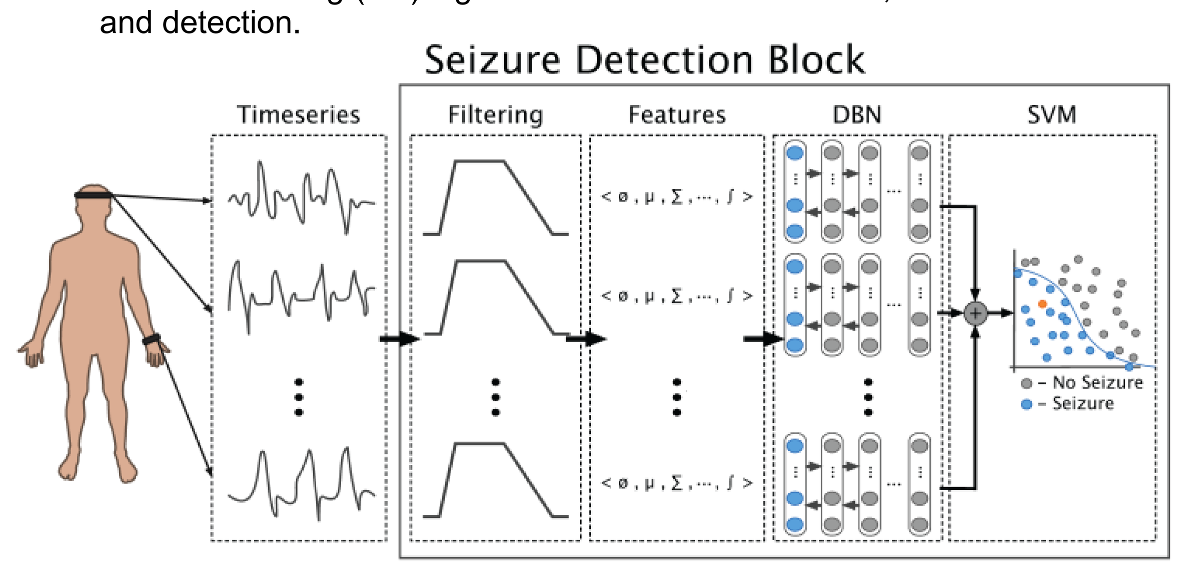
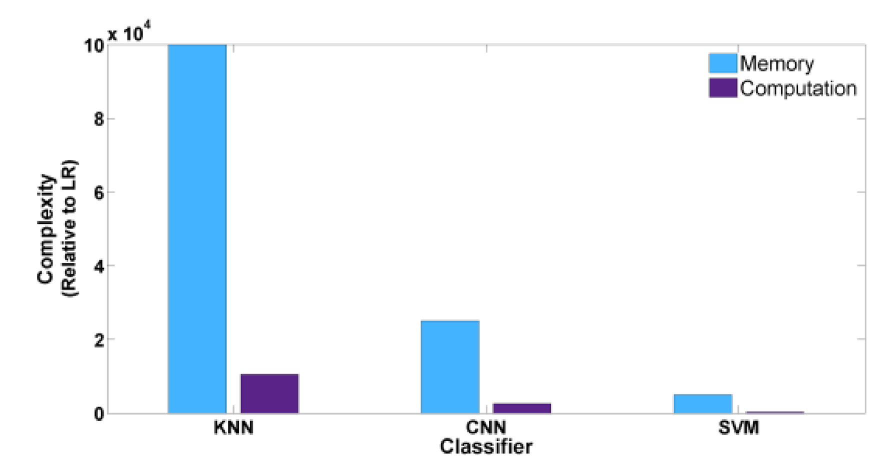
Layered Learning Approach for multi-physiological signal processing

- Use multi-physiological sensors such as EEG, EOG, 3-axis gyroscope, heart rate, accelerometer, blood flow, and blood oxygenation to compensate for ambulatory noise and loss of information.
- Combine a unique sequence of digital signal processing (DSP) and machine learning (ML) algorithms for feature extraction, noise reduction and detection.



Computation and Memory Complexity Comparison

- Complexity comparison between KNN, CNN, SVM, and LR relative to LR for Simple Features



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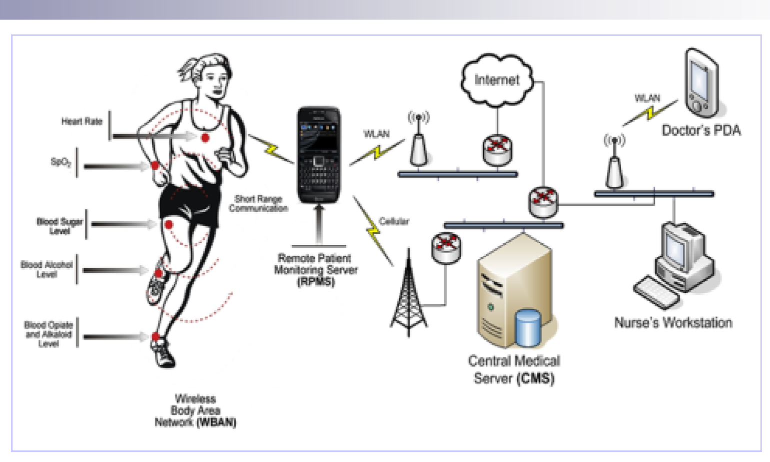
Smart Health Monitoring: Analysis & Delivery



- Wearable medical monitoring systems
  - Reliable and seamless multi-physiological signal processing and monitoring integrated into patients daily life routine
- Data analysis
  - Real-time data analysis and diagnosis for efficient healthcare delivery
- Data delivery
  - Real time data transmission to healthcare providers (e.g. nurses, primary care physicians, and first responders) through networks

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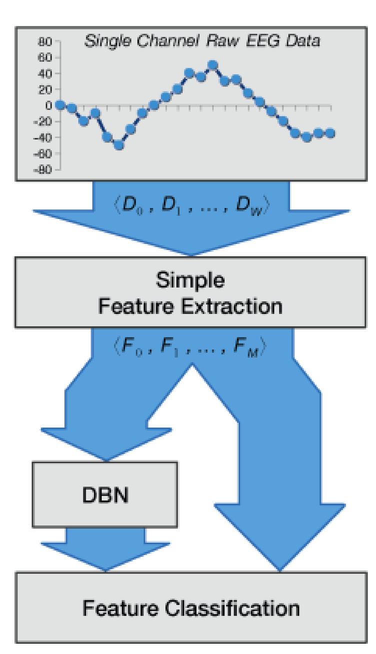
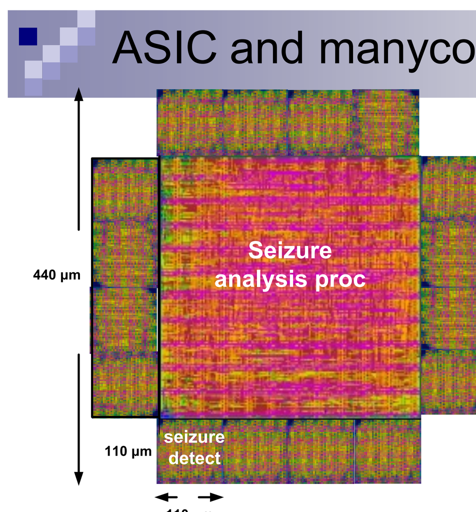
Feature Extraction and Classifiers Used

- Feature extraction
  - Total of 9 features of the dataset are derived from the raw time series signal
- Deep belief network (DBN)
  - Learn deep structures in the time-series data
- Classifiers
  - Classify the incoming DBN abstraction of the time-series with a certain class label.
  - Support vector machine (SVM)
  - K-nearest neighbor (KNN)
  - Logistic regression (LR)

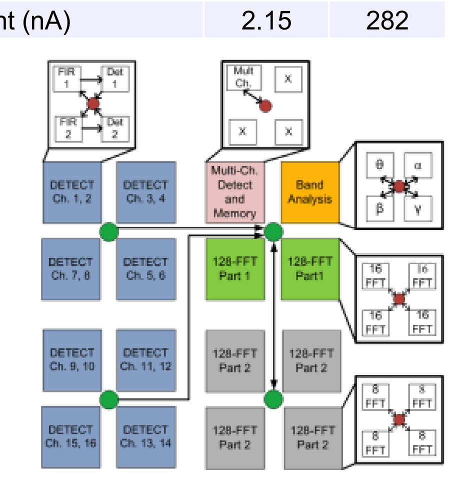


ASIC and manycore mapping of DSP algorithms



ASIC implementation		
	Detection	Analysis
Technology	65 nm, 1.3V	
Logic Utilization	96%	92%
Area per block (mm^2)	0.01	0.19
Total Area (mm^2)	0.43	
Performance (KHz)	0.256	1.85
Power (uW)	0.04	0.36
Current (nA)	2.15	282

- Blocks include 33 tap high pass FIR filter and 128 point FFT
- For customized manycore:
  - 60 processing cores utilized
  - All cores operate at nominal frequency and voltage
    - Detection latency: 900 ns
    - Energy: 240 nJ



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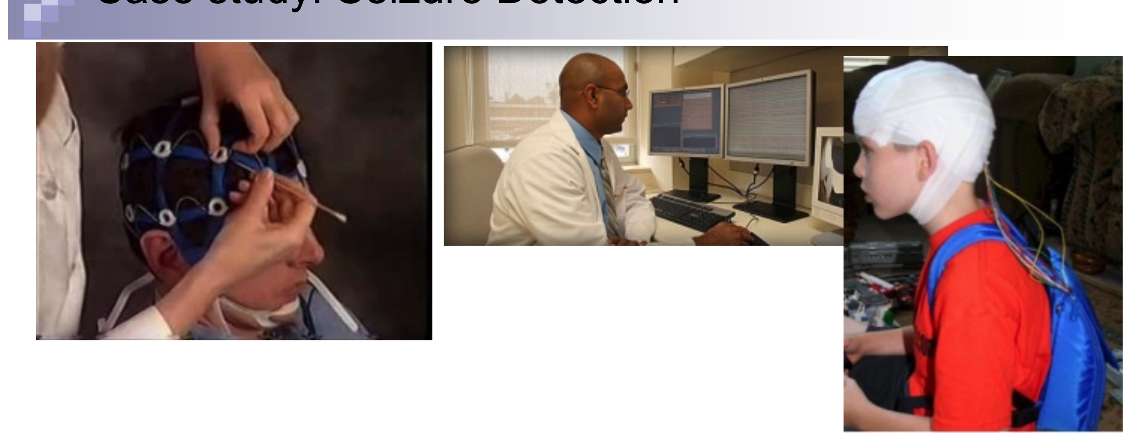
Case study: Seizure Detection



- Epilepsy is the 4th most common neurological disorder and affects about 2.2 million in the US, and 1 in 26 people may develop epilepsy in their lifetime.
- Current ambulatory seizure monitoring devices are infeasible for long-term, continuous use due to large false positive/negative signals, noise due to patient activity, bulky equipment, high power consumption, and the inability of patients to carry on with their daily lives.

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