Multichannel EEG Compressive Sampling, Feature Extraction and Classification for 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.
  - Using Compressive Sensing to reduce the data and consequently reduce computation expenses.

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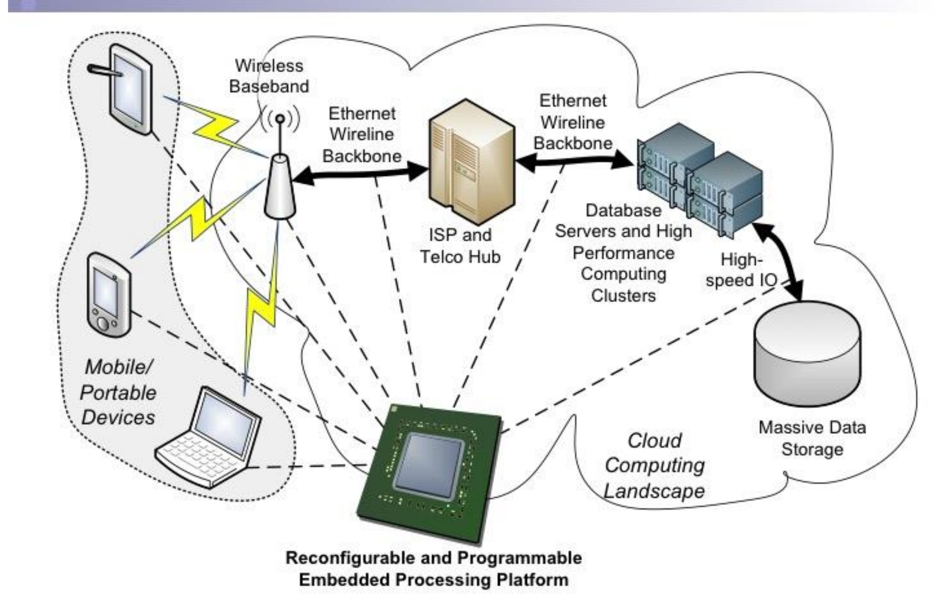
Embedded Processors in the Big Data Infrastructure



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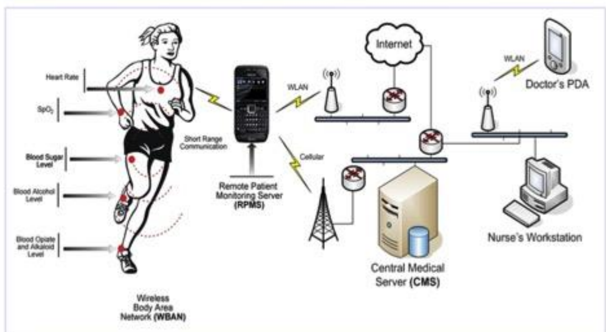
Smart Health Monitoring: Analysis & Delivery



- 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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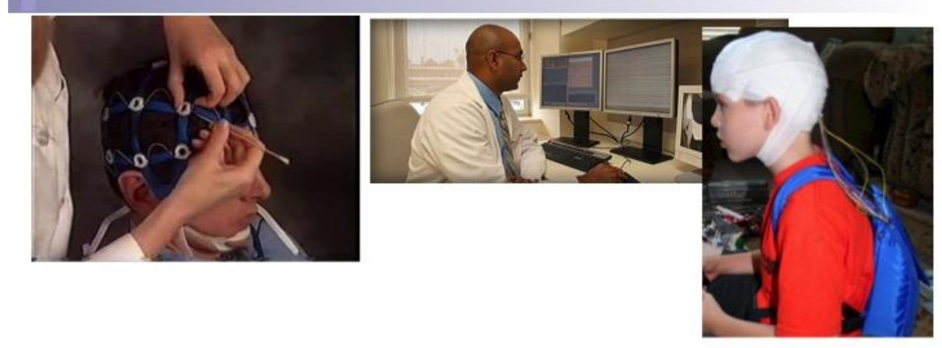
Case study: Seizure Detection



- 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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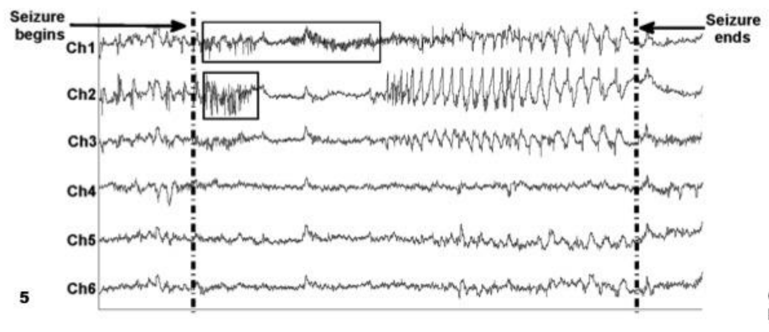
Wearable EEG Seizure Detection

- 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



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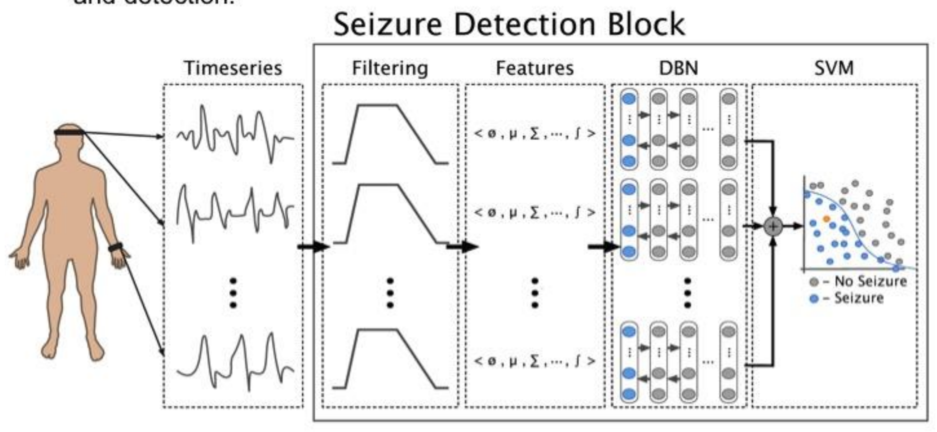
Chandler et al BioCass 2011

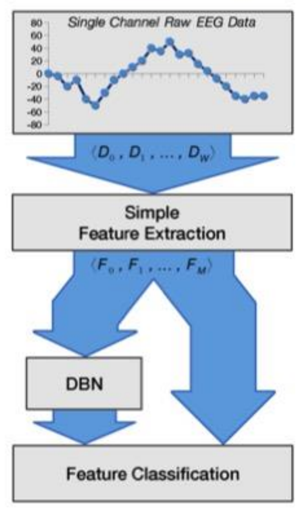
Layered Learning Approach for multi-physiological signal processing

- 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.



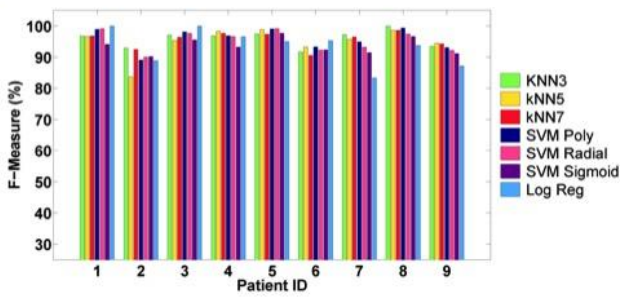
Feature Extraction and Classifiers Used

- 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)

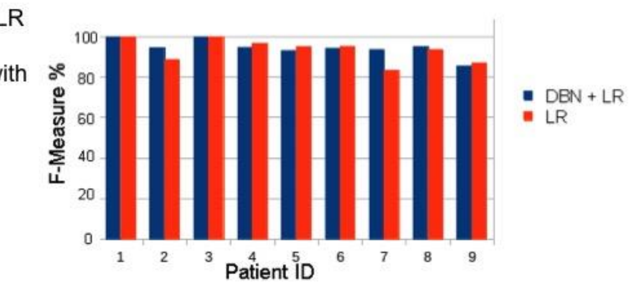


Detection accuracy comparison

- 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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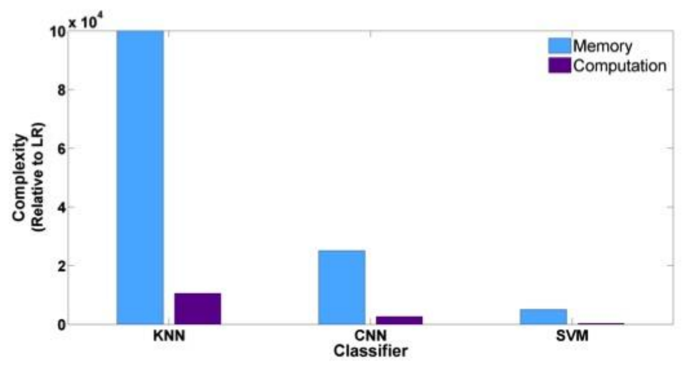
Computation and Memory Complexity Comparison

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



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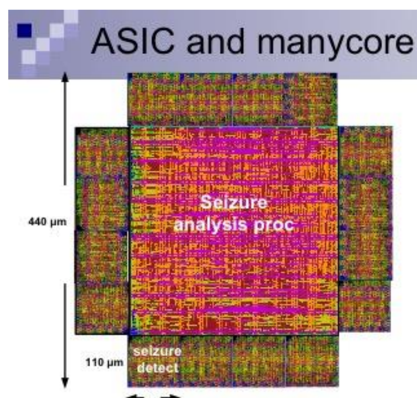
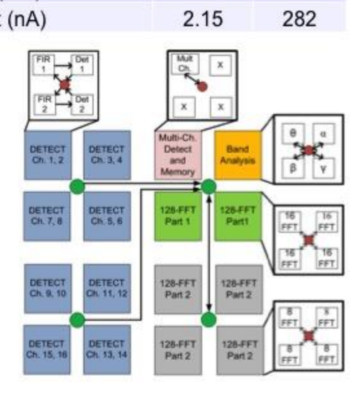
ASIC and manycore mapping of DSP algorithms



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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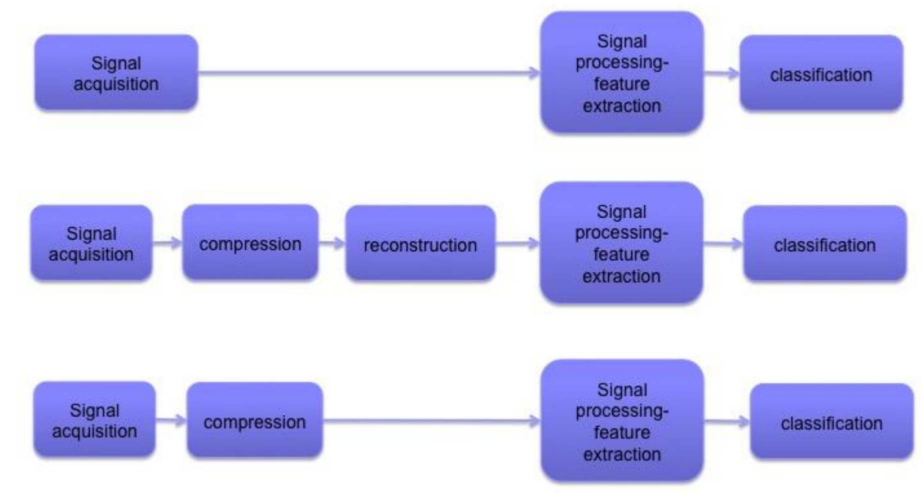
Three system models that can be used for comparisons



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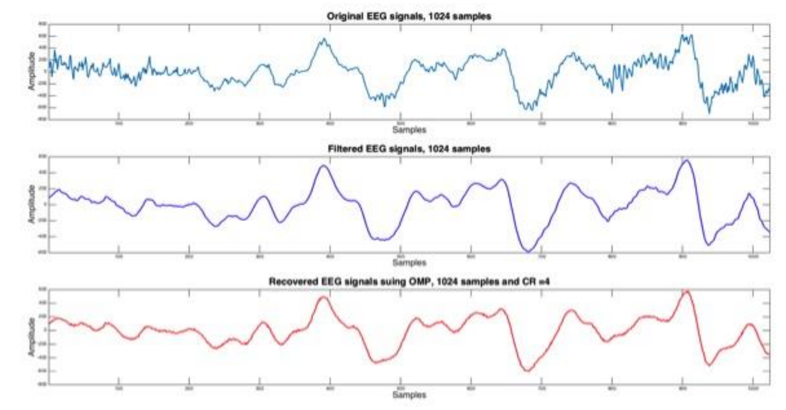
Original, filtered and OMP reconstructed EEG signal for seizure detection purpose, compression rate = 4

First figure shows the original EEG signal. After applying a filter to the signal, signal is smoother and it is shown in the second figure. The third figure shows the reconstructed EEG signal after EEG signal is sampled compressively. As it can be seen, the original and reconstructed signals is pretty similar.



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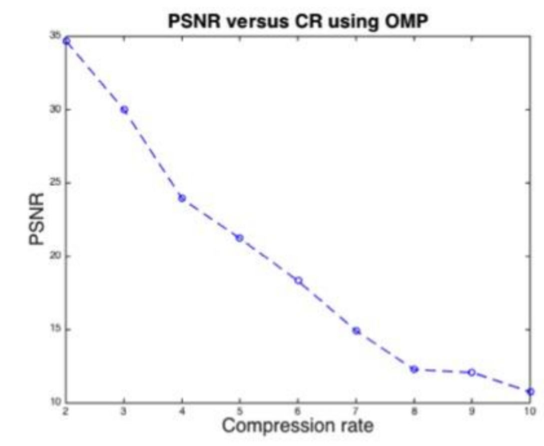
PSNR versus compression rate for signal reconstruction using OMP

The figure shows PSNR versus compression rate from 1 to 10, and reconstruction has been done using OMP algorithm. As it can be seen, as the compression rate is increased, PSNR decreases.



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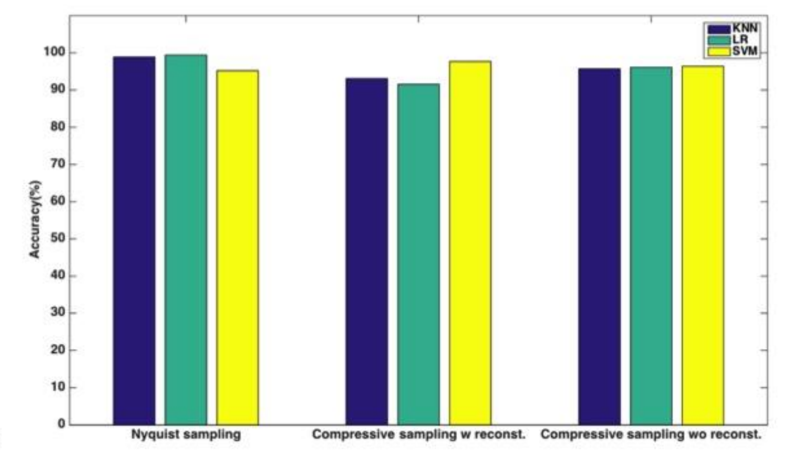
Accuracy of different seizure detection systems with same compression rate = 4

In this figure, the accuracy of different classifiers are provided for original signal, compressed sampled EEG data with reconstruction and compressed sampled data without reconstruction. As it can be seen from the figure, accuracy of classification algorithm is highest for original signal using KNN, and the accuracy of classifiers using compressed sampled data still are pretty close to the original data.



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Simulation using HPC facility

- Currently utilizing neural networks for learning using nearly raw data.
- Training these networks is extremely time intensive.
  - Network w/ 6 layers and 5,000 nodes trained for 3,000 epochs
    - CPU: 100 sec/epoch -> 3.5 days for training
    - GPU: 3.5 sec/epoch -> 2.9 hours
  - By utilizing the NVIDIA Tesla K20 GPUs, each experiment obtains 20-50x speedup. Further with 36 GPUs, 36 simultaneous experiments can be performed.
  - GPU utilization is accomplished using Theano that utilizes CUDA backend with cuBLAS and cuDNN frameworks.

- Acknowledgement
  - UMBC High Performance Computing Facility (HPCF)
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