Wearable-Sensor System for Monitoring Motor Function

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Goal: To develop a Personal Status Monitor (PSM) that automatically identifies and tracks motor disorders, medication states, and mobility in patients with Parkinson's disease

Project 1: Technical Infrastructure

Problem: Involuntary movement disorders are a major problem in long-term management of the majority of patients with Parkinson's disease (PD). Physicians must rely on patient motor diaries to monitor these complications. Diaries need to be recorded frequently, have poor temporal and spatial resolution, are prone to subjective bias, poor memory, and they are difficult for patients to manage.

Proposed Solution:
An intelligent wearable sensor system

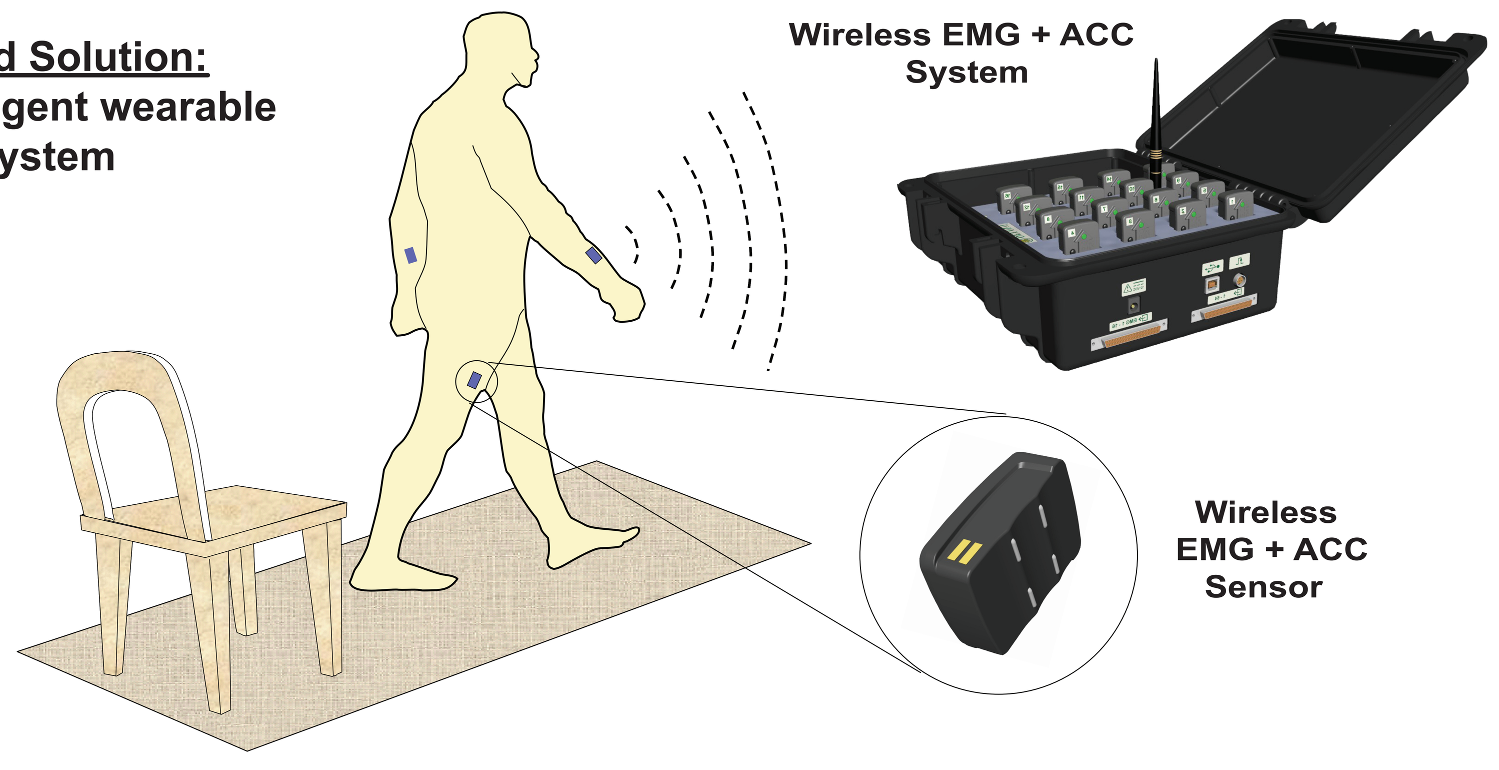


Diagram of the proposed Personal Status Monitor (PSM) for identifying movement disorders, medication states, and mobility in patients with Parkinson's disease (PD) by the automatic analysis and interpretation of electromyographic (EMG) and accelerometer (ACC) signals. In this example, the PSM device is monitoring the patient while detecting signals recorded from the surface of the body using wireless sensors. The proposed system will provide a continuous history and statistical summarization that can be made available to the clinician to help manage drug and surgical interventions, or develop new ones.

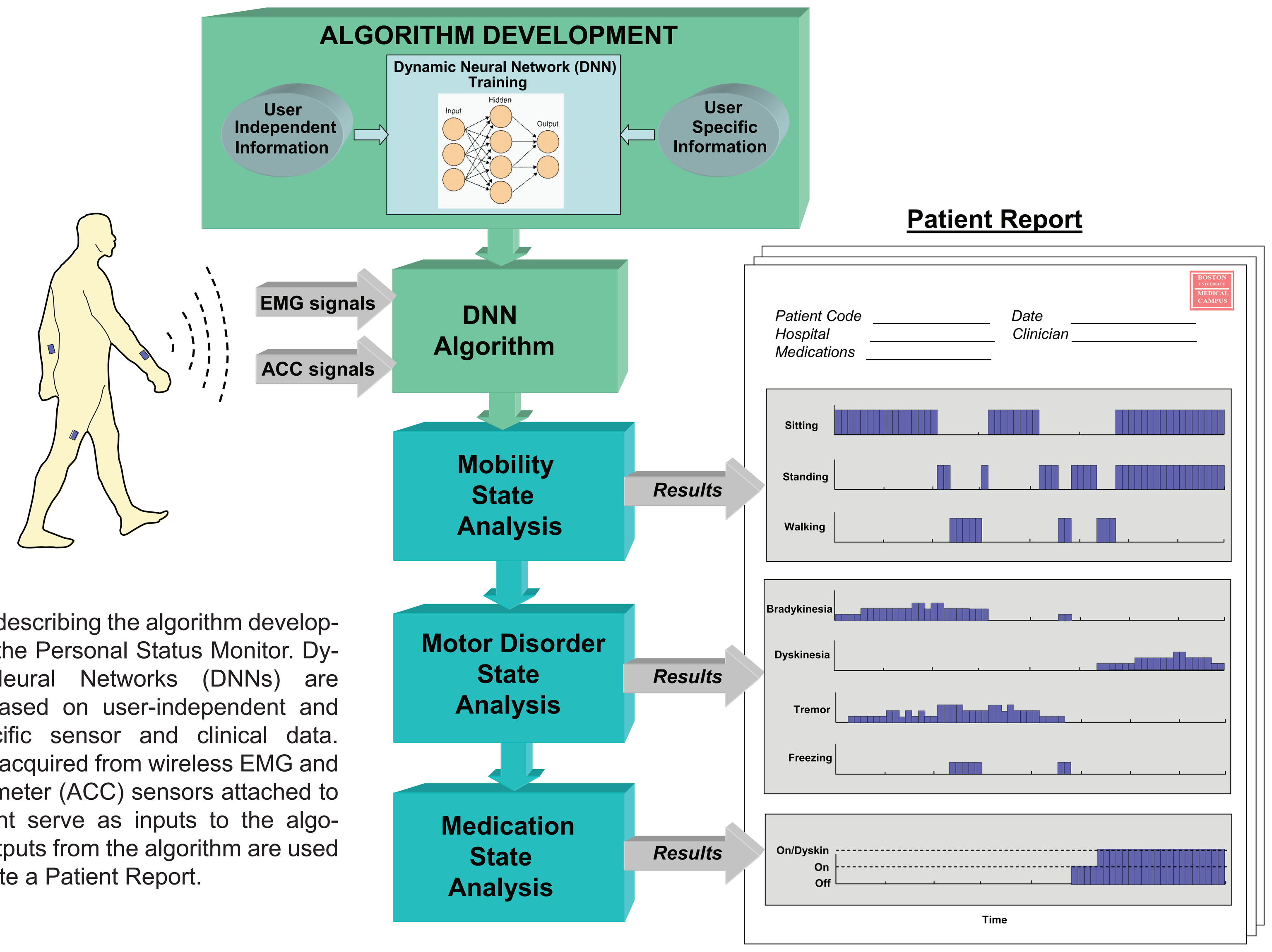


Diagram describing the algorithm development for the Personal Status Monitor. Dynamic Neural Networks (DNNs) are trained based on user-independent and user-specific sensor and clinical data. Features acquired from wireless EMG and Accelerometer (ACC) sensors attached to the patient serve as inputs to the algorithm. Outputs from the algorithm are used to generate a Patient Report.

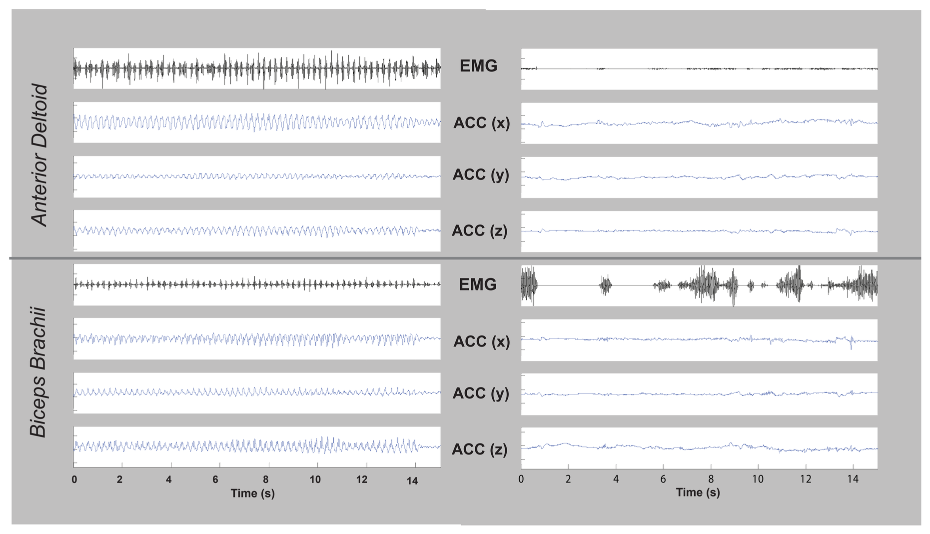
Project 2: Clinical Application to PD

Data Collection Protocol: Patients were monitored using the Personal Status Monitor (PSM) and were videotaped during an approximately 4-hour period that was timed to coincide with a complete medication cycle ("On", "On w/Dyskinesia", and "wearing Off"). Activities were conducted in a laboratory configured as a studio apartment. The activities included standardized motor tests used for clinical assessment (e.g. motor scales from UPDRS), scripted functional tasks (e.g. "sit-stand-and-walk"), and free-roaming unconstrained activity.

Annotation: The patient's videotaped data were annotated by movement disorder specialists to grade the different movement disorders, medication states, and mobility states to create a "gold-standard" for comparison with the PSM.

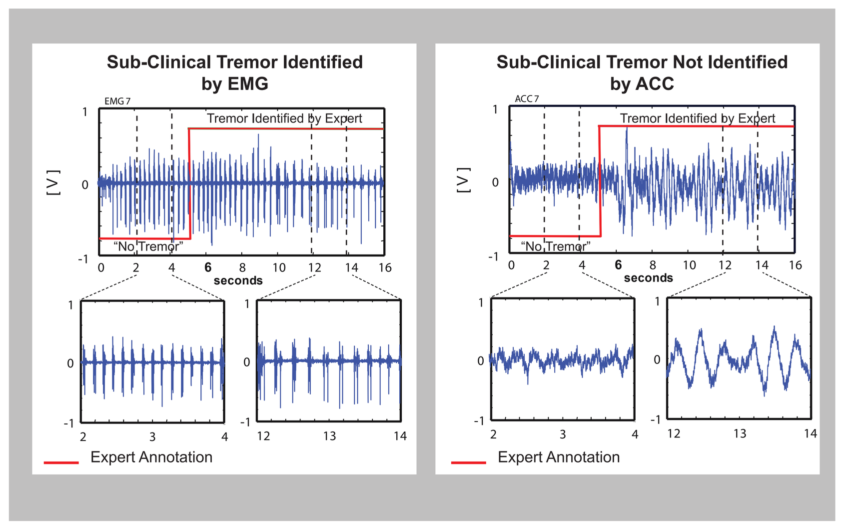
Sensor Data from PD Patient

Tremor While Sitting **Dyskinesia While Sitting**



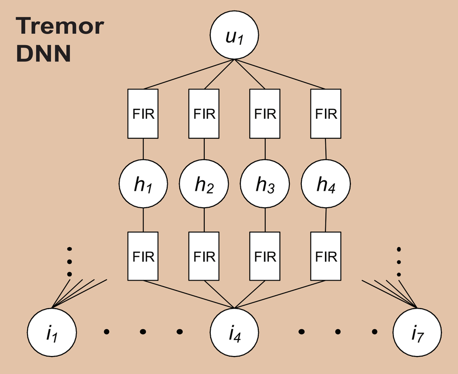
Sample data from a patient asked to sit quietly. The left figure indicates the "Off" period when the patient experienced Tremor, and the right figure indicates the "On w/ Dyskinesia" period. Data were recorded from the Anterior Deltoid and Biceps brachii muscles. EMG signals are in black; ACC signals are in blue.

EMG Data Identifies "sub-clinical" Motor Signs



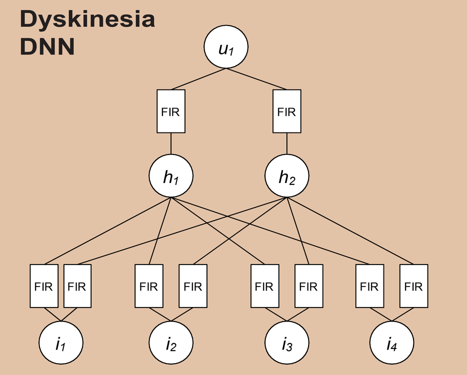
Sample EMG (left) and ACC (right) data from the same sensor on the TA muscle in a patient with resting Tremor. The figures demonstrate that sub-clinical signs of tremor (at 0-5 s) are identifiable by the EMG data patterns (left) but not by the ACC patterns (right), or the expert annotator (red line).

Analysis - Dynamic Neural Network Solutions



DNN used for detecting Tremor. There are 7 input nodes (*i1-i7*), 4 hidden nodes (*h1-h4*), and one output node (*u1*). Each FIR filter has 5 weights.

Dynamic (as opposed to static) neural networks (DNNs) were used to design machine-learning algorithms for detecting time-varying tremor (left) and dyskinesia (right). For inputs, both DNNs used four ACC features derived from the RMS amplitude and from the autocorrelation function. In addition, the Tremor DNN used three features from the EMG signal based on the RMS and autocorrelation envelope. The networks were trained on datasets selected from a pool of 8PD and 4 Control subjects, and then tested on: i) a second dataset from the same pool, and ii) another dataset from a separate pool of 2 PD subjects that were not part of the training set.



DNN used for detecting Dyskinesia. There are 4 input nodes (*i1-i4*), 2 hidden nodes (*h1-h2*), and one output node (*u1*). Each FIR filter has 5 weights.

Group Results - Unconstrained Activity

Training and Test Data
Non-Exclusive (Overlap Present)

Network	Test Data	Sensitivity	Specificity
Tr-DNN-A	B	92.4%	96.7%
Tr-DNN-B	A	92.9%	93.7%
Dy-DNN-A	B	93.5%	91.2%
Dy-DNN-B	A	90.3%	95.1%

Tr-DNN-A and Tr-DNN-B refer to the tremor DNNs that were respectively trained on dataset A and B. Dy-DNN-A and Dy-DNN-B refer to the dyskinesia DNNs that were respectively trained on dataset A and B. Each dataset contained 10 mins tremor, 10 mins dyskinesia, 10 mins normal data; selected from a pool of 8 PD patients and 4 Controls.

Training and Test Data
Exclusive (No Overlap)

Network	Sensitivity	Specificity
Tr-DNN-A	87.2%	92.0%
Tr-DNN-B	91.7%	93.0%
Dy-DNN-A	93.4%	94.9%
Dy-DNN-B	95.7%	93.6%

The tremor and dyskinesia DNNs were trained as described in the table to the left; however, each DNN was tested on a similarly sampled dataset derived from a completely separate population of 2 PD patients. The sensitivity and specificity results are comparable to the table at the left.

Summary

- ► Sensitivity and specificity for tremor and dyskinesia in the upper limb were consistently greater than 90% at 1 s resolution, based on data from a single hybrid (ACC and EMG) sensor placed on the forearm.
- ► Similar sensitivity and specificity results were obtained when the DNNs were tested using data from the training set or a seperate population.
- ► sEMG data may be helpful in identifying pre-clinical motor signs of tremor.
- ► In our ongoing research we are developing and evaluating DNN solutions for detecting PD motor signs from a single sensor on the lower limb, as well as other motor signs (e.g., bradykinesia and freezing).

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