

# Chapter 41

## Electromyogram and Inertial Sensor Signal Processing in Locomotion and Transition Classification

**Deepak Joshi**

*Indian Institute of Technology (IIT) Delhi, India*

**Michael E. Hahn**

*University of Oregon, USA*

### ABSTRACT

*Signal processing in biomedical engineering is essentially required for classification while serving mainly two aims. The first is noise removal and the second is signal representation. Signal representation deals with transforming the signal in such a way that the signal is most informative in that particular domain for the application at hand. This chapter will describe signal processing methods like spectrogram with specific applications to locomotion and transition classification using Electromyography (EMG) data. A wavelet analysis application on foot acceleration signals for automatic identification of toe off in locomotion and the ramp transition is also shown. Finally, the performance of EMG and accelerometer performance across different time windows of a gait cycle in locomotion and transition classification is presented with an emphasis on fusing the data from both sensors for better classification.*

### INTRODUCTION

A signal is a single-valued representation, real or complex, of information as a function of an independent variable recorded from some sensing device. Physically, it is a form of energy being produced by a process. Various types of signals exist and the method of signal processing needed to process a signal heavily depends on the type of the signal. Broadly, there are four types of signals:

DOI: 10.4018/978-1-7998-1204-3.ch041

1. Deterministic,
2. Stochastic,
3. Chaotic, and
4. Fractal.

Deterministic signals can be represented mathematically using certain parameters and hence prediction of deterministic signal in future, based on past values, is possible. Stochastic signals are random in nature with no closed loop mathematical expression and hence are not predictable in future. Fractal signals have interesting property of scale-invariance i.e. at any level of magnification the signal looks similar in structure. Chaotic signals lie somewhere between deterministic and stochastic signals. They are deemed to be deterministic in a very sensitive sense and hence are not predictable in future with reasonable accuracy. Biomedical signals are generally stochastic in nature and need signal processing methods for various applications. Biomedical signal processing in various applications serves mainly two aims. The first is noise removal and the second is signal representation. The main source of noise in biomedical signals is noise in electronic instrumentation. Other sources consist of electromagnetic interference and skin motion or physiological artifacts. For example, while recording electromyogram (EMG) nearby the chest one can observe the artifacts of electrocardiogram (ECG) in the EMG profile. There have been many provisions in hardware and experimental protocols to remove such noise and artifacts, however complete removal is not possible without using signal processing tools. Signal representation deals with transforming the signal in such a way that the signal is most informative in that particular domain for the application at hand. One such application is classification of locomotion and transitions in assistive devices where noise removal and signal representation are critical for successful, rapid and safe classification.

Locomotion classification is crucial in lower limb prosthesis control. Powered lower limb prosthesis provides sufficient torque and stability to the amputee so that they can negotiate in different terrains with reduced energy consumption. The key component for powered prosthesis to be facilitated with such features is accurate locomotion classification. Based on the classified locomotion, the artificial limb changes the damping profile to provide with net required torque output. For seamless transition in a powered prosthesis it is critical to classify the upcoming locomotion ahead of time (ideally before toe off of the transitional gait cycle) to ensure safe transition. Hence the selection of required data is critical and depends on the application at hand. For example, if someone is interested in analyzing the offline data of a cerebral palsy patient then the full gait cycle (heel strike to heel strike) may be available. However, for the application of real time actuation in prosthesis and orthosis control, the data available is limited. Hence, within this framework of classification the selection of sensors is critical. EMG represents the muscular activity and has been used widely for various applications like prosthetic control, gait analysis, disease diagnosis, and neuro-muscular coordination (Gea Drost et.al. 2006; Anjana Goen and D. C. Tiwari 2013). With the advancement in technology, miniaturized inertial sensors like accelerometers have shown promise in locomotion classification and other clinical gait analysis applications. Ambulatory monitoring of daily activities is the other area where accelerometer is of great importance as a sensing device.

EMG is the summation of electrical activity, action potential, of all the motor units recorded by the electrode. EMG signals are recorded by placing electrodes in, on, or near a muscle and amplifying the electric potential between two electrodes, that results from the generation and propagation of action potentials along muscle fibers. These muscle fibers are innervated by motor neurons from the spinal cord. The electrodes used are generally made of silver/silver chloride (Ag/AgCl) with some application of conductive gel at the skin-electrode interface. The electrodes serve as a transducer which converts

15 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage:

[www.igi-global.com/chapter/electromyogram-and-inertial-sensor-signal-processing-in-locomotion-and-transition-classification/243143](http://www.igi-global.com/chapter/electromyogram-and-inertial-sensor-signal-processing-in-locomotion-and-transition-classification/243143)

## Related Content

---

### Parametric Optimization of Electrochemical Discharge Machining Using Particle Swarm Optimization Algorithm

Arindam Debroy (2021). *Data-Driven Optimization of Manufacturing Processes* (pp. 179-193).

[www.irma-international.org/chapter/parametric-optimization-of-electrochemical-discharge-machining-using-particle-swarm-optimization-algorithm/269313](http://www.irma-international.org/chapter/parametric-optimization-of-electrochemical-discharge-machining-using-particle-swarm-optimization-algorithm/269313)

### An Article on Big Data Analytics in Healthcare Applications and Challenges

Jaimin Navinchandra Undaviaand Atul Manubhai Patel (2020). *International Journal of Big Data and Analytics in Healthcare* (pp. 58-64).

[www.irma-international.org/article/an-article-on-big-data-analytics-in-healthcare-applications-and-challenges/259988](http://www.irma-international.org/article/an-article-on-big-data-analytics-in-healthcare-applications-and-challenges/259988)

### Overview of IoT and Machine Learning for E-Healthcare in Pandemics and Health Crises

Mohsin Raza, Muhammad Awais, Imran Haider, Muhammad Usman Hadiand Ehtasham Javed (2021). *Data Science Advancements in Pandemic and Outbreak Management* (pp. 16-43).

[www.irma-international.org/chapter/overview-of-iot-and-machine-learning-for-e-healthcare-in-pandemics-and-health-crises/275088](http://www.irma-international.org/chapter/overview-of-iot-and-machine-learning-for-e-healthcare-in-pandemics-and-health-crises/275088)

### Point Analysis

(2018). *Spatial Analysis Techniques Using MyGeoffice®* (pp. 44-67).

[www.irma-international.org/chapter/point-analysis/189716](http://www.irma-international.org/chapter/point-analysis/189716)

### A Machine Learning-Based Exploration of Relationship Between Security Vulnerabilities of IoT Devices and Manufacturers

Ritu Chauhanand Gatha Varma (2020). *International Journal of Data Analytics* (pp. 1-12).

[www.irma-international.org/article/a-machine-learning-based-exploration-of-relationship-between-security-vulnerabilities-of-iot-devices-and-manufacturers/258917](http://www.irma-international.org/article/a-machine-learning-based-exploration-of-relationship-between-security-vulnerabilities-of-iot-devices-and-manufacturers/258917)