Signal Processing Techniques for Human Activity Recognition Using an Inertial Measurement Unit

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Introduction

The ability for a machine to determine a human's activity has significant applications in multiple domains including healthcare monitoring, assisted living systems for smart homes, and sports performance analysis. The premise of Human Activity Recognition (HAR) is to determine the physical activities of a human through both sensor data and prior knowledge about the context of the activities taking place. A common sensor used to accomplish this is the Inertial Measurement Unit (IMU), which typically consists of an accelerometer that measures acceleration in three axes (x, y, and z) and a gyroscope that measures angular velocity about three axes (pitch, roll, and yaw). In recent years, machine learning (ML) has revolutionized the processing of this data through the use of algorithms capable of universal approximation, reducing the need for complex domain-specific feature engineering. However, signal processing techniques still offer the generation of expressive features that capture important context about an activity from raw sensor data, often improving the performance of these ML classifiers [1, 5]. This paper reviews signal processing techniques for state-of-the-art human activity recognition using IMU data with a focus on the sports performance analysis market.

Underlying Algorithms for IMU-Enabled Human Activity Recognition

IMU activity data inherently contains both temporal and frequency characteristics. Direct processing of continuous, raw IMU data typically does not result in optimal performance due to arbitrary length and lack of expressive features about frequency content [2]. The first stage of processing typically involves the segmentation of accelerometer data into smaller segments called windows prior to feature extraction. The sliding window approach, in which data is segmented by a fixed or variable length window at incrementing starting times, is still considered the state-of-the-art approach. Because the determination of window size is difficult and often impacts performance, Alhammad et al. developed a dynamic segmentation algorithm that identifies optimal window boundaries [3].

Feature extraction is then performed on each window using a variety of operators including mean, standard deviation, Fast Fourier Transform (FFT), spectral energy, jerk, discrete wavelet transform, and frequency domain entropy [2, 4]. These metrics effectively summarize the defining temporal and frequency characteristics of the signal, often allowing increased performance of ML classifiers over the use of only temporal features [2]. However, further increased performance can be attained by using more advanced processing techniques such as the Dual-Tree Complex Wavelet Transform, a computationally-efficient approach to the Discrete Wavelet Transform that overcomes the lack of shift invariance that limits activity recognition performance [5]. Following feature extraction, the collected information of each window can be passed into numerous machine learning classifiers to determine the human's activity at a rate equivalent to the window size.

Market Overview of Sports Performance Commercial Products

HAR system products for sports performance analysis typically take one of three forms: wearable IMUs strategically positioned on the user's body, use of the IMU within mobile devices, or embodiments— external, compact IMU attachments placed directly on sporting equipment [13]. Very low cost is achieved by products that use the existing IMU on mobile devices because no additional hardware is needed, but this implementation is limited to applications where the user can conveniently carry their mobile device, such as running and daily activity tracking. The products include Google Fit, Samsung Health, and Apple Health, all of which are free [6].

Wearable IMU devices often offer more informative activity information such as sport movement analysis and rehabilitation training, though at a greater cost. One notable example is the IMU Step, a lower-limb monitoring tool offering advanced limb dynamics analysis for $6600 to $22,000 per year [7]. Another example is FitBit, which offers various wrist wearable IMU's that offer sports activity tracking with prices ranging from $60 to $230 [8].

For sports that involve skilled use of equipment, an IMU placed directly on the equipment itself often affords the most in-depth analysis of game performance. One product is the Diamond Kinetics SwingTracker, a $100 sensor module that can be attached to a baseball bat to analyze swing metrics including max barrel speed and swing-to-impact time [9]. Another example is the Zepp Tennis2 Swing Analyzer, a $220 tennis racquet sensor module that records metrics including swing type and speed [10].

State-of-the-Art Algorithm Implementation for Sports Analysis

Achieving state-of-the-art HAR performance for sports requires implementation tailored for the dynamics of the specific sport. Research into baseball swing evaluation algorithms found that encoding the specific sequence of actions within a proper swing in addition to traditional signal processing techniques was necessary. [11]. The Babolat Pure Drive, another smart tennis racquet, leverages domain knowledge about the amount of time typically taken between serves and overheads and the vibration of the racquet when a ball hits the sweet spot in order to optimize segmentation and classification of the swings [12]. In general, signal processing techniques generalize well to HAR within different domains but in-depth domain analysis and experimentation reveals how to best optimize these techniques for the application at hand.

References

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