Accelerometry-based inference of constrained motions

Chris Isaac Larnder, John Abbott College

The reconstruction of motion from accelerometer data is, in the general case, difficult. One problem is the noise-amplification drift inherent to double-integration techniques. Another fundamental problem is the seperation of the proper acceleration into gravitational and coordinate-acceleration components. Einstein's equivalence principle precludes any hardware-level solutions to this latter problem, recently-announced atom interferometry technologies notwithstanding.

For motions subject to mechanical constraints, however, appropriate exploitation of the reduction in the degrees of freedom could lead to significant improvements in or complete elimination of these problems. In such an approach, a set of differential equations provides a parametrised characterisation of both the constraints imposed on the physical object and the geometrical relationship between the object and the sensor. By evaluating the convergence of multi-dimensional minimization algorithms, we expect to automatically infer the type of constraint at play. A corollary of the successful detection of such "constraint signatures" in the accelerometer data is the recovery of reliable estimates for all parameters in the model, including, for a broad class of constraints, state variables for the reduced-coordinate degrees of freedom.

A methodical exploration of some of these opportunities is the subject of a recently-awarded 3-year FRQNT grant whose scope and goals will be outlined in this presentation. Although our study begins with models having a small number of parameters, the development of such techniques promises broad applicability as a low-level classification layer in machine-learning architectures involving more complex physical systems. Recognizing that traditional ML systems suffer from inflexibility and poor transfer to related domains, there is increasing interest in hybrid systems that incorporate domain-specific knowledge. Different deep networks specialized for distinct application domains could eventually re-use the same "physics layer" whose output is also human-interpretable, leading to improved system comprehensibility and reduced development costs.