Learning for motion control in bonding machines:
Bridging data-driven learning and physical modelling[*]

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Abstract

Semiconductor back-end machines require high position accuracy, throughput, and reliability in a variety of industrial environments. Motion control is essential to meet future challenges. Systems have to perform varying motion tasks with (sub-)micrometer precision. The high demands on throughput require movements with high velocity and accelerations. Robustness and reliability for changing industrial environments is needed to minimize machine-to-machine differences and obtain uniform system performance. The use of data-driven learning in conjunction with model-based control approaches is envisaged to overcome these challenges.

Regarding the first challenge, fast and safe learning is required while maintaining flexibility under varying motion tasks. Traditional ILC enables high performance with fast and safe learning for repeating motion [1]. Advanced ILC algorithms are required for operation for varying motion tasks. Herein, the feedforward signal is parameterized by basis functions that incorporate model knowledge [2]. Traditionally, the basis functions are chosen using typical motion profiles, i.e., velocity, acceleration, and snap. For semiconductor back-end machines, substantial non-linear dynamics are present. Therefore, non-linear terms are included in the basis functions, which are derived from first principle modelling of the system. Experimental tests on a XYZ-motion stage of a commercial wire bonder shows significant performance improvement despite varying motion tasks.

By leveraging on concepts from machine learning, the basis functions are extended to further reduce the error up to the reproducible level using Gaussian processes. First, inverse model feedforward is applied using kernel-based system identification using non-causal kernels [3]. Second, unmeasured performance evaluation at the bonding location is investigated. Special attention is given to compliance as well as interaction between axis and position- and time-dependent system dynamics [4]. Thirdly, the

necessity of (prior) model knowledge for fast and safe learning is revisited by applying reinforcement learning techniques, in particular PILCO, which uses Gaussian processes to describe the non-linear system dynamics to enhance performance under changing environments [5]. By data-driven learning and physical modelling, major performance improvements are enabled for a large range of operating conditions.

References

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