Tool wear prediction and damage detection in milling using dynamic Bayesian networks

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Abstract

It is widely accepted that tool wear has a direct impact on a machining process, playing a key part in surface integrity, part quality and therefore, process efficiency. By establishing the state of a tool during a machining process, it is possible to estimate both the surface properties and the optimal process parameters, while allowing intelligent predictions about the future state of the process to be made; thus ultimately reducing unexpected component damage. This state estimate can be achieved by implementing a variety of in-process monitoring techniques and observing the development of selected data features as the wear state of the tool progresses. This paper builds upon previous work making use of hidden Markov models (HMM) along with in-process recorded acoustic emission (AE) data, to probabilistically classify a tool's current wear state, its likely future state, and to detect potential damage during ball-nosed milling of Titanium-5Al-5Mo-5V-3Cr (Ti-5553). More specifically, this work develops a Gaussian process (GP) based nonlinear autoregressive network with exogenous inputs (NARX) model to improve upon previous prediction accuracy while allowing independence from machining conditions and specific process parameters.

Previous work shows that it is entirely possible to make informed, probabilistic estimates of machine state and tool wear levels based upon acquired AE data and a trained HMM, resulting in an accuracy of around 98% for a particular process. The inherent nature of a Markov model, however, means that all future state estimates are based on the current state only, and poses a potential problem when assessing a process with variable parameters and, therefore, varying wear rates. The model will still predict the state in this instance, although may not be as accurate if progressing through wear states more quickly for example. It is also limited in its ability to predict the future state with an associated time-frame and likelihood due to its time- independent nature, and lack of knowledge of previous state transitions. Thus, this model is capable of wear diagnosis more so than state prognosis. An example of such wear states can be seen in Figure 1 with HMM classified points shown in Figure 2. It is for this reason that this work explores the use of GP NARX models as an alternative to the HMM to allow process-parameter-independent state predictions.
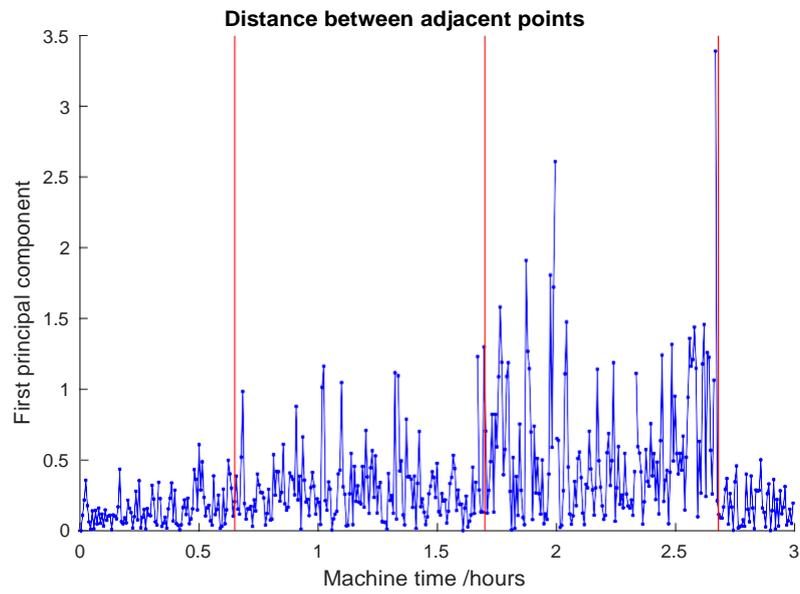
Figure 1: Plot showing first principal component input sequence and state separators for example trial dataset.
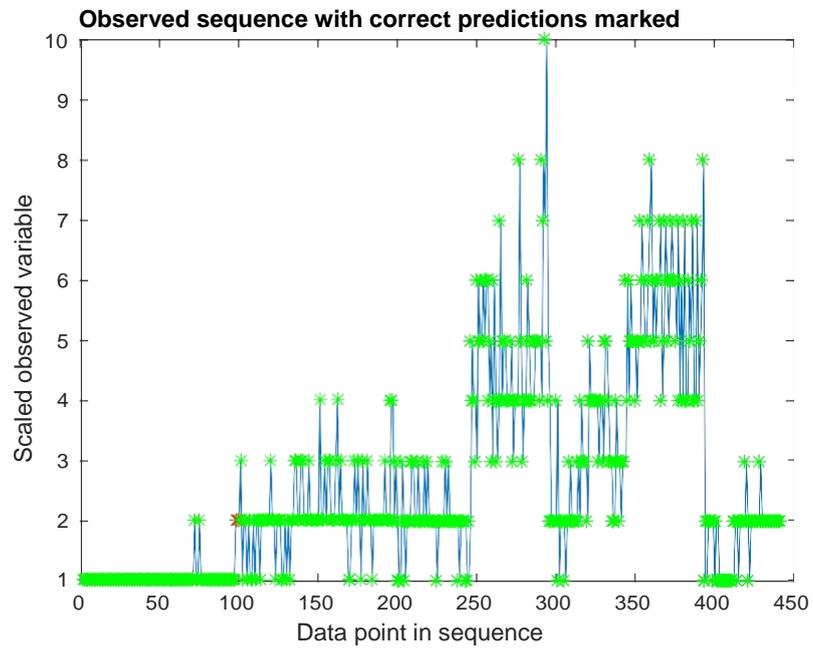

Figure 2: Plot showing testing data points marked in green when correctly classified and red when misclassified.