CHAPTER 6

Conclusion

6.1 Review of results

In this study discrete hidden Markov models were trained for tool wear classification. The data was generated manually on a lathe with a cemented carbide tool insert cutting an EN19 steel alloy. Some of the parameters, such as the depth of cut and the feed rate was kept constant while the cutting speed had some variation. This variation was around $\pm 8\%$ of the cutting speed.

This has been the first work where a reduced feature space was used to train the HMM. The "essence" of the signals were compressed into a very relevant and robust single feature using the principal component analysis which lowers the dimensionality of the feature space. If more than one sensor signal is used, this single feature will be very robust indeed. Also in the case where more that one sensor is used the feature will probably give good results even if some of the other sensors fail.

The training and testing data was generated from one tool. The data encompassed only the first third of the life of the tool. This devalues the statistical integrity of the data. The samples for training and testing however, were selected randomly from the respective classes, and the performance of the classification is the average result of 20 iterations. This mitigates to a degree, the fact that only one tool was used. In cases where more than one tool will be used, the performance of the classification might be expected to be a little lower. It is however believed that comparable results will be achieved. Also if a total tool life might be used, even better separation between classes will be achieved and consequently better results will be achieved.

An HMM classification system was created from the data . This system scored the forward probabilities to create a binary, "sharp"/"worn" classification. Two HMMs were trained for the system, one corresponding to each wear state to be classified. The system achieved a 91, 5% correct classification of sharp tools and a 94, 5% correct classification of worn tools. This was compared to a Bayesian classifier that achieved 96, 8% correct classification for a sharp tool and a 72, 7% correct classification for a worn tool.

In order to establish the relationship between the amount of available data for training and testing and the performance of the system, the whole recognition procedure was repeated with a reduced data set. In this reduced data set the separation between classes was very poor. The system achieved an average result of 65% correct classifications for worn tools and an 92% correct classifications for sharp tools. This is comparable with the performance of the Bayesian classifier. This investigation proves that with more data there will be more clearly identifiable classes which will make for a better classification system.

Optimal state topology of the HMMs were obtained by an exhaustive method. It was found that for this application a 7 state, ergodic HMM works well and for sharp tools and a 2 state, ergodic HMM works well for worn tools. The signals were discretized into 150 levels and this was kept constant through the experiments. Lowering this number might actually improve the performance of the system.

The HMMs achieved very good recognition considering that the tool has only reached a third of its total life and that the experimental results could not be kept very constant. Even through this, the HMMs achieved a robust recognition.

Finally, because the data used in this classification scheme is only limited to a part of a lifetime of one tool, it compromises the statistical integrity of the data and the results. Good generalisation of the classification scheme with the HMMs is therefore not guaranteed. The technique is however successfully demonstraded.

6.2 Suggestions on Improvements

The nature of HMMs lends itself very much to the detection of wear condition. It is however even better suited for discrete event detection. Events like excessive vibration of the workpiece (eg. where the workpiece might not be lined up) or self-excited vibration of the tool (eg. chatter), or breakage events, might be very well suited to be detected by HMMs. No work, to the knowledge of the author, has been done in the area of TCM using HMMs to detect these conditions. This may be an interesting future field to explore.

Measuring in the machining environment is exceedingly difficult and more work is needed to produce a cheap sensor integrated machining tool. A problem with strain gauges that are covered is that they might be torn off by the very same covering that is meant to protect it. This is a future area which could be explored to produce a covering for the strain gauges to not hinder their performance. Another option might be to embed the sensor into the tool holder itself.

A problem still relevant to neural network TCM systems is the automation of the process of generation-and-selection features that are sensitive to tool wear. This problem is also relevant to systems that will use HMMs for the classification. More research in needed in this direction.

The techniques for using HMM for the classification of tool wear has been proved in this study, although the very simplest of the HMM family was used. Investigation into more complex models might improve the results. More configurations of the HMMs might also be used where Viterbi decoding could be used to determine the tool state.