BIOLOGICALLY-INSPIRED ACOUSTIC WEAR ANALYSIS

S. Varma, J.S.Baras and S.A.Shamma

Center for Auditory and Acoustics Research,
University of Maryland at College Park
varma@eng.umd.edu, baras@eng.umd.edu, sas@eng.umd.edu

1. INTRODUCTION

Trying to predict the wear of a tool from the sound it makes, has a long history. People have always been interested in real-time monitoring of machinery to detect faults as and when they occur, rather than wait until the next maintenance period. This way, unnecessary maintenance, as well as long runs in a faulty condition, can be avoided. In the case of a cutting tool, trying to cut with a blunt tool can lead to the breakage of the tool and degradation of the job, while pulling the tool off for frequent assessments are expensive in terms of the machinist's time. It is of interest to develop a method that can give an estimate of the wear from easily observable signals. This estimate, along with some kind of a confidence measure, can be used by the machinist to help his own intuition.

To a machinist, the most important cue is the sound of the tool. Our goal in this work is to develop a system of classifying sounds according to the wear level of the tool that makes it.

This problem has many parallels with speech recognition, but there are some difficulties unique to the tool monitoring problem. Classifying the sound is not the final goal here, as it is in the case of speech recognition. Here the aim is to classify sounds and then correlate these classes to the physical state of the tool. Efficient ways of using wear measurements are of the utmost importance. In addition, modifications are needed because the training data is very sparsely labeled (2-3 wear measurements per lifetime of tool).

Previous work on estimating tool wear or damage from acoustic emissions include using the power density spectrum ([7], [8],[6] and [4]). Other approaches include looking for high energy transients in the sound signal [2], and using torque and thrust information in addition to vibration data [5] .

Determining the effect of wear on the acoustic emissions of a piece of machinery is complicated by the fact that machine tools have very complex vibration modes. Usually such machines can be modeled accurately only as 3-dimensional, non-linear, distributed systems, whose outputs (measured vibration)depends on the inputs (tool and job surfaces) in a very complex way. Non-linear phenomena like chatter are evidence for this [1].

Since simple models of the tool surface - vibration relationship are not available, one is forced to look for non-parametric solutions to this problem. Our approach in this paper, is to first extract a feature vector from the sound, and then do a non-model-based classification using Vector Quantization [12]. Obviously, the selection of the feature vector is of paramount importance for this approach to give any good results.

In this investigation we use filters based on a model of mammalian audition, followed by a tree structured classifier, based on vector quantization.

2. AUDITORY FILTERS

We use two auditory filters, developed by Shamma et.al., for preprocessing. The first one is a model of the filter banks and nonlinear operations that take place in the inner ear [9]. The second filter mimics the analysis of the filtered signal that take place in the primary auditory cortex [10].

2.1. Inner Ear

This filter describes the mechanical and neural processing in the early stages of the auditory system. In the Analysis Stage, a bank of constant-Q filters, approximate the function of the eardrum and the basilar membrane in the cochlea with the continuous spatial axis of the cochlea as the scale parameter. Another way to interpret the output of the cochlear filters is as an affine wavelet transform of the stimulus. The Transduction Stage models the conversion of the mechanical displacements in the basilar membrane into electrical activity along a dense, topographically ordered array of auditory nerve fibers. The third stage called the Reduction Stage effectively computes an estimate of the spectrum of the stimulus, through a *lateral inhibitory network* (LIN). The details can be found in [9].

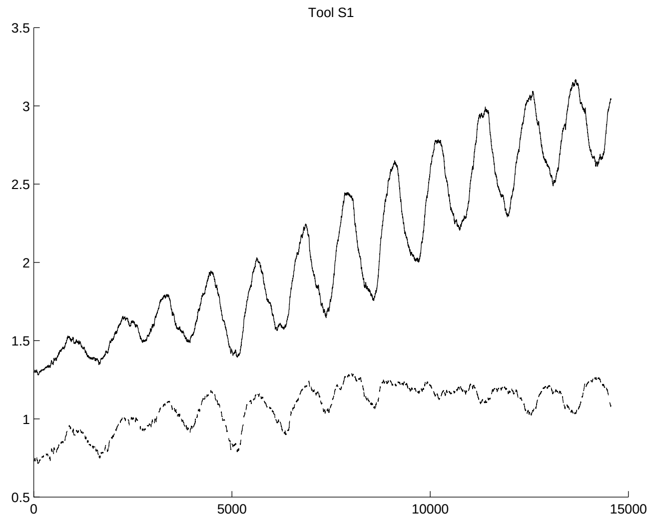

Figure 1: Mean and variance of wear estimates (in thousandths of an inch) versus time (in frames) for tool s1

2.2. The Auditory Cortex

The second filter that acts on the output (spectral estimate) of the first filter is based on the action of the primary auditory cortex (A1). In the A1, the 1-D acoustic spectrum is analyzed along three feature axes: the *spectral symmetry* on the ϕ axis, the *local bandwidth* on the scale s axis, and the *frequency components* on the tonotopic x axis. This analysis can be thought of as a local Fourier (technically, affine wavelet) transform of the acoustic spectrum.

3. TREE STRUCTURED VECTOR QUANTIZER (TSVQ)

TSVQ is an example of a classification tree where the given test vectors are classified stage by stage, with each stage giving a sharper classification than the previous. Each node of the tree is associated with a centroid, which can be thought of as a paradigm for a particular class. All test vectors start out by belonging to the root node. Then the vector is compared with the centroids of all nodes which are children of the node it currently belongs to. The vector is classified into the child with the centroid that is "closest" to it according to some metric. The vector eventually ends up in a leaf node, and is assigned a class according to the class of the leaf node.

The challenge is to preserve fidelity in the classification. Any substituting of an optimal partitioning of the signal vector-space by a tree structured partitioning reduces the optimality. Our goal is to make this difference as small as possible. Proper choice of the pre-processing and the tree-growing algorithm is crucial to this end.

3.1. MULTI-RESOLUTION TSVQ (MRTSVQ)

One special kind of a tree classifier using VQ is the Multi-Resolution TSVQ (MRTSVQ). Data vectors in an MRTSVQ is represented in multiple resolutions or scales. One obvious method of creating such a representation is through affine wavelet transforms. In this paper, the auditory cortex filter used is an example of a multi-resolution transform that follows from studies of the primary cortex.

This method of classification offers one advantage over the unembellished TSVQ. At the higher levels, where more comparisons have to be made, we can use a vector with lesser number of bits, thus doing many simple computations. As we go down the tree (and sharpen our classification), we do lesser number of progressively longer distance-calculations. This computational advantage is very important in online algorithms.

4. TRAINING

In one way of combining class labels in growing TSVQ, we build a tree for each class, using only the appropriately labeled data. This method, usually called Parallel TSVQ, gives better results than making one tree for all the classes combined. In the combined tree, an initial wrong misclassification into one particular sub-tree can end in a vector being incorrectly classified. This problem is avoided, to a great extent, in the parallel case. The Parallel TSVQ is also quicker to execute when we have a large number of classes. Testing on each tree can be done in parallel, which reduces computational time.

5. TESTING

Testing was done on data corresponding to three different tool geometry and job material configurations. Tools that had not been used in training were used in the testing procedure. The preprocessing was similar to what was done for training. Each vector was dropped down all five trees and the distance to the centroids of the leaf nodes it fell into, was compared. The vector is assigned a wear-class according to the wear level of the tree that gives the least distance from the centroid to the vector. This way, we get a time series of wear-class prediction for all the frames for all the passes.

Next we take a sliding window of 500 frames and find the mean wear estimate for this window. An example of the plot of the mean wear estimate vs. tool-life in frames (revolutions) is given in Fig.1. The solid line is the mean and the dotted line is the variance of the wear estimate. It is apparent that our method has picked up features in the sound that seem to be correlated to the tool-life and the wear of the tool. The periodic variation in the wear estimate is a result of variation in wear rate during the period of one pass.

6. CONCLUSIONS

In conclusion, the mammalian ear model coupled with a TSVQ seems to pick out features that are strongly indicative of wear. Furthermore, trees trained on one particular tool-job configuration seem to generalize easily to other configurations. This indicates that our features are not tool or material specific, but are characteristic of the cutting process, in general. Algorithms that seek to predict tool wear based on just the spectrum cannot do this.

7. REFERENCES

[1] Berger B.S., Rokin M. and Minis I. *Complex dynamics in metal cutting* Quarterly of App. Math., Vol. 51, 1993, pp 601-612

[2] Owsley, L.M.D., Atlas, L.E. and Bernard, G.D. *Self-Organizing Feature Maps and Hidden Markov Models for Machine-Tool Monitoring* IEEE Trans. on Sig. Proc., Vol. 45, No. 11, Nov. 1997, pp. 2787-2798

[3] Baras, J.S., and Wolk, S.I. *Hierarchical wavelet representations of ship radar returns* Institute for Systems Research Technical Report-TR 93-100, 1993, University of Maryland at College Park.

[4] Chen, M-F., Natsuake, M. and Ito, Y. *Preventive monitoring system for main spindle of machine tool - comparision of signal processing methods* Proc. 27th Inter. MATADOR Conf., April 1988, pp. 179-186

[5] S.Y. Hong, *Self-learning system for knowledge based diagnosis of drill condition in fully automatic manufacturing system* Proc. SPIE, Vol. 1707, 1992, pp. 195-206

[6] Inasaki, I. and Yonetsu, S. *In-process detection of cutting tool damage by acoustic emission measurement* Proc. 22nd Inter. Machine Tool Design and Res. Conf., 1981, pp. 261-268

[7] Noh, A. and Kobayashi, A. *Cutting tool failure detector* “Adv. in Hard Material Tool Tech.” Proc. Inter. Conf. on Hard Materials Tool Tech., 1976, pp. 414-426

[8] Shumsheruddin, S. and Lawrence, J.C. *In-process prediction of milling tool wear* Proc. 24th Inter. Machine Tool Design and Res. Conf., 1983, pp. 201-214

[9] Yang, X., Wang, K. and Shamma, S.A. *Auditory representations of acoustic signals* IEEE Trans. Info. Theory, Vol. 38, No. 2, March 1992, pp. 824-839

[10] Wang, K. and Shamma, S.A. *Spectral shape analysis in the central auditory system* IEEE Trans. on Speech and Audio Proc., Vol. 3, No. 5, Sept. 1995, pp. 382-395

[11] Linde, Y., Buzo, A. and Gray, R.M. *An Algorithm for Vector Quantizer Design* IEEE Trans. on Comm., Vol. COM-28, No. 1, Jan. 1980, pp. 84-95

[12] Gersho, A. and Gray, R.M. *Vector quantization and signal compression* Kluwer Academic Press, 1991