Wavelets, Fourier Transforms, and Neural Networks for Ford Classification

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Outline

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Percentages for the pre-announced data sets

	Train	**Validation**
Ford A	93.4 % (6.3 % fpr)	93.9 % (7.1 % fpr)
Ford B	96.1 % (3.8 % fpr)	88.1 % (14.8 % fpr)

The above table gives the train and validation accuracy and false positive rate (fpr) for the competition data sets Ford A and Ford B. It's fun to see on July 4th, what the outcome was on the undisclosed testing set.

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I used a quite traditional processing path (Ford B described)

- Tukey window, zero-padding $\rightarrow$ 512 samples, FFT and DWT applicable
- DWT $\rightarrow$512 wavelet coefficients; threshold for de-noising.
- Relative distribution of energy into the different fluctuation levels $\rightarrow$ just a couple of Wavelet-based features.
- Inverse DWT $\rightarrow$ presumably de-noised signal.
- FFT $\rightarrow$ spectrum; normalization $\rightarrow$ spectrum with energy of one.
- Linear scaling of the input variables to the range $[-1, 1]$.
  $\rightarrow$ balanced training of an MLP with *tanh* activation.
- Simple MLP neural network (3 hidden neurons)
  $\rightarrow$ Classification of a signal.
- Train MLP using only training set (Ford A)
  and with validation set included (Ford B).
  Fixed (small) number of iterations.

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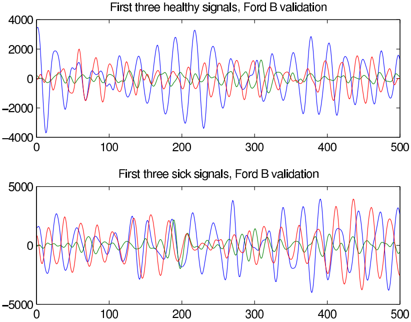
Time domain



- No conspicuous differences between classes.
- Obvious variance in amplitude between signals.
- This seemed like a dead end immediately.

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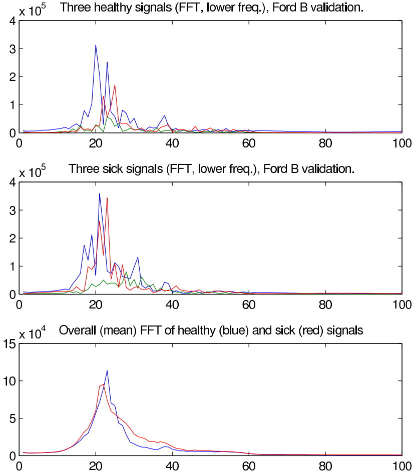
Frequency domain



- Basic discrete fourier transform seems to give some differences.
- Overall, there might be a difference in the peak frequencies.
- Interplay of different bands?

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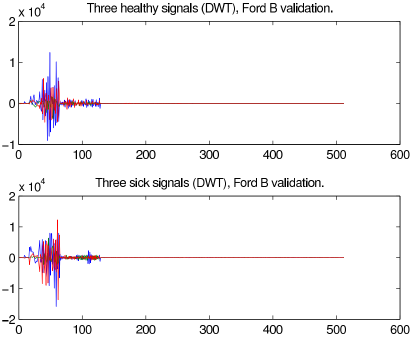
My Trip to Wavelets: first steps



- I took this as an opportunity to learn about the Wavelet transform.
- On the left there is one possible discrete wavelet transform (DWT) of some of the Ford B signals.

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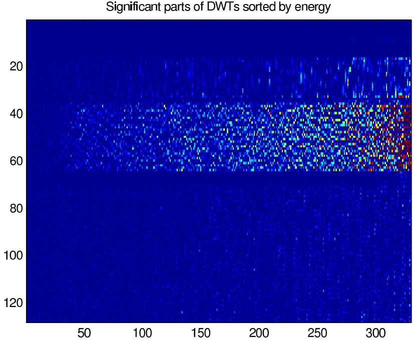
My Trip to Wavelets: fiddling around



- A plot of side-by-side DWTs.
- Some of the signals are very weak compared to others.
- Also, the weak signals seem to contain mostly noise (as guessed from a normalized plot)
- So . . . What, if anything, can I do with those?

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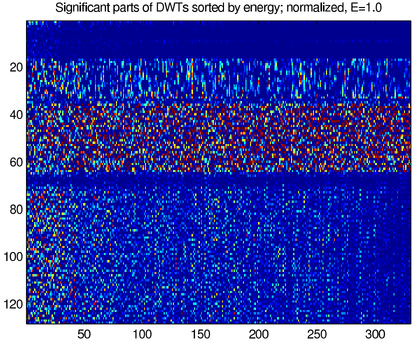
The normalized DWT image is here:



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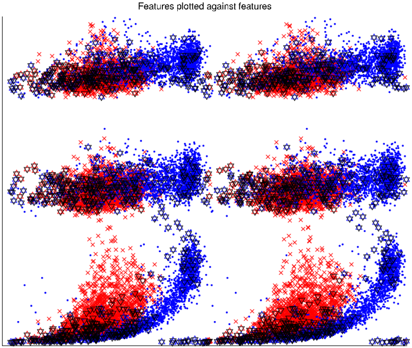
What do the features tell



- I wanted to visualize the features somehow, and assess the usability of them.
- Here are some scatter plots of feature-pairs (Ford B).
- At the bottom we have the interplay of wavelet fluctuation distributions.
- Others are DFT bin magnitudes.

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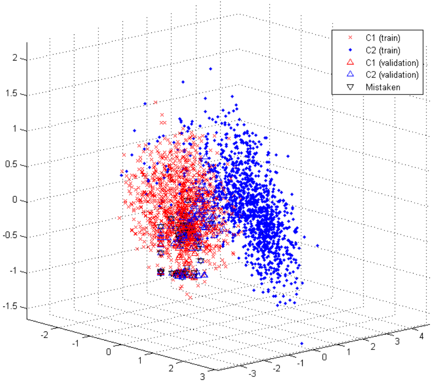
The data in 3 dimensions (PCA from final features)

Ford B, with DWT and DFT features



- What can we find from a 3D-projection?
- At least zooming and rotating is much fun.
- In reality, this tells that some signals are, in fact, very easy to classify. Problems occur within a well-located minority.
- Unfortunately, my features take the noisy validation set close to this!

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Shortcomings that I realize only afterwards:

- Why on earth didn't I use a smaller window?
  - The interesting things might happen only sporadically!
  - A sliding window yields translation-invariance!
- I should have selected only the "most discriminant training signals" using some between-class distance metric.
  - What if the training data contains some false labels?
  - What if the sought-after, but elusive, discriminant feature does not occur within each 500-sample batch?
- Should I have excluded the most noisy batches from the training? What can you learn from plain noise!
- I didn't try out classifiers other than the simple MLP.

Summary

- It seems that for this case, traditional and simple methods performed quite well.
- Most of the work was done by trial and error.
- Interactive visualizations of data aid a lot in understanding what is possible and what perhaps is not.
- I thank the organizers and co-competitors. There was fun in computing this time!

Big thanks also to the Department of Mathematical Information Technology, University of Jyväskylä, for providing a travel grant to WCCI 2008, and to prof. Tommi Kärkkäinen for tipping me off about the competition.

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Greetings from Finland. Please, make a visit some time!



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