Envelope coding in the Cochlear Nucleus: a Data Mining Approach

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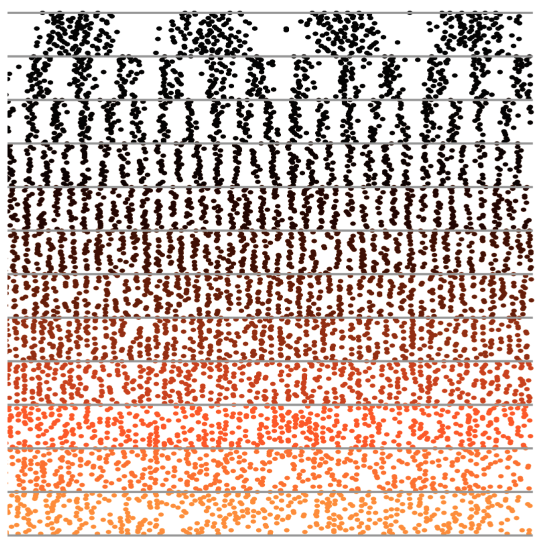
Introduction

The Cochlear Nucleus (CN) processes the auditory information received from the inner hair cells in the cochlea, directly via the auditory nerve. It is well established that the timing of spikes in the CN precisely reflect the fine structure and envelope of sounds. Conventionally it has been assumed that the relationship between the stimulus and the timing of spikes can be approximated as linear. Classically the Vector Strength (VS) has been used to evaluate the information contained in the spike trains. Such analysis leads to a particular interpretation of temporal coding in the CN.

Recent findings suggest that this measure is not universally appropriate as it does not accurately reflect the information contained in the spike trains. To extract as much information as the spike trains recorded and with less assumptions, we developed a computational architecture to use modern tools of Data Mining as a means to extract the modulation frequency of an Amplitude-Modulated tone from the patterns of spikes produced by CN neurons, using a supervised learning framework. We present the results of these computations and conclusions we can draw about processing in the CN.

1 CN Spike Trains



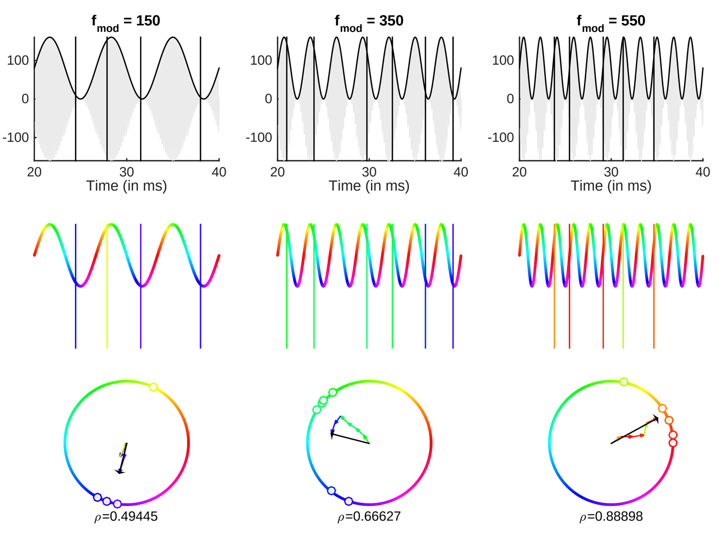
- **Raster plot** of 300 spike trains: responses of one cochlear nucleus neuron in stationary state over 80ms.
- For each modulation frequency $f_m \in \{50, 150, \ldots, 1150\}$Hz, an **amplitude modulated tone** is played 25 times to the anaesthetised animal:

$$s(t) = M\,(1 + \sin(2\pi f_m t))\sin(2\pi f_c t)$$

for fixed modulation level M and carrier frequency f_c.

- **463** such datasets with 300 spike trains.
- Cats' cochlear nucleus data recorded by Rhode & Greenberg [1].

2 Vector Strength



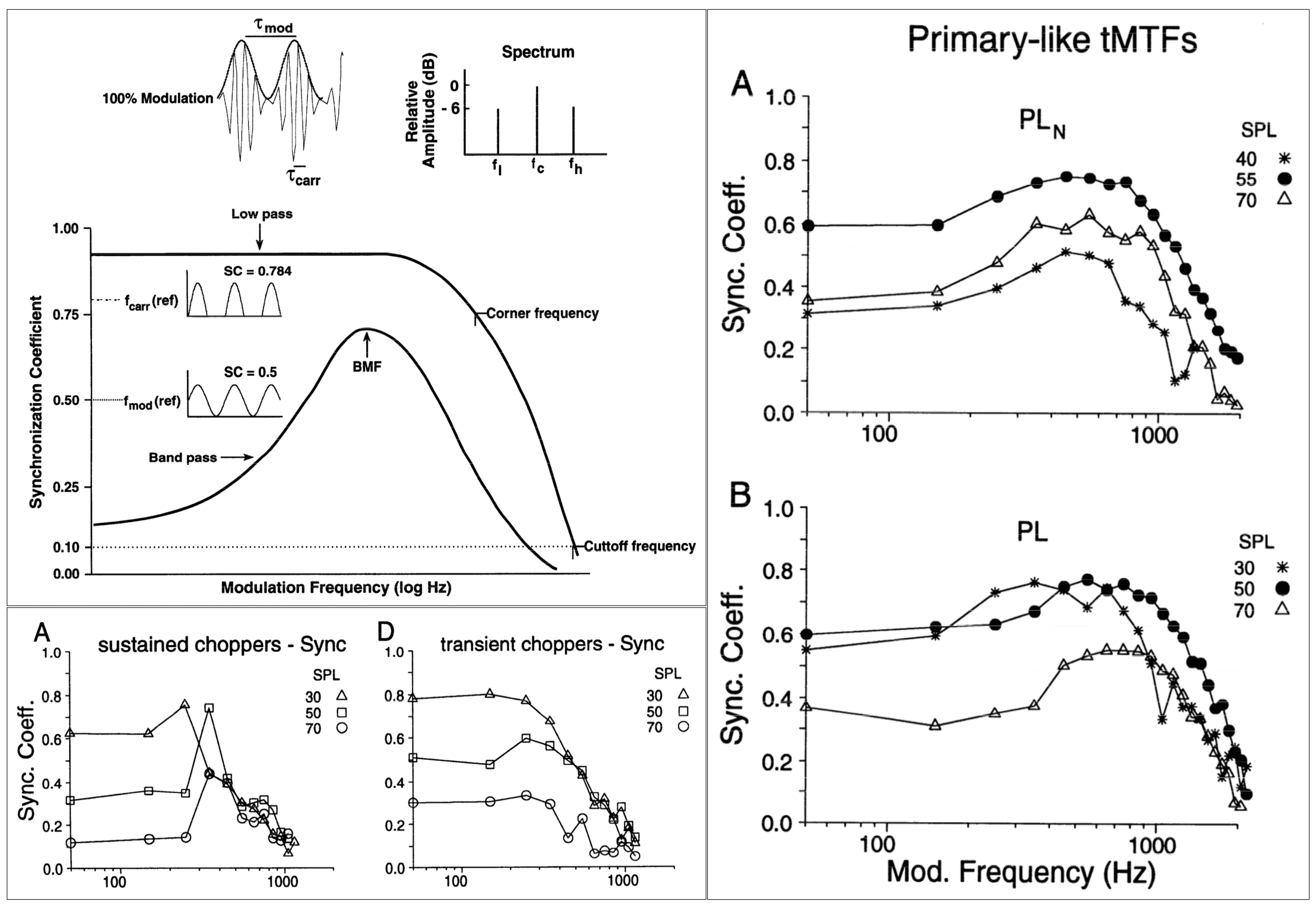
Vector Strength [2] computation on 3 spike trains from an Onset unit, knowing the input (grey AM tone): each spike is associated with a phase ϕ_k (phase-coloured).

The VS $\rho \in [0,1]$ is the length of the black arrow:

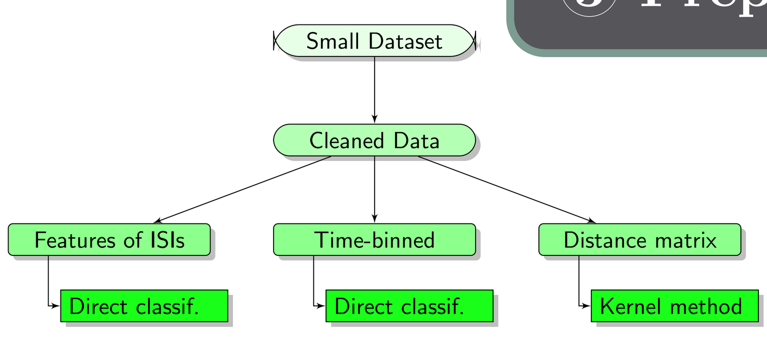
$$\rho = \left| \frac{1}{n} \sum_{k=1}^{n} e^{i\phi_k} \right|.$$

The transfer modulation transfer function (tMTF) is a trace of modulation gain as a function of modulation frequency. It characterises the range of modulation frequencies a neuron encodes. Cf [1]:

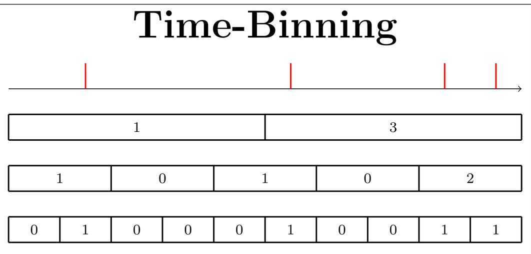
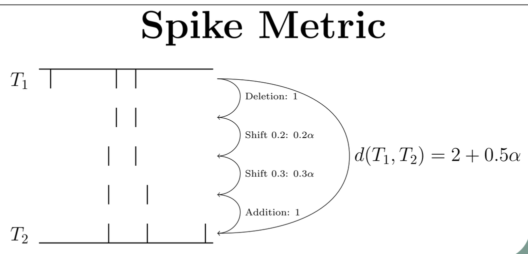
- PL units are low pass envelope encoders like the AN.
- Choppers show modulation tuning: bandpass tMTF (higher VS than PLs and a peak VS).
- Onset units are the best at encoding periodicity.



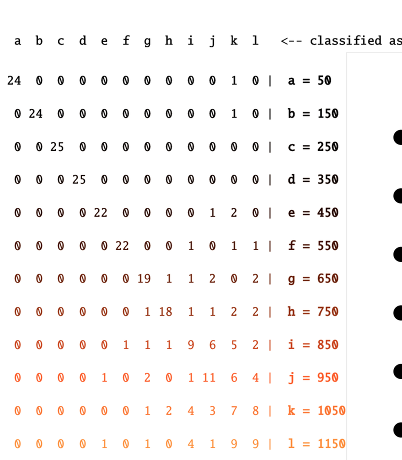
3 Preprocessing



Each dataset is preprocessed in 3 different ways: features from the interspike intervals, time-binning, or using a spike metric [3]. We then apply all available classification algorithms from the data mining toolbox Weka [4].

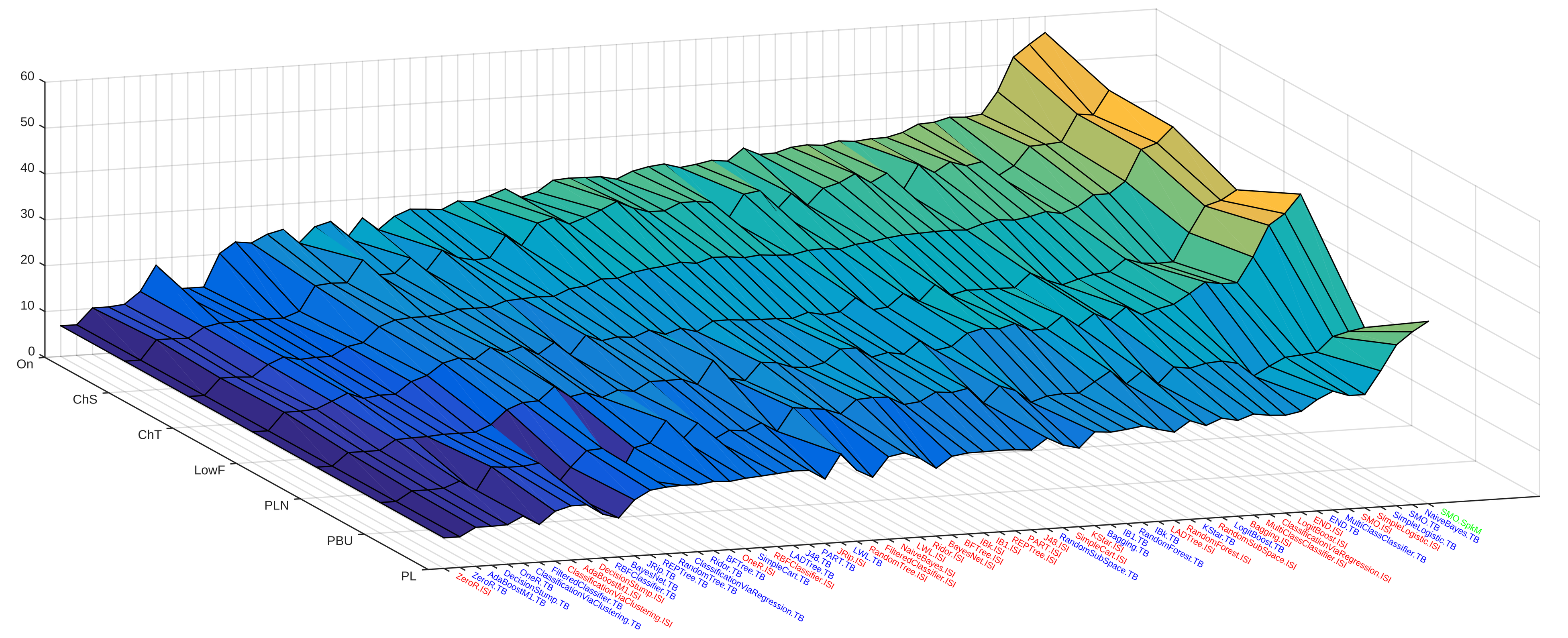
ISI Features	Time-Binning	Spike Metric
Mean, variance, coefficient of variation, skewness, number of spikes, histogram values, …		

4 Supervised Learning



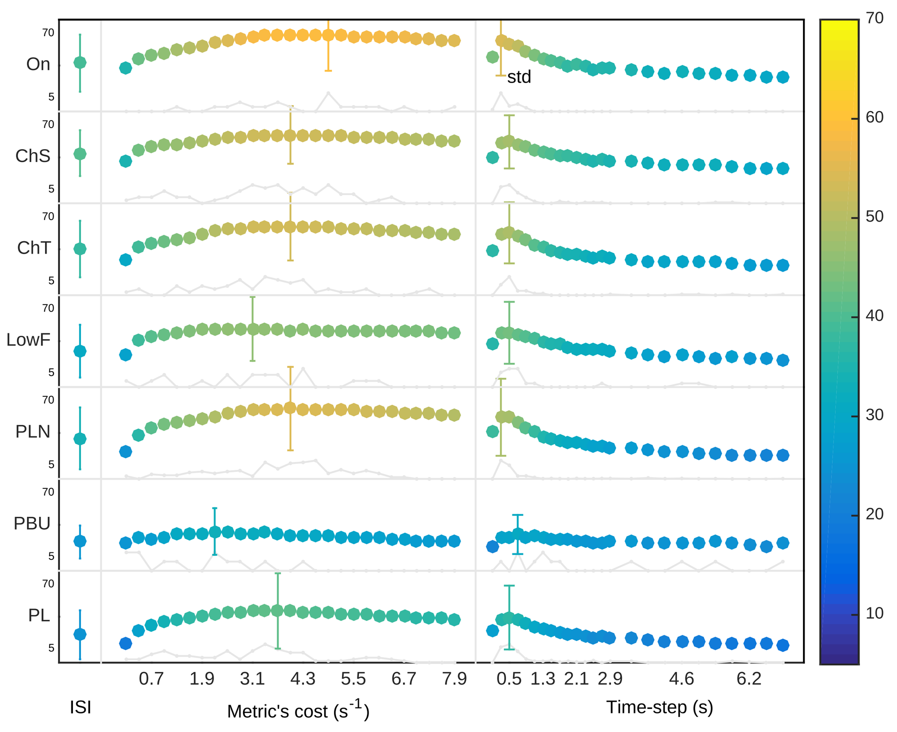
- Typical **confusion matrix** as output by **Weka** [4].
- $\#(i,j) = $#instances of **class** i **classified as belonging to class** j.
- Algorithms evaluated by stratified 10-fold **cross-validation**.
- Spike trains corresponding to low f_m are easily classified.
- At high f_m, the algorithm is mostly guessing.
- **Low-pass tMTF** in this chopper unit for AM frequency transmission.

5 Average accuracy per classifier and unit type



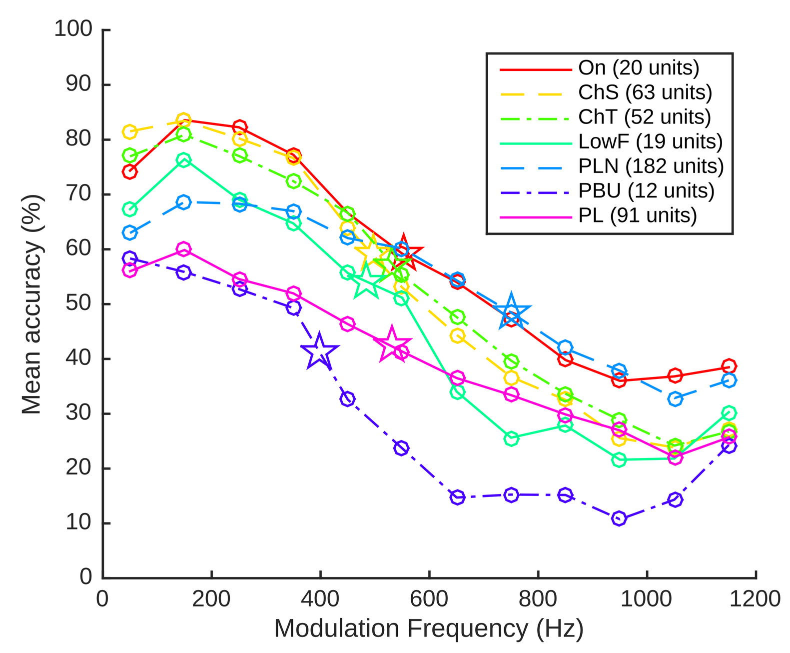
- Mean accuracy (percentage of correct guesses, z-axis) of all classification algorithms (x-axis) and unit types (y-axis).
- Both **algorithms** and **unit types are overall ordered**: no preference from some algorithms to specific unit types.
- Unit types differ in their ability to transmit AM frequencies. Overall we confirm previous findings that **regular** firing cells are good at encoding envelopes. We obtain the order $On > Ch > LowF > PLN > PBU > PL$ while [1] obtain the following rank order for phase-locking capability: $PLN > (On = PL) > Ch > PBU$.
- Different measures of performance generally yield the same relative performance, but different absolute performance.

6 Comparing preprocessing methods.



- Figure shows mean performance across all recordings from a given unit type for the SMO classifier, with each preprocessing method.
Left: ISI features. Centre: V&P spike metric. Right: Time-binning.
- Renormalised histograms of the best parameter across datasets are shown in grey in each box.
- SpkM and time-binning give very similar peak values, which correspond to similar time resolutions.
- In general both SpkM and time binning outperform summary ISI statistics.

7 Transfer Function



Mean percentage correct classification vs modulation frequency for each unit type, using SMO classifier and spike-metric preprocessing.

Stars show the cut-off frequencies

$$H(\omega_{co}) = ||H||_\infty / \sqrt{2}.$$

Curves are low-pass for all unit types.

Primary-Like units' slope is low.

8 Optimal time-scales

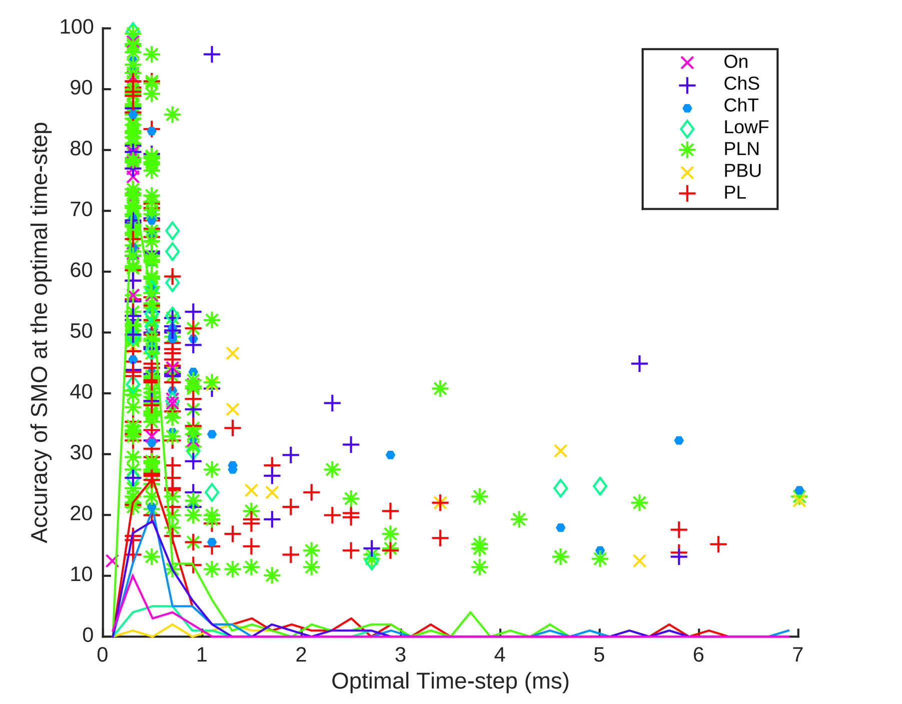


Figure shows, for each recording, the **optimal time bin resolution vs accuracy** for classification using SMO.

Optimal time-step is sub-millisecond.

Units where spikes were putatively less well timed gave low performance.

Subtle differences between units: PLN preferring smallest time windows. i.e. being most precise.

[1]: W. S. Rhode and S. Greenberg. Encoding of amplitude modulation in the cochlear nucleus of the cat. Journal of Neurophysiology, May 1994.

[2]: J. Leo van Hemmen. Vector strength after Goldberg, Brown, and von Mises: biological and mathematical perspectives. Biological Cybernetics, August 2013.

[3]: Jonathan D. Victor and Keith P. Purpura. Metric-space analysis of spike trains: theory, algorithms and application. Network: Computation in Neural Systems, January 1997.

[4]: Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, and Ian H. Witten. The WEKA Data Mining Software: An Update. SIGKDD Explor. Newsl., November 2009.