MULTIPITCH ESTIMATION USING A PCLA-BASED MODEL: IMPACT OF PARTIAL USER ANNOTATION

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1. Introduction

- **Context:** Multipitch estimation in musical recordings based on a probabilistic framework (PLCA).
- **Applications:** Main melody extraction, cover song identification, music transcription, etc.
- **Objective:** Can we improve the transcription performance if a user partially annotates the musical recording? How can we better take into account the user inputs?

2. The BHAD Model [1]

The absolute value of the normalised constant-Q transform (CQT) of a signal is modeled as a probability distribution $P(f,t)$.

Main characteristics:
- Better model for real signals: fundamental frequency and spectral envelope variations across note repetitions
- Entirely unsupervised
- Decomposes the signal as the sum of a polyphonic harmonic and a noise signal

Polyphonic harmonic signal:
- All possible pitches considered, with possibly zero weights
- All parameters estimated with the EM algorithm

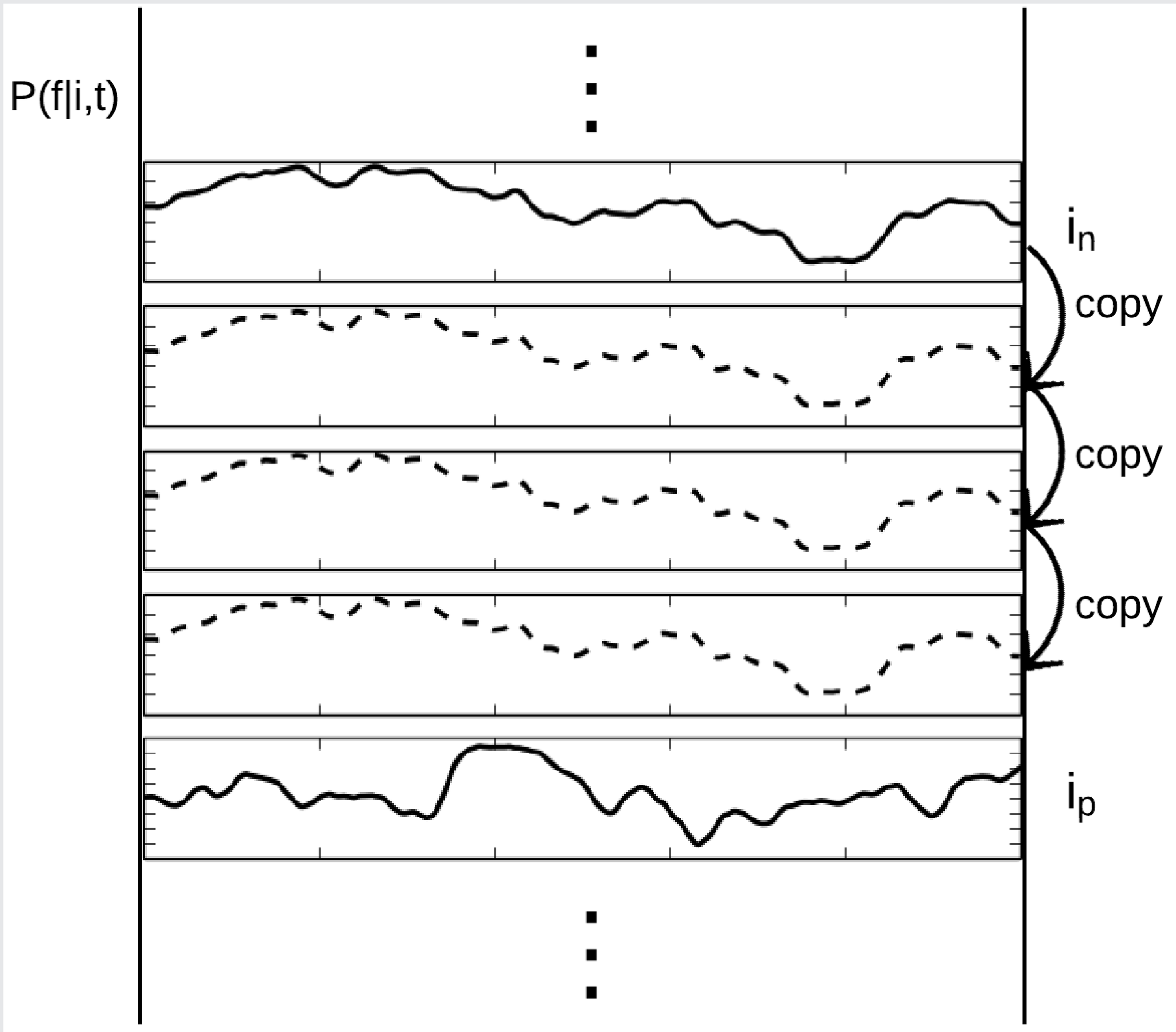
Spectral envelopes:
- Well initialised parameters
- Slower convergence rate by using a "brake"
- The "brake" influences the direction in which the algorithm goes

Use of priors:
- Resemblance prior applied to the spectral envelopes for each pitch
- Sparsness prior applied to the time-frequency activations

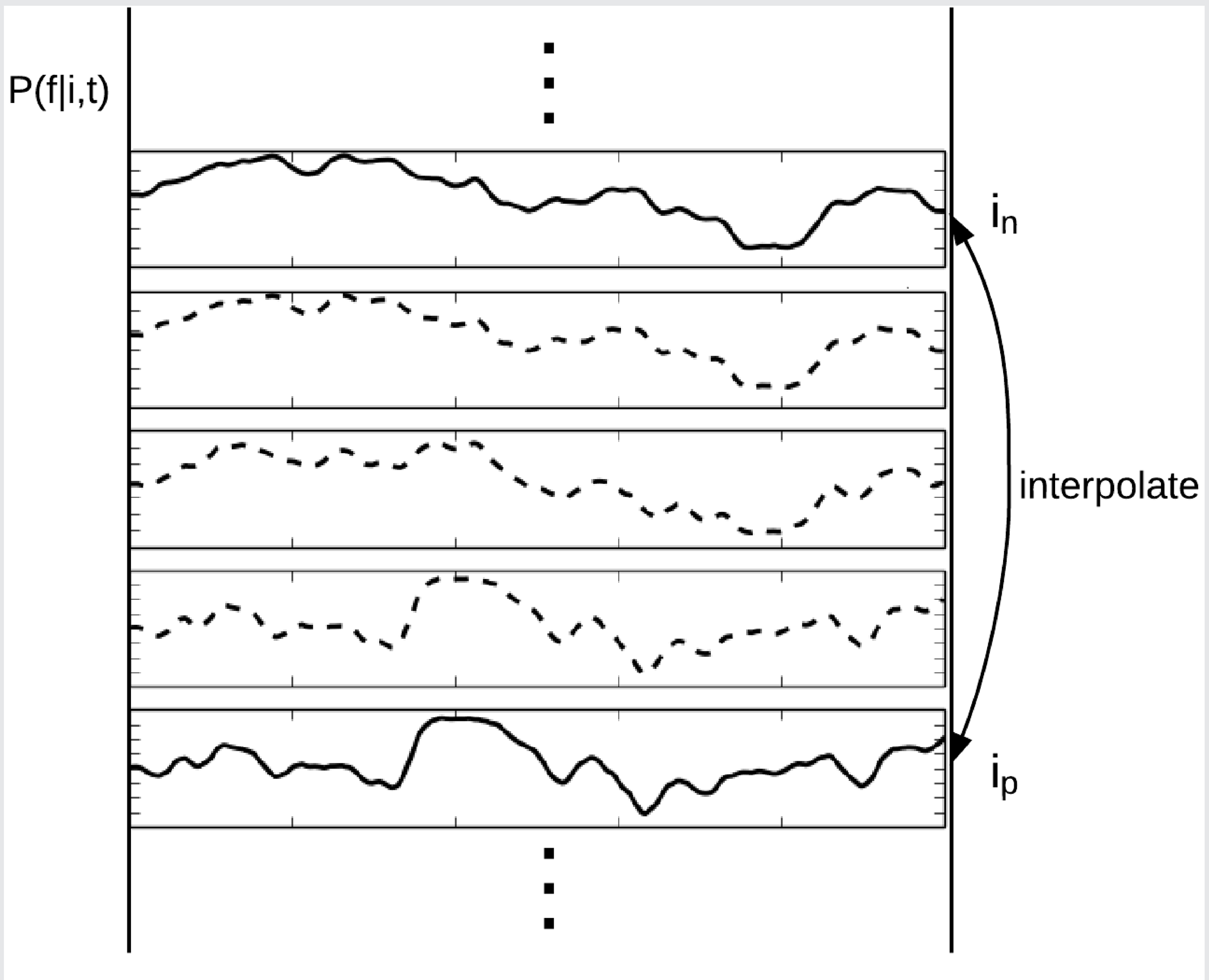
3. Note initialisation

Annotated notes: For each note, the average of all occurrences of this given note.

Non-annotated notes: Three strategies proposed: keep the original slope initialisation, copy previous notes templates or interpolate neighbour notes' templates.



Schematic representation of the copy strategy.



Schematic representation of the interpolate strategy.

4. Convergence rate

Goal: exploit the user input by controlling the convergence rate of the spectral envelopes when compared to other parameters of the model which are less well initialised.

Idea: convergence rate coefficient $\beta_{brake}(n)$ depends on the notes n:

$$\beta_{brake}(n) = \begin{cases} \beta_1, & \text{if } i_n \in \text{learning base} \\ \beta_0, & else \end{cases}, \quad \beta_1 > \beta_0$$

5. Results

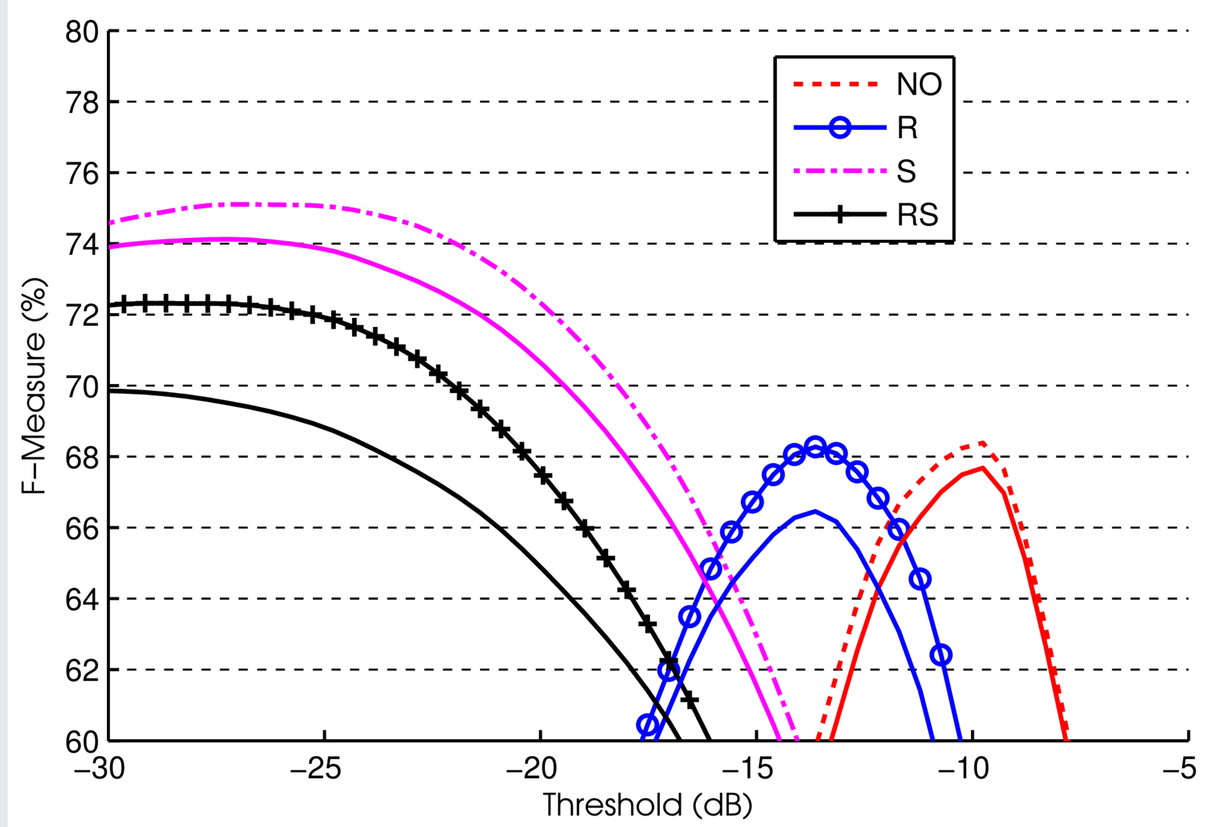
Options	Unsup.	Semi-Guided		
		Slope	Copy	Interp.
NO	67.68	**68.38**	65.00	43.68
S	73.91	**75.07**	71.44	52.07
R	66.46	**68.28**	64.13	47.05
RS	69.51	**72.30**	67.60	52.35
B	77.85	**78.63**	75.88	50.90
SB	74.64	**76.54**	72.47	45.68
RB	77.39	**79.49**	73.89	50.79
RSB	74.85	**77.02**	70.52	47.00

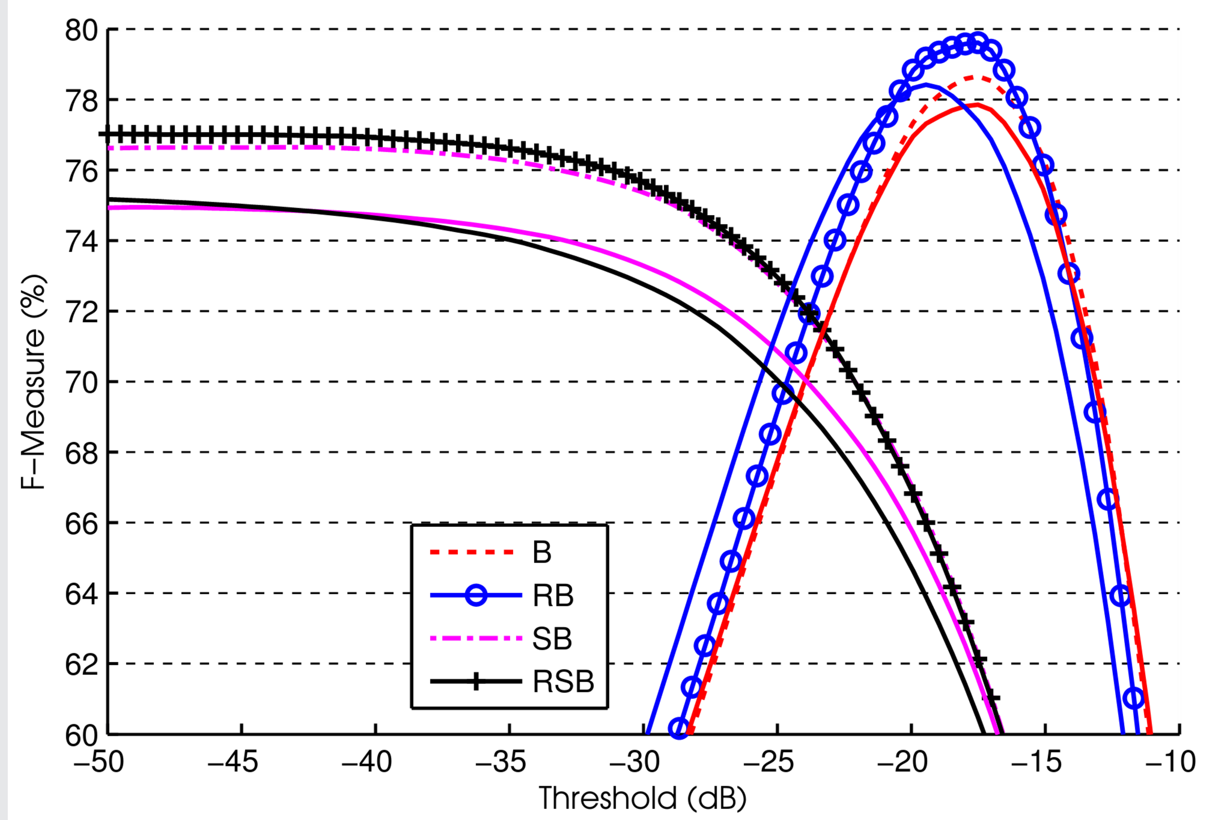
Mean F-Measure for the semi-guided and unsupervised approaches, considering the different initialisations of the non-annotated notes.

	No brake	Brake annotated notes		
	$\beta_{0,1}=0$	$\beta_1=0.1$	$\beta_1=1$	$\beta_1=10$
B	**68,38**	68,25	66,43	62,93
SB	**75,07**	74,84	74,29	72,74
RB	68,28	68,53	**69,20**	69,16
RSB	72,30	72,35	72,53	**72,66**

	Even	Brake all notes		
	$\beta_{0,1}=10$	$\beta_1=10.1$	$\beta_1=11$	$\beta_1=20$
B	78,63	78,63	**78,66**	**78,66**
SB	76,54	76,54	**76,55**	**76,55**
RB	79,49	79,49	79,51	**79,61**
RSB	77,02	77,02	**77,03**	76,98

Mean F-Measure considering the different strategies for controlling the convergence rate of the annotated notes and the different options of the BHAD algorithm (priors).





Results for the non-annotated notes (symbols) and the unsupervised approach without and with brake coefficients ($\beta_1=20$ and $\beta_0=10$).

6. Conclusions

Contributions:
- Substantial gain in performance by using a learning step
- Better initialisation of the model parameters

Future work:
- Alternative strategies for the user annotation
- Involve the user in a more interative way

References:

[1] B.Fuentes, R. Badeau & G. Richard, "Blind harmonic adptive decomposition applied to supervised source separation", EUSIPCO 2012