



Joint f_0 and inharmonicity estimation using second order optimization

Henrik Hahn Axel Röbel

henrik.hahn@ircam.fr

IRCAM - CNRS - UMR 9912 - STMS, Paris, France

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Introduction

Proposed Method

A piano tessitura model for the inharmonicity coefficient

Results

Conclusions



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Target applications

- ▶ Partial tracking
- ▶ Pitch estimation
- ▶ A priori knowledge for synthesizers
- ▶ ...

What is the problem?

- ▶ Harmonics are not at ideal, but increased positions → **inharmonicity**
- ▶ Tracking of harmonics will fail, if inharmonicity is not taken into account

Where is the problem?

- ▶ plucked or striked strings only (Piano, Guitar, Harp, pizzicato violin, ...)



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- ▶ is defined by the inharmonicity coefficient β

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The harmonic series

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- ▶ Length, diameter, stiffness and tension of a string
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The inharmonic series (by Fletcher, 1964)

$$f_k = k \cdot f_0 \cdot \sqrt{1 + k^2 \beta} \quad k = 1 \dots K; \quad \beta > 0 \quad (1)$$



State of the Art

Existing Methods

- ▶ Inharmonic Comb Filters (ICF) [1]
- ▶ Median Adjustive Trajectories (MAT) [2]
- ▶ Non-negative Matrix Factorization with inharmonicity constraint (NMF) [3]

Drawbacks

- ▶ Estimation accuracy of ICF and MAT method is too low to track all relevant partials present in low pitched piano signals
- ▶ All methods show instabilities for low intensity signals or highly inharmonic signals.

- 1 "Signal Representation And Estimation Of Spectral Parameters By Inharmonic Comb Filters With Application To The Piano", Galembo A., Askenfelt A., IEEE, 1999
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Introduction

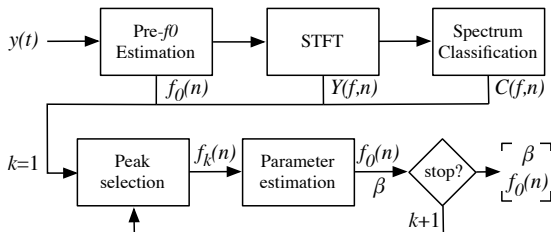
Proposed Method

A piano tessitura model for the inharmonicity coefficient

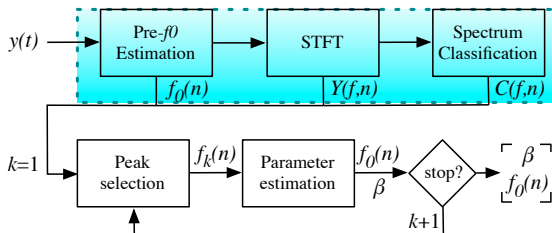
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Mode of Operation

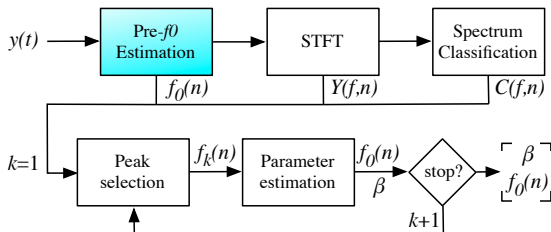


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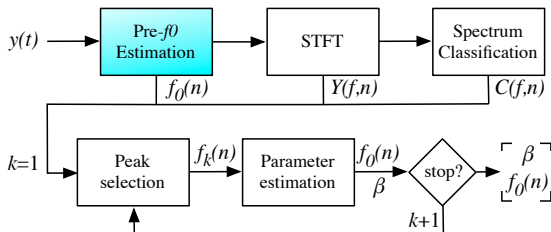
- Preprocessing:

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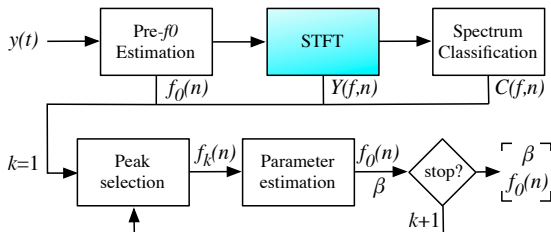
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- ▶ result is biased due to increased partial frequency positions

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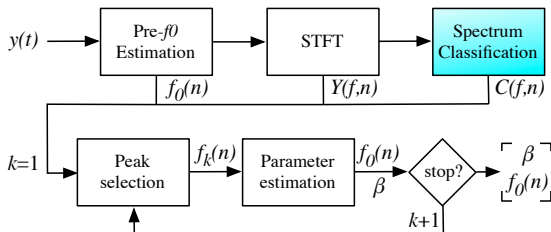
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- ▶ Preprocessing:
- ▶ STFT with adaptive frame and hopsizes based on previous estimate of f_0

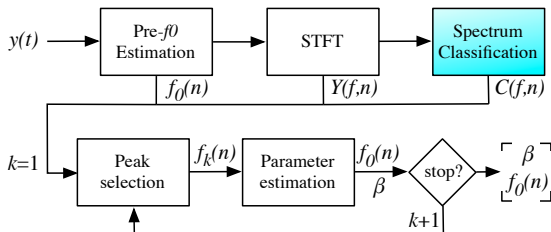
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- ▶ Preprocessing:
- ▶ Classification of each spectral bin into 3 classes: mainlobes, sidelobe, noise [4]
 - ▶ based on descriptors derived from time-frequency distributions

4 "A new approach to spectral peak classification", Miroslav Zivanovic et. al., EUSIPCO 2004

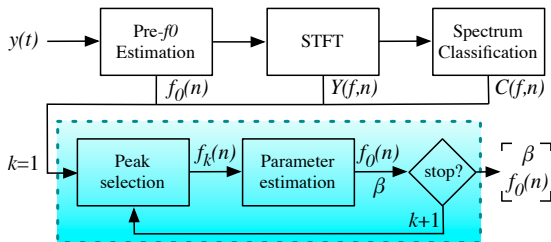
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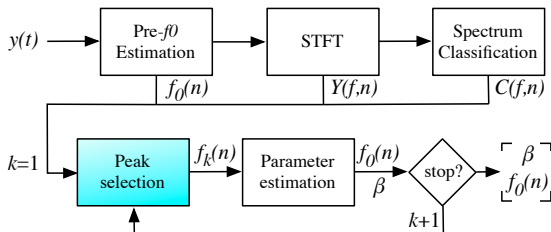
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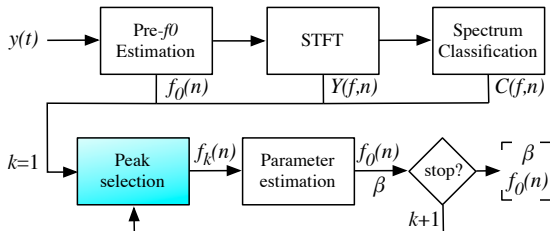
- Iteration [subset of frames, initial: f_0 and $\beta = 0$]:

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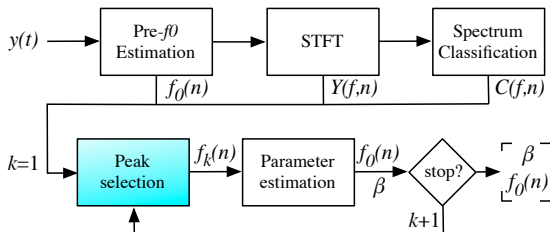
- ▶ Iteration [subset of frames, initial: f_0 and $\beta = 0$]:
- ▶ Estimate the current partials frequency position according to inharmonic series (1)
 - ▶ Select all main lobe peaks within a small band around the estimation position
 - ▶ If more than 2 peaks are found, apply a hann window amplitude weighting to select the strongest

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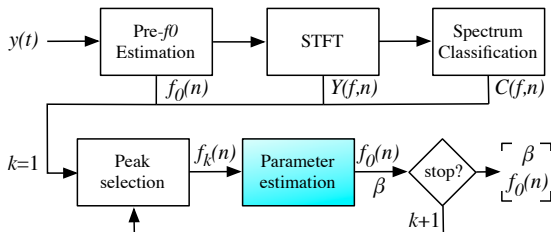
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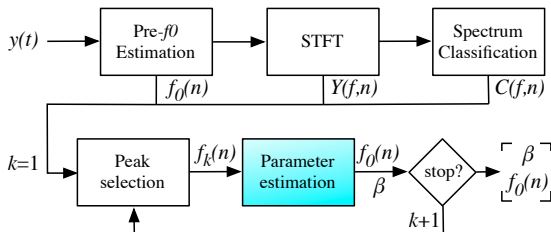


- ▶ Iteration [subset of frames, initial: f_0 and $\beta = 0$]:
- ▶ Least-Mean-Squares (LMS) adaptation of parameters β and f_0 in eq. (1) using a conjugate gradient descent approach [5]
- ▶ Yields revised estimates in each iteration as amount of data increases

5 "A scaled conjugate gradient algorithm for fast supervised learning", Martin F. Møller, Neural Networks, 1993

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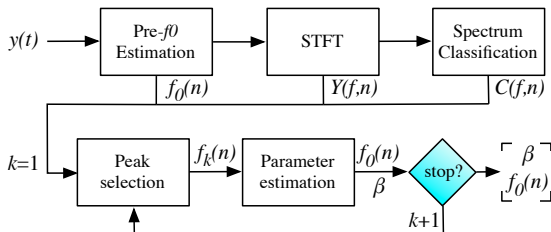


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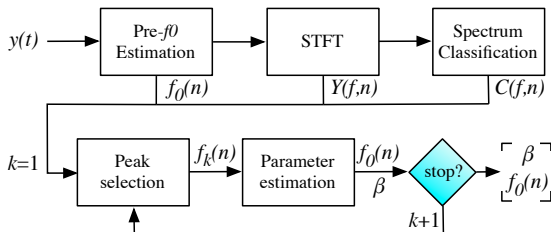
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- ▶ Iteration [subset of frames, initial: f_0 and $\beta = 0$]:
- ▶ Stop if next partial frequency would be above Nyquist
- ▶ Stop if no new valid partials have been found for more than 3 iterations

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A piano tessitura model for β

- ▶ To evaluate each algorithm on the whole tessitura of a grand piano
- ▶ Model is derived from physical considerations (bass and treble boards)
- ▶ Model is created using two linear asymptotes in log scale [3]:

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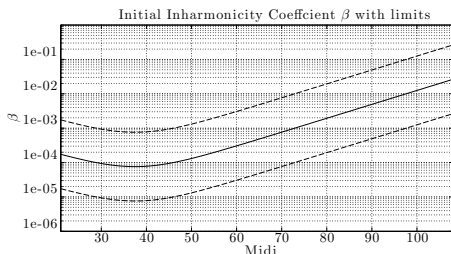
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- ▶ LMS adaptation of parameters $\phi_i, i = 1 \dots 4$ using conjugate gradient descent approach [5]
- ▶ Optimization finally yields a model with minimum variance σ^2 according to estimates of β
- ▶ These variances can be compared between algorithms for evaluation.
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- ▶ An artificial data set, created using the initial tessitura model of β
- ▶ Real world examples taken from RWC (3 pianos) [6] and IRCAM Solo Instruments (1 Piano, stereo)
- ▶ β and f_0 have been estimated for all pitches and intensities.
- ▶ Tessitura models of β have been created using the estimates for all sets and methods to obtain the variances of each method
- ▶ Our method will be denoted CG.

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Artificial sounds

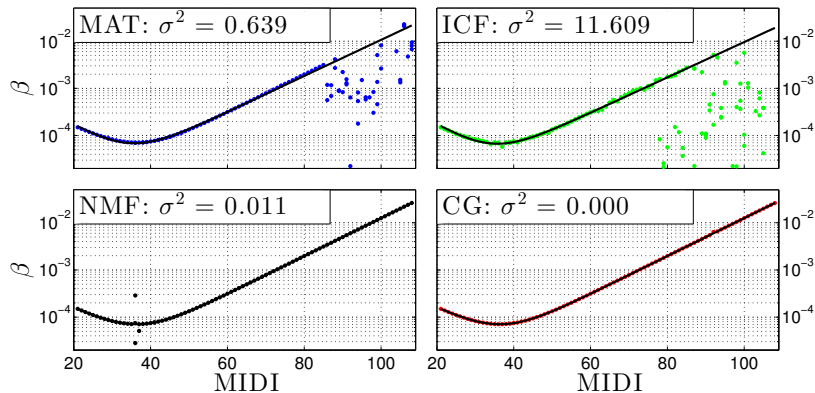


Figure: Artificial sounds

Piano sounds (RWC)

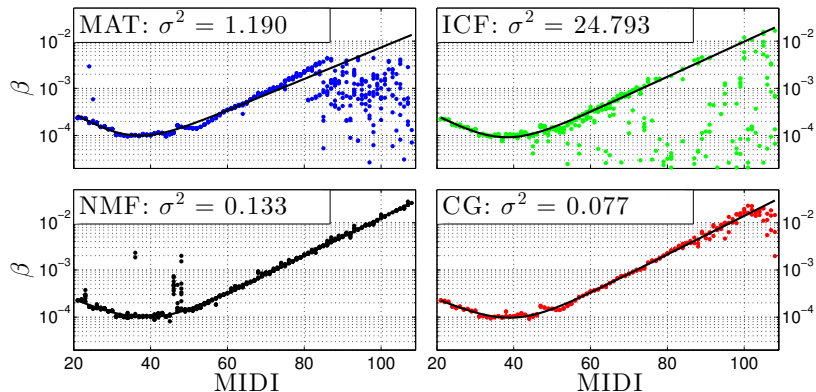


Figure: RWC piano 1

Piano sounds (RWC)

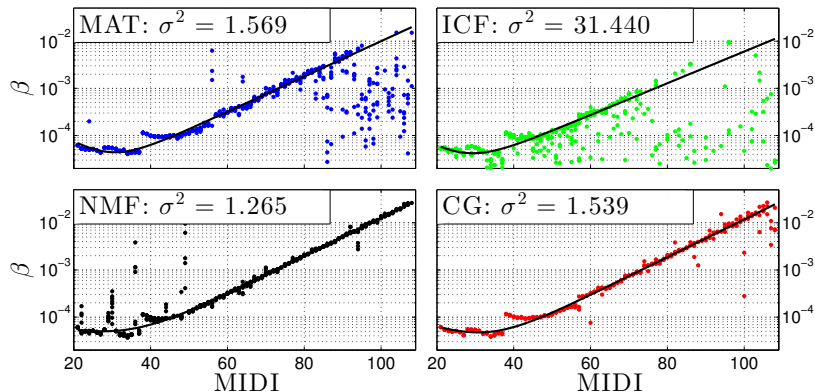


Figure: RWC piano 2

Piano sounds (RWC)

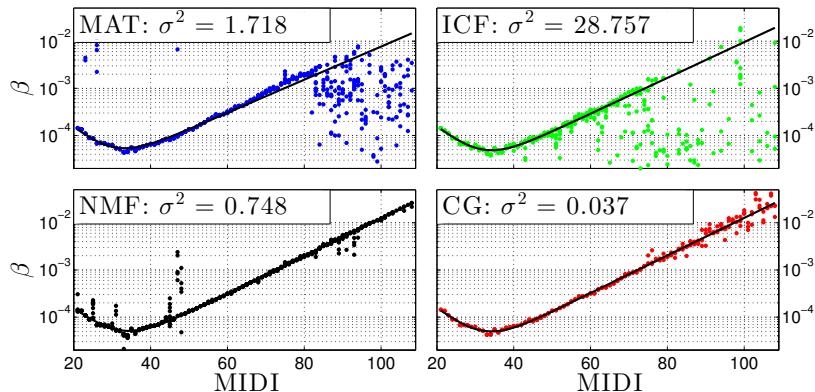
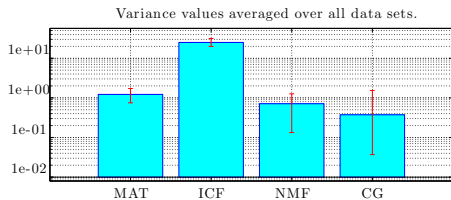


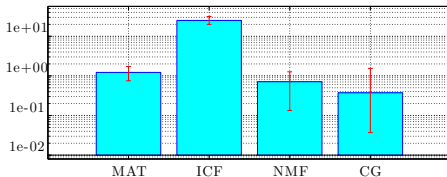
Figure: RWC piano 3

Piano sounds (RWC)

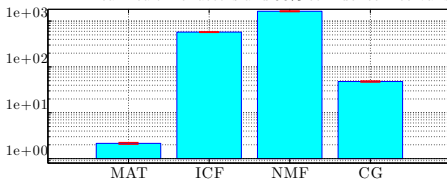


Piano sounds (RWC)

Variance values averaged over all data sets.



Mean realtime factors and 95% confidence intervals





Introduction

Proposed Method

A piano tessitura model for the inharmonicity coefficient

Results

Conclusions



Conclusions

We presented:

- ▶ A novel approach to jointly estimate f_0 and β
- ▶ A new adaptation technique for a tessitura model of β
- ▶ Results for several grand pianos.

We conclude:

- ▶ the proposed algorithm outperforms ICF and MAT methods
- ▶ the proposed algorithm has similar accuracy as the NMF based method, but
- ▶ outperforms NMF in terms of computational efficiency.



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Fin



Thanks for listening