Reducing F0 Frame Error of F0 Tracking Algorithms Under Noisy Conditions with an Unvoiced/Voiced Classification Frontend

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Noise Robust F0 Tracking

Motivation

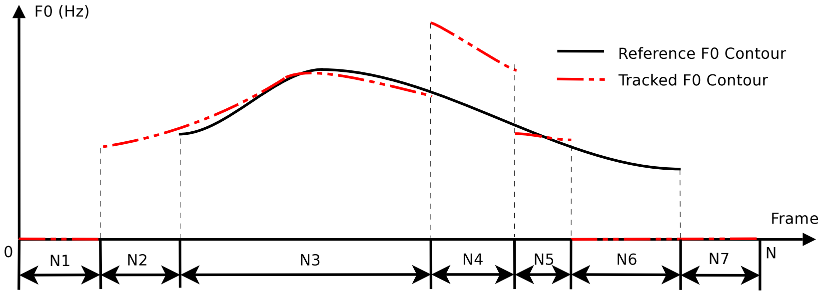
- Develop an error metric that provides a good assessment for F0 tracking algorithms
- Accuratley estimate and track F0 contours under noisy conditions.

Outline

- I. Error Metrics
- II. Statistically-based Unvoiced/Voiced Classifier
- III. Experimental Results and Analysis

I. Error Metrics

An Example of a Tracked and Reference F0 contour



3 possible types of error in any frame *i*

- Unvoiced → Voiced Error;
- Voiced → Unvoiced Error;
- F0 Value Estimation Error.

Current Error Metrics

Two error metrics are currently used:

Voicing Decision Error (VDE)) [NAI08]

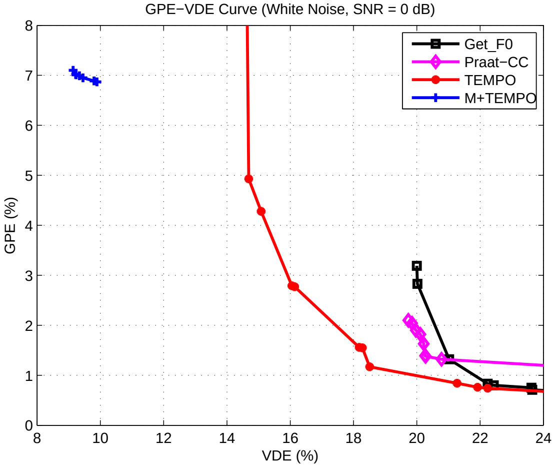
$$VDE = \frac{N_{V \to U} + N_{U \to V}}{N} \times 100\% \quad (1)$$

Gross Pitch Error (GPE) [RCR76]

$$GPE = \frac{N_{F0E}}{N_{VV}} \times 100\% \quad (2)$$

N_{VV}: # of frames which both the F0 tracker and the ground truth consider to be voiced;
N_{F0E}: # of frames for which $\left|\frac{F0_{i,estimated}}{F0_{i,reference}} - 1\right| > 20\%$

GPE-VDE Curve (M+: using U/V classifier output as a mask) in White Noise



A Metric That Combines Two Different Errors

F0 Frame Error (FFE)

$$\begin{aligned} FFE &= \frac{\#\text{ of error frames}}{\#\text{ of total frames}} \times 100\% \\ &= \frac{N_{U\to V} + N_{V\to U} + N_{F0E}}{N} \times 100\%. \end{aligned} \tag{3}$$

FFE is also a combination of GPE and VDE:

$$\begin{aligned} FFE &= \frac{N_{F0E}}{N} \times 100\% + \frac{N_{U\to V} + N_{V\to U}}{N} \times 100\%. \\ &= \frac{N_{VV}}{N} \times GPE + VDE \end{aligned} \tag{4}$$

Therefore, FFE takes both GPE and VDE into consideration.

Why FFE

Look at the Word Error Rate (WER) in ASR:

$$
\begin{aligned}
WER &= \frac{\text{\# of error words}}{\text{\# of total words}} \times 100\% \qquad (5)\\
&= \frac{\text{\# Insertions} + \text{\# Deletions} + \text{\# Substitutions}}{\text{\# All Words}} \times 100\%.
\end{aligned}
$$

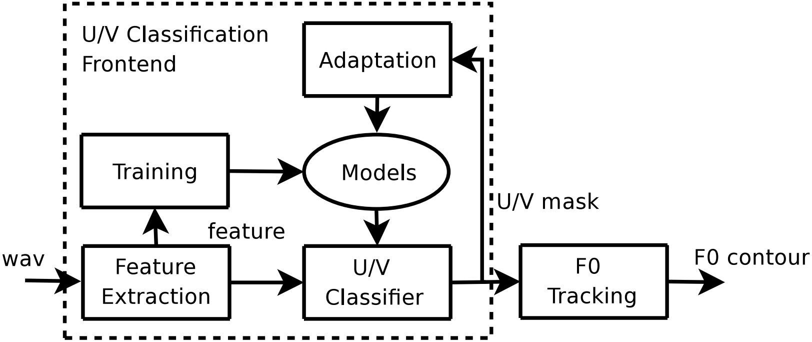
Analogy

- Unvoiced $\rightarrow$ Voiced Error $\Longleftrightarrow$ Insertion Error;
- Voiced $\rightarrow$ Unvoiced Error $\Longleftrightarrow$ Deletion Error;
- F0 Value Estimation Error $\Longleftrightarrow$ Substitution Error.

Thus, FFE in F0 tracking $\Longleftrightarrow$ WER in ASR.

II. Statistically-Based Unvoiced/Voiced Classification Frontend

Figure: 1. The flowchart of our statistically-based U/V classification frontend



Phoneme to Unvoiced/Voiced Dictionary

Table: 1. The mapping from Phonemes to Unvoiced and Voiced

	Stops	Affricates & Fricatives	Nasals & Vowels	Semivowels & Glides	Others
U	p(cl) t(cl) k(cl) bcl dcl gcl q	ch s f th sh	-	hh	epi h pau
V	b d g dx	jh z v zh dh	m n ng em en eng nx iy ih eh ey ae aa aw ay ah ao oy ow uh uw ux er ax ix axr ax-h	l r el w y hv	-

- Phone symbols are used in the TIMIT phone level transcription.
- Two acoustic models were trained: unvoiced(U) and voiced (V).
- The models are left-to-right HMMs

Data Set

For Training the U/V Models: TIMIT corpus

- Only the training data (4 hours) are used.

For Testing the F0 Tracking: KEELE corpus

- A simultaneous recording of speech and laryngograph signals for a phonetically-balanced text.
- The total length: 5 min 37 s, 5 male and 5 female speakers.

White and babble noise are artificially added to training and testing set, SNR = 0 dB

Adaptation to the Speaker Variance

Existing Mismatch

- Only American English corpus (TIMIT) is available for training the U/V models.
- The test set (KEELE) is a British English corpus.

Adaptively learn the distribution of 'Unseen data'!

Maximum Likelihood Linear Regression (MLLR) speaker adaptation [LW95]

A linear transformation $\mathbf{W}_s$ to all the mean vectors of the Gaussians:

$$\mu_s' = \mathbf{W}_s \mu_s \tag{6}$$

III. Experimental Results and Analysis

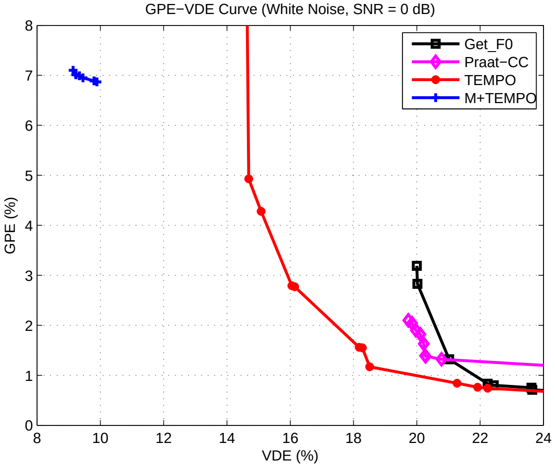
VDE of the U/V Classifier Using the KEELE Corpus

Table: 2. Error rates at SNR = 0 dB, **SI**: speaker independent models, **GSD/RSD**: global style/regression tree style adapted models. (error rates)

VDE	White Noise		Babble Noise	
	MFCC	ETSI	MFCC	ETSI
SI	11.57%	10.84%	30.70%	26.27%
GSD	10.98%	9.81%	27.61%	**22.48%**
RSD	**10.18%**	**9.14%**	**27.23%**	23.54%

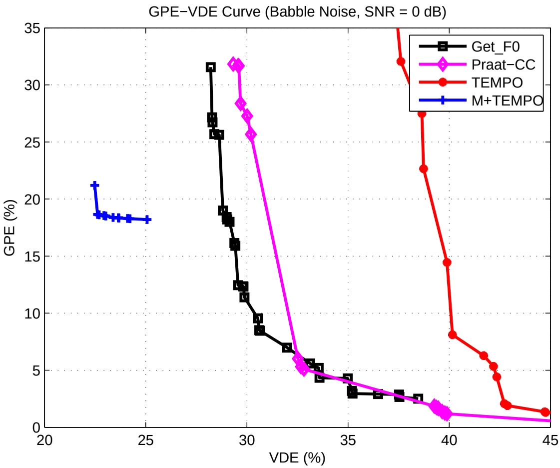
- MFCC: Mel-Frequency Cepstral Coefficients
- ETSI: feature output of the European Telecommunications Standard Institute (ETSI) advanced frontend.
  - before MFCCs extraction: two stage mel-warped Wiener filtering.
  - after MFCCs extraction: blind equalization.

GPE-VDE Curve (M+: using U/V classifier output as a mask) in White Noise



Experiments

GPE-VDE Curve (M+: using U/V classifier output as a mask) in Babble Noise



Analyze the GPE-VDE Curve

For every F0 tracker without the U/V mask, GPE $\searrow$ when VDE $\nearrow$. A possible explanation could be:

- If the VDE $\nearrow$, it may be because the F0 tracker only takes voiced frames with high SNR as voiced.
- Since it is easier to estimate the F0 value over a voiced frame with a higher SNR, the GPE $\searrow$.

Recall: GPE and VDE

$$GPE = \frac{N_{F0E}}{N_{VV}} \times 100\%, \qquad VDE = \frac{N_{V\to U} + N_{U\to V}}{N} \times 100\%$$

GPE, VDE and FFE for the KEELE Corpus Under Default Parameters

Table: 3. Error rates at SNR = 0 dB, **M+**: U/V mask provided by model-based classifier

	White Noise			Babble Noise		
	GPE	VDE	FFE	GPE	VDE	FFE
Get_F0	**0.59**%	35.95%	36.04%	18.89%	30.54%	35.15%
Praat	0.73%	30.77%	30.93%	27.36%	30.99%	38.70%
TEMPO	1.49%	21.92%	22.38%	**8.90%**	47.37%	47.89%
M+TEMPO	6.99%	**9.34%**	**12.64%**	21.19%	**22.48%**	**30.86%**

GPE, VDE and FFE for the KEELE Corpus

Table: 4. SNR = 0 dB, **M+**: U/V mask provided by model-based classifier, **min VDE/FFE**: when VDE/FFE is minimized. (error rates)

		White Noise			Babble Noise		
		GPE	VDE	FFE	GPE	VDE	FFE
Get_F0	min VDE	3.19%	20.00%	21.04%	31.56%	28.21%	37.58%
	min FFE	2.83%	20.02%	20.94%	8.51%	30.65%	32.79%
Praat	min VDE	**2.10%**	19.72%	20.41%	31.82%	29.32%	38.69%
	min FFE	**2.10%**	19.72%	20.41%	**5.31**%	32.67%	33.86%
TEMPO	min VDE	15.87%	14.52%	20.59%	58.05%	36.51%	50.35%
	min FFE	4.93%	14.69%	16.56%	8.11%	40.16%	41.24%
M+TEMPO	min VDE	7.10%	**9.14%**	**12.52%**	18.65%	**22.48%**	**29.86%**
	min FFE	7.10%	**9.14%**	**12.52%**	18.65%	**22.48%**	**29.86%**

Integrating our model-based U/V classifier into an F0-tracking algorithm can improve its FFE and VDE.

Summary

- The F0 Frame Error (FFE) and GPE-VDE curve can be used to evaluate the F0 tracking algorithms in a unified framework.
- The model-based U/V classifier can output robust U/V masks for F0 trackers under both white and babble noise conditions which is helpful for reducing the overall FFE.

Future Work

- Better features for U/V classification to improve VDE.
- Explore noise robust F0 value estimation methods to reduce GPE.

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Q & A?

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