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Parameters Automation of Dynamic Range Compressor

Literature Review - Project Work

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Outline

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Outline

- Introduction
- Theory
- Automation
- Approach 1
- Approach 2
- Discussions
- Conclusion

Introduction

Dynamic Range Compressor

Dynamic range of a signal is defined as the logarithmic ratio of maximum to minimum amplitude of a signal and is expressed in dB.

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Motivation:

- Project work involved building DRC application
- Application accepts static set of parameters
- Adapting parameters to signal dynamics gives better results
- Compressor with automated parameters is better approximation

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Theory
Block Diagram

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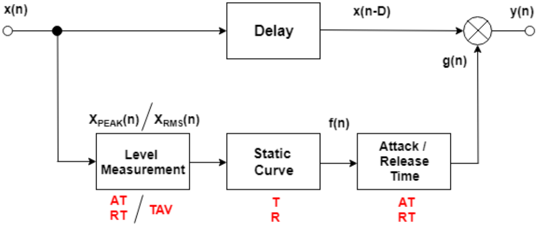
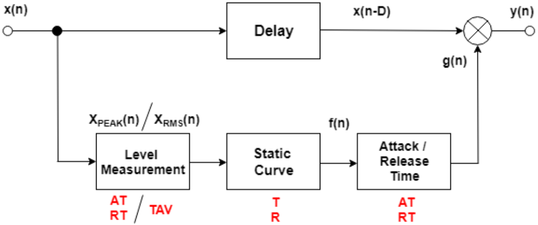


The figure above represents a basic Dynamic Range Compressor system.

Theory
Block Diagram



The figure above represents a basic Dynamic Range Compressor system.

$$y(n) = x(n - D) \cdot g(n) \quad (1)$$

Theory
Parameters for Automation

- Threshold (T)

Parameters for Automation

- Threshold (T)
- Ratio (R)

Theory

Parameters for Automation

- Threshold (T)
- Ratio (R)
- Knee Width (W)

Theory
Parameters for Automation

- Threshold (T)
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- Attack Time (τ_A)

Parameters for Automation

- Threshold (T)
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Theory

Parameters for Automation

- Threshold (T)
- Ratio (R)
- Knee Width (W)
- Attack Time (τ_A)
- Release Time (τ_R)
- Make-up Gain (g)

Outline

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- Theory
- **Automation**
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- Approach 2
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Automation

Goals and Approaches

- Based on signal

Automation
Goals and Approaches

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- Based on signal
  - Calculate signal metrics

Automation

Goals and Approaches

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Automation

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  - Extract audio features from reference audio

Automation

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  - Map features to effect Compressor parameters
  - Process target audio with estimated parameters for similar effect
  - Music similarity measure between reference and processed audio

Outline

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Approach 1

Attack and Release Times

- **Crest Factor Method:**

Approach 1
Attack and Release Times

- **Crest Factor Method:**
  - Ratio of Peak to RMS signal level

Approach 1

Attack and Release Times

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Approach 1
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$$y_C[n] = y_{PEAK}[n]/y_{RMS}[n] \tag{2}$$

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$$y_C[n] = y_{PEAK}[n]/y_{RMS}[n] \tag{2}$$

$$\tau_A[n] = 2 \cdot \tau_{Amax}[n]/y_C^2[n] \tag{3}$$

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$$\tau_R[n] = 2 \cdot \tau_{Rmax}[n]/y_C^2[n] - \tau_A[n] \tag{4}$$

Approach 1

Attack and Release Times (contd..)

- **Spectral Flux Method:**

Approach 1

Attack and Release Times (contd..)

- **Spectral Flux Method:**
  - Rapidity in change of power spectrum of signal

Approach 1
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Approach 1

Attack and Release Times (contd..)

- **Spectral Flux Method:**
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Approach 1
Attack and Release Times (contd..)

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- **Spectral Flux Method:**
  - Rapidity in change of power spectrum of signal
  - Low for steady state signal
  - High for signal with transients
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  - **Calculation:**

$$SF(n) = \frac{\sum_{k=-N/2}^{N/2-1} H(|X(n,k)| - |X(n-1,k)|)}{\sum_{k=-N/2}^{N/2-1} |X(n,k)|} \tag{5}$$

Approach 1

Attack and Release Times (contd..)

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$$SF_{smooth}[n] = max(x[n], \alpha \cdot SF_{smooth}[n-1] + (1-\alpha) \cdot SF[n]) \quad (6)$$

Approach 1
Attack and Release Times (contd..)

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$$\tau_R[n] = 2 \cdot \tau_{Rmax}[n] / SF_{smooth}^{\gamma}[n] - \tau_A[n] \quad (8)$$

Approach 1

Attack and Release Times - Evaluation

- Subjective evaluation based on human preference of parameters

Approach 1

Attack and Release Times - Evaluation

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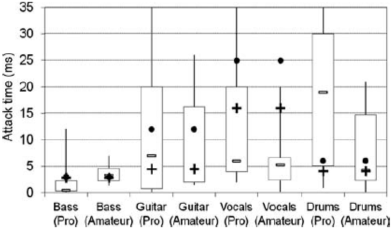

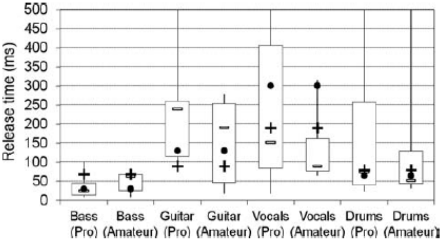

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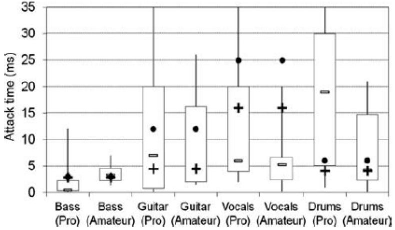

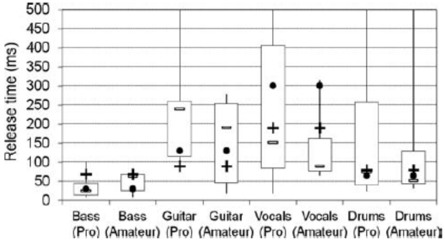

(−) Median value of response
(•) Crest Factor Automation
(+) Spectral Flux Automation

Approach 1
Threshold and Ratio

- **Threshold:**

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Threshold and Ratio

- **Threshold:**
  - Defines desired compression

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Threshold and Ratio

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Approach 1
Threshold and Ratio

- **Threshold:**
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- **Ratio:**
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  - Soft Knee with variable width equivalent to automatic ratio

Approach 1
Knee Width

- **Basic Method:** Bases on gain reduction of input signal

Approach 1
Knee Width

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$$g_{Dev}[n] = \alpha \cdot g_{Dev}[n-1] + (1-\alpha) \cdot (g[n] - g_{Est}) \tag{9}$$

Approach 1
Knee Width

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Approach 1

Knee Width

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$$W[n] = 2.5\cdot g_{Avg}^{k}[n] \tag{13}$$

$$k = \begin{cases} 0.6, & SF_{min,avg} > 0.1 \\ 0.05, & SF_{min,avg} <= 0.1 \end{cases} \tag{14}$$

Approach 1

Knee Width - Evaluation

- Subjective evaluation based on human preference of parameters

Approach 1

Knee Width - Evaluation

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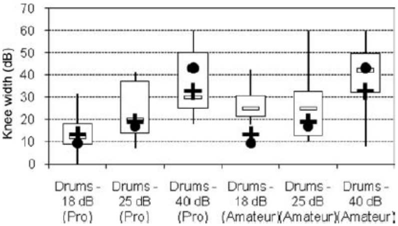

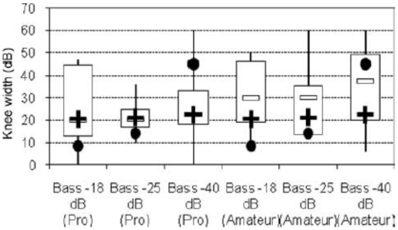

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Knee Width - Evaluation

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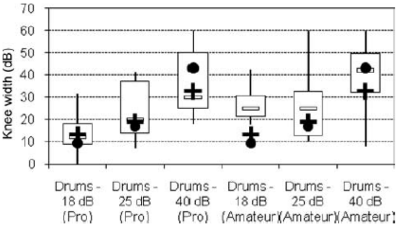

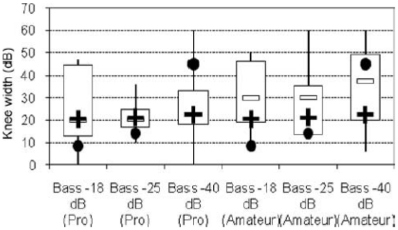

(−) Median value of response
(•) Gain Reduction Dependent Automation
(+) Signal Information Dependent Automation

Approach 1
Make-up Gain

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- **Compression based Method:**

Approach 1
Make-up Gain

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Make-up Gain

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Approach 1
Make-up Gain

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- **Loudness based Method:**
  - Compares perceived loudness before and after compression
  - Calculates make-up gain from loudness difference

Approach 1
Make-up Gain - Evaluation

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- Subjective evaluation based on human preference of parameters

Approach 1
Make-up Gain - Evaluation

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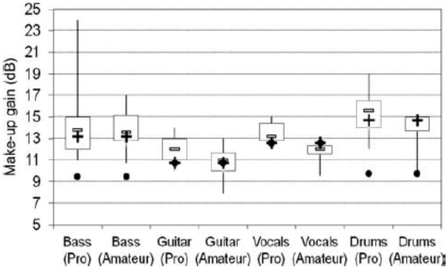

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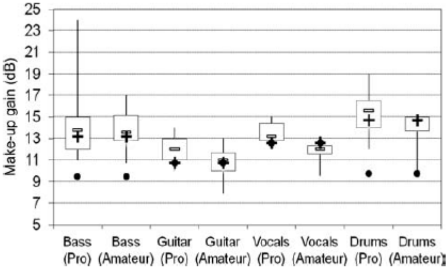

(–) Median value of response
(•) Compression based Automation
(+) Loudness based Automation

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Approach 2

Audio Features Extraction

$$SC_{mean} = E[\frac{\sum_{k=0}^{K-1} k \cdot Y(n,k)}{\sum_{k=0}^{K-1} Y(n,k)}], Y(n,k) = |X(n,k)| \tag{16}$$

Approach 2
Audio Features Extraction

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Approach 2
Audio Features Extraction

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$$SV_{mean} = E[\sqrt{E[Y(n,k)^2] - (E[Y(n,k)])^2}] \quad (18)$$

Approach 2
Audio Features Extraction

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$$RMS_{mean} = E[\sqrt{\frac{1}{M} \cdot \sum_{m=0}^{M-1} x(m)^2}] \tag{20}$$

Approach 2
Audio Features Extraction

$$SC_{mean} = E[\frac{\sum_{k=0}^{K-1} k \cdot Y(n,k)}{\sum_{k=0}^{K-1} Y(n,k)}], Y(n,k) = |X(n,k)| \tag{16}$$

$$SC_{var} = Var[\frac{\sum_{k=0}^{K-1} k \cdot Y(n,k)}{\sum_{k=0}^{K-1} Y(n,k)}] \tag{17}$$

$$SV_{mean} = E[\sqrt{E[Y(n,k)^2] - (E[Y(n,k)])^2}] \tag{18}$$

$$SV_{var} = Var[\sqrt{E[Y(n,k)^2] - (E[Y(n,k)])^2}] \tag{19}$$

$$RMS_{mean} = E[\sqrt{\frac{1}{M} \cdot \sum_{m=0}^{M-1} x(m)^2}] \tag{20}$$

$$RMS_{var} = Var[\sqrt{\frac{1}{M} \cdot \sum_{m=0}^{M-1} x(m)^2}] \tag{21}$$

Approach 2

Regression Model - Training

- **Training Data:** Violin Samples (RWC isolated note database)

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Training sets (size)	Conditions			
	Thr(dB)	Ratio	Att(ms)	Rel(ms)
A (60*50)	0:1:49	2	5	200
B (60*50)	37.5	1:0.4:20	5	200
C (60*100)	37.5	2	1:1:100	200
D (60*100)	37.5	2	5	50:10:1000

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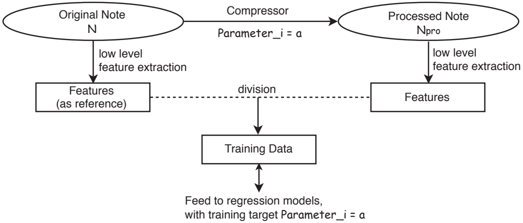
- **Training Data Generation:**



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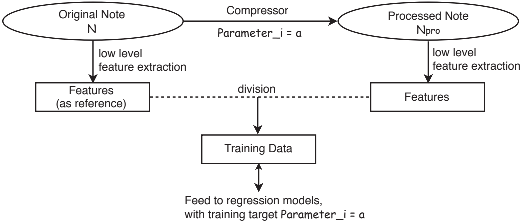

- **Regression Models:** Linear and Random Forest Regression

Approach 2
Automation Process

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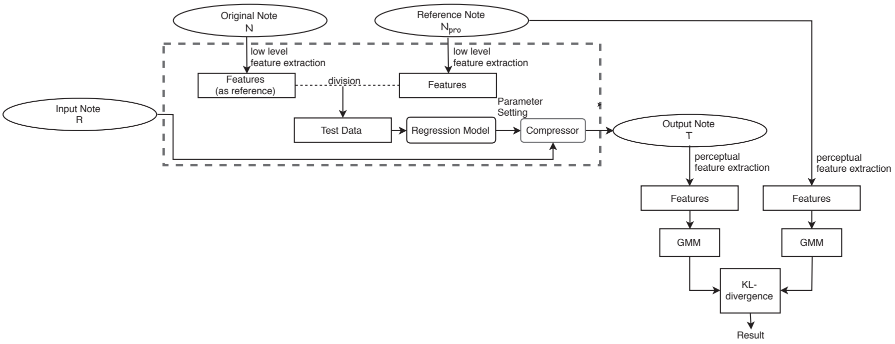

Approach 2
Similarity Measure

- **Crest Factor Difference:**

Approach 2

Similarity Measure

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Approach 2
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Violin	Threshold	Ratio	Attack	Release
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$D_{Crest}(N_{pro}, T)_{LR}$	**12.53**	39.72	46.76	48.62
$D_{Crest}(N_{pro}, T)_{RF}$	15.27	**38.24**	**45.23**	**47.19**

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Approach 2
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Violin	Threshold	Ratio	Attack	Release
$D(N_{pro}, R)$	38.122	53.187	44.018	55.206
$D(N_{pro}, T)_{LR}$	19.799	20.911	22.852	20.994
$D(N_{pro}, T)_{RF}$	**19.742**	**20.856**	**22.213**	**20.807**

Outline

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Discussions

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Comp	Fast Attack	Slow Attack	Fast Release	Slow Release
EDM	0.38	0.62	0.65	0.35
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- **Deduction:**
  - Different preference of Attack and Release across different styles
  - Machine Learning approach can make use of this information

Outline

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- Better results with approaches using Spectral Flux, SF based Optimization and Loudness

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- Better results with approaches using Spectral Flux, SF based Optimization and Loudness
- Better results with Random Forest Regression

Conclusion

Summary

- Better results with approaches using Spectral Flux, SF based Optimization and Loudness
- Better results with Random Forest Regression
- Variation of preference of ballistics across styles

Conclusion
Future Work

- Include additional audio features mentioned in Approach 1 to train Regression Model in Approach 2 for better results

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- Include human preference information for parameters across different styles while training Regression Model
- Evaluation on more complex tracks

1. Dimitrios Giannoulis, Michael Massberg, Joshua D. Reiss, "Parameter automation in a dynamic range compressor", J. Audio Eng. Soc., Vol. 61, No. 10, October 2013
2. Di Sheng, György Fazekas ,"Automatic control of the dynamic range compressor using a regression model and a reference sound", Proceedings of the 20th International Conference on Digital Audio Effects (DAFx-17), Edinburgh, UK, September 5-9, 2017
3. Gary Bromham, David Moffat, Mathieu Barthet, György Fazekas ,"The impact of compressor ballistics on the perceived style of music", Audio Engineering Society, Convention Paper 10080, presented at the 145th Convention New York, NY, USA, October 17-20, 2018

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Thanks for your time

Any Question or Suggestion?