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## using Teager based DSCC features **Emotion Recognition from Speech**

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#### Outline

- Motivation
- Emotion Recognition Overview
- Proposed Feature Extraction Technique
- Proposed Feature Recognition Technique
- Conclusion
- References

# Why Emotion Recognition?

- help line Detecting frustration of callers to automated
- Computer tutorials via virtual avatars
- Lie detection
- **Humanoid Robots**

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### **Basic Emotions**

NEUTRAL



*FEAR* 

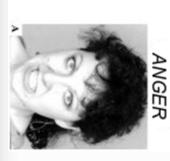
SADNESS











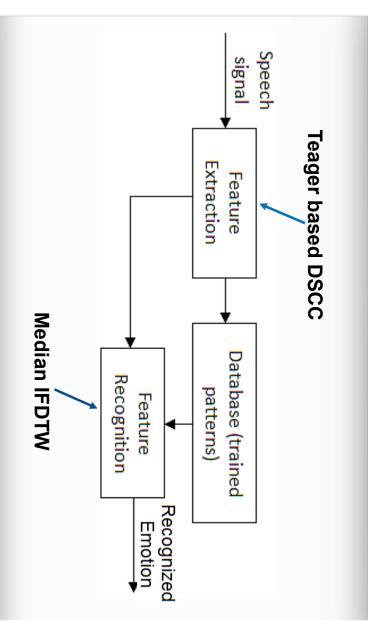
## Speech Database

- Berlin Emotional Database (EMO-DB) [1]
- Total 535 utterances:

- 70% used for training, 30% for testing
- Sampling frequency 16KHz
- 16-bit resolution, mono channel samples

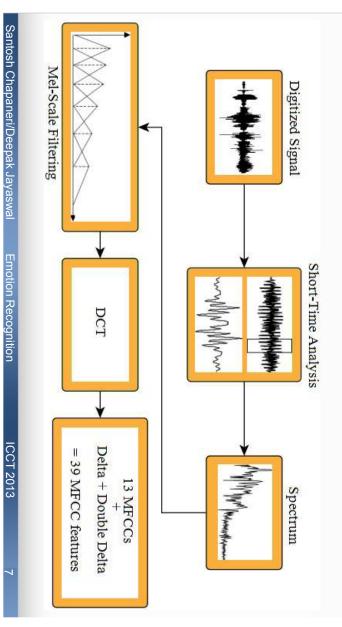
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# **Emotion Recognition Overview**



## Conventional MFCC

Computation of Mel Frequency Cepstral Coefficients [2]:

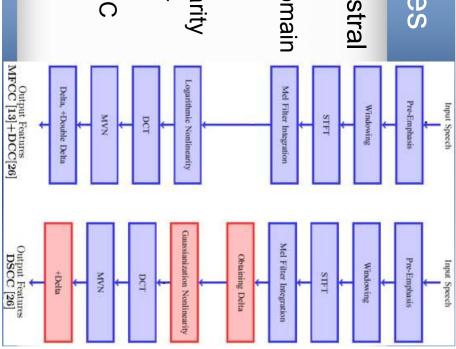


### DSCC Features

- Delta Spectral Cepstral Coefficients [3]
- Delta in spectral domain domain instead of cepstral
- Gaussian non-linearity instead of Log nonlinearity
- 2<sup>nd</sup> Delta over DSCC features instead of MFCC

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Output Features MFCC [13]+DCC[26]



# Teager Energy Operator (TEO)

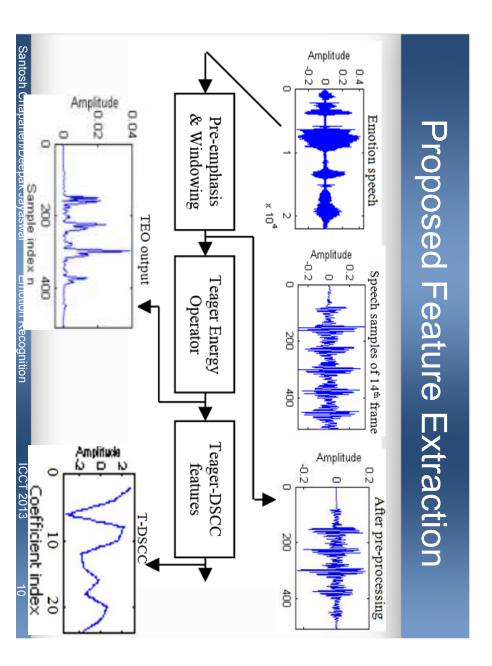
- Non-linear energy tracking operator
- Useful mathematical model of vocal tract

$$\psi\left[x(n)\right] = x^{2}(n) - x(n+1)x(n-1)$$

$$y(x(n)) = x^{2}(n) - x^{2}(n) - x^{2}(n)$$

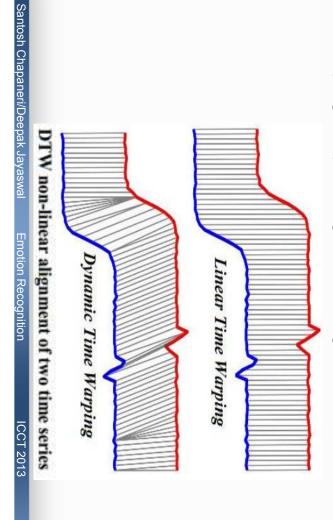
$$y(x(n)) = x^{2}(n) - x^{2}(n) - x^{2}(n)$$

$$y(x(n)) = x^{2}(n)$$



## Feature Recognition

- Dynamic Time Warping (DTW)
- Warping expanding/contracting the time dimension



### DTW Algorithm

- Popular algorithm for automatic speech recognition based on template matching
- Dynamic programming approach based on Bellman's optimality principle
- Solutions to slightly smaller problems used to find larger solutions

#### DTW Variants

- feature values DTW ignores temporal relationship between
- Derivative DTW (DDTW) [4]
- Improved Features for DTW (IFDTW) [5]
- Fast DTW [6] to reduce computations from  $O(N^2)$  to O(N)

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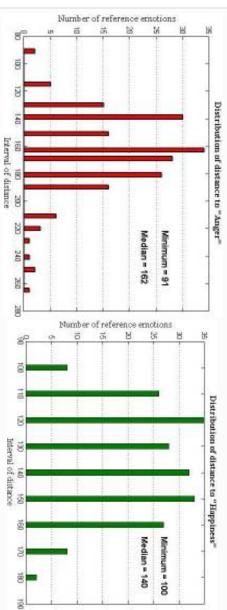
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# Proposed Feature Recognition

reference emotions "Anger" & "Happiness" Distribution of distances between test emotion "Happiness" to



- Median found to be accurate compared to Minimum distance
- Proposed Feature Recognition: Median Filtered IFDTW

## Experimental Results

- Clean speech + Speech under 10 dB Gaussian noise
- 161 utterances for testing against 374 trained samples

## Overall Recognition Accuracy (%)

	#Features	DTW	IFDTW	Median IFDTW
MFCC + $\Delta + \Delta \Delta$	39	84.52	87.39	91.29
DSCC	26	93.82	95.14	96.73
T-DSCC	26	94.18	95.69	97.52

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## **Experimental Results**

## Confusion Matrix (23 utterances/emotion)

(A: Anger, B: Boredom, D: Disgust, F: Fear, H: Happiness, S: Sadness, N: Neutral)

N	S	Н	F	D	В	Α	
0	0	0	0	0	0	23	Α
1	1	0	0	0	23	0	В
0	0	0	0	22	0	0	D
0	1	0	23	0	0	0	F
0	0	23	0	0	0	0	Н
0	21	0	0	0	0	0	S
22	0	0	0	1	0	0	Z

#### Conclusion

- to noise in input speech signal Proposed Teager-DSCC features are robust
- accurate classification of test emotion Proposed Median Filtered IFDTW gives
- to existing systems Overall recognition accuracy higher compared
- Future scope:
- Indian native speech
- App for Aakash tablets

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#### Thank You

#### References