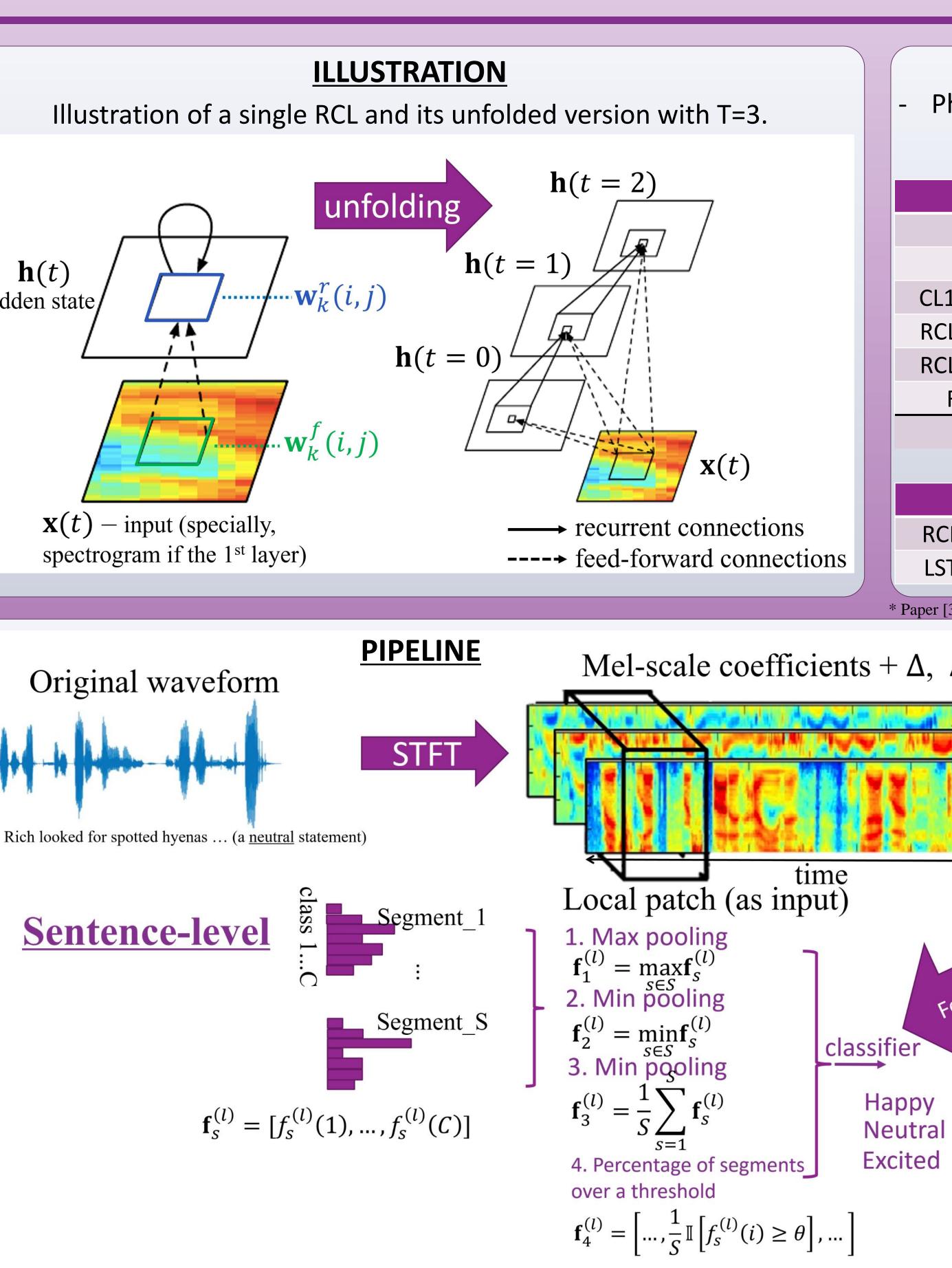


# **RECURRENT CONVOLUTIONAL NEURAL NETWORKS FOR SPEECH PROCESSING**

Department of Electronic Engineering, TNList, Tsinghua University, Beijing, 100084, China

### MOTIVATION Existing CNN and RNN have specific disadvantages. - CNN has not exhibited significant improvement in speech processing. RNN is expected to function well in modeling $\mathbf{h}(t)$ sequential, but is harder to train efficiently. hidden state/ A new architecture of Recurrent Convolutional Neural Network (RCNN) [1, 2] works well in object recognition and scene labeling. In view of the embedded RNN structure, RCNN is expected to function well in modeling speech, a typical temporally sequential data. FORMULATION Conventional RNN: (neglecting bias term) $\mathbf{h}(t) = \sigma \big( W_{xh} \mathbf{x}(t) + W_{hh} \mathbf{h}(t-1) \big)$ $(\mathbf{x}(t))$ : feed-forward input, $\mathbf{h}(t)$ : hidden state at time t) Recurrent Convolutional Layer (RCL): $\mathbf{h}^{(t)}(i,j)$ i'=s j'=s $W_k^f(i',j') \mathbf{x}^{(t)}(i-i',j-j')$ $= \sigma$ i'=-s j'=-si'=s'j'=s' $W_k^{r}(i',j') \mathbf{h}^{(t-1)}(i-i',j-j')$ $i' = -s' \quad j' = -s$ $(W_k^J: k^{th} feedforward kernel, W_k^r: k^{th} recurrent kernel)$ Nonlinearity $\sigma(x) = f_{bn}(g(x))$ is realized by Rectified Linear (ReLU) $g(x) = \max(x, 0)$ and batch normalization $f_{bn}(x_i; \gamma, \beta)$ . "time step" (t) in RCL: a RCL processes information from neighboring *time slots* and frequency banks at each iteration.

## Yue Zhao, Xingyu Jin



### Xiaolin Hu

Department of Computer Science and Technology, TNList, Tsinghua University, Beijing, 100084, China

				_					
<u>RESULTS</u>					<u>RESULTS</u>				
Phoneme recognition on TIMIT									
- Unfolding more times yields lower PER but there is a limit.					- Emotion recognition on IEMOCAP				
- Outperform most ANN-HMM models. Competitive to existing methods. (More in paper)					- Spectral features, relatively lower-level feature than MFCC, can achieve competitive, even better results.				
		PER (dev set)	PER (core test set)			Framewise	Weighted	Unweighte	
	4-layer MLP	19.9%	22.0%			accuracy	accuracy	d accuracy	
	pooling + 3-layer MLP	18.4%	20.0%		3-layer MLP	41.4%	48.5%	39.9%	
	2 + pooling + 3-layer MLP	19.2%	20.5%		CL+2-layer MLP	43.1%	53.4%	41.6%	
-	) + pooling + 3-layer MLP	18.3%	20.3%		-				
-	) + pooling + 3-layer MLP	17.3%	19.2%		RCL+2-layer MLP	43.5%	53.6%	42.8%	
RCL(T=2) + CL + 3-layer MLP		17.0%	18.0%	-	(MFCC+pitch) MLP+SVM [4]	-	~50%	~45%	
3-layer LSTM + HMM [3]* 17.7% 18.8% - The speed of RCNN is faster than LSTM module, both when training and decoding.				Log Spec(+PCA	_	_	35.98%		
	train train			whitening)+CNN [5]			(40.02%)		
RCNN	2012 samples per seco	nd 1.721 utte	erances per second						
LSTM	275 samples per second 0.944 utterances per second				CONCLUSIONS				
er [3] works on another dataset. We borrow the structure for comparison of speed. Parameters may not be perfectly tuned.					- Propose to use RCNN originally from computer				
					vision to speech processing.				
, $\Delta\Delta$ <u>Segment-level</u>									
					- RCNN achieves competitive results with existing				
$f_{c} = f_{c} = f_{c$					models. Also, it runs faster than LSTM networks.				
					<ul> <li>Inspire more generic and efficient cross-modal</li> </ul>				
$\int \text{frequency} \left[ \begin{array}{c} 1 \\ 1 \\ \text{RCL} \end{array} \right] \left[ \begin{array}{c} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 $					deep learning models in the future.				
	* Multiple RCLs can be stacked				<b>REFERENCES</b> [1] M. Liang and X. Hu. Recurrent convolutional neural network for object recognition. CVPR 2015. [2] M. Liang, X. Hu, and B. Zhang. Convolutional neural networks with intra-layer recurrent connections for scene labeling. NIPS 2015.				
** Nonlinearity and pooling is omitted for simplicity									
Feature	e.g., pooling				[3] Y. Zhang, G. Chen, D. Yu, K. Yaco, S. Khudanpur, and J. Glass. Highway long short-				
					term memory RNNs for distant speech recognition. ICASSP 2016. [4] K. Han, D. Yu, and I. Tashev. Speech emotion recognition using deep neural				
					network and extreme learning machine. INTERSPEECH 2014.				
/ × al √					[5] W. Zheng, J. Yu, and Y. Zou. An experimental study of speech emotion recognition based on deep convolutional neural networks. In International Conference on				
d X	XXXX				Affective Computing and Intelligent Interaction (ACII), pages 827–831. IEEE, 2015				
					SOURCE CODES				
	h# r - ih - tcl ch - epi				The source codes can be downloaded at: <u>https://github.com/zhaoyue-</u> <u>zephyrus/RecurrentConvNet-for-Speech</u>				
11# 1 - 111 - ttt tti - epi					Contact: Yue Zhao, <u>thuzhaoyue@gmail.com</u>				