EXPLORING SPARSE REPRESENTATION FOR IMPROVED ONLINE HANDWRITING RECOGNITION

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INTRODUCTION

Variabilities in Online Handwriting:

- Writing style variations among individuals.
- Stroke order and stroke direction variability.

Existing Approaches:

- Allograph modeling: Build model for each Allograph.
- Hidden Markov Model (HMM), Support Vector Machine (SVM).

Shortcoming of Existing Approaches:

- Added Complexity due to Allograph.
- Smoothing effect in HMM.
- A subset of training sample is selected in SVM.

Advantage of Sparse Representation (SR):

- Can accommodate all diverse training samples in the dictionary.
- Can adopt the support adaptively for each test sample.
- Lower decoding complexity compare to HMM and SVM.

OBJECTIVES

1. Development of SRC-based HR approach for character and limited vocabulary word recognition tasks.
2. Exploration of exemplar and learned exemplar dictionaries for online HR.
3. Sparse codding based on l_0- and l_1- norm minimization.

SPARSE REPRESENTATION

• Given: $\mathcal{D}\mathbf{z} = \mathbf{x}$, $\mathcal{D} \in \mathbb{R}^{M\times N}$, $\mathbf{x} \in \mathbb{R}^M$ such that $M < N$. Find $\mathbf{z} \in \mathbb{R}^N$ as: $\min ||\mathbf{z}||_0$ subject to $||\mathcal{D}\mathbf{z} - \mathbf{x}||_2 < \epsilon$. $\mathcal{D}$ is *dictionary*, $\mathbf{x}$ is the *signal* and $\mathbf{z}$ is the *sparse vector*.

• Dictionary creation: Exemplar dictionary, learned exemplar dictionary using KSVD algorithm.

• Sparse codding algorithm: Orthogonal Matching Pursuit (OMP), Least Angle Regression (LARS).

PROPOSED SRC-BASED HANDWRITING RECOGNITION SYSTEM

Preprocessing: $\{(x_1, y_1), (x_2, y_2), ..., (x_i, y_i), ..., (x_q, y_q)\}$. **Features:** (x, y) and its first/second derivatives, writing direction, curvature, aspect ratio, linearity, slope, context map.

Exemplar and learned exemplar dictionaries: • C classes and n_j training samples for each class. • A set of M-dim. supervectors are extracted from the training samples. A matrix $\mathcal{D}_j$ is created using the supervectors of the j^{th} class as its columns. • Exemplar dict. $\mathcal{D} = [\mathcal{D}_1 \mid \mathcal{D}_2 \mid \ldots \mid \mathcal{D}_j \mid \ldots \mid \mathcal{D}_C] \in \mathbb{R}^{M\times N}$, $N = n_1 + n_2 + ... + n_C$. • A learned dict. $\mathcal{D}_L \in \mathbb{R}^{M\times P}$ is also derived using K-SVD on $\mathcal{D}_j$.

Classification process: Test supervector $\mathbf{x}_t$ is sparse coded over $\mathcal{D}$ and generate sparse vector $\mathbf{z}$. The $\mathbf{z}$ can be split using class labels as $(\beta_1, \ldots, \beta_C)$. Classification: $k = \underset{j\in[1,2,\ldots,C]}{\arg\min} ||\mathbf{x_t} - \mathbf{D}_j\, \boldsymbol{\beta}_j||_2$.

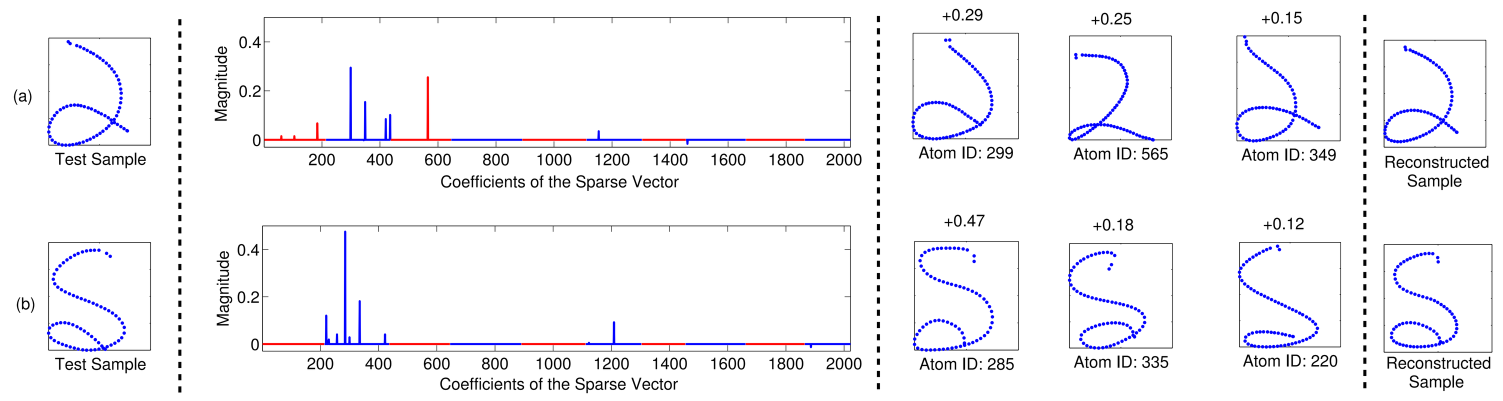

Figure 1: Illustration of sparse coding with 11 sparsity. (a) First panel represents a test sample, second panel shows the plot of the corresponding sparse vector (with red and blue colors marking the indices that correspond to different class labels and the atom IDs 214-436 correspond to the 'true' class of the test sample), the next three panels show the digit patterns corresponding to top three atoms (with weights shown on the top) in sparse coding, and the rightmost shows the reconstructed sample involving all 11 atoms. (b) Shows the same for another test sample.

RESULT AND DISCUSSION

Database	Task	# Class	# Samples
Assamese	Digit	10	3100
UNIPEN (English)	Digit	10	14638
	Uppercase	26	24639
	Lowercase	26	40847

Table 1: Samples in Assam. and UNIPEN databases.

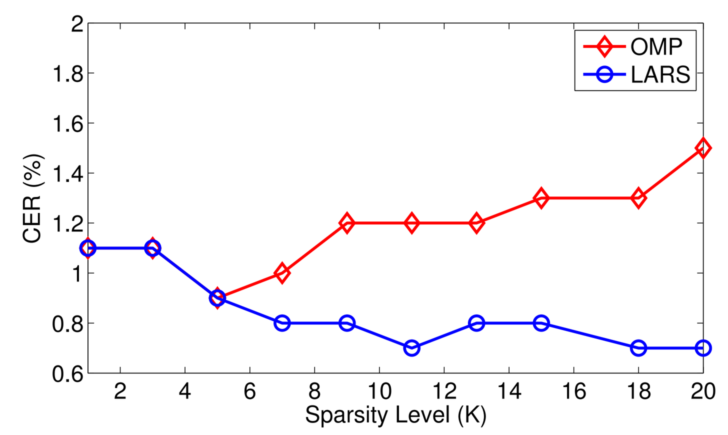

Figure 2: Tuning of the sparsity (K) for Assam. digit.

	K↓	Learned Dict. Size				Exemplar Dict.
		400	600	1000	1400	
CER	3	3.30	2.60	1.70	1.60	1.10
Run-time		2.7	3.3	5.7	7.7	10.1
CER	5	2.70	2.30	1.50	1.20	0.90
Run-time		3.4	4.4	8.0	11.2	14.1
CER	7	2.50	2.00	1.30	1.10	0.80
Run-time		4.4	5.4	10.5	14.5	18.7
CER	9	2.20	1.70	**1.10**	0.90	0.80
Run-time		5.4	6.7	**12.9**	18.8	24.7
CER	11	2.10	1.70	1.00	0.90	0.70
Run-time		6.4	7.7	15.7	24.4	31.0

Table 2: Tuning of the dictionary size and the sparsity value (K) in the case of SRC over learned dictionary based approach employing the LARS algorithm on Assamese digit recognition task.

Method			Assamese	English		
			Digit	Digit	Upper	Lower
SRC	Exmp. Dict.	OMP	1.05	1.48	4.28	6.17
		LARS	0.76	0.77	2.94	4.81
	Learn. Dict.	OMP	1.25	1.50	4.79	7.25
		LARS	1.01	1.09	3.49	5.12
SVM			0.69	1.18	3.15	5.11
HMM			1.12	1.07	3.76	6.90

Table 3: CER (in %) of the proposed SRC-based and the contrast HR systems for character recognition tasks.

Method	Digit	Upper	Lower
DTW [1]	2.90	7.20	9.30
OnSNT [2]	1.10	4.30	7.90
ANN [3]	0.80	3.10	5.10
LARS-SRC (this work)	**0.77**	**2.94**	**4.81**

Table 4: Performance comparison on UNIPEN dataset.

Method			Assamese	English		
			Digit	Digit	Upper	Lower
SRC	Exmp. Dict.	OMP	9.6	41.4	52.0	114.3
		LARS	29.0	123.1	164.9	324.0
	Learn. Dict.	OMP	3.2	8.3	24.9	45.8
		LARS	11.9	25.9	77.5	135.8
SVM			14.71	69.5	162.3	335.5
HMM			13.1	15.0	39.5	40.1

Table 5: Run-time (in millisecond) of proposed SRC-based as well as existing online HR approaches.

Method	WER
HMM [4]	16.69
SVM (our implementation)	16.20
OMP-SRC	21.34
LARS-SRC (this work)	**13.79**

Table 6: WER (in %) on limited vocabulary word recognition task on UNIPEN ICROW-03 database.

FUTURE RESEARCH

• The advanced dictionary learning techniques such as label consistent and block K-SVD algorithms can be explored for online handwriting recognition.

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