Efficient Neural Network Approximation of Robust PCA for Automated Analysis of Calcium Imaging Data

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TL; DR: We introduce computationally efficient, scalable, and differentiable implementation of RPCA.

Motivation

- Robust Principal Component Analysis (RPCA) separates the background and foreground from data.
- Conventional algorithms are slow or not scalable for large data.
- **BEAR** is **FAST**, **SCALABLE**, and **DIFFERENTIABLE**.

Robust Principal Component Analysis

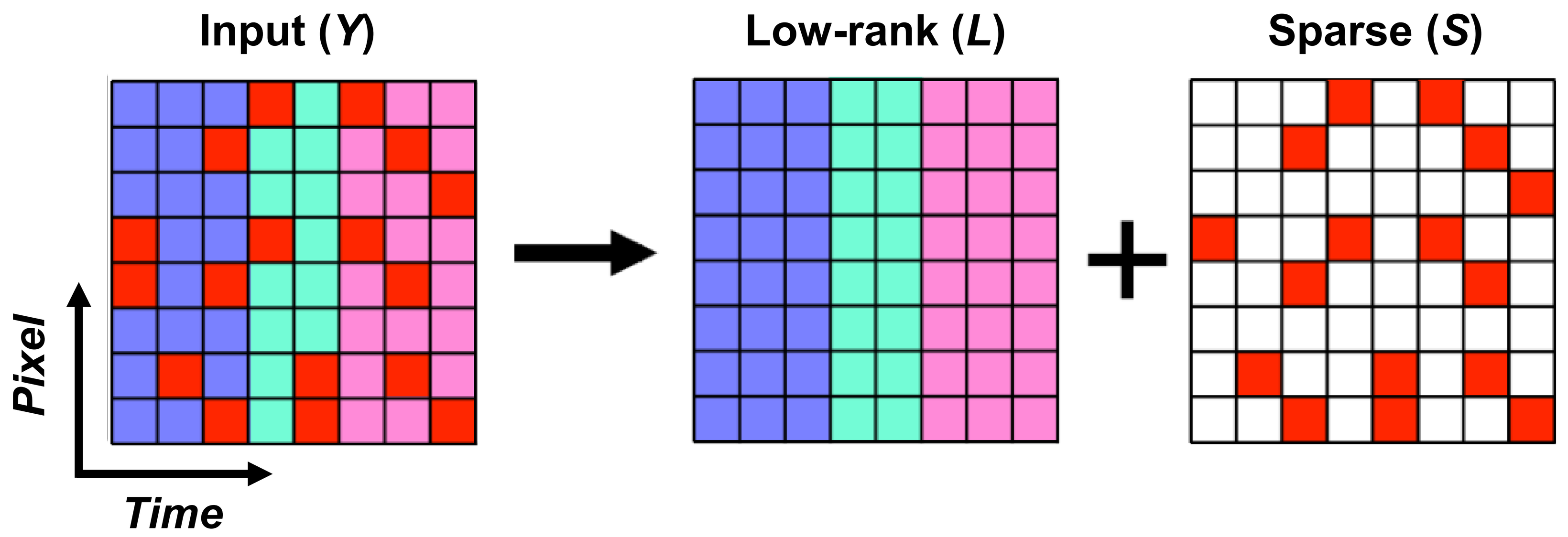

Fig 1. RPCA finds low-rank matrix and sparse matrix from input data.

With modeling the background and foreground as follows,

- Background → Low-rank matrix (***L***)
- Foreground → Sparse matrix (***S***)

we can find ***L*** and ***S*** from input (***Y***) by solving the following,

$$\min_{L,S}(rank(L) + \lambda||S||_0) \text{ subject to } Y = L + S,$$

where $Y, L, S \in \mathbb{R}^{m \times n}$, m : # of pixels, n : # of timeframes.

This can be reformulated as,

$$\min_{L,S}(||L||_* + \lambda||S||_1) \text{ subject to } Y = L + S,$$

It involves **SVD** which requires lots of memory and time.

Fig 2. BEAR for surveillance camera data.
(Left) Input video (***Y***) (Middle) ***L***, (Right) ***S*** [VIDEO]

BEAR − Efficient, Scalable, and Differentiable RPCA

Based on the following surrogate optimization which replaced minimization of $||L||_*$ by the maximum rank constraint on L,

$$\min_{L,S} ||S||_1 \text{ subject to } Y = L + S \text{ and } rank(L) \leq r,$$

By setting $L = WW^TY$, we obtain a surrogate optimization problem that is differentiable by $W \in \mathbb{R}^{m \times r}$.

$$\min_{W} ||S||_1 \text{ subject to } Y = L + S \text{ and } L = WW^TY.$$

FAST no SVD, only matrix multiplication, GPU acceleration
SCALABLE gradient descent using mini-batch
DIFFERENTIABLE $||S||_1$ is differentiable by parameter W

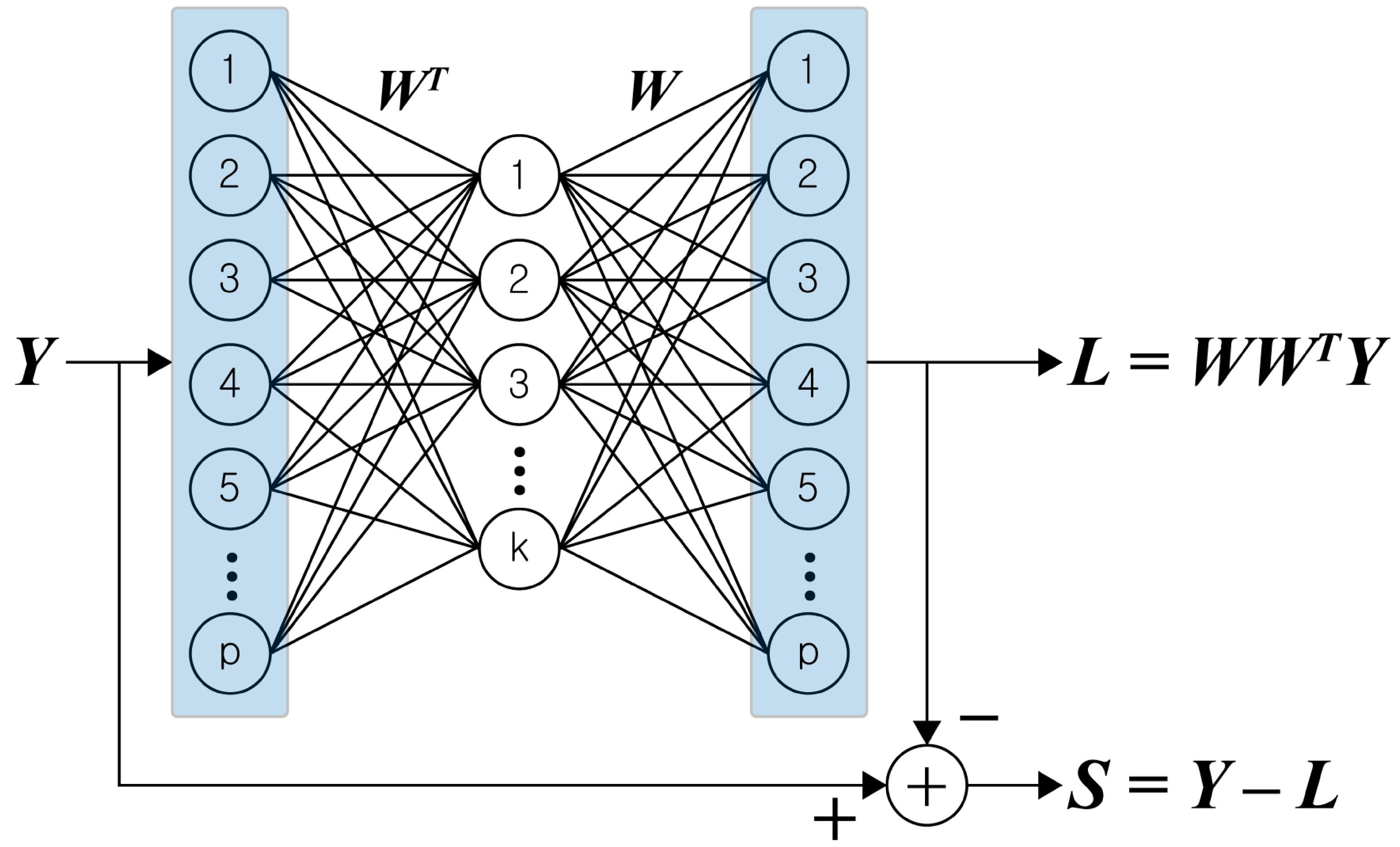

Fig 3. Solving the problem for BEAR is same as training a Bilinear neural network to minimize $||S||_1$ objective.

Experimental results

BEAR is FAST and SCALABLE

data size	PCP	IALM	GreGoDec	BEAR
5313600 ×150	13814	1211	429	**134**
5313600 ×1000	OOM*	OOM*	OOM*	**537**

Table 1. Computation times (s) for several algorithms. BEAR was the fastest, without *Out Of Memory (OOM) for large data

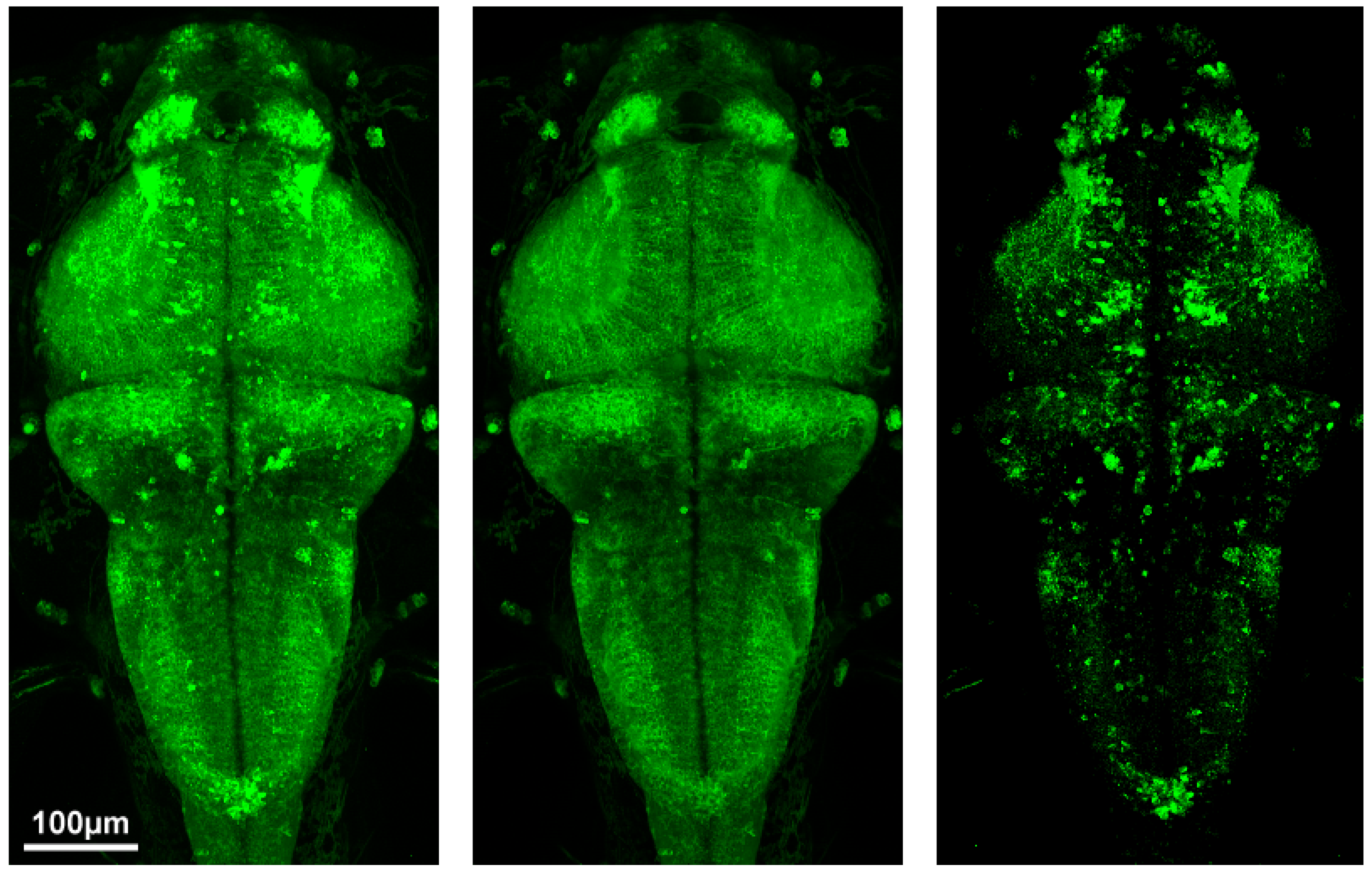

Fig 4. BEAR for large zebrafish calcium imaging data.
(Left) Input video (***Y***) (Middle) ***L***, (Right) ***S*** [VIDEO]

BEAR is DIFFERENTIABLE

BEAR can be combined with other networks.
Example) BEAR with NMF for neuron segmentation.

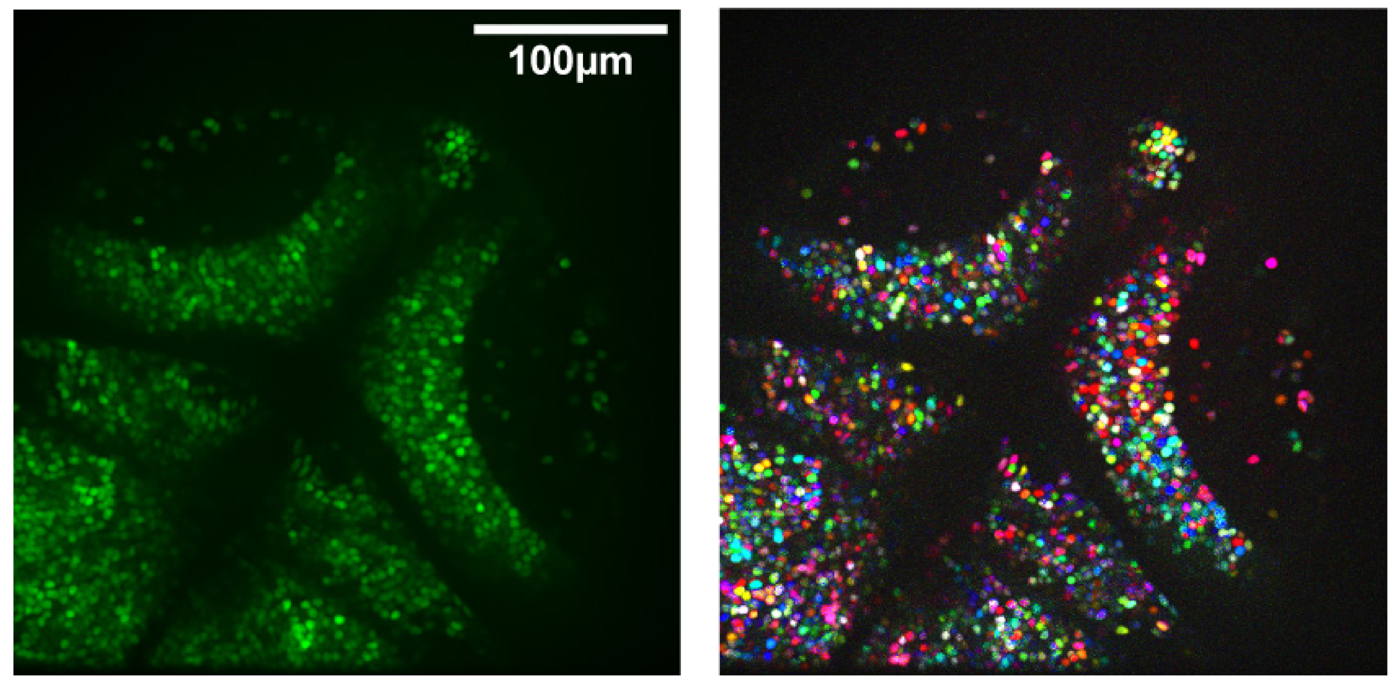

Fig 5. (Left) Calcium imaging video of zebrafish.
(Right) Extracted spatial components are colored and overlaid.

Conclusion

- BEAR is fast and scalable RPCA algorithm.
- It can be combined with other neural networks for end-to-end training.
- BEAR is suitable for analyzing calcium imaging data.
- Also, BEAR can be used for general RPCA applications.