CSIC5011 Mini-Project 1: Four variants of Principal Component Analysis on Video Background/Foreground Separation

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INTRODUCTION

High-dimensional data analysis is crucial in many fields, and effective processing is a challenge due to the massive amount of data. Principal Component Analysis (PCA) is a popular technique that reduces the complexity of high-dimensional data by identifying essential patterns or features and representing them in a low-dimensional space. There are several variants of PCA, including incremental PCA, kernel PCA, sparse PCA, and robust PCA (RPCA), each with its unique advantages. Many algorithms, such as ADMM, SPCP-max-QN, AccAltProj, and OMWRPCA, have been developed to address specific challenges. As high-dimensional data becomes increasingly prevalent in various fields, PCA and its variants are expected to continue playing critical roles in machine learning, bioinformatics, image processing, and genomics.

Objective: Use four variants of PCA to separate the background/foreground of video clip and compare their performance.

DATA ACQUISITION

The experimental data and objects are obtained from the shopping mall surve illance video data is retrieved from Professor Yao, https://drive.google.com/file/d/10-wwUl10fzzgvVF_YX0E1bEuU2Q9hGNG/view?usp=sharing, which are c haracterized by multiple layers and with noise. The moving object and the fixe d background in the surveillance video will be divided into two layers as the subject.

METHODOLOGY

ADMM: Have the problem defined, an alternative optimization approach ADMM has been introduced for the problem. We utilize a relaxed Robust PCA problem can be solved by $min \; \|L\|_* + \lambda\|S\|_1$

To obtain a more general RPCA formulation for the problem, a term E denoting the noise has been introduced, and the problem can be written as $min \; \|E\|_F^2 + \gamma_2\|S\|_1 + \gamma_3\|L\|_* \;\; s.t. X = L + S + E$

Defining the RPCA problem, the original problem could be converted into the augmented Lagrangian $\mathcal{L}(E, L, S; B) = \|E\|_F^2 + \gamma_2\|S\|_1 + \gamma_3\|L\|_* + \ldots - \langle B, X - L - S - E\rangle + \frac{\rho}{2}\|X - L - S - E\|_F^2$

Setting the initial conditions of the variables ρ, γ of augmented Lagrangian, we could iteratively obtain the E, S, L and the Lagrangian multiplier B by sequence.

METHODOLOGY (Continue)

SPCP-max-QN: A new convex formulation for stable principal component pursuit (SPCP) is introduced to achieve a comparison. SPCP is an algorithm aiming to decompose a perturbated image into low-rank and sparse representations. A convex variational framework has been established first and then accelerated with quasi-Newton methods, with the problem $min \; \frac{1}{2}\|L + S - X\|_F^2, \; s.t. max \; (\|L\|_*, \|S\|_1) \le \tau_{sum}$ to be solved, where τ_{sum} is a corresponding parameter.

AccAltProj: It is also an algorithm based on RPCA, aims to decompose the noisy objective into a low-rank matrix and sparse matrix, but with a difference of solving the problem $min \; \|X - L - S\|_F \;, \; s.t. rank(L) \le r, \|S\|_0 \le |\Omega|$ by singular value decomposition (SVD) instead.

OMWRPCA: Another efficient online RPCA method has been introduced to our report which is online moving window robust principal component analysis (OMWRPCA). OMWRPCA could trace slowly and abruptly changing subspaces efficiently. And the problem modeled by OMWRPCA is defined as the following $min \; \|E\|_F^2 + \gamma_2\|S\|_1 + \gamma_3\|L\|_* \;, \; s.t. X = L + S + E$ with a update for the empirical loss minimized

$$g_t^* U \triangleq \frac{1}{n_{win}} \sum_{n_{win}}^{t} \left(\frac{1}{2}\|m_i - Uv_i\|_2^2 + \frac{\lambda_i}{2}\|v_i\|_2^2 + \lambda_i\|s_i\|_1\right) + \frac{\lambda_i}{2n_{win}}\|U\|_F^2$$

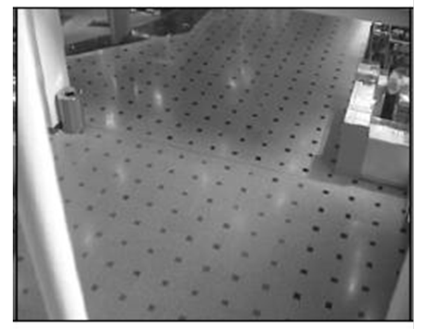
RESULTS

Selected frame 370 to display:

Original

ADMM (2011)

AccAltProj (2019)



Background

SPCP-max-QN (2014)

OMWRPCA (2019)

CONCLUSION

In conclusion, our study has demonstrated the efficacy of four PCA variants in separating the low-rank background and sparse foreground matrices in surveillance video data. We found that the three other PCA methods outperformed ADMM in terms of accuracy. AccAltProj and SPCP-max-QN implemented in MATLAB with AccAltProj being faster than SPCP-max-QN. Meanwhile, ADMM and OMWRPCA both implemented in Python with OMWRPCA being faster than ADMM. These findings provide insights into the selection of appropriate PCA methods for efficient and accurate surveillance video decomposition.

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CONTRIBUTION

Xiao MENG: Introduction, study design, methodology, reference

Ziyu ZHONG: ADMM model & OMWRPCA model reproducing and application

Shunpeng YANG: Fast PCA model & AccAltProj RPCA model reproducing and application

Tianshu JIANG: Management, revision and poster making