ARTICLE IN PRESS

Neurocomputing xx (xxxx) xxxx–xxxx

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

# A BRMF-based model for missing-data estimation of image sequence

Yang Liu[a], Zhan-Li Sun[a,*], Xia Chen[a], Li Shang[b]

[a] School of Electrical Engineering and Automation, Anhui University, Hefei, China
[b] Department of Communication Technology, Electronic Information Engineering College, Suzhou Vocational University, Suzhou, China

ARTICLE INFO

Communicated by Prof. Zidong Wang

*Keywords:*
Missing-data estimation
Structure from motion
Matrix factorization
Weaker estimator

ABSTRACT

How to effectively deal with occlusion is an important step of structure from motion. In this paper, an accurate missing data estimation method is proposed by combining Bayesian robust matrix factorization (BRMF) and particle swarm optimization (PSO). As BRMF is primely designed for outlier detection, in the proposed method, the missing entries of the observation matrix are firstly replaced by the values that are significantly larger than the non-missing entries. Then, the low-rank factorization matrices are computed via the BRMF to recover the observations. One issue of the BRMF model is that the fluctuation of output results caused by the variation of rank values. Analogously to the classifier-committee learning algorithm, a BRMF-based weaker estimator is constructed to alleviate the unfavorable condition. Moreover, a PSO-based weighting strategy is devised to integrate the outputs of weaker estimators. Experimental results on several widely used image sequences demonstrate the effectiveness and feasibility of the proposed algorithm.

## 1. Introduction

Recovering 3D shape from a sequence of 2D point tracks, known as structure from motion (SFM), is one focus in the areas of computer vision [1,2]. In terms of the shape deformation model, SFM is divided into two types, i.e. rigid SFM and non-rigid SFM. Under the rigid model, the 3D shape is invariant along with time. Compared to the rigid SFM, how to obtain the solution of non-rigid SFM is a more intractable problem because the 3D shape is deformable. As we know, shape deformation causes the under-constrained nature of non-rigid SFM model. In order to alleviate the ambiguity, one common assumption is the low-rank constraint of 3D shape, i.e. the deformation of non-rigid objects can be represented by a linear combination of a few 3D shape basis [3–5].

As the occlusion is frequently encountered in SFM, the low-rank property is often destructed by the missing feature points. Thus, in order to get an accurate reconstruct result, it is essential to recovery the missing data at first.

By now, some methods have been proposed to deal with the occlusion encountered in SFM. In [6], an iterative multiresolution scheme is proposed for missing data estimation and 3D structure reconstruction of single and multiple object scenes. A low-rank matrix factorization approach is proposed in [7] by establishing a constrained model on the missing entries. In [8], an evolutionary agent and an incremental bundle adjustment strategy are devised to improve both the efficiency of data recovery and the robustness to outliers. A new affine factorization algorithm is proposed in [9] by employing a robust factorization scheme to handle outlier and missing data. In [10], an adaptive online learning algorithm for non-rigid SFM is proposed, and it is also capable to handle missing data. A method that exploits temporal stability and low-rank property of motion data is proposed in [11], and it has been proved effective to deal with missing data and noise.

In this paper, a Bayesian robust matrix factorization (BRMF) [12] based model is proposed for missing data estimation of image sequence. For the proposed method, the missing entries of the observation matrix are firstly replaced with the values that are significantly larger than the non-missing entries. A BRMF-based weaker estimator is then constructed by inputting the observations to the BRMF with a specific rank value. Further, a particle swarm optimization (PSO)-based weighting strategy is designed to obtain the weighting coefficients for the weaker estimators with different rank values. Finally, the weighted outputs of the weaker estimators are computed and used as the final estimations. Experimental results on several widely used image sequences demonstrate the effectiveness and feasibility of the proposed algorithm.

The remainder of the paper is organized as follows. In Section 2, we present the proposed approach. Experimental results and the related discussions are given in Section 3, and our concluding remarks are presented in Section 4.

* Corresponding author.
*E-mail address:* zhlsun2006@126.com (Z.-L. Sun).

http://dx.doi.org/10.1016/j.neucom.2016.09.088
Received 27 December 2015; Received in revised form 26 March 2016; Accepted 8 September 2016
Available online xxxx

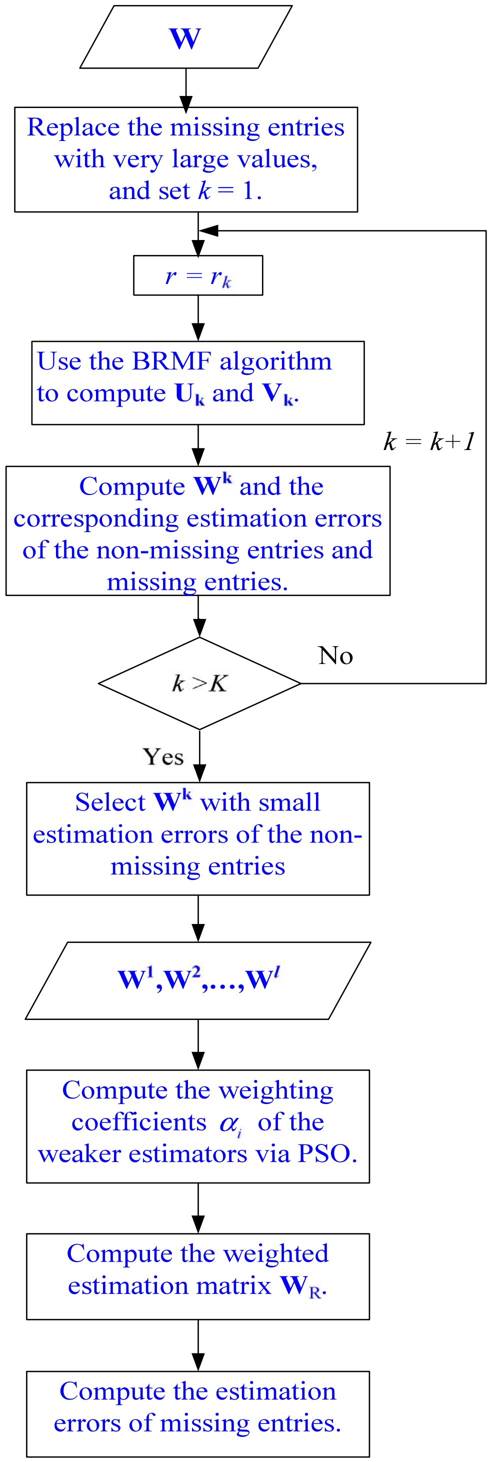


**Fig. 1.** Flowchart of the BRMF-based missing-data estimation algorithm for image sequences.

## 2. Methodology

Fig. 1 shows the flowchart of the BRMF-based missing-data estimation algorithm for image sequences. There are two main steps in the proposed method: construct the BRMF-based weaker estimator; optimize the weighting coefficients with PSO. A detailed description of these two steps is presented in the following subsections.

**Table 1**
The optimization process of the PSO-based weighting coefficients.

**Algorithm**:Particle swarm optimization

- For each particle $i = 1, \ldots, n$:

·Initialize the particle's position: $\mathbf{p}_i \sim U(\mathbf{p}_{min}, \mathbf{p}_{max})$.
·Initialize the particle's velocity: $\mathbf{v}_i \sim U(\mathbf{v}_{min}, \mathbf{v}_{max})$.
·Initialize the best position of each particle:
$\mathbf{p}_i^{best} = \mathbf{p}_i$.
·Initialize the best position of the whole particle swarm:
$\mathbf{g}| f(\mathbf{g}) = min(f(\mathbf{p}_i^{best})), i = 1, \ldots, n$.
•**while** $j \le$ max-iteration
·For each particle $i = 1, \ldots, n$:
**if** $f(\mathbf{p}_i^j) < f(\mathbf{p}_i^{best})$ do:
$\mathbf{p}_i^{best} = \mathbf{p}_i^j$;
**if** $f(\mathbf{p}_i^{best}) < f(\mathbf{g})$ do: $\mathbf{g} = \mathbf{p}_i^{best}$.
Update $\mathbf{v}_i^{j+1}$ use Eq. (12).
Update $\mathbf{p}_i^{j+1}$ use Eq. (13).
·j=j+1.
**end while**

- Output: $\mathbf{g}$.

**Table 2**
The number of frames ($F$) and the number of points tracked ($n$) for four image sequences.

| Sequences | $F$ | $n$ |
|---|---|---|
| dance | 264 | 75 |
| face1 | 74 | 37 |
| shark | 240 | 91 |
| drink | 1102 | 41 |

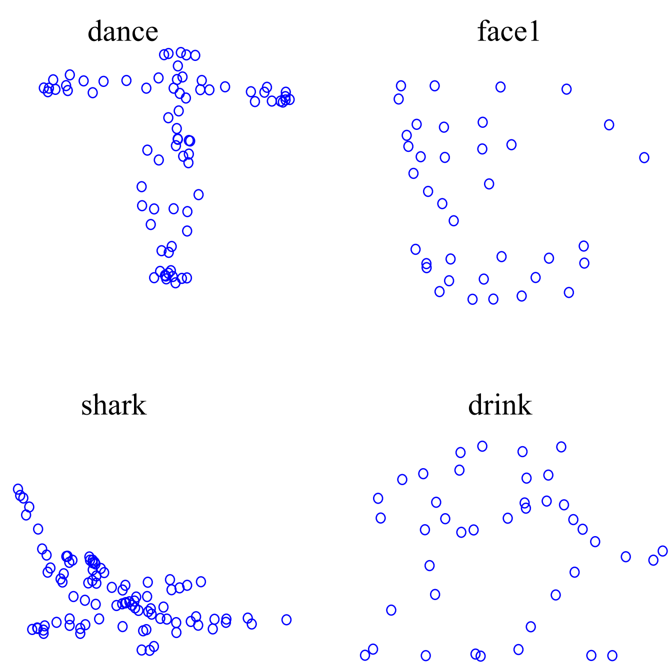


**Fig. 2.** One frame of the four image sequences.

### 2.1. BRMF-based weaker estimator

For an image sequence with $F$ frames, the observation matrix $\mathbf{W}$ can be represented as a $2F \times n$ observation matrix,