

# GLOBAL MOTION ESTIMATION

## An indirect, multiscale and robust approach

Samuele Conti   Filippo Daniotti

Department of Information Engineering  
and Computer Science

April 20, 2022



① Introduction

② The problem

③ Implementation

④ Results

⑤ Conclusions

# Table of Contents

## ① Introduction

## ② The problem

## ③ Implementation

Block-based motion estimation

Global motion estimation

## ④ Results

Qualitative: motion compensation

Quantitative: PSNR

## ⑤ Conclusions

# Introduction

In this work we are going to present:

- a broad introduction to the problem of global motion estimation
- an overview of the theoretical foundations of our solution
- the framework we developed from the aforementioned literature
- an analysis of the performances of our solution
- a brief discussion of the limitations and possible improvements

# Table of Contents

① Introduction

② The problem

③ Implementation

- Block-based motion estimation
- Global motion estimation

④ Results

- Qualitative: motion compensation
- Quantitative: PSNR

⑤ Conclusions

# Global motion estimation

The motion in videos can be analyzed as the displacement of pixel per pair of frames

Is usually the combination of two different motions:

- the actual motion of objects in the scene
- the egomotion of the camera

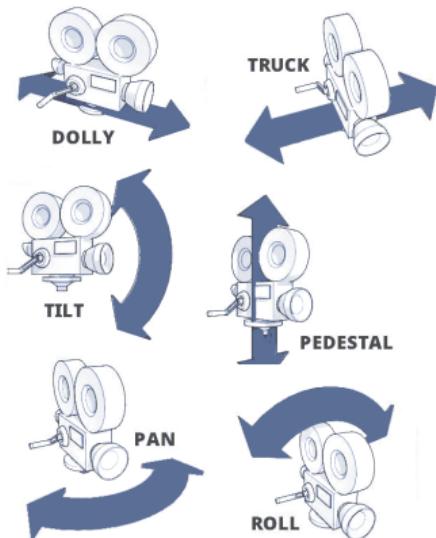
Figure: Local motion vs. egomotion

## The problem

Global motion estimation aims to extract the camera global motion patterns in a video

# Motion models

Motion models describe camera motion patterns through equations



The displacement of a pixel across frames as a function of some parameters

$$p' = \begin{bmatrix} X' \\ Y' \\ Z' \end{bmatrix} = \begin{bmatrix} r_1 & r_2 & r_3 \\ r_4 & r_5 & r_6 \\ r_7 & r_8 & r_9 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} + \begin{bmatrix} T_X \\ T_Y \\ T_Z \end{bmatrix} = Rp + T \quad (1)$$

E.g. for the **affine model** (our choice) parameter vector is  
 $a = [a_0, a_1, a_2, b_0, b_1, b_2]$

Figure: Different models describe different types of camera motion

# Estimating parameters

There are two main approaches, both of which aim to minimize a prediction error

- **direct methods** work in the pixel domain
- **indirect methods** work with motion fields

For our solution we opted for **indirect methods**

## Indirect parameter update

The parameter vector  $a$  is updated by choosing the parameters that minimize the dissimilarity of the  $gt(p)$  and the prediction  $MM(p, a)$  for a point  $p$

$$a = \arg \min_a \sum_p E(gt(p) - MM(p, a)) \quad (2)$$

# Table of Contents

① Introduction

② The problem

③ Implementation

Block-based motion estimation

Global motion estimation

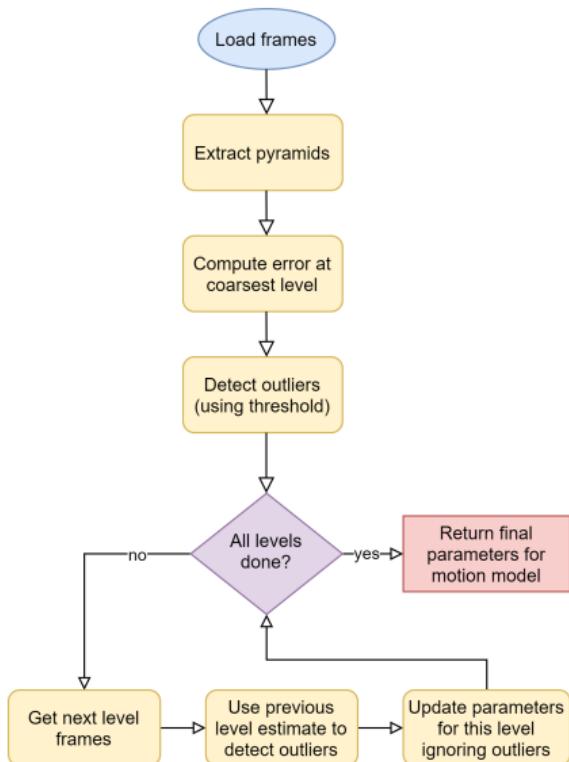
④ Results

Qualitative: motion compensation

Quantitative: PSNR

⑤ Conclusions

# Overview



Implementation choices:

- Affine model
- Indirect method
- Block-based motion estimation
- Multiscale
- Robust

Figure: Flowchart of our framework

# Block-based motion estimation

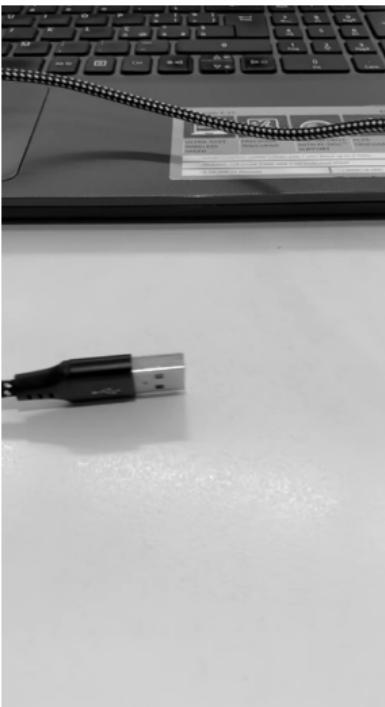
BBME algorithms perform motion estimation and return the motion field to use as ground truth for indirect parameter estimation

## Chosen algorithms

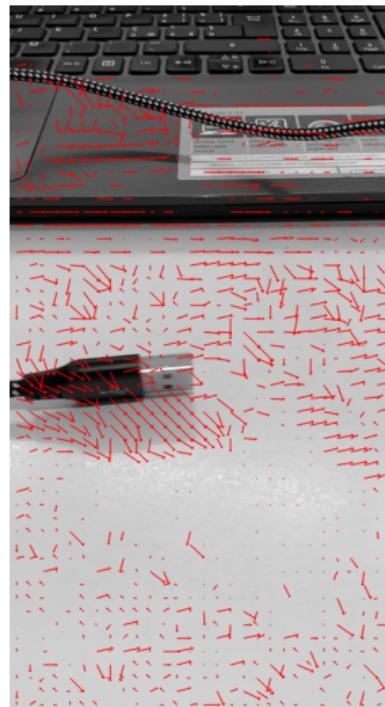
We implemented 4 well-known BBME algorithms:

- exhaustive search
- three-step search
- 2D log search
- diamond search

# Exhaustive search



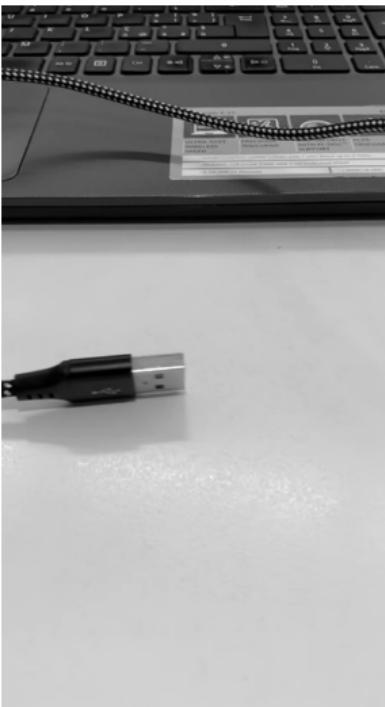
(a) Target frame



(b) Needle diagram

Figure: Motion field result of our EBBME implementation

# Three-step search



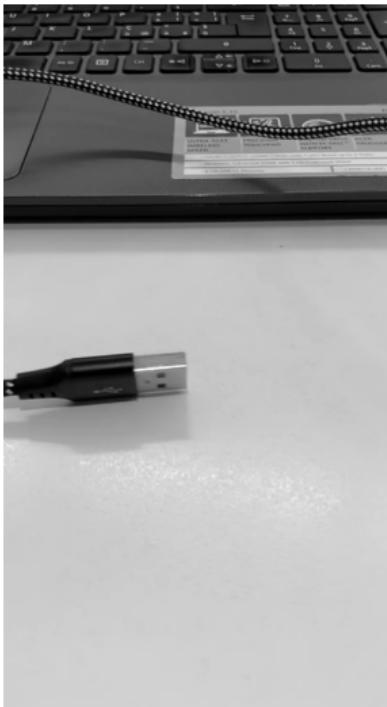
(a) Target frame



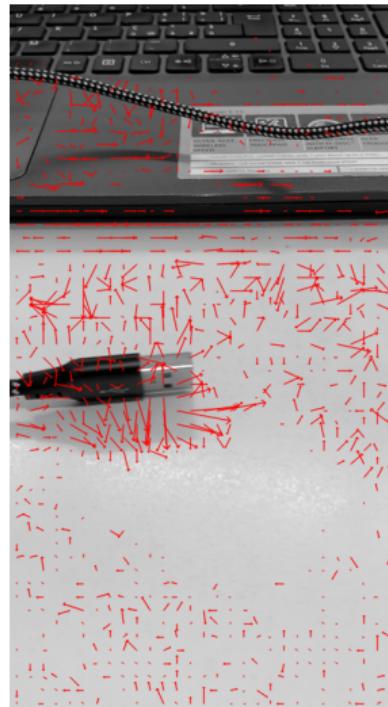
(b) Needle diagram

Figure: Motion field result of our TSS implementation

# 2D Log search



(a) Target frame



(b) Needle diagram

Figure: Motion field result of our TDLS implementation

# Diamond search

BBME algorithm presented in Zhu and Ma, 2000.

Better performances than classic algorithms (TSS) and comparable to latest ones (NTSS), yet more efficient in computation.

It uses two different diamond-shaped search patterns:

- large diamond search pattern (LDSP)
- small diamond search pattern (SDSP)

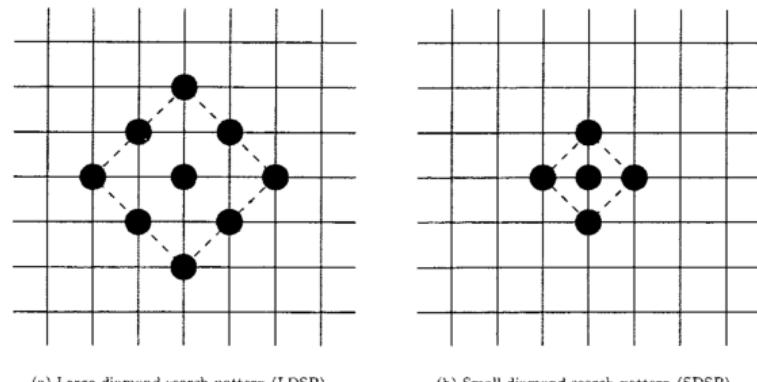


Figure: The shape of LDSP and SDSP

# DS algorithm

## Diamond search procedure

For each block:

- ① place LDSP in the center of the block and compute DFD for all of the 9 displacements;
  - ▶ if the minimum DFD is in the center position, then go to 3
  - ▶ else, go to 2
- ② reposition LDSP in the minimum DFD of the previous operation and recompute DFD;
  - ▶ if the minimum DFD is in the center position, then go to 3
  - ▶ else, repeat
- ③ place SDSP, compute DFD and return coordinates of the minum DFD block as motion vector

## DS algorithm visualized

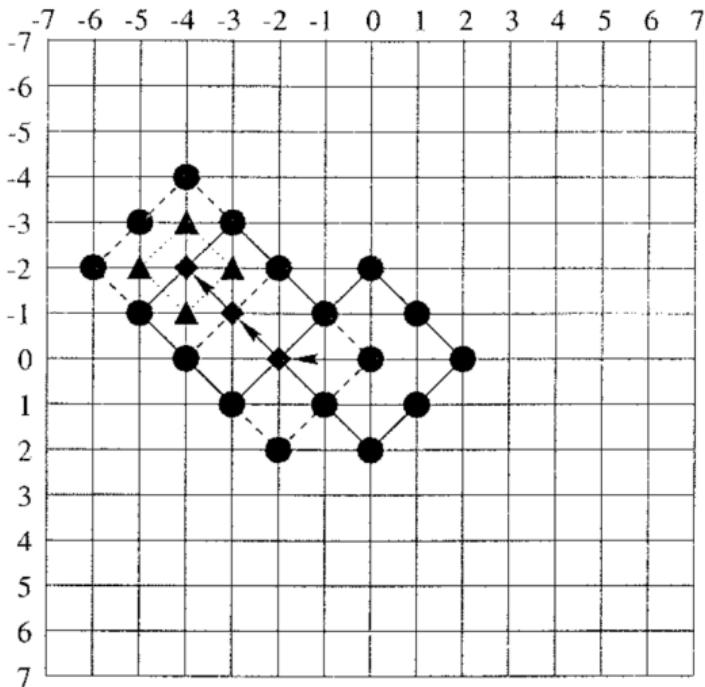
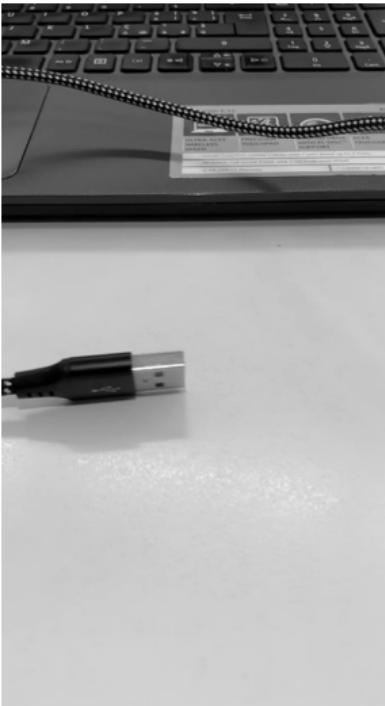


Figure: Example of a full execution cycle of diamond search

## DS results



(a) Target frame



(b) Needle diagram

Figure: Motion field result of our DS implementation

# Affine model prediction error

The affine model computes the displacement of a given pixel wrt parameters  $a$  as

$$d(p, a) = A[p] a \quad (3)$$

where  $A[p]$  is an intermediate matrix

$$A[p] = \begin{bmatrix} 1 & x & y & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & x & y \end{bmatrix}$$

## Fitting error

The fitting error computation gets rewritten as

$$E = \sum_p |d(p, a) - d(p)|^P \quad (4)$$

# Affine model parameter estimation

We are interested in the parameters that minimize the fitting error  $\rightarrow \nabla_a E = 0$

## Parameter update

Assuming  $p = 2$ , we get

$$a = \left( \sum_p A[p]^T A[p] \right)^{-1} \left( \sum_p A[p]^T d(p) \right) \quad (5)$$

## Refinement

- each point  $p$  can be weighted
- parameter vector  $a$  can be split:  $a_x = [a_1, a_2, a_3]$  and  $a_y = [b_1, b_2, b_3]$ 
  - ▶ reduce the overall complexity

$$a_x = \left( \sum_p w(p) A_x[p]^T A_x[p] \right)^{-1} \left( \sum_p w(p) A_x[p]^T d_x(p) \right) \quad (6)$$

# Pseudocode

---

**Algorithm 1:** High-level pseudocode of our solution.**Input:** *previous\_frame*, *current\_frame***Output:** *a* // parameter vector

```
prev_prys = get_pyr(previous_frame)
cur_prys = get_pyr(current_frame)
a = first_estimation(prev_prys.next(), cur_prys.next())
foreach l in levels do
    prev_frame = prev_prys.next()
    cur_frame = cur_prys.next()
    ground_truth_mfield = BBME(prev_frame, cur_frame)
    estimated_mfield = affine(a)
    outliers = detect_outliers(ground_truth_mfield, estimated_mfield)
    a = minimize_error(prev_frame, cur_frame, outliers)
end
return a
```

# Table of Contents

① Introduction

② The problem

③ Implementation

Block-based motion estimation

Global motion estimation

④ Results

Qualitative: motion compensation

Quantitative: PSNR

⑤ Conclusions

# Motion compensation



(a) Previous frame



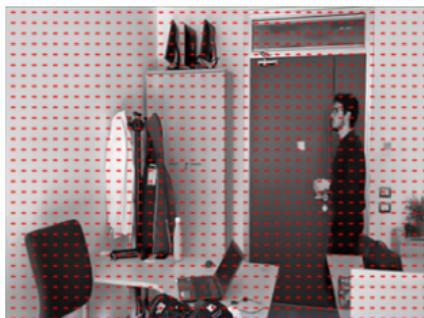
(b) Previous frame



(c) Compensated frame



(d) Absolute difference between current and previous frame



(e) Global motion field estimated by our procedure



(f) Absolute difference between current and compensated frame

# Motion compensation



(a) Previous frame



(b) Previous frame



(c) Compensated frame



(d) Absolute difference between current and previous frame



(e) Global motion field estimated by our procedure



(f) Absolute difference between current and compensated frame

Figure: Block size: 24, frame distance: 1

# Motion compensation



(a) Previous frame



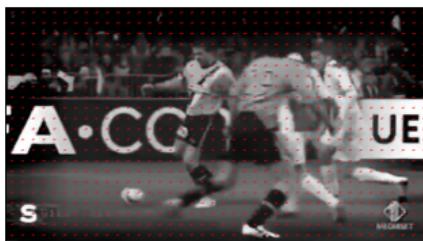
(b) Previous frame



(c) Compensated frame



(d) Absolute difference between current and previous frame



(e) Global motion field estimated by our procedure



(f) Absolute difference between current and compensated frame

Figure: Block size: 16, frame distance: 3

# PSNR results

Video	Properties	Average	Variance	Maximum	Minimum
pan240.mp4	Fast motion	22.724	5.125	27.802	17.981
coastguard_qcif.mp4	Two objects moving, background moving	22.733	2.194	26.875	15.158
foreman.mp4	Big object moving, still background	19.677	18.443	30.436	11.746
numeri_del_piero.mp4	Medium object moving, moving background	19.072	13.642	47.722	16.323

Table: PSNR result on a some example video sequences

# Table of Contents

① Introduction

② The problem

③ Implementation

Block-based motion estimation

Global motion estimation

④ Results

Qualitative: motion compensation

Quantitative: PSNR

⑤ Conclusions

## Summary

In this work, we have presented:

- a broad introduction to the problem of global motion estimation
- an in-depth explanation of the theoretical foundations of our solution
- the framework we developed from the aforementioned literature
  - ▶ the BBME algorithms chosen
  - ▶ the computation of the parameter for the affine model
  - ▶ the removal of outliers
  - ▶ the implementation of the multiscale approach
- an analysis of the results of our solution
  - ▶ qualitative results, using motion compensation
  - ▶ quantitative results, comparing PSNR values