Robust Visual Tracking using L_1 Minimization

Xue Mei
Center for automation Research, Electrical & Computer Engineering Dept.
University of Maryland, College Park, MD, USA
xuemei@umiacs.umd.edu

Haibin Ling
Center for Information Science & Tech., Computer & Information Science Dept.
Temple University, Philadelphia, PA, USA
hbling@temple.edu

ICCV 2009

ICCV 2009

Introduction

Challenges

- Partial occlusion
- Illumination change
- Background clutter
- Scale and pose

Motivation

- Sparse representation and L_1 minimization (Donoho 2006, Candes, Romberg, & Tao 2006).
- Robust recognition using sparse representation (Wright et al. 2009).

Proposed Method

- Casting tracking as sparse approximation.
- Enforcing non-negativity constraints.
- Updating the target templates dynamically.

L1 Minimization Tracking

Sparse Representation of a tracking target

- A candidate **y** approximately lies in a linear subspace
- We rewrite it as (Wright et al 2009)
- Our task is to find a sparse solution for **a** and **e**.

$$y \approx a_1 t_1 + a_2 t_2 + \cdots + a_n t_n$$

$$y = a_1 t_1 + a_2 t_2 + \cdots + a_n t_n + \varepsilon$$

$$= a_1 t_1 + a_2 t_2 + \cdots + a_n t_n + e_1 i_1 + e_2 i_2 + \cdots + e_d i_d$$

$$\triangleq [T, I] \begin{bmatrix} a \\ e \end{bmatrix}$$

y : *a candidate*, **T**: *target template*
I : *trivial templates (identity matrix)*

a : *target coefficient vector*, **e** : *trivial coefficient vector*

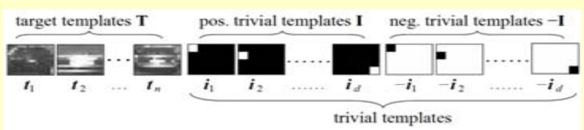
Non-negativity Constraints

- The intensity pattern of a false target can be roughly reversed compared to a target template.
- Enforcing non-negativity constraints.
- Including negative trivial templates.

A template | *Result without non-negativity constraint* | *Result with non-negativity constraint*

$$y = a_1 t_1 + \cdots + a_n t_n + e_1 i_1 + \cdots + e_d i_d + e_1^-(-i_1) + \cdots + e_d^-(-i_d)$$

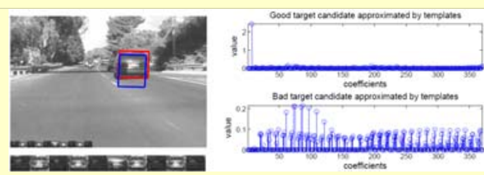
$$\triangleq [T, I, -I] \begin{bmatrix} a \\ e^+ \\ e^- \end{bmatrix} \triangleq Bc, \quad c \geq 0$$



Achieving Sparseness through L1 Minimization

$$\min \|Bc - y\|_2^2 + \lambda \|c\|_1$$

- The tracking result is obtained by finding the smallest residual by projecting on the target template subspace.



Left: good (red) and bad (blue) target candidates, and templates. Right: good (top) and bad (bottom) target candidate approximation.

Template Update

- Template replacement
- Template updating
- Weight updating
  - the larger the weight, the more important the template

Algorithm 1 Template Update

y is the newly chosen tracking target.
a is the solution to (8).
w is current weights, such that $w_i \leftarrow \|t_i\|_2$.
τ is a predefined threshold.
Update weights according to the coefficients of the target templates. $w_i \leftarrow w_i * exp(a_i)$.
if ($sim(y, t_m) < \tau$), where sim is a similarity function. It can be the angle between two vectors or SSD between two vectors after normalization. t_m has the largest coefficient a_m, that is, $m = arg\max_{1 \leq i \leq n} a_i$ **then**
  $i_0 \leftarrow \arg\min_{1 \leq i \leq n} w_i$
  $t_{i_0} \leftarrow y$, /*replace an old template*/.
  $w_{i_0} \leftarrow$ median(w), /*replace an old weight*/.
end if
Normalize w such that $sum(w) = 1$.
Adjust w such that $max(w) = 0.3$ to prevent skewing.
Normalize t_i such that $\|t_i\|_2 = w_i$.

Experiments

- Five public video sequences
- Challenges
  - low target-background contrast
  - high noise level
  - drastic illumination changes
  - background clutter
  - heavy occlusion
  - large pose change
- Four methods
  - Our method (L_1)
  - Mean shift (MS) (Comaniciu et al. 2003)
  - Covariane tracker (CV) (Porikli et al. 2006)
  - Active appearance particle filter (AAPF) (Zhou et al. 2004)