

Bayesian Constrained Local Models with Depth Data

Pedro Martins, João Faro, Patrick Brandão, Jorge Batista http://www.isr.uc.pt/~pedromartins pedromartins@isr.uc.pt

> Institute of Systems and Robotics (ISR) University of Coimbra Portugal



IEEE International Conference on Image Processing (ICIP) 2016, Phoenix, AZ, USA

Introduction

- Constrained Local Model (CLM) Extension
- Fitting with Intensity and Depth Data
- Bayesian CLM Framework
- Likelihood Fusion Strategies
- Evaluation Results (EURECOM and ISR-Z datasets)

CLM Fitting with RGBD Data (video)



Constrained Local Model (CLM)

$$\underset{\mathbf{b}}{\operatorname{arg\,max}} \sum_{i=1}^{v} \mathbf{I}(\mathbf{s}_{i}) * \mathbf{h}_{i} - \lambda_{0} \mathbf{b}^{T} \Sigma_{\mathbf{b}}^{-1} \mathbf{b}$$



Local Search Regions







Local Detectors

Shape Model

Bayesian Inference CLM



 $p(\mathbf{b}_l | \mathbf{y}_l, \dots, \mathbf{y}_0) \propto \mathcal{N}(\mathbf{b}_l | \boldsymbol{\mu}_l^{\mathbf{F}}, \boldsymbol{\Sigma}_l^{\mathbf{F}})$

[P. Martins et.al., ECCV 2012] [P. Martins et. al., TPAMI 2016]

Local Landmark Detectors (SVM)





Local Landmark Detectors (MOSSE Filters)

$$\begin{aligned} & \operatorname{Figure}_{N_{i}} \left(\sum_{j=1}^{N} \mathcal{F}\{\mathbf{I}_{j}\} \odot \mathcal{F}\{\mathbf{I}_{j}\}^{\dagger} \odot \mathcal{F}\{\mathbf{I}_{j}\}^{\dagger} \right)^{2} + \lambda ||\mathbf{H}_{i}||^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{I}_{j}\} \odot \mathcal{F}\{\mathbf{I}_{j}\} \odot \mathcal{F}\{\mathbf{I}_{j}\}^{\dagger} \right)^{2} + \lambda ||\mathbf{H}_{i}||^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{I}_{j}\} \odot \mathbf{H}_{i}^{\dagger} - \mathcal{F}\{\mathbf{g}_{j}\} \right)^{2} + \lambda ||\mathbf{H}_{i}||^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{I}_{j}\} \odot \mathbf{H}_{i}^{\dagger} - \mathcal{F}\{\mathbf{g}_{j}\} \right)^{2} + \lambda ||\mathbf{H}_{i}||^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{I}_{j}\} \odot \mathbf{H}_{i}^{\dagger} - \mathcal{F}\{\mathbf{g}_{j}\} \right)^{2} + \lambda ||\mathbf{H}_{i}||^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{I}_{j}\} \odot \mathbf{H}_{i}^{\dagger} - \mathcal{F}\{\mathbf{g}_{j}\} \right)^{2} + \lambda ||\mathbf{H}_{i}||^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{I}_{j}\} \odot \mathbf{H}_{i}^{\dagger} - \mathcal{F}\{\mathbf{g}_{j}\} \right)^{2} + \lambda ||\mathbf{H}_{i}||^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{I}_{j}\} \odot \mathbf{H}_{i}^{\dagger} - \mathcal{F}\{\mathbf{g}_{j}\} \right)^{2} + \lambda ||\mathbf{H}_{i}||^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{I}_{j}\} \odot \mathbf{H}_{i}^{\dagger} - \mathcal{F}\{\mathbf{g}_{j}\} \right)^{2} + \lambda ||\mathbf{H}_{i}||^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{I}_{j}\} \odot \mathbf{H}_{i}^{\dagger} - \mathcal{F}\{\mathbf{g}_{j}\} \right)^{2} + \lambda ||\mathbf{H}_{i}||^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{I}_{j}\} \odot \mathbf{H}_{i}^{\dagger} - \mathcal{F}\{\mathbf{g}_{j}\} \right)^{2} + \lambda ||\mathbf{H}_{i}||^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{I}_{j}\} \odot \mathbf{H}_{i}^{\dagger} - \mathcal{F}\{\mathbf{g}_{j}\} \right)^{2} + \lambda ||\mathbf{H}_{i}||^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{I}_{j}\} \odot \mathbf{H}_{i}^{\dagger} - \mathcal{F}\{\mathbf{g}_{j}\} \right)^{2} + \lambda ||\mathbf{H}_{i}||^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{I}_{j}\} \odot \mathbf{H}_{i}^{\dagger} - \mathcal{F}\{\mathbf{g}_{j}\} \right)^{2} + \lambda ||\mathbf{H}_{i}||^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{I}_{j}\} \odot \mathbf{H}_{i}^{\dagger} - \mathcal{F}\{\mathbf{H}_{i}\} \right)^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{H}_{i}\} \odot \mathbf{H}_{i}^{\dagger} - \mathcal{F}\{\mathbf{H}_{i}\} \right)^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{H}_{i}\} \odot \mathbf{H}_{i}^{\dagger} - \mathcal{F}\{\mathbf{H}_{i}\} \right)^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{H}_{i}\} \right)^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{H}_{i}\} \odot \mathbf{H}_{i}\} \right)^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{H}_{i}\} \right)^{2} \\ & \operatorname{Figure}_{N_{i}} \left(\mathcal{F}\{\mathbf{H}_{i$$



Local Optimization Strategies



Patches under occlusion



Multiple Detectors per Landmark (video)



CLM with Depth Data

- Strategy Employed:
 - Multiple Channel Local Detectors (RGBD w/ single response map)
 - Fast CLM Inference (Gaussian)

Multiple Channel Correlation Filters

Spatial Domain $\arg\min_{\mathbf{h}_{i}^{(1)},...,\mathbf{h}_{i}^{(D)}} \sum_{j=1}^{N} \sum_{k=1}^{D} \left(\mathbf{h}_{i}^{(k)} * \mathbf{I}_{j}^{(k)} - \mathbf{g}_{j}\right)^{2} + \lambda \sum_{k=1}^{D} ||\mathbf{h}_{i}^{(k)}||^{2}$

Minimization across all channels

[J. Henriques et.al., ICCV 2013] [H. Galoogahi et.al., ICCV 2013] [V. Boddeti et.al., CVPR 2013]

Multiple Channel Correlation Filters

Efficient Solution (w/ variable re-ordering)

$$\{\mathbf{h}_{i(l)}^{(k)}\} = \mathcal{F}^{-1} \left\{ \left(\sum_{j=1}^{N} \nu \left(\mathcal{F}\{\mathbf{I}_{j}\}_{l} \right)^{H} \nu \left(\mathcal{F}\{\mathbf{I}_{j}\}_{l} \right) + \lambda \mathbf{I} \right)^{-1} \sum_{j=1}^{N} \nu \left(\mathcal{F}\{\mathbf{I}_{j}\}_{l} \right)^{H} \nu \left(\mathcal{F}\{\mathbf{g}_{j}\}_{l} \right) \right\}^{\dagger}$$
gues et.al., ICCV 2013]
$$\nu \left(\mathbf{A}_{l}\right) = \left[\begin{array}{cc} \mathbf{A}_{l}^{(1)} & \cdots & \mathbf{A}_{l}^{(D)} \end{array} \right]^{T}$$

[J. Henrig [H. Galoogahi et.al., ICCV 2013] 13

Single Channel vs Multiple Channels Filters

Depth Data (Noise Removal)

Response Map Fusion Strategies

$$p(\mathbf{z}_i)^{\text{AVG}} = \frac{1}{D} \sum_{k=1}^{D} p(a_i | \mathcal{D}_i^{(k)}, \mathbf{I}(\mathbf{z}_i)^{(k)})$$

[T. Baltrusaitis et.al., CVPR 2012] [S. Cheng et.al. ICIP 2014]

$$p(\mathbf{z}_i)^{\text{MAX}} = \max_{\mathbf{z}_i} p(a_i | \mathcal{D}_i^{(k)}, \mathbf{I}(\mathbf{z}_i)^{(k)})$$

[P. Martins et.al., ICIP 2014]

$$\mathcal{D}_i^{\text{MDF}} = \sum_{k=1}^{D} \mathbf{h}_i^{(k)} \mathbf{I}(\mathbf{z}_i)^{(k)}$$
$$\mathbf{z}_i)^{\text{MDF}} = p(a_i | \mathcal{D}_i^{\text{MDF}}, \mathbf{I}(\mathbf{z}_i)^{(k)})$$

Qualitative Results EURECOM Database

Results EURECOM Kinect Face Database

BCLM MDF EURECOM Fitting (video)

Qualitative Results ISR-Z Dataset

Results ISR-Z Face Database

ISR-Z Database ~250 Images 19 Individuals 58 Landmarks

BCLM (MDF)	Area Below CDF
Grey	49.0
Depth	16.6
Grey+Depth	52.5
RGB	61.7
RGBD	65.8

Error Standard Deviation

Conclusions

- Constrained Local Model (CLM) Extension
- Seamless Fitting of RGB and Depth Data
- Multiple Channel Correlation Filters (Local Detector)
- Evaluation Results (EURECOM and ISR-Z datasets)
- Acknowledgements
 - Work supported by the Portuguese Science Foundation (Fundação para a Ciência e Tecnologia FCT) through the grant SFRH/BDP/90200/2012.

BCLM MDF ISR-Z Fitting (video)

Questions?

http://www.isr.uc.pt/~pedromartins pedromartins@isr.uc.pt

