Monocular human upper body pose estimation for sign language analysis

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3dmedia

Université de Liège

Context

3D(Stereo)Media

- Part of the Wallonian “Marshall plan”
- Motion capture
- Animation of virtual characters

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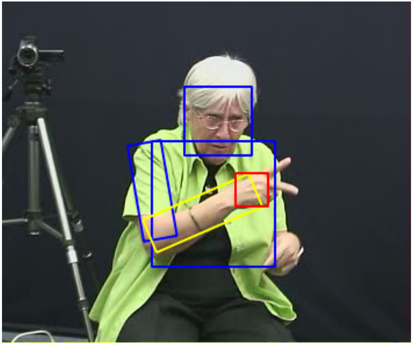
Signspeak

- European project
- Automatic sign language analysis
- ULg: Focus on feature extraction: hand motion, facial expressions

Objective

Upper Body Tracking

- Provide hand position and velocity
- Head position and arm configuration
- 2D tracking



Main Difficulties

Segmentation issues

- Motion blur
- Self occlusion
- Clothing variability, etc.

Motivates a top-down approach

Too many ambiguities

- Separate tracking of parts difficult
- Joint tracking is more promising

→ **Multi-part statistical models**

Pictorial models

- Combine structural *a priori* and likelihood
- Tree-shaped models allow fast inference

Main issues

1. Likelihood and *a priori* models
2. Computational complexity

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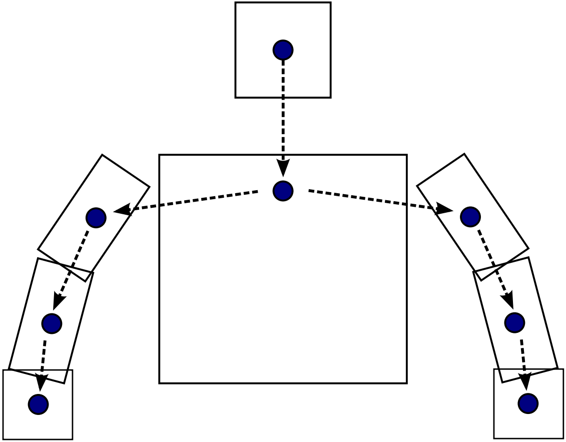
Tree-shaped Bayesian Model

- Each part is a square or oriented rectangle (arms)
- Parameters are $(x, y, width, [height, angle])$



Required probabilistic quantities

Notations

- Image I
- Pose $L = \{L_{head}, L_{tr}, L_{lUpArm}, L_{rUpArm}, L_{lLowArm}, L_{rLowArm}, L_{lHd}, L_{rHd}\}$

A posteriori probability of a configuration L

$$P(L|I) \propto P(I|L) \times P(L)$$

- $P(L)$: structural *a priori*
- $P(I|L)$: likelihood

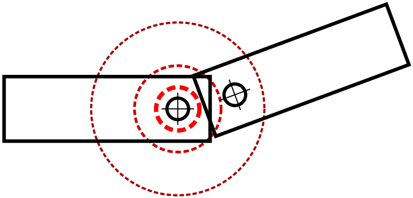
Structural *a priori*

Decomposition thanks to tree independence

$$
\begin{aligned}
P(L) \quad \propto \quad & P(L_{tr}|L_{head})P(L_{lUpArm}|L_{tr})P(L_{rUpArm}|L_{tr}) \\
& \times P(L_{lLowArm}|L_{lUpArm})P(L_{rLowArm}|L_{rUpArm}) \\
& \times P(L_{lHd}|L_{lLowArm})P(L_{rHd}|L_{rLowArm})
\end{aligned}
$$

Chosen models

- Gaussian for junctions distances
- Uniform for orientations



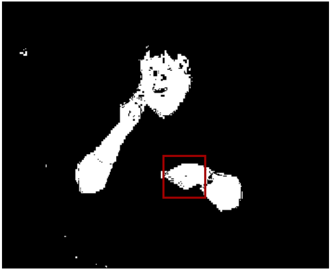
Likelihood terms

Independence assumption between parts

- $P(I|L) \propto \prod_{i=1}^{8} P(I|L_i)$
- One color model per part (HS histogram)
- Histogram back-projection gives per pixel likelihood
- Can be thresholded

Hand example

Likelihood issues



Likelihood for a rectangle candidate

- Intuitively: proportional to the number of white pixels
- ☹ Depend upon the rectangle size
  - ➔ Less significant for small rectangles
- ☹ Depend upon the chosen threshold
  - ➔ Less significant if the threshold is low

A contrario likelihood

A contrario reasoning

- Based on a perceptual principle (Helmholtz)

"The lower the probability for the proportion of white pixels to be high by accident, the most significant it is."

Concretely

- “Accident” H_0 = pixels i.i.d. in the image
- $P_{H_0}(N_w \geq N_w(L_i) \mid N, p_w) = \mathcal{B}_{\geq}(N_w(L_i), N, p_w)$
- N: size of the rectangle
- N_w: number of white pixels in the rectangle
- p_w: number of white pixels in the image

A contrario likelihood [2/2]

Deducing the likelihood

- $P_{H_0}(N_w \geq N_w(L_i) \mid N, p_w)$ quantifies the significance of the white pixel concentration
- The lower it is, the higher is the probability that the concentration is not due to chance, and thus to a part

Final likelihood

$$P(I|L_i) \propto 1.0 - [P_{H_0}(N_w \geq N_w(L_i) \mid N, p_w)]^{\alpha}$$

- α: quantifies how the non-accidentality increases the confidence that the part is actually there
- Can be learned

Inference

Objective

- We can compute $P(L|I)$ for a given pose L
- How to we find the most probable one?
- ☹ The number of possible poses is too large to test them all

Classical solution 1: coarse discretization

- ☺ Efficient inference algorithms in trees (Belief Propagation)
- ☹ Needs to be very coarse to remain efficient

Classical solution 2: non-parametric belief propagation (NBP)

- Approximate all quantities by particle filters
- ☺ Accurate sampling of candidates
- ☹ Time-consuming (several minutes per frame)

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Discretization by importance sampling

Overall idea

- Use some proposal distribution q to sample candidates
- Assign them a weight $\frac{p}{q}$ (importance sampling)
- Find the best pose using classical BP (max-product)

→ **Less accurate but faster than sampling from posterior**

Different kind of proposals can be used

- Detection-based, e.g. gaussian around a detector output
- Temporal, e.g. gaussian around the position predicted by a constant velocity model
- Structural: e.g. sample a position from a parent candidate using the *a priori* model
- Can be combined, e.g. into a mixture of gaussians

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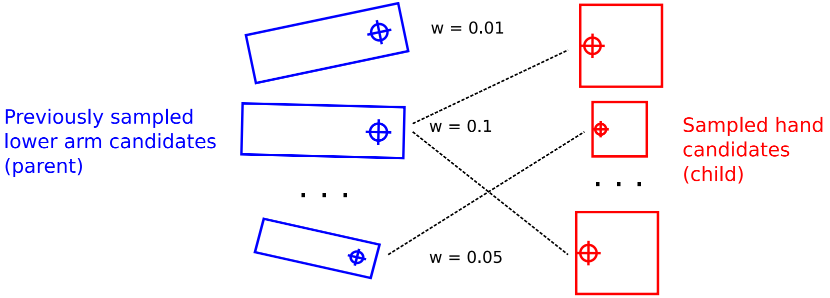
Example of structural proposal

1. Draw a parent candidate according to their weights
2. Sample a child candidate according to the *a priori* model



Preliminary results

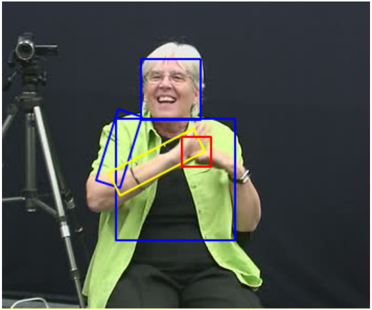
Settings

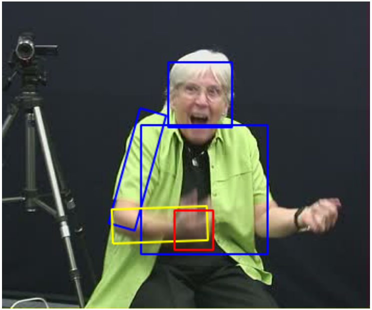
- Color models estimated from rough manual segmentation in one frame
- No temporal term
- Detection proposal for the head
- Structural proposals for other parts
- About 200 sampled candidates per part
- Only the left parts are shown

Dataset

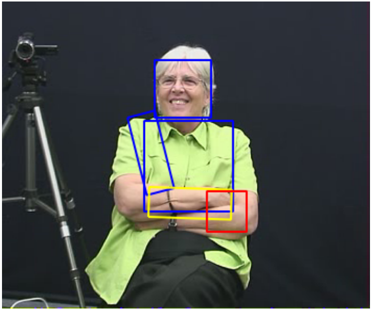
- NGT Corpus of sign language
- Mostly static backgrounds

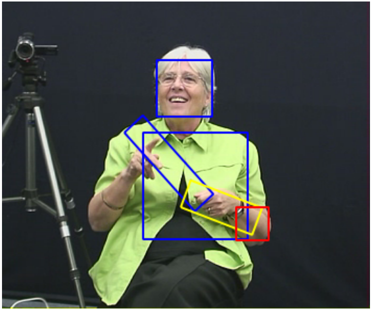
Examples of frames correctly estimated





Examples of frames incorrectly estimated





Conclusion

First results are encouraging

- Less than one second per frame
- Able to find the right pose on “easy” frames

Two originalities

- *A contrario* likelihoods
  - → Combine quantities in a principled way
  - → Can use multiple thresholds to increase robustness
- Discretization by importance sampling + BP
  - → Focus on promising regions
  - → Can integrate various heuristics
  - → Inference remains efficient

Perspectives

Quantative evaluation

- Need for a labelled database
- Comparison with existing approaches

Improve the model

- Temporal terms
- Contour-based terms
- Learn parameters
- Handle self-occlusions explicitely to improve likelihood
- Automatic color model initialization
- Language analyzis predictions

Questions ?