Silhouette Area Based Similarity Measure for Template Matching in Constant Time

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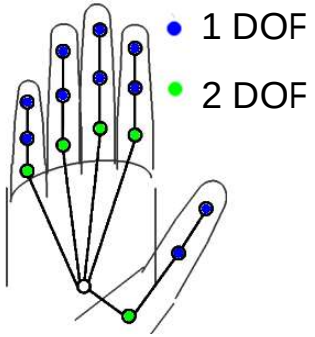
Motivation: Camera Based Hand Tracking

- Given an image, estimate hand parameter
  - Global position (3 DOF)
  - Global orientation (3 DOF)
  - Joint angles (20 DOF)

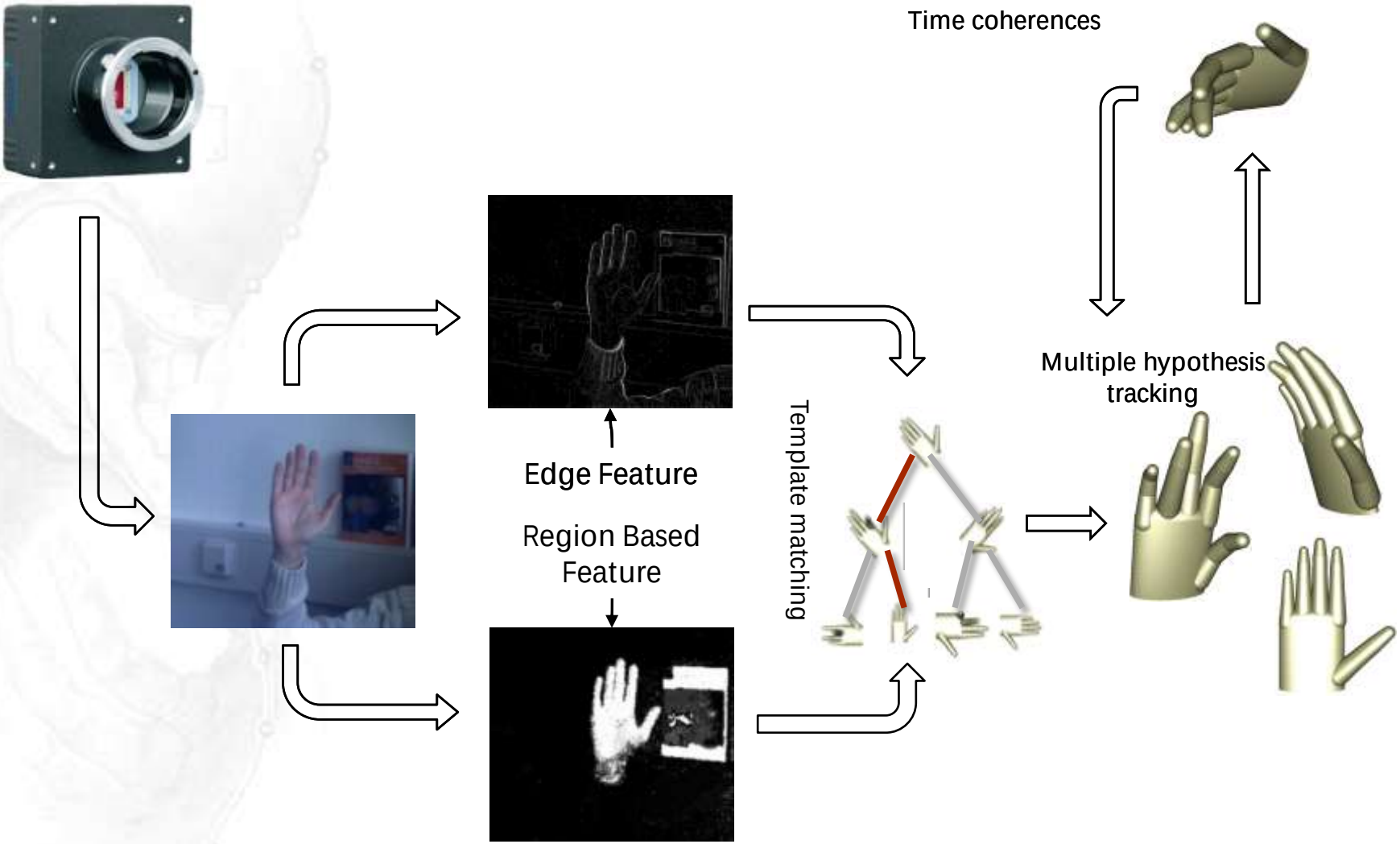


global state

local state

- Tracking approach
  - Sample hand parameter space $\theta_1, \cdots, \theta_N, \quad \theta_i \in \mathbb{R}^{26}$
  - Project hand models onto 2D and compare with query image
  - Estimate global position by position/scale of the hand in the query image and orientation/joint angles by different templates

Hand Tracking Pipeline



Template Matching

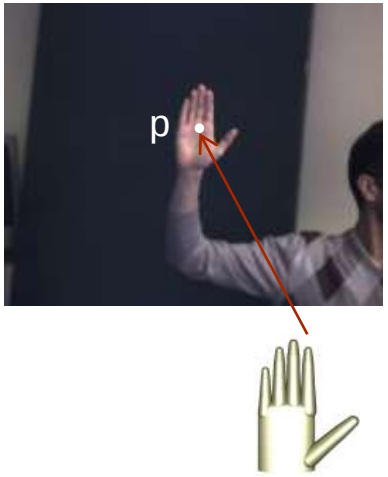
	Generate templates on-the-fly	Precompute templates
Number of templates	unlimited	limited to precom-puted poses
Storage space	constant	linear in #templates
Matching time	high	low
Additional structures (e.g. hierarchy)	almost impossible	possible
Appropriate for	local search	global search e.g. (re-)initialization

Related Work

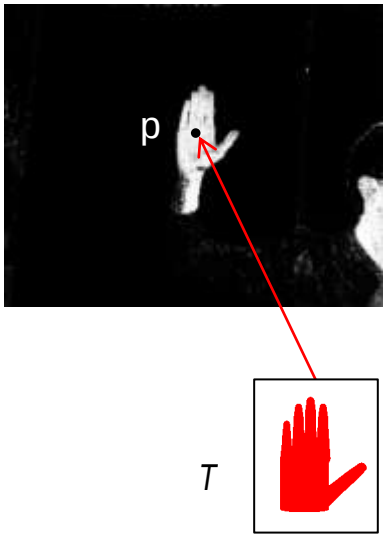
- Binary-Binary matching: template and input image segmentation are binary
  - Direct comparison of foreground regions:
    - Intersection between template and input image segmentation *[Lin et. Al AFGR2004][Kato et. al AFGR2006][Ouhaddi et. al 1999]*
  - Extract higher level features
    - Compare difference vectors between gravity center and points at silhouette contour *[Amai et. al AFGR2004][Shimada et. al ICCV2001]*
- Binary-Scalar matching: binary template, scalar segmentation
  - Joint probability *[Stenger et. al PAMI2006][Sudderth et. al CVPR2004]*
  - Efficient computation through prefix sum for each line in segmentation *[Stenger et. al PAMI2006]*

Joint Probability

- Given
  - Input image
  - Position p
  - Template *T*

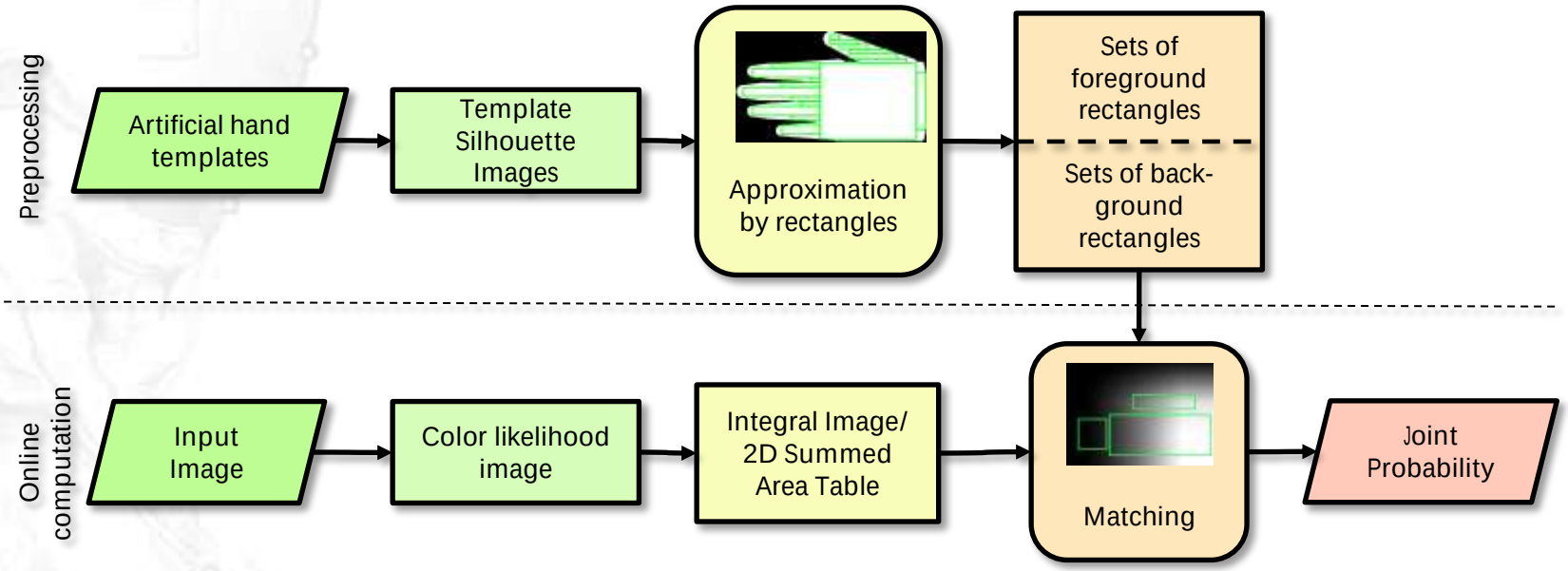


- Foreground segmentation *S* (we use skin color)
- Similarity measure given by joint probability between *T* and *S*(p)



$$P(S,\mathbf{p},T) = \prod_{\mathbf{x}\in \mathrm{fg}(T)} S(\mathbf{p}+\mathbf{x}) \cdot \prod_{\mathbf{x}\in \mathrm{bg}(T)} \neg S(\mathbf{p}+\mathbf{x})$$

Fast Area Based Template Matching



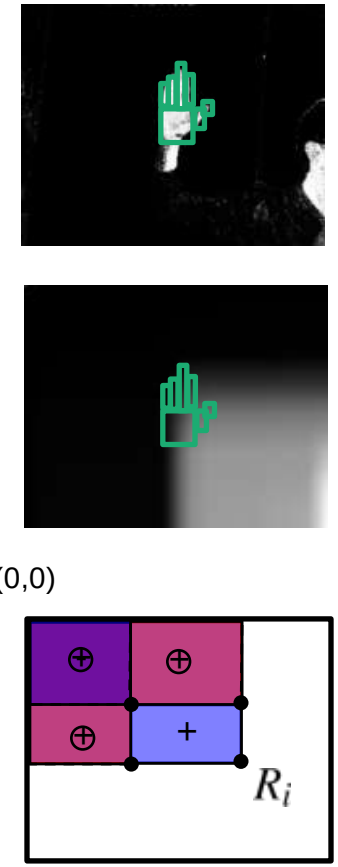
- Preprocess input image Segmentation :
  1. Take logarithm of segmentation S
  2. Compute 2D summed area table IS of log-image
- Use rectangular representation R of template T
  - Joint probability for a rectangle

$$h(R_i) = \sum_{\mathbf{x} \in R_i} \log S(x) = IS(R_i.\text{lower.right}) + IS(R_i.\text{upper.left}) - IS(R_i.\text{lower.left}) - IS(R_i.\text{upper.right})$$

Computation cost per rectangle: 4 look-ups in IS

  - Joint probability

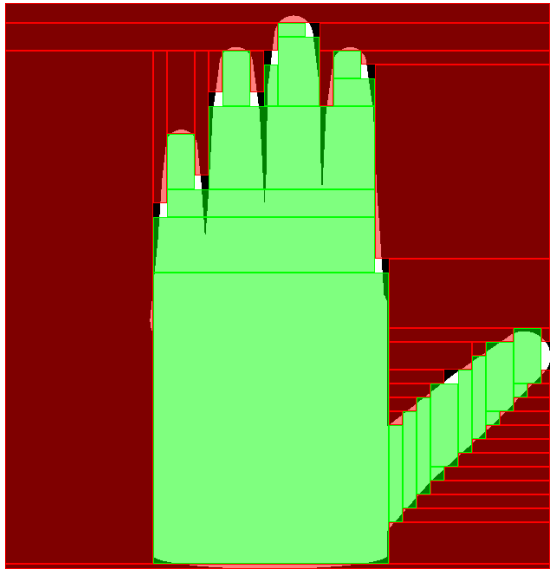
$$P(S, \mathbf{p}, T) \approx P(IS, \mathbf{p}, R^*) = \exp\Big(\sum_{R_i \in R^*} h(R_i + \mathbf{p}) \Big)$$



Template Representation Computation

- For all templates T
  - Approximate foreground/background area by a set R of axis-aligned rectangles
- Criteria for rectangle covering
  1. Cover as much area as possible (param τ)
     - High matching accuracy
  2. Use as few rectangles as possible (param θ)
     - Faster matching
     - Less memory consumed by template

     $\rightarrow$ Trade-off between criteria
- Define benefit function



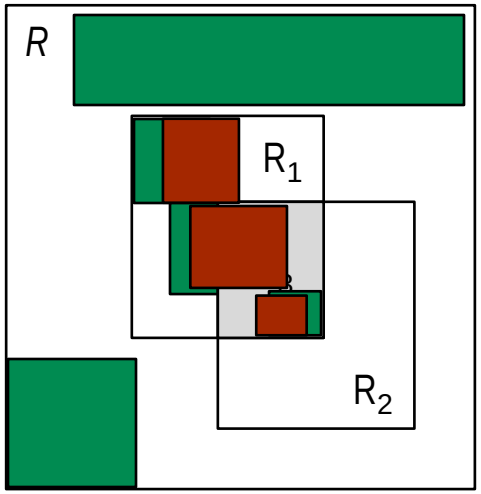
$$g(R_i) = -\theta + \sum_{(x,y)\in R_i} (T(x,y) - \tau), \quad R_i \in R$$

Our Rectangle Covering Algorithm Computation

- Optimization Function

$$R^* = \underset{R \subset \mathcal{R}}{\operatorname{argmax}} \sum_{R_i \in R} g(R_i)$$

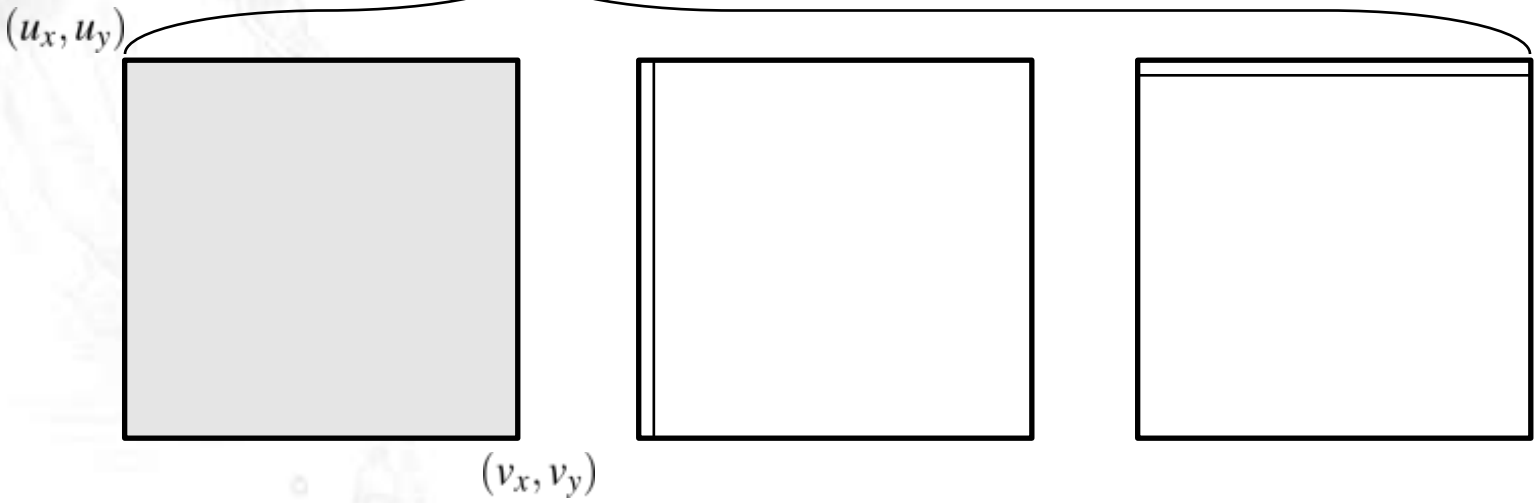
- Solve our rectangle covering problem by dynamic-programming
  - *Optimal substructure property:*
    - Let R_1^* be the optimal solution for a rectangle $R_1 \subset R$
    - If R_1 or any subset is in the optimal solution R^* of R, then $R_1^* \subset R^*$
  - *Overlapping subproblems*
    - $R_3 = R_1 \cap R_2$ is needed to computing the optimal solution of R_1 and R_2



Template Representation Computation

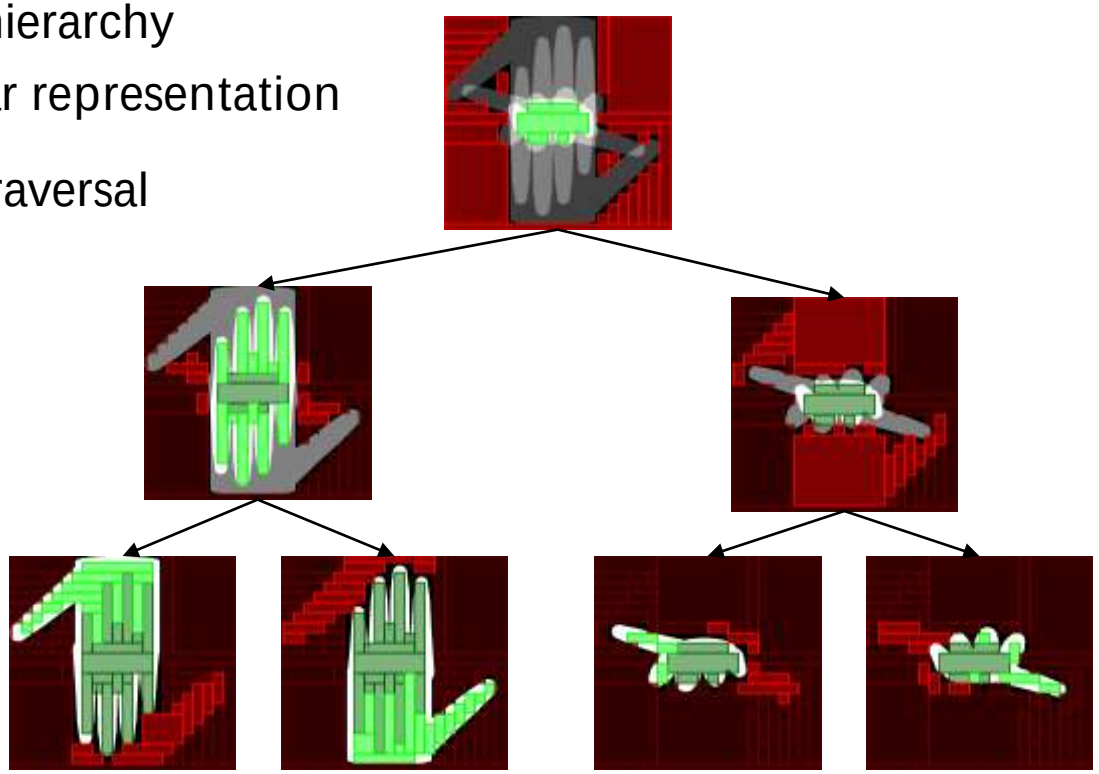
- Recursive equation

$$\mathscr{D}(R_{v_x,v_y}^{u_x,u_y}) = \max\Big\{ g(R_{v_x,v_y}^{u_x,u_y}),$$
$$\max_{u_x<x<v_x} \left\{ \mathscr{D}(R_{x,v_y}^{u_x,u_y}) + \mathscr{D}(R_{v_x,v_y}^{x,u_y}) \right\},$$
$$\max_{v_x<y<v_y} \left\{ \mathscr{D}(R_{v_x,y}^{u_x,u_y}) + \mathscr{D}(R_{v_x,v_y}^{u_x,y}) \right\} \Big\}$$



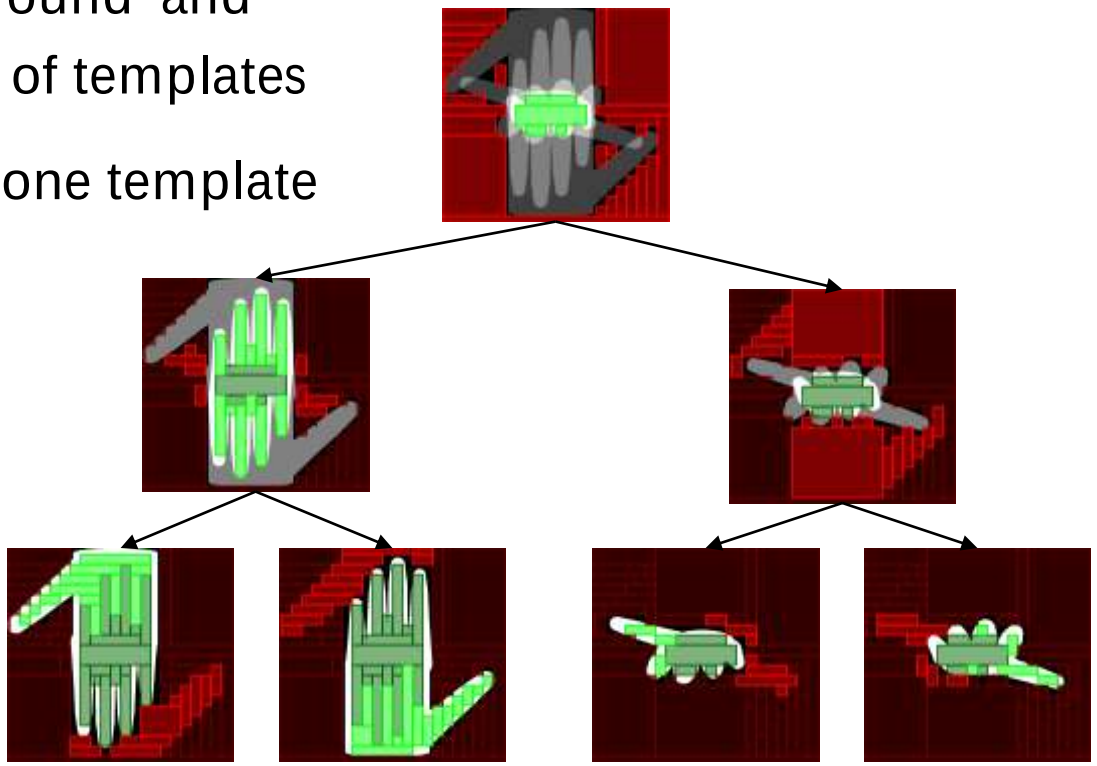
Template Hierarchy

- Match a set of *n* templates at a large number of positions in the input image
- Hierarchical approach
  - Generate template hierarchy based on rectangular representation
  - Matching through traversal
  - Complexity reduced from $O(n)$ to $O(\log n)$

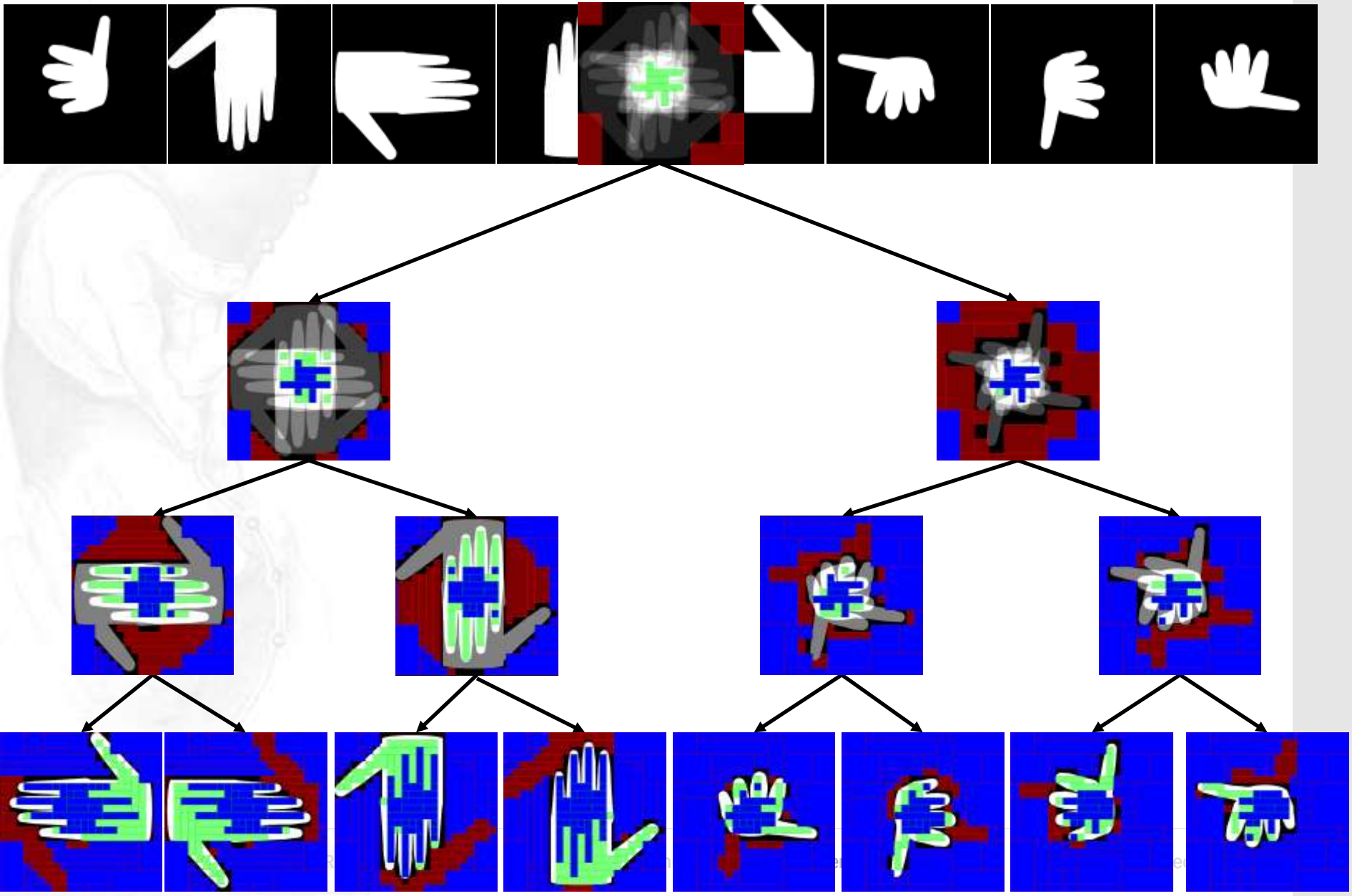


Hierarchy Generation

- Templates with similar shapes should end up in the same subtree
- Each node contains a set of axis-aligned rectangles that represent the foreground and background regions of templates
- Each leaf represents one template



Hierarchy Generation: Algorithm

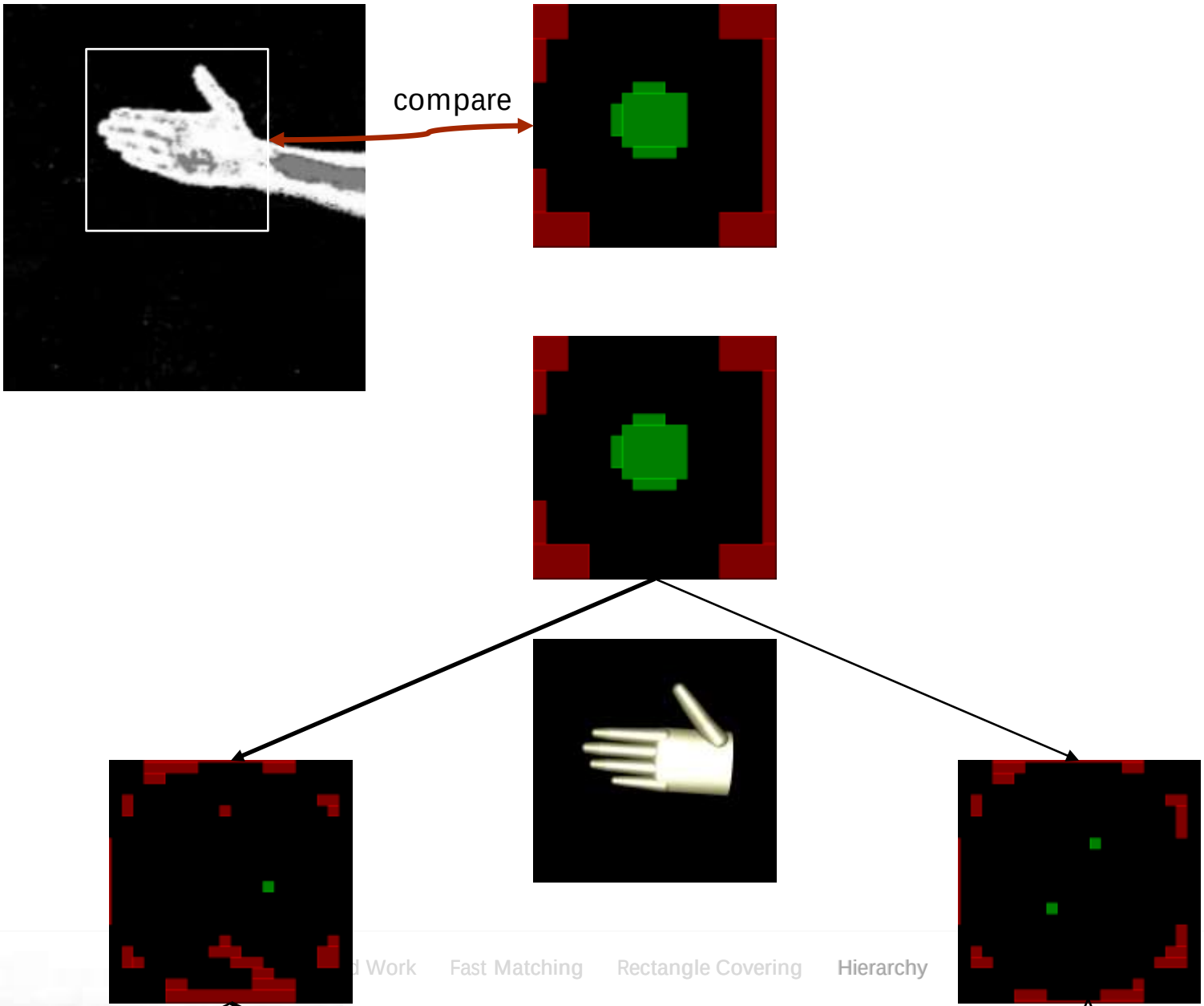


Hierarchical Matching

1. Start at root node
2. Compute joint probability of regions stored in current node
   - Areas in the template bounding box not yet matched are treated with probability 0.5 (i.e. foreground and background have same probability)

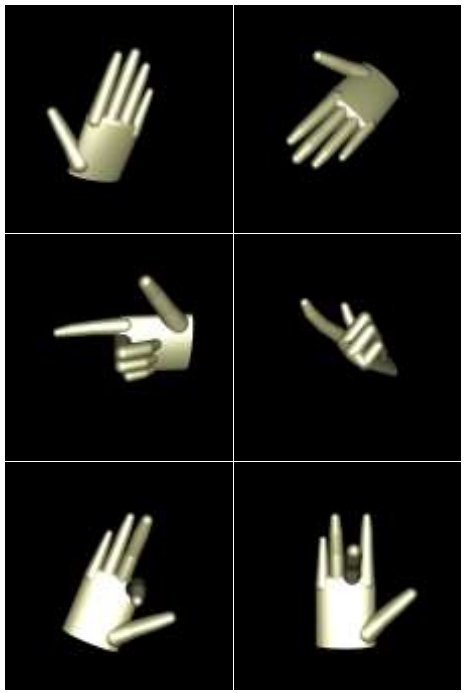
   → Ensure non-decreasing probabilities while moving along a path to a well matching template
3. Compute joint probability at all child nodes
4. Visit child with highest matching probability
   - Multi-hypothesis tracking: follow *n* instead of *1* path during traversal
5. If "is inner node" Goto step 2 else finished

Hierarchical Matching



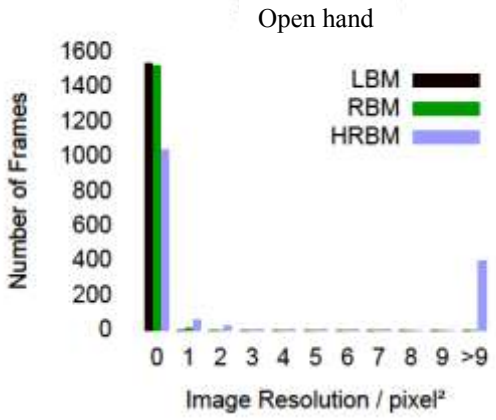
Experimental Results

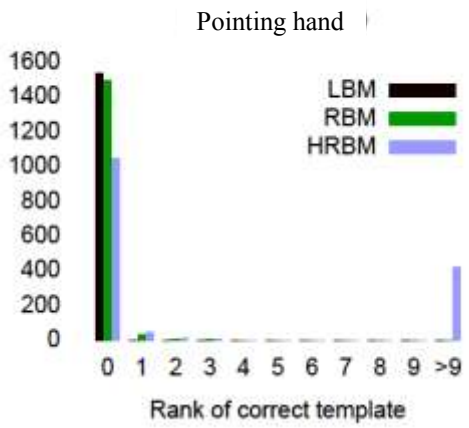
- We use the templates itself as input images because
  - We compare distance measures and not full tracker approaches and thus disturbing factors like bad illumination, segmentation noise, varying hand shapes are undesired
  - Ground truth available
- Three datasets
  - Open hand (2 rotational DOF)
    - 1536 templates
  - Pointing hand (2 rotational DOF)
    - 1536 templates
  - Flexing fingers (flex fingers,1 rotational DOF)
    - 1080 templates

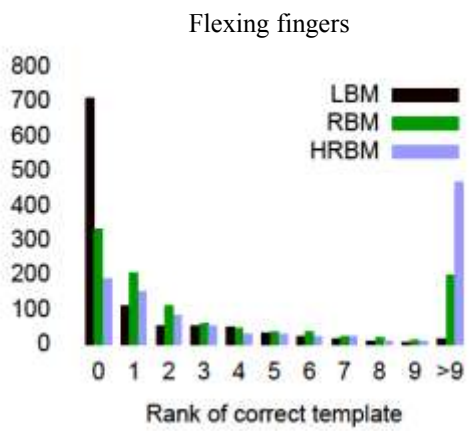


Matching quality

- The ranks 0-9 of the best matching template are recorded
- The plot shows the rank-histogram for a set of input image







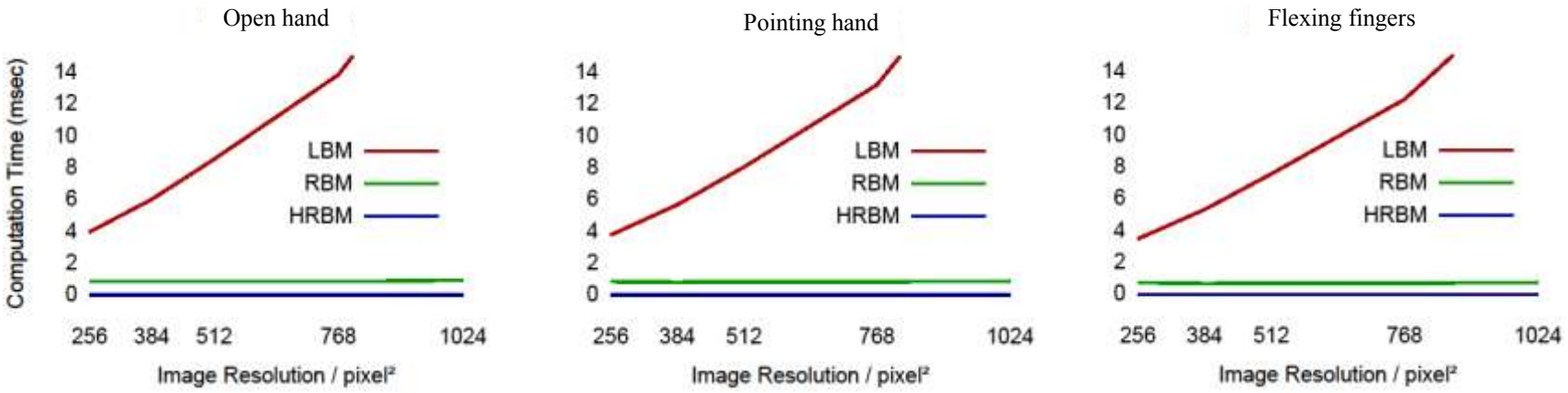
LBM: Stengers approach using prefix sum per line

RBM: Our approach with axis-aligned rectangles

HRBM: RBM using our hierarchy

Computation time

- Average computation time for each template set



- A resolution of 1024x1024 our approach (RBM) is about 25 times faster than Stengers method (LBM)

LBM: Stengers approach using prefix sum per line

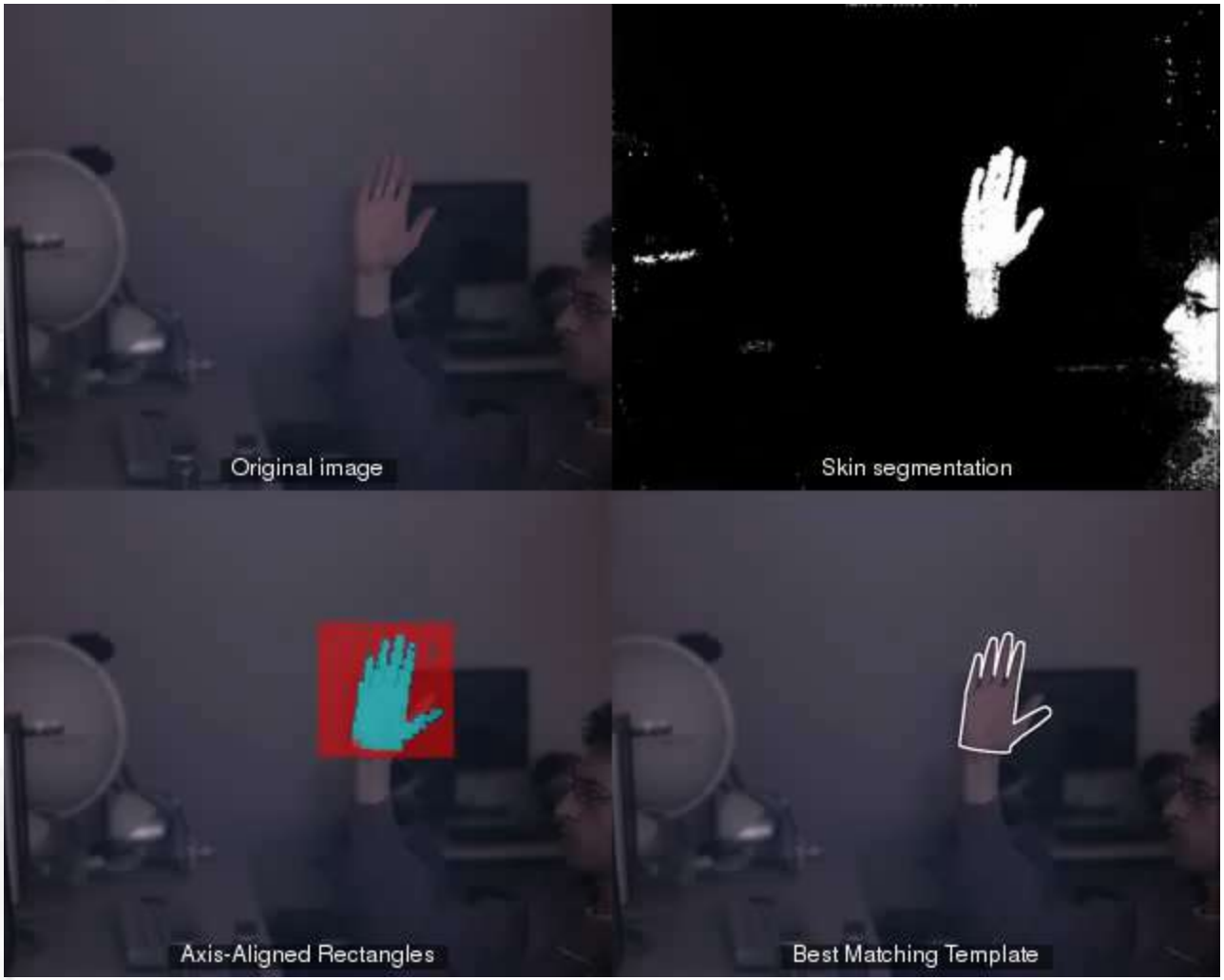
RBM: Our approach with axis-aligned rectangles

HRBM: RBM using our hierarchy

Conclusions

- Novel template representation
  - Resolution-independent
  - Low memory cost *(~0.6 KByte / template)*
- Matching is fast and resolution-independent *(0.7μs / template)*
- Template hierarchy with hierarchical matching
  - Complexity *O*(log *#templates*) *(28μs to traverse a tree with ~1500 templates)*
  - Hierarchy offers time critical matching: accuracy can be chosen online; stop traversal at inner node still delivers usable result
- Approach is not limited to hand tracking

Video



Hierarchical matching on short real dataset