1. Overview

**GOAL:** Propose an efficient and exact inference algorithm based on branch-and-bound (BB) to solve the human pose estimation problem on loopy graphical models.

**Motivation:**
- Cast human pose estimation problem as MAP-MRFs inference problem
- Solving MAP inference on general MRFs is challenging

**Contributions:**
- Source code available online (http://www.eecs.umich.edu/vision/BBproj.html)
- Cast human pose estimation problem as MAP-MRFs inference problem
- Novel data structure (BMT) and an efficient search routine
- Flexible bound by relaxing the loopy model into a mixture of star models.
- Up to 74 times faster than competing techniques [2]!

**Cons:**
- Approximated model;
- Stopping criteria:
  \[ \sum_i \beta_i (h_i, \cdot) + \sum_j \beta_j (h_j, \cdot) = 0 \]

2. Branch-and-Bound Basic

- **Bound:** \[ UB(H_{\text{map}}), LB(H_{\text{map}}) \] of \( f(h; \theta) \)
- **Branching:** \( H_{\text{map}} = H_N \cup H_{\text{map}} \cap H_N \)
- **Stopping criteria:** \( UB(H_{\text{map}}) = LB(H_{\text{map}}) \)

3. Flexible Bound

**Mixture of Star Models:**

\[
f(h; \theta; \phi) = \sum_i \lambda_i \beta_i (h_i, \cdot) + \sum_{ij} \beta_{ij} (h_i, h_j)
\]

**S.t.:** \( \beta_i (h_i, \cdot) + \beta_j (h_j, \cdot) = \delta (h_i, h_j) \)

**Models:**
- Tree Model [3,11]
- Loopy Model [6,7,9,10]

**Pros:**
- Efficient inference by dynamic programming (O(H^2)).
- More interactions between parts.

**Cons:**
- Exact inference NP-hard.
- Common misclassification errors.

4. Efficient Bound

**Naive Bound:**

\[
UB(H_{\text{map}}), LB(H_{\text{map}}) \quad \text{is states.}
\]

**Branch-Max-Tree (BMT):** Similar to [5]
- 1D array:
  \[ \lambda(\beta_{ij}) = \max_{h \in H} \beta_{ij}(h, \cdot) \]
- **Efficient data structure:** given A = [10 8 -1 5].

**BMT:**
- Building time: O(H)
- Query time: O(1)
- Time complexity: O(H).

5. Branching Strategy

**Guided Variable Selection (GVS):** Split the selected variable, e.g., human pose: select a specific body part.

- Re-define Upper Bound [2]:
  \[
  UB(H_{\text{map}}; \phi) = \max_{h} f(h; \theta, \phi) = \sum_i \lambda_i \beta_i (h_i, \cdot)
  \]
- Define node-wise Local-Primal-Dual-Gap (NLPDG)
  \[ \delta(h) = \lambda(h) - \lambda^*(h) \]

**Properties of NLPDG:**

- Non-Negative:
  \[ \sum_{ij} \beta_{ij}(h_i, h_j) \geq 0 \]

**Primal-Dual Gap (PDG):**

- Solve 13 out of 18 sequences within 20 minutes.

6. Experiment Results

**Baseline Methods:** CP [2] \( O(H^4) \)

**Objective:**

**Extending a tree model:**

- CPA: 7 out of 18 sequences within 20 minutes.

**References**


7. Conclusion

**Flexible bound for MRFs with different structures (HPE and SM).**

- BMT and OBMS are used to speed up from \( O(H^4) \) to \( O(log(H)) \).
- Faster than state-of-the-art exact Inference (CP) [2].
- Loopless model achieves superior accuracy than tree model.

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