In The Name of God.
The Merciful, The Compassionate.

PMBP: PatchMatch Belief Propagation for Correspondence Field Estimation

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1 Abstract and Introduction

This paper draws a new connection between PatchMatch(PM) and Particle Belief Propagation (PBP). The key contributions are as follows:

1. description of PM and BP in terms that allow the connection between them be clearly described.
2. use of this analysis to define a new algorithm PMBP which is more accurate than PM and faster than BP.

Belief Propagation (BP)

Correspondence field is parametrized by a vector grid $\{\mathbf{u}_s\}_{s=1}^{n}$ where s indexes nodes (correspondence to image pixels) and $\mathbf{u}_s \in \mathbb{R}^d$ parametrizes the correspondence vector at s.

Problems with the data term for weighted patch flow are as follows:

1. it implicitly assumes a constant correspondence field in the $(2h+1) \times (2h+1)$ patch surrounding every pixel (?). Large h over-smooths the output. More complex parametrization of flow field can be suggested. However, they are not computationally tractable.
2. h may be reduced. This causes the data term to be ambiguous. This causes the introduction of pairwise terms.

For discrete problems, where $\mathbf{u}$ live in finite set of size D, energy can be minimized in $O(nD)$ time, while with pairwise terms, the worst case complexity is $O(D^n)$. BP finds good minimizers in times far below the worst case. However, for correspondence problems, where $\mathbf{u}$ lives in an effective continuous space, D must be very large. So, even minimizing unary only costs is too expensive.

PatchMatch

An efficient way to compute a nearest neighbour field (NNF) between 2 images. It is considered as an efficient global minimizer for unary term only energies.

In PatchMatch Stereo [3] disparity is over-parametrized by 3D vector $\mathbf{u}_s = [a_s, b_s, c_s]^T$, parametrizing planar disparity surface $\Delta_s(x, y) = a_s(x - x_s) + b_s(y - y_s) + c_s$.

A key deficiency of PM is that it lack an explicit smoothness control on output field (has deficiency in finding reliable correspondences in very large smooth regions). A related deficiency is tendency of PM to require a form of early stopping: global optimum of unary energy is not necessarily the best solution in terms of image error (?) $\rightarrow$ *error versus energy trade-off*.

$$f(S) := \{f(s) | s \in S\}$$

$$\text{fargmin}_K(S, f) := S_K \subset S \,\text{s.t.}\, |S_K| = \min(K, |S|) \,\text{and}\, \max f(S_K) \leq \min f(S \backslash S_K)$$

1.1 PatchMatch with Particles

A set of K particles $P_s \subset \mathbb{R}^d$ is associated to each node s. Each particle $p \in P_s$ is a candidate solution $\mathbf{u}_s^*$ for the minimization problem. These sets are initialized randomly (data driven initialization is also applicable).

One PM iteration is linear sweep through all nodes. The order is defined by $\phi(s)$ so that s is visited before s' if $\phi(s) < \phi(s')$. Predecessor set $\Phi_s = \{s' | \phi(s') < \phi(s)\}$. Usually the order is from top-left to bottom-right and inverse on odd/even iterations.

Two update steps are performed:

1. Propagation: P_s is updated:

$$C_s = \bigcup \{P_t | t \in N(s) \cap \Phi_s\},$$
$$P_s \leftarrow \text{fargmin}_K(P_s \cup C_s, \psi_s)$$

2. Resampling: perturbs particles locally by $\mathcal{N}(0, \sigma)$:

$$R_s = \{p + \mathcal{N}(0, \sigma) | p \in P_s\},$$
$$P_s \leftarrow \text{fargmin}_K(P_s \cup R_s, \psi_s)$$

1.2 Particle Belief Propagation