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Proposal Flow

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Abstract

Finding image correspondences remains a challenging problem in the presence of intra-class variations and large changes in scene layout. Semantic flow methods are designed to handle images depicting different instances of the same object or scene category. We introduce a novel approach to semantic flow, dubbed proposal flow, that establishes reliable correspondences using object proposals. Unlike prevailing semantic flow approaches that operate on pixels or regularly sampled local regions, proposal flow benefits from the characteristics of modern object proposals, that exhibit high repeatability at multiple scales, and can take advantage of both local and geometric consistency constraints among proposals. We also show that proposal flow can effectively be transformed into a conventional dense flow field. We introduce a new dataset that can be used to evaluate both general semantic flow techniques and region-based approaches such as proposal flow. We use this benchmark to compare different matching algorithms, object proposals, and region features within proposal flow, to the state of the art in semantic flow. This comparison, along with experiments on standard datasets, demonstrates that proposal flow significantly outperforms existing semantic flow methods in various settings.

1. Introduction

Classical approaches to finding correspondences across images are designed to handle scenes that contain the same objects with moderate view point variations in applications such as stereo matching [42, 47], optical flow [23, 46, 52], and wide-baseline matching [41, 54]. Semantic flow methods, such as SIFT Flow [35] for example, on the other hand, are designed to handle a much higher degree of variability in appearance and scene layout, typical of images depicting different instances of the same object or scene category. They have proven useful for many tasks such as scene recognition, image registration, semantic segmentation, and image editing and synthesis [20, 29, 35, 54, 57].

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Figure 1. Proposal flow generates a reliable semantic flow between similar images using local and geometric consistency constraints among object proposals, and it can be transformed into a dense flow field. (a) Region-based semantic flow. (b) Dense flow field and image warping using the flow field. (Best viewed in color.)

In this context, however, appearance and shape variations may confuse similarity measures for local region matching, and prohibit the use of strong geometric constraints (e.g., epipolar geometry, limited disparity range). Existing approaches to semantic flow are thus easily distracted by scene elements specific to individual objects and image-specific details (e.g., background, texture, occlusion, clutter). This is the motivation for our work, where we use robust region correspondences to focus on regions containing prominent objects and scene elements rather than clutter and distracting details.

Concretely, we introduce an approach to semantic flow computation, called proposal flow, that establishes region correspondences using object proposals and their geometric relations (Fig. 1). Unlike previous semantic flow algorithms [4, 20, 22, 25, 29, 35, 45, 49, 50, 54, 57], that use regular grid structures for local region generation and matching, we leverage a large number of multi-scale object proposals [1, 24, 40, 51, 58], as now widely used in object detection [19, 27]. The proposed approach establishes region correspondences by exploiting their visual features and geometric relations in an efficient manner, and generates a region-based semantic flow composed of object proposal matches. We also show that the proposal flow can be effectively transformed into a conventional dense flow field. Finally, we introduce a new dataset that can be used to evalu-
Propose matching and semantic flow, in particular when handling
object proposals yields substantial gains in generic region
proposals. We show that the use of local regularization with
regularization based on co-occurrence and overlap of the
ports \([1, 24, 40, 51, 58]\), and uses an irregular form of spatial
regions in the pyramid models \([29, 35]\). In contrast, our work
at each region or pixel on (a pyramid of) regular grids, and
spatial regularization: The appearance similarity is defined
spatially, and assume that appearance match-

**2. Related work**

Correspondence problems involve a broad range of top-
ics beyond the scope of this paper. Here we briefly de-
scribe the context of our approach, and only review repre-
sentative works pertinent for ours. Classical approaches to
stereo matching and optical flow estimate pixel-level dense
correspondences between two nearby images of the same
scene \([23, 41, 42]\). While advances in invariant feature de-
tection and description have revolutionized object recogni-
tion and reconstruction in the past 15 years, research on
image matching and alignment between images have long
been dominated by instance matching with the same
scene and objects \([18]\). Unlike these, several recent ap-
proaches to semantic flow focus on handling images con-
taining different scenes and objects. Graph-based matching
algorithms \([10, 14]\) attempt to find category-level fea-
ture matches by leveraging a flexible graph representation
of images, but they commonly handle sparsely sampled or
detected features due to their computational complexity.
Inspired by classic optical flow algorithms, Liu et al.
pioneered the idea of dense correspondences across different
scenes, and proposed the SIFT Flow \([35]\) algorithm that
uses a multi-resolution image pyramid together with a hi-
archical optimization technique for efficiency. Kim et
al. \([29]\) extended the approach by inducing a multi-scale
regularization with a hierarchically connected pyramid of
grid graphs. More recently, Long et al. \([36]\) have investi-
gated the effect of pretrained ConvNet features on the SIFT
Flow algorithm, and Bristow et al. \([4]\) have proposed an
exemplar-LDA approach that improves the performance of
semantic flow. Despite differences in graph construction,
optimization, and similarity computation, existing seman-
tic flow approaches share grid-based regular sampling and
spatial regularization: The appearance similarity is defined
at each region or pixel on (a pyramid of) regular grids, and
spatial regularization is imposed between neighboring re-
gions in the pyramid models \([29, 35]\). In contrast, our work
builds on generic object proposals with diverse spatial sup-
ports \([1, 24, 40, 51, 58]\), and uses an irregular form of spatial
regularization based on co-occurrence and overlap of the
proposals. We show that the use of local regularization with
object proposals yields substantial gains in generic region
matching and semantic flow, in particular when handling
images with significant clutter and intra-class variations.

Object proposals \([1, 24, 40, 51, 58]\) have originally been
developed for object detection, where they are used to re-
duce the search space as well as false alarms. They are now
an important component in many state-of-the-art detection
pipelines \([19, 27]\). Despite their success on object detection
and segmentation, they have seldom been used in matching
tasks \([9, 26]\). In particular, while Cho et al. \([9]\) have shown
that object proposals are useful for region matching due to
their high repeatability on salient part regions, the use of
object proposals has never been thoroughly investigated in
semantic flow computation. The approach proposed in this
paper is a first step in this direction, and we explore how the
choice of object proposals, matching algorithms, and fea-
tures affects matching robustness and accuracy.

**Contributions.** The contributions of this paper are three-
fold: (i) We introduce the proposal flow approach to es-
tablishing robust region correspondences between related,
but not identical scenes using object proposals. (ii) We in-
roduce a benchmark for semantic flow that can be used to
evaluate both general semantic flow algorithms and region
matching methods. (iii) We demonstrate the advantage of
proposal flow over state-of-the-art semantic flow methods
through extensive experimental evaluations.

**3. Proposal flow**

Proposal flow can use any type of object proposals \([1, 24,
40, 51, 58]\) as candidate regions for matching two images of
related scenes. In this section, we introduce a probabilis-
tic model for region matching, and describe three matching
strategies including two baselines and a new one using local
regularization. We then describe our approach to generating
a dense flow field from the region matches.

**3.1. A Bayesian model for region matching**

Let us suppose that two sets of object proposals \(\mathcal{R}\) and
\(\mathcal{R}'\) have been extracted from images \(\mathcal{I}\) and \(\mathcal{I}'\) (Fig. 2(a-b)).
A proposal \(r\) in \(\mathcal{R}\) is an image region \(r = (f, s)\) with ap-
pearance feature \(f\) and spatial support \(s\). The appearance
feature represents a visual descriptor for the region (e.g.,
SPM \([31]\), HOG \([11]\), ConvNet \([30]\)), and the spatial sup-
port describes the set of all pixel positions in the region,
that forms a rectangular box in this work. Given the data
\(\mathcal{D} = (\mathcal{R}, \mathcal{R}')\), we wish to estimate a posterior probability
of the event \(r \mapsto r'\) meaning that proposal \(r\) in \(\mathcal{R}\) matches
proposal \(r'\) in \(\mathcal{R}'\):

\[
p(r \mapsto r' \mid \mathcal{D}) = p(f \mapsto f')p(s \mapsto s' \mid \mathcal{D}),
\]

where we decouple the probabilities of appearance and spa-
tial support matching, and assume that appearance match-
ing is independent of \(\mathcal{D}\). In practice, the appearance term
\(p(f \mapsto f')\) is simply computed from a similarity between
feature descriptors \(f\) and \(f'\), and the geometric consistency
term \(p(s \mapsto s' \mid \mathcal{D})\) is evaluated by comparing the spatial
supports \(s\) and \(s'\) in the context of the given data \(\mathcal{D}\), as
described in the next section. We set the posterior probability
as a matching score and assign the best match $\phi(r)$ for each proposal in $\mathcal{R}$:

$$\phi(r) = \arg\max_{r' \in \mathcal{R}} p(r \mapsto r' \mid \mathcal{D}).$$

Using a slight abuse of notation, if $(f',s') = \phi(f,s)$, we will write $f' = \phi(f)$ and $s' = \phi(s)$.

### 3.2. Geometric matching strategies

We now introduce three matching strategies, using different geometric consistency terms $p(s \mapsto s' \mid \mathcal{D})$.

**Naive appearance matching (NAM).** A straightforward way of matching regions is to use a uniform distribution for the geometric term so that

$$p(r \mapsto r' \mid \mathcal{D}) \propto p(f \mapsto f').$$

NAM considers appearance only, and does not reflect any geometric relationship among regions (Fig. 2(d)).

**Probabilistic Hough matching (PHM).** The matching algorithm in [9] can be expressed in our model as follows. First, a three-dimensional location vector (center position and scale) is extracted from the spatial support $s$. We denote it by a function $\gamma$. An offset space $\mathcal{X}$ is defined as a feasible set of offset vectors between $\gamma(s)$ and $\gamma(s')$:

$$\mathcal{X} = \{ \gamma(s) - \gamma(s') \mid r \in \mathcal{R}, r' \in \mathcal{R}' \}.$$  

The geometric consistency term $p(s \mapsto s' \mid \mathcal{D})$ is then defined as

$$p(s \mapsto s' \mid \mathcal{D}) = \sum_{x \in \mathcal{X}} p(s \mapsto s' \mid x)p(x \mid \mathcal{D}),$$

which assumes that $p(s \mapsto s' \mid x, \mathcal{D}) = p(s \mapsto s' \mid x)$. Here, $p(s \mapsto s' \mid x)$ measures an offset consistency between $\gamma(s) - \gamma(s')$ and $x$ by a Gaussian kernel in the three-dimensional offset space. From this model, PHM substitutes $p(x \mid \mathcal{D})$ with a generalized Hough transform score:

$$h(x \mid \mathcal{D}) = \sum_{(r,r') \in \mathcal{D}} p(f \mapsto f')p(s \mapsto s' \mid x).$$

which aggregates individual votes for offset $x$, from all possible matches in $\mathcal{D} = \mathcal{R} \times \mathcal{R}'$. Hough voting imposes a spatial regularizer on matching by taking into account a global consensus on the corresponding offset [33, 39]. However, it often suffers from background clutter that distracts the global voting process (Fig. 2(e)).

**Local offset matching (LOM).** Here we propose a new method to overcome this drawback of PHM [9] and obtain more reliable correspondences. Object proposals often contain a large number of distracting outlier regions from background clutter, and are not perfectly repeatable even for corresponding object or parts across different images (Fig. 2(c)). The global Hough voting in PHM has difficulties with such outlier regions. In contrast, we optimize a translation and scale offset for each proposal by exploiting only neighboring proposals. That is, instead of averaging $p(s \mapsto s' \mid x)$ over all feasible offsets $\mathcal{X}$ in PHM, we use one reliable offset optimized for each proposal. This local approach substantially alleviates the effect of outlier regions in matching as will be demonstrated by our experiment results.

The main issue is how to estimate a reliable offset for each proposal $r$ in a robust manner without any information about objects and their locations. One way would be to find the corresponding region of the region $r$ through a multi-scale sliding window search in $\mathcal{D}$ as in object detection [16], but this is expensive. Instead, we assume that nearby regions have similar offsets. For each region $r$, we first define its neighborhood $\mathcal{N}(r)$ as the regions with overlapping spatial support:

$$\mathcal{N}(r) = \{ \hat{r} \mid s \cap \hat{s} \neq \emptyset, \hat{r} \in \mathcal{R} \}.$$  

Using an initial correspondence $\phi(r)$, determined by the best match according to the appearance term, each neighboring region $\hat{r}$ is assigned its own offset, and all of them form a set of neighbor offsets:
\(X(r) = \{ \gamma(\hat{s}) - \gamma(\hat{\phi}(\hat{s})) \mid \hat{r} \in \mathcal{N}(r) \}. \quad (7)\)

From this set of neighbor offsets, we estimate a local offset \(x_r^*\) for the region \(r\) by the geometric median \([37]\):

\[
x_r^* = \arg\min_{x \in \mathbb{R}^3} \sum_{y \in X(r)} \| x - y \|_2,
\]

which can be globally optimized by Weiszfeld’s algorithm \([6]\) using a form of iteratively re-weighted least squares. Based on the local offset \(x_r^*\) optimized for each region, we define the geometric consistency function:

\[
g(s \mapsto s' | \mathcal{D}) = p(s \mapsto s' | x_r^*) \sum_{\hat{r} \in \mathcal{N}(r)} p(\hat{\phi} \mapsto \hat{\phi}(\hat{\phi})), \quad (9)\]

which means that \(r\) in \(\mathcal{R}\) is likely to match with \(r'\) in \(\mathcal{R}'\) if their offset is close to the local offset \(x_r^*\), and \(r\) has many neighboring matches with a high appearance fidelity.

By using \(g(s \mapsto s' | \mathcal{D})\) as a proxy for \(p(s \mapsto s' | \mathcal{D})\), LOM imposes local smoothness on offsets between neighboring regions. This geometric consistency function effectively suppresses matches between clutter regions, while favoring matches between regions that contain objects rather than object parts (Fig. 2(f)). In particular, the use of local offsets optimized for each proposal regularizes offsets within a local neighborhood that incorporates an overlap relationship between spatial supports of regions. This local regularization avoids a common problem with PHM, where the matching results often depend on a few strong matches.

### 3.3. Flow field generation

The proposal flow gives a set of region correspondences between images, but it can be easily transformed into a conventional dense flow field. Let \(p\) denote a pixel in image \(I\) (yellow point in Fig. 3(a)). For each pixel \(p\), its neighborhood is defined as the region in which it lies, i.e., \(\mathcal{N}(p) = \{ r \in \mathcal{R} : p \in r \}\). We define an anchor match \((r^*, \phi(r^*))\) as the region correspondence that has the highest matching score among neighboring regions (red boxes in Fig. 3(a)) where

\[
r^* = \arg\max_{r \in \mathcal{N}(p)} p(r \mapsto \phi(r) \mid \mathcal{D}). \quad (10)\]

Note that the anchor match contains information on translation and scale changes between objects. Using the geometric relationships between the pixel \(p\) and its anchor match \((r^*, \phi(r^*))\), a correspondence \(p'\) in \(I'\) (green point in Fig. 3(a)) is obtained by linear interpolation.

The matching score for each correspondence is set to the value of its anchor match. When \(p\) and \(q\) in \(I\) are matched to the same pixel \(p'\) in \(I'\), we select the match with the highest matching score and delete the other one. Finally, joint image filtering \([21]\) is applied under the guidance of the image \(I\) to interpolate the flow field in places without correspondences. Figure 3(b-c) shows examples of the estimated flow field and corresponding warping result between two images: Using the dense flow field, we warp all pixels in the right image to the left image. Our approach using the anchor match aligns semantic object parts well while handling translation and scale changes between objects.

### 4. A new dataset for semantic flow evaluation

Current research on semantic flow lacks an appropriate benchmark with dense ground-truth correspondences. Conventional optical flow benchmarks (e.g., Middlebury [2] and MPI-Sintel [5]) do not feature within-class variations, and ground truth for generic semantic flow is difficult to capture due to its intrinsically semantic nature, manual annotation being extremely labor intensive and somewhat subjective. All existing approaches are thus evaluated only with sparse ground truth or in an indirect manner (e.g. mask transfer accuracy) \([4, 29, 35, 45, 49, 57]\). Such benchmarks only evaluate a small number of matches, that occur at ground-truth keypoints or around mask boundaries in a point-wise manner. To address this issue, we introduce in this section a new dataset for semantic flow, dubbed proposal flow (PF) dataset, built using ground-truth object bounding boxes and keypoint annotations, (Fig. 4(a-b)), and propose new evalu-
4.1. Ground-truth correspondence generation

We assume that true matches only exist within object bounding boxes. Let us assume two sets of keypoint annotations at positions $k_i$ and $k'_i$ in $I$ and $I'$, respectively, with $i = 1, \ldots, m$. Assuming the objects present in the images and their parts may undergo shape deformation, we use thin plate splines (TPS) [3, 13] to interpolate the sparse keypoints. Namely, the ground truth is approximated from sparse correspondences using TPS warping.

For each region, its ground-truth match is generated as follows. We assume that true matches only exist between a subset of regions, i.e., regions around object bounding boxes (Fig. 4(c)): $\mathcal{R}_r = \{r | b \cap r | r| \geq 0.75, r \in \mathcal{R} \}$ where $b$ denotes an object bounding box in $I$, and $|r|$ indicates the area of a region $r$. For each region $r \in \mathcal{R}_s$, the four vertices of the rectangle are warped to the corresponding ones in $I'$ by the TPS mapping function. The region formed by the warped points is a correspondence of region $r$. We fit a tight rectangle for this region and set it as a ground-truth correspondence for the region $r$ (Fig. 4(d)).

4.2. Evaluation criteria

We introduce two evaluation metrics for region matching performance in terms of region matching precision and match retrieval accuracy. Basically, the metrics build on the intersection over union (IoU) score between $r$’s correspondence $\phi(r)$ and its ground truth $r^*$:

$$\text{IoU}(\phi(r), r^*) = |\phi(r) \cap r^*| / |\phi(r) \cup r^*|. \quad (11)$$

For region matching precision, we propose the probability of correct region (PCR) metric\(^2\) where region $r$ is correctly matched to its ground truth $r^*$ if $1 - \text{IoU}(\phi(r), r^*) < \tau$ (e.g., Fig. 5(a) top). We measure the PCR metric while varying the IoU threshold $\tau$ from 0 to 1. For match retrieval accuracy, we propose the average IoU of $k$-best matches (mIoU@$k$) according to the matching score (e.g., Fig. 5(a) bottom). We measure the mIoU@$k$ metric while increasing the number of top matches $k$. These two metrics exhibit two important characteristics of matching: the PCR reveals the accuracy of overall assignment, and the mIoU@$k$ shows the reliability of matching scores that is crucial in match selection.

4.3. Dataset construction

To generate our dataset, we start from the benchmark for sparse matching of Cho et al. [8], which consists of 5 object classes (Face, Car, Motorbike, Duck, WineBottle) with 10 keypoint annotations for each image. Note\(^2\)This region-based metric is based on a conventional point-based metric, the probability of correct keypoint (PCK) [55]. In the case of pixel-based flow, PCK can be adopted instead.
that these images contain more clutter and intra-class variation than existing datasets for semantic flow evaluation, e.g., images with tightly cropped objects or similar background [29, 45, 57]. We exclude the Face class where the number of generated object proposals is not sufficient to evaluate matching accuracy. The other classes are split into sub-classes according to viewpoint or background clutter. We obtain a total of 10 sub-classes. Given these images and regions, we generate ground-truth data between all possible image pairs within each class.

5. Experiments

5.1. Experimental details

Object proposals. We evaluate four state-of-the-art object proposal methods: EdgeBox (EB) [58], multi-scale combinatorial grouping (MCG) [1], selective search (SS) [51], and randomized prim (RP) [40]. In addition, we consider three baseline proposals [24]: Uniform sampling (US), Gaussian sampling (GS), and sliding window (SW). See [24] for more details. For fair comparison, we use 1,000 proposals for all the methods. To control the number of proposals, we use the proposal score provided by EB, MCG, and SS. For RP, we randomly select among the proposals.

Feature descriptors and similarity. We evaluate three popular feature descriptors: SPM [31], HOG [11], and ConvNet [30]. For SPM, dense SIFT features [38] are extracted every 4 pixels and each descriptor is quantized into a 1,000 word codebook [48]. For each region, a spatial pyramid pooling [31] is used with $1 \times 1$ and $3 \times 3$ pooling regions. We compute the similarity between SPM descriptors by the $\chi^2$ kernel. HOG features are extracted with $8 \times 8$ cells and 31 orientations, then whitened. For ConvNet features, we use each output of the 5 convolutional layers in AlexNet [30], which is pre-trained on the ImageNet dataset [12]. For HOG and ConvNet, the dot product is used as a similarity metric.

5.2. Proposal flow components

We use the PF benchmark in this section to compare three variants of proposal flow using different matching algorithms (NAM, PHM, LOM), combined with various object proposals [1, 24, 40, 51, 58], and features [11, 30, 31].

Figure 4(e-g) shows a qualitative comparison between region matching algorithms on a pair of images and depicts correct matches found by each variant of proposal flow. In this example, at the IoU threshold 0.5, the numbers of correct matches are 16, 5, and 38 for NAM, PHM [9], and LOM, respectively. This shows that PHM may give worse performance than even NAM when much clutter exists in background. In contrast, the local regularization in LOM alleviates the effect of such clutter.

Figure 5 summarizes the matching and retrieval performance on average for all object classes with a variety of combination of object proposals, feature descriptors, and matching algorithms. Figure 5(a) compares different types of object proposals with fixed matching algorithm and feature descriptor (LOM w/ HOG). RP shows the best matching precision and retrieval accuracy among the object proposals. An upper bound on precision is measured for object proposals (around a given object) in the image $I$ using a corresponding ground truths in image $I'$, that is the best matching accuracy we can achieve with each proposal method. The upper bound (UB) plots show that RP generates more consistent regions than other proposal methods, and is adequate for region matching. RP shows higher matching precision than other proposals especially when the IoU threshold is low. The evaluation results for different features (LOM w/ RP) are shown in Fig. 5(b). The HOG descriptor gives the best performance in matching and retrieval. The CNN features in our comparison come from AlexNet [30] trained for ImageNet classification. Such CNN features have a task-specific bias to capture discriminative parts for classification, which may be less adequate for patch correspondence or retrieval than engineered features such as HOG. Similar conclusions are found in recent papers [36, 43]. See, for example, Table 3 in [43] where SIFT outperforms all AlexNet features (Conv1-5). Among ConvNet features, the fourth and first convolutional layers (Conv4 and Conv1) show the best and worst performance, respectively, while other layers perform similar to SPM. This confirms the finding in [56], which shows that Conv4 gives the best matching performance among ImageNet-trained ConvNet features. Figure 5(c) compares the performance of different matching algorithms (RP w/ HOG), and shows that LOM outperforms others in matching as well as retrieval. Figure 5(d and e) shows the area under curve (AuC) for PCR and mIoU@k plots, respectively. This suggests that combining LOM, RP, and HOG performs best in both metrics.

In Table 1, we show AuCs of PCR plots for each class (LOM w/ RP and HOG). From this table, we can see that 1) higher matching precision is achieved with objects having a similar pose (e.g., mot(S) vs. mot(M)), 2) performance decreases for deformable object matching (e.g., duck(S) vs. car(S)), and 3) matching precision can increase drastically by eliminating background clutters (e.g., win(w/o C) vs. win(w/ C)).

5.3. Flow field

To compare our method with state-of-the-art semantic flow methods, we compute a dense flow field from
our proposal flows (Sec. 3.3), and evaluate image alignment between all pairs of images in each subset of the PF dataset. We test four object proposal methods (MCG, EB, SS, RP) with HOG descriptors. For an evaluation metric, we use PCK between warped keypoints and ground-truth ones [36, 55]. Ground-truth keypoints are deemed to be correctly predicted if they lie within $\alpha \times \min(h, w)$ pixels of the predicted points for $\alpha$ in $[0, 1]$, where $h$ and $w$ are the height and width of the object bounding box, respectively. Table 2 shows the average PCK ($\alpha = 0.1$) over all object
Table 2. PCK comparison for dense flow field on the PF dataset.

<table>
<thead>
<tr>
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<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>NAM</td>
<td>0.46</td>
<td><strong>0.50</strong></td>
<td>0.52</td>
<td>0.53</td>
</tr>
<tr>
<td>PHM</td>
<td>0.48</td>
<td>0.45</td>
<td>0.55</td>
<td>0.54</td>
</tr>
<tr>
<td>LOM</td>
<td><strong>0.49</strong></td>
<td>0.44</td>
<td><strong>0.56</strong></td>
<td><strong>0.55</strong></td>
</tr>
<tr>
<td>DeepFlow [46]</td>
<td>0.20</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GMK [14]</td>
<td>0.27</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SIFT Flow [35]</td>
<td>0.38</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DSP [29]</td>
<td>0.37</td>
<td></td>
<td></td>
<td></td>
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</tbody>
</table>

Table 3. Matching accuracy on the Caltech-101 dataset.

<table>
<thead>
<tr>
<th>Proposals</th>
<th>Methods</th>
<th>LT-ACC</th>
<th>IoU</th>
<th>LOC-ERR</th>
</tr>
</thead>
<tbody>
<tr>
<td>NAM</td>
<td>SS [51]</td>
<td>0.68</td>
<td>0.44</td>
<td>0.41</td>
</tr>
<tr>
<td>PHM</td>
<td>LOM</td>
<td>0.78</td>
<td><strong>0.50</strong></td>
<td><strong>0.25</strong></td>
</tr>
<tr>
<td>DeepFlow [46]</td>
<td>RP [40]</td>
<td>0.70</td>
<td>0.44</td>
<td>0.39</td>
</tr>
<tr>
<td>GMK [14]</td>
<td></td>
<td>0.75</td>
<td>0.48</td>
<td>0.31</td>
</tr>
<tr>
<td>SIFT Flow [35]</td>
<td>LOM</td>
<td>0.78</td>
<td><strong>0.50</strong></td>
<td><strong>0.26</strong></td>
</tr>
<tr>
<td>DSP [29]</td>
<td></td>
<td>0.77</td>
<td>0.47</td>
<td>0.35</td>
</tr>
</tbody>
</table>

Matching results on Caltech-101. We also evaluate our approach on the Caltech-101 dataset [15]. Following the experimental protocol in [29], we randomly select 15 pairs of images for each object class, and evaluate matching accuracy with three metrics: Label transfer accuracy (LT-ACC) [34], the IoU metric, and the localization error (LOC-ERR) of corresponding pixel positions. For LT-ACC, we transfer the class label of one image to the other using dense
Figure 7. Examples of dense flow field on PASCAL parts. (a-b) Source images are warped to the target images using the dense correspondences estimated by (c) DSP [29] and (d) Proposal Flow w/ LOM, SS and HOG. (e-f) Similarly, annotated part segments for the source images are warped to the target images using the dense correspondences computed by (g) DSP and (h) Proposal Flow w/ LOM, SS and HOG. (Best viewed in color.)

Table 4. Matching accuracy on the PASCAL VOC classes.

<table>
<thead>
<tr>
<th>Proposals</th>
<th>Methods</th>
<th>IoU</th>
<th>PCK</th>
</tr>
</thead>
<tbody>
<tr>
<td>SS [51]</td>
<td>NAM</td>
<td>0.35</td>
<td>0.13</td>
</tr>
<tr>
<td></td>
<td>PHM</td>
<td>0.39</td>
<td>0.17</td>
</tr>
<tr>
<td></td>
<td>LOM</td>
<td>0.41</td>
<td>0.17</td>
</tr>
<tr>
<td>Congealing [32]</td>
<td></td>
<td>0.38</td>
<td>0.11</td>
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<tr>
<td>RASL [46]</td>
<td></td>
<td>0.39</td>
<td>0.16</td>
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<tr>
<td>CollectionFlow</td>
<td></td>
<td>0.38</td>
<td>0.12</td>
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<tr>
<td>DSP [29]</td>
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<td>0.17</td>
</tr>
<tr>
<td>FlowWeb [57]</td>
<td></td>
<td>0.43</td>
<td>0.26</td>
</tr>
</tbody>
</table>

correspondences, and count the number of correctly labeled pixels. Similarly, the IoU score is measured between the transferred label and ground truth. Table 3 compares quantitatively the matching accuracy of proposal flow to the state of the art. It shows that proposal flow using LOM outperforms other approaches, especially for the IoU score and the LOC-ERR of dense correspondences. Note that compared to LT-ACC, these metrics evaluate the matching quality for the foreground object, separate from irrelevant scene clutter. Our results verify that proposal flow focuses on regions containing objects rather than scene clutter and distracting details, enabling robust image matching against outliers.

Matching results on PASCAL parts. We use the dataset provided by [57] where the images are sampled from the PASCAL part dataset [7]. We first measure part match-
ing accuracy using human-annotated part segments. For this experiment, we measure the weighted IoU score between transferred segments and ground truths, with weights determined by the pixel area of each part (Table 4). To evaluate alignment accuracy, we measure the PCK metric ($\alpha = 0.05$) using keypoint annotations for the 12 rigid PASCAL classes [53] (Table 4). We use the same set of images as in the part matching experiment. Proposal flow has an advantage over existing approaches on images that contain cluttering elements (e.g., background, instance-specific texture, occlusion), but in this dataset [57], such elements are confined to only a small portion of the images, compared to the PF and the Caltech-101 [15] datasets. This may be a reason that, for the PCK metric, our approach with SS [51] gives similar results to other methods. While FlowWeb [57] gives better results than ours, it relies on a cyclic constraint across multiple images (at least, three images). Thus, directly comparing our pairwise matching to FlowWeb is probably not fair. FlowWeb uses the output of DSP [29] as initial correspondences, and refines them with the cyclic constraint. Since our method clearly outperforms DSP, using FlowWeb as a post processing would likely increase performance. Figure 7 visualize the part matching results.

For more examples and qualitative results, see our project webpage.

6. Discussion

We have presented a robust region-based semantic flow method, called proposal flow, and showed that it can effectively be mapped onto pixel-wise dense correspondences. We have also introduced the PF dataset for semantic flow, and shown that it provides a reasonable benchmark for semantic flow evaluation without extremely expensive manual annotation of full ground truth. Our benchmark can be used to evaluate region-based semantic flow methods and even pixel-based ones, and experiments with the PF dataset demonstrate that proposal flow substantially outperforms existing semantic flow methods. Experiments with Caltech and the VOC parts datasets further validate these results.

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References


