

# Introducing Authority and Hubness into Graph Matching

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**Abstract**—Spectral matching is an efficient approach for inexact graph matching. Many spectral matching methods boil down to power iteration which calculate the confidence vector iteratively. Inspired by the Web page ranking method *Hypertext Induced Topic Search* (HITS), we introduce hubness vector and authority vector to replace the traditional confidence vector, and an iterative algorithm is proposed to solve the subgraph matching problem. The incorporation of hubness and authority can help reduce the distraction caused by outliers, and provides better robustness against outliers. The performance of the proposed algorithm is evaluated on both synthetic graphs and real-world images.

**Index Terms**—Graph Matching, HITS, Power Iteration

## I. INTRODUCTION

Graph matching provides a powerful tool for pattern recognition and machine vision tasks [1], such as 3D reconstruction [2]–[4], object detection [5], [6], shape retrieval [7], and image stitching [8].

The performance of graph matching deteriorates when faced with outliers [9]–[12]. In practice, it is usually necessary to match a model graph to a scene graph which is contaminated with noise from background and other targets, which makes the outlier a challenge for graph matching algorithms.

Traditional spectral matching methods such as spectral matching (SM) [13] and graduated assignment (GA) [14] are vulnerable to outliers because they assume that pairwise affinity matrix is an empirical estimate of the pairwise assignment probability, which is false when outliers exist [9]. To deal with outliers, the pairwise assignment probabilities are reweighed in each iteration in probabilistic graph matching (PGM) [9] so that the influence of outliers is gradually eliminated. Recently, a max-pooling based graph matching (MPM) [15] algorithm has been proposed to address the challenge of matching a model graph to a scene graph with large amount of outliers. It calculates the score of each candidate match using the maximal support from nearby matches, and hence prevents the calculation from being contaminated by outliers or mismatched pairs.

In this paper, we propose an authority and hubness based algorithm for graph matching with outliers. Graph matching can be treated as ranking of candidate matches given relations between the matches, while Web page ranking algorithms

rank the pages given the links connecting the Web pages [11]. Many Web page ranking algorithms have emerged in the last two decades, and a most famous one is Hypertext Induced Topic Search (HITS) [16]. Inspired by HITS, we introduce the concept of authority and hubness into graph matching. Specifically, we introduce an authority and hubness based algorithm where they are iteratively updated. Authority measures how confident a match is, while hubness measures how well a match supports other matches and thus helps to distinguish inliers from outliers.

The rest of the paper is organized as follows. Related works are discussed in Section II, while Section III presents the novel authority and hubness based graph matching (AHM) algorithm. Experiment results are shown in Section IV, and Section V concludes the paper.

## II. RELATED WORKS

In this section we discuss related works on spectral matching. Many spectral matching algorithms boil down to power iteration. Power iteration is a well-known eigenvalue algorithm which finds the largest eigenvalue (absolute) of a matrix and its corresponding eigenvector. Specifically, the procedure of power iteration takes the following form:

**initialize**  $\mathbf{x}$  to  $\mathbf{x}_0$

**repeat**

$\mathbf{x} \leftarrow \mathbf{A}\mathbf{x}$

$\mathbf{x} \leftarrow \frac{\mathbf{x}}{\|\mathbf{x}\|_2}$

**until** convergence

The sequence of  $\mathbf{x}$  converges to the principal eigenvector.

Power iteration has different interpretations in different graph matching algorithms. Typically, the objective function of the graph matching problem is formulated by:

$$\begin{aligned} \max_{\mathbf{X}} \quad & \text{vec}(\mathbf{X})^T \mathbf{A} \text{vec}(\mathbf{X}) \\ \text{s.t.} \quad & \mathbf{X} \in \{0, 1\}^{M \times N}, \sum_i \mathbf{X}_{i,j} \leq 1, \sum_j \mathbf{X}_{i,j} \leq 1 \end{aligned} \quad (1)$$

where  $\text{vec}(\mathbf{X})$  is the row-wise vectorization of  $\mathbf{X}$ , and  $\mathbf{A}$  is a  $\mathcal{R}^{MN \times MN}$  affinity matrix which stores the pairwise similarity between two graphs  $\mathcal{G}$  and  $\mathcal{H}$ .

Power iteration has been treated as a method for solving for the principle eigenvector (SM [13]), the Taylor series expansion of the original objective function (GA [14]), or the probabilistic transition (RRWM [11], PGM [9]). All these algorithms share a general iterative framework:

```

initialize
repeat
  Update  $\mathbf{x}$ 
  Update  $\mathbf{A}$  (Optional)
  constraint enforcement on  $\mathbf{x}$  by normalization
until convergence
Discretization of  $\mathbf{x}$ 

```

SM [13] turns out to be one simple yet effective power iteration based graph matching algorithm. The graph matching problem is cast as a leading eigenvector solving problem, where the power iteration serves as a method to compute the principal eigenvector of the affinity matrix  $\mathbf{A}$ . However, no constraint enforcement was conducted during the iterations:

```

repeat
   $\mathbf{x} \leftarrow \mathbf{A}\mathbf{x}$ 
   $\mathbf{x} \leftarrow \frac{\mathbf{x}}{\|\mathbf{x}\|_2}$ 
until convergence
Discretization

```

Other successful power iteration based graph matching algorithms improve the original power iteration by updating the confidence of assignments or the transition matrix (updated affinity matrix) in different ways.

In GA [14], power iteration is used to solve the one-order Taylor series approximation of the original objective function. Compared to the original power iteration method, the confidence of assignments  $\mathbf{x}$  are manipulated before multiplied with the affinity matrix:

```

repeat
   $\mathbf{x} \leftarrow \mathbf{A}\mathbf{r}, \mathbf{r} \leftarrow \exp(\beta\mathbf{x}), \beta \leftarrow \beta * \delta\beta$ 
   $\mathbf{x} \leftarrow$  row and column normalization of  $\mathbf{x}$ 
until convergence
Discretization

```

The procedure enhances the matches with high confidence by using their exponentials and gradually increases the amplification factor. The soft-assign operator allows the confidence to gradually approximate the discrete solution. The row and column normalization is also used to make sure that  $\mathbf{x}$  is a doubly stochastic matrix in each iteration.

A method which is closely related to SM and GA is RRWM [11]. The affinity matrix is first transformed into a stochastic transition matrix  $\bar{\mathbf{A}}$  in RRWM, some key steps are as follows:

```

repeat
   $\mathbf{x} \leftarrow \bar{\mathbf{A}}\mathbf{x}, \mathbf{r} \leftarrow \exp(\beta\mathbf{x})$ 
   $\mathbf{r} \leftarrow$  row and column normalization of  $\mathbf{r}$ 

```

$\mathbf{x} \leftarrow \alpha\mathbf{x} + (1 - \alpha)\mathbf{r}$

**until** convergence

**Discretization**

Even though interpreted in a random walk framework, the first two step are similar to GA, with a fixed inflation parameter  $\beta$ . The confidence derived in each iteration is a linear combination of the result from SM and GA. It turns out that the moderated procedure performs better than both GA and SM.

In PGM [9], the affinity matrix  $\mathbf{A}$  is updated to ensure the convergence to discrete solutions. Its procedure is as follows:

```

repeat
   $\mathbf{A}(i, j) = \mathbf{A}(i, j) * \mathbf{x}_{t+1}(i) / \mathbf{x}_t(i)$ 
   $\mathbf{x}_{t+1} \leftarrow \mathbf{A}\mathbf{x}_t$ 
   $\mathbf{x}_{t+1} \leftarrow$  row and column normalization of  $\mathbf{x}_{t+1}$ 
until convergence
Discretization

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In MPM [15], apart from the manipulation on the confidence of assignment and the transition matrix, the transition manner is changed. In traditional transition paradigms, the confidences of a match is calculated by averaging across its neighbours. While in MPM, only the neighbour with the highest supporting confidence is selected, similar to the max-pooling operation in classification and feature selection tasks [17], [18].

### III. INTRODUCING AUTHORITY AND HUBNESS INTO GRAPH MATCHING

We introduce authority and hubness into graph spectral matching inspired by the Web page ranking method Hypertext Induced Topic Search (HITS) [16]. We first briefly review the HITS model, then the connection between Web page ranking and graph matching is analyzed. Finally, the authority and hubness based graph matching algorithm (AHM) is introduced.

#### A. Hubs and Authorities of Web Pages

In HITS model, the Web pages are treated as authorities and hubs. The basic idea is:

*Good authorities are pages that are pointed to by good hubs, and good hubs are pages that point to good authorities.* [16]

Let  $\mathbf{L} = (l_{i,j})$  be the adjacency matrix of Web graph, i.e.  $l_{i,j} = 1$  if page  $i$  links to page  $j$  and  $l_{i,j} = 0$  otherwise. Then the hubness vector  $\mathbf{h}$  and the authority vector  $\mathbf{a}$  are recursively updated as follows:

$$\mathbf{h} = \mathbf{L}^T \mathbf{a}, \mathbf{a} = \frac{\mathbf{a}}{\|\mathbf{a}\|_2} \quad (2)$$

$$\mathbf{a} = \mathbf{L} \mathbf{h}, \mathbf{h} = \frac{\mathbf{h}}{\|\mathbf{h}\|_2} \quad (3)$$

Note that it is equivalent to:

$$\mathbf{a} = \mathbf{L}^T \mathbf{L} \mathbf{a}, \mathbf{a} = \frac{\mathbf{a}}{\|\mathbf{a}\|_2} \quad (4)$$

$$\mathbf{h} = \mathbf{L} \mathbf{L}^T \mathbf{h}, \mathbf{h} = \frac{\mathbf{h}}{\|\mathbf{h}\|_2} \quad (5)$$

The iterations are exactly the power iteration method for solving the dominant eigenvector of  $\mathbf{L}^T \mathbf{L}$  and  $\mathbf{L} \mathbf{L}^T$ . Hence the HITS model is a spectral method in essence.

The advantage of HITS model is that it provides two scores on each page. Hence the highly ranked hub pages and pages with high authority are identified. A good hub represented should point to many high authority pages, and a good authority should be linked by many different hubs. The hubs and authorities enforce each other, such that outliers (unrelated Web pages) are gradually thrown out.

### B. Hubs and Authorities in Graph Matching

Suppose that we are given two graph  $\mathcal{G}$  and  $\mathcal{H}$  of size  $M$  and  $N$  respectively. In the context of graph matching, the candidate pairs  $(i, i')$  with  $i \in \mathcal{G}$  and  $i' \in \mathcal{H}$  are the subjects. The relation among these candidate pairs are stored in the affinity matrix  $\mathbf{A}$ :

$$\mathbf{A}_{i,i',j,j'} = \mathbf{A}_{(i-1)N+j, (i'-1)N+j'} \quad (6)$$

$$= \begin{cases} m(d_{ij}, d_{i'j'}), & \text{if } i \neq j, i' \neq j', \\ & \text{and } i \text{ and } j \text{ are neighbors} \\ & \text{and } i' \text{ and } j' \text{ are neighbors} \\ 0, & \text{otherwise.} \end{cases}$$

where  $m(e_{ij}, e_{i'j'})$  calculates the similarity between two edges  $e_{ij}$  and  $e_{i'j'}$ . The affinity matrix  $\mathbf{A}$  plays a similar role to that of the adjacency matrix in Web graph.

In traditional spectral based graph matching algorithms, the "confidence" is estimated for each candidate match as the confidence vector  $\mathbf{x}$ . Inspired by the HITS model for webpage ranking, we further divide the confidence into two parts: hubness  $\mathbf{h}$  and authority  $\mathbf{a}$ . Hubness and authority are assigned to each candidate match. A match with high hubness is a match who provides many support to highly authoritative matches (as shown in Fig.1), while a match with high authority is a match who is supported by many matches with high hubness.

However, the update strategy of (2) is not directly applicable to the graph matching problem due to different constraint. Apart from the discrete constraint in (1), the basic constraint for subgraph matching is that each node in the model graph should be matched to only one node in the scene graph. Two matches with a same node involved in either side results in a contradiction. Taking this constraint into consideration, we propose to update the authority and hubness as follows.

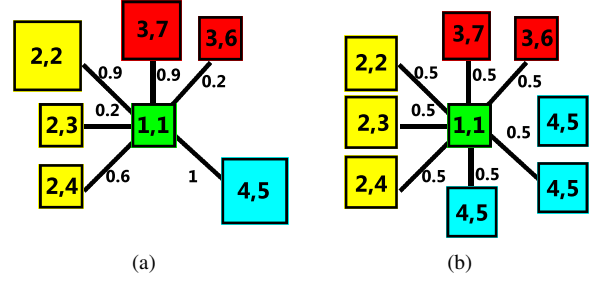


Fig. 1. Two example to explain hubness. Each square represents a candidate match and the size of squares indicate the authority of a match. Number on the link indicates the affinity between matches. The match (1,1) in both (a) and (b) have high authority, however it has larger hubness in (a) than in (b).

The authority vector  $\mathbf{a}$  is update as:

$$\mathbf{x} = \mathbf{A} \mathbf{h} \quad (7)$$

$$\mathbf{a} = \exp(\beta \mathbf{x}) \quad (8)$$

Note that the update is followed followed by an inflation step of  $\mathbf{a} = \exp(\beta \mathbf{x})$  as in [14] and [11]. The inflation forces the constraint by attenuating small authority and amplifying large authority.

The hubness vector  $\mathbf{h}$  is updated as:

$$\mathbf{h}_{ii'} = \left( \prod_{j \in \mathcal{N}(i)} \max_{j'} \mathbf{A}_{ii'jj'} \mathbf{x}_{jj'} \right)^{(1/|\mathcal{N}(i)|)} \quad (9)$$

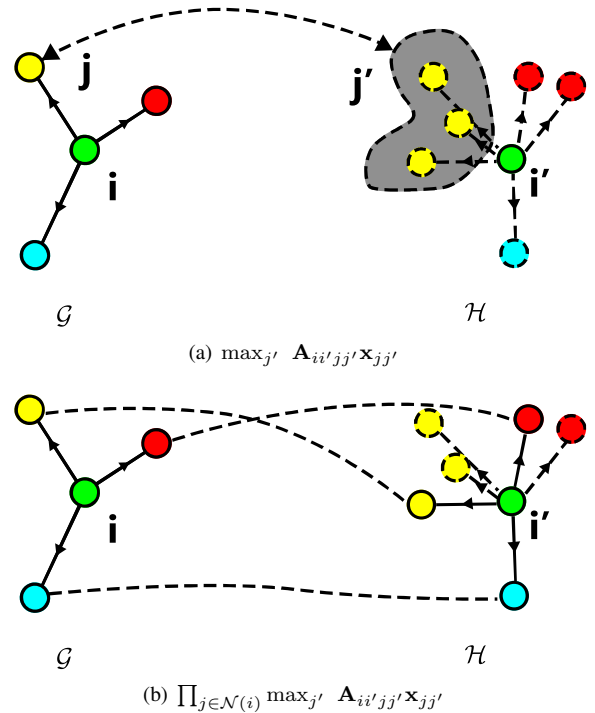


Fig. 2. The calculation of hubness for one candidate match  $(i, i')$ .

Specifically, given a match  $(i, i')$ , the contradiction free set of neighbor matches with the max multiplied authority  $\times$  pairwise similarity is found as shown in Fig.2. The score is then normalized with  $|\mathcal{N}(i)|$ -th root to form the hubness of  $(i, i')$ , where  $\mathcal{N}(j)$  denote the neighbors of  $j$  and  $\mathcal{N}(j)$  is the number of neighbours of  $j$ . The reason of using maximization and multiplication to calculate the hubness is as follows:

- 1) The maximization helps filter out outlier matches. The affinity matrix is filled with entries associated with outlier matches and the outlier-free entries only occupy a quite small portion. Using summation will result in flattened hubness among inliers and outlier.
- 2) Multiplication (which is equivalent to logarithmic pooling) rather than summation (which is equivalent to average pooling) is used such that the hubness bias towards matches who highly support *all* the neighbours with high authority rather than matches who only highly support several neighbours with *surprisingly high* authority.

### C. The Algorithm

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**Algorithm 1** Graph Matching with Locally Scale Estimation

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**Require:** Two graphs  $\mathcal{G}_1$  and  $\mathcal{G}_2$  and their edge distance matrix  $D_1$  and  $D_2$ ;

**Ensure:** The assignment vector  $\mathbf{y}$ ;

- 1: Initialize  $\mathbf{h}_0, \mathbf{a}_0, \mathbf{x}_0$  as  $\frac{1}{N} \mathbf{1}^{MN \times 1}$
  - 2: **repeat**
  - 3:    $\mathbf{x}_{t+1} = \mathbf{K} \mathbf{h}_t$
  - 4:    $\mathbf{a}_{t+1} = \exp(\beta \mathbf{x}_{t+1})$
  - 5:   Normalize  $\mathbf{a}$
  - 6:    $\mathbf{h}_{ii'} = (\prod_{j \in \mathcal{N}(i)} \max_{j'} \mathbf{A}_{ii'jj'} \mathbf{x}_{jj'})^{(1/|\mathcal{N}(i)|)}$
  - 7:   Normalize  $\mathbf{h}$
  - 8: **until**  $\frac{\|\mathbf{a}_{t+1} - \mathbf{a}_t\|_2}{MN} \leq \epsilon$  or  $t \geq \text{MaxIter}$
  - 9:  $\mathbf{X} = \text{reshape}(\mathbf{a}, M, N)$ , and discretize  $\mathbf{X}$
- 

The normalization of hubness vector  $\mathbf{h}$  and authority vector  $\mathbf{a}$  is conducted by first reshape them into  $M \times N$  matrix and normalize each row to 1, then transform them back to vectors, similar to the strategy in [9]. The algorithm is terminated when a predefined threshold is reached or *MaxIter* round of iteration have been conducted. The discretization is performed using greedy or Hungarian based algorithm.

### D. Computational Complexity

The computational complexity of hubness updating and authority updating is  $O(M^2 N k_s)$ , where  $M$  is the number of nodes in the model graph,  $N$  is the number of nodes in the scene graph,  $k_s$  is the average number of edges of each node in the scene graph. The complexity of row-wise normalization is  $O(M k_s)$ . Hence, the computational complexity of each iteration is  $O(M^2 N k_s)$ , which is faster or comparable to recent state-of-the-art algorithms.

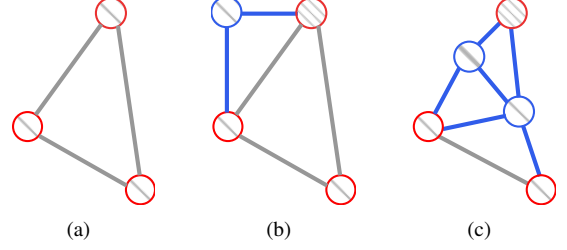


Fig. 3. Different kinds of outliers affect the structure of the graph constructed with Delaunay triangle. (a) The model graph. (b) A scene graph contaminated with an outlier which do not break the original structure of the model graph. (c) A scene graph contaminated with outliers which break two of the original edges in the model graph.

## IV. EXPERIMENT

We evaluate the proposed algorithms on standard synthetic benchmarks and real image datasets. For comparison to the state of the art, graduated assignment (GA) [14], probabilistic graph matching (PGM) [9], and spectral matching (SM) [13] are evaluated in the same setting.

Two typical ways to construct the graph is using full connection graph and Delaunay triangulation. For full connection graph, the long-range connections may be helpful in rigid transformations, they can only confuse the matches since the long-range connections are more vulnerable in the presence of deformation compared to the short-range connections. Besides, the full connection makes the association graph dense and hence increases the computational complexity for matching.

For the Delaunay triangulation, the formation of edges are sensitive to outliers. There are two interpretations for outliers in graph matching literature. Basically, outliers are referred to the vertexes that have no corresponding vertex in the other graph. In some other literatures, the mismatched pairs are also called outliers. In this paper, we consider the first scenario. In this scenario, there are still two kinds of outliers. The first kind of outliers do not sabotage the graph's structure. For the sake of sparseness of the association matrix, Delaunay triangulation has been used to build the graphs in many works. For graphs constructed this way, if the outliers spread around the model graph in the scene graph, most of the structure in the model graph will be preserved in the scene graph as shown in Fig.3(b), and hence the performance of graph matching algorithms can be guaranteed. This usually makes the inliers have higher density than the outliers, and it is the reason why many mode-seeking based algorithms worked. On the other hand, if the outliers are highly mixed in the territory of the inliers, then the original graph structure of the inliers may be totally destroyed as shown in Fig.3(c). This prevents us from finding good matches because the endorsement from one good match to another is blocked with outliers.

A good graph construction method should preserve the

structure of the model graph in the scene graph as much as possible. For the ease of scale estimation, we constructed the graphs in such a way: the model graph is constructed with  $k_m$  nearest neighbours while the scene graph is constructed with  $k_s$  nearest neighbours, where  $k_s > k_m$  such that all the edges in model graph are covered in the scene graph.

#### A. Synthetic point set matching

The proposed algorithm is first evaluated on the task of random point set matching, which is used for testing in other algorithms [9], [13], [14]. The synthetic point sets are generated as follows. The model graph  $\mathcal{G}$  consists of 15 inlier points under uniform distribution in  $[0, 1]$ . All the points in  $\mathcal{G}$  are copied to the scene graph  $\mathcal{H}$ . To test against disturbance noise, each node was added with an independent Gaussian disturbance following the distribution  $N(0, \eta)$ , where  $\eta \in [0, 0.1]$ . To test against outliers, 1 to 10 outliers are added to the scene graph with step size of 1. For all the

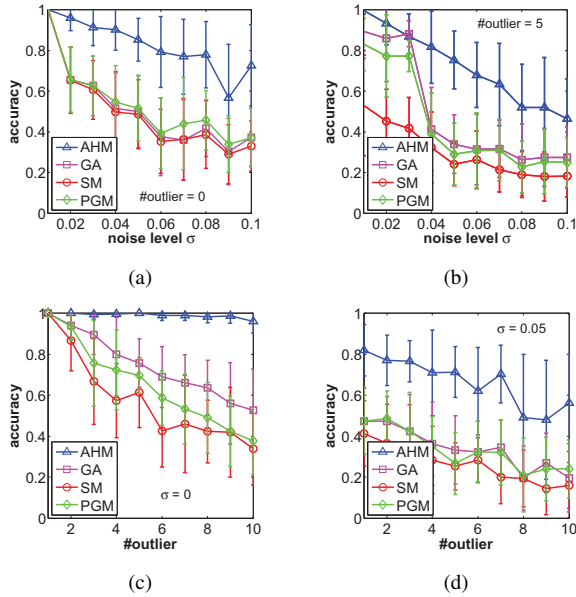


Fig. 4. Matching result on synthetic graphs.

experiments, we constructed the graphs  $G$  and  $H$  following the method introduced at the beginning of this section. No unary similarity is used. Normalized distance is used as edge features calculated as  $d_{ij} = \|p_i, p_j\|_2 / \max_{a,b} \|p_a, p_b\|_2$ , and the similarity used in (6) is defined as  $m(d_{ij}, d_{i'j'}) = \exp(-(d_{ij} - d_{i'j'})^2 / \sigma)$  with  $\sigma = 0.15$ . For all the methods, Hungarian algorithm is used to project the final result into binary assignment matrix.

The results are shown in Fig.4. AHM performs better than other methods against disturbance and outliers. And AHM performs surprisingly well when the noise level is low and the number of outliers is large.

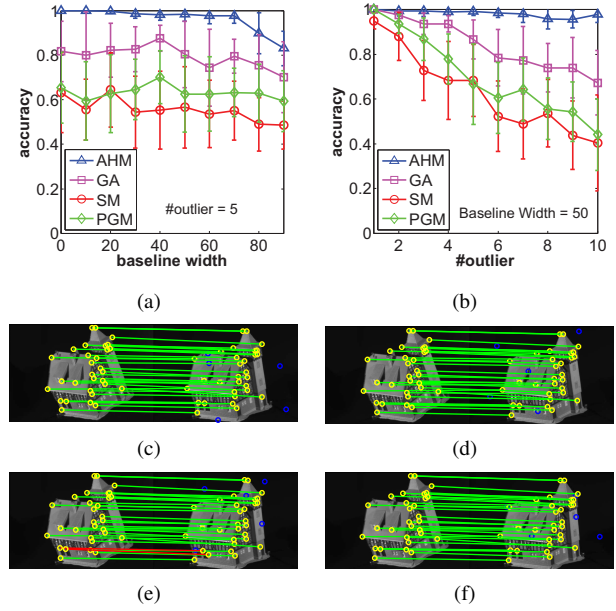


Fig. 5. Experimental results on CMU house sequence. (a) Comparison of accuracy with respect to baseline width. (b) Comparison of accuracy with respect to #outlier. (c)-(f) Matching samples.

In practice, SGM performs well against outliers as well as deformation as shown in the following real image experiments.

#### B. Experiment on House Sequence

The CMU house image dataset is a benchmark dataset for graph matching. It consists of 111 frames of a house with a varying view of point, the wider the baseline, the larger the deformation. Each of them has been manually labeled with 30 landmarks. Outliers are randomly added to the point set. The accuracies were compared as the baseline width increased from 0 to 90 with the number of outliers set to be 5 (with a step size of 10). Then the accuracies were compared with respect to the number of outliers when the baseline width was set to be 50 (with a step size of 1). No unary feature was used in this experiment. The affinity matrix is calculated in the same way as in The results are depicted in Fig.5.

Essentially, the points undergo perspective deformation in each pair of images. The results are similar to that of the evaluation on synthetic point set perspective deformation. The proposed algorithm outperforms other algorithms, especially when the number of outliers is large and the baseline is wide.

#### C. Experiment on Zurich Building Image Database (ZuBud)

The dataset contains images of different viewpoints acquired from various scenes. 30 pair of images are select for this experiment, including the figures shown in Fig.6. Feature points are detected on each image pair. As we can observe, the images in each pair contain many repetitive pattern. Which means for each keypoint there exist multiple possible



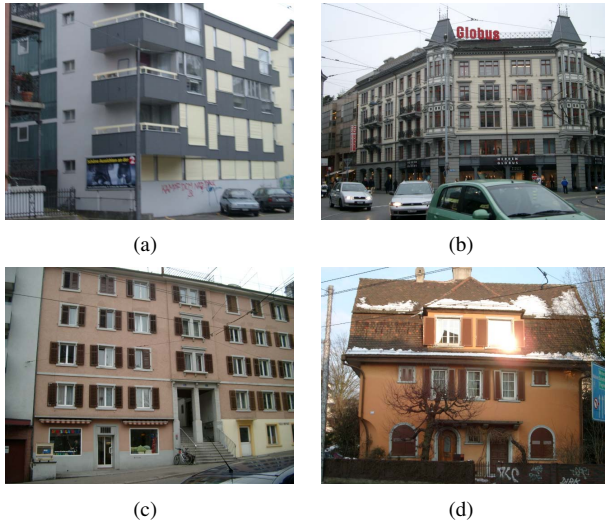


Fig. 6. Images samples in Zubud dataset [19].

correspondences. To examine the algorithms on the datasets, we first manually labeled 30 ground truth correspondence for each pair of images (since there lacks ground truth label for this dataset). Then we extend each point set with 1 to 10 outliers by adding nearest neighbor in SIFT feature space for the keypoint. The results are shown in Fig.7 together with some matching samples.

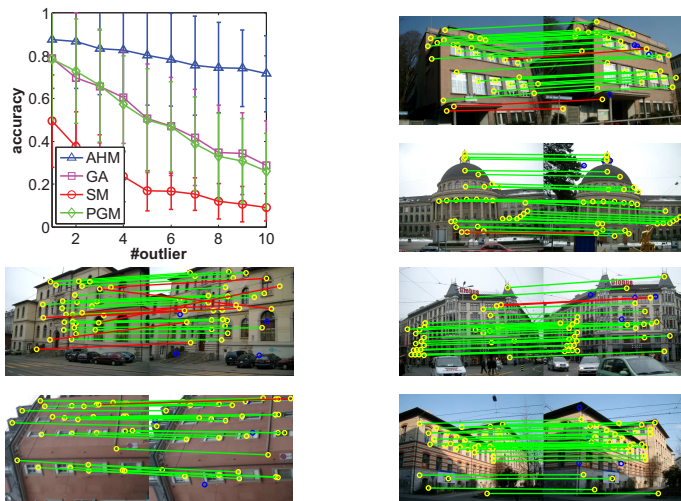


Fig. 7. Matching result on Zubud.

## V. CONCLUSION

In this paper we introduce the authority and hubness to graph matching. The relation between graph matching and the Hypertext Induced Topic Search method is discussed. By introducing the concept of authority and hubness, an iterative algorithm is proposed with a novel hubness updating

scheme. The proposed approach is experimentally shown to outperform other algorithms, especially when the matching becomes difficult due to outliers.

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