Solving Partial Assignment Problems using Random Clique Complexes

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Abstract

We present an alternate formulation of the partial assignment problem as matching random clique complexes, that are higher-order analogues of random graphs, designed to provide a set of invariants that better detect higher-order structure. The proposed method creates random clique adjacency matrices for each k-skeleton of the random clique complexes and matches them, taking into account each point as the affine combination of its geometric neighborhood. We justify our solution theoretically, by analyzing the runtime and storage complexity of our algorithm along with the asymptotic behavior of the quadratic assignment problem (QAP) that is associated with the underlying random clique adjacency matrices. Experiments on both synthetic and real-world datasets, containing severe occlusions and distortions, provide insight into the accuracy, efficiency, and robustness of our approach. We outperform diverse matching algorithms by a significant margin.

1. Introduction

The assignment problem finds an assignment, or matching, between two finite sets U and V, each of cardinality n, such that the total cost of all matched pairs is minimized. The assignment problem can also be generalized to finding matchings between more than two sets. This is a fundamental problem in computer science and has been motivated by a wide gamut of research areas spanning diverse areas such as structural biology (Singer & Shkolinsky, 2011), protein structure comparisons in bioinformatics (Zaslavskiy et al., 2009), and computer vision (Conte et al., 2004). Computer vision especially boasts a broad range of applications that include object matching, image registration (Shen & Davatzikos, 2002), stereo matching (Goesele et al., 2007), shape matching (Petterson et al., 2009; Berg et al., 2005), structure from motion (SfM) (Szeliski, 2010), and object detection (Jiang et al., 2011), to name a few.

Various assignment approaches can broadly be classified as those that find a bijective assignment in the form of a permutation matrix by posing the problem as a linear assignment problem (LP) versus ones that solve a quadratic assignment problem (QAP) via graph matching, where each graph’s nodes represent the objects and the edges encode their corresponding distances; the goal of QAP then is to find node-wise correspondences between the graphs so that the overall discrepancy between their corresponding edge-wise counterparts is minimized and the overall relational structure is best preserved.

Partial assignment implies that only subsets of U and V can actually be assigned to each other successfully. This phenomenon is of particular interest to applications where either objects are absent due to incomplete observations, undergo deformations, and/or the objects in question cannot clearly be disambiguated because the objects in question along with their related objects are embedded in clutter. This variant of the assignment problem is widely accepted as a formidable challenge.

Although graph matching methods were found to be instrumental, they too perform poorly when faced with non-similar geometric transformations or transformations that produce degenerate triangulations. This is attributed to assigning weights to only node and edge assignments, while ignoring the interplay of higher-order connections/relations. For example, using triplet weights can alleviate the above
mentioned problem to a very large extent by defining a measure invariant to scale and other transformations (Chertok & Keller, 2010).

Motivated by the aforementioned observations and inspired by Kahle (Kahle, 2006)'s work on combinatorial topological models like the random clique complex, we focus our attention to matching higher-order components between two sets of points in the setting of some points missing completely at random. We pose our assignment problem as finding a matching between two sets of points, each represented as a random clique complex, which is a higher-order analogue of random graphs. Figure 1 illustrates such a matching of cliques of corresponding dimensionality, between two different scenes (taken from different camera angles) of the same house. Given an Erdős-Rényi (ER) graph, its clique complex is the simplicial complex with all complete subgraphs (i.e., cliques) as its faces. The Erdős-Rényi graph forms the 1-skeleton of the random clique complex, where the cliques have at most a dimension of 2, i.e., edges in the graph. The clique topology of a random adjacency matrix is analogous to its eigenvalue spectrum, as it provides a set of invariants that help detect structure (Giusti et al., 2015). This probabilistic and combinatorial framework of random clique complexes allows us to further study the assignment problem under various assumptions of the underlying distribution of the matrix entry distributions, its robustness to missing values, and its asymptotic behavior for large-scale cases.

Contributions: We present the following contributions.

1. To the best of our knowledge, our proposed approach is a first attempt to formulate higher-order matching between two sets of points, given partial or incomplete information, as a matching between two random clique complexes. We also propose an efficient matching algorithm and study both its time and storage complexity.

2. (i) We provide new bounds on the concentration inequality of eigenvalues of the QAP trace formulation for random symmetric matrices, (ii) we give tighter concentration inequality bounds on the largest eigenvalue for the Lawler QAP formulation on random matrices, in the context of affinity matrices that are used by some earlier works. Furthermore, we theoretically analyze and discuss the robustness of affinity-matrix-based schemes to missing points, and (iii) we perform asymptotic analysis on the worst to best case ratio of a QAP solution for our higher-dimensional clique adjacency matrices in the clique percolation regime (Bollobás & Riordan, 2009), where the entries follow a Poisson distribution.

3. Finally, we present a comprehensive empirical study that compares our method’s matching accuracy to that of a diverse set of matching approaches (Zhou & De la Torre, 2016; Zhou & De la Torre, 2013; Cho et al., 2010; Feizi et al., 2016; Leordeanu & Hebert, 2005; Cour et al., 2007; Pachauri et al., 2013; Gold & Rangarajan, 1996; Kuhn, 1955; Leordeanu et al., 2009; Zass & Shashua, 2008; Li et al., 2013; Duchenne et al., 2011). We conducted our experiments on both synthetic and well-known hard real-world datasets that span across affine/non-affine transformations, severe occlusions, and clutter. Our study reveals much better accuracy for the popular datasets against several of the state-of-the-art matching methods.

2. Matching Random Clique Complexes

We consider the problem of capturing higher-order feature groups among landmark points in an image by representing them as a random clique complex (RCC) and then using these RCCs to match two sets of groupings from two different images. We begin this section by describing the construction of a random clique complex, followed by our proposed method of matching two RCCs, and we finally analyze the runtime and storage complexity of our algorithm.

2.1. Structure of a Random Clique Complex

We begin with general definitions pertaining to the structure of simplicial complexes and then accordingly adapt these definitions to our domain of random graphs to build random clique complexes.

Let $G(n, p)$ be an Erdős-Rényi graph with a set of $n$ vertices denoted by $V$, whose edges $\{v, v'\} \in \binom{V}{2}$, are i.i.d Bernoulli$(p)$ distributed. Recall, that a $k$-clique in $G(n, p)$ is a complete subgraph that comprises of $k$ vertices and $\binom{k}{2}$ edges. Here onwards, for ease of notation, we will denote $G(n, p)$ as $G$. Given any affinely independent set $V = \{v_i\}_{i=0}^{k}$ of $(k+1)$ points in $\mathbb{R}^n$, the $k$-simplex $\sigma(k)$ is the convex hull of $V$, i.e., it is the set of all points of the form $w_0 v_0 + \cdots + w_k v_k$, where $\sum_{i=0}^{k} w_i = 1$ and $w_i \geq 0$ for all $i$. If we imagine the vertices of $G$ embedded generically in $\mathbb{R}^n$, then each $(k+1)$-clique consisting of $k+1$ vertices is represented by a $k$-dimensional simplex $\sigma(k)$ in our random clique complex. For example, a 2-clique (edge) and a 3-clique (triangle) in $G$ is represented as $\sigma(1)$ and $\sigma(2)$, respectively.

Given $0 \leq i \leq k$, the $i$-th face $f_i$ of $\sigma(k)$ is the subspace of points that satisfy $w_i = 0$; it is the $(k-1)$-simplex $\sigma(k-1)$ whose vertices are all those of $\sigma(k)$, except the $i$-th vertex. In other words, when $\sigma(k)$ is a clique of $G$, then all its subsets are also cliques and hence considered faces of $\sigma(k)$. For example, a 3-clique (triangle) has three 2-cliques (edges) in it.

With the aforementioned definitions in mind, we define our
random clique complex $\mathcal{X}(G)$ as the set of all cliques in $G$ such that $\mathcal{X}(G) = \{ \sigma \in [n] \mid \sigma \text{ is a clique of } G \}$. We denote a set of $(k + 1)$-cliques as $X_k(G)$. Additionally, $\mathcal{X}(G)$ also satisfies the following conditions of a simplicial complex: (i) Any face in $\mathcal{X}(G)$ is also a simplex in $\mathcal{X}(G)$ and (ii) the intersection of any two simplexes $\sigma_i, \sigma_j$ is a face (lower dimensional clique) of both $\sigma_i$ and $\sigma_j$.

The faces of $\sigma^{(k)}$ are copies of $\sigma^{(j)}$ for $j < k$, which are glued together inductively. The $k$-skeleton of $\mathcal{X}(G)$, for $k \in \mathbb{N}$, is defined as the following quotient space

$$\mathcal{X}^{(k)}(G) := \left( \mathcal{X}^{(k-1)}(G) \cup \prod_{\sigma \text{dim } \sigma = k} \sigma^{(k)} \right) / \sim$$

where $\sim$ is the equivalence relation that identifies faces of $\sigma^{(k)}$ to the corresponding faces of $\sigma \in \mathcal{X}^{(j)}(G)$ where $j < k$. Finally, $\mathcal{X}(G) = \cup_{k=0}^{\infty} \mathcal{X}^{(k)}(G)$.

**k-skeleton as adjacency matrix**: Given a random graph $G$ and its $k$-skeleton $\mathcal{X}^{(k)}(G)$ that contains all its $(k + 1)$-cliques, we follow the idea from Bollobás et al. (Bollobás & Riordan, 2009), to represent $\mathcal{X}^{(k)}(G)$ as an adjacency matrix $G^{(k)}$ whose vertex set is the set of all $(k + 1)$-cliques in $G$ and in which two vertices (i.e., $(k + 1)$-cliques) are adjacent when they share a common face that has a minimum of $l$ vertices, where $k \geq 1$ and $1 \leq l \leq k$. Such an adjacency matrix is built for each $k$-skeleton and therefore $\mathcal{X}(G)$ is expressed as a set of matrices $\{G^{(k)}(G)\}_{k=0}^{\infty}$, where $(k + 1)$ is the dimension of the cliques.

### 2.2. Problem Setup

The problem of matching random clique complexes each of dimension $h$, is the estimation of a set of optimal bijective maps of the form $M_i: \mathcal{X}^{(i)}(G) \rightarrow \mathcal{X}^{(i)}(G')$, for all $i \leq h$, subject to assignment constraints. This can be formulated as a constrained quadratic assignment problem, which can later be relaxed to a linear programming optimization problem.

Given two $h$-dimensional random clique complexes $X(G) = \{G^{(k)}(G)\}_{k=0}^{h}$ and $X'(G') = \{G^{(k)}(G')\}_{k=0}^{h}$, let $X = \{X_0, \ldots, X_h\} \in \Pi$ be a set of permutation matrices such that $X_k$ encodes assignments/matchings from $G^{(k)}$ to $G'^{(k)}$. The combinatorial matching requires the optimal set of permutation matrices that best align $\mathcal{X}(G)$ and $\mathcal{X}(G')$. More formally, this can be expressed as the following constrained optimization problem

$$\arg\min_{X_0, \ldots, X_h} \sum_{k=0}^{h} \|G^{(k)}(X_k - X_kG^{(k)}(G'))\|_F^2 \quad \text{subject to } \forall k \leq h, 1^T X_k = 1, X_k^T 1 = 1$$

### 2.3. Our Algorithm

At a high level, our goal is to minimize $\|\mathcal{X}(G) - \mathcal{X}(G')\|_C$, where $C$ is a combinatorial distance between two random clique complexes. Traditional metrics like Hausdorff distance are not suitable here because random clique complexes are combinatorial topological spaces. Recall that $\mathcal{X}(G)$ is comprised of a family of $k$-skeletons $\{\mathcal{X}^{(k)}(G)\}_{k=0}^{h}$, where each $k$-skeleton contains cliques whose dimension is at most $k + 1$ and $\mathcal{X}^{(k)}(G)$ has a maximum dimension $h$. The solution of the optimization problem outlined in Equation (1) aims to find a set of permutation matrices $\{X_1, \ldots, X_h\}$ that minimizes the overall number of misalignments between equi-dimensional faces of $\mathcal{X}(G)$ and $\mathcal{X}(G')$, i.e., cliques belonging to the corresponding $k$-skeletons, and thus producing the optimal least cost assignment between $\mathcal{X}(G)$ and $\mathcal{X}(G')$.

Algorithm 1 presents our method to solve the combinatorial optimization problem (Equation (1)). In decreasing order of clique dimensionality, for a fixed dimension $k$ and given the adjacency matrices $G^{(k)}$ and $G'^{(k)}$ for $k$-skeletons $\mathcal{X}^{(k)}(G)$ and $\mathcal{X}^{(k)}(G')$, respectively. In every iteration, our objective is to solve $\arg\min_{X_k} \|G^{(k)}(X_k - X_kG'^{(k)}(G'))\|_F^2$ to find the optimal permutation $X_k$. We assume the barycenters of every clique is pre-computed (Step 3).

Next, the neighborhood $N_i$ of the $i$-th clique is computed as the set of entries with 1$s in the $i$-th row of $G^{(i)}$ (Step 5). We denote the collection of every clique’s neighborhood as $N$ (Step 6). An important objective of our method is to capture the geometric properties of the neighborhood of every clique. We achieve this by characterizing the $i$-th clique’s barycenter...
We use a seminal result by Bollobás (Bollobás & Riordan, 2009) to consider the distribution of a random variable which causes an explosion in the number of possible cliques. To begin our analysis, we must first ascertain the dimensionality measured by the number of non-zero rows, i.e., the number of cliques in an effective skeleton for a given dimension in the underlying random graph. This can be expressed in asymptotic notation as \( O(n \alpha^k) \). Setting \( k = k \) gives \( knp^k \) expected relocations, which in turn estimates \( n \alpha^k(G(k,l)) \).

Recall from our definition of \( G(k,l) \), that two cliques are adjacent if they share at least \( l \) vertices. To analyze this further, we assume an entry in \( G(k,l) \) occurs when we can migrate a \((k + 1)\)-clique from its original position to an adjacent clique by relocating exactly \((k + 1 - l)\) vertices and leaving the remaining \( l \) vertices intact. The expected number of such relocations is given by \( \left(\frac{(k + 1)}{l} - 1\right) \left(\frac{n}{k + 1 - l}\right) \left(\frac{(k + 1)}{l} - \left(\frac{1}{l}\right)\right) \), where the first term denotes the number of possible vertices in a \((k + 1)\)-clique that can be chosen for relocation, the second term counts the number of new adjacent positions a clique can relocate to, and the final term decides the probability of relocations that are correct and acceptable. In our case, we define cliques to be adjacent to one another when they share at least \( l = k \) vertices. This is done in order to keep the number of adjacent cliques to a manageable size during experiments.

3. Theoretical Analysis of QAP

In this section, we present three related results in the context of matching random matrices, namely: (i) concentration inequality of eigenvalue bounds on the QAP trace formulation for random symmetric matrices, (ii) tighter concentration inequality of eigenvalue bounds on the Lawler QAP formulation on random symmetric matrices in the context of works that use affinity matrices, and (iii) provide an asymptotic analysis on the worst to best case ratio of a QAP for higher-dimensional clique adjacency matrices. For ease of notation, we will refer to the random clique adjacency matrices simply as \( A \) and \( B \).

3.1. Eigenvalue Bounds of Trace QAP Formulation on Random Matrices

Let \( A = (a_{ij}) \), \( B = (b_{ij}) \in \mathbb{R}^{n \times n} \) be random real-symmetric matrices. Let \( X = (x_{ij}) \in \mathbb{R}^{n \times n} \) be a permutation matrix. Then, the trace formulation of a QAP is given by

\[ \text{minimize } \text{Tr}(AXBX^T) \text{ s.t. } X \in \Pi_X \]

where \( \Pi_X \) is the set of permutation matrices.
Let $\lambda_1(A) \leq \lambda_2(A) \leq \cdots \leq \lambda_n(A)$ and $\lambda_1(B) \geq \lambda_2(B) \geq \cdots \geq \lambda_n(B)$ be the eigenvalues of $A$ and $B$, respectively. Let the corresponding eigen-decompositions of matrices $A$ and $B$, be given by $A = Q_A \Lambda_A Q_A^T$ and $B = Q_B \Lambda_B Q_B^T$, where $\Lambda_A = \text{diag}(\lambda_1(A), \ldots, \lambda_n(A))$ and $\Lambda_B = \text{diag}(\lambda_1(B), \ldots, \lambda_n(B))$ with their corresponding orthogonal eigenvector matrices $Q_A$ and $Q_B$. Finke et al. (Martello et al., 1987) gave the following eigenvalue bounds.

**Theorem 1.** Let $A$ and $B$ be symmetric matrices. Then for all $X \in X_n$,

1. $\text{Tr}(AXBX^T) = (\lambda(A))^T Q(X) \lambda(B)$, where $Q(X) = (Q_A^{(i)}, XQ_B^{(i)})^2$ with vectors of eigenvalues given by $\lambda(A) = (\lambda_i(A))$ and $\lambda(B) = (\lambda_i(B))$. $Q_A^{(i)}$ and $Q_B^{(i)}$ denote the $i$-th eigenvectors of $A$ and $B$, respectively;

2. $\mathcal{L} \leq \text{Tr}(AXBX^T) \leq \mathcal{U}$, where
   
   $\mathcal{L} = \sum_{i=1}^n \lambda_i(A) \lambda_i(B)$, and
   
   $\mathcal{U} = \sum_{i=1}^n \lambda_{n-i+1}(A) \lambda_i(B)$

It was also noticed by Finke (Martello et al., 1987) that these bounds can further be tightened by reducing the spreads of matrices $A$ and $B$, where the spread of a matrix $\mathcal{A}$, denoted by $\mathcal{S}(\mathcal{A})$, is given by $\mathcal{S}(\mathcal{A}) = \max_i \lambda_i(\mathcal{A}) - \min_i \lambda_i(\mathcal{A})$. There is no formula to compute the spread of a matrix directly, so Finke et. al. (Martello et al., 1987) suggested a reduction method to further sharpen the bound by replacing matrices $A$ and $B$ by **smaller spread** symmetric matrices $\tilde{A}$ and $\tilde{B}$. The reductions are achieved as $\tilde{A} = A - M_A - M_A^T - \mathcal{D}_A$ and $\tilde{B} = B - M_B - M_B^T - \mathcal{D}_B$, where $M_A, M_B$ are matrices with constant columns and $\mathcal{D}_A, \mathcal{D}_B$ are diagonal matrices, whose values are chosen appropriately in order to tighten the bounds on spreads $\mathcal{S}(\tilde{A})$ and $\mathcal{S}(\tilde{B})$.

**Our bounds on Random Matrices:** We propose new measure concentration inequalities on the spread of a random matrix, by redefining the spread in an alternate fashion that is more amenable to our analysis. Consider our reduced random symmetric matrix $\tilde{A} \in \mathbb{R}^{n \times n}$, with eigenvalues $\lambda_1(\tilde{A}) \leq \cdots \leq \lambda_n(\tilde{A})$, we define the gap (spacing) between its consecutive eigenvalues as $\delta_i(\tilde{A}) := |\lambda_{i+1}(\tilde{A}) - \lambda_i(\tilde{A})|$ for $1 \leq i \leq n - 1$. Then, the spread $\mathcal{S}(\tilde{A})$ for the reduced matrix $\tilde{A}$ can be redefined as: $\mathcal{S}(\tilde{A}) = \sum_{i=1}^{n} \delta_i(\tilde{A})$

We begin by upper bounding $\delta_i(\tilde{A})$ using the following lemma (proof in supplementary notes).

**Lemma 1.** Let $\|\cdot\|$ denote an algebraic matrix norm on a space of real $n \times n$ matrices $\mathcal{M}_n$, then for any $A \in \mathcal{M}_n$,

$$\delta_i(A) \leq 2 \|\cdot\| |A||$$

To the best of the author’s knowledge there does not exist a known distribution of eigenvalue gaps for a symmetric random matrix. We now attempt to give concentration inequalities for the tail probabilities of the sum of eigenvalue gaps, i.e., the spread. For our i.i.d. random matrix $A \in \mathbb{R}^{n \times n}$, consider the sequence of independent eigenvalue gaps $\delta_1(A), \ldots, \delta_n(A)$, where each $\delta_i(A)$ is upper bounded by $2\|\cdot\|$, as shown in Lemma 1. Let us denote their sum as $S_n(A) := \delta_1(A) + \cdots + \delta_n(A)$. As $\delta_1(A), \ldots, \delta_n(A)$ are independent scalar random variables with $\delta_i(A) \leq \|\cdot\|$ a.s, with mean $\mu_i(A)$ and variance $\sigma_i^2(A)$. Then, using Chernoff bounds, for any $\epsilon > 0$, we have

$$\mathbb{P}(|S_n(A) - \mu| \geq \epsilon \sigma) \leq K \max \left( e^{-\epsilon^2}, e^{-\epsilon \sigma/2\|\cdot\|} \right)$$

for some absolute constants $K, p > 0$. The Chernoff inequality above, shows that $S_n(A)$ is sharply concentrated in the range $n \mu + O(\sqrt{n})$, when $\epsilon$ is not too large.

### 3.2. Eigenvalue bounds on Lawler’s QAP on Random Affinity Matrices

In literature, many graph matching algorithms use Lawler’s QAP formulation. Recall, $A = (a_{ij}), B = (b_{uv}) \in \mathbb{R}^{n \times n}$. Let $\Omega(a_{ij}, b_{uv})$ denote the pairwise affinity score of assigning the $(i, j)$-th entry in $A$ to the $(u, v)$-th entry in $B$, implying that node $a_i$ is matched to node $b_u$ and node $a_j$ to node $b_v$, simultaneously. Then, the affinity matrix $\mathcal{A} \in \mathbb{R}^{n \times n}$ is given by $\mathcal{A}[(i-1)n + u, (j-1)n + v] = \Omega(a_{ij}, b_{uv})$ and the optimal assignment to Lawler’s QAP is the one that maximizes the sum total pairwise affinity scores. Leordeanu et. al. (Leordeanu & Hebert, 2005) show via a spectral relaxation that Lawler’s WAP reduces to solving $w^* = \arg\max_w w^\top Aw, w \in \mathbb{R}^n$. This is solved by finding the leading eigenvalue $\lambda_1(\mathcal{A})$.

As illustrated in (Alon et al., 2002), we also use Talagrand’s concentration inequality (Talagrand, 1995). We provide a tighter bound in the case of our affinity matrix using Rayleigh’s quotient.

**Theorem 2.** For a random affinity matrix $\mathcal{A} \in \mathbb{R}^{m \times m}$ and for a positive constant $t$, $\mathbb{P}(|\lambda_1(\mathcal{A}) - \mathcal{M}| \geq t) \leq 4e^{-t^2/8}$, where $\mathcal{M}$ is the median of $\lambda_1(\mathcal{A})$.

**Discussion:** We further investigate the robustness of affinity-matrix based graph matching solutions when dealing with missing or incomplete data. We show the sharpness of our result in Theorem 2 on the affinity matrix, similar to (Alon et al., 2002), who analyze their results using fat matrices as an example. Consider an affinity matrix $\mathcal{A} = (a_{ij}) \in \mathbb{R}^{m \times m}$, whose entries are i.i.d. Bernoulli distributed. Simulating missing affinity scores due to missing edge assignments, we set $a_{ij} = 1$ with probability $1/4$ and $a_{ij} = 0$ with probability $3/4$. Notice that our random
affinity matrix represents the Erdős-Rényi graph $G(m, 1/4)$. As shown in (Alon et al., 2002), the median and expectation of $\lambda_1(A)$ differ by a constant factor. Let $G = (V, E)$ denote a general undirected graph, where the degree of each vertex $v \in V$ is given by $d_c : V \to \mathbb{Z}$. Then, the average degree of $G$ is given by $\bar{d} = \sum_{v \in V} d_c(v)/|V|$ and its maximum degree is $\Delta = \max_{v \in V} d_c(v)$. It is then well known that $\bar{d} \leq \lambda_1(A) \leq \Delta$, i.e., the largest eigenvalue of a graph is squeezed between its average and maximum degree.

Let $|E|$ denote the total number of edges in $G(m, 1/4)$, then the average degree of $G(m, 1/4)$ is given by $2|E|/n$, where $|E| = (m(m-1))/2, 1/4)$ and the standard deviation of $|E|$ is $\sqrt{(m(m-1))/(1/4)(3/4)} = \Theta(m)$. For large $m$, our binomial distribution converges to a normal distribution. Therefore, we calculate the probability for the total number of edges $|E|$ to deviate from its expectation by $t$ standard deviations as $e^{-\Theta(t^2)}$. Furthermore, we know that if $|E|$ exceeds its expectation by $\Theta(m)$, then the average degree $\bar{d}$ must also correspondingly exceed its expectation by $\Theta(t)$. Therefore, the probability of the average degree $\bar{d}$ exceeding its expectation by $t$ standard deviations is at least $e^{-\Theta(t^2)}$. Given that $\bar{d} \leq \lambda_1(A)$, it follows that $\lambda_1$ exceeding its expectation is also lower bounded by the same $e^{-\Theta(t^2)}$. The bounds achieved are tight up to a constant factor in the exponent. Our experimental results on Factorized Graph Matching (FGM) by Zhou et al. (Zhou & De la Torre, 2016) and Re-weighted Random Walk Matching (RRWM) (Cho et al., 2010) also support the finding that affinity matrix based matching solutions are more robust to missing edges due to occlusions in data.

3.3. Asymptotic Analysis of Higher-Order Clique Assignment

Following along the same lines as Finke et al. (Martello et al., 1987), we study the asymptotic behavior of the worst to most optimal ratio and present it as the following theorem.

**Theorem 3.** Given random clique adjacency matrices $A_{mm}^{k,l}, B_{mm}^{k,l} \sim \text{Pois}(\lambda)$ and their associated cost matrix $C_{mm}^{k,l} \sim \text{Pois}(\lambda)$, we denote by $\lambda_c := \mathbb{E}(C_{mm}^{k,l})$ and $\lambda_v := \mathbb{V}(C_{mm}^{k,l})$ the expectation and variance of our Poisson distributed cost function. For $t > 0$ and $p = \Theta(n^{-2/\epsilon^2})$, we have the following bound on the ratio of the worse to the best solution as

$$\min_{\pi} \sum_{v \in V} C_{v \pi(v)} \geq \bar{d} - \epsilon \sqrt{\lambda_v}$$

$$1 - 2|\Pi| \exp \left( -2|S_{\pi}| \left( \frac{\epsilon \sqrt{\lambda_v}}{\epsilon + 2\lambda_v} \right)^2 \right) =: \psi(n, \epsilon)$$

where, $|\Pi| = n!$, $|S_{\pi}| = (n+1)/2$, $\lim_{n \to \infty} \psi(n, \epsilon) = 1$.

4. Experiments

Here, we study the robustness of various matching algorithms when affected by missing or incomplete information and transformations (both affine and non-affine) on synthetic and real-world datasets. For the sake of brevity, we report detailed dataset descriptions in our supplementary notes. The graph matching algorithms can broadly be classified based on their use of (i) affinity-matrix: FGM (Zhou & De la Torre, 2016; Zhou & De la Torre, 2013)$^2$, RRWM (Cho et al., 2010), (ii) Eigenvalues: EigenAlign (Feizi et al., 2016)$^3$, SM (Leordeanu & Hebert, 2005), SMAC (Cour et al., 2007), PermSync (Pachauri et al., 2013)$^4$, (iii) LP relaxation: GA (Gold & Rangarajan, 1996), Kuhn-Munkres (Kuhn, 1955), (iv) Integer QAP: IPFP (Leordeanu et al., 2009), (v) Probabilistic matching: PM (Zass & Shashua, 2008), (vi) Higher-order matching given complete data: Tensor (Duchenne et al., 2011)$^5$, and (vii) Geometric and Feature matching: LAI-LP (Li et al., 2013)$^6$.

4.1. Effect of Affine Transformations

Simulated Dataset: We perform affine transformations on CMU House, which is a sequence of $N$ frames extracted from a video. More specifically, we uniformly sample frames (at 20% and 40%) and perform affine transformations on the selected frames to distort them. Figure 2 shows examples of affine transformations on house frame sequences. Table 1 shows the comparative error in matching for all the algorithms. We now describe each affine transformation as performance metrics in our experiments.

**Rotation:** Figure 2(b) shows a $180^\circ$ rotated version of the original house frame (Figure 2(a)). Table 1 shows errors in matching when 20% of the frames are rotated by both $20^\circ$ and $60^\circ$, respectively and when the same transformations are applied to 40% of the frames. As the percentage of transformed frames with greater degree increases, we note a substantial increase in error for other methods in comparison to our method’s error increase.

**Reflection:** The reflected version of a house frame is shown in Figure 2(c). Table 1 shows that affinity-based approaches also performed equally well for reflection of house frame sequences.

**Scaling:** Resizing an image both horizontally and vertically scales the image as is shown in Figure 2(d). We fixed the scales to 0.5, 0.75, 1.25, and 1.5 randomly in both the directions in order to transform the images. Our method in Table 1 produces much better matchings than the other methods.

**Shearing:** We randomly apply shearing on house in one of $^2$ FGM $^3$ EigenAlign $^4$ PermSync $^5$ Tensor $^6$ This algorithm serves as our naive baseline as it directly uses neighborhood properties of the underlying graph (LAI-LP).
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Figure 2. (a) Original House Frame, (b)–(e) Four transformations on house frame: Rotation, Reflection, Scaling and Shear (green markers show true matching case with the original frame (a)).

| Algorithm          | 20° Rotation | 40° Rotation | 60° Rotation | 20° | 40° | 60° | 20° | 40° | 60° | 20° | 40° | 60° |
|--------------------|--------------|--------------|--------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| On/Method          |              |              |              |     |     |     |     |     |     |     |     |     |
| EigenAlign         | 65.97 ± 1.0  | 70.19 ± 1.0  | 70.88 ± 1.9  | 62.5 ± 0.4 | 64.97 ± 0.2 | 62.37 ± 0.6 | 65.42 ± 1.1 | 61.04 ± 0.2 | 62.36 ± 0.7 |
| FGM                | 3.6 ± 0.5    | 7.4 ± 0.5    | 18.0 ± 0.0   | 0.0 ± 0.0  | 0.0 ± 0.0  | 2.20 ± 1.0  | 3.4 ± 0.5   | 0.0 ± 0.0  | 0.0 ± 0.0  |
| LapSolve           | 40.90 ± 0.0  | 43.07 ± 1.2  | 49.9 ± 1.2   | 0.0 ± 0.0  | 0.0 ± 0.0  | 2.20 ± 1.0  | 3.4 ± 0.5   | 0.0 ± 0.0  | 0.0 ± 0.0  |
| PermSync           | 13.36 ± 1.1  | 16.18 ± 2.0  | 23.58 ± 1.4  | 41.49 ± 0.7 | 42.31 ± 0.8 | 43.12 ± 0.5 | 45.91 ± 0.3 | 39.04 ± 0.7 | 38.77 ± 0.6 |
| RRWM               | 2.0 ± 0.0    | 4.0 ± 0.0    | 14.0 ± 0.0   | 0.0 ± 0.0  | 0.0 ± 0.0  | 5.6 ± 0.0   | 13.2 ± 0.5  | 10.19 ± 0.8 | 6.23 ± 3.2  |
| Tensor             | 6.88 ± 0.0   | 14.39 ± 0.8  | 23.24 ± 0.6  | 17.1 ± 0.5  | 14.69 ± 0.4 | 2.91 ± 0.6  | 6.19 ± 0.7  | 0.0 ± 0.0  | 0.0 ± 0.0  |
| IPFP               | 6.8 ± 1.5    | 11.6 ± 0.5   | 18.2 ± 0.5   | 0.0 ± 0.0  | 0.0 ± 0.0  | 5.6 ± 0.0   | 13.2 ± 0.5  | 10.19 ± 0.8 | 6.23 ± 3.2  |
| PM                 | 43.2 ± 1.0   | 49.4 ± 1.5   | 64.6 ± 1.0   | 0.0 ± 0.0  | 0.0 ± 0.0  | 5.6 ± 0.0   | 13.2 ± 0.5  | 10.19 ± 0.8 | 6.23 ± 3.2  |
| SM                 | 126.6 ± 0.5  | 20.0 ± 0.0   | 19.0 ± 0.0   | 0.0 ± 0.0  | 0.0 ± 0.0  | 5.6 ± 0.0   | 13.2 ± 0.5  | 10.19 ± 0.8 | 6.23 ± 3.2  |
| GA                 | 32.6 ± 0.5   | 37.8 ± 1.0   | 87.0 ± 1.0   | 0.0 ± 0.0  | 0.0 ± 0.0  | 5.6 ± 0.0   | 13.2 ± 0.5  | 10.19 ± 0.8 | 6.23 ± 3.2  |
| Munkres            | 34.0 ± 1.5   | 37.0 ± 1.0   | 87.0 ± 1.0   | 0.0 ± 0.0  | 0.0 ± 0.0  | 5.6 ± 0.0   | 13.2 ± 0.5  | 10.19 ± 0.8 | 6.23 ± 3.2  |

Table 1. Error (%) of transformation on CMU House: inserted 20% and 40% impurity in CMU House frame sequence randomly for rotation (20°, 60°), reflection, scaling and shear. Minimum error (%) is shown in bold. Matching is computed for 111 frames from the 1st frame to the other 110 frames. Our method shows best performance among all the methods.

the directions with shear factor 0.5 (shown in Figure 2(e)) and measured the performance shown in Table 1. In addition to our method, we find that affinity-based algorithms also produce robust matchings.

4.2. Effect of Incomplete and Occluded Landmarks

To understand the effect of occlusions, we took two real-world datasets, i.e., Books and Building (Pachauri et al., 2013) with severe occlusions which are scenes of the same 3D object taken from arbitrary camera angles. These datasets have widely been used in Structure from Motion (SfM) problems and are known to be difficult for matching. Focusing our attention to the last two columns of Table 2, it is evident that our method gives the best results. Figure 3 shows the Books dataset where books are placed on a table in various orientations with varying levels of occlusion, along with two sample matchings between different pairs of images. Note that in Figure 3, when a corresponding matching clique is not found in the other image, a match isn’t forced but rather there is no match reported, which doesn’t degrade the matching accuracy. Matching as many random cliques, in order of decreasing dimensionality, as possible, manifests itself as an advantage over existing methods, especially when dealing with clutter and/or occlusions. Simulating missing points: In order to gain a deeper insight into the behavior of all the matching algorithms, we omit 2, 4, 6, 8, and 10 (6.66%, 13.33%, 20%, 26.66%, and 33.33%) points out of total House landmark points (i.e., 30 points) from 40% (Figure 4) of frame sequences randomly. In general, all algorithms show an increase in error as more points are removed, but our method has a less gradual increase, while eigenvalue related methods show a rather steep increase in error. Our method is comparable to FGM and RRWM, but the gap in error increases with more missing points. We also observed that FGM incurs the longest runtime for matching in this scenario.
Solving Partial Assignment Problems using Random Clique Complexes

| Methods | Car | Bike | Butterfly | Magazine | Building | Book |
|---------|-----|------|-----------|----------|----------|------|
| OurMethod | 4.14 ± 2.45 | 3.15 ± 0.32 | 3.89 ± 0.23 | 0.48 ± 0.62 | 4.17 ± 0.32 | 22.20 ± 1.16 |
| EigenAlign | 60.68 ± 0.29 | 57.44 ± 0.37 | 66.57 ± 0.00 | 81.23 ± 0.93 | 90.51 ± 0.67 | 98.41 ± 0.89 |
| FGM | 55.51 ± 0.00 | 48.17 ± 0.00 | 61.12 ± 0.00 | 78.73 ± 0.1/184.153 | 87.98 ± 0.03 | 96.38 ± 0.04 |
| LAI-LP | 73.06 ± 0.23 | 52.14 ± 0.24 | 161.06 | 79.88 ± 0.00 | 64.00 ± 0.00 | 70.00 ± 0.00 |
| PermSync | 10.35 ± 0.00 | 8.90 ± 0.00 | 46.93 ± 0.00 | 79.88 ± 0.00 | 64.00 ± 0.00 | 70.00 ± 0.00 |
| RRWM | 60.91 ± 0.00 | 54.53 ± 0.00 | 30.99 ± 0.00 | 1.0/187.39 | 72.87 ± 0.01 | 87.04 ± 0.00 |
| Tensor | 24.37 ± 0.9/93.36 | 15.07 ± 1.0/93.97 | 1.07 ± 0.17 | 182.07 | 43.24 ± 2.98 | 32.35 ± 0.15 |
| IFPP | 65.12 ± 0.00 | 60.81 ± 0.00 | 40.99 ± 0.00 | 12.31 | 76.19 ± 0.05 | 87.74 ± 0.01 |
| PM | 74.63 ± 0.00 | 71.93 ± 0.00 | 70.27 ± 0.00 | 1.69 | 83.79 ± 0.02 | 91.43 ± 0.24 |
| SMAC | 70.01 ± 0.00 | 67.36 ± 0.00 | 50.53 ± 0.00 | 6.90 | 78.56 ± 0.2 | 87.88 ± 0.11 |
| SM | 68.54 ± 0.00 | 67.18 ± 0.00 | 65.98 ± 0.00 | 8.32 | 80.27 ± 0.07 | 88.66 ± 0.09 |
| GA | 65.06 ± 0.00 | 64.00 ± 0.00 | 61.58 ± 0.00 | 5.83 | 77.20 ± 0.27 | 87.02 ± 0.16 |
| Munkres | 33.71 ± 0.00 | 29.99 ± 0.00 | 51.87 ± 0.00 | 2.45 | 74.00 ± 0.00 | 92.00 ± 0.00 |

Table 2. Car, Motorbike (Cho et al., 2013), Butterfly, Magazine (Jiang et al., 2011), Building and Books error (%) for pairwise matchings. Computation time (in seconds) is mentioned after the "f" in the above Table.

5. Conclusion

To the best of our knowledge, we have presented the first approach towards partial higher-order matching by initially capturing higher-order structure as random clique complexes and then proposing a corresponding matching algorithm. From a theoretical point of view, we studied matching as a QAP on random clique adjacency matrices that represented the $k$-skeleton of our random clique complexes and gave bounds on the concentration inequality of the spread of its eigenvalues. We also improved bounds on the largest eigenvalue of the Lawler QAP formulation, used by affinity-matrix based approaches. We discussed the robustness of such approaches to missing points and also showed the sharpness of our result. Furthermore, inspired by Finke et. al. (Martello et al., 1987) we studied the asymptotic behavior of our higher dimensional clique adjacency matrices. A more detailed investigation of the distribution of eigenvalue gaps for such random matrices with Poisson distributed entries is left for future work.

From an empirical perspective, we compared the matching accuracies of diverse algorithms on both synthetic and real-world datasets that were known to have severe occlusions and distortions, thus posing a daunting challenge to matching algorithms. We argue that our experiments show strong evidence that our approach outperforms all the state-of-the-art matching methods on a diverse range of datasets.

4.3. Effect of Frame Separation

Here, we pick two frames from a video for matching and vary the separation in their frame sequence number. The farther apart two frames are the more pronounced is the effect we seek between the frame images. For example, as the frame separation increases, CMU Hotel undergoes a more severe 3D rotation, while Horse-Shear (Caetano et al., 2009) undergoes a larger degree of shear. We set $p = 0.7$ and $k = 7$ as nearest neighbors to get the correct matchings. In Figure 5, in both the left and right plots we notice that most methods show a very sharp rise in error, while our method is quite stable and reports a 0% error. We observe that the naive baseline, LAI-LP also does well and doesn’t exhibit steep changes in error with larger frame separation.

Experimental Summary: In general, we find that the affinity matrix based methods like FGM and RRWM are more robust to affine transformations than other competing algorithms. Our method performs the best as the weight vectors in our algorithm effectively capture even the higher-order geometric properties of the neighborhood and nearly preserves them under affine transformations. The naive baseline, i.e., LAI-LP, does not perform as well because it also has a feature-based component like SIFT which is known to fail on some affine transformations.

Figure 4. Error (%) in matching when varying the number of missing landmarks in 40% of the images in the frame sequence.

Figure 5. Error (%) in matching by various methods with different frame separation level for CMU Hotel (on left) and Horse Shear (on right).

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