

Point Set Pattern Matching under Rigid Motion

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Outline

- 1 Introduction
- 2 Previous Work
- 3 Exact Point Set Pattern Matching
- 4 Approximate Point Set Pattern Matching
- 5 Translation
- 6 Rigid Motion

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Introduction

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- A problem in pattern matching is to design efficient algorithms for testing how closely a **query set** Q of k points resembles a **sample set** P of n points, where $k \leq n$.
- In image processing, computer vision and related applications like finger print matching, point sets represent some spatial features.
- The problem has several variants [Alt and Guibas, 1999] based on:
 - class of allowable transformations
 - exact or approximate matching
 - equal cardinality, subset, or largest common point set matching

Problem Variants

Allowable Transformations

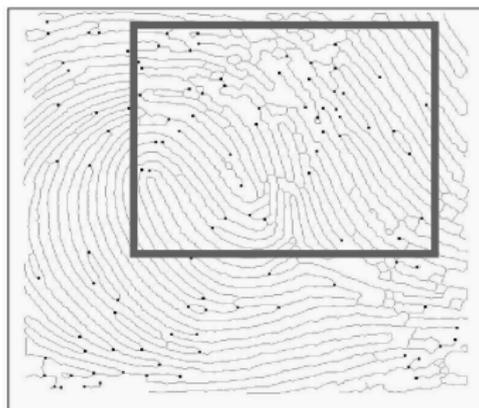
- Translation
- Translation and Rotation - **Rigid Motion Transform**
- Translation, Rotation and Scaling - **Similarity Transform**

Distances are preserved in Translation and rigid motion.

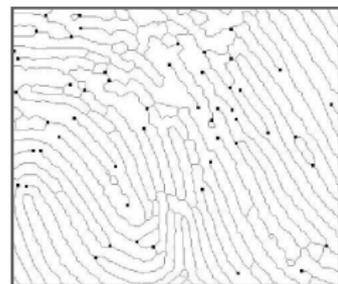
Types of Matching

- Exact matching: points in query set match exactly with points in sample set after the requisite transform.
- Approximate matching: points in query set after the requisite transform go to a **neighborhood** of points in the sample set.

Motivation

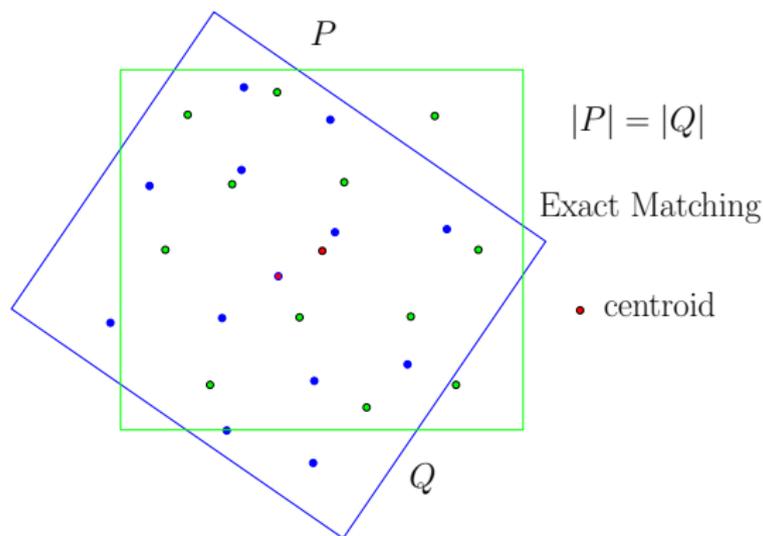


Reference fingerprint



Query fingerprint

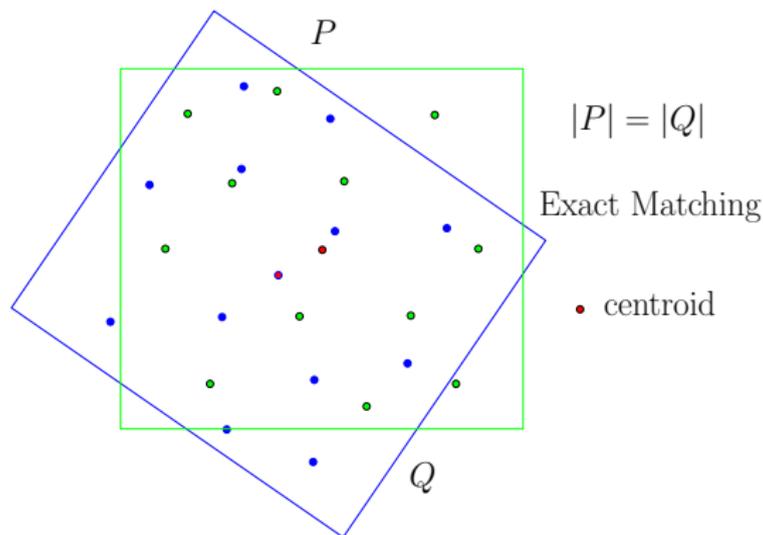
Exact Matching under Rigid Motion



Anchor

- Anchor centroids and match distances.
- But anchoring centroids do not help when we match Q with a set of points $P' \subseteq P$.

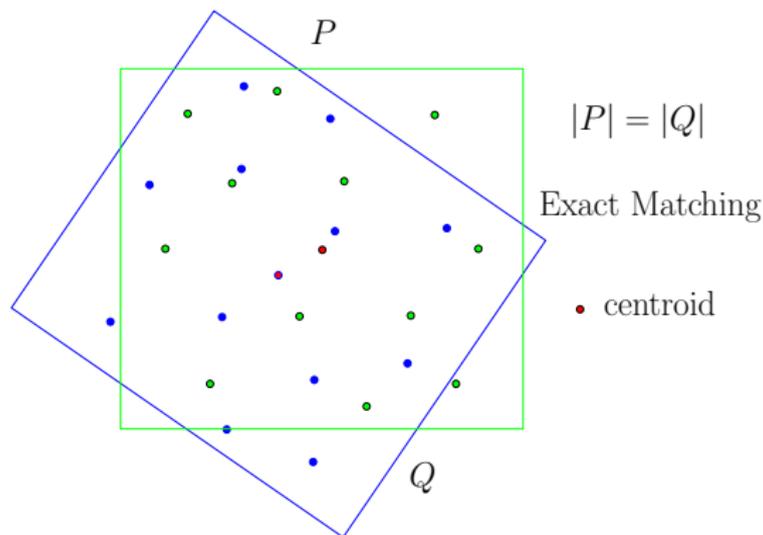
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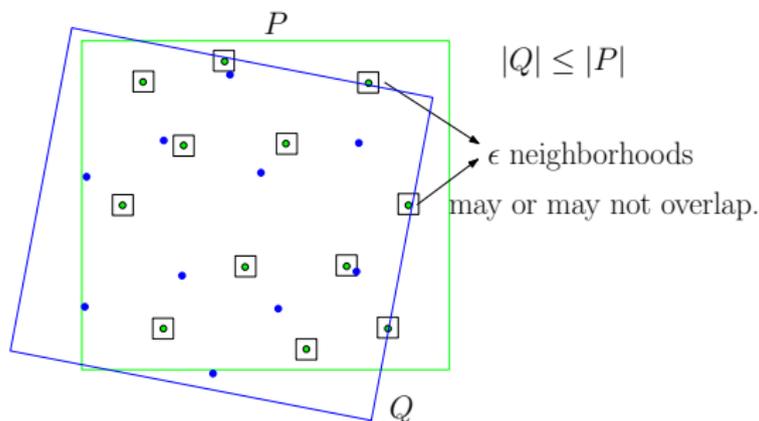
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Approximate Partial Matching under Rigid Motion



Given two point sets P and Q ($|P| = |Q|$), check if there is a bijection $\ell : Q \rightarrow P$ and a congruence T , such that $T(q) \in U_\epsilon(\ell(q))$, $\forall q \in Q'$, where $Q' \subseteq Q$, and $U_\epsilon(p)$ denotes the closed ϵ -neighborhood of a point $p \in P$.

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Previous Work

Exact Matching

- Rezende and Lee (1995) proposed an $O(kn^d)$ time algorithm for partial point set pattern matching, where
 d (* dimension of the plane *)
 $n = |P|$ (* size of sample set *)
 $k = |Q|$ (* size of pattern set *).
It allows translation, rotation and scaling.
- Akutsu, Tamaki and Tokuyama (1998) proposed an $O(kn^{\frac{4}{3}} + \mathcal{A})$ time algorithm for testing the congruence in 2D,
where \mathcal{A} = time complexity for locating r -th smallest distance among a set of n points in 2D.
 $= O(n^{\frac{4}{3}} \log^{\frac{8}{3}} n)$ (on an average).
- Akutsu, Tamaki and Tokuyama (1998) proposed a Las Vegas expected time algorithm of time complexity
 $O(n^{\frac{4}{3}} \log^{\frac{8}{3}} n + \min(k^{0.77} n^{1.43} \log n, n^{\frac{4}{3}} k \log n))$ using parametric search.

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Previous Work

Approximate Matching (for $k = n$ case)

- Alt et al. (1988) designed a general algorithm of $O(n^8)$ time that works for overlapping and non-overlapping ϵ -circles and ϵ -boxes.
- They use a geometric fact and bipartite graph matching.
- A valid matching of Q with P exists **iff** there is a matching where $q_i, q_j \in Q$ are matched exactly to the boundaries of $U_\epsilon(p_\alpha), U_\epsilon(p_\beta)$ of two points $p_\alpha, p_\beta \in P$.
- The algorithms are of high time complexity and involve computing the intersection of complex algebraic curves.
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Previous Work

Approximate Matching (for $k \neq n$ case)

- Chew et al. (1997) proposed an $(n^2 k^3 \log^2 kn)$ time algorithm for approximate partial point set pattern matching under rigid motion.

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Exact Point Set Pattern Matching

The Problem

Input: $P = \{p_1, p_2, \dots, p_n\}$ (* Sample Set *)
 $Q = \{q_1, q_2, \dots, q_k\}$ (* Query Set *),
 $k \leq n$.

Output: A subset of points in P that are matched with the points in Q if match exists under rigid motion.

Trivial Algorithm

Choose all possible $\binom{n}{k}$ subset of P and test for a match under rigid motion.

Exact Point Set Pattern Matching

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Exact Point Set Pattern Matching

An obvious improvement

Preprocessing: Use circular sorting to create a data structure attached with each point in P .

Space: $O(n^2)$

Time: $O(n^2)$.

Query:

- Sort the query point set angularly.
- Anchor a pair of query point with each pair of sample point.
- It determines the rotation angle and scaling.
- Match the other query points with a subset of sample points.

Time: $O(k \log k + kn(n - 1))$

Exact Point Set Pattern Matching

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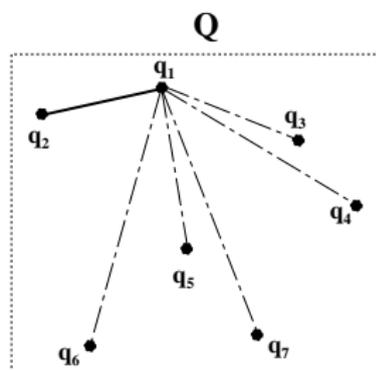
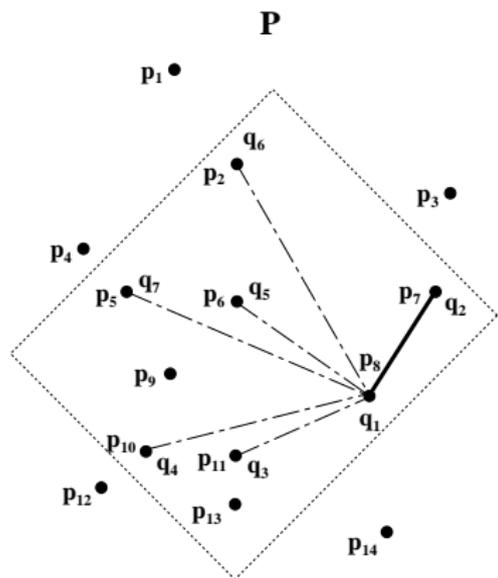
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Demonstration



An Efficient Algorithm for Rigid Motion

Fact 1

All the $\binom{k}{2}$ distances must occur in the $\binom{n}{2}$ distances in P

Fact 2

[Szekely 1997] In a sample set P of size n , the maximum number of equidistant pairs of points is $O(n^{\frac{4}{3}})$ in the worst case.

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Preprocessing

- Sort the $\binom{n}{2}$ distances of P distances in P .
- Create a height balanced binary tree \mathcal{T} with distinct distances.
- Attach an array χ_δ with each element δ of the tree. Its each element is a triple (p_i, p_j, ψ_{ij}) , where ψ_{ij} is the angle of the line (p_i, p_j) with x -axis.
- Each point $p_i \in P$ is attached with a height-balanced binary tree \mathcal{S}_i . Its elements are tuples (r_{ij}, θ_{ij}) .

Time Complexity: $O(n^2 \log n)$

Space Complexity: $O(n^2)$

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An Efficient Algorithm for Rigid Motion

Query

- Take two points (q_1, q_2) , and check whether $\lambda(q_1, q_2) \in \mathcal{T}$. If not, report no match found.
- Let $\lambda(q_1, q_2) = \delta$.
- We consider each member $\lambda(p_i, p_j) \in \chi_\delta$.
- Anchor (q_1, q_2) with (p_i, p_j) , and search in S_i for the presence of a match.

Time Complexity

For each $\lambda(p_i, p_j) = \delta$, searching for a match needs $O(k \log n)$ time. So,

Time Complexity: $O(n^{\frac{4}{3}} k \log n)$

An Efficient Algorithm for Rigid Motion

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An Important Note

Though the worst case number of equidistant pairs in a point set of size n is $O(n^{\frac{4}{3}})$, in a random instance actually the number is very less.

Number of points (n)	100	200	500	1000
$\lceil n^{\frac{4}{3}} \rceil$	465	1170	3969	10001
Maximum number of Equidistant pairs observed	4	6	20	53

Experimental Results

No. of points in sample	No. of points in query	No. of anchoring	CPU time for Rezende and Lee	CPU time for our Algorithm	% savings
200	50	1	730.0	22.0	97.0
	100	1	807.4	23.4	97.0
	150	2	867.6	31.2	96.0
500	100	2	1905.0	32.2	98.0
	200	1	1937.2	23.0	99.0
	400	2	1952.8	32.0	98.0
1000	300	12	4037.6	129.0	97.0
	500	7	4054.0	76.0	98.0
	800	11	4098.0	11.0	97.0

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Approximate Point Set Pattern Matching

Our Effort

We assume that

- the ϵ -neighborhoods are axis-parallel squares of side length ϵ .
- P is **well separated**, i.e. each pair of points $p, p' \in P$ satisfy either $|x(p) - x(p')| \geq \epsilon$ or $|y(p) - y(p')| \geq 3\epsilon$ or both.

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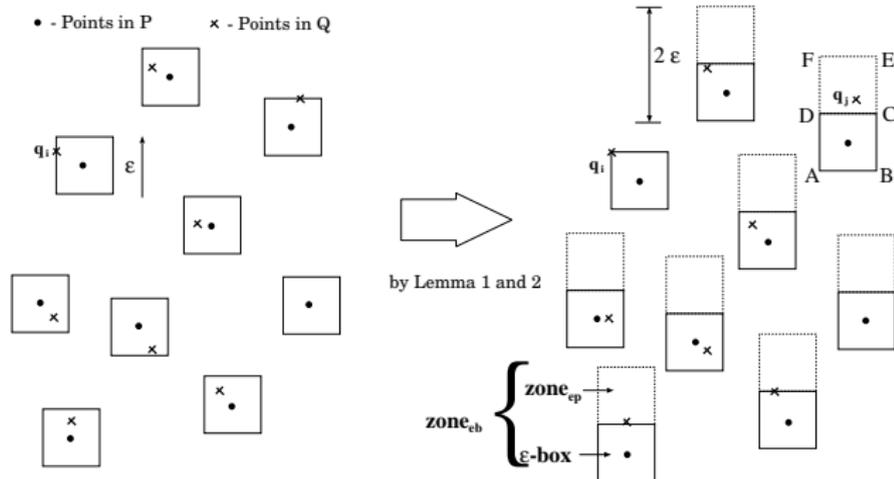
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A Necessary Characterization for a Matching



Lemma (an iff condition)

If \exists a transformation $T(Q)$ for the said match, then \exists another transformation $T'(Q)$, such that one point of Q lies on the left boundary of the ϵ -box of a point in P , and one point of Q lies on the top boundary of the ϵ -box of a point in P .

Definition

Consider an ϵ -box $ABCD$ around $p \in P$. The *extended ϵ -box* of p is a $\epsilon \times 2\epsilon$ box formed by attaching another $\epsilon \times \epsilon$ square $CDFE$ above the ϵ -box $ABCD$. $CDFE$ is called the *extended portion* of the ϵ -box.

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Lemma (an if condition)

If \exists a transformation $T(Q)$ for the said match, \exists another transformation $T'(Q)$, such that

- a point $q \in Q$ lies at the top-left corner of the ϵ -box of a point in P .
- at least one point lies in the extended portion of the ϵ -box
- each of the remaining members in Q lie in the extended ϵ -box

Anchoring for Finding the Transformation

Anchoring for Translation

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} t_x \\ t_y \end{bmatrix} + \begin{bmatrix} x \\ y \end{bmatrix}$$

- Two unknown parameters, t_x and t_y . So, one anchoring is needed.

Anchoring for Rigid Motion

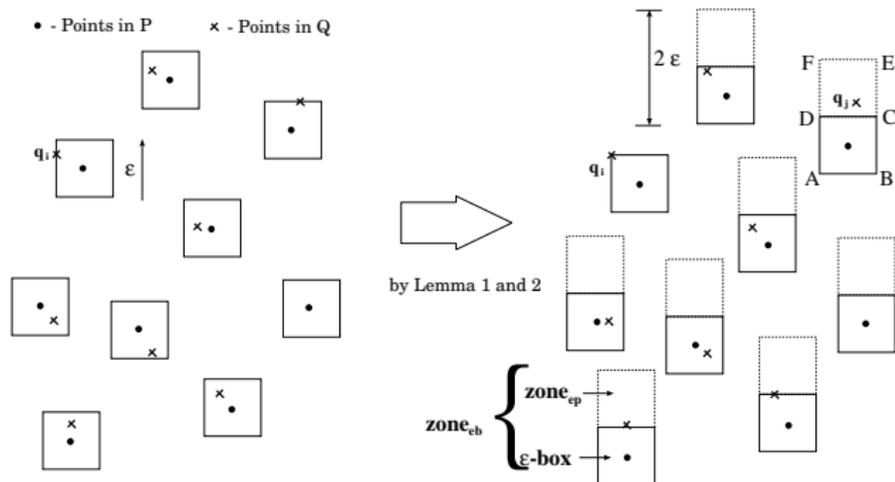
$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} t_x \\ t_y \end{bmatrix} + \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix}$$

- Three unknown parameters, t_x , t_y and θ . So, two anchorings are needed.

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Matching under Translation



Translation

The Algorithm

- Position q at the top-left corner of the ϵ -box of p , and check whether each point in $Q \setminus \{q\}$ lies inside the **extended box** of some point of P .
- If the above checking returns **false**, then no match exists with q at the top-left corner of the ϵ -box of p .
- If it returns **true**, then the points in $Q \setminus \{q\}$ can be partitioned into Q_1 and Q_2 . Each $q_1 \in Q_1$ lies in the ϵ -box of some point in P . Each $q_2 \in Q_2$ lies in the extended portion of ϵ -box of some member in P .
- Push points in Q_2 down such that points in Q_1 do not go out.

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The Analysis

The Algorithm

- Maintain a **planar straight line graph (PSLG)** data structure with the ϵ -boxes around each point in P .
- Anchoring a point $q \in Q$ with the top-left corner of an ϵ -box, we perform k point location queries in the PSLG. This needs $O(k \log n)$ time.
- Pushing points down take another $O(k)$ time.
- There can be $O(nk)$ anchorings in the worst case.

Theorem

The worst case time complexity of the approximate matching of Q with a k -subset of P in 2D when only translation is considered is $O(nk^2 \log n)$.

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The worst case time complexity of the approximate matching of Q with a k -subset of P in 2D when only translation is considered is $O(nk^2 \log n)$.

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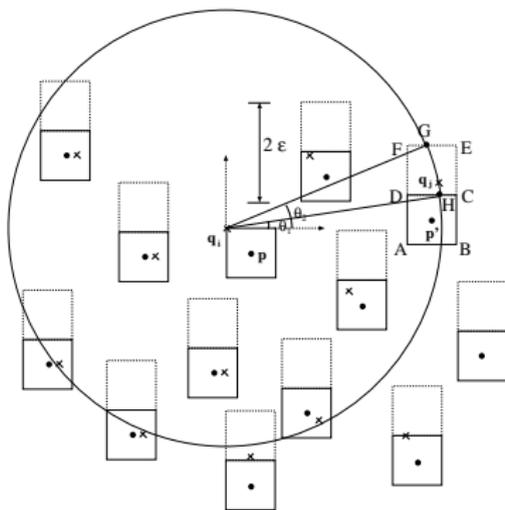
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Outline

- 1 Introduction
- 2 Previous Work
- 3 Exact Point Set Pattern Matching
- 4 Approximate Point Set Pattern Matching
- 5 Translation
- 6 Rigid Motion**

Matching under Rigid Motion



The Algorithm

- Consider the $k - 1$ concentric circles $C_{ij} \forall q_j \in Q \setminus \{q_i\}$. Each circle C_{ij} **intersects** some extended ϵ -boxes.
- As P is well-separated, these **intersections** contribute a set of non-overlapping arcs that define a **circular arc graph** G .
- Each circle C_{ij} may intersect $O(n)$ boxes making $O(nk)$ nodes in G . So, there can be $O(nk)$ cliques of size $k - 1$.
- Each clique χ corresponding to an anchoring of q represents an angular interval $\mathcal{I}^* = [\theta_1^*, \theta_2^*]$ such that all points in $Q \setminus q$ lie in some extended ϵ -box.

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Processing Each Clique

Processing Cliques

- Each clique χ represents an angular interval (an arc) $\mathcal{I}^* = [\theta_1^*, \theta_2^*]$. For any angle of rotation $\theta \in \mathcal{I}^*$, each of the $k - 1$ points of $Q \setminus q_i$ lies inside $k - 1$ disjoint extended ϵ -boxes.
- Partition the arcs corresponding to the points in $Q \setminus \{q_i\}$ into two subsets Q_1 and Q_2 . Arcs in Q_1 are all inside the ϵ -boxes, and those in Q_2 are all inside the extended portion of the ϵ -boxes.
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Homogeneous Splitting

Homogeneous splitting of \mathcal{I}^*

- Consider a $\theta \in \mathcal{I}^*$.
- For each $q \in Q_1$, let $f_q^1(\theta)$ denotes the distance of q from the bottom of the corresponding ϵ -box.
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- The functions $f_q^i(\theta)$ $i = 1, 2$ are like $\overline{q_a q} \sin(\alpha + \theta) - c$.

Observation

For a given $q \in Q_i$, the above functions are univariate, continuous, and unimodular.

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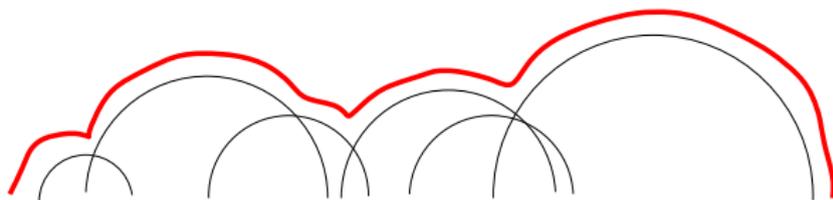
Envelope of Functions

Definition($\mathcal{L}(\theta)$ for $\theta \in \mathcal{I}^*$)

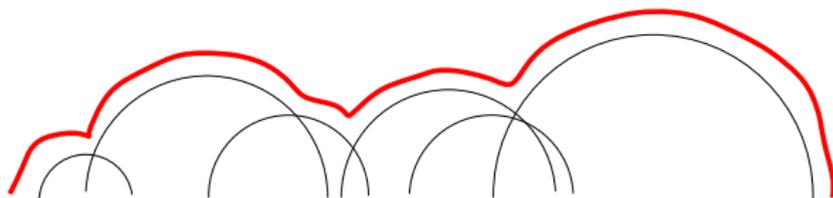
$\mathcal{L}(\theta)$ denotes the lower envelope of $|Q_1|$ functions, namely $f_q^1(\theta)$, $q \in Q_1$.

Definition($\mathcal{U}(\theta)$ for $\theta \in \mathcal{I}^*$)

$\mathcal{U}(\theta)$ denotes the upper envelope of $|Q_2|$ functions, namely $f_q^2(\theta)$, $q \in Q_2$.



Envelope of Functions



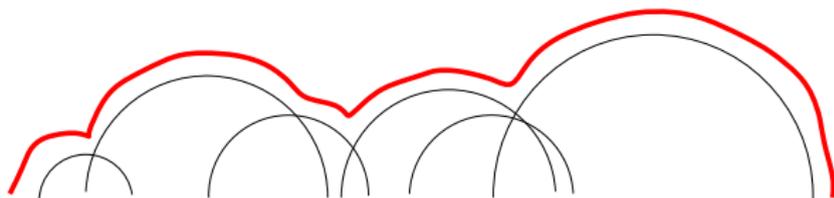
Minimum Amount of Downward Translation for Q_2

At a rotation angle $\theta \in \mathcal{I}^*$, the minimum amount of downward translation required to place the points in Q_2 in the corresponding ϵ -box is $\max_{q \in Q_2} f_q^2(\theta) = \mathcal{U}(\theta)$.

Maximum Amount of Downward Translation for Q_1

Similarly, the maximum amount of downward translation that may retain all the points in Q_1 in its corresponding ϵ -box is $\min_{q \in Q_1} f_q^1(\theta) = \mathcal{L}(\theta)$.

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Maximum Amount of Downward Translation for Q_1

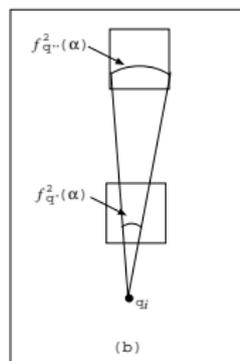
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A rotation angle θ is said to be a **break-point** in \mathcal{L} if $\mathcal{L}(\theta) = f_{q_a}^1(\theta) = f_{q_b}^1(\theta)$ for $q_a, q_b \in Q_1$, $q_a \neq q_b$. Similarly, the break-points of the \mathcal{U} function is defined.

Lemma

A pair of functions $f_{q'}^1(\theta)$ and $f_{q''}^1(\theta)$ (corresponding to $q', q'' \in Q_1$, $q' \neq q''$) w.r.t. $\theta \in \mathcal{I}^*$ may intersect in at most two points. The same is true for a pair of functions $f_{q'}^2(\theta)$ and $f_{q''}^2(\theta)$ for a pair of points $q', q'' \in Q_2$.

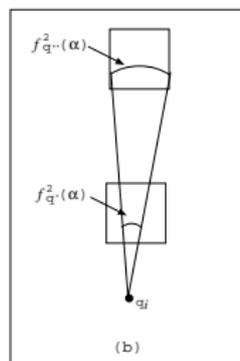


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Observation

The collection of functions $\{f_q^1(\theta), q \in Q_1\}$ follows a $(k, 2)$ -Davenport-Schinzel sequence. The same result is true for the collection of functions $\{f_q^2(\theta), q \in Q_2\}$.

Lemma

The maximum number of break-points in the function $\mathcal{L}(\theta)$ is $\lambda_2(|Q_1|) = 2|Q_1| - 1$, and it can be computed in $O(|Q_1| \log |Q_1|)$ time. Similarly, for $\mathcal{U}(\theta)$.

Moral of Homogeneous Splitting of \mathcal{I}^*

$\mathcal{I}^* = [\theta_1^*, \theta_2^*]$ is split into $O(k)$ sub-intervals defined by **break-points** of $\mathcal{L}(\theta)$ and $\mathcal{U}(\theta)$.

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Critical Angle

Definition (Critical Angle)

If a match is found by a rotation of Q by the angle $\theta^* \in \mathcal{I}^*$ and a vertical downward shift, then θ^* is said to be a **critical angle**.

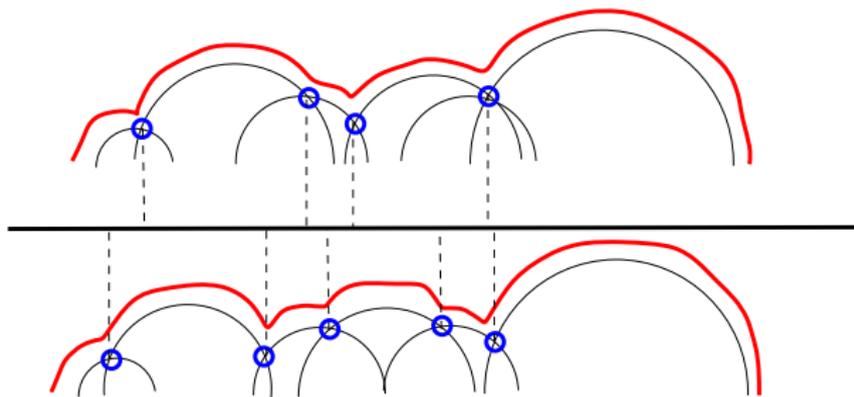


Figure: Envelopes and break points.

Computation of Critical Angle

Critical Angle Computation

Δ_1 = Minimum amount of downward shift required to bring q_a inside the ϵ -box of p' . Thus,

$$\Delta_1 = \delta(q_i, q_\alpha) \sin(\theta + \theta_1) - (y(p') + \frac{\epsilon}{2}).$$

Δ_2 = Maximum amount of permissible downward shift keeping q_b inside the ϵ -box of p'' . Thus,

$$\Delta_2 = \delta(q_i, q_\beta) \sin(\theta + \theta_1 + \psi) - (y(p'') - \frac{\epsilon}{2}).$$

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Complexity Analysis

Complexity Analysis

- Each point of Q needs to be anchored at the top-left corner of the ϵ -box of each point in P .
- The nodes of the circular arc graph G are obtained in $O(nk)$ time and the cliques of G can be obtained in $O(nk \log n)$ time.
- While processing a clique, computation of functions \mathcal{U} and \mathcal{L} needs $O(k \log k)$ time.
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The Final Result

Theorem

The time complexity of the proposed algorithm for ϵ -approximate matching of Q with a subset of P where the neighbourhood around a point (in P) is defined as an ϵ -box, is $O(n^2 k^2 (\log n + k \log k))$.

Further reading I



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Thank You!