A Fully-Automated Solver for Multiple Square Jigsaw Puzzles Using Hierarchical Clustering

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- First computation jigsaw puzzle solver introduced in 1964.
- Solving a jigsaw puzzle is NP Complete [1, 2]

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  - In most cases, the original, “ground-truth” image is unknown.

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- All pieces are equal-sized squares
- Substantially more difficult

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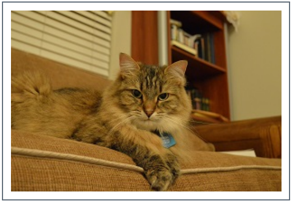

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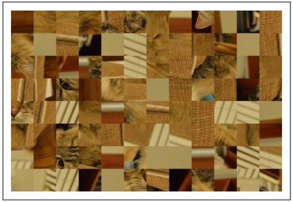

Randomized Jig Swap Puzzle

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There are four primary jig swap puzzle types as formalized by [3]. In all cases, the “ground-truth” input is unknown.

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Mixed-Bag Puzzles are the focus of this thesis.

- **Basis of all Modern Jig Swap Solvers**: The more compatible two pieces are on their respective sides, the more likely they are to be adjacent.
- **Best Buddies**: Any pair of puzzles pieces that are more compatible with each other on their respective sides than they are to any other piece [4]

$$\forall p_k \forall s_z, C(p_i, s_x, p_j, s_y) \geq C(p_i, s_x, p_k, s_z)$$

$$\text{and} \tag{1}$$

$$\forall p_k \forall s_z, C(p_j, s_y, p_i, s_x) \geq C(p_j, s_y, p_k, s_z)$$

- **Importance of Best Buddies**: Strong indicator of piece adjacency

Previous Work

- **Cho *et al.*** [5] – Introduced the first Modern Jig Swap Puzzle Solver Introduced
  - Graphical model-based Type 1 solver
  - Puzzle dimensions are known
  - Used one or more anchor pieces
  - Defined quality metrics for Type 1 and Type 2 puzzles
  - Established the standard comparative test conditions

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  - Defined quality metrics for Type 1 and Type 2 puzzles
  - Established the standard comparative test conditions
- **Pomeranz *et al.*** [4] – Iterative, greedy Type 1 puzzle solver
  - Eliminated the use of anchor pieces
  - Created multiple solver benchmarks of various sizes
  - Introduced the concept of “best buddies”

Paikin & Tal [6] – Current State of the Art

- Greedy, kernel growing solver
- Supports Type 1, Type 2, and Mixed-Bag puzzles
- Immune to missing pieces

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Limitations

- **Poor Seed Selection**: All decisions are made at runtime using as few as 13 pieces
- **Externally Supplied Information**: The solver must be told the number of input puzzles

Primary Goal: Develop a puzzle solver for Mixed-Bag jig swap puzzles with performance that exceeds the state of the art.

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Additional Goals:

- Develop new metrics for quantifying the performance of Mixed-Bag puzzles
- Design new best buddy and solver output visualizations

The Mixed-Bag Solver

Paikin & Tal’s Algorithm

- Begin each puzzle with a single piece
- Place all pieces around the expanding core

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Alternate Jigsaw Puzzle Solving Strategy

- Correctly assemble small puzzle regions (i.e., segments)
- Iteratively merge smaller regions to form large ones

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Alternate Jigsaw Puzzle Solving Strategy

- Correctly assemble small puzzle regions (i.e., segments)
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- **Advantages of this Approach**:
  - Reduces the size of the problem
  - Provides structure to the unordered set of puzzle pieces.

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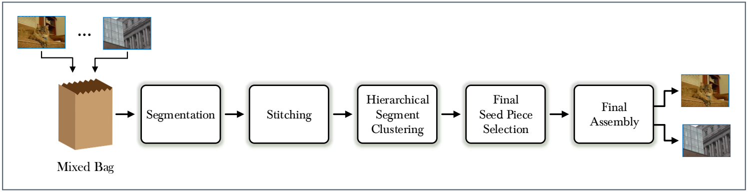
The latter strategy is the basis of the **Mixed-Bag Solver**.

Mixed-Bag Solver

Overview

- The Mixed-Bag Solver is fully-automated. It makes no assumptions concerning the piece orientation, puzzle dimensions, or number of puzzles.
  - **Input**: Set of puzzle pieces
  - **Output**: One or more disjoint, solved puzzles.
- The Mixed-Bag Solver consists of five distinct stages:



- **Role**: Place the individual pieces in the solved puzzle.
  - Mixed-Bag Solver is independent of the assembler used, giving the solver significant upgradability and flexibility.

Assembler

Mixed-Bag Solver Component

- **Role**: Place the individual pieces in the solved puzzle.
  - Mixed-Bag Solver is independent of the assembler used, giving the solver significant upgradability and flexibility.
- **Assembler Used in this Thesis**: Paikin & Tal
  - Current state of the art
  - Allows for more direct comparison of performance
  - Natively supports Mixed-Bag puzzles
- **Implementation**: Assembler re-implemented as part of this thesis based off the description in [6]
  - Written in the Python language and fully open source.

Segmentation

Mixed-Bag Solver Stage #1

- **Segment**: Partial puzzle assembly where this is a high degree of confidence pieces are placed correctly.
- **Role of Segmentation**: Provide structure to the set of puzzle pieces by partitioning them into disjoint segments
  - **Input**: Set of puzzle pieces
  - **Output**: Set of saved segments
- **Relationship between Puzzle Pieces and Segments**:
  - Pieces from a single ground-truth input may be separated into multiple segments
  - A piece can be assigned to at most one segment

Segmentation

Algorithm Overview

- Iterative process consisting of one or more rounds
- In each round, all pieces not yet assigned to a segment are assembled as if they are all from the same input image.
- Segments of sufficient size are saved to be used in future Mixed-Bag Solver stages
- Pieces in a saved segment are not placed in future rounds.
- Segmentation terminates if all pieces are assigned to a saved segment or no segment is larger than the minimum allowed size.

PLACEHOLDER

Segmentation

Example – Input Images

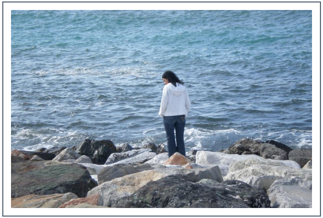


Image (a) – 805 Pieces [7]

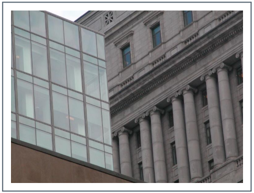
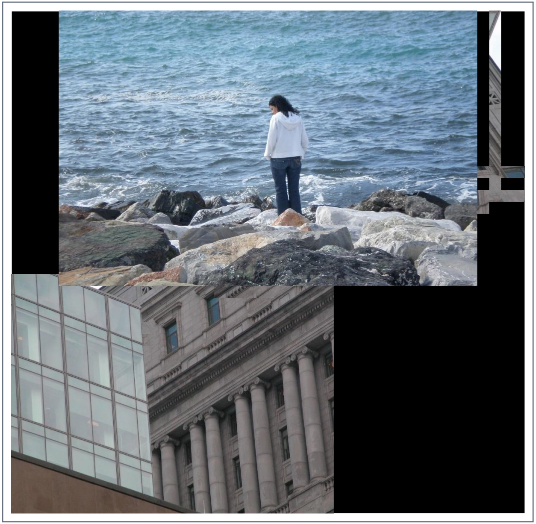


Image (b) – 540 Pieces [8]

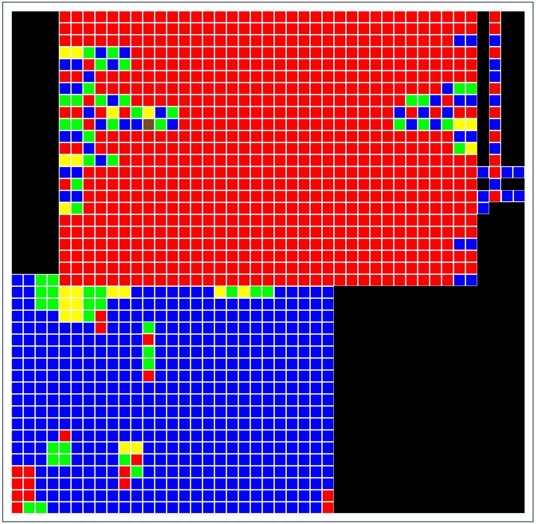
Segmentation

Example – First Segmentation Round Output Image



Segmentation

Example – Segmented Output Image



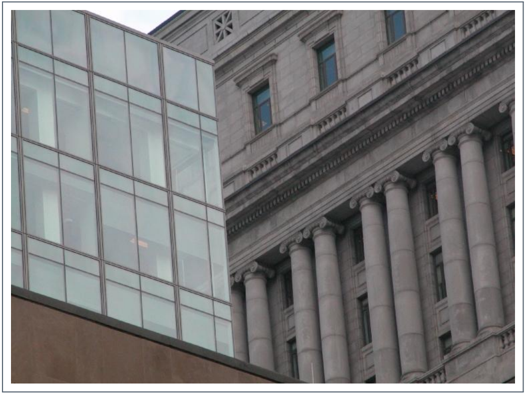
Stitching

Mixed-Bag Solver Stage #2

- **Role of Stitching**: Quantify the extent that any pair of segments is related.
  - **Input**: All puzzle pieces and the set of saved segments
  - **Output**: Segment overlap matrix

Stitching

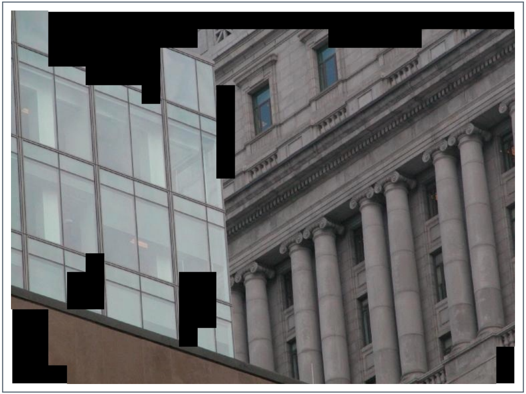
Example – Input Image



Stitching

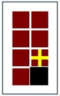
Example – Two Segment Images

Segment #1



Segment #2

Stitching
Example – Stitching Piece Locations



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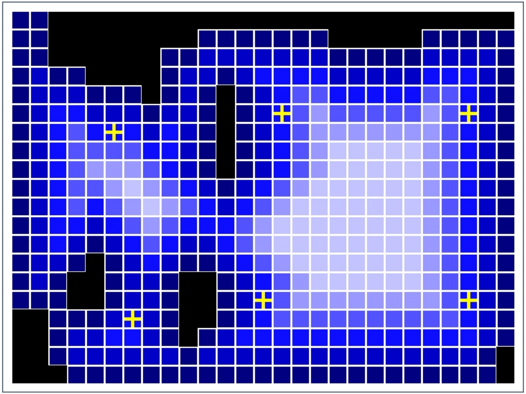

Segment #2

Stitching

Example – Stitching Piece Locations

Stitching Result from Segment #1

Segment Overlap:

$$Overlap_{\Phi_1,\Phi_2} = 0.83 \quad (2)$$

Hierarchical Segment Clustering

Mixed-Bag Solver Stage #3

PLACEHOLDER

Paikin & Tal

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Mixed-Bag Solver

- **Role of Final Seed Selection**: Determine the pieces that will be used as the seed for the final output puzzles.
  - **Input**: Set of cluster segments
  - **Output**: Final seed pieces
- A single seed piece is selected from each segment cluster
- Each seed piece is "distinctive" as defined by Paikin & Tal

Final Assembly Stage

Mixed-Bag Solver Stage #5

- **Role of Final Assembly**: Generate the solved puzzles that will be returned by the solver. by placing all pieces around the previously selected seeds.
    - **Input**: Set of puzzle pieces with the seeds marked
    - **Output**: Final solved puzzles
- All pieces are placed around the seeds selected in the previous stage.
- Assembly proceeds in this stage normally without any custom modifications.

Quantifying Solver Quality

Quantifying Solver Quality

- Jigsaw puzzle solvers are not yet able to always correctly reconstruct the input puzzle(s)
  - Metrics compare the quality of solved outputs
- **Two Most Common Quality Metrics**:
  - Direct Accuracy
  - Neighbor Accuracy

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Quantifying Solver Quality

- Jigsaw puzzle solvers are not yet able to always correctly reconstruct the input puzzle(s)
  - Metrics compare the quality of solved outputs
- **Two Most Common Quality Metrics**:
  - Direct Accuracy
  - Neighbor Accuracy
- **Disadvantages of Current Metrics**: Neither account for:
  - Pieces misplaced in different puzzles
  - Extra pieces from other puzzles
- **Goal**: Define new Mixed-Bag puzzle quality metrics.

Quantifying Solver Quality

Standard and Enhanced Direct Accuracy

- **Standard Direct Accuracy**: Fraction of pieces (c) placed in the same location in both the ground-truth and solved image versus the total number of pieces (n)

$$DA = \frac{c}{n} \tag{3}$$

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- **Enhanced Direct Accuracy Score (EDAS)**: Modified direct accuracy that accounts for missing and extra pieces.

$$EDAS_{P_i} = \underset{S_j \in S}{\arg\max} \frac{c_{i,j}}{n_i + \sum_{k \neq i}(m_{k,j})} \tag{4}$$

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- **Direct Accuracy Range**: 0 to 1
- **Perfectly Reconstructed Image**: All pieces are placed in their original location ($DA = EDAS = 1$)

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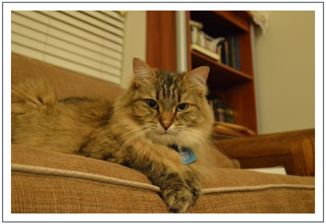

Ground-Truth Image

Direct Accuracy
Effect of Shifts

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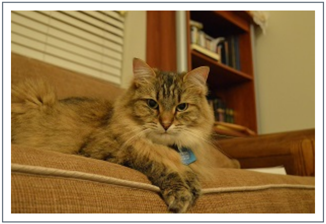
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Solver Output

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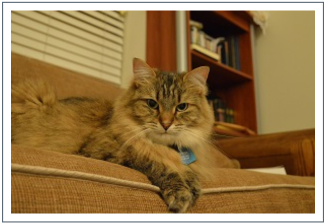

Ground-Truth Image

Solver Output

Conclusion: Direct accuracy can be overly punitive.

Direct Accuracy

Shiftable Enhanced Direct Accuracy Score (SEDAS)

- **Solution**: Allow the reference point for direct accuracy to shift beyond the upper left corner of the image
- **Shiftable Enhanced Direct Accuracy Score (SEDAS)**: Select the reference point, l, within radius d_{min} of the upper left corner of the solved puzzle
  - d_{min} - Manhattan distance between the upper left corner of the solved image and the nearest puzzle piece
- **Formal Definition of SEDAS**:

$$SEDAS_{P_i} = \underset{l \in L}{\arg\max} \left(\underset{S_j \in S}{\arg\max} \frac{c_{i,j,l}}{n_i + \sum_{k \neq i}(m_{k,j})} \right) \tag{5}$$

- **SEDAS Range**: 0 to 1

- **Standard Neighbor Accuracy**: Ratio of puzzle piece sides adjacent in both the original and solved images (a) versus the total number of sides ($n \cdot q$)

$$NA = \frac{a}{n \cdot q} \quad (6)$$

Quantifying Solver Quality
Standard and Enhanced Neighbor Accuracy

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- **Neighbor Accuracy Range**: 0 to 1
- **Advantage of Neighbor Accuracy**: Less vulnerable to shifts than direct accuracy

- The thesis includes visualization standards for direct and neighbor accuracy.
- They are not reviewed here due to limited time.

Quantifying Solver Quality

Best Buddy Density

- **Best Buddies Review**: Any pair of puzzles pieces that are more compatible with each other on their respective sides than they are to any other piece
  - **Note**: Not all puzzle pieces will have a best buddy.

- **Best Buddy Density** (BBD): A metric for quantifying the best buddy profile of an image that is independent of image size.

$$BBD = \frac{b}{n \cdot q} \tag{8}$$

- A greater BBD means the pieces are more differentiated making the puzzle easier to solve.

Visualizing Best Buddy Density

- Transform each puzzle piece into a square consisting of four isosceles triangles.
- Color each triangle according to whether the adjacent piece is a best buddy. The scheme used in this thesis:

No Best Buddy	Non-Adjacent Best Buddy	Adjacent Best Buddy	No Piece Present

- Areas with higher best buddy density will have more green triangles.

Best Buddy Density
Visualization Example

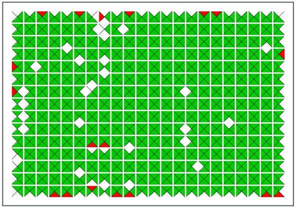
(a) Original Image [9]

Figure: Visualization of Best Buddy Density

Best Buddy Density

Visualization Example

(a) Original Image [9]



(b) Best Buddy Visualization

Figure: Visualization of Best Buddy Density

Experimental Results

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- **Standard Test Conditions**
  - **Puzzle Type**: 2
  - **Dimensions Fixed**: No
  - **Piece Width**: 28 pixels
  - **Benchmark**: Twenty 805 piece images [7]
  - **Image Encoding**: LAB colorspace

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- **Number of Ground-Truth Inputs**: 1 to 5

# Puzzles	1	2	3	4	5
# Iterations	20	55	25	8	5

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- **Test Condition Variation**: Only Paikin & Tal's algorithm was provided the number of input puzzles.

- **Goal**: Measure the Mixed-Bag Solver's accuracy determining the number of input puzzles
  - **Importance** – The Mixed-Bag Solver must estimate this accurately to provide meaningful outputs.

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- **Two Subexperiments**:
  - **Single Puzzle Accuracy** – This represents the solver's performance ceiling
  - **Multiple Puzzle Accuracy** – A more general estimate of the solver's performance

Determining Input Puzzle Count

Single Input Puzzle Results

- **Summary**: 17 out of the 20 images were correctly identified as a single ground-truth input
- **Misclassified Images**: 3 out of the 20 images misclassified as if they were two images.
  - All three images have large areas with little variation (e.g., blue sky, smooth water)
  - The solver's performance on these puzzles is due to the assembler as noted in [6]

Determining Input Puzzle Count

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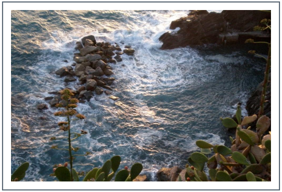
  - All three images have large areas with little variation (e.g., blue sky, smooth water)
  - The solver's performance on these puzzles is due to the assembler as noted in [6]
- **Note**: 85% (17/20) represents the maximum accuracy when solving multiple puzzles.

Determining Input Puzzle Count
Comparison of Best Buddy Density for Misclassified Images

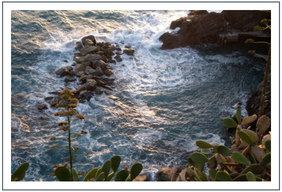


Perfectly Reconstructed Image (a)

Misclassified Image (b)

Determining Input Puzzle Count

Comparison of Best Buddy Density for Misclassified Images



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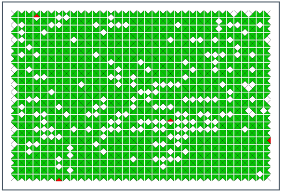
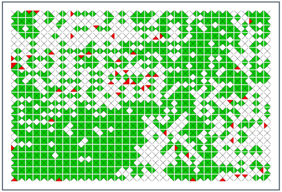


Best Buddy Visualization (a)

Misclassified Image (b)



Best Buddy Visualization (b)

Determining Input Puzzle Count
Multiple Input Puzzles

- **Goal**: Measure the Mixed-Bag Solver's accuracy determining the input puzzle count for multiple images
- **Procedure**: Randomly select the specified number of images (between 2 and 5) from the 20 image data set.

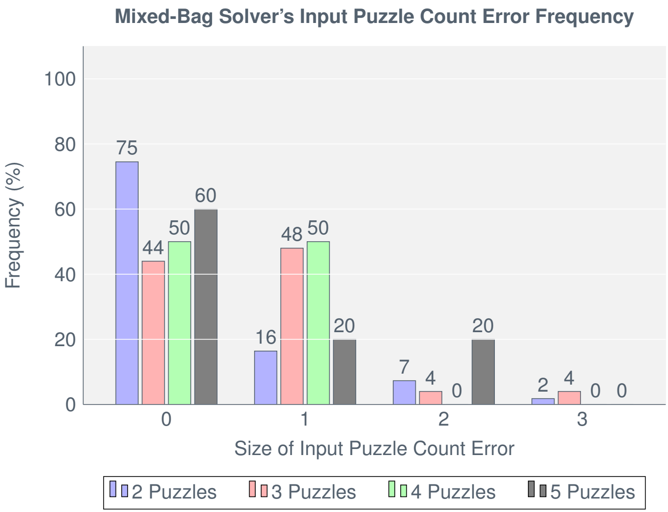
Determining Input Puzzle Count

Multiple Input Puzzles

- **Goal**: Measure the Mixed-Bag Solver's accuracy determining the input puzzle count for multiple images
- **Procedure**: Randomly select the specified number of images (between 2 and 5) from the 20 image data set.
- **Input Puzzle Count Error**: Difference between the actual number of input puzzles and that found by the Mixed-Bag Solver.
  - **Example**: If 3 images were supplied to the solver, but it determined there were 4, the error would be 1.

Determining Input Puzzle Count

Multiple Input Puzzles – Results



Determining Input Puzzle Count

Multiple Input Puzzles – Results Summary

- **Overall Accuracy**: 65%
- **Iterations with Error Greater than One**: 8%
- Accuracy did not significantly degrade as the number of input puzzles increased.

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Determining Input Puzzle Count

Multiple Input Puzzles – Results Summary

- **Overall Accuracy**: 65%
- **Iterations with Error Greater than One**: 8%
- Accuracy did not significantly degrade as the number of input puzzles increased.
- **Over-Rejection of Cluster Merges**: The Mixed-Bag Solver never underestimated the number of input puzzles.
  - Performance may be improved by reducing the minimum clustering similarity threshold or minimum segment size

Experimental Results

Performance on Multiple Input Puzzles

- **Goal**: Compare the performance of the Mixed-Bag Solver and Paikin & Tal's algorithm
- **Procedure:** Randomly select a specified number of images and input them into both solvers.
- **Quality Metrics Used**:
  - Shiftable Enhanced Direct Accuracy Score (SEDAS)
  - Enhanced Neighbor Accuracy Score (ENAS)
  - Perfect Reconstruction Percentage

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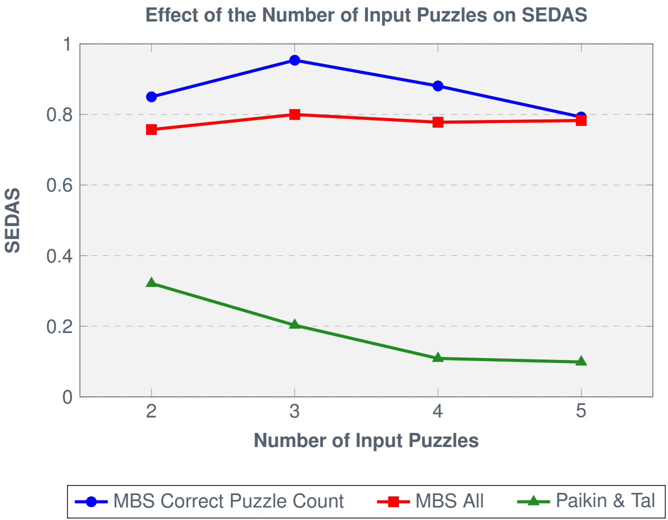
- **Note**: The results include the Mixed-Bag Solver's performance when it correctly estimated the puzzle count.
  - This represents the performance ceiling for optimal hierarchical clustering.

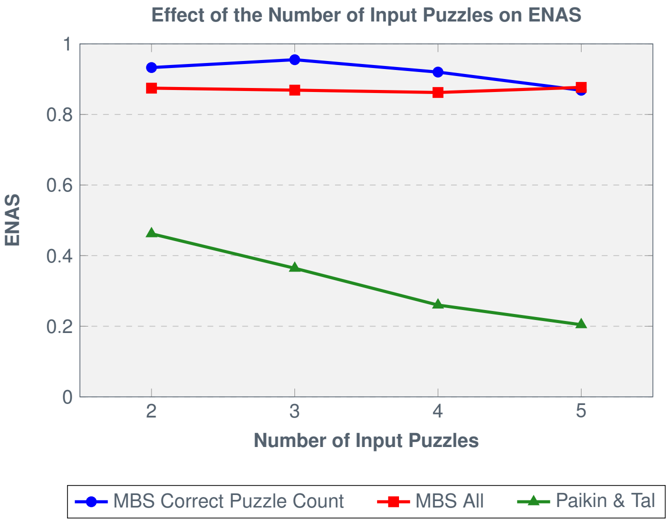
Performance on Multiple Input Puzzles

Shiftable Enhanced Direct Accuracy Score (SEDAS)



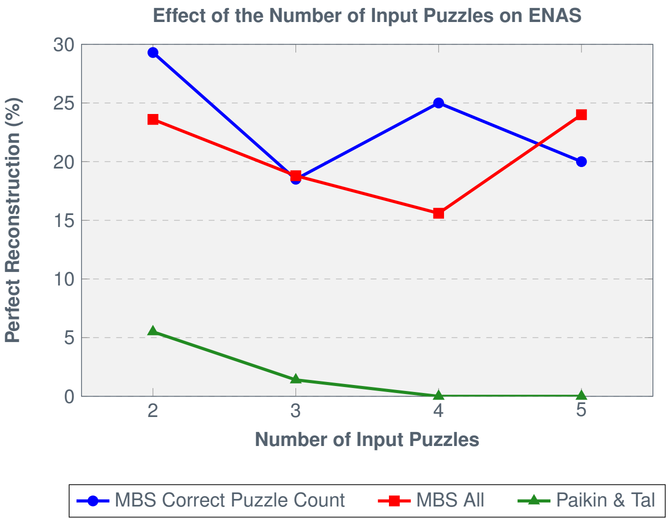
Performance on Multiple Input Puzzles

Enhanced Neighbor Accuracy Score (ENAS)



Performance on Multiple Input Puzzles

Perfect Reconstruction Percentage



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Performance on Multiple Input Puzzles

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Performance on Multiple Input Puzzles

Results Summary

- **Summary**: The Mixed-Bag Solver significantly outperformed Paikin & Tal's algorithm across all metrics.
  - This is notwithstanding that only their algorithm was supplied with the number of input puzzles.
- **Puzzle Input Count**: Unlike Paikin & Tal's algorithm, the Mixed-Bag Solver saw no significant decrease in performance with additional input puzzles
- **Effect of Clustering Errors**: Performance only decreased slightly when incorrectly estimated input puzzle count.
  - Many of the extra puzzles were relatively insignificant in size

Conclusions

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- This thesis presented a fully-automated solver for Mixed-Bag jig swap puzzles.
- Mixed-Bag Solver significantly outperforms the current state of the art while receiving no externally supplied information.
- Introduced the first set of solver quality metrics for Mixed-Bag puzzles.

- Improved Assembler
  - Prioritize placement using multiple best buddies

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- Improved Assembler
  - Prioritize placement using multiple best buddies
  - Address placement performance in regions with low best buddy density
- Dynamic determination of the segment clustering threshold

Conclusions
Future Work

- Improved Assembler
  - Prioritize placement using multiple best buddies
  - Address placement performance in regions with low best buddy density
- Dynamic determination of the segment clustering threshold
- Expanded stitching piece selection

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Appendix

Experimental Results

Solving More than Five Puzzles

- As the number of puzzles increases, the difficulty of simultaneously reconstructing them also increases.

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- **Current State of the Art**: Paikin & Tal [6] solved up to five puzzles simultaneously.

Experimental Results

Solving More than Five Puzzles

- As the number of puzzles increases, the difficulty of simultaneously reconstructing them also increases.
- **Current State of the Art**: Paikin & Tal [6] solved up to five puzzles simultaneously.
- **Goal**: Compare the performance of the Mixed-Bag Solver and Paikin & Tal's algorithm on 10 puzzles.

Ten Puzzle Results

Summary

- **Paikin & Tal**
  - Seed of nine images came from just three input images
  - SEDAS and EDAS greater than 0.9 for only one image
  - No perfectly reconstructed images

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  - Four images perfectly reconstructed
  - Results comparable to Paikin & Tal's algorithm solving each puzzle individually
- **Conclusion**: The performance difference between the Mixed-Bag Solver and Paikin & Tal's algorithm is even starker with more input puzzles.

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