**SIT789 - Robotics Computer Vision And Speech Processing**

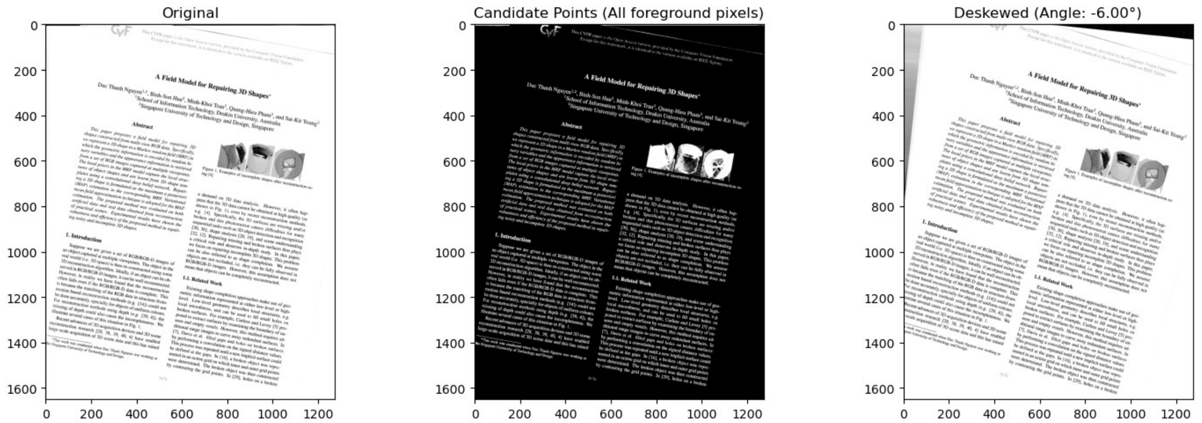
**Distinction Task 2.3: Document analysis and recognition**

**Introduction**

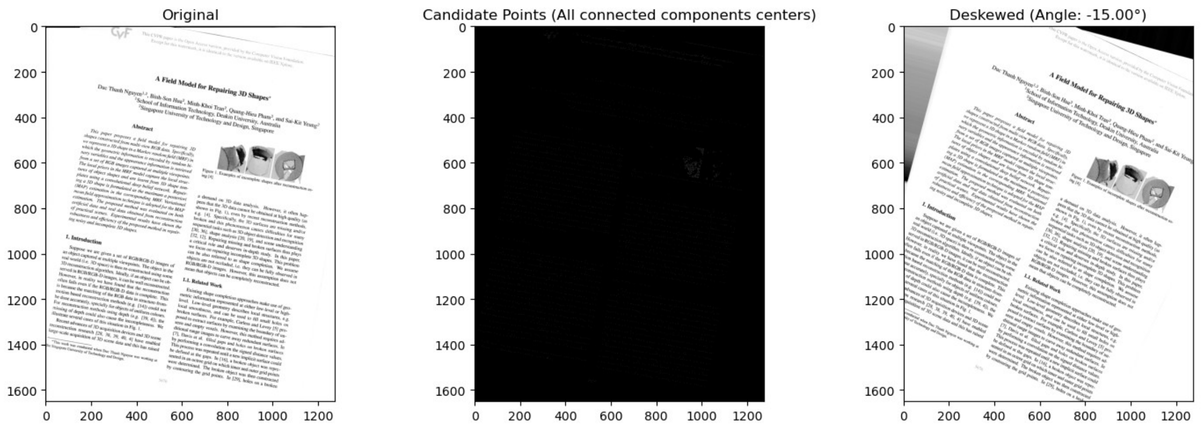
Document analysis and recognition play a vital role in transforming document images into text-based formats. This transformation facilitates various functionalities such as content retrieval, searching, indexing, and document compression.

1.

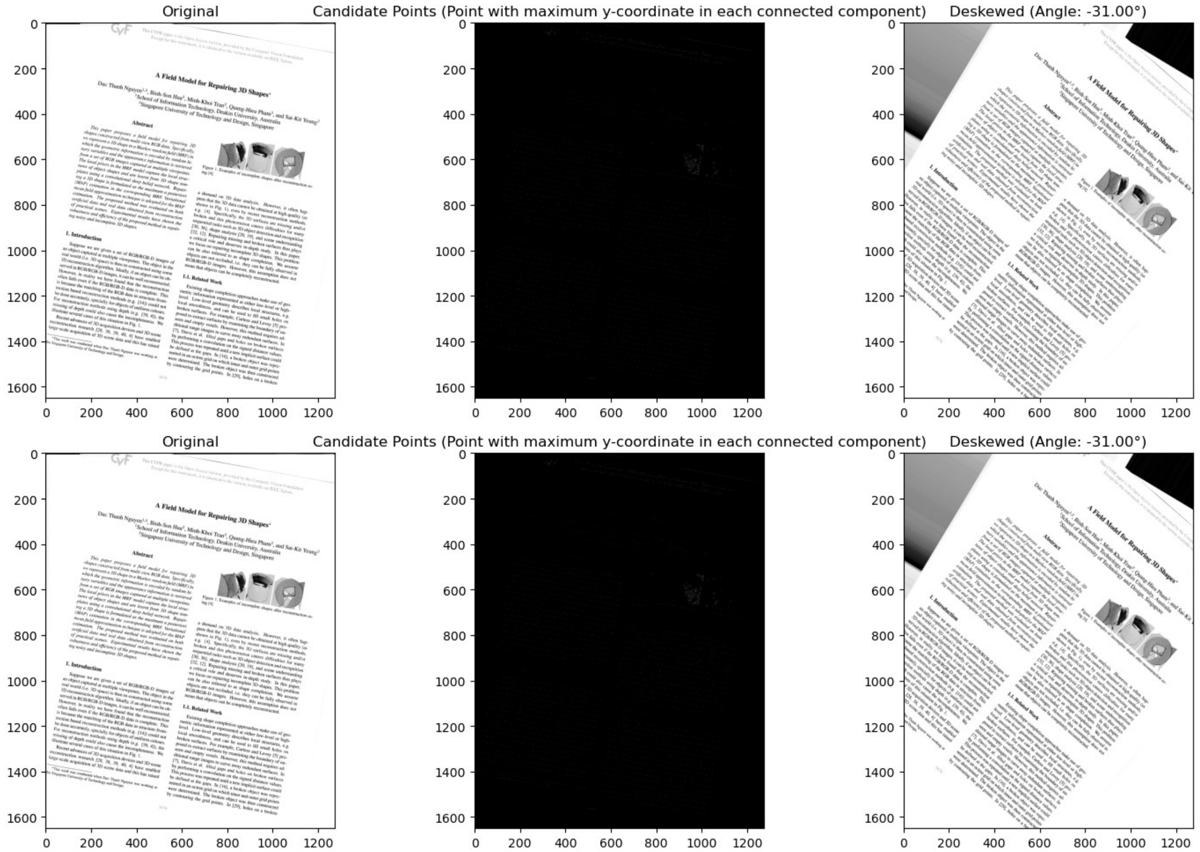
(a) All foreground pixels strategy




(b) All connected components centers:



(c) Point with maximum y-coordinate in each connected component




## 2. De-skewing results:

**Strategy: A) All foreground pixels strategy**

**Density threshold: 5**

# A Field Model for Repairing 3D Shapes*

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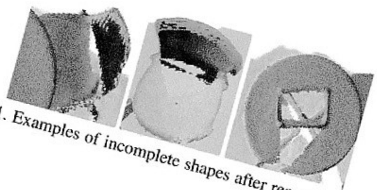

Figure 1. Examples of incomplete shapes after reconstruction using [4].

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Density threshold: 10

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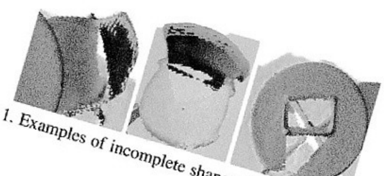

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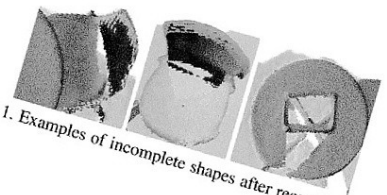

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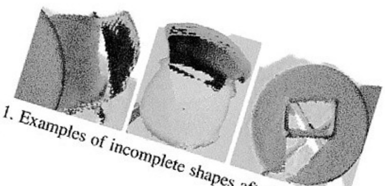

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**Strategy: B) All connected components' centers**

**Density threshold: 5**



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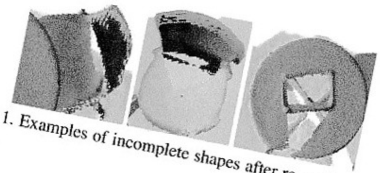

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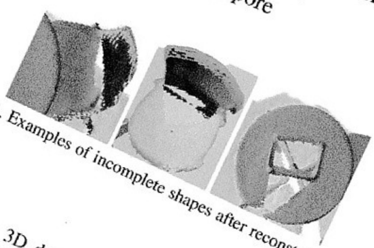

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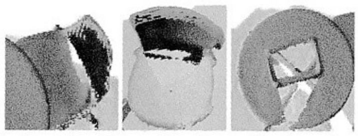

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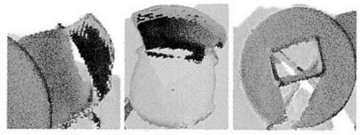

Figure 1. Examples of incomplete shapes after reconstruction using [4].

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**Strategy: C) Point with maximum y-coordinate in each connected component.**

**Density Threshold: 5**



# A Field Model for Repairing 3D Shapes*

Duc Thanh Nguyen[1,2], Binh-Son Hua[2], Minh-Khoi Tran[2], Quang-Hieu Pham[2], and Sai-Kit Yeung[2]
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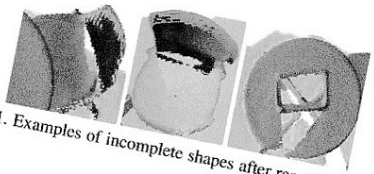

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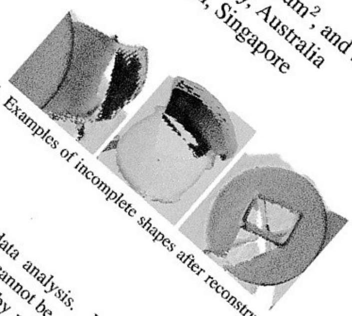

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**Density Threshold: 15**



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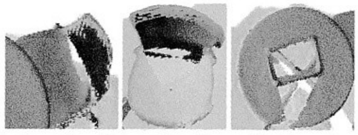

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Density threshold: 20



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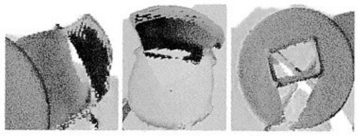

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**Speed of Computational Experiments Conducted:**

2.1 Candidate Point Selection Analysis:
-------------------------------------

Strategy a:
  Estimated angle: 6.00 degrees
  Selection time: 0.0090 seconds
  Hough transform time: 0.0295 seconds
  Total time: 0.1579 seconds

Strategy b:
  Estimated angle: 15.00 degrees
  Selection time: 0.0000 seconds
  Hough transform time: 0.0024 seconds
  Total time: 0.0071 seconds

Strategy c:
  Estimated angle: 31.00 degrees
  Selection time: 18.1280 seconds
  Hough transform time: 0.0024 seconds
  Total time: 18.1348 seconds

2.2 Parameter Setting Analysis:
------------------------------

Density Threshold: 5
----------------------------
Strategy a:
  Estimated angle: 5.00 degrees
  Selection time: 0.0060 seconds
  Hough transform time: 0.0302 seconds
  Total time: 0.1421 seconds
Strategy b:

```
  Estimated angle: 1.00 degrees
  Selection time: 0.0000 seconds
  Hough transform time: 0.0032 seconds
  Total time: 0.0098 seconds
Strategy c:
  Estimated angle: 1.00 degrees
  Selection time: 17.9041 seconds
  Hough transform time: 0.0033 seconds
  Total time: 17.9142 seconds

Density Threshold: 10
----------------------------
Strategy a:
  Estimated angle: 6.00 degrees
  Selection time: 0.0057 seconds
  Hough transform time: 0.0308 seconds
  Total time: 0.1463 seconds
Strategy b:
  Estimated angle: 15.00 degrees
  Selection time: 0.0000 seconds
  Hough transform time: 0.0022 seconds
  Total time: 0.0066 seconds
Strategy c:
  Estimated angle: 31.00 degrees
  Selection time: 17.9144 seconds
  Hough transform time: 0.0023 seconds
  Total time: 17.9212 seconds

Density Threshold: 15
----------------------------
Strategy a:
  Estimated angle: 6.00 degrees
  Selection time: 0.0059 seconds
  Hough transform time: 0.0306 seconds
  Total time: 0.1440 seconds
Strategy b:
```

```
  Estimated angle: -10.00 degrees
  Selection time: 0.0000 seconds
  Hough transform time: 0.0022 seconds
  Total time: 0.0068 seconds
Strategy c:
  Estimated angle: -10.00 degrees
  Selection time: 17.8879 seconds
  Hough transform time: 0.0023 seconds
  Total time: 17.8945 seconds

Density Threshold: 20
------------------------------
Strategy a:
  Estimated angle: 7.00 degrees
  Selection time: 0.0057 seconds
  Hough transform time: 0.0294 seconds
  Total time: 0.1378 seconds
Strategy b:
  Estimated angle: -10.00 degrees
  Selection time: 0.0000 seconds
  Hough transform time: 0.0022 seconds
  Total time: 0.0062 seconds
Strategy c:
  Estimated angle: -10.00 degrees
  Selection time: 17.8826 seconds
  Hough transform time: 0.0024 seconds
  Total time: 17.8891 seconds
```

The analysis reveals variations in performance and accuracy across different candidate point selection strategies and density thresholds. Visual inspection of the deskewed images provides crucial information that supports and extends the numerical analysis.

- **Strategy 'a' (All foreground pixels):**

    - Consistently estimates the skew angle between 5-7 degrees
    - Moderate processing times (0.14-0.17 seconds)
    - Visual inspection confirms this strategy produces accurate deskewing results

- **Strategy 'b' (All connected components centres):**
    - Extremely fast (0.006-0.01 seconds)
    - Inconsistent angle estimations ranging from 1 to 15 degrees
    - Visual inspection shows good deskewing results, despite the inconsistency in angle estimation

- **Strategy 'c' (Point with maximum y-coordinate in each connected component):**
    - Slowest by far (17.9-18.8 seconds)
    - Widely varying angle estimates (1 to 31 degrees)
    - Visual inspection shows good deskewing results, despite the inconsistency in angle estimation and long processing time

Density threshold adjustments appear to have a minimal impact on processing times but can affect the estimated angles, particularly for strategies 'b' and 'c'. The inconsistency in angle estimations across different strategies and thresholds confirms that the skew correction method's reliability depends on the specific characteristics of the input document.

Visual inspection of the deskewed images shows that:

- All strategies produce well-aligned documents that are easily readable.
- Despite the numerical inconsistencies in angle estimation for strategies 'b' and 'c', their visual results are comparable to strategy 'a' for this document.

**Chosen Strategy:**

Based on both the numerical results and visual inspection, strategy "a" (using all foreground pixels as candidate points) remains the optimal choice. The density threshold of 20, as originally determined, appears to provide the best balance between accuracy and processing time. The deskewed image using the strategy 'a' with a threshold of 20 shows proper alignment and readability.

This choice is supported by:

- Consistent angle estimation for strategy 'a'
- Acceptable processing time
- Visual confirmation of well-aligned, readable results
- The original analysis indicated that a threshold of 20 yielded the best outcome

While strategies 'b' and 'c' can produce visually similar results in this case, their inconsistencies in processing time and angle estimation make them less reliable options for a wider range of documents. However, if processing speed is a critical factor, strategy 'b' might be considered as an alternative, with the caveat that its performance may vary more across different documents.

## 3. Test images and Results:

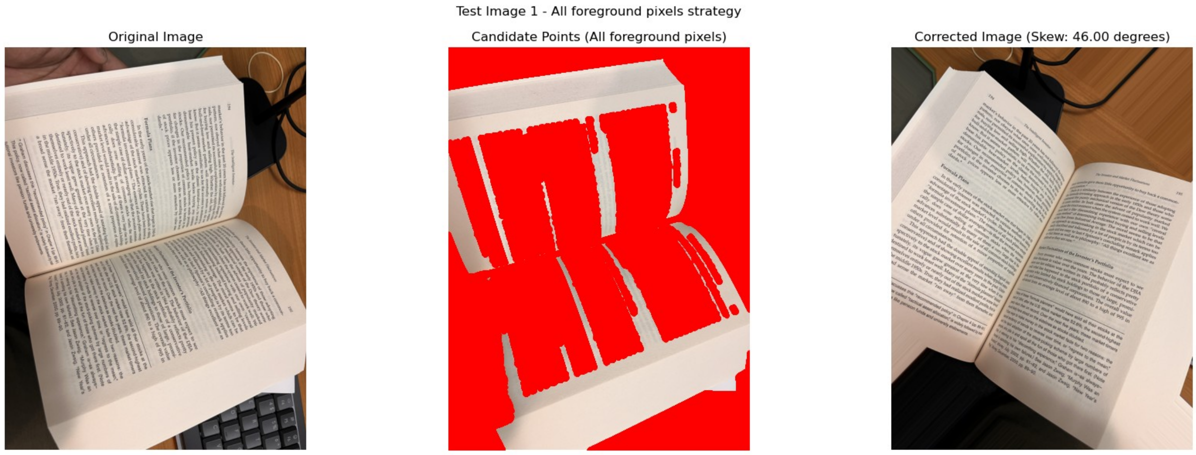


Image 1: Skew = 46.00°, Selection Time = 0.0575s, Points = 4185914

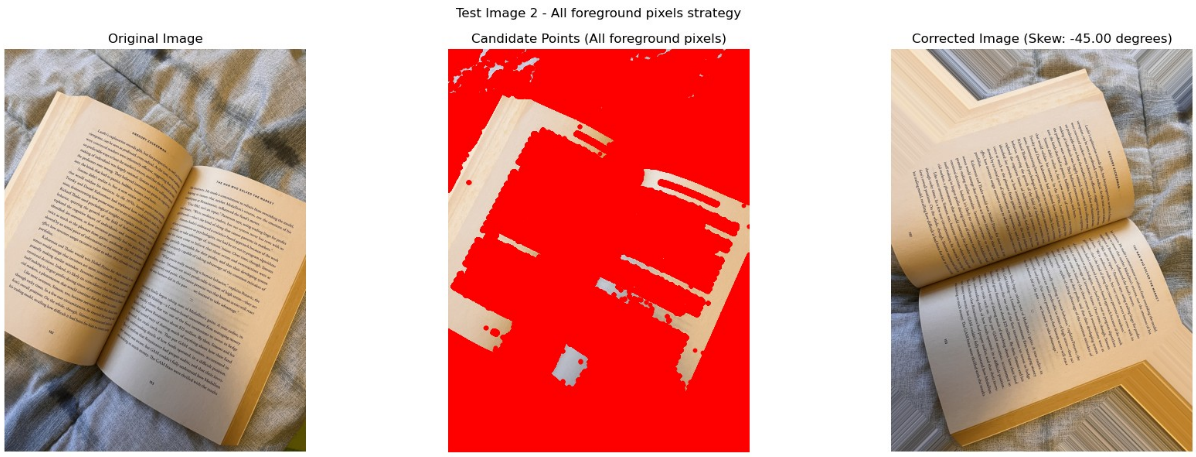


Image 2: Skew = -45.00°, Selection Time = 0.0684s, Points = 5653923

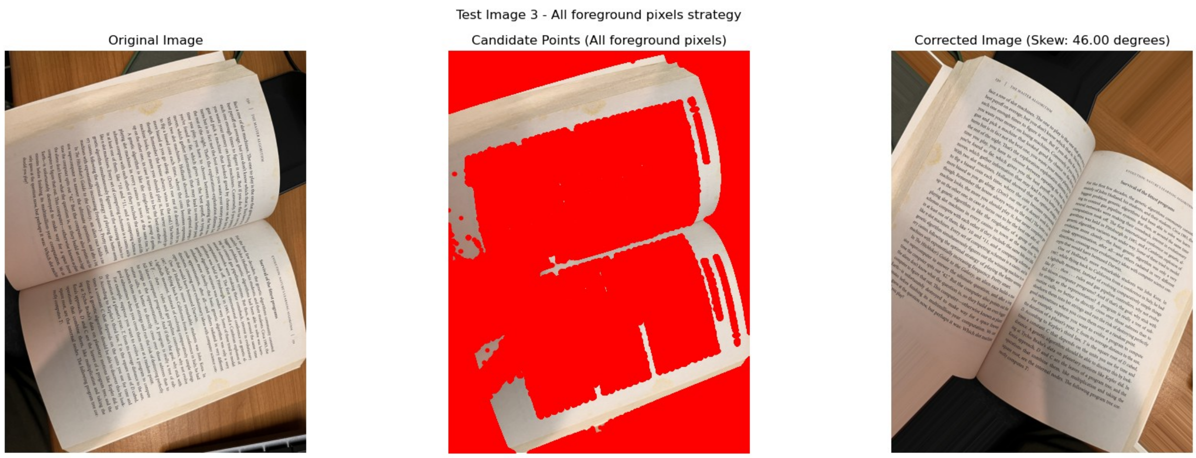


Image 3: Skew = 46.00°, Selection Time = 0.0569s, Points = 4128387

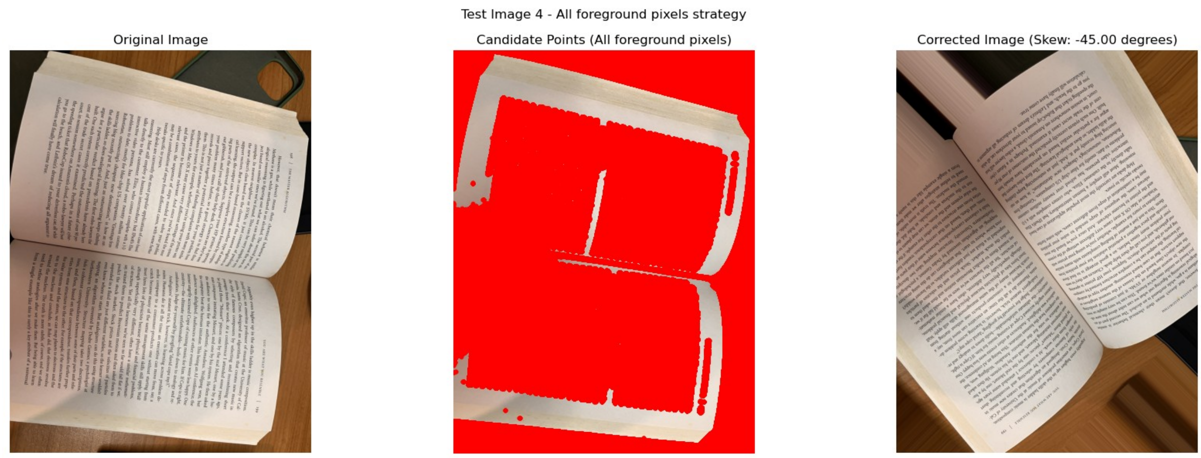


Image 4: Skew = -45.00°, Selection Time = 0.0468s, Points = 4275403

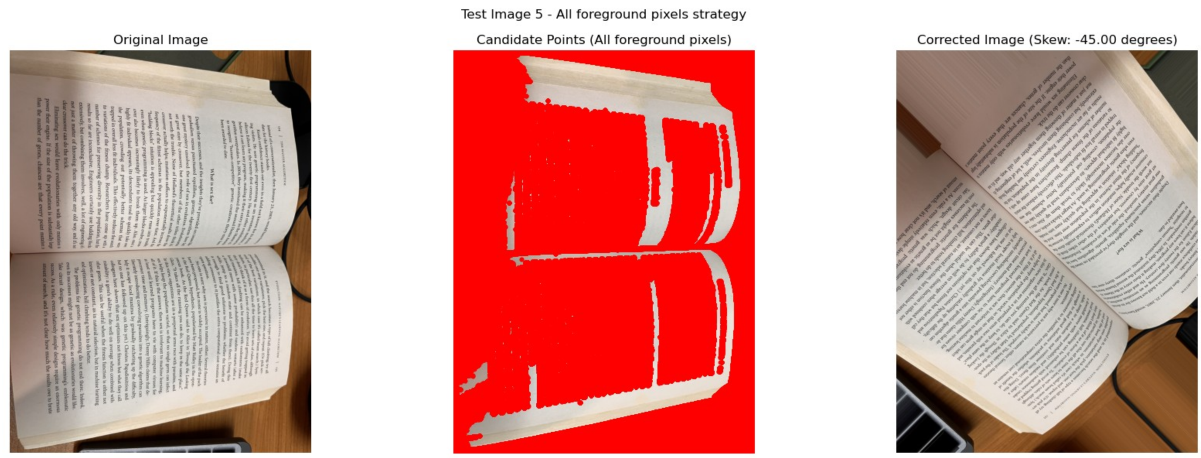


Image 5: Skew = -45.00°, Selection Time = 0.0586s, Points = 4628999

The algorithm successfully detected significant skew angles of either 45 or 46 degrees (positive or negative) for all five images, indicating its effectiveness in identifying large skew angles. Processing times for candidate point selection were relatively uniform, ranging from 0.0407 to 0.0606 seconds, suggesting efficient implementation. The number of candidate points varied between 3.7 to 4.6 million across images, reflecting the all-foreground-pixels strategy. Visual inspection of the corrected images confirms the algorithm's ability to effectively straighten severely skewed documents, demonstrating its robustness in handling various book and document orientations.

4. Recognized text from doc.jpg:

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Recognized Text:
This CVPE

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large-scale acquisition of 3D scene data and this has raised
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For both the original and deskewed images, the system successfully extracted text content, focusing on the paper's title, authors, and abstract. The processing times were similar for both images (4.03 and 4.09 seconds respectively), indicating that the pre-deskewing didn't significantly impact overall performance. The recognized text appears largely accurate, capturing key details of the academic paper, though some minor errors are present (e.g., "This CVPE" at the start of the original image output). The consistent performance across both images suggests that the built-in skew correction is effective, as it produced similar results to the pre-deskewed image.