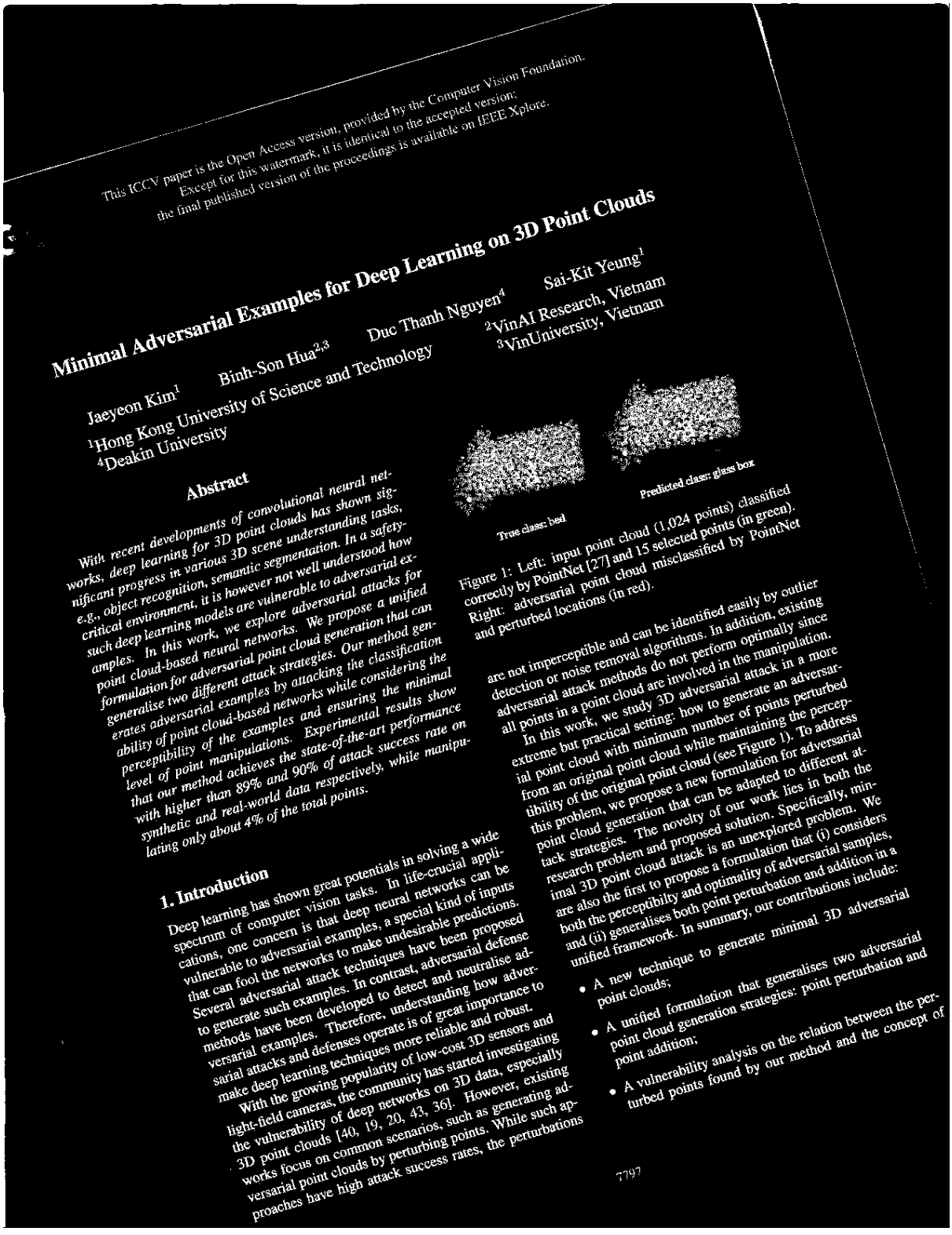
SIT 789

Task 2.3: Document analysis and recognition

Task 1:



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Except for this watermark, it is identical to the accepted version;
the final published version of the proceedings is available on IEEE Xplore.

Minimal Adversarial Examples for Deep Learning on 3D Point Clouds

Jaeyeon Kim[1] Binh-Son Hua[2,3] Duc Thanh Nguyen[4] Sai-Kit Yeung[1]
[1]Hong Kong University of Science and Technology
[2]VinAI Research, Vietnam
[3]VinUniversity, Vietnam
[4]Deakin University

Abstract

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Fig 1.1: Negative image with candidate points where foreground pixels are candidates. [Mode 1]

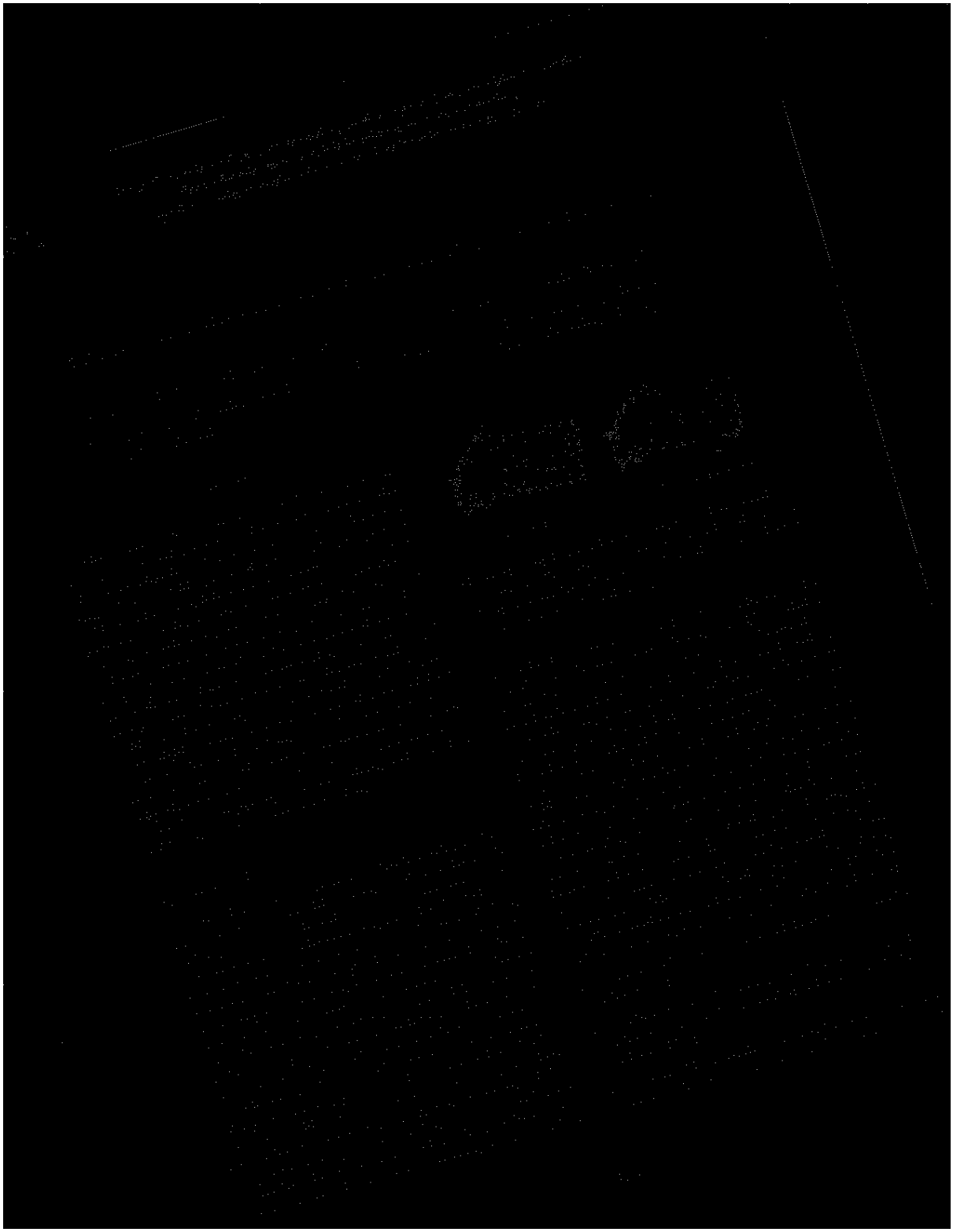

Fig 1.2: Negative Image where candidate points are the mean of all coordinates in a component. [Mode 2]

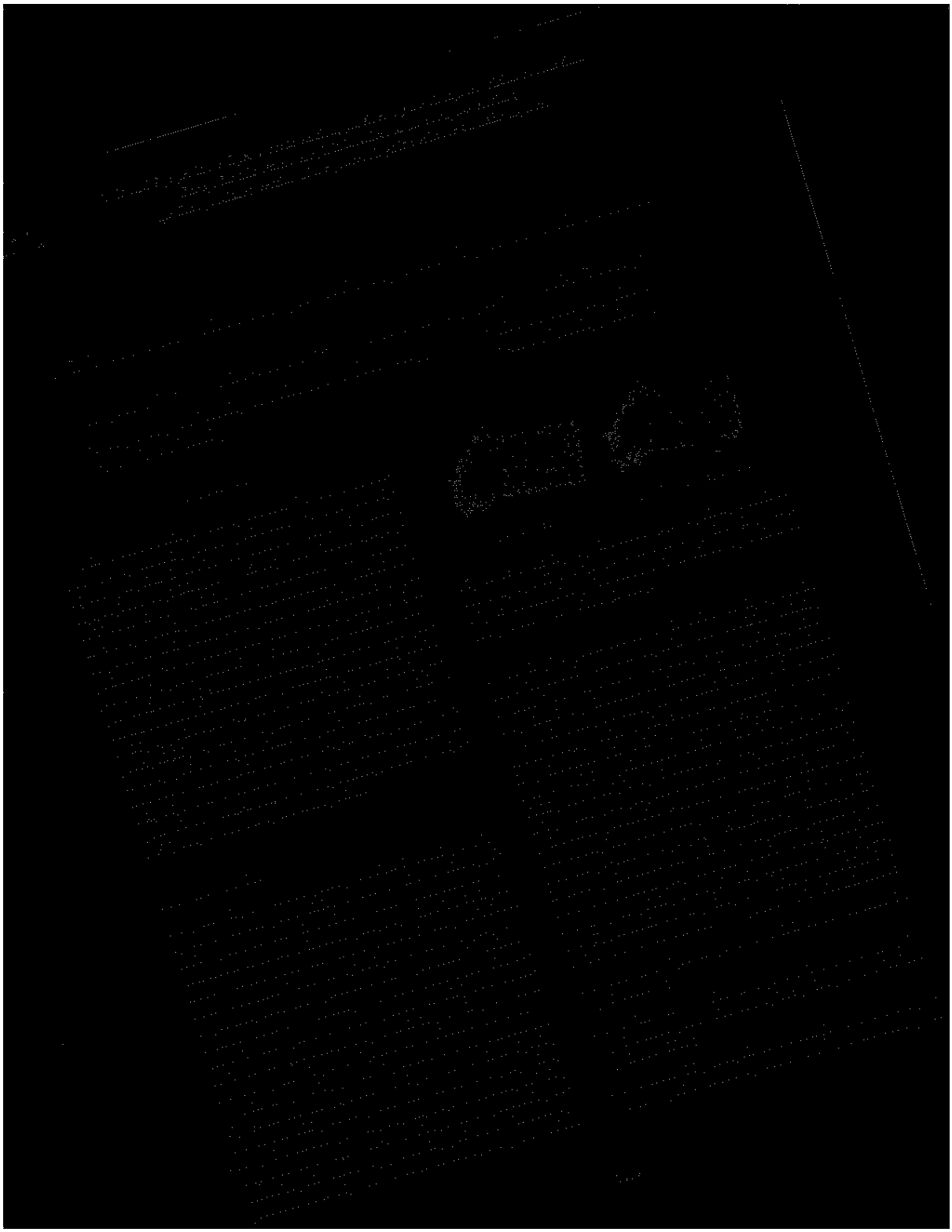

Fig 1.3: Negative Image where point with max y coordinate value in a component is the candidate point. [Mode 3]

Task 2:

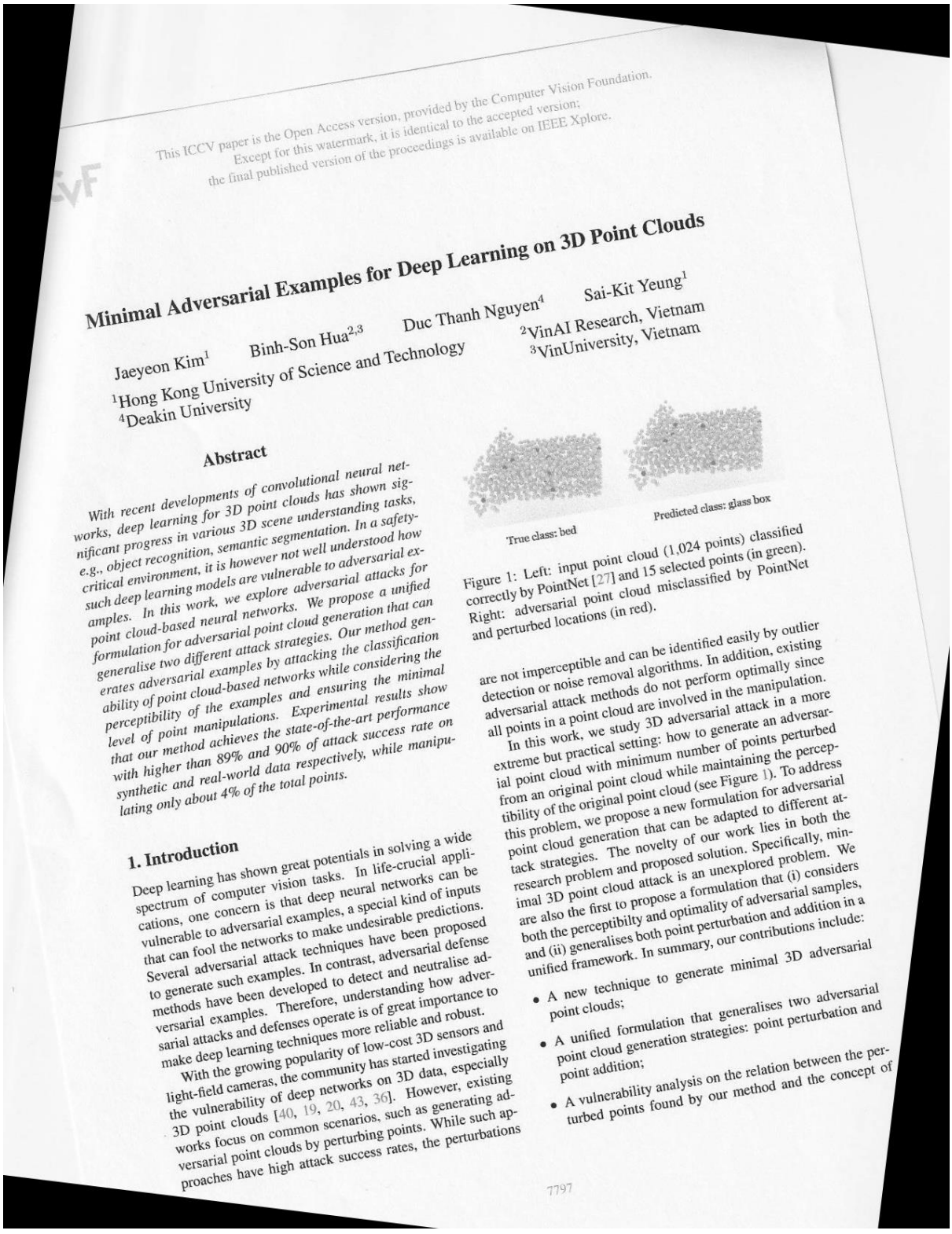

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Fig 2.1: De-skewed doc with strategy 1 [All foreground pixels]

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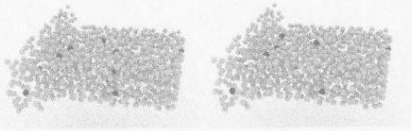

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Fig 2.2: De-skewed doc with strategy 2 [mean of all coordinates]

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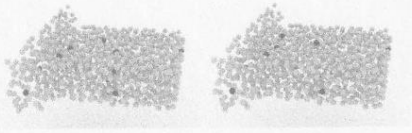

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Fig 2.3: De-skewed doc with strategy 3 (Point with max y coordinate)

Task 3:

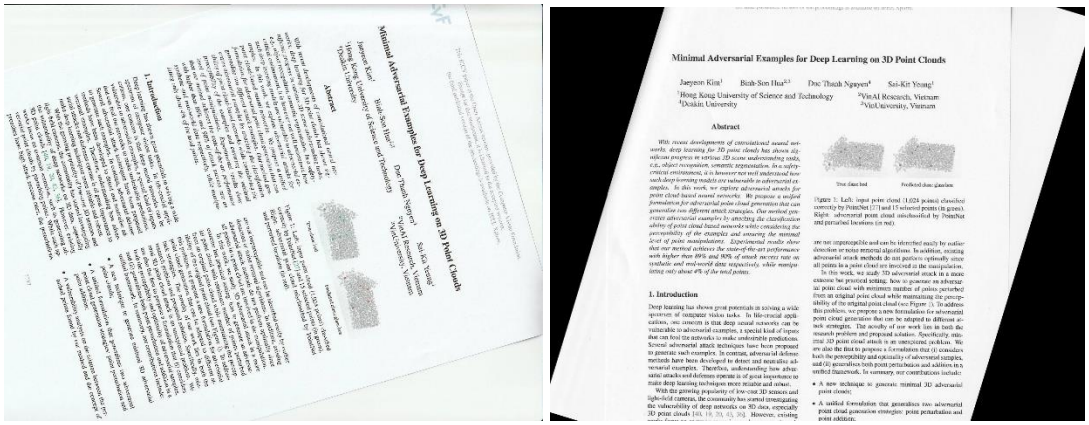

Fig 3.1: (a) doc_1 (b) doc_1 de-skewed

This shows the strength of the algorithm on too skewed images, we can see that the algorithm works fine on images with large skew values with same set of parameters. This shows Hough lines can be used with proper candidate selection strategy to de-skew documents.

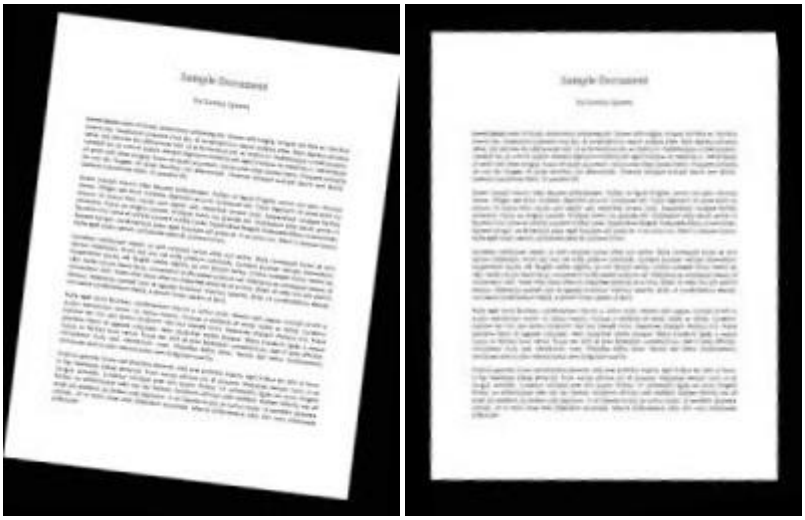

Fig 3.2: (a) doc_2 (b) doc_2 de-skewed

We can see that the algorithm works fine on this image where the skew angle is not large and Hough lines can be used to estimate the mean angle of the document. The algorithm works properly but because of low resolution (198 x 255) pytesseract is not able to parse pdf from this image.

Fig 3.3: doc_3

This image was added to the dataset to include high cropping scenario, the algorithm fails on this image. The algorithm is not able to calculate angle on this image.

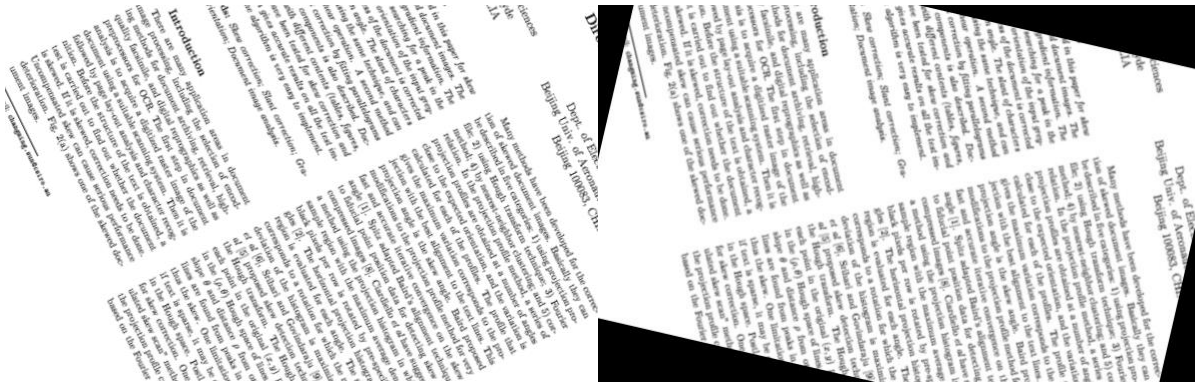

Fig 3.4: (a) doc_4 (b) doc_4 de-skewed

This document was included for another difficult scenario for this algorithm where we can see that the same parameters which work for slightly skewed document, will not work for documents that have a larger skew value. Although the document is horizontally aligned

Fig 3.5: doc_5

The algorithm is not able to calculate lines angle for this document. This shows that the algorithm fails with the same set of parameters on such images.

The above experiments show that while the algorithm can work well with the same set of parameters on variety of images (doc, doc_1, doc 2, and doc 4) but it will fail on images where candidate selection strategy fails, and no lines can be plotted. e.g.: (doc_3 and doc_5).

Although it is important to highlight that doc 4 was correctly aligned horizontally and doc 2 was correctly aligned but the text could not be parse due to low resolution.

Thus, we can conclude that Hough Transform is a strong method to de-skew a document provided the image is a ***good quality image*** and ***not too low resolution***. Also, the image should have visible characters so that the ***angles can be calculated***.

Task 4:

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Fig 4.1: Result of print text from skewed document

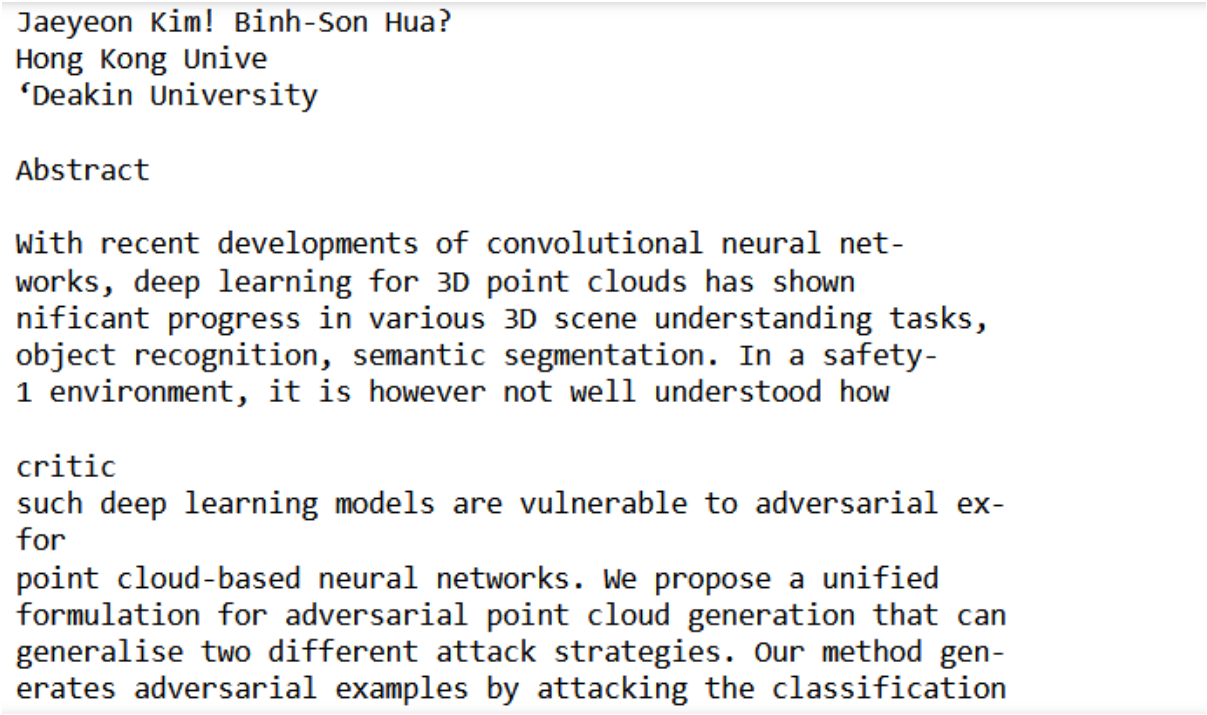


Fig 4.2: Result of print text from de-skewed document. This highlights the importance of de-skewing in the domain of Document Recognition.

Please Note: The ablation study for different thresholds has been shown in the notebook with visualisations. Task 2.2 (Parameter Setting)

The summary of ablation study:

Parameters tried: 5, 10, 15

Density_threshold of 15 yields best accuracy visually.

The summary of candidate points:

Mode 1 time: 5.16 seconds

Mode 2 time: 0.62 seconds

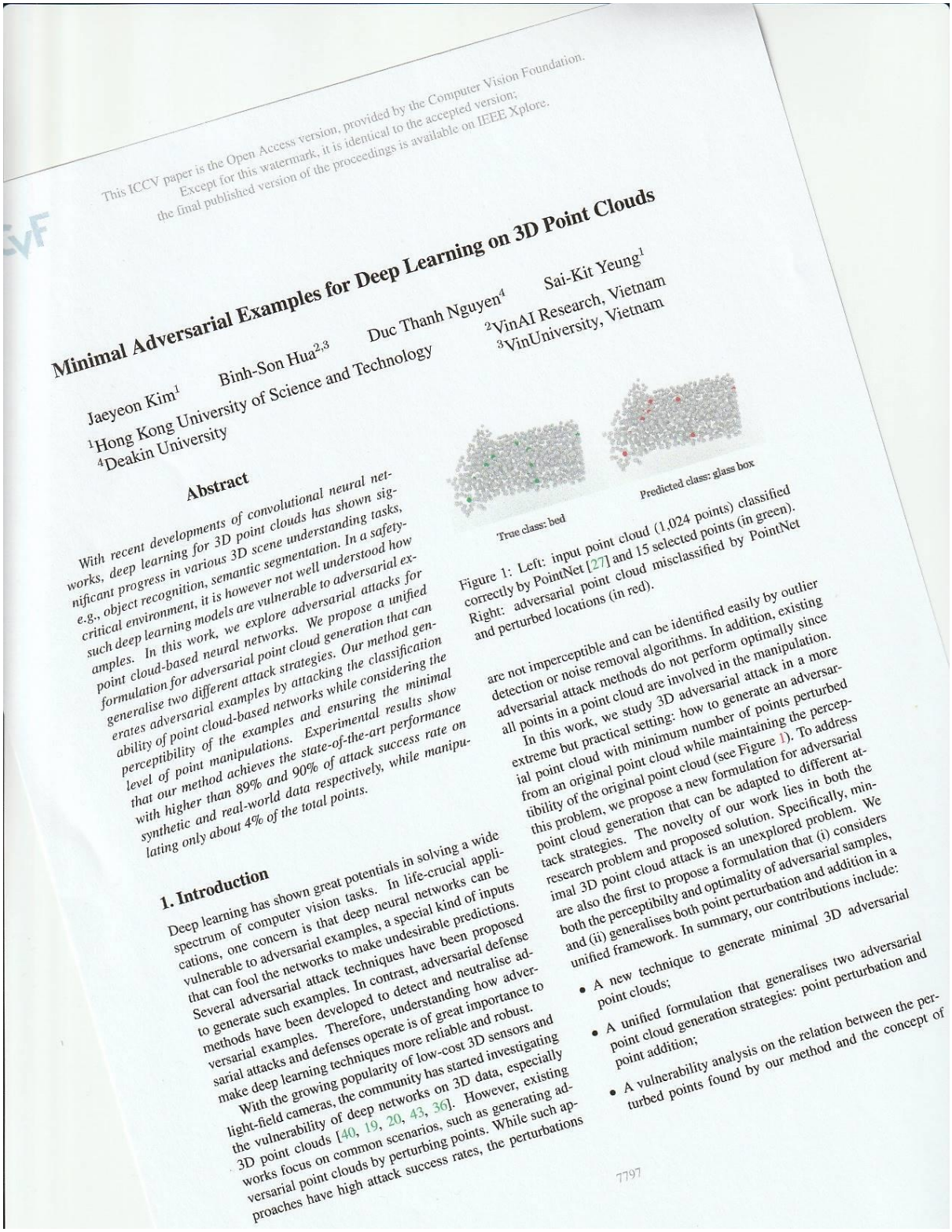
Mode 3 time: 0.24 seconds

Mode 3 was the fastest and most accurate, hence the optimal candidate points selection strategy.

This PDF contains all the images required for running the notebook in the appendix. The appendix also contains the pdf of doc.jpg and its de-skewed version.

Appendix

doc.jpg



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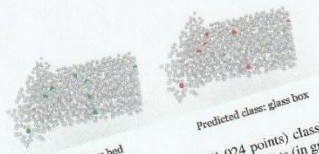

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doc_2.png

doc3.png

doc_4. png

doc_5. png

PDFs of doc and doc de-skewed:

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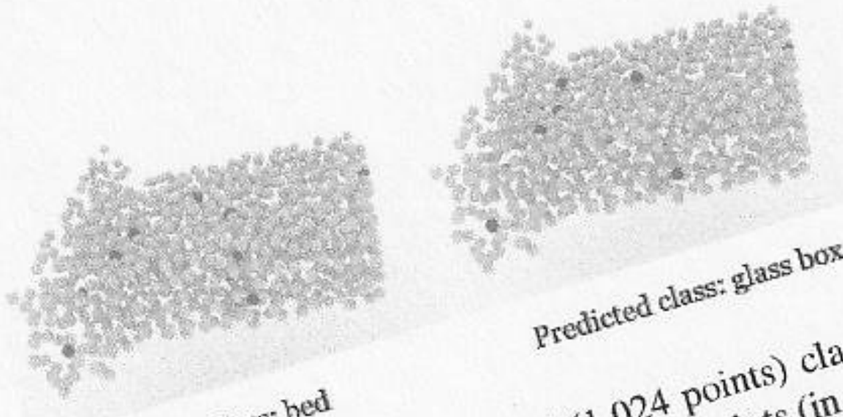

Figure 1: Left: input point cloud (1,024 points) classified correctly by PointNet [27] and 15 selected points (in green). Right: adversarial point cloud misclassified by PointNet and perturbed locations (in red).

are not imperceptible and can be identified easily by outlier detection or noise removal algorithms. In addition, existing adversarial attack methods do not perform optimally since all points in a point cloud are involved in the manipulation. In this work, we study 3D adversarial attack in a more extreme but practical setting: how to generate an adversarial point cloud with minimum number of points perturbed from an original point cloud while maintaining the perceptibility of the original point cloud (see Figure 1). To address this problem, we propose a new formulation for adversarial point cloud generation that can be adapted to different attack strategies. The novelty of our work lies in both the research problem and proposed solution. Specifically, minimal 3D point cloud attack is an unexplored problem. We are also the first to propose a formulation that (i) considers both the perceptibilty and optimality of adversarial samples, and (ii) generalises both point perturbation and addition in a unified framework. In summary, our contributions include:

- A new technique to generate minimal 3D adversarial point clouds;
- A unified formulation that generalises two adversarial point cloud generation strategies: point perturbation and point addition;
- A vulnerability analysis on the relation between the perturbed points found by our method and the concept of

Minimal Adversarial Examples for Deep Learning on 3D Point Clouds

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Abstract

With recent developments of convolutional neural networks, deep learning for 3D point clouds has shown significant progress in various 3D scene understanding tasks, e.g., object recognition, semantic segmentation. In a safety-critical environment, it is however not well understood how such deep learning models are vulnerable to adversarial examples. In this work, we explore adversarial attacks for point cloud-based neural networks. We propose a unified formulation for adversarial point cloud generation that can generalise two different attack strategies. Our method generates adversarial examples by attacking the classification ability of point cloud-based networks while considering the perceptibility of the examples and ensuring the minimal level of point manipulations. Experimental results show that our method achieves the state-of-the-art performance with higher than 89% and 90% of attack success rate on synthetic and real-world data respectively, while manipulating only about 4% of the total points.

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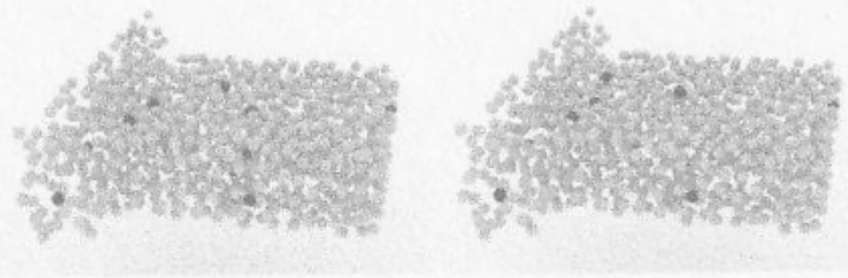

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