Chessy3D: A study of 3D Chessboard Detection and Pose Estimation

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Abstract—In this paper, we present a novel framework for chessboard corners detection and chess-pieces object detection. Our approach tackles the significant challenges posed by the variability of the photos taken of the chessboard and sizes, color and differences of the chess pieces. We propose a new method for chessboard keypoint detection that utilizes a combination of deep learning and geometric constraints to accurately identify the keypoints on the chessboard and the squares within it. This method is robust to variations in lighting, angle, and chessboard designs, making it suitable for real-world applications. Additionally, we developed a chess-piece object detection model that can accurately detect and classify chess pieces in various conditions. Our study delves into the intricacies of chessboard detection, addressing the challenges of different chessboard designs and piece variations. The proposed approach using YOLOv8 for chess-piece detection demonstrates superior performance in terms of accuracy and robustness compared to existing methods. We used two datasets for training and testing our models: ChessRed2K and another small dataset found on Roboflow. After the object detection we will propose a FEN annotation method for converting the chessboard state into a FEN (Forsyth-Edwards Notation) string, which is a standard notation for describing the state of a chess game. Additionally we show a method for retrieving similar images using one hot encoding and a similarity search algorithm.

I. INTRODUCTION

The detection and analysis of keypoints in images have become crucial tasks in the field of computer vision, with applications ranging from object recognition and tracking to augmented reality and autonomous driving.

Identifying keypoints on vehicles from different perspectives poses sig- nificant challenges. Traditional methods often rely on ex- tensive manual annotation, which is both time-consuming and prone to errors. Moreover, models trained on synthetic data frequently suffer from domain-shift when applied to real-world images, resulting in decreased performance. This study aims to address these challenges by developing a comprehensive keypoint detection framework inspired by FastTrakAI [1], thus focusing on enhancing automotive safety and efficiency through innovative AI solutions. However, the inherent variability in the shapes, sizes, and appearances of these vehicles presents significant challenges for developing robust keypoint detection models. Our approach involves identifying a set of 3D models representing

a category of vehicles and defining a set of keypoints common to all vehicles. This step ensures that our approach is adaptable across various vehicle types. To build our dataset, we rendered over 2000 images of these vehicles from dif- ferent perspectives and enriched them with keypoint anno- tations. To avoid the laborious task of manually annotating each image, we devised a strategy that automates a signifi- cant portion of this process. After creating the dataset, we trained a keypoint detection model tailored to these anno- tated images. We then rigorously tested the model on cap- tures of a 3D model never seen during the training phase. This testing approach evaluates the model's robustness and its ability to generalize to new, unseen data. By following this methodology, we aimed to develop a keypoint detection system that is both accurate and robust, capable of handling the variability inherent in vehicle categories. The insights gained from this research can contribute to the advancement of computer vision technologies in the automotive industry and beyond, fulfilling the objectives of FastTrakAI by DAT and Prometeia to push the boundaries of AI-driven automo- tive innovation..

II. CHESSBOARD CORNERS DETECTION

III. CHESSBOARD SQUARES DETECTION

IV. CHESS-PIECES OBJECT DETECTION

V. FEN ANNOTATION METHOD

VI. IMAGE SIMILARITY SEARCH

VII. CONCLUSION

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