

**PENGEMBANGAN MODEL *DEEP REINFORCEMENT LEARNING*
DENGAN SISTEM PERSEPSI TERINTEGRASI UNTUK OPTIMALISASI
JALUR LINTASAN PADA SISTEM PARKIR OTONOM**



SKRIPSI

Diajukan untuk memenuhi sebagian syarat untuk memperoleh gelar
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ABSTRAK

Parkir otonom adalah fungsi krusial dalam pengembangan kendaraan otonom, dengan *Deep Reinforcement Learning* (DRL) menjadi metode kontrol yang menjanjikan. Penelitian ini bertujuan untuk mengembangkan sistem parkir otonom dengan mengintegrasikan sistem persepsi berbasis visi stereo yang akurat dengan model DRL menggunakan algoritma *Twin Delayed Deep Deterministic Policy Gradient* (TD3) untuk optimalisasi jalur lintasan. Penelitian dilakukan dalam lingkungan simulasi CARLA. Dua metode persepsi visi stereo untuk estimasi jarak dievaluasi: berbasis koordinat *bounding box* dan berbasis peta disparitas yang dihasilkan oleh algoritma *Semi-Global Block Matching* (SGBM). Metode persepsi terbaik kemudian diintegrasikan dengan agen DRL, yang dilatih untuk skenario parkir tegak lurus dan paralel. Sistem persepsi berbasis peta disparitas menunjukkan akurasi yang jauh lebih tinggi dibandingkan sistem persepsi berbasis koordinat *bounding box* (RMSE 1.69). Namun, proses *training* model DRL untuk kedua skenario menunjukkan kegagalan. Metrik *training* menunjukkan *cumulative reward* yang terus menurun secara drastis dan *loss* pada *critic network* yang divergen, mengindikasikan kegagalan agen untuk mempelajari *policy* yang efektif. Hasil *testing* salah satu jalur lintasan mengonfirmasi kegagalan ini, di mana kendaraan tidak mampu menyelesaikan manuver parkir. Meskipun sistem persepsi berhasil dikembangkan, integrasinya dengan model DRL TD3 gagal menghasilkan sistem parkir otonom yang fungsional. Kegagalan *learning* DRL menunjukkan adanya masalah fundamental dalam kerangka pelatihan, kemungkinan besar terkait dengan desain *reward function* atau pemilihan *hyperparameter*. Disimpulkan bahwa pendekatan yang diusulkan dalam konfigurasi saat ini tidak efektif.

Kata Kunci: Parkir otonom, *deep reinforcement learning*, TD3, sistem persepsi, *stereo vision*, *computer vision*, YOLO

**THE DEVELOPMENT OF DEEP REINFORCEMENT LEARNING MODEL
WITH INTEGRATED PERCEPTION SYSTEM FOR PATH TRAJECTORY
OPTIMIZATION IN AUTONOMOUS PARKING SYSTEM**

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ABSTRACT

Autonomous parking is a crucial function in the development of autonomous vehicles, with Deep Reinforcement Learning (DRL) being a promising control method. This research aims to develop an autonomous parking system by integrating an accurate stereo vision-based perception system with a DRL model using the Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm for trajectory optimization. The research was conducted in the CARLA simulation environment. Two stereo vision perception methods for distance estimation were evaluated: bounding box coordinate-based and disparity map-based generated by the Semi-Global Block Matching (SGBM) algorithm. The best perception method is then integrated with a DRL agent, which is trained for perpendicular and parallel parking scenarios. The disparity map-based perception system showed significantly higher accuracy than bounding box coordinate-based perception system (RMSE 1,69). However, the DRL model training process for both scenarios showed failure. The training metrics showed a drastically decreasing cumulative reward and a diverging loss in critic network, indicating the agent's failure to learn an effective policy. The results of testing one of the trajectories confirmed this failure, where the vehicle was unable to complete the parking maneuver. Although the perception system was successfully developed, its integration with the TD3 DRL model failed to produce a functional autonomous parking system. The failure of DRL learning indicates a fundamental problem in the training framework, most likely related to the design of the reward function or the selection of hyperparameters. It is concluded that the approach proposed in the current configuration is ineffective.

Keyword: Autonomous parking, deep reinforcement learning, TD3, perception system, stereo vision, computer vision, YOLO

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