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# Dynamic Harris Hawks Optimization and deep reinforcement learning framework for autonomous vehicle path planning

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**A B S T R A C T**

Urban intelligent transportation systems require real-time, near-optimal routing for autonomous vehicles navigating dynamic and uncertain traffic. We propose a Harris Hawks Optimization–deep reinforcement learning framework (HHO-DRL) that unites HHO's global exploration with DRL's adaptive policy search through (i) a dynamic-weight fusion scheme that continuously balances exploration and exploitation and (ii) a bidirectional experience-feedback loop that exchanges elite solutions between the two solvers. On 23 CEC-2014 benchmark functions and five classical multimodal tests, HHO-DRL lowers mean error by up to three orders of magnitude relative to PSO and adaptive HHO, demonstrating superior robustness and precision. In 30 × 30 grid-world simulations with 30 % obstacle density, it generates vehicle routes 35 % shorter than those produced by Grey Wolf Optimization and 25 % shorter than adaptive HHO, while preserving smooth, collision-free trajectories. These results confirm that the proposed dual-mechanism delivers fast, high-quality solutions for high-dimensional, dynamic path-planning and other complex engineering optimization tasks.

**A R T I C L E   I N F O**

*Keywords:*
Dynamic path planning;
Harris Hawks optimization;
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# Dinamična optimizacija s Harrisovimi jastrebi in pristop globokega učenja z okrepitvijo za načrtovanje poti avtonomnih vozil

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**P O V Z E T E K**

Urbani inteligentni prometni sistemi zahtevajo realnočasovno, skoraj optimalno usmerjanje avtonomnih vozil v dinamičnem in negotovem prometnem okolju. Predlagamo pristop, ki združuje optimizacijo s Harrisovimi jastrebi (HHO) in globoko učenje z okrepitvijo (DRL), pri čemer se globalno raziskovanje algoritma HHO povezuje s prilagodljivim iskanjem strategij v DRL prek (i) sheme dinamičnega uteževanja, ki neprekinjeno uravnoveša raziskovanje in izkoriščanje, ter (ii) dvosmerne zanke povratnih izkušenj, ki omogoča izmenjavo elitnih rešitev med obema reševalnikoma. Na 23 referenčnih funkcijah CEC-2014 in petih klasičnih multimodalnih testih HHO-DRL zmanjša povprečno napako za do tri velikostne rede v primerjavi s PSO in prilagodljivo HHO, kar potrjuje izjemno robustnost in natančnost. V simulacijah mrežno diskretiziranega okolja velikosti 30 × 30 s 30 % gostoto ovir generira poti vozil, ki so 35 % krajše od poti, dobljenih z optimizacijo sivega volka, in 25 % krajše od poti, dobljenih s prilagodljivo HHO, pri čemer ohranja gladke trajektorije brez trkov. Ti rezultati potrjujejo, da predlagani dvojni mehanizem omogoča hitro in kakovostno reševanje visokodimenzionalnih dinamičnih problemov načrtovanja poti ter drugih zahtevnih optimizacijskih nalog v inženirstvu.

**P O D A T K I   O   Č L A N K U**

*Ključne besede:*
Dinamično načrtovanje poti;
Optimizacija s Harrisovimi jastrebi;
Globoko učenje z okrepitvijo;
Avtonomna vozila;
Dinamično uteževanje;
Dvosmerna povratna zanka;
Inteligentni prometni sistemi;
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