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Intelligent Control for Insulin Delivery

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Abstract

This project presents an intelligent glucose management system for Type 1 Diabetes (T1D), integrating deep learning and reinforcement learning techniques to improve automated insulin delivery. The proposed framework combines a Long Short-Term Memory (LSTM) model for blood glucose prediction with two reinforcement learning algorithms, Soft Actor-Critic (SAC) and Proximal Policy Optimization (PPO), for insulin dosing decisions.

The LSTM model was trained using real-world continuous glucose monitoring data from the HUPA-UCM dataset, while the reinforcement learning agents were trained and evaluated in the SimGlucose simulation environment. Experiments were conducted under single-patient and multi-patient settings involving 30 virtual patients.

The results demonstrate that SAC combined with LSTM achieved the best performance, reaching a Time in Range (TIR) of 98.0% in the single-patient scenario and 85.7% in the multi-patient evaluation. These findings highlight the effectiveness of combining glucose prediction with reinforcement learning for adaptive insulin control and artificial pancreas applications.

Keywords: Type 1 Diabetes, Artificial Pancreas System, Blood Glucose Prediction, LSTM, Reinforcement Learning, Soft Actor-Critic (SAC), Proximal Policy Optimization (PPO), SimGlucose, Time in Range (TIR).

Résumé

Ce projet présente un système intelligent de gestion de la glycémie destiné au traitement du diabète de type 1 (DT1), intégrant des techniques d'apprentissage profond et d'apprentissage par renforcement afin d'améliorer l'administration automatisée de l'insuline. Le cadre proposé combine un modèle Long Short-Term Memory (LSTM) pour la prédiction de la glycémie avec deux algorithmes d'apprentissage par renforcement, à savoir Soft Actor-Critic (SAC) et Proximal Policy Optimization (PPO), pour la prise de décision relative aux doses d'insuline.

Le modèle LSTM a été entraîné à partir de données réelles de surveillance continue du glucose issues de la base de données HUPA-UCM, tandis que les agents d'apprentissage par renforcement ont été entraînés et évalués dans l'environnement de simulation SimGlucose. Les expériences ont été menées dans des scénarios à patient unique ainsi que dans des scénarios multi-patients impliquant 30 patients virtuels.

Les résultats obtenus montrent que la combinaison SAC–LSTM a offert les meilleures performances, atteignant un Time in Range (TIR) de 98,0 % dans le scénario à patient unique et de 85,7 % dans l'évaluation multi-patients. Ces résultats mettent en évidence l'efficacité de l'intégration de la prédiction glycémique et de l'apprentissage par renforcement pour le contrôle adaptatif de l'insuline et le développement de systèmes de pancréas artificiel plus performants.

Mots-clés : Diabète de type 1, Pancréas artificiel, Prédiction de la glycémie, LSTM, Apprentissage par renforcement, Soft Actor-Critic (SAC), Proximal Policy Optimization (PPO), SimGlucose, Time in Range (TIR).

الملخص

يقدم هذا المشروع نظامًا ذكيًا لإدارة مستوى الجلوكوز لدى مرضى السكري من النوع الأول، من خلال دمج تقنيات التعلم العميق والتعلم المعزز بهدف تحسين الإعطاء الآلي للأنسولين. يعتمد النظام المقترح على نموذج الذاكرة طويلة وقصيرة المدى للتنبؤ بمستويات الجلوكوز في الدم، بالإضافة إلى خوارزميتي التعلم المعزز لاتخاذ قرارات جرعات الأنسولين.

تم تدريب النموذج باستخدام بيانات حقيقية للمراقبة المستمرة للجلوكوز من قاعدة بيانات، بينما تم تدريب وتقييم وكلاء التعلم المعزز داخل بيئة المحاكاة. أُجريت التجارب في حالتي المريض الواحد ومتعدد المرضى، وشملت ثلاثين مريضًا افتراضيًا.

أظهرت النتائج أن النموذج المقترح حقق أفضل أداء، حيث بلغ معدل البقاء ضمن النطاق المستهدف نسبة 98.0٪ في حالة المريض الواحد، و85.7٪ في تقييم المرضى المتعددين. وتبرز هذه النتائج فعالية دمج التنبؤ بالجلوكوز مع التعلم المعزز لتحسين التحكم التكيفي في الأنسولين، ودعم تطوير أنظمة البنكرياس الاصطناعي.

الكلمات المفتاحية:

التعلم المعزز، السكري من النوع الأول، البنكرياس الاصطناعي، التنبؤ بالجلوكوز، الذاكرة طويلة وقصيرة المدى، بيئة المحاكاة، معدل البقاء ضمن النطاق المستهدف.