



## Introduction

In this study, we present a control approach based on reinforcement learning applied to a magnetically flexible endoscope (MFE). This device, designed to reduce pain and increase ergonomics in colonoscopy, is composed of one external permanent magnet (EPM) and one internal permanent magnet (IPM) in the tip of the endoscope. The aim of this work is to guarantee an autonomous waypoint tracking of the endoscope able to navigate the entire colon, simultaneously maintaining contact between the endoscope and the tissue.

The advantages of magnetic manipulation in colonoscopy have been proven [1] and closed loop controls, enabled by reliable localization systems [3] have demonstrated satisfactory performances as well as smooth motion[2]. However, navigation is hindered from obstacles, folds and deformations, and the complexity associated to the presence of a flexible tether, difficult to model analytically. For these reasons, dynamic modelling of the system is a very complex task. These issues are evident in tasks like drug delivery and use of intraluminal ultrasound [4], in which a continuous and controlled contact is required. Adaptive control approach [5] has proven potential in colon navigation, although used to obtain magnetic levitation.

In this work, we propose a fast, model-free, reinforcement learning based control. By adapting the control policy, the control system overcomes the asperities of the colon during the navigation and achieve the target pose. Moreover, it guarantees controlled contact during colon navigation.

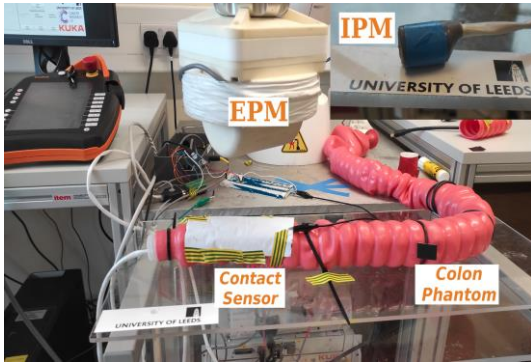


Figure 1 - Experimental setup of colon phantom with contact sensor and the IPM (inside the endoscope tip) and EPM attached to the robotic arm.

## Results

We perform the preliminary experiments on the setup shown in the figure(1) including the robotic arm, the contact sensor, and the colon phantom. as we needed a flexible and a small sensor, we made a contact sensor using a conductive ink on the top of the endoscope tip and the colon.

Each experiment is performed starting with no contact between the endoscope tip top surface and the colon followed by a phase of coupling between the EPM and IPM before starting the reinforcement control routine as shown in the figure(2). The graphs report the results of one colon navigation experiment. Figure (2.a) shows that the endoscope -colon interaction force remains inside the safety limits for painless colonoscopy while keeping a rich endoscope -colon contact. The pose error can be evaluated from the figure (2.b) where we can appreciate an average steady state position and heading error of 1 mm and 0.2 rad respectively. These remaining error is due to the localization accuracy of approximately 4 mm and 0.5 rad in orientation. Therefore, we can say satisfied of the results.

## Method

We assume the EPM and the IPM to be modelled as magnetic dipoles whose interaction force can be computed as  $\tau = f(x, q)$ . Here,  $x$  is referred to as the endoscope tip pose and  $q$  as the robot joint configuration. The endoscope tip force dynamics can be derived as

$$\dot{\tau} = J_x \dot{x} + J_q \dot{q}$$

where  $J_x = \frac{\partial f}{\partial x}$  and  $J_q = \frac{\partial f}{\partial q}$ .

The control input is given by a parallel force/position control as follow, given the desired force  $\tau_d$  and the desired endoscope tip pose  $x_d$

$$\begin{cases} u = (K_p e_x - K_p \dot{x} + G(x) + \tau_d - \tau) \\ \dot{q} = J_q^\dagger (K u - (I - K_p + J_x - u^\dagger \tau_d) \dot{x}) \end{cases}$$

Where  $e_x = x - x_d$ ,  $G(x)$  is the gravity on the endoscope,  $I$  is the identity matrix and  $(\cdot)^\dagger$  is the Moore-Penrose pseudoinverse. The controller parameters  $K$  and  $K_p$  are computed in order to minimize the value function  $V$

$$\min_{K_p, K} V(e_x, \tau_e, u); \quad V = \theta^T \Phi;$$

Where  $\Phi$  is formed by quadratic term of  $e_x$ ,  $e_\tau = \tau_d - \tau$  and  $u$ . The value function is updated at each time step  $k$  according to policy iteration and state-action-reward-state-action (SARSA) algorithm as

$$\begin{cases} \delta_k = r_{k+1} + \gamma \hat{V}(e_{x_{k+1}}, e_{\tau_{k+1}}, u_{k+1}, \theta_k) - \hat{V}(e_{x_k}, e_{\tau_k}, \theta_k) \\ \theta_{k+1} = \theta_k + \alpha_k \delta_k \nabla_{\theta_k} \hat{V} \end{cases}$$

$\alpha = 1/k$  and  $0 < \gamma < 1$ . The cost  $r_{k+1}$  is computed as quadric cost over the error ( $e_x, e_\tau$ ) and the input ( $u$ ) at each time step. In the end the control parameters are updated introducing a gaussian noise  $\mathcal{N}$  as

$$K_i \leftarrow \mathcal{N}(K_i, k e^{-\frac{1}{|K_i|}}) \quad k > 0$$

For each element  $K_i$  of the gains  $K, K_p$ . We demonstrated the controller **uniformly ultimately bounded (UUB) stability** when the control parameters are greater than zero which guarantee convergence to the desired endoscope tip pose for bounded disturbance on the endoscope. Moreover, the SARSA algorithm converges since the control parameters are updated following a **Lipschitz continuous** function.

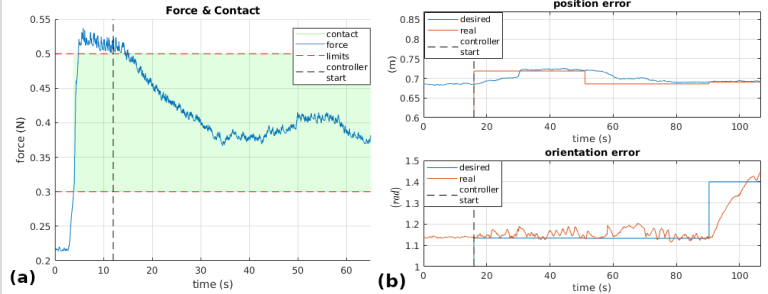


Figure 2 - (a) force and contact graph: the colon-endoscope contact is highlighted in green while the black line shows when the reinforcement control starts; the red lines are the force limits (b) pose error: desired and real position along the endoscope heading; desired and real endoscope tip heading.

## Discussion

A reinforcement learning based control of a magnetic actuated endoscope for robotic assisted colonoscopy was presented. Our main aim was to prove that, without the knowledge of the system and the environment, the reinforcement adaptability allows to perform good navigation of the colon beside obstacles and deformations while keeping contact between the endoscope and the colon wall. In fact, this is specifically required in different applications like colonoscopy ultrasound scanning.

Future work will be focused on generate a free-obstacle path which avoids camera obstruction and performing a completely autonomous trajectory in the whole colon.

## References

- [1] Martin, James W., et al. "Enabling the future of colonoscopy with intelligent and autonomous magnetic manipulation." Nature machine intelligence 2.10 (2020): 595-606.
- [2] Pittiglio, Giovanni, et al. "Magnetic levitation for soft-tethered capsule colonoscopy actuated with a single permanent magnet: a dynamic control approach." IEEE robotics and automation letters 4.2 (2019): 890-911.
- [3] Taddese, Addisu Z., et al. "Enhanced real-time pose estimation for closed-loop robotic manipulation of magnetically actuated capsule endoscopes." The International journal of robotics research 37.8 (2018): 890-911.
- [4] Norton, Joseph C., et al. "Intelligent magnetic manipulation for gastrointestinal ultrasound." Science robotics 4.31 (2019).
- [5] Barducci, Lavinia, et al. "Adaptive dynamic control for magnetically actuated medical robots." IEEE robotics and automation letters 4.4 (2019): 3633-3640.