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The future of anaesthesia robotics and artificial Intelligence: Will computers take over from doctors?

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Abstract
Discussions concerning technology's inventive potential are becoming increasingly mainstream as it continues to develop at an exponential rate. This pattern is also present in medicine and the practise of anaesthesia. Among both current and aspiring professionals, discussions about artificial intelligence (AI) provoke a range of emotions, from enthusiasm about its potential to improve patient care to worry about the effect that it could have on future generations of the profession. Despite these mixed reactions, practically everyone can agree that the field of anesthesiology will be affected by future technological developments.

Keywords: Anesthesiology, AI, Clinicians, Data, Clinical decision support

Introduction

A reputation as "early adopters" of new technologies has been built up by anesthesiologists throughout time. The practise of anaesthesia has been steadily moving towards automation [2] ever since positive pressure mechanical breathing was developed in 1951 during the Copenhagen polio epidemic. In the 1950s, the first attempts were made to automate anaesthesia monitoring and administration [1], coinciding with the widespread introduction of ventilators. The first generation of anaesthetic robots relied on the electroencephalograph (EEG) signal to monitor the patient's level of sedation and provided feedback according to a set of predetermined rules [1]. These gadgets were designed from the top down, thus they use predetermined algorithms to perform their job in a wide variety of clinical settings [3]. Human-programmed machines were limited in their applicability by this design since they couldn't meet the needs of complex clinical contexts the way a human anesthesiologist could. Machine learning, a subfield of AI with a great deal of potential, has emerged in recent decades. Without the requirement for upfront programming, machine learning allows a computer to incrementally improve its function in response to new data. The system's ability to learn from its own experience gives it an advantage in highly dynamic clinical settings where it must constantly adapt to new data. An increasing number of machine learning technique types are finding applications in anaesthetics [4].

There are two main types of anaesthesia robots: closed loop systems and clinical decision support (CDS) systems, regardless of whether the underlying algorithm was developed manually or using machine learning. By continuously measuring the parameter of interest, comparing it to the target, and adjusting its output accordingly, closed loop systems adhere to the idea of feedback control [3]. The primary benefit of closed loop systems is that the variable of interest may be reliably held within a narrow range of the target value. Because of this, pharmacologic robots for anaesthetic administration and blood pressure regulation have been developed using these algorithms [5].

The ability to reliably detect anaesthesia depth and create dependable management of medicine administration rate is essential for pharmacologic robots to perform their duty. Parameters generated from EEG tracings, such as the bispectral index traditionally and the more advanced measures developed in recent years, are frequently used to track the depth of anaesthesia [4]. Recent studies show that machine learning techniques have greatly benefited the field of anaesthesia depth monitoring, with recent developments achieving an accuracy of 88-93% in differentiating between awake and anaesthetized patients [4].

The first step towards automating drug delivery was taken with the development of target control infusion (TCI) systems.

TCIs were developed before closed-loop systems and are configured to control the medication rate of delivery based on population pharmacokinetic models [3]. As systems with open loops, these robots function independently of the patient, putting their effectiveness dependent on the precision of the underpinning models. The latest pharmacologic robots are closed loop devices that take patient input and use it to adjust drug delivery. These tools have outperformed traditional controls and TCIs in recent decades when it comes to sustaining the desired depth of isoflurane and propofol anaesthesia, respectively [5].

Earlier pharmacologic robots were built as SISO systems, meaning they could only monitor a single parameter of interest and dispense a single drug. In the recent decade, new designs have arisen that can monitor many patient characteristics and administer various drugs at once; these are known as multiple input multiple output (MIMO) systems [5]. Devices like these have been found to be more effective than manual controls at keeping the depth of anaesthesia within the desired range [6]. Rather than enabling full automation, the current generation of MIMOs operates on a semi-autonomous basis [1], meaning that they are designed to aid the doctor in anaesthetic management. So that vital signs, hemodynamic variables, and EEG-derived data can all be incorporated into an entire clinical picture, cross-communication across multiple feedback loops must be established throughout the development of completely autonomous systems.

Pharmacologic robots' closed-loop designs make them ideal for administering medical treatments, but they lack the intelligence to pinpoint the most effective areas to treat. On the other hand, medical decision-support (CDS) systems are meant to aid physicians in improving patient management through the use of prompts, assessments, and recommendations based on established clinical guidelines [5]. From perioperative medication administration reminders to ultrasound guidance aids, CDSs have found their way into a wide range of clinical contexts [4].

One of the most promising uses of CDS now under development is in predictive therapy. In recent years, there has been a surge in the creation of tools to identify the precursors to hemodynamic instability. In order to predict dehydrated events as much as fifteen minutes in advance, Hatib and coworkers developed an algorithm that analyses arterial pressure waveforms. The method has a sensitivity of 88% and a specificity of 87% [7]. Artificial intelligence has been used by other groups with higher success than qualified professionals at predicting the hypnotic4 and hemodynamic [8] effects of anaesthetic induction. These early results demonstrate the great potential of CDSs to improve risk assessment and reduce complications across the entire perioperative period.

The final step towards the creation of autonomous anaesthetic robots is the integration of CDS tools' cognitive support capabilities with the precise regulation of therapy delivery provided by closed loop systems. We are getting closer to establishing devices that are competent of both - identifying and giving the ideal medical therapy [5] as we continue to improve our capacity to grasp the important clinical targets and transfer them to AI systems. These totally autonomous devices are a promising new frontier with the potential to radically alter the way anaesthesia is administered, but they are not expected to appear anytime soon.

The rising automation of the discipline of anaesthesia offers numerous potential benefits but also presents several obstacles that must be carefully considered. Disruption of workflow, atrophy of clinician skills, and direct patient damage are some of the clinical concerns highlighted in the research [5, 9]. Loss of patient anonymity in light of the requirement for medical information for machine learning is a major ethical concern [7, 9], as is the natural lag between new technologies and the legislation that govern them. This is not just an abstract worry; according to a health IT report published by the FDA in 2014, the agency intends to impose stringent supervision over only a subset of CDS applications [10]. There are still many unknowns that must be addressed in order to ensure the smoothest possible transition to incorporating AI within our health care system.

Even the most basic forms of anaesthesia cannot be entirely automated at this time. Most machine learning and anaesthetic robot concepts have not been used in clinical practise yet. Despite having received FDA clearance for widespread market release, many medical technologies never make their way into regular clinical use. The semi-autonomous sedation system Sedasys robot [1] was taken off the market in 2016 due to low sales despite its promise to improve the administration of propofol during endoscopic operations.

Implications

However, artificial intelligence-assisted anaesthesia is not science fiction nor a far-off possibility. As machine learning advances, it opens up new possibilities for automating therapeutic procedures. There will be fewer efforts and hours needed from the provider for many regular treatments as anaesthetic robots advance. As a result, anesthesiologists may be able to take on more responsibilities and broaden their areas of expertise. Additional anesthesiology involvement is needed in non-operating rooms such pain healthcare, pre-operative clinics, and critical care.

Because of the limitations of existing AI technology, anesthesiologists will still need to do many of the hands-on aspects of their jobs, even while advances in the field are geared towards helping them do so. This suggests a number of promising avenues where innovations may extend rather than restrict the horizons of clinicians' work. To make this ideal scenario a reality, doctors need to take the lead in shaping and implementing new technology in healthcare settings. Anesthesiologists as a community can use AI to shape the practice in a way that improves physician capacity, promotes evidence-based medicine, and, most importantly, enhances patient outcomes if they keep in mind the consequences of the ongoing advancement of technology and establish an unambiguous picture of the desired future of their field [11-14].

Conflict of Interest

Not available

Financial Support

Not available

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