Title The use of artificial intelligence and robotics in regional anaesthesia

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The current Fourth Industrial Revolution is a distinct technological era characterised by the blurring of physics, computing and biology. The driver of change is data, powered by artificial intelligence. The NHS Topol Report embraced this digital revolution and emphasised the importance of artificial intelligence to the NHS. Application of artificial intelligence within regional anaesthesia, however, remains limited. An example of the use of a convoluted neural network applied to visual detection of nerves on ultrasound images is described. New technologies that may impact on regional anaesthesia include robotics and artificial sensing. Robotics in anaesthesia fall into three categories. The first, used commonly, is pharmaceutical, typified by targeted controlled anaesthesia using EEG within a feed-back loop. Other types include mechanical robots that provide precision and dexterity better than humans, and cognitive robots that act as decision support systems. Our feeling is that the latter technology will expand considerably over the next decades and provide an auto-pilot for anaesthesia. Technical robotics will focus on the development of accurate sensors for training that incorporate visual and motion metrics. These will be incorporated into augmented reality and visual reality environments that will provide training at home or the office on life-like simulators. Real-time feedback will be offered that stimulates and rewards performance. In discussing the scope, applications, limitations and barriers to adoption of these technologies, we plan to stimulate discussion towards a framework for the most optimal application of current and emerging technologies in regional anaesthesia.

We are living within the Fourth Industrial Revolution - a distinct technological era characterised by the blurring of physics, computing and biology, that will disrupt humanity, and transform the way we work and live. The driver of change is data, powered by artificial intelligence - a means of finding solutions to complex problems by imitating neural activity. Artificial intelligence will impact on scientific disciplines as diverse as data analytics, artificial sensing, robotics, connectivity, nanotechnology, biotechnology, materials science, energy storage, quantum computing, and 3-D printing. The scope for artificial intelligence within regional anaesthesia is enormous. Applications include the creation of advanced clinical decision support tools, analysis of performance metrics during simulation training, and ultimately the development of robots that optimise needle tip accuracy and local anaesthetic injection.

Artificial intelligence

Artificial intelligence is forecast to contribute 16% to UK gross domestic product by 2030 [1], and save £115 billion from the US healthcare economy by 2026 [2]. Artificial intelligence forms one of the four Grand Challenges of the UK Industrial Strategy alongside dealing with an ageing society, clean growth and the future of mobility [3]. The Topol Report [4] acknowledged the importance of artificial intelligence, informatics and genetics to the NHS. Amongst its recommendations were that the NHS should expand research and development programmes to co-create digital technologies and work within Industry Exchange Networks. In response, NHS England appointed 18 clinical digital fellows in September 2019 in order to lead digital health improvements and innovation [5]. The basic mechanisms underpinning artificial intelligence actually reflect biology rather than computing. Interconnected processing elements or nodes communicate dynamically in the same way as human neurons and behave as an artificial neural network. A glossary of terms is given in Table 1 and examples of artificial neural networks used in imaging are shown in Fig 1.[6,7]

The application of artificial intelligence to regional anaesthesia will require a transformative change to patient data and digital image collection, linkage to pre-operative data, surgical functional outcome registries, prescription databases, deprivation indexes and cancer databases. The advantage of machine learning is that it can find patterns in large unwieldy, complex datasets and provides an attractive alternative to the rigidity of classical statistical methods. The NHS is uniquely placed to merge data from all hospitals, and artificial intelligence offers an opportunity to answer how much regional anaesthesia impacts on short and long-term clinical outcomes and side effects.

For regional anaesthesia, tracking of nerves ideally lends itself to application of AI-driven computer vision, but is more difficult than facial recognition because the area of interest is constantly changing its appearance. Acoustic impedance is similar between nerves and surrounding tissues [8], and the brightness and shape of nerves changes along their course. A typical example of the latter is the change in shape of the sciatic nerve from round/oval in the posterior thigh to triangular in the subgluteal region. Analysis of images requires interrogation of all pixels in ultrasound scans recorded at 20 images per second for between 30 and 60 seconds. This is a slow, inefficient, computer intensive process.

The discovery in 1962 by Hubel and Wiesel [9] that the transmission of visual information from the retina to the brain was attributed to multi-level receptive fields inspired Fukushima to design a multi-layered neural network named Neocognitron [10]. This was the prototype for a convolutional neural network (Table 1 and Fig 1), a self-organizing multilayer artificial neural network which could recognise handwritten numbers and characters [11]. Today, the study of images, otherwise termed Computer Vision, has become ubiquitous with convolutional neural networks which capture the sophisticated spatial and temporal features of images using filtering and pooling and can be divided into two types: 2D [12] and 3D [13]. V-Net networks, for example, are used for volumetric medical image segmentation of MRI images [14].

Three studies have been conducted in regional anaesthesia using convolutional neural networks. The objective of the first study was to quantify texture, a metric that reflects the grayscale spatial arrangement pixels within ultrasound images. The median nerve was scanned in 10 anonymous patients [15]. The authors compared seven texture feature extraction methods and showed that a method termed Adaptive Median Binary Pattern showed better performance than six other tracking algorithms. Although automatic, the method used a frame by frame tracking system. The disadvantage of this method is that within the time course of each frame, echoes will have changed, and measurements lag behind screen changes.

The second study evaluated the performance of 13 deep learning networks when used to identify the median and sciatic nerves during scanning of the upper arm and posterior thigh [16]. Twenty-five median nerves and 17 sciatic nerves were scanned on 42 anonymous patients. Accuracy (%), based on the ratio of pixels kept within a predefined bounding box was 0.94 for the median nerve and 0.80 for the sciatic nerve, indicating that the median nerve was easier to track.

A recent, as yet unpublished study from our group built a convolutional neural network to identify the sciatic nerve as it was scanned over the posterior thigh. The network consisted of six parts highlighted in Fig 2. The aim was to teach the system to pay attention, i.e. focus on important information and ignore irrelevant information. This is tricky because each frame has a unique background which reduces the accuracy of segmentation. Five scans of the sciatic nerve were conducted on soft embalmed Thiel cadavers from the popliteal fossa to the upper sub-gluteal area of the thigh. In total 3,789 frames were analysed. The performance of the convolutional network was compared with a traditional 2D U-Net network using the Dice Score and Intersection-over-Union score (Table 1). The in-house study approach performed better (Intersection-over-Union score and Dice score 0.87 and 93.2 respectively compared to the standard 2D U-Net approach (0.82 and 90.2).

The aforementioned studies demonstrate that nerve detection is possible in regional anaesthesia but more research is required to develop a more robust tracking system for application to patients.

Robotics

The uptake of robotics in Healthcare is now set to expand within a global marketplace worth over £15 billion by 2023. Until now, medical robotics has focused on telepresence, surgical assistance, rehabilitation, medical transportation, sanitation and drug dispensing [17]. Even for surgery, use of robotics is not universal. Whilst the distant future may yield self-autonomous machines, robots are presently used to improve surgical accuracy and efficiency, albeit this may interfere with anaesthesia by modifying patient position and hindering communication [18].

Robotics in anaesthesia fall into three categories [19]. The most common are pharmaceutical, typified by targeted controlled anaesthesia using EEG within a feed-back loop. Others include mechanical robots that provide precision and dexterity better than humans, and cognitive robots that act as decision support systems. Pharmaceutical robots have been used for hypnosis and ventilation and to assist with pain temperature control and homeostasis, with evidence of reductions in workload and increased safety compared to manual systems. Systems such as McSleepy, designed to autonomously control hypnosis, analgesia and neuromuscular block can be overridden by the anaesthetist [20].

The use of mechanical robots for anaesthesia is still in its relative infancy. Most of the work has been trialled for tracheal intubation or regional anaesthesia to date. COVID-19 has heralded rapid redeployment of anaesthetists and there is a clear need to enhance airway skills [21]. An example of robotic application to anaesthesia airway management is the robotic endoscope-automated via laryngeal imaging for tracheal intubation device (REALITI) [22]. This provides real-time image recognition and automated distal tip orientation towards the glottis. A proof of concept study on manikins showed that lay participants with no medical training performed the procedure faster in the automated mode compared to manual control [22].

In regional anaesthesia, a recent training study used a robotic arm (Magellan) driven by a joystick to assess learning curves. When tested by five anaesthetists on a nerve phantom [23], learning curves were improved across 10 needle insertions compared to manual insertion. However, the study was limited by sample size, few repetitions, and lack of performance criteria. The steeper learning curve likely reflected the novelty of the technology as performance times were considerably longer in the earlier trials. This phenomenon was also witnessed during testing of a regional block needle tip tracker system [24] and underlines the need for thorough training when adopting new technology. Moreover, there is a potential danger of overreliance on robotic-assistance during training. Although variability may be reduced amongst trainees, overall competence may be inadequate. Such deskilling would expose anaesthetists during airway emergencies and equipment failure. Therefore, it is important to carefully design robotic interventions in training as a feedback system to aide and not supersede the learning process.

Future clinical systems will have the capacity to not only inform the anaesthetist of a problem but may also suggest or administer treatment [20]. Cognitive robots [25] may be passive (operated by a manual trigger based on a pre-defined decision) or active (provide real-time alerts and assessments). Recent examples [26] include medical devices such as SAFIRA (safer injection for regional anaesthesia). This eliminates the need for an assistant during nerve block but retains the capacity to aspirate and cuts off flow when injection pressure exceeds 17psi (117kPa). it seems likely that robots will be compliment anaesthetic practice, given the multiple skill set required to understand complex medical histories, monitor vital signs and make critical judgments in anomalous situation. In the near future, robotic systems are likely to work in autopilot mode until manual override is required, but clinical decision making will remain in the human domain. Even when artificial intelligence attains competencies without human error and cognitive biases, it must be remembered that they are still potentially open to error through programming errors or anomalous events.

Future developments

We envisage artificial intelligence and robotics in the future informing mixed reality technologies including advanced sensing systems, display systems and simulation platforms [27]. Augmented and virtual reality (Table 1) are already available and are impacting on training and practice. Sensory modalities such as movement, sight and touch will not only add realism to augmented and virtual environments and provide operator feedback, but will also be incorporated onto autonomous mechanical robots in the future. Thus, virtual environments and physical robots will both contain integrated objective metrics that will measure training and guide clinical performance.

Motion

Fine motor control is an essential element of safe regional blockade. The Imperial College Surgical Assessment Device (ICSAD) is a validated measure of hand movement during surgical training. Application to supraclavicular block showed differences in performance between experts and novices on time taken, number of movements, and path length [28], as well as improvements in performance over the course of regional anaesthesia fellowships. More recently, hand motion analysis was used to evaluate needle tip tracking technology on a pork phantom. Again, reduction in hand movements and path length were seen but only for out-of-plane blocks [29]. A study of volunteers undergoing lumbar plexus block confirmed these initial results [30]. Hand motion analysis provides some explanation about the role of hand movements in specific tasks and the relationship between these movements and efficiency but does not provide a full index of hand eye coordination. Tools to address the acquisition of hand eye-coordination have been developed for UGRA using self-assessment video-based methods [31] but, without a precise way of measuring visual attention, these remain partially subjective.

Vision

The identification and interpretation of anatomy of ultrasound scans is a key skill that takes time to develop. Novices rely mostly on a selective visual processing pathway using limited top-down processing [32]. Visual search is time consuming, based on a serial search for one feature at a time that matches their explicit expectation but depends on the extent of trainees' knowledge [33]. Experts combine top down knowledge with holistic visual pattern recognition (termed bottom up saliency) to produce an implicit priority map [34] enabling faster and more accurate visual scanning and attend more to task relevant areas according to the Information Reduction Hypothesis [35]. Eye tracking has been used in laparoscopy, radiology, pathology [36] and more recently in ultrasound guided regional anaesthesia to objectively assess decision making and attention allocation (Fig 3). By doing so, it can help to explain difficulties in the learning experience. It can also be used to cluster trainee performance levels and track the learning curve. Technical advances include neural network linked automatic calibration of glasses and software that allows provides real time updates of performance that can be tracked over repeated blocks. UGRA studies using eye tracking technology [37-39] indicate that eye movements can distinguish between experienced UGRA practitioners from novices. Furthermore, reflective feedback based on real-time performance has potential to accelerate the UGRA learning process.

Touch

Whilst scanning procedures rely heavily on visual attention, injection needs haptic feedback. An example of a haptic simulator is the SAILOR system used 3-D rendering on a desk mounted virtual system with mouse and keyboard control [40]. However, validation was limited to self-report subjective scores of satisfaction. The Regional Anaesthesia Simulator and Assistant

(RASimAs) system combined virtual feedback using MRI or CT images of a real patients [41] coupled with haptic feedback using grounded haptics. More widely, grounded kinaesthetic haptics have introduced a somewhat realistic experience of feedback, but this has not always transferred into performance in other domains such as laparoscopy [42,43]. More progress has been gained from ungrounded cutaneous haptics with vibration feedback and this approach had been used with the Intuitive Surgical da Vinci Standard robot with some evidence of performance improvement [44].

Virtual, augmented and mixed realities

Two studies enhanced the navigation of epidural needles using augmented reality. In the first, identification of vertebral spaces in volunteers was more accurate than traditional palpation [45]. The second was more complex. Both the B-mode ultrasound transducer and the needle were visualized in a 3-D augmented environment, and the epidural space identified using a single-element transducer at the needle tip. All trials were successful in a phantom compared to only 50% of trials using ultrasound alone [46]. In addition to anatomical navigation, augmented reality may be useful in regional anaesthetic training. Whilst high fidelity cadaveric training provides realistic simulation for mastery learning, poor accessibility and high cost reduce widespread use. There is a pressing need for virtual training platforms in order to provide cadaver-like simulation training.

Application of virtual reality (VR) to UGRA has also focused on patient centred anxiety reduction and training. Use of VR distraction has met with mixed results. Two studies [47,48] reported this as a successful distraction method for UGRA, with increased satisfaction and reduced pre-operative to mid-operate anxiety compared to conventional care but another reported no differences [49]. Virtual gamification worlds have also been created to reward learning in a fun environment. Success is scored on leader boards as points, badges, performance graphs. Avatars, may be either patients or team members [50]. A study of cardiothoracic trainees found that engaging in a live ‘Top Gun’ competition improved performance on anastomosis techniques [51]. A commercial Nintendo WiiU game 'Underground' (Cutting Edge Surgical Games, the Netherlands) has been validated for laparoscopy as the gameplay manoeuvres are based on the dexterity skills required in laparoscopy but without haptic feedback and a similar approach can be developed for regional anaesthesia. Another potential application is non-technical virtual skills training [52] within scenarios that emphasise teamwork, human factors and ergonomics [53], all of which are relevant to patient care.

More recently a gamification approach with haptic forces has been developed for epidural anaesthesia [54]. This was based on a grounded haptics needle with force models using Unity, a cross-platform game engine (Unity Technologies, US). Nerves were modelled in virtual space using data from magnetic resonance imaging (MRI) and magnetic resonance angiography [55] but scans were limited to only a few individuals, thus limiting scope for anatomic variation. In an eLearning programme [56], trainee anaesthetists were randomised to watching an educational video with or without moving a virtual ultrasound (US) probe over a cartoon anatomical schematic of the thigh muscles whilst viewing the MRI and ultrasound images. Written test results were enhanced in the virtual simulation group, but there were no differences in performance in live scanning. This may reflect different learning rates for knowledge and skill acquisition.

Cross reality (XR), Internet of things and Digital Twins

Combinations of robotics, extended realities and objective metrics have the potential to provide a comprehensive educational and clinical experience. Evidence from manufacturing, indicates that robots can reduce costs and exceed human performance for tasks that are repetitive, tiresome and induce physical strain. Extended realities offer an opportunity for clinicians to be actively involved in procedures in a cognitively rewarding way [57]. Potential applications of extended realities, the internet of things and digital twins (Table 1) include drug dosage decision making [58], or mapping patient data directly into simulator environments prior to a procedure to enable practice. This would be beneficial both for learning UGRA and for practice before undertaking complex cases.

Reinforcement learning uses goal-oriented algorithms which learn how to achieve a strategic outcome over many steps. Reinforcement algorithms are penalised when they make the wrong decisions and rewarded when they make the right ones. The advantage of machine learning is that it can find patterns in large unwieldy, complex datasets and provides an attractive alternative to the rigidity of classical statistical methods. Besides deep learning, reinforcement learning is frequently used in robotic control, especially for solving complex sequential decision-making problems [59]. The control of robotic movement, which can be regarded as a multi-agent system, needs comprehensive multi-agent reinforcement learning methods [60]. Another interesting area for future developments lies within high frequency band 5G networks. These will cover three application scenarios in the future: enhanced mobile broadband, Massive Machine-type Communications and Ultra-Reliable and Low-Latency Communications. Whilst these technologies appear to not have much in common, if they were to be applied together, this could make the use of smart robotics in anaesthesia an everyday occurrence.

Barriers to technology implementation

The governance of AI is important. Governance needs to provide stability and transparency but account for rapid change that innovation brings. Similar to clinical research, ethical considerations alleviate potential harm by providing values and principles that guide researchers. Governance procedures should be adopted, like a clinical trial, for each project. The Alan Turing Institute provides guidance on AI ethics and safety [61]. Its framework of ethical values is called ‘SUM Values’. These embrace respectfulness, openness, inclusivity and justice. Because AI systems lack accountability, the Institute has developed ‘FAST Track Principles’ based on fairness (data, design, implementation, outcomes); accountability, sustainability (safety, accuracy, reliability, security, and robustness); and transparency in order to gain public trust.

Cost remains a significant barrier to robotic large platforms but over the longer term can be cost effective if fewer complications ensue. Robotic assistance does not necessarily increase procedural efficiency and the evidence on reducing learning curves is mixed across surgical contexts [62]. Regulatory processes can be a barrier to technology implementation in clinical areas. However, an opportunity exists to develop medical technologies for medical education purposes in the first instance. This would: create a testbed for medical devices and provide a means of enhancing skills and reducing clinician variability. In fact, reduction of inter-operator variability has been a key driver of robotics technology but may also be achieved with simulation training and the appropriate objective performance metrics.

Simulation teaching and technology can offer opportunities for a learning experience that exposes clinicians to procedures and context that will reflect the skills requires for them to develop expertise, rather than rely entirely on a robot. However, at this point in time, barriers still exist [63]. Some technologies may not offer a realistic enough environment, leading to an uncanny valley effect or a mismatch between confidence in completing simulated procedures and ability to perform these in real life. It is therefore important to develop objective and subjective assessments for core technical and non-technical skills that may be required in practice. More research into formative and summative assessment types and a standardised approach is required.

In conclusion, we envisage the main thrust of AI in regional anaesthesia to be the support of clinical decision making. However, this will require a seismic change in attitudes in departments of anaesthesia towards the routine collection of accurate pre-operative, interventional and postoperative pain and functional outcome data. Clinicians will, as in all AI-driven industries, have to become mathematically and computing literate. AI, as in radiology will help recognise structures on ultrasound images. However, interpretation of ultrasound videos is difficult and not yet accurate enough for clinical application. We recognise a need for the application of AI to robotics for training regional anaesthesia rather than clinical practice at this moment in time. Training will change towards mastery learning and dedicated practice on both low and high-fidelity simulators. Performance will be measured using validated accurate sensors that incorporate visual and motion metrics and offer real-time feedback. These will be incorporated into augmented reality and visual reality environments. Eventually training will be possible at home or in the office on life-like virtual simulators, but detailed environments, such as an aircraft simulator, will take many years to achieve. Autonomous robots will be a hallmark of the 5th industrial revolution. Whatever their form, successful development of technology in the 4th industrial revolution will influence their role in future regional anaesthesia.

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MM is CEO of Optomize Ltd, a psychology and eye tracking company
GM is a member of the European Scientific Advisory Board of B.Braun/Philips.
He received payment to present research on their behalf at ESRA 2018, Dublin and ESRA 2019, Bilbao
GM is a member of the advisory board of the Medical Device Manufacturing Centre, Heriot Watt University, Edinburgh, UK

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Table

Table 1 Concepts and definitions

Figures

Fig 1 Fig. Examples of neural networks used in imaging. The simplest network has two input cells and one output cell and is termed a perceptron (a). The extension of this network contains a parallel hidden layer (b) and is termed a feed forward neural network (FF or FFNN). Their use is limited but they can be combined with other networks. Autoencoders (AE) compress (encode) information (c). They are characterised by small hidden layers and symmetry around the mid-point (termed the code). Up to this point layers are encoding; after it they decode. Variational autoencoders (VAE) use Bayesian mathematics and thus apply probabilities (d). Convolutional neural networks (CNN or deep convolutional neural networks, DCNN) are used for recognition of objects during image processing (e). They use a small square scanning matrix that passes pixel by pixel over the image. This data is fed through convolutional layers that only connect to neighbouring cells. The number of convolutional cells decrease with sequential layers. Pooling layers act as filters. Deconvolutional networks (DN) are reversed convolutional neural networks (f). They can produce images from data. Deep convolutional inverse graphics networks (DCIGN) are VAEs but with CNNs and DNNs for the respective encoders and decoders (g). Images can be re-rendered to different viewpoints, lighting conditions, and variations in shape. Deep residual networks (DRN) are very deep FFNNs that are efficient at training hundreds of layers (h). Connections pass from one layer to a later layer as well as the next layer.

Fig 2 Convolutional network structure designed to identify the sciatic nerve on scanning of the posterior thigh on soft embalmed Thiel cadavers. Manually labelled frames for training are shown in (a). The prediction from the trained neural network is shown in (b-d) Images sequentially reduced into a form which is easier to process, and takes less computer power without losing accuracy. The vital element involved in carrying out convolution is the filter or kernel(K). It is much smaller than the image and moves over the image until it has been fully scanned. The first convolutional layer captures low-level features such as lines and colour. Extra layers add high-level features as shapes. Pooling acts a noise suppressant and dimension reducer by identifying either the maximum or averaged value from the kernel. Maximum pooling is generally regarded as better. Data is then fed to a conventional neural network.

Fig 3 Example of sensor technology in regional anaesthesia. Trainee anaesthetist (a) shown before undergoing formal video assessment of interscalene block on a patient as part of a trial funded by the NIAA (BJA/RCoA and RA-UK project grants). The trainee is wearing Pupil Core 200 Hz binocular eye tracking glasses (Pupil Lab, Berlin). The glasses are connected to Optimal analysis software V1.14 (Optomize Ltd., Glasgow, UK). A calibration check is being carried out. Image (b), from a development study, shows an example of metric based feedback. Eye gaze fixation points (red circles) linked by saccades (red lines). The blue circle shows the final eye fixation point and the number in green indicates the number of eye fixations measured (n = 9) to completion of the task. Image (c), from a third study, shows an overall reduction in the number of eye gaze fixations per task over ten repeated procedures. The best-fit line is shown and suggests a clear improvement in performance.