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Review Article

The use of artificial intelligence and robotics in regional anaesthesia

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Summary

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 UK National Health Service Topol Report embraced this digital revolution and emphasised the importance of artificial intelligence to the health service. 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 falls into three categories. The first, used commonly, is pharmaceutical, typified by target-controlled anaesthesia using electroencephalography within a feedback loop. Other types include mechanical robots that provide precision and dexterity better than humans, and cognitive robots that act as decision support systems. It is likely that the latter technology will expand considerably over the next decades and provide an autopilot 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 aimed to stimulate discussion towards a framework for the optimal application of current and emerging technologies in regional anaesthesia.

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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 three-dimensional (3D) 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. Among 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 Figure 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 artificial intelligence-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 s. 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 multilevel receptive fields inspired Fukushima to design a multilayered neural network named "Neocognitron" [10]. This was the prototype for a convolutional neural network, a self-organising multilayer artificial neural network which could recognise handwritten numbers and characters [Ronneberger et al., preprint, https://arxiv.org/abs/1505.04597].

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: two dimensional (2D) [11] and 3D [Milletari et al., preprint, https://arxiv.org/abs/1606.04797]. Networks such as V-Net are used for volumetric medical image segmentation of magnetic resonance imaging (MRI) [Kaiming H et al., preprint, https://arxiv.org/abs/1512.03385].

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 greyscale spatial arrangement pixels within ultrasound images. The median nerve was scanned in 10 patients [12]. 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 [13]. 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 94% for the median nerve and 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. Figure 2 shows the network which consists of six parts, five that abstract the ultrasound image features and one that generates a masked output after all features have been abstracted. The aim was to teach the system to pay attention, that is, focus on important information and ignore irrelevant information. This is challenging because each frame has a unique

Table 1 Concepts and definitions of artificial intelligence and robotics relevant to anaesthesia.

Concept	Definition
Artificial intelligence	A non-human programme or model that can solve sophisticated tasks.
Augmented reality	A technology that superimposes a computer-generated image on a user's view of the real-world, thus providing a composite view.
Bayesian neural network	A probabilistic neural network that relies on Bayes' theorem and accounts for uncertainty in weights and outputs.
Bounding box	In an image, the (x, y) co-ordinates of a rectangle around an area of interest.
Convolutional network	A neural network typically consisting of convolutional, pooling and dense (fully connected) layers.
Deep learning	A multi-layered, non-linear extension of machine learning inspired by neural networks in the brain.
Digital twins	Computerised representations of a physical system that can be used for event detection and predictions and can optimise IoT deployment for efficiency.
Extended realities	Mixture of augmented, virtual and mixed realities that enables operator to bring digital objects into the physical world and physical objects into the virtual world.
Eye tracking	A method of measuring eye movements that reflects attention. Includes gaze (the direction); fixations (stationary period when information encoding occurs); and saccades (eye movements between locations).
Grounded haptics	A haptics device with a fixed ground that provides the feeling of touch in a remote or virtual environment.
Intersection-over-union	Measures the accuracy of the model's predicted bounding box with respect to the ground-truth bounding box. It is the ratio between the overlapping area and the total area.
Keypoints	Co-ordinates of particular features in an image.
Machine learning	A subset of artificial intelligence, characterised by improvements in performance through iterative tuning of weights or coefficients within mathematical models.
Massive machine-type communications	A type of communication between machines (over wired or wireless networks) where data and information can be exchanged.
Mixed reality	A form of augmented reality in which virtual objects can be placed in the real-world.
Multi-agent reinforcement learning methods	Relate to sequential decision-making across multiple autonomous agents that operate in a common environment where each agent engages with other agents in co-operative or competitive tasks.
Normalisation	The process of converting an actual range of values into a standard range of values, typically −1 to + 1 or 0 to 1.
Over-fitting	A model that matches the training data so closely that the model fails to make correct predictions on new data.
Perceptron	A system (node) that takes in one or more input values, runs a function on the weighted sum of the inputs and computes a single output value.
Pooling	Reducing a matrix created by an earlier convolutional layer to a smaller matrix by taking the maximum or average value.
Reinforcement learning	A family of algorithms that maximise return.
Supervised learning	Training a model from input data and their corresponding labels.
Test set	The subset of the dataset used to test the model after validation.
The dice score	Twice the area of overlap divided by the total number of pixels in both images.
The internet of things	Enables the exchange of data across a network of physical devices for machine to machine communication.
Training set	The subset of the dataset used to train a model.
Under-fitting	A model with poor predictive ability that has failed to capture the complexity of the training data.
Ungrounded haptics	A haptics device that is not fixed but provides tactile or kinaesthetic feedback.
Unsupervised learning	Training a model to find patterns in a dataset, typically an unlabelled dataset. Uses clustering methods or principal components analysis.
Validation set	A subset of the dataset, disjoint from the training set, used in validation.
Virtual reality	A computer-generated reality in which the user is immersed in the virtual world.

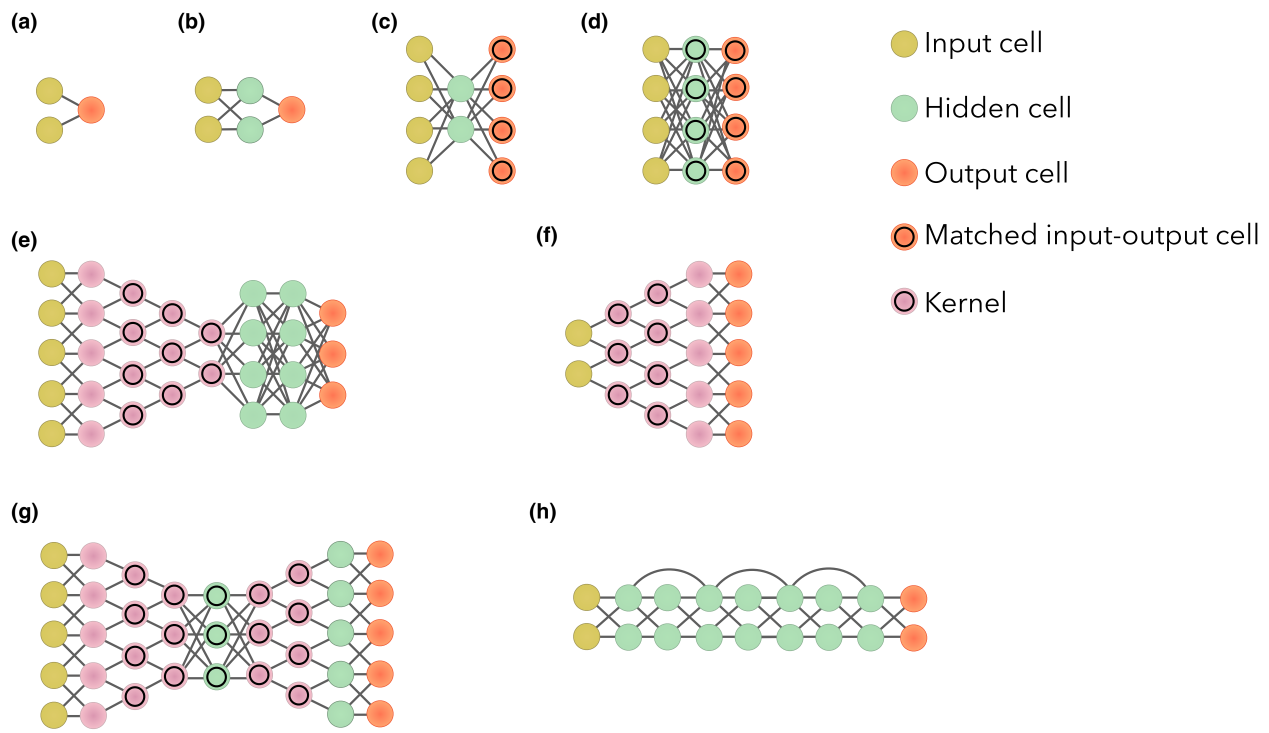

Figure 1 Examples of neural networks used in imaging. The simplest network has two input cells and one output cell and is termed a perceptron (a). The extension of this network contains a parallel hidden layer (b) and is termed a feed-forward neural network. Their use is limited but they can be combined with other networks. Auto-encoders 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 auto-encoders use Bayesian mathematics and thus apply probabilities (d). Convolutional neural networks (or deep convolutional neural networks) 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. These data are 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 are reversed convolutional neural networks (f). They can produce images from data. Deep convolutional inverse graphics networks are variational auto-encoders but with convolutional neural networks and deep convolutional neural networks for the respective encoders and decoders (g). Images can be re-rendered to different viewpoints, lighting conditions and variations in shape. Deep residual networks are very deep feed-forward neural networks that are efficient at training hundreds of layers (h). Connections pass from one layer to a later layer as well as the next layer.

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 with the standard 2D U-Net approach (0.82 and 90.2)). The aforementioned studies demonstrate that nerve detection is possible in regional anaesthesia but further research is required to develop a more robust tracking system for clinical application.

Robotics

The uptake of robotics in healthcare is now set to expand within a global marketplace worth over £15 billion by 2023. To date, medical robotics has focused on telepresence; surgical assistance; rehabilitation; medical transportation; sanitation; and drug dispensing [14]. Even for surgery, use of robotics is not universal. While the distant future may yield 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 [15].

Robotics in anaesthesia fall into three categories: pharmaceutical; mechanical; and cognitive [16]. Pharmaceutical robots are typified by target-controlled

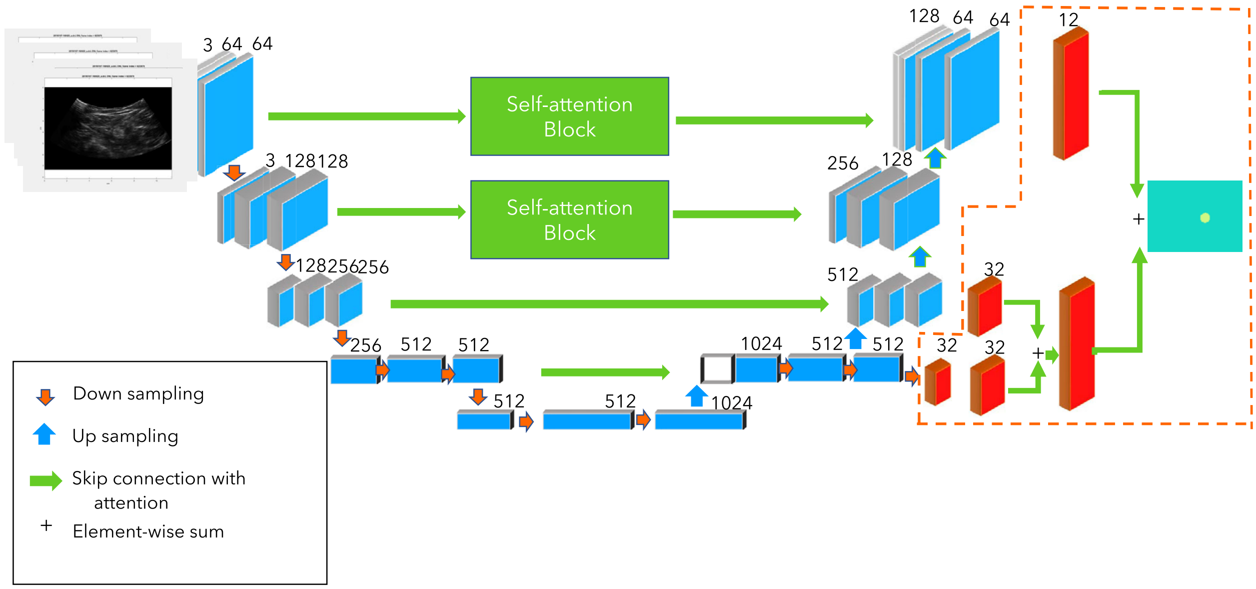

Figure 2 Convolutional network structure designed to identify the sciatic nerve on scanning of the posterior thigh on soft embalmed Thiel cadavers. Manually labelled ultrasound frames for training are shown in the top left corner. Images are sequentially reduced into a form which is easier to process and takes less computer power without losing accuracy. The vital element involved in carrying out convolution is the filter or kernel. 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 are then fed to a conventional neural network. Self-attention is a term used to describe the enhanced feature extraction of neighbouring elements.

anaesthesia using EEG within a feedback loop. Mechanical robots provide precision and dexterity better than humans and cognitive robots 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 work-load and increased safety compared with manual systems. Systems such as McSleepy, designed to autonomously control hypnosis, analgesia and neuromuscular blockade can be overridden by the anaesthetist [17].

The use of mechanical robots for anaesthesia is still in its relative infancy. Most of the work has been trialed for tracheal intubation or regional anaesthesia to date. Coronavirus disease 2019 (COVID-19) has heralded rapid redeployment of anaesthetists and there is a clear need to enhance airway skills [18]. An example of robotic application to anaesthesia airway management is the robotic endoscope-automated via laryngeal imaging for tracheal intubation device (REALITI) [19]. 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 with manual control [19].

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 [20], learning curves were improved across 10 needle insertions compared with 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 tracking system [21] 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 among 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 [17]. Cognitive robots [22] may be passive (operated by a manual trigger based on a predefined decision) or active (provide real-time alerts and assessments). Recent examples [23] include medical devices such as safer injection for regional anaesthesia (SAFIRA). This eliminates the need for an assistant during nerve block but retains the capacity to aspirate and cuts off flow when injection pressure exceeds 117 kPa. It seems likely that robots will 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 err through programming errors or anomalous events.

Future developments

Artificial intelligence and robotics in the future will inform mixed reality technologies including advanced sensing systems, display systems and simulation platforms [24]. 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 anaesthesia. The Imperial College surgical assessment device (ICSAD) is a validated measure of hand movement during surgical training. Application to supraclavicular brachial plexus block showed differences in performance between experts and novices on time taken; number of movements; and path length [25], 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 [26]. A study of volunteers undergoing lumbar plexus block confirmed these initial results [27]. 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 co-ordination. Tools to address the acquisition of hand eye co-ordination have been developed for ultrasound-guided regional anaesthesia using self-assessment video-based methods [28] but without a metric of 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 [29]. Visual search is time consuming, based on a serial search of one feature at a time that matches their explicit expectation but depends on the extent of trainees' knowledge [30]. Experts combine top-down knowledge with holistic visual pattern recognition (i.e. bottom-up saliency) to produce an implicit priority map [31] enabling faster and more accurate visual scanning and attend more to task-relevant areas according to the information reduction hypothesis [32]. Eye-tracking has been used in laparoscopy, radiology, pathology [33] 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 provides real-time updates of performance that can be tracked over repeated blocks. Ultrasound-guided regional anaesthesia studies using eye-tracking technology [34–36] indicate that eye movements can distinguish between experience ultrasound-guided regional anaesthesia practitioners from novices. Furthermore, reflective feedback based on real-time performance has potential to accelerate the ultrasound-guided regional anaesthesia learning process.

Touch

While scanning procedures rely heavily on visual attention, injection needs haptic feedback. An example of a haptic simulator is the simulator of anaesthesia for loco-regional procedure (SAILOR) system that uses 3D rendering on a desk mounted virtual system with mouse and keyboard control [37]. However, validation was limited to self-reporting of subjective satisfaction scores. The regional anaesthesia simulator and assistant (RASimAs) system combined virtual feedback using MRI or computed tomography (CT) images of real patients [38] 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

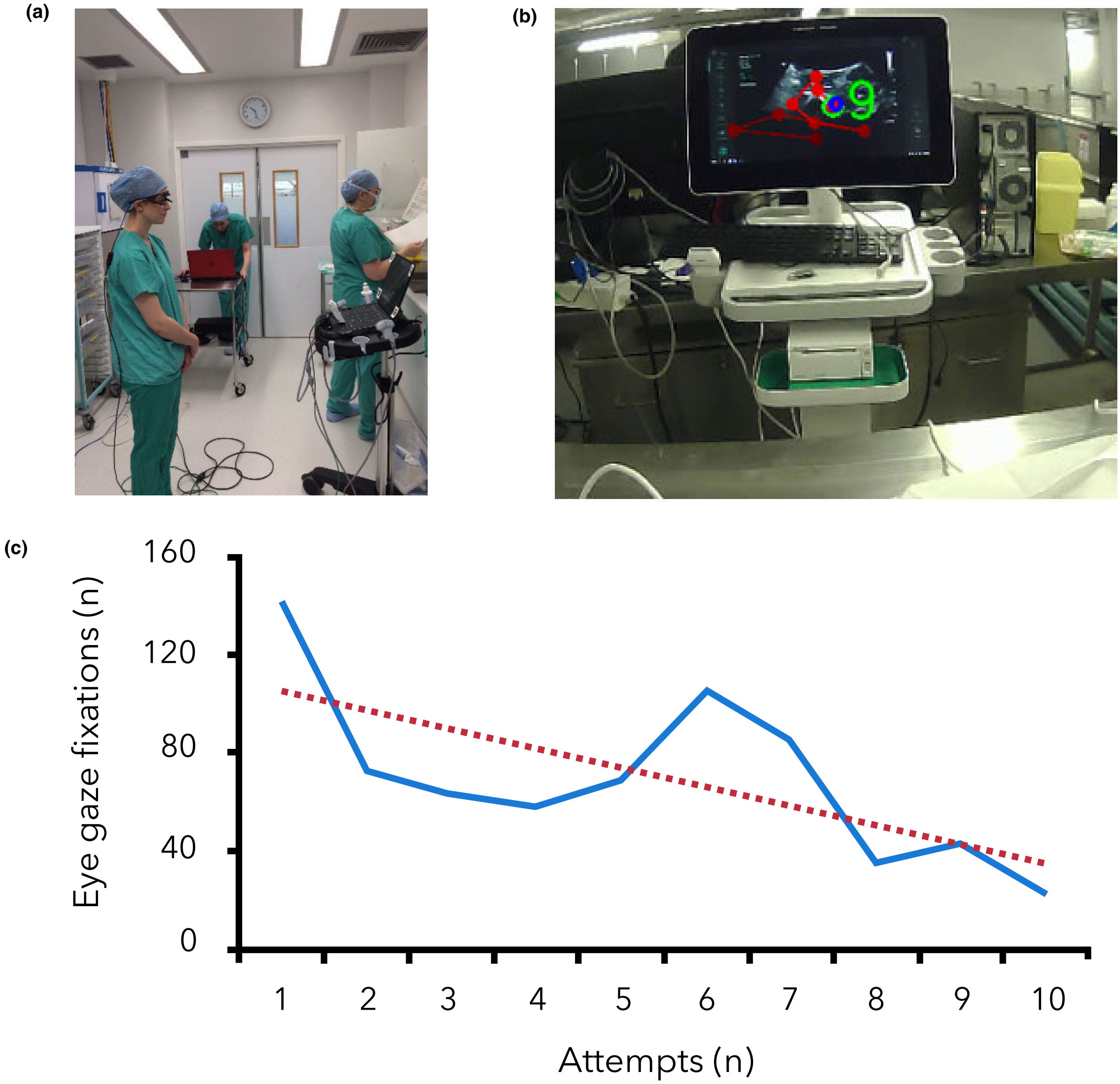

Figure 3 Example of sensor technology in regional anaesthesia. (a) Trainee anaesthetist shown before undergoing formal video assessment of interscalene brachial plexus block on a patient as part of a trial funded by the NIAA (BJA/RCoA and RA-UK project grants). The trainee is wearing Pupil Core 200 Hz binocular eye tracking glasses (Pupil Lab, Berlin, Germany). The glasses are connected to Optimal analysis software V1.14 (Optomize Ltd., Glasgow, UK). A calibration check is being carried out. (b) Output from a development study showing 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. (c) Results from a third study, showing an overall reduction in the number of eye gaze fixations per task over 10 repeated procedures. The best fit line is shown and suggests an improvement in performance.

laparoscopy [39,40]. 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 (Intuitive Surgical, Inc., Sunnyvale, CA, USA) with some evidence of performance improvement [41].

Virtual, augmented and mixed realities

Two studies investigated the application of augmented reality to detection of anatomical landmarks during simulated epidural anaesthesia. In the first, identification of vertebral spaces in volunteers was more accurate than traditional palpation [42]. The second was more complex.

Both the ultrasound transducer and the needle were viewed in a 3D-augmented environment, and the epidural space identified using a single-element transducer at the needle tip. All attempts were successful in a phantom compared with only 50% of attempts using ultrasound alone [43]. In addition to anatomical navigation, augmented reality may be useful in regional anaesthesia training. While 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 to ultrasound-guided regional anaesthesia has also focused on patient-centred anxiety reduction and training. Use of virtual reality distraction has been met with mixed results. Two studies [44,45] reported this as a successful distraction method during the performance of ultrasound-guided regional anaesthesia, with increased satisfaction and reduced pre-operative to intra-operative anxiety compared with conventional care, but another reported no differences [46].

Virtual gamification worlds have also been created to reward learning in a fun environment. Success is scored on leader boards as points, badges or performance graphs. Avatars may be either patients or team members [47]. A study of cardiothoracic trainees found that engaging in a live 'Top Gun' competition improved performance on anastomosis techniques [48]. A commercial Nintendo Wii U (Nintendo Co., Ltd., Kyoto, Japan) game 'Underground' (Cutting Edge Surgical Games, Leeuwarden, The Netherlands) has been validated for laparoscopy as the gameplay manoeuvres are based on the dexterity skills required in laparoscopy but without haptic feedback; a similar approach can be developed for regional anaesthesia. Another potential application is non-technical virtual skills training [49] within scenarios that emphasise teamwork, human factors and ergonomics [50], all of which are relevant to patient care.

More recently, a gamification approach with haptic forces has been developed for epidural anaesthesia [51]. This was based on a grounded haptics needle with force models using Unity, a cross-platform game engine (Unity Technologies, San Francisco, CA, USA). Nerves were modelled in virtual space using data from MRI and magnetic resonance angiography [52] but scans were limited to only a few individuals, thus limiting scope for anatomic variation. In an e-learning programme [53], trainee anaesthetists were randomised to watching an educational video with or without moving a virtual ultrasound probe over a cartoon anatomical schematic of the thigh muscles while 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, 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 [54]. Potential applications of extended realities, the internet of things and digital twins (Table 1) include drug dosage decision-making [55], or mapping patient data directly into simulator environments before a procedure to enable practice. This would be beneficial both for learning ultrasound-guided regional anaesthesia 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 [56]. The control of robotic movement, which can be regarded as a multi-agent system, needs comprehensive multi-agent reinforcement learning methods [57]. 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. While 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 artificial intelligence is important. Governance needs to provide stability and transparency but account for the rapid changes 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 for each project, similar to governance frameworks for clinical trials. The Alan Turing Institute provides guidance on artificial intelligence ethics and safety [58]. Its framework of ethical values is called 'SUM values'. These embrace respectfulness, openness, inclusivity and justice. Because artificial intelligence 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 [59]. 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, reducing clinician variability and improving regional block success rates. 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 [60]. 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.

Conclusion

In conclusion, we envisage the main thrust of artificial intelligence 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 artificial intelligence-driven industries, have to become mathematically and computing literate. Artificial intelligence, 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 artificial intelligence 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 fifth industrial revolution. Whatever their form, successful development of technology in the fourth industrial revolution will influence their role in future regional anaesthesia.

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