Neurosurgical Ethomics: Using Machine Learning to Decode the Language of Neurosurgery

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Background.
The hierarchical structuring of motor actions as a "language" is the basis of the theory of Action Grammars, whereby actions/sentences can be broken down to a series of tasks/words When arranged correctly, they could spell out another sentence (i.e., another task or procedure). In this work, we undertake the first decoding of the action grammars of neurosurgery. We adapted and integrated machine learning algorithms, in particular Sparse Eigenmotion Decomposition to construct a dictionary of neurosurgical actions, and Dynamic Time Warping, to provide a metric for the distance between the analysed actions of junior neurosurgeons from a global mean of the actions of expert neurosurgeons.

Methods.
A motion capture full-body suit utilising Inertial Measurement Units (Xsens Technologies B.V., Netherlands) was used to capture the motion of expert neurosurgeons whilst performing a neurosurgical procedure on an anatomically accurate 3D-printed brain model (see Figure 1). The statistics of the motion data, as well as inter-group divergence metrics and dimensionality reduction were investigated. The motion data from novice junior surgeons was then collected and analysed in a similar fashion. The expert kinematic data was utilised to create a "dictionary" of neurosurgical actions using a Dictionary Learning algorithm developed in our lab (Sparse Eigenmotion Decomposition). Dynamic Time Warping was then used to measure the distance of the motion signals of junior surgeons from those of expert neurosurgeons. We furthermore compared the recorded motion signals of the expert neurosurgeons to "real-world" motion datasets (natural movement when undertaking everyday tasks such as cooking) using the methodology outlined above.

Results.
Sparse Eigenmotion Decomposition was able to faithfully recreate the motion data using the "words" (atoms) captured from the recorded kinematic signals. With Principal Component Analysis, we find that fewer components are needed to explain 70% of the variability of surgical motion when compared to other "real-world" motion datasets. However, after an inflection point occurs, more components are needed to explain variance in surgery than in natural real-world motion. This is challenging to explain and poses an interesting neuroscientific question. We posit that, although stereotypical movements may explain the majority of surgical kinematics, the finer movements that differentiate one surgical subtechnique from another may account for this phenomenon.When using Dynamic Time Warping, the inter-group distance between the motion signals of expert surgeons showed a remarkable similarity, while the distance between experts and novices motion signals was far greater. Further investigation may allow the development of an "expertise" metric in surgical motion.

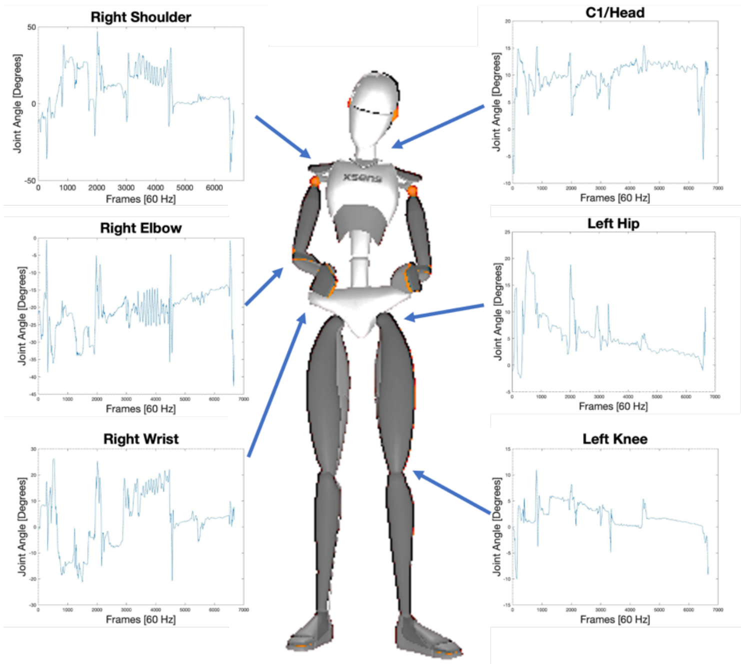

Figure 1: A sample of motion data recorded from a neurosurgical procedure undertaken by an expert neurosurgeon (x-axis: frames at 60 Hz, y-axis: joint angles in degrees).

Conclusion.
To the best of our knowledge, this is the first behavioural characterisation study of neurosurgical experts. We furthermore compare this kinematic data to other motion datasets, and show that the statistics of surgical motion differ significantly from real-world motion data. We discovered an "inflection point" after which more components are needed to explain the variance in surgery than natural data, which may represent the finer delicate movements unique to every surgeon. The Sparse Eigenmotion Decomposition algorithm was able to recreate the motion data signals to a satisfactory degree. Our analysis of expert vs. novice motion utilising Dynamic Time Warping showed a quantitative significant difference between the two groups. This work has considerable scope for future data-driven analyses of expert surgical motion which we aim to further study by capturing motion data of surgeries with varying degrees of complexity.