Real-time Monitoring of Upper Limb Kinematics Using Self-Placed Wearable Sensors and Generative Adversarial Networks

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Summary

This study presents a deep learning approach to computing upper limb kinematics using raw IMU data. Thirty-five participants performed upper-limb tasks with expert- and self-placed sensor configurations. Generative adversarial networks were trained to convert IMU signals to joint angles. The findings showed that a single sensor on upper arm can generate the most accurate humeral angle predictions. Elbow angles were predicted with less than 10° of error using a forearm sensor alone or combined with one on the thorax or upper arm. This framework may be useful for sports, telemedicine and remote monitoring applications.

Introduction

Accurate assessment of upper extremity joint angles is important for evaluating performance of daily living activities, for example, in evaluating joint disease, treatment and in rehabilitation [1]. Most human movement assessments are conducted in laboratory environments; however, estimating joint angles in home settings could support clinicians in tailoring continuous and personalized treatment and rehabilitation plans. Previous studies have demonstrated the potential of Generative Adversarial Networks (GANs) for predicting lower limb angles using wearable sensors [2]. The objective of this study was to develop and validate deep learning models for predicting humerothoracic and elbow angles using IMUs, and to assess the effect of reduced number of sensors worn on kinematics accuracy.

Methods

Thirty-five healthy participants (15 female and 20 male, age: 28±3 years) were recruited. First, participants performed full-range shoulder flexion and abduction with straight arms, and elbow flexion-extension and pronation-supination motions. They then completed four daily tasks: reaching, head touching, waving, and throwing a ball. Three inertial measurement unit (IMU) sensors were placed on subjects' thorax, upper arm and forearm. For the first set of tasks, which included planar shoulder and elbow motions, sensor placement was performed by a trained operator and then repeated under self-placed condition. In the second set, tasks were performed only under self-placed conditions. All tasks were performed at slow and fast speeds. Three-dimensional trajectories of retro-reflective markers attached to each subject's upper limbs were simultaneously derived using a 12-camera video motion capture system (Mocap). Two GAN models were trained on the planar shoulder and elbow motions data to convert IMU signals into humeral and elbow angles. Daily tasks served as a test set to compare GAN-predicted with motion-capture-measured angles. The models were trained and validated seven times using all possible combinations of the three sensors to assess the effect of sensor placement on prediction accuracy.

Results and Discussion

The GAN trained with the upper arm sensor generated the lowest humeral root mean square (RMS) errors, compared to MoCap-measured angles across all tasks, with 6.4° and 4.5° for the plane of elevation and elevation, respectively (Figure 1). The combination of thorax and upper arm sensors generated the lowest RMS for axial rotation at 8.6°. Using all three sensors did not improve overall accuracy for either joint. No significant differences were observed between the predicted and measured maximum humeral angles in any degree of freedom ($p>0.05$). For the elbow, the combination of thorax and forearm sensors produced the lowest overall RMS error, with 7.0° for flexion and 9.9° for pronation. There were no significant differences in maximum elbow angles during ball throwing and waving between predicted and measured values ($p>0.05$). However, maximum predicted elbow flexion was significantly higher than the measured angles during slow reaching (mean difference: 13.8°, 95%CI: [4.6°, 23.0°], $p=0.006$).

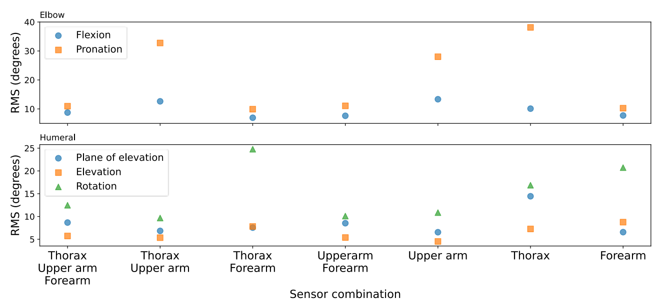

Figure 1: Average RMS errors of predicted humeral and elbow angles with different sensor combinations.

Conclusions

This study proposes a GAN framework to convert IMU signals into humeral and elbow angles. The results demonstrated that using one or two IMUs can produce reliable predictions, particularly for humeral angles. Employing two IMUs on the upper arm and forearm segments can further improve predictions for both humeral and elbow joints. Our findings were validated under self-placed sensor conditions across various tasks at two different speeds, highlighting the potential to adapt this approach to home settings and deliver a reliable real-time monitoring system for joint kinematics.

References

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