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Motion capture without markers using the leap motion controller and artificial neural networks

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1. Introduction

The Leap Motion controller (LM) can reconstruct joint centres and a hand skeleton in real-time without the need of markers. Compared to a gold-standard optoelectronic system, the LM is inaccurate when calculating angles between two adjacent finger segments [1]. Artificial neural networks (NN) learn multi-dimensional patterns between two data sets and after training can predict output data based on input data presented to it.

2. Research question

Can an artificial Neural Network improve the accuracy of angles calculated from Leap Motion data?

3. Methods

Two young, healthy adults were fitted with 16 clusters (48 markers) on the dorsum of the hand and each phalanx. Markers were captured with 15 Vicon cameras (Vicon Nexus 2.5). The LM was placed ~25 cm underneath the hand and captured 3D finger joint (carpometacarpal, metacarpophalangeal, proximal interphalangeal (PIPJ), distal interphalangeal) and tip coordinates. The systems were synced and 15 cycles of self-selected hand movements were collected in D-Flow at 300 Hz (Motek Forcelink, Amsterdam). Vicon marker data was imported into Visual3D (C-Motion) where functional joint centres were computed (GILLETTE algorithm). The first 8 principle components of LM and Vicon data (explaining 97.6% of data variance) were used to train a backpropagation NN in Matlab including 10 fold-cross validation. After training, the NN performance was tested with previously unseen test data set (10% of all data). Computed and predicted joint centre locations were correlated. Joint angles were calculated in Matlab using the cosine rule, for LM, Vicon computed and NN predicted joint centres. The RMSE was calculated between Vicon and NN joint centres as well as joint angles.

4. Results

Correlation coefficients (R) between 0.94–0.99 were calculated between computed and predicted functional joint centres (Fig. 1) across the 10-fold validation ($r^2=0.89-0.99$). The RMSE between computed and predicted joint centre locations ranged from 0.13mm to 2.05mm (mean: 0.55 mm). RMSE increased from proximal to distal end of each finger. The RMSE between Vicon joint angles and NN predicted joint angles at the Index PIPJ (Fig. 2) was 6.45° , compared to 12.54° between the LM and Vicon data, reflecting an error reduction of 48.56% when the NN was applied.

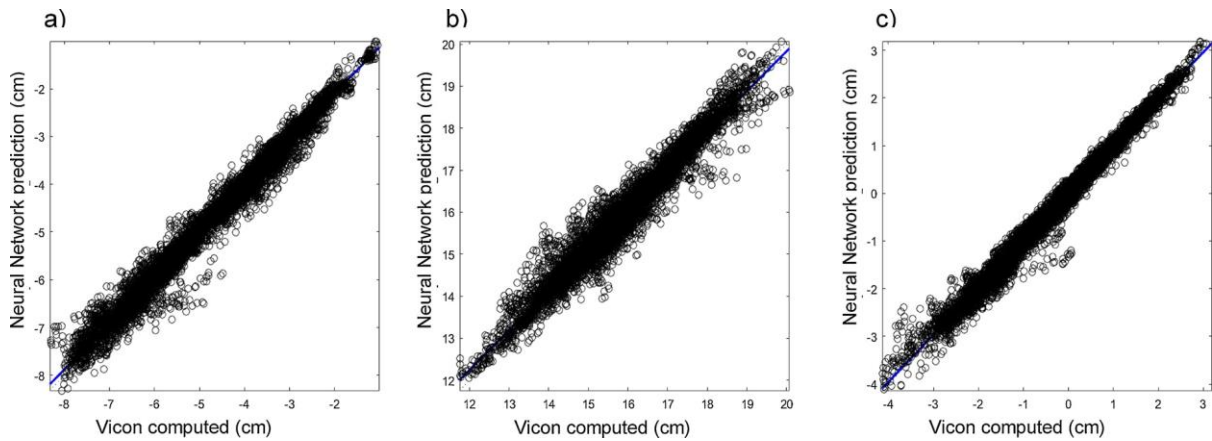


Fig. 1. Correlation between Vicon computed (X-axis) and Neural (Y-Axis) network predicted joint centre coordinates. Strength of the correlation was assessed by calculating the correlation coefficient (R) and coefficient of determination (r^2). a) Correlation of joint centre X coordinates ($R=0.98953$, $r^2=0.9792$) b) correlation of joint centre Y coordinates ($R=0.97689$, $r^2=0.9543$) c) correlation of centre Z coordinates ($R=0.99238$, $r^2=0.9848$).

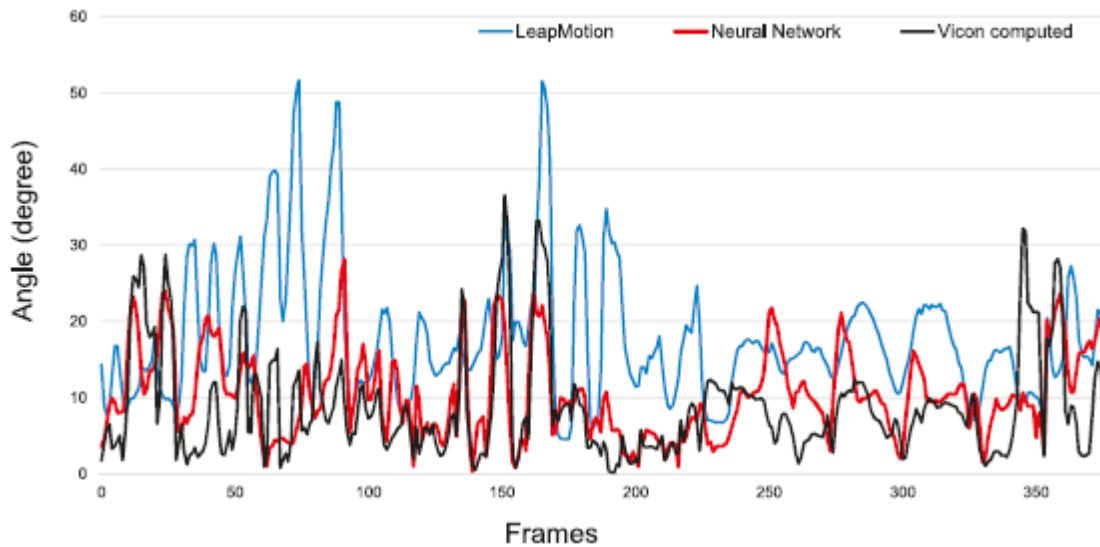


Fig. 2. Flexion/Extension angles at the Proximal Interphalangeal joint from reconstructed test data for the neural network (previously unseen data). Angles (degree) computed using cosine rule for the Leap Motion input data (blue), Vicon target data (black) and Neural Network prediction (red).

5. Discussion

The neural network was able to improve the accuracy of the LM as shown by the angle error reduction between NN and Vicon, compared to LM and Vicon. The angles were computed using cosine rule, which is limited if the angle of interest is close to 0° , however, despite this the results are convincing. In future, the LM will be used to assess movement limitations in patients.

References

[1] Eusterwiemann, et al., Is that a Vicon in your pocket? An evaluation of the leap motion capturing finger movements, CMAS Annual Meeting, Salford, UK, 2017.