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Research article

A New Approach for Quantification of Finger Angles with Applications in Rehabilitation and Medical Assessment

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Abstract: The biomechanical evaluation of the finger joint angle (FJA) is a fundamental aspect in medical diagnosis and neuromuscular rehabilitation, with direct implications for planning therapeutic strategies and optimizing functional recovery. Currently, FJA quantification methods range from conventional techniques, such as goniometer measurements, to advanced approaches based on Bragg grating fibre-optic strain sensors (FBG) and inertial measurement units (IMU). This study proposes an innovative computational geometric methodology for estimating the flexion and extension angles of finger joints, utilizing IMU sensors integrated into a hardware system based on the ESP32 microcontroller, capable of transmitting real-time data to a dedicated system. A MATLAB graphical user interface (GUI) is used for visualizing and interpreting relevant kin-ematic parameters. Experimental results analysis revealed a maximum approximation error of approximately 3% after implementing a rigorous calibration procedure, using a classical reference method. These findings demonstrate the feasibility of integrating the proposed method into a broader clinical framework for objective monitoring of patient progress in functional rehabilitation programs. The study opens new perspectives for the development of advanced data processing algorithms, including the integration of deep learning neural networks for modelling and optimizing joint movements.

Keywords: finger angles; kinematic chain; computational geometry; rehabilitation, deep learning neural networks;

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1. Introduction

The assessment of motor performance helps physicians to identify to eventually problems of integrity of central nervous system. Finger tapping is a test used to assess the motor speed of the index finger [1]. Tapping test proved to be effective in Bradykinesia in Parkinson's disease, assessment of ataxia, stroke recovery, and Alzheimer's disease. It is essential in definition of tapping angle, it is necessary to calculate the angles of the kinematic model of the hand using 3D gyroscopes are placed on the thumb and index-finger [1].

Finger joint coordination during tapping is analysed through joint kinematics and torques to identify muscle activation patterns [2]. The results suggest that motor control strategies in tapping, the muscle forces and joint torques are connected to accomplish successful the task of tapping [3], [4].

In hand therapy, the usually test is the Beighton score, a nine-point scoring system, that measures joint hypermobility (flexibility). It involves simple manoeuvres, such as bending your pinkie finger backward to check the joint angle. The higher the score, the more flexible the hand joints are. Hand therapists record any change in flexibility of joints during treatment by measuring the joint angle repeatedly, daily, over a long period of time [5], [6]. It is interesting to develop an automatic method to record these angles and use them to modify the patient's therapy according to progress of the treatment [7], [8].

Traditionally, the hand angles are measured by goniometer and assessment questionnaires to quantify/evaluate the disease progression and/or to monitor the rehabilitation process [9]. Other sensor has been proposed to measure the joint finger angles as stretchable carbon nanotube strain sensor [10]. A Multi-Sensor Source method was proposed in [11]. In order to estimate the finger muscle strength were used sEMG, finger biomechanical relationship, calculation of finger joint angles, and contact force finger grip (mathematical model of finger muscle strength) [11].

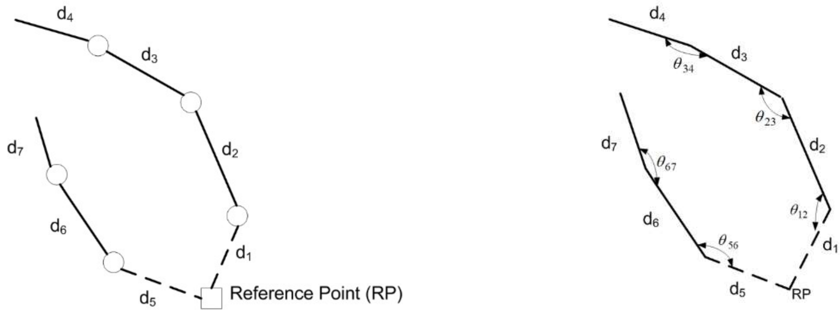
The Leap Motion Controller (LMC) and a camera-based 2D marker detection system (two-dimensional marker) were used to measure joint angles of the mannequin hand [12].

A more extensive list of sensors used or can be used in measurement of joint angles of fingers, including IMUs (inertial measurement units) is presented in [13].

2. Materials and Methods

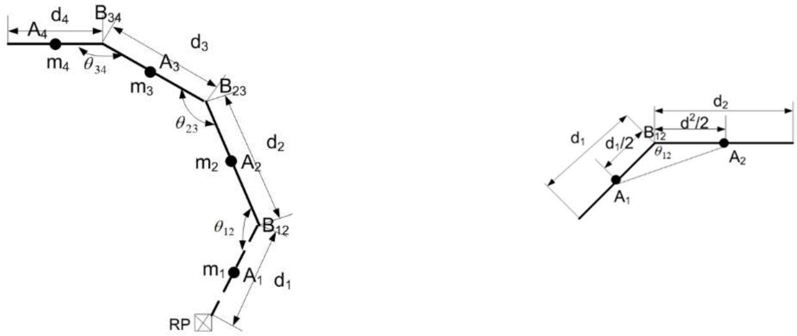
The kinematic model of human hand takes into account the geometrical parameters of the model [14]. The specific geometry imposes also constraints to the joints characterized by minimum/maximum values and anatomic limitations [15]. Concrete values of the anatomical model can be found in many paper that deal with subject related anthropological hand but also in direct/inverse kinematic model of the hand/fingers using Denavit–Hartenberg parameters [16], [17], kinematics of the hand [18], [19] and placement of the IMU sensor (Inertial Measurement Unit) [20].

The approach presented in this paper uses the direct kinematic of the finger and the thumb model in the reference frame for angle calculation as in Fig. 1 ,2.



(a) (b)

Figure 1. Kinematics of the index-thumb model in the reference frame: (**a**) direct kinematic model (RP-Reference point); (**b**) angle of the joint fingers used for hand assessment rehabilitation.



(a) (b)

Figure 2. The schematic of the new approach: (**a**) the kinematic chain of the of segments with joints; (**b**) the proposed approach to calculate the angle θ_{12} between the elements of length d_1 and d_2.

The carpus is composed of 15 bones excluding the supernumerary and sesamoid bones. The joint trapezometacarpial (TM) and Carpus (C) are used in approximation by superposition of point in order to mount a reference sensor on carpus as Reference Point (RP) [18]. The dotted segments are connection of MC (metacarpal) wit TM point, used for reference and calibration only.

The segments for index are: d_4 - distal phalanx, d_3 - middle phalanx and d_2 - proximal phalanx. The segments for index are: d_7 - distal phalanx and d_6 - proximal phalanx.

A kinematic model of the hand [18] and a set of IMU sensors are mounted on the index and thumb fingers on the middle of each segment as in Fig. 2. The anthropological measures of the lengths of each element of the finger for index thumb is figured in Fig. 1a. Anthropometric measures is used are different for each subject and it in concordance with the values indicates in [21], [22].

In Fig. 2b, the length of segment $\overline{A_1A_2}$ is given by IMU position of the two IMUs Located in $A_1(x_1, y_1, z_1)$ and $A_2(x_2, y_2, z_2)$:

$$\overline{A_1A_2} = d_3 = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2}, \quad (1)$$

Using the cosines theorem, the value of the angle between segments $\overline{A_1B_{12}}$ and $\overline{A_2B_{12}}$ is given by:

$$p = \cos(\theta_{12}) = \frac{(d_1/2)^2 + (d_2/2)^2 - d_3^2}{2(d_1/2)(d_2/2)}, \quad (2)$$

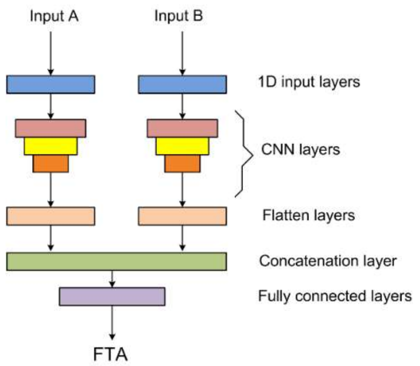
$$\theta_{12} = \text{acos}(\theta_{12}), \text{ inverse cosine in radians} \quad (3)$$

If $p \le 0$, $\theta_{12} \in [\pi/2, \pi]$, otherwise , $\theta_{12} \in [0, \pi/2]$. The calculus is repeated for each angle joint of both fingers, index and thumb resulting a vector of angles $V=[\theta_{12}, \theta_{23}, \theta_{34}, \theta_{56}, \theta_{67}, \theta_{51}]$. The angle θ_{51} is calculated from position of the segments d1, d5 and the RP is given by a IMU sensor mounted on the glove in this position.

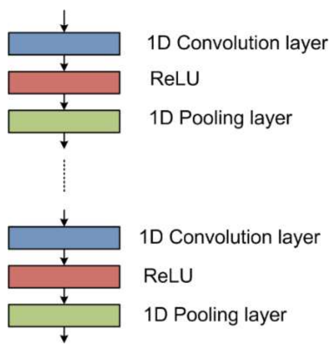
A set of seven sensors were mounted on the glove, and a RP sensor is mounted as reference point (RP). The data are collected by an ESP-32-development board and sent via Bluetooth to a MATLAB GUI for display the results.

3. Results

A 1D CNN (Convolutional Neural Network) Multi-Step Forecast [17]-[18] is used to predict the tapering angle from two vector inputs: Input A-ordered anthropometric length of segments of index and thumb and Input B- ordered finger angles (Fig. 3). Three variants of CNN were used: Fig. 3b), three blocks, 1D CNN-LSTM, and 1D ResNet, with the output being FTA, as calculated in (3). [1]

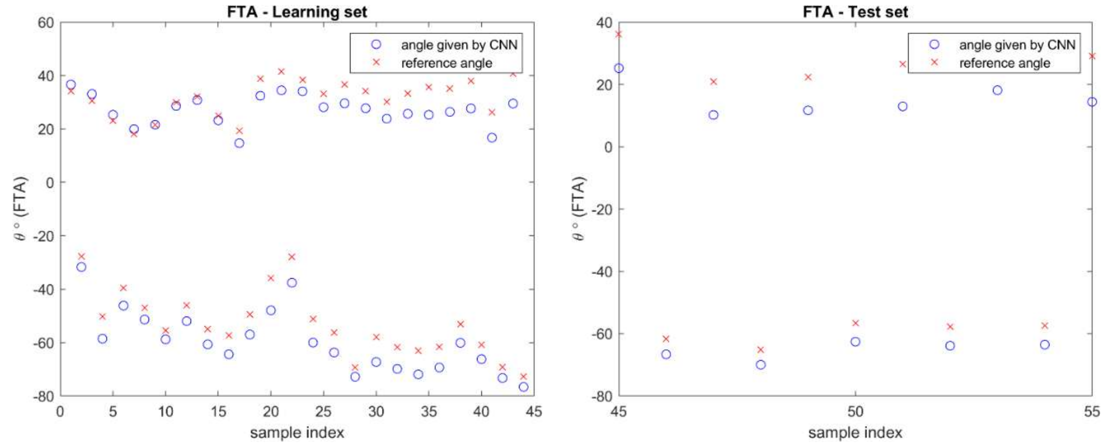


(a)



(b)

Figure 3. DLNN (Deep Learning Neural Network) used as predictor FTA (Finger Tapering Angle) (**a**) General schema of DLNN; (**b**) details of CNN layers used in experiments.



(a) (**b**)

Figure 4. Experimental result of FTA using 1D ResNet52 as CNN Layers from Fig. 3a: (**a**) The learning stage; (**b**) The test stage.

An approach with five subjects and five measurements were used to verify the proposed approach is a 11×5=35 set of measurements (11 individuals, 5 measurement of each individual). The set of data was split in two random sets: 80% training data (44 measurements) and 20% test data (11 measurement at the first sight).

The results were compared with a classic goniometer measurement and using the formula from [1]. The error was around 3.5% comparing as reference the results from [1], with a standard deviation of the results SD = 0.5%. The results are good but further improvements are taken into account as the usage of gyroscopes also in more complex quaternion measures as pattern for FTA calculation.

4. Discussion and Conclusions

The results obtained in this study support the feasibility and accuracy of the proposed method for quantifying finger joint angles through the integration of IMU sensors and deep learning techniques. The values were measured in two positions: start and stop, demonstrating that accurate sensor calibration is crucial in minimizing the error between the measured TAP (Tapering Angle Prediction) and the reference TAP. The best results were achieved using the residual network (1D ResNet), where the error was 3.4%, although other, simpler CNN architectures also provided acceptable results.

An essential aspect of this research is its potential for clinical applications. The proposed method enables objective assessment of finger mobility, eliminating subjective errors associated with traditional measurement techniques. This technology can be employed for monitoring patient progress during neuromotor rehabilitation, providing therapists with quantifiable data to adjust treatment plans in real-time.

However, certain limitations were observed during the study, particularly regarding sensor positioning and individual variability in anthropometric parameters. To mitigate these potential sources of error, it is necessary to implement rigorous sensor calibration and integrate error compensation methods.

Thus, this study advocates for the integration of IMU sensors and artificial intelligence technologies as a viable solution for kinematic evaluation of finger movements. Intelligent methods provide a precise and efficient alternative to traditional approaches, contributing to the optimization of therapeutic strategies and the improvement of patients' quality of life.

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