[[1]](#footnote-1)

Experimental Validation of a Contactless Finger Displacement Measurement System Using Electrical Near Field Sensing

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*Abstract*— This research investigates the potential of contactless finger motion measurement, focusing particularly on ease of use to improve the success of home-based hand rehabilitation exercises. Previously, a mathematical model was developed based on a finite element method (FEM) simulation. This paper validates this model on multi-finger noncontact measuring under laboratory conditions. Twenty-three healthy subjects with normal hand and finger functions participated. An independent near field distance measurement was developed and compared to the output from an optical sensor. It was observed from the experiment that the prediction model worked well with the measuring system reported here. The average uncertainties of measurement using the prediction model are 0.68mm and 0.55mm, which are 3.5% and 2.7% of the full-scale range, for index finger and middle finger respectively. The results from the experiment show that, the reported system is capable of measuring the small movements of fingers. With the combination of the noncontact measuring feature and the lack of complicated set-up, this system is easy-to-use as the basis of a home-based independent rehabilitation system.

*Index Terms*— contactless finger movement detection; nonlinear regression analysis; electrical field sensing; finite element method; hand rehabilitation; finger extension and flexion.

# INTRODUCTION

H

OME-BASED therapy takes place in the home of a person rather than in a clinical setting. It can enhance the conventional physiotherapy and the occupational therapy, and promote continuous functional training in the long run [1]. Considering the significant financial burden of patients and the great dependence on medical facilities, it can further benefit people with its advantages, including: reduced hospital stay, individualized rehabilitation sessions, savings in time and money for both treatment and transportation [2].

Home-based therapy provides alternative rehabilitation means to encourage hand recovery from some physiological and pathological conditions [3], including: stroke, tremor and Parkinsonism. As an example, stroke is the most common cause of disabilities and the second leading cause of death in the world [2]. In the UK, stroke treatment costs £8.9 billion per year, accounting for 5% of the total National Health Service expenditure [4]. About 70% of stroke patients suffer from reduced arm and hand function even after they have been discharged from rehabilitation [5]. Given the large number of patients who can benefit from a readily available form of treatment, research into home-based hand rehabilitation is particularly important.

There is no consensus on the best provision of home-based hand rehabilitation. An important purpose of rehabilitation treatment is the neuroplasticity gained through repetitive training. However, the disability itself may be a major obstacle to the implementation of these exercise sessions [1]. A system is less likely to be used for a complete course of treatment, if it requires complicated setups and contraptions to be worn [3]. Another major obstacle to the home-based methods is the implementation without continuous supervision of therapists. For instance, patient deviating from the expected procedures may increase the possibility of injury.

A survey for application of assistive technologies in stroke rehabilitation confirms the easy setting and comfortable use as the key factors of any ‘popular’ therapy in clinical practice [1]. Towards this target, measurement techniques compatible with the overall aim are explored and selected, as summarized in Table I. The glove-based techniques [6], the ‘exoskeleton’ [7] and Electromyography (EMG) [8] have been proposed to support hand rehabilitation, and are particularly useful when patients cannot move their hands on their own. However, these techniques require sensing elements precisely attached and have an overhead in setting up, which results in the necessity of other people’s help. To reduce these overheads to a minimum and investigate the home-based hand rehabilitation with emphasis on ease of use, in this study, the MGC3030 motion sensor was chosen for contactless finger motion detection [9]. Based on the quasi-static electrical field sensing, it is capable of measuring the movements of fingers without attaching sensing elements to the limbs. Characterized by the user-friendly setting and donning requirements, this measuring system is easy for patients to use at home, without the assistance from either therapists or carers [10]. The extension and flexion of fingers was chosen as an exemplar movement in this research [10]. It can effectively exercise and strengthen the impaired hand [11], and could be applied with simple implementation methods [10]. In light of the typical fine motor function of an impaired hand, the target system should be able to measure the tiny movements of fingers. Due to the quasi-static electrical sensing mechanism of the MGC3030, its sensitivity is inversely proportional to its distance from the human body [9]. Hence, it is particularly sensitive for small distance applications, where the resolutions of depth based systems [12-14] such as the Kinect systems [15], are of limited application. Optical sensing is also a noncontact measurement [16], but has potential issues as multiple optical sensors will be required when measuring the movements of multiple fingers. This will cause occlusions when placing the sensors, and requires significant calibration work.

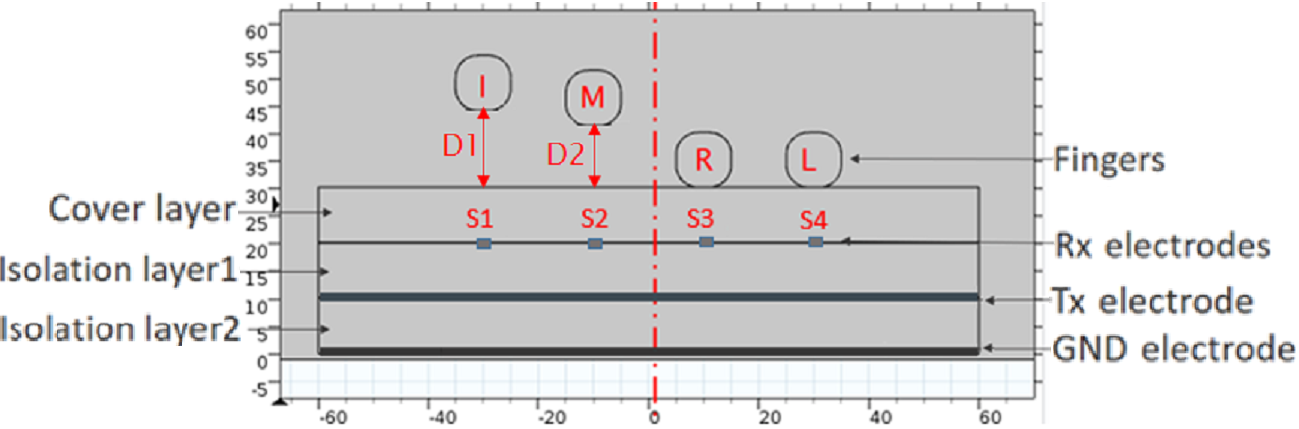


Fig. Cross section view of the Comsol® simulation model

Notes: 1) Scale unit: mm; 2) Electrode potential: TX --3.3V, RX--VX, GND & Fingers —0V

Targeting an easy-to-use device for home-based hand rehabilitation, this research investigates a noncontact measuring system, based on the MGC3030 motion sensor. Previous work has investigated a finite element method (FEM) simulation model based on the MGC3030 three-layer electrodes design using Comsol Multiphysics® [10]. In this paper, initial trials were conducted, to extend the practical understanding of this prediction model on multi-finger noncontact measuring, with human subjects under laboratory conditions. Twenty-three healthy subjects (13 males and 10 females) with normal hand and finger functions participated in this study. The experiment was approved by the institutional research ethics committee of the University of Southampton (ERGO/FEPS/48109).

Table I

Measurement techniques for hand rehabilitation

| Sensing Technology | Advantages (A) & Disadvantages (D) |
| --- | --- |
| Glove-based [6] Exoskeletons [7] | A: Useful when patients cannot move their hands on their own  D: Sensing devices attached; An overhead in setting up; Limit the freedom of patients’ movement |
| Electromyography (EMG) [8] | A: Useful when patients cannot move their hands on their own; Accurate  D: Difficulty in placing the electrode on precise muscles; Requiring the supervision of therapists |
| Depth-based [12-14] (Kinect [15]) | A: Noncontact measurement; Accurate  D: Relatively low resolution; Costly and bulky; Easily affected by ambient light conditions and cluttered backgrounds; A large overhead in signal processing |
| Optical sensing [16] | A: Noncontact measurement  D: Multiple sensors required for multiple fingers; Easily affected by ambient conditions |
| Quasi-static electrical sensing (MGC3030 [3]) | A: Noncontact measurement; Low cost; Sensitive for small distance applications  D: Best detection range is 0 – 100mm for general applications [9] |

# MATERIALS AND METHODS

## FEM Simulation Model

Fig. 1 shows the schematic structure of the simulation model, consisting of four receive electrodes (Rx), a transmit electrode (Tx), a ground electrode (GND), a cover layer, two isolation layers and four fingers (I: index; M: middle; R: ring; L: little) [10]. By applying a sinusoidal voltage (3.3V, 100 kHz) to the Tx electrode, a quasi-static electrical near field directed from Tx electrode to GND electrode is generated and propagated three-dimensionally [9]. When fingers move towards the receptacle, they will decrease the electrical field locally [9]. Four Rx electrodes are placed under the four fingers accordingly. Therefore, the fingers’ motion can be measured by the electrical field variations detected using the Rx electrodes. The signal detected by Rx electrodes under the index finger and the middle finger are labeled S1 and S2 respectively. Similarly, the corresponding distances due to the vertical movement of the index finger and the middle finger are related to D1 and D2.

Considering multifingered movement in the proposed electrical field, measurement of one finger will be affected by the movements of other fingers, especially the neighbors. When a finger moves, the MGC3030 signal of its adjacent finger might change, for two main reasons. In most cases, the signal changes are due to an electrical field leakage from the neighboring moving finger. This is a systematic error of the MGC3030 measuring system, and is also what the term ‘crosstalk’ refers to in this paper. When a finger performs its intended movements, real movements of other fingers may occur [17], which will also contribute to MGC3030 signal changes. Precautions were taken during the data collection and analysis steps of the experiment to prevent the unwanted movements. Particularly, a thumb can be considered completely independent during flexion-extension movements:--it has the highest average individuation index which refers to the ability to move without any accompanying motion of the other ﬁngers; and remained most stationary during instructed movements of other ﬁngers [17]. Therefore, the simulation started with only the index finger, middle finger, ring finger and little finger.

To compensate for the crosstalk due to the electrical field leakage, a nonlinear regression analysis was conducted using Matlab® [10]. The mathematical relationship between the simulated signals detected (S1, S2) from Rx electrodes and the corresponding distance due to fingers’ vertical motion (D1, D2) were found to satisfy the following equation [10]:

x=1,2(1)

where b1, b2, b3, and b4 are parameters. The parameter, b1, is related to the movement of the first finger. As this finger moves away from the electrodes, the magnitude of S1 decreases and the expression. Similarly, the parameter, b2, is related to the movement of the middle finger. The parameter, b3, can be regarded as a sensitivity or gain factor. It represents the receiver signal sensitivity of the Rx electrode and is also dependent on the individual hand electrical characteristics. The parameter, b4, is an offset which is related mainly to the MGC3030 electrode design, and the electrical environment may have a small contribution. Here, the index finger and the middle finger have different fitted parameters. Since this prediction model determines the moving distance of a finger with the Rx signals from both electrodes, crosstalk in the two fingers’ case can be compensated. According to the simulated results, the average resolution of the target system after applying equation (1) is reported to be 0.94mm [10]. It indicates that this measuring technique is capable of finger motion detection and worth investigating practically.



Fig. 2 Experimental system design

## Experiment Platform

Fig. 2 conceptualizes the experiment platform to test the prediction model. The controller unit of the MGC3030 motion sensor is connected to the electrodes as illustrated in Fig. 1, to produce high-resolution output corresponding to the movement of fingers. To validate this system, an independent distance measurement to measure the distance that a finger moves away from the receptacle is required. This was accomplished using an optical sensor system based on a commercial sensor from Sharp® [18], which allows a comparing technique for real-time contactless measurement, although this optical sensor has problems, as discussed later. Two optical sensors are located directly above the fingertips of the index finger and the middle finger, and are fixed on a height-adjustable platform. The design of the receptacle and its electrodes has the same dimensions as the simulation model shown in Fig. 1 [10]. Details of the design parameters are given in Table II.

TABLE II

Design parameters of the MGC3030 electrode stack-up

|  |  |  |
| --- | --- | --- |
| Name | Material | Dimension (mm) |
| Rx electrode | Copper | 2\*50\*0.2 |
| Tx/GND electrode | Copper | 110\*100\*0.2 |
| Cover/isolation layers | Acrylic plastic | 110\*110\*10 |
| Spacing between the midpoint of Rx electrodes | | 20 |

## Data Collection

Participants were seated at a table and remained still throughout the experiment. As shown in Fig. 2, their hand was put on the receptacle with a horizontal posture, pronated with the fingers extended. Each finger could be extended from the flat posture but not into hyperextension. The thumb abducted to the side of the receptacle has very little impact on the MGC signals. Data collection of each participant consists of two parts: the optical sensors’ calibration against a millimeter scaled ruler, and the experiment investigating the fingers’ movement measured simultaneously with both the optical sensors and the MGC3030 measuring system.

Calibration of the optical sensors was conducted for each participant. While a participant’s hand was kept still on the receptacle, the platform holding the optical sensors was adjusted to get varied distance points. Approximately ten distance points were measured for each participants, over a range up to 40mm. At each distance point, the optical system was sampled for 1000 times. Output of the optical sensor (Vo) from the sampling process was filtered using the ‘medfilter’ function in Matlab® to remove high frequency noise. Then, the average of the 1000 sampling data (Vo) and the corresponding distance read from the ruler (D) were recorded as a distance point (D, Vo). With ten distance points, distance characteristics D=f(Vo) could be obtained. Therefore, when measuring the combined movement of fingers, the output of the optical sensors (Vo) could be applied to this distance characteristics equation to obtain real-time distance values (Dx, x=1,2).

While testing of a combined movement of the index finger and middle finger, each participant was required to move their fingers in following order: the index finger extension away from the receptacle and then flexion back to the receptacle, the middle finger extension and then flexion, both fingers extension and then flexion. During this process, the participants were required to keep the palm flat and still on the receptacle, and avoid the movement of the other fingers (thumb, ring and little fingers). Then, they were asked to move their hand away from the receptacle, and finally place their hand back to the receptacle to prepare for the next movement. For the best accuracy, participants were asked to position their hand back to the receptacle with respect to the guidance line on the cover layer to avoid position changes. These movements were repeated 10 times. As the index finger and middle finger moved, the vertical movement was measured simultaneously with the optical system (D1, D2) and the MGC3030 measuring system (S1, S2, S3, S4) at sampling rate of 106 Hz for all the four fingers. The signals detected from the Rx electrodes under the ring finger and the little finger (S3, S4) were checked at the end of the experiment, to avoid both the unwanted movements and the position changes of the ring finger and the little finger.

## Data Analysis

Fig. 3 presents the signal changes from the optical system and the MGC3030 measuring system in one sample movement, which includes 3 steps: i.Index, the index finger extension and then flexion; ii.Middle, the middle finger extension and then flexion; iii.IndexMiddle, both fingers extension and then flexion. Here, optical sensor1 and optical sensor2 are placed directly above the fingertips of the guideline for the index finger and the middle finger, to measure the finger movements (D1 and D2) respectively, as shown in Fig. 3(a). Simultaneously, these movements are measured with the MGC3030 measuring system by signals detected from Rx electrodes under index finger and middle finger (S1 and S2, as shown in Fig. 1). These MGC3030 signals depend on the hand to Rx electrode capacitance, Tx transmit signal (frequency and voltage) and capacitance of the three-layer electrodes [19]. The units from the MGC3030 have arbitrary float values [9]. When a hand is at a distance and has no influence to the electrodes, the signals are approximately zero as a baseline. In this experiment, a zero value will be obtained when the hand is taken away, while the maximum value for a person will be reached when the hand and all fingers are placed on the receptacle. A hand approaching the MGC3030 system increases the hand-Rx capacitance and causes the MGC signal to rise [19]. Hence, the MGC3030 signals have an inverse relation with the distances moved away from the receptacle, as presented in Fig. 3(b) and Fig. 3(c).

If only one finger is considered, there should be a one-to-one relationship between the position of a finger, and the MGC3030 signal from the Rx electrode under this finger [10]. However, due to the nature of electrical field, the movement of the middle finger will affect the MGC3030 Signal1 (S1), as circled in Fig. 3(b). Similarly, signal changes in S2 are also observed in Fig.3 (c), due to the movement of the index finger. This phenomenon is consistent with the FEM simulation, where crosstalk is observed especially between near neighbors [10].

To compensate for this crosstalk, the output of the MGC3030 measuring system (S1, S2) together with the simultaneous output of the optical sensors (D1, D2) was fitted to the prediction model as presented in equation (1), using the Matlab® function block ‘fitnlm’. This function fits the model to variables in the dataset/table, and returns the nonlinear model which presents a least-square fit of the response to the data. From the nonlinear regression, the fitted parameters b1, b2, b3, b4 and the R2 values were be obtained from the Matlab® output. With the fitted parameters and equation (1), predicted values of distance (Dp1, Dp2) can be obtained using the MGC3030 signals (S1, S2).



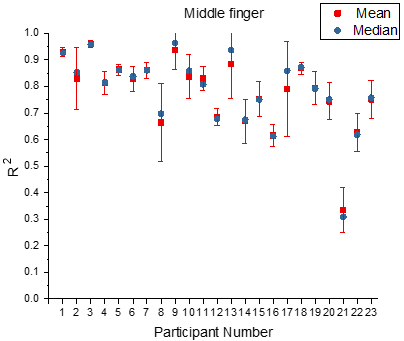
Fig. 3 Signal changes in one sample movement.

# RESULT

In the nonlinear regression process, the distance calculated from the optical sensors (D1, D2) and the MGC3030 signals (S1, S2) fit well with the prediction model (1). Fig. 4 presents the distribution of the R2 values of the regression analysis from the repeated movements of the 23 participants. For each participant, the mean value of R2 values is marked with ‘■’, while the median value is marked with ‘●’. The error bar line ‘-’ represents the standard deviation of the R2 values from the repeated movements. In Fig. 4 (a), the main distribution of R2 values for the index finger is 0.9~1. For most of the participants, the R2 values are significant and precise, which ensures a good nonlinear fit. Similarly, Fig. 4 (b) shows the R2 values for the experiment results from the middle finger. Here, the main distribution of R2 values is 0.6~1. In this experiment, better performance was expected and observed in the index finger, since the only neighboring finger influencing the measurements of the index finger is the middle finger. However, the middle finger is adjacent to both the index finger and the ring finger. Particularly, for participant 21-F, although its R2 value for both fingers are outliers comparing to the other participants, the distribution of the R2 value is quite repetitive.



(a)



(b)

Fig. 4 Standard distribution of R2 values for the regression analysis





Fig. 5 Improvement on crosstalk after using the prediction model

Fig. 5 compares the crosstalk before and after using the prediction model to compensate for both fingers. To better evaluate the performance of the prediction model, data analyses are focused on the steps i and ii where the index finger and middle extend and flex in turn and separately. Fig. 5(a) shows the MGC3030 signal from Rx electrode under the index finger. S1-i refers to the signal change of MGC3030 Signal1 due to the measured movement of index finger. Since S1-ii represents the signal change of MGC3030 Signal1 when the middle finger moves, it shows the largest crosstalk when measuring the movement of index finger using the MGC3030 measuring system. Accordingly, Fig. 5(b) presents the predicted distance after applying the MGC3030 signals (S1, S2) to the prediction model (1). Dp1-i is the predicted distance change of the MGC3030 measuring system for index finger’s movement, whereas Dp1-ii refers to the distance change due to the crosstalk resulted from the movement of middle finger. By comparing the MGC3030 signals in Fig. 5(a) and the predicted distance after fitting to the prediction model in Fig. 5(b), it was observed that the prediction model works well to compensate for the crosstalk. Particularly, there were tiny fluctuations when the middle finger of the participant reached a large height at step iii. These fluctuations were recorded by the MGC3030 system (S2-iii), as shown in Fig.5 (c), while the optical signal remained unchanged (D2-iii), as shown in Fig.3 (a). Possible reasons for the optical sensor tracking loss can be found in Section IV. Sensitivity of the MGC3030 sensor is inversely proportional to its distance from the human body. Therefore, the same MGC signal change will represents a larger distance change at the far end (Dp2-iii), as presented in Fig.5 (d). The predicted distance for index finger (Dp1-iii) also fluctuated because it is a function of S2 as well. Therefore, the MGC3030 signals here show different values compared with the optical sensors. To further evaluate the prediction model on reducing crosstalk for index finger, S1-ii/S1-i, Dp1-ii/ Dp1-i were used to reflect the impact of crosstalk before and after applying the prediction model.

Similarly, Fig. 5(c) presents the MGC3030 Signal2 from the Rx electrode under the middle finger, whereas Fig. 5(d) shows the results after applying MGC3030 signals to the prediction model. S2-i/S2-ii and Dp2-i/ Dp2-ii compare the signal changes due to crosstalk before and after compensated by the prediction model (1) when measuring the middle finger. Here, S2-ii refers to the signal change when middle finger moved, whereas S2-i represents biggest crosstalk due to the movement of index finger. Dp2-ii is the predicted distance change of middle finger’s movement after being compensated, whereas Dp2-i refers to the predicted distance change from crosstalk.

To take a general view on the performance of the prediction model for 23 participants, the impact of crosstalk before and after using the prediction model for both fingers were investigated, as shown in Table III. Here, the experimental result for each participant is the average of the 10 repeated movements. The output of the optical sensors (D1, D2) were analyzed to evaluate the performance of the optical distance measuring system. The comparison with Dx-ii/Dx-i (x=1,2) for both index finger and middle finger is presented in Table III. Here, D1-ii/D1-i refers to the impact of crosstalk on optical sensor1 when measuring the index finger, due to the movement of the middle finger. Based on the experimental results, D1-ii/D1-i of the 23 participants remained below 1%, with an average of 0.38%. Similarly, D2-ii/D2-i represents the impact of crosstalk due to the movement of the index finger, when optical sensor2 measures the middle finger. The D2-ii/D2-i from the output of the optical system is 0.70% on average, and most of them remain below 1%. Possible reasons of outliers here can be found in the discussion. In general, the comparison with D1-ii/D1-i and D2-ii/D2-i demonstrates the good reliability of the optical sensor as a comparing system.

On the basis of the results from the index finger, the average level of crosstalk in MGC3030 Signal1 (S1-ii/S1-i) is 27.14%, which is reduced to 5.49% after applying to the prediction model (Dp1-ii/ Dp1-i). For the middle finger, a bigger crosstalk is expected and observed, considering the anatomical structure of the hand. In this case, the average impact of crosstalk in MGC3030 Signal2 (S2-i/S2-ii) is 70.10%. It indicates that, the crosstalk (S2-i) and the effective signal (S2-ii) in MGC3030 Signal2 have similar magnitudes, as shown in Fig. 5(c). Therefore, simply relating the MGC3030 signal to the distance will bring in a great variation of distance. However, after using the prediction model, the level of uncertainty is greatly reduced, from 70.10% to 6.08% on average. In brief, the experimental results is in accordance with the simulation [10]. For all the tested participants, the crosstalk can be effectively compensated by applying the prediction model to MGC3030 signals.

TABLE III

Experimental results of twenty-three participants: the average percentage of crosstalk before and after using the prediction model

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **Index finger** | | | **Middle finger** | | |
| D1-ii/ D1-i | S1-ii/  S1-i | Dp1-ii/ Dp1-i | D2-i/  D2-ii | S2-i/  S2-ii | Dp2-i/  Dp2-ii |
| **1-F** | 0.88 | 33.13 | 14.95 | 0.79 | 34.69 | 5.05 |
| **2-M** | 0.14 | 32.77 | 3.73 | 0.66 | 47.73 | 7.51 |
| **3-M** | 0.31 | 23.90 | 13.47 | 0.50 | 62.92 | 2.36 |
| **4-F** | 0.89 | 24.56 | 2.90 | 3.31 | 62.11 | 0.68 |
| **5-M** | 0.37 | 26.19 | 8.83 | 0.86 | 49.32 | 13.02 |
| **6-M** | 0.36 | 43.31 | 5.04 | 2.80 | 33.84 | 6.17 |
| **7-M** | 0.55 | 31.07 | 1.78 | 0.58 | 43.62 | 1.72 |
| **8-M** | 0.39 | 42.45 | 0.99 | 0.22 | 59.35 | 1.15 |
| **9-M** | 0.18 | 37.03 | 2.91 | 0.29 | 39.91 | 5.55 |
| **10-M** | 0.56 | 15.08 | 8.84 | 0.24 | 77.69 | 5.24 |
| **11-M** | 0.42 | 39.56 | 2.33 | 0.42 | 36.95 | 3.01 |
| **12-M** | 0.47 | 12.06 | 8.03 | 0.10 | 128.37 | 5.81 |
| **13-F** | 0.52 | 20.84 | 5.73 | 0.54 | 105.71 | 4.45 |
| **14-M** | 0.12 | 21.91 | 4.63 | 0.19 | 102.91 | 3.58 |
| **15-F** | 0.24 | 20.07 | 6.39 | 0.62 | 60.19 | 1.72 |
| **16-F** | 0.25 | 12.09 | 2.48 | 0.03 | 121.01 | 1.11 |
| **17-F** | 0.18 | 25.62 | 2.67 | 0.12 | 52.49 | 2.89 |
| **18-M** | 0.05 | 26.53 | 6.62 | 1.00 | 54.69 | 1.56 |
| **19-F** | 0.30 | 32.33 | 1.67 | 0.59 | 63.05 | 1.98 |
| **20-M** | 0.30 | 26.31 | 6.52 | 1.31 | 50.07 | 5.31 |
| **21-F** | 0.39 | 39.80 | 10.25 | 0.27 | 121.75 | 45.81 |
| **22-F** | 0.42 | 14.92 | 4.06 | 0.26 | 136.74 | 11.13 |
| **23-F** | 0.41 | 22.76 | 1.46 | 0.50 | 67.23 | 2.95 |
| **Mean** | 0.38 | 27.14 | 5.49 | 0.70 | 70.10 | 6.08 |

Note: The first column shows the participant identification number.

In addition to the level of uncertainty reported above, the resolution of absolute distance measurement is also important in real use. Table IV details the uncertainty of measurement and the whole movement range of each participant. The average of the distance change due to crosstalk—Dp1-ii and Dp2-i as presented in Fig. 5--were calculated to represent the resolution of the index finger and the middle finger respectively. With interpersonal difference considered, the average uncertainties using the prediction model are 0.68mm and 0.55mm, which are 3.5% and 2.7% of the average movement range, for index finger and middle finger respectively. Collectively, the average resolutions suggest that, the MGC3030 measuring system is capable of measuring the small movements of fingers.

TABLE IV

Experimental results of twenty-three participants: The uncertainty of measurement and the movement range

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Index finger** | | **Middle finger** | |
| Uncertainty | Movement range | Uncertainty | Movement range |
| **1-F** | 1.29 | 16.33 | 0.68 | 17.33 |
| **2-M** | 0.72 | 26.60 | 1.19 | 25.70 |
| **3-M** | 1.19 | 15.33 | 0.32 | 17.50 |
| **4-F** | 0.12 | 10.33 | 0.04 | 10.00 |
| **5-M** | 0.79 | 12.67 | 0.93 | 16.33 |
| **6-M** | 0.29 | 18.40 | 0.24 | 16.60 |
| **7-M** | 0.29 | 18.64 | 0.30 | 20.82 |
| **8-M** | 0.14 | 24.00 | 0.23 | 29.29 |
| **9-M** | 0.96 | 27.60 | 0.84 | 30.00 |
| **10-M** | 0.88 | 21.17 | 0.98 | 23.50 |
| **11-M** | 0.21 | 17.00 | 0.35 | 15.57 |
| **12-M** | 0.93 | 14.14 | 0.36 | 10.71 |
| **13-F** | 1.01 | 30.75 | 0.68 | 34.38 |
| **14-M** | 1.42 | 29.86 | 0.81 | 32.14 |
| **15-F** | 0.33 | 8.88 | 0.12 | 11.50 |
| **16-F** | 0.43 | 21.75 | 0.16 | 22.25 |
| **17-F** | 0.53 | 24.27 | 0.61 | 27.82 |
| **18-M** | 0.63 | 14.75 | 0.20 | 18.50 |
| **19-F** | 0.63 | 40.88 | 0.55 | 39.50 |
| **20-M** | 0.83 | 17.00 | 0.44 | 19.60 |
| **21-F** | 1.35 | 18.33 | 5.60 | 21.83 |
| **22-F** | 0.47 | 19.67 | 1.63 | 27.67 |
| **23-F** | 0.07 | 8.40 | 0.12 | 8.30 |
| **Average** | 0.68 | 19.46 | 0.55 | 20.59 |

Note: Unit of uncertainties and movement ranges: mm.

# DISCUSSION

This study conducted initial physical trials with twenty-three healthy subjects to validate a noncontact easy-to-use approach for finger displacement measurement. With the experimental results, the vertical moving distance (D1, D2) and the detected MGC3030 signals (S1, S2) fit well with the prediction model in the nonlinear regression process in Matlab®. From the results in Table III and Table IV, the prediction model can greatly reduce the resolution uncertainty, and improve the performance of the MGC3030 measuring system on the contactless multi-finger movement measurement. Although the unintended finger movement is avoided in this experiment, the MGC3030 measuring system can also be used for detecting and recording these movements. It could be helpful in clinical diagnosis and in supporting research into independent finger movement.

Using the prediction model, the average uncertainty of index finger is 0.68mm for individual maximum movement ranges across the participants from 8.40mm to 40.88mm, while the uncertainty for the middle finger is 0.55mm, with the movement range from 8.30mm to 39.50mm. This aligns with the resolution of the prediction model in FEM simulation, which is 0.94mm over a range of 30mm [10]. Additionally, the MGC3030 measuring system can work without a great overhead in signal processing. For each participant, once the personalized fitted parameters (b1, b2, b3, b4) of the prediction model are obtained from the calibration steps reported in this paper, this individualized model can be download to the microcontroller controlling the MGC3030 measuring device. Unlike Electromyography [8] or vision based systems [12], it can be realized with a low cost MCU, such as the microcontroller (NXP LPC1768) used in this research. Together with the low-cost feature of the MGC3030 chip (4 GBP), the system can be realized as an inexpensive and portable system. The option of not having individual calibration, but to share a standard fitted parameters (b1, b2, b3, b4), will also be investigated in the future. Although this gives reduced absolute accuracy, it may be suitable for relative measurements for tracking improvements. Coupled with the contactless measurement function, the MGC3030 measuring system requires no additional effort such as set-up and wearable attachments, and is particularly user-friendly for patients for independent home-based use.

It was also observed from the experiments that the optical sensors had unpredictable tracking failures while the MGC3030 measuring system worked consistently well with robust outputs. Fig. 6 presents two example movements recorded from experiment, each contains the output from both the optical sensor and the MGC3030 measuring system. Fig. 6(a) present the example output from optical sensor with tracking failures and shown in Fig. 6(b) is the simultaneous MGC3030 output. Fig. 6(c) and Fig. 6(d) are the example outputs from the optical system without tracking failures and from the MGC3030 measuring system, respectively, which are presented for comparison. For each movement, a participant was required to extend and flex their index finger twice. Therefore, the signal from the optical sensor1 should be smooth with two peaks, as presented in Fig. 6 (c). In plot (a), the optical sensor signal increases until it reaches about 25 mm at 9.5s, as marked in the figure. Here, the signal should continue but instead falls down to below zero at 9.8s, as the sensor has lost track of the index finger. The distance below zero refers to the movement when the whole hand has moved away from the receptacle, which is obviously not true considering the standard movement required. Meanwhile, there are very sharp spikes observed in plot (a), which indicate abnormal movements for human fingers.

These spikes and sharp signal changes in output of the optical sensors were hard to avoid for many participants in this study. Therefore, the output from the optical sensors and MGC3030 system were reviewed at the end of each set of 10 movements. If tracking failure was observed, the participant was asked to repeat the whole 10 movements again, until 10 available movements for data analyzing was obtained. The record for the repeated movements conducted by each participant due to tracking failure, is presented in Fig. 7. Here, participant 1-F completed the experiment in 1 attempt, while participant 4-F conducted 5 attempts before a set of 10 measurements was acceptable. It suggests the alignment of the optical system is critical to obtaining high quality data.

One possible reason is that, there were very small tremors or adductive/abductive movements when participants were extending and flexing their fingers, which resulted in a horizontal offset. However, the outer surface of a finger is complex and uneven, and therefore, vertical errors were introduced. These horizontal movements were naturally hard to avoid, especially for patients with hand impairment. A fiducial marker can effectivley reduce the errors of the optical system resulting from these horizontal movements under laboratory conditions. However, it has to be well placed and attached, which requires great effort and might hinder the movement of fingers. On the contrary, the signal detected by the MGC3030 measuring system is dominated by the closest object intruding the field lines. This refers to fingers in this application with a certain horizontal width. Hence, one of the advantages of the reported measuring system compared to an optical system is its insensitivity to small horizontal errors, which is in accordance with the experimental results. Future experiments with measurements in the horizontal direction will be carried out to quantitatively analyze the tolerance of the horizontal offset.

Another possible reason is that, when fingers move up, the increasing angle of incidence (AoI) could potentially affect the accuracy of the optical sensors. A positive correlation between AoI value and error magnitude was reported on short range distance measurement [14]. As an example, when AoI is 0°, the mean absolute error of an IR-ToF sensor (VL6180X) is 1.5mm. Errors reached 7.8mm (static) and 25.6mm (dynamic) for AoI equal to 60°. In contrast, the prediction model for the MGC3030 measuring system can be defined as the integration of the cross section simulation models, as presented in Fig. 1. When a finger is inclined to the horizontal plane in the experiment, it can be represented by the superposition of multiple 2D simulation models where the Dx were set to different numbers accordingly.





Fig. 6 Example outputs from experiment: a) Output from optical sensor with tracking failures; b) Output from the MGC3030 measuring system measured simultaneously with plot (a); c) Output from optical sensor without tracking failures; d) Output from the MGC3030 measuring system, measured simultaneously with plot (c)

Collectively, although the optical measuring technique has limitations for finger motion measurement, reliable data was obtained and used in this study. The prediction model works well with the MGC3030 measuring system in most of the 23 participants. The application of the MGC3030 measurement system as a repeatable measurement has been demonstrated, and gives confidence that such a system is an excellent candidate for application in a home based system.

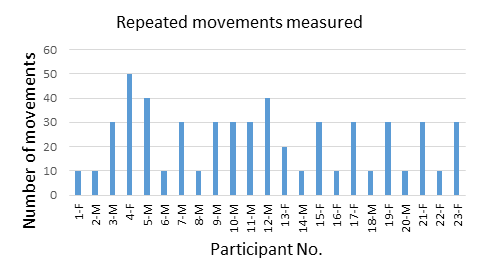


Fig. 7 Repeated movement conducted due to tracking failure

# CONCLUSION

This article reports on initial physical trials to extend the understanding of the performance of the prediction model on multi-finger non-contact measurements, performed by 23 healthy subjects under laboratory conditions. It was observed from experiments that the MGC3030 measuring system worked well with robust and repeatable outputs, whereas the optical comparison sensors had unpredictable tracking failures. The prediction model performs well on measuring the combined finger motion, and greatly compensates the crosstalk. The average resolution of the MGC3030 measuring system are 0.68mm and 0.55mm, which are 3.5% and 2.7% of the full-scale range, for index finger and middle finger respectively. It demonstrates the ability of the proposed system on measuring the movements of fingers. The MGC3030 measuring system also provides the potential to be realized in an inexpensive and portable device. The combination of the noncontact measuring feature and the lack of complicated set-up (physical connection of electronics), makes it particularly attractive as the basis of an easy-to-use home-based independent rehabilitation system.

Acknowledgment

We acknowledge the support of the University of Southampton, United Kingdom, the China Scholarship Council, and Xiamen University, China.

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1. Manuscript received January 27, 2020. This work was supported by University of Southampton, Hampshire, United Kingdom, the China Scholarship Council, Beijing, and Xiamen University, Fujian, China.

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