Development and Preliminary Validation of a Low-Cost Portable Tool for Assessing Joint Mobility

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Abstract. This paper presents the development and preliminary feasibility evaluation of a small, low-cost computer-aided device for joint measurements in humans with the aid of a flex sensor attached to an Arduino Nano. Commercially available goniometers are frequently either costly or complex and require a calibration kit that is not feasible for healthcare and rehabilitation facilities with scarce resources. A solution is therefore needed that does not rely on extensive access facilities, and the proposed device is designed to fill this requirement. Preliminary measurements on a single healthy participant verified the system's initial functionality as proof of principle. Descriptive comparison with readings from a reference goniometer of joint-angle measurements. Finally, the system achieved a mean absolute error (MAE) of 8.21° and a mean absolute percentage error (MAPE) of 16.73% with better performance in joints that present larger ranges (e.g., elbow and knee) compared to smaller ones or rotational movements. As a proof-of-concept, this study sets the stage for future research that will include multi-participant testing and post-processing and improved mechanical alignment and calibration procedures to further improve measurement accuracy.

Keywords: flex; joint mobility; range of motion; biomedical device; validation; low-cost tool.

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1 Introduction

Evaluating the biomechanical properties of body joints is necessary for diagnosing and monitoring muscular and skeletal conditions and for rehabilitation objectives [1]. Joint stiffness and range of motion are frequently estimated to determine joint functionality. Advanced dynamic measurements are accurate yet often expensive, unwieldy, and impractical for routine clinical use [2]. Traditional methods such as manual goniometers are affordable, but accuracy relies on the operator and is not suitable for continuous measurements. Inertial Measurement Unit (IMU)-based systems have higher accuracy with greater costs and calibrations. These limitations indicate the necessity for a cheap, portable, and low-cost device with an acceptable precision in monitoring rehabilitation [3–9].

Latest advancements in joint-mobility estimation have explored a wide spectrum of sensing techniques, ranging from simple wearable devices to advanced camera-based systems. Kobayashi et al. proposed a wearable setup that relies on plantar pressure sensors to estimate lower limb motion [10]. In a related direction, Jinke Chang et al. created a boron nitride nanotube (BNNT)-based sensor integrated with artificial intelligence algorithms to examine joint movements. This work meditates on the rising consent of smart materials and machine learning techniques to improve the precision of motion analysis systems [11]. Researchers in Ref. [12] assessed six deep learning models to analyze running kinematics, viewing that camera-based systems may challenge traditional sensor-based procedures in assessing angles of trunk, hip, and knee joints.

Despite the presentation of several motion measurement technologies, such as goniometers, IMU-based systems, and flexible sensors in the literature, it appears that the applied technique in each category has respective limitations that prevent extensive clinical use. Manual goniometers are relatively cheap and simple to use, but they depend significantly on the operator's proficiency, provide variable accuracy, and cannot be used to monitor joint motion continuously. distortion supply improved accuracy but are prone to signal distortion, require frequent calibration, and are often expensive. Flexible sensors are investigated as an alternative, but most of today's implementations require multi-sensor arrays, complex electronics, or machine learning and run into issues of price and complexity. These limitations emphasize a significant gap between simple, low-cost tools and complex laboratory systems.

The work presented in this paper is an attempt to fill this gap by creating a low-cost and compact device using a single sensor for initial joint angle detection that can be employed for motor rehabilitation purposes. The main contribution of this work is its minimalistic component specification and ease of calibration. This proof-of-concept study sets the stage for larger studies comprising a larger number of participants and more solid validation.

2 Methods and Materials

The system was built based on simple, available and low-cost electrical parts for biomedical applications. The system consists of a combination of hardware and software parts, outlined below.

2.1 Hardware Elements

The hardware for this project was selected to be inexpensive and, especially, highly compatible with the biological environment. A flex sensor is the main component for measuring bending, as its resistance changes with joint movement [13]. An Arduino Nano (3.3 V) board was used to read the analog signal and process the data directly during movement. An organic light-emitting diode (OLED) screen was also added to display the joint angle in real time during movement. whole system, with a 10-kilohm resistor looped in to constitute a voltage divider circuit.

The full electronic diagram of the device used is shown in Fig. 1. The system works as a voltage divider with the flex sensor serving as a variable resistor in series to $R2$ of 10 KΩ. The voltage at the junction of this divider (1/2 scaling) is provided to analog input pin A0 on the Arduino Nano.

Power needs of the Arduino are met by a 3.7 V lithium-ion battery supported by a step-up converter to keep voltage consistent at 5 V. The 0.96" OLED display working with the I^2C protocol is connected via sets of lines serial data line (SDA) and serial clock line (SCL) hooked up to $A4$ and $A5$ pins. This arrangement enables a compact and efficient sensor data visualization.

The operational characteristics of the flex sensor include a sensitivity 0.5–1.0 kΩ change per 10° of bending, hysteresis 3–5% depending on bending speed, temperature dependence resistance approximately ±0.36% per $°C$ and response time of <50 ms. The features were considered during calibration, and temperature was controlled to reduce thermal drift.

2.2 Calibration Procedure

For calibration, a mechanical reference device (Baseline® HiRes Plastic Goniometer, USA; accuracy ±1°; range 0–180°) was used, and known joint angles from 0–150°, were recorded in increments of 10°. Three resistance measurements for each angle were taken from the sensor and averaged to obtain a stable and consistent value. Subsequently, from an electrical standpoint, the employed voltage divider configuration introduces a nonlinear relationship between the measured output voltage and the sensor resistance, which can be expressed as following:

$$V_{out}=V_{in}\frac{R_2}{R_2+R_{\text{flex}}}, \quad (1)$$

where R_2 is the fixed resistor and R_{flex} is the variable resistance of the flex sensor.

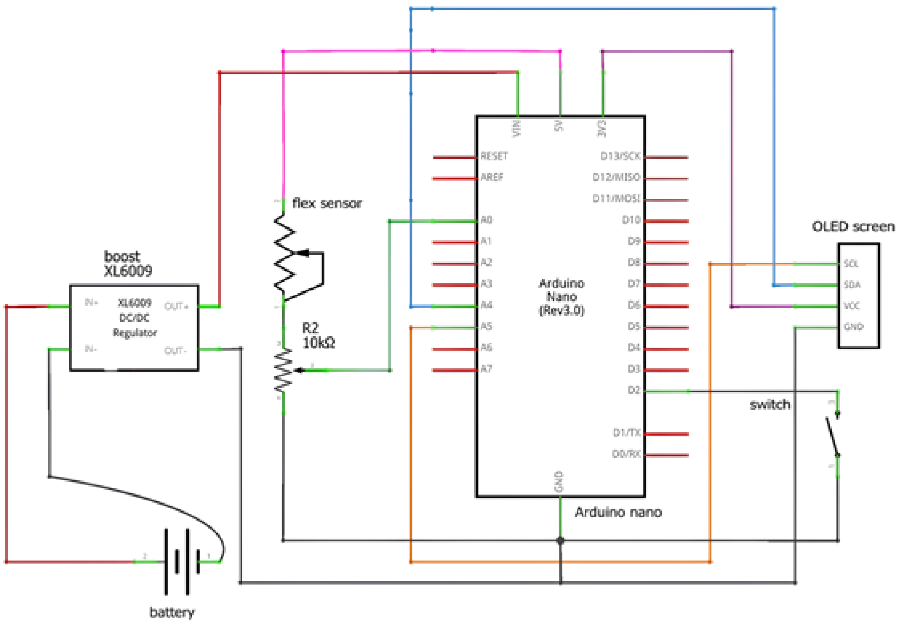


Fig. 1 System schematic diagram.

However, when considering the experimentally obtained resistance-angle data within the calibrated angular range, the relationship between sensor resistance and joint angle exhibited a monotonic and quasi-linear behavior. Therefore, a linear regression model was adopted as a first-order empirical approximation to map the measured resistance values to joint angles:

$$\theta = mR + b, \tag{2}$$

where θ is the joint angle, R is the measured resistance, and m and b are the regression coefficients.

A first-order linear regression model was employed to facilitate real-time angular estimation. This approach prioritizes computational efficiency for mobile rehabilitation monitoring, while the observed quasi-linear response of the sensor within the target angular range (0–150°) justifies the use of a linear approximation for this preliminary proof-of-concept.

Fig. 2 illustrates the experimental calibration curve obtained using a reference goniometer. The relationship between joint angle and flex sensor resistance demonstrates a monotonic and quasi-linear trend within the calibrated angular range. Although the electrical voltage divider configuration introduces an inherently nonlinear relationship between voltage and resistance, the experimentally measured resistance values vary approximately linearly with joint angles for the range of motion considered in this study. Therefore, a first-order linear regression model was adopted as an empirical approximation to enable real-time angle estimation with minimal computational complexity. This approximation is suitable for the proof-of-concept nature of the proposed system, while deviations from linearity, particularly at small angles and rotational movements, are acknowledged and discussed. This curve was implemented in the Arduino code for providing resistance-to-joint angle conversion during device use.

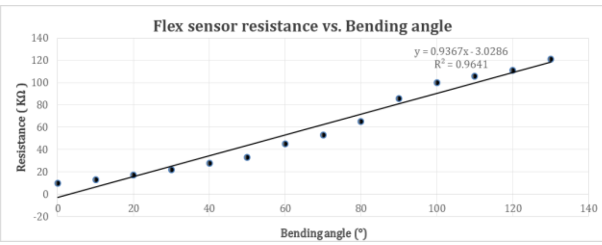


Fig. 2 Flex sensor bending angle and the corresponding sensor resistance.

2.3 Data Collection and Software Processing

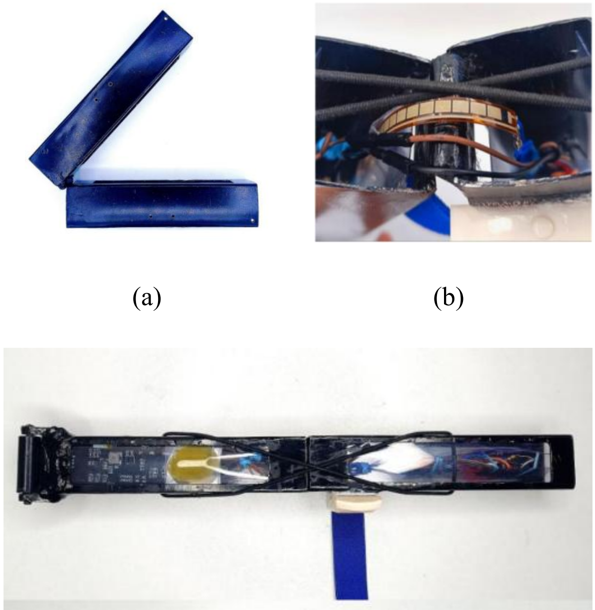
The system was based on an Arduino Nano at 3.3 V using a 10-bit ADC. Implementation of the calibration model results in an angular resolution of 0.1° per ADC step. Sensor recording was sampled at 50 Hz, adequate to track the slow and moderate movement performed in most rehabilitation exercises.

A moving average filter of 5 sample points was applied to reduce high-frequency noise and decrease the flexure hysteresis. These processed signals were displayed on an OLED screen (refresh rate = 10 Hz) to have the smoothed and real-time display with no lags that are perceived.

With a 10-bit ADC (0–1023) counts, this system gives a theoretical angular resolution of approximately 0.09° per ADC step in the 0–90° field. The effective measurement resolution is currently limited by sensor hysteresis, temperature sensitivity and mechanical alignment.

2.4 Mechanical Design

The mechanical structure is composed of two segments, each measuring 10 cm in length: a fixed section attached to the proximal part of the limb and a movable section aligned with the distal part. The flex sensor was placed over the joint so that it will bend with the movement of the limb. A soft and adjustable strap was used to secure the device in place and ensure suitable alignment with the joint's axis of rotation. Fig. 3 shows the physical prototype of the device applied to various joints.



(a) (b)

(c)

Fig. 3 Apparatus set-up of the proposed flex sensor-based joint mobility device: (a) side view, (b) sensor placement, and (c) top view.

2.5 Measurement Protocol

A standardized measurement protocol was performed to ensure logicality across all evaluated joint movements. All movements were performed 3 times, and the mean value was used for analysis. The participant was seated or supine based on accepted clinical measurement protocols to account for body positioning variability. to install the device for getting accurate readings, a belt with a width of 2.5 cm was used for both fixed and movable parts.

Movements were performed at a controlled speed of approximately 30° per second, and participants were instructed to start from a neutral position (0°) and move to the farthest comfortable range of motion. take A two-second pause between reps to prevent fatigue and possible sensor drift.

To minimize other sources of systematic error, such as strap tension, small misalignments between the sensors and sensor straps, or hysteresis related to the curvature of the sensor assemblies, apparatus alignment was checked before each group of movements. All observations were made in a controlled indoor environment at 30 ºC with constant illumination and surface condition so that interference factors are minimized.

3 Results

This work was conducted as a pilot on a single healthy participant aged 22 years to evaluate the initial device performance before further studies are conducted with a larger pool of participants. Several joints at multiple movements (elbow, wrist, shoulder, cervical spine, knee and ankle) were measured [14]. The results were benchmarked against those from a reference device to test the correctness of the system.

3.1 Joint Angle Measurements

Twelve joint motions were measured, with each motion recorded three times; thus, 36 measurements were collected for accuracy assessment.

Table 1 summarizes the measured joint angles for different movements and shows the configuration for each region and its optimal placement. Results show variability depending on joint type and range of motion.

3.2 Accuracy Evaluation

Table 2 provides a comparison of the proposed system with the reference device and shows the absolute differences in scores and percentage errors. The results include the following:

- Low Error (< 10%): in elbow flexion, shoulder forward flexion and knee flexion with average differences ranging from 4° to 15°.
- Moderate Error (10–29%): Found in wrist palmar/dorsiflexion, shoulder extension and cervical lateral flexion
- High Error (> 29%): Primarily associated with complex or small-range motions, such as cervical flexion (29.67%) and internal knee rotation (52.56%).

Table 1 Measured joint angles for different movements.

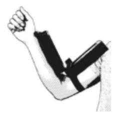
	Joint Name	Elbow
	Joint Movement	Elbow flexion
	Measured Angle	128°
	Joint Name	Wrist
	Joint Movement	Wrist radial deviation
	Measured Angle	15.73°
	Joint Name	Wrist
	Joint Movement	Wrist dorsiflexion
	Measured Angle	50°
	Joint Name	Wrist
	Joint Movement	Wrist palmar flexion
	Measured Angle	60°
	Joint Name	Shoulder
	Joint Movement	Shoulder extension
	Measured Angle	66.52°
	Joint Name	Shoulder
	Joint Movement	Shoulder forward flexion
	Measured Angle	160°
	Joint Name	Cervic
	Joint Movement	Cervical flexion
	Measured Angle	30.24°
	Joint Name	Cervic
	Joint Movement	Cervical lateral flexion
	Measured Angle	35.37°
	Joint Name	Knee
	Joint Movement	Knee flexion
	Measured Angle	136.31°
	Joint Name	Knee
	Joint Movement	Internal rotation
	Measured Angle	13.73°
	Joint Name	knee
	Joint Movement	External rotation
	Measured Angle	9.98°
	Joint Name	Ankle
	Joint Movement	Ankle dorsiflexion
	Measured Angle	18°
	Joint Name	Ankle
	Joint Movement	Ankle plantar flexion
	Measured Angle	40.5°

Table 2 Comparison between user device measurements and reference device.

Joint Movement	User Device (°)	Reference Device (°)	Difference (°)	Difference (%)
Elbow flexion	128.0	140	–12.0	–8.57
Wrist radial deviation	15.73	18	–2.27	–12.61
Wrist dorsiflexion	50.0	65	–15.0	–23.08
Wrist palmar flexion	60.0	75	–15.0	-20.0
Shoulder extension	66.52	55	11.52	20.95
Shoulder forward flexion	160.0	175	–15.0	–8.57
Cervical flexion	30.24	43	–12.76	–29.67
Cervical lateral flexion	35.37	42	–6.63	–15.79
Knee flexion	136.31	130	6.31	4.85
Knee internal rotation	13.73	9	4.73	52.56
Knee external rotation	9.98	9	0.98	10.89
Ankle dorsiflexion	18.0	18	0.0	0.0
Ankle plantar flexion	40.5	45	–4.5	–10.0

3.3 Statistical Analysis

Since this study included only one participant, all statistical values (MAE and MAPE) are reported as descriptive indicators rather than inferential statistics. No hypothesis was performed. The overall performance of the device was assessed using two statistical metrics: MAE and MAPE. MAE was calculated using the following Eq. (3):

$$MAE = \frac{1}{n}\Sigma|y_i - \hat{y}|. \tag{3}$$

A mean absolute percentage error (MAPE) was calculated using the following Eq. (4):

$$MAPE = \left(\frac{100\%}{n}\right)\Sigma\left|\frac{(y_i - \hat{y}_i)}{y_i}\right|, \tag{4}$$

where y_i represents the actual value, $\hat{y}_i$ denotes the predicted value, and n signifies the total number of samples, in this study $n = 36$, corresponding to 12 joint movements recorded three times each [15, 16].

The analysis yielded the following results: MAE = 8.21 and MAPE = 16.73%.

4 Discussion

The prototype was sufficiently accurate for joint angle measurements involving a large range of motion, such as flexion angles in the elbow and knee. The system had low accuracy in detecting small motion or rotational movements, which was related to factors including hysteresis, declination and minor changes of the tension of fixing ligaments. This work should be considered a proof-of-principle preliminary investigation. Given the single-participant nature of this pilot study, the findings serve as a preliminary validation rather than a generalizable clinical assessment. Consequently, the reported MAE (8.21°) and MAPE (16.73%) function as descriptive performance indicators to guide future multi-subject trials. The lack of heterogeneity within subjects also limits the assessment of uniformity of device performance when limb geometry, tissue stiffness or anatomical structures vary.

In clinical settings, the performance of the device is close to acceptable for basic rehabilitation monitoring (tolerance around 5–10°). Studies examining the minimal clinically important difference (MCID) for ROM measurement of joints suggest that changes are considered clinically meaningful within a range of 6–10°, depending on the joint and patient population [17, 18]. Patients generally consider changes below this threshold as undetectable, and they do not impact clinical management. Additionally, standard clinical instruments like manual goniometers have an inter-rater error of 5–10° and are therefore accepted as tolerable in rehabilitation. Considering this evidence, the measuring error found in our study (5–15°) is compatible with a clinically acceptable degree of error for assessing patients' follow-up, especially to measure joints that have large angular displacements like the knee, hip and elbow. Thus, although not appropriate for diagnostic nor high-precision use, the device provides precise enough information for simple rehabilitation follow-up and longitudinal monitoring. The large errors regarding rotational motion are, as mentioned above, the modality's limitations and indicate that this design is not suitable for diagnostic purposes or high-precision measurements with an error of less than 3°. Potential improvements include the use of a dual-sensor arrangement and better mechanical mounting to increase measurement accuracy and system efficiency. The use of a linear calibration model represents a trade-off between computational simplicity and accuracy, which was deemed acceptable for preliminary rehabilitation monitoring applications.

5 Cost Analysis

Table 3 indicates that the prototype device is priced at $27, which is seen as economical in comparison to commercial devices that may reach costs of up to $500.

Table 3 Device cost.

Component Name	Cost
Flex sensor	12$
Arduino nano	6$
OLED display	5$
Battery	3$
Wiring	1$
Total	27$

6 Limitations

Although the prototype yielded promising initial results, the limited sample size makes it difficult to statistically synthesize the findings. Furthermore, the positional accuracy of measurements is very sensitive to the alignment of a sensor relative to the joint's axis of rotation. Rotational measurements are also inaccurate because the design uses a single sensor, which is not good at capturing complex movements.

7 Conclusion

This paper presented an inexpensive, single-sensor implementation for preliminary joint-angle estimation. For movements of large angular changes, the prototype showed uniformity in performance, further indicating the application potential of the flex-sensor technology to essential rehabilitative settings. The increased errors for rotating and small amplitude motions reveal inherent limitations of the current structure. The study was single-subject, and the results cannot be generalized because of the statistical limitations that it is a preliminary (proof-of-concept) rather than definitive assessment of device effectiveness. Further research efforts will focus on addressing the methodological limitations affecting measurement precision, as highlighted by preliminary results that revealed drawbacks in using only one flex sensor. This analysis will include devising temperature-compensation algorithms that can compensate for changes in the resistance of the sensor caused by environmental and/or physiologically induced changes in temperature. The mechanical rigidity and its alignment with the joint anatomic axis of rotation will be improved and dual-sensor configurations can also be investigated to better follow multi-planar movement while significantly mitigating inaccuracies related to hysteresis. Together, these improvements, when combined, should enhance the overall accuracy of the system, especially for small-range and spinning movements.

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Disclosures

All authors declare that there is no conflict of interest in this paper.

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