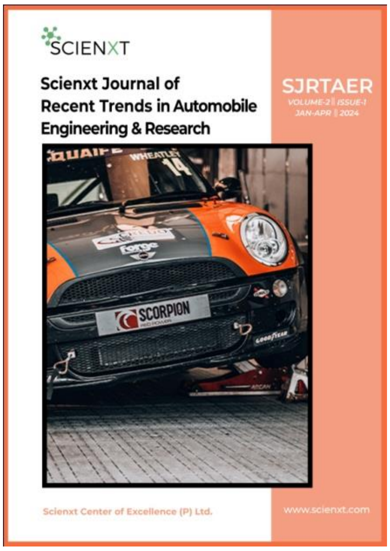

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Motion velocity, acceleration and energy expenditure estimation using micro flow sensor motion

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Abstract:

This paper presents a groundbreaking solution for quantitatively assessing physical recovery and designing exercise interventions for post-stroke patients with neurological impairments. By leveraging a micro flow sensor, our proposed wearable device enables accurate estimation of motion velocity, acceleration, and energy expenditure during human limb motion.Our approach utilizes a homemade micro thermal flow sensor to precisely detect motion velocity. To extract motion acceleration, we introduce a Jerk–Kalman based algorithm, enhancing the reliability of our estimations. By integrating motion velocity and acceleration data, we are able to estimate the energy expenditure associated with limb motion.We conducted calibration experiments and applied our methodology to real-world scenarios to validate its effectiveness. The results demonstrate that our micro flow sensor-based motion estimation method is not only free from accumulated errors but also robust for dynamic motion measurements. This promising approach offers a valuable auxiliary tool for evaluating energy expenditures during rehabilitation training, providing crucial insights for post-stroke patient care and recovery.

Keywords:

Flowsensor, Kalmanfilter, motionacceleration, motionvelocity, energyexpenditure.

1. Introduction:

Stroke, also known as a cerebrovascular accident (CVA), is characterized by a sudden interruption in blood flow to the brain, resulting in brain cell death and subsequent neurological deficits. In China, stroke-related deaths exceed 1.6 million annually, surpassing heart disease as the leading cause of adult mortality and disability. Long-term disability often involves persistent upper limb impairments, with studies indicating limited functional recovery in patients with significant arm weakness. The restoration of upper limb function through exercise-based interventions administered by healthcare professionals is crucial for improving post-stroke patients' quality of life. However, current assessmentequipment for rehabilitation training is bulky and impractical for daily use, highlighting the need for a wearable and reliable device for quantitative evaluation of human limb training and motor function recovery.

Energy expenditure (EE) is a key metric for assessing exercise and recovery status. Conventional methods like Doubly Labeled Water (DLW) and room calorimetry provide whole-body EE assessments, making them unsuitable for assessing partial segments such as post-stroke patients' limb recovery in daily life. With advancements in microelectromechanical technology, wearable devices utilizing micro inertial sensors like accelerometers or inertial measurement units (IMUs) have emerged as promising solutions for EE estimation. However, accurately estimating mechanical energy of human limbs involving motion velocity and acceleration remains challenging due to accumulated errors and drifts associated with IMU-based integral methods.

To address this challenge, we propose a novel motion estimation device using a micro flow sensor to detect surface flow induced by human limb movement, enabling the determination of motion velocity and acceleration. We introduce a Jerk–Kalman filter to extract motion parameters from the flow sensor outputs, facilitating quantitative assessment of EE through the calculation of kinetic powers of the upper arm and forearm. Experimental validation confirms the effectiveness of motion velocity and acceleration measurements using the flow sensor, offering a promising approach for estimating human limb EE during rehabilitation training. The developed device is wearable, user-friendly, and cost-effective, providing a valuable tool for objective evaluation of human limb motion in rehabilitation settings.

The combination of "jerk" and the "Kalman filter" in the context of dynamic systems suggests an approach to state estimation that considers not only acceleration but also the rate of change of acceleration (jerk). In dynamic systems analysis, jerk represents the third derivative of Position with respect to time and reflects how quickly acceleration is changing. Integrating jerk into the Kalman filter algorithm could enhance state estimation accuracy in scenarios where sudden changes in acceleration are significant. By incorporating jerk measurements alongside acceleration and possibly other parameters, such as velocity and position, the filter could better predict the state of a dynamic system, especially in applications like robotics, autonomous vehicles, or motion control systems.

2. Literature survey:

Microscale flow sensors are integral to advancing scientific and technological frontiers, particularly those based on microelectromechanical systems (MEMS), which have gained prominence in monitoring gas flow in industrial settings, environmental sensing, marine condition detection, and biomedical analysis. MEMS-based sensors offer compactness, energy efficiency, high sensitivity, and compatibility with mass production, making them essential components in applications like "smart skin," the Internet of Things (IoT), and flight control.Over the past three decades, numerous MEMS flow sensing methods have emerged, primarily operating on thermal or mechanical principles. Thermal sensors, though widely adopted for their robust manufacturing processes, linear characteristics, and absence of moving parts, suffer from drawbacks such as high power consumption, calibration needs, heat dissipation, and challenges in miniaturization.

Efforts have been directed towards reducing the power consumption of thermal flow sensors, leveraging advancements in microelectronic device design and fabrication.Mechanical flow sensors, on the other hand, remain crucial, particularly in measuring water flow, especially in laminar conditions. They utilize principles such as drag or lift force sensing, frequency monitoring, or artificial hair sensor designs. Despite being adept at detecting low flow rates, mechanical sensors face difficulties in measuring higher flow rates.Recent studies have introduced an innovative flow sensing principle that combines thermal and mechanical responses in a bifurcation-type sensor. This sensor utilizes an initially curved double-clamped silicon microbeam, exhibiting bistablebehavior, thus showing high responsiveness to external stimuli near equilibrium states. This property makes it highly sensitive to changes in heat transfer caused by flow, with potential for significant power consumption reduction. The sensitivity of this sensor is comparable to or better than state-of-the-art thermal flow sensors.

While the feasibility of employing such devices for airflow sensing has been demonstrated through theoretical analysis and experimental testing, further exploration is needed to understand their response to various influencing factors, including overheat ratios, sensitivity to flow loading, and noise and vibrations during turbulent flow measurements. This study investigates these interactions, employing a multi-point Doppler laser vibrometer to visualize the beam's shape during transitions between equilibrium states, revealing previously predicted phenomena and highlighting the need for refining mathematical models.

Injection molding is widely acknowledged as a cost-effective method for producing intricate polymer components with high replication accuracy. However, the complexity of the process, involving multiple devices and intricate molds, presents challenges in ensuring consistency across various parameters such as material flow, machine status, and product quality.Throughout the injection molding process, various parameters such as plasticization temperature, injection pressure, and holding pressure are crucial but subject to fluctuations influenced by the manufacturing environment. Monitoring these parameters alone may not provide detailed.

During plasticization and injection, monitoring melt viscosity is essential as it reflects flow resistance and aids in adjusting material processing. The clamping mechanism's kinematics and dynamics, along with clamping force, significantly influence mold closure consistency.In the packing and cooling stages, pressure and temperature in the cavity affect polymer shrinkage, impacting product quality. Careful detection of ejector force is vital to ensure surface quality during component ejection.Sensing technologies such as in-cavity sensors, nozzle sensors; tie-bar sensors, ultrasonics, and magnetic levitation have advanced measurement techniques in injection molding, providing data on machine status, melt flow, and product quality.

Maintaining stable machine conditions is crucial for consistent material processing and product quality. Advancements in parameters related to machine status, such as clamping force and demolding friction force, have been significant, ensuring optimal performance and prolonging equipment lifespan.Proper application and monitoring of clamping force and friction force during ejection minimize product shrinkage and surface damage. The kinematics and dynamics of the clamping mechanism, especially in five-point double-toggle units, directly impact production efficiency and force amplification during mold-closing and melt-filling processes.Machine status measurement is essential for optimal manufacturing performance, with numerous recent studies focusing on these topics.

A rising demand for micro- and nano-fluidic applications underscores the necessity for precise management of fluid flows at scales as small as nanoliters per minute. These applications, including drug infusion, nano-electrospray ionization, and high-pressure liquid chromatography, hinge on exact flow rate measurement to optimize their functioning. Minute fluctuations in flow rates can have pronounced effects on outcomes, such as fluctuations in ionization response in nanoESI or the blurring of chromatography peaks in HPLC.Nevertheless, there are significant challenges in accurately quantifying and controlling uncertainty in dynamic flows. While some research groups have devised traceable calibration systems to measure rapidly changing flow rates down to 5 nl/min, these measurements are typically of short duration and cannot be continuously monitored. Gravimetric methods, which are considered the benchmark for traceable microflow measurements, encounter limitations when it comes to dynamic nanoflows due to prolonged integration times and uncertainties related to evaporation and system geometries.Micro-particle imaging velocimetry offers high precision but demands detailed knowledge of system parameters, sophisticated microscopy equipment, and extended observation periods, making it less practical for real-time monitoring of nanoflows.Given these obstacles, there exists a pressing need for a novel metrology technique capable of accurately assessing fast-changing flows in the nanoliter per minute range, effectively bridging the gap between existing measurement methodologies and the demands of emerging microfluidic systems.

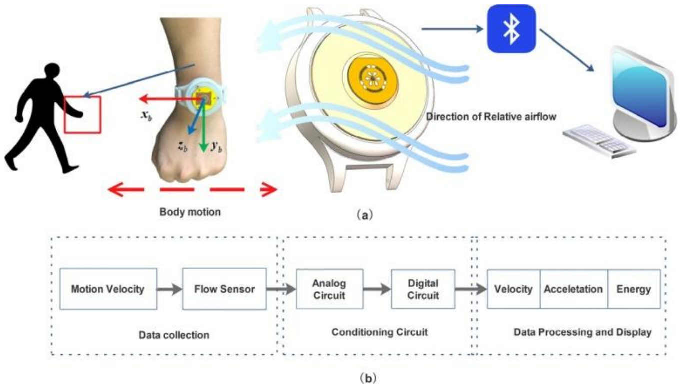

Figure. 1: (a) A brief process of motion tracking based on the flow sensor. (b) A briefchart of motion tracking system

3. System and measurement principle:

In certain cases of biomechanics, simpler two-dimensional (2D) analyses are applicable, such as in walking and sprinting, which predominantly occur in sagittal planes. Similarly, prescribed limb rehabilitation movements can be viewed as 2D movements in the sagittal plane. In this study, we propose utilizing a micro flow sensor to detect surface flow induced by limb movement. An illustration of motion estimation using the micro flow sensor is depicted in Fig. 1. The sensor's coordinate system (xbybzb) shown in Fig. 1 is defined as Left-Forward-Upward, where xb points leftward, yb points forward, and zb points upward.

Airflow is generated along the surface of the flow sensor attached to the limb during limb movement, and this airflow is detected by the sensor. Electrical signals are then generated from the flow signal and sent to either a PC or a mobile phone. Motion velocity and acceleration are subsequently derived using a Jerk–Kalman filter. Additionally, the energetic expenditure (EE) of the limb is evaluated by integrating the motion velocity and acceleration product.

In Fig. 2 (a), the estimation device is depicted, consisting of a custom-made micro thermal flow sensor, a signal conditioning circuit, a Bluetooth module, and a rechargeable lithium battery, all enclosed within a watch-like casing. Fig. 2 (b) illustrates the flexible flow sensor, composed of three inner circular Pt wires and three outer concentric Pt wires mounted on a flexible polyimide substrate. The outer Pt wires, known as cold films, serve for temperature compensation, while the inner circular Pt wires, referred to as hot films, and are responsible for wind velocity detection. These Pt wires are fabricated on a 50 µm thick polyimide substrate using lithography and sputtering techniques. The temperature coefficients of resistance for the manufactured Pt thermal elements are measured to be approximately 2000 ppm/K.

The thermal flow sensor operates on the principle of heat transfer from the hot film elements to the surrounding area, creating a temperature distribution known as the hot zone above the sensor surface. These hot films function within a constant temperature difference (CTD) circuit, serving both as Joule heaters and temperature sensors. In a stationary state, the sensor does not induce surface flow, resulting in the hot zone being centrally located on the sensor surface, as depicted in Fig. 2(c). However, when the sensor moves with a certain velocity and direction, surface airflow is generated over the hot zone, causing the hot zone to deviate from its central position along the flow direction. This deviation is detected by the three hot-film elements, enabling the extraction of motion velocity and direction angle.

The thermal flow sensor functions on the principle of heat transfer, where the hot film elements transfer heat to the surrounding environment, creating a temperature distribution known as the hot zone above the sensor's surface. This distribution is pivotal in detecting surface airflow induced by motion.In detail, the hot films are integral components of a constant temperature difference (CTD) circuit, serving dual roles as both Joule heaters and temperature sensors. This configuration ensures consistent operation and accurate sensing capabilities. During static conditions, when there is no surface flow generated, the hot zone remains centrally positioned on the sensor surface, as depicted in Fig. 2(c). However, when the sensor undergoes motion with a specific velocity and direction, airflow is generated over the sensor's surface; leading to a deviation of the hot zone from its central location along the flow direction. This deviation in the hot zone is meticulously detected by the three hot-film elements. By analyzing the deviations.

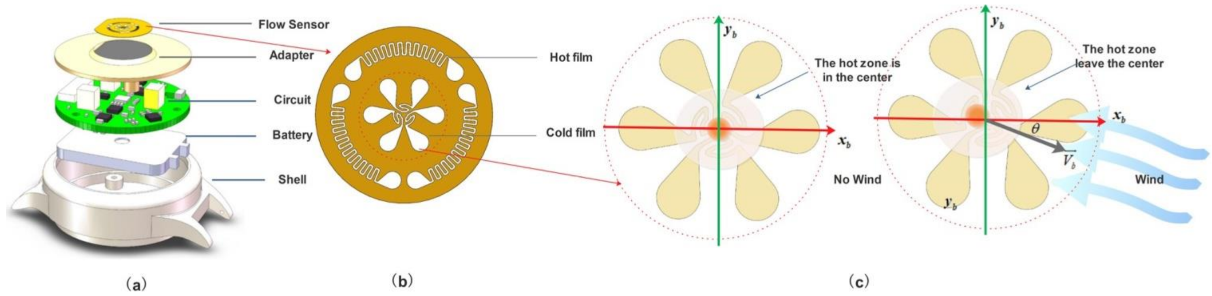

Figure. 2: (A) The motion tracking system,(b)Flow sensor, comprised of hot film and cold film,(c)Wind velocity measurement principle of the flow sensor

4. Algorithm:

4.1 Velocity determination:

Determining velocity without delving into formulas involves a straightforward approach focused on observation and estimation. Imagine you're tracking a moving object, like a car on a road. You start by keeping your eyes on it, following its path as it moves. While doing so, you pay attention to the time, either using a clock or simply counting seconds. With time as your guide, you estimate the distance the object covers during specific intervals. This could involve mentally comparing landmarks or using visible markers on the ground. Simultaneously, you note the direction in which the object is moving, whether it's going straight, turning, or changing direction. If you're comparing velocities between objects, you ensure they're observed under similar conditions for a fair assessment. This approach prioritizes keen observation and simple estimation, offering a practical way to understand how fast something is moving and in what direction without the need for mathematical intricacies.

4.2 Motion acceleration determination:

The velocity measured by the flow sensor contains inherent measurement noise, making direct differentiation to determine acceleration prone to significant errors. Moreover, limb movement acceleration exhibits dynamic characteristics requiring consideration of kinematical models. Various models, such as the Singer model, Jerk model, current statistical model, and White-noise model with constant acceleration (CA), constant velocity (CV), and coordinated turn (CT), have been proposed to characterize motion dynamics. Model selection depends on algorithm robustness, computational complexity, and accuracy. Jerk model, involving one additional derivative, offers slightly higher accuracy than Singer and Current Statistical models at an acceptable computational cost.

4.3 Kinetic power estimation:

Sure! Kinetic power estimation involves determining how fast an object's kinetic energy is changing over time. Imagine you're watching a race car on a track. The kinetic power would tell you how quickly the car's speed is increasing or decreasing. It's like knowing how much "oomph" the car has at any given moment.

Think of kinetic energy as the energy of motion. When something's moving, it has kinetic energy. If you push a ball, it gains kinetic energy. If you apply the brakes to a moving car.

Now, power is how fast energy is being used or produced. So, kinetic power is all about understanding how quickly that kinetic energy is changing. If the car is speeding up, its kinetic energy is increasing, and it has high kinetic power. If it's slowing down, its kinetic energy is decreasing, and its kinetic power is lower.

Estimating kinetic power involves observing how an object's speed changes over time. The faster the speed changes, the higher the kinetic power. But to get a precise estimation, you'd need to measure both the object's mass and its velocity changes.

4.4. Motion acceleration determination:

Determining motion acceleration involves observing changes in an object's speed over time without necessarily relying on complex mathematical formulas. Imagine you're watching a car driving along a road. To assess its acceleration, you focus on how its speed changes as it moves. You might notice if the car gradually speeds up, slows down, or maintains a constant pace. This observation allows you to infer whether the car is accelerating, decelerating, or moving at a steady velocity.

Additionally, you can look for visual cues such as the distance covered by the car during specific time intervals. By comparing its position at different points in time, you can gauge the rate at which its speed is changing. For instance, if the car covers more ground in each successive time interval, it's likely accelerating. Conversely, if it covers less ground over time, it may be decelerating.

Moreover, paying attention to the car's movement relative to its surroundings can provide valuable insights into its acceleration. For instance, you might notice if it's pulling away from other vehicles or gradually catching up to them. These observations, coupled with a keen eye for changes in speed and position, offer a practical approach to understanding motion acceleration without the need for complex mathematical calculations.

As you continue to observe the car's movement, you might notice other factors influencing its acceleration. For example, Environmental conditions such as road incline or surface friction can affect how quickly the car accelerates or decelerates. If the road is steep, the car might struggle to maintain its speed or require more effort to accelerate. Conversely, a smooth, flat road might facilitate quicker acceleration. By keenly observing the object's movement, environmental conditions, external forces, and driver behavior; you can gain a comprehensive understanding of its acceleration dynamics without resorting to mathematical formula.

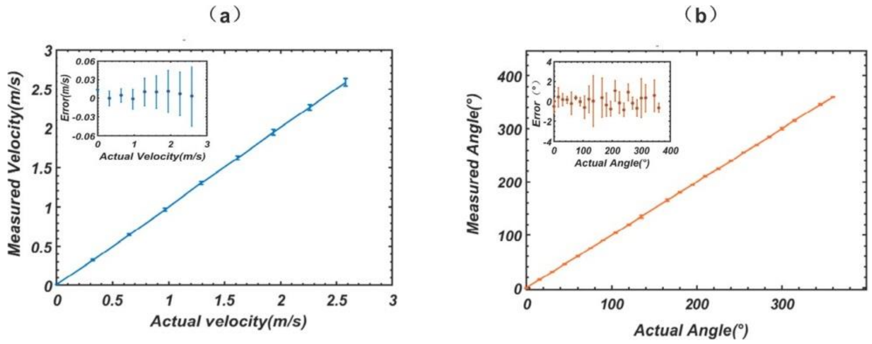

Figure. 4: Experiment results of measured motion velocity (a) and angle (b) using the micro flow sensor

5. Experiment and results:

5.1 Measurement validation of motion velocity and direction angle using the flow sensor:

To calibrate and validate the flow sensor's ability to detect motion velocity and direction angle, an experiment was conducted using a precise turntable as a reference standard for motion detection. The flow sensor was affixed to the turntable to validate the measurement accuracy of both motion velocity and direction angle. Actual velocity and angle values were obtained via the turntable's encoder. The experiment involved setting motion velocity increments from 0 to 2.58 m/s at intervals of 0.32 m/s, and angular movement from 0 to 360 degrees at 15-degree increments.

Fig. 4(a) displays the results of the measured motion velocity, demonstrating a root-mean-square error (RMSE) of less than 0.05 m/s. Fig. 4(b) presents the results of the measured angular movement, showing an RMSE of less than 2.5 degrees.

5.2 Measurement validation of motion velocity and acceleration using the flow sensor:

To further assess the accuracy of motion velocity and acceleration measurements during dynamic motion, an arm swing experiment was conducted. Fig. 5(a) illustrates the experimental setup, where the flow sensor was affixed to a level arm mounted on a swing table. The swing table replicated a human arm swing in the horizontal plane.

Additionally, an accelerometer and a rate gyroscope were attached to the level arm to capture actual motion acceleration and velocity. The accelerometer detected motion acceleration, while motion velocity was calculated using the product of rotation velocity and arm length. The sensor's X-axis was aligned with the direction of motion.

Fig. 5(b) and (c) depict the velocity (vxb) and acceleration (axb) detected by the flow sensor, compared with the actual motion velocity and acceleration. Mean error (ME) and root-mean-square error (RMSE) results are summarized in Table 1 under windless conditions.

Table. 1: Motion velocity and acceleration measuremen tresults

Measurement errors of motion velocity and acceleration using flow sensor				
	Velocity (m/s)		***Acceleration (g)***	
	Windless	Windy	Windless	Windy
ME	0.003	-0.005	-0.001	-0.001
RMSE	0.04	0.09	0.01	0.02

In the typical setting where rehabilitation training is usually conducted, indoor wind velocities are reported to be less than 0.3 m/s with an 85% probability, as per reports. Consequently, the experiment was carried out under a wind flow of approximately 0.3 m/s. Fig. 5(d) and (e) display the measurement outcomes, while the mean error (ME) and root-mean-square error (RMSE) are detailed in TABLE 1 under windy conditions. These findings affirm the flow sensor's capability to accurately measure motion velocity and acceleration in both calm and breezy conditions.

5.3 Kinetic power estimation for human upper limb in arm swing motion:

To quantify the energetic expenditure (EE) for upper limb neurological rehabilitation, we conducted a human arm swing experiment. Arm swing, inherent to bipedal walking, serves as a natural and effective movement for this purpose. The experiments involving human participants were ethically approved by the Institution Review Board of Tsinghua University (Approval No. 20180009). The participant performed arm swings at varying frequencies: 0.9 Hz and 1.3 Hz, respectively. During these movements, the flow sensors captured the motions of the two limb segments, enabling estimation of motion velocity, acceleration, and kinetic powers.

A conventional sensor fusion technique based on Kalman filtering, integrating data from an Inertial Measurement Unit (IMU) equipped with an accelerometer and gyroscope, was employed. This method aimed to enhance the accuracy and reliability of motion measurements.

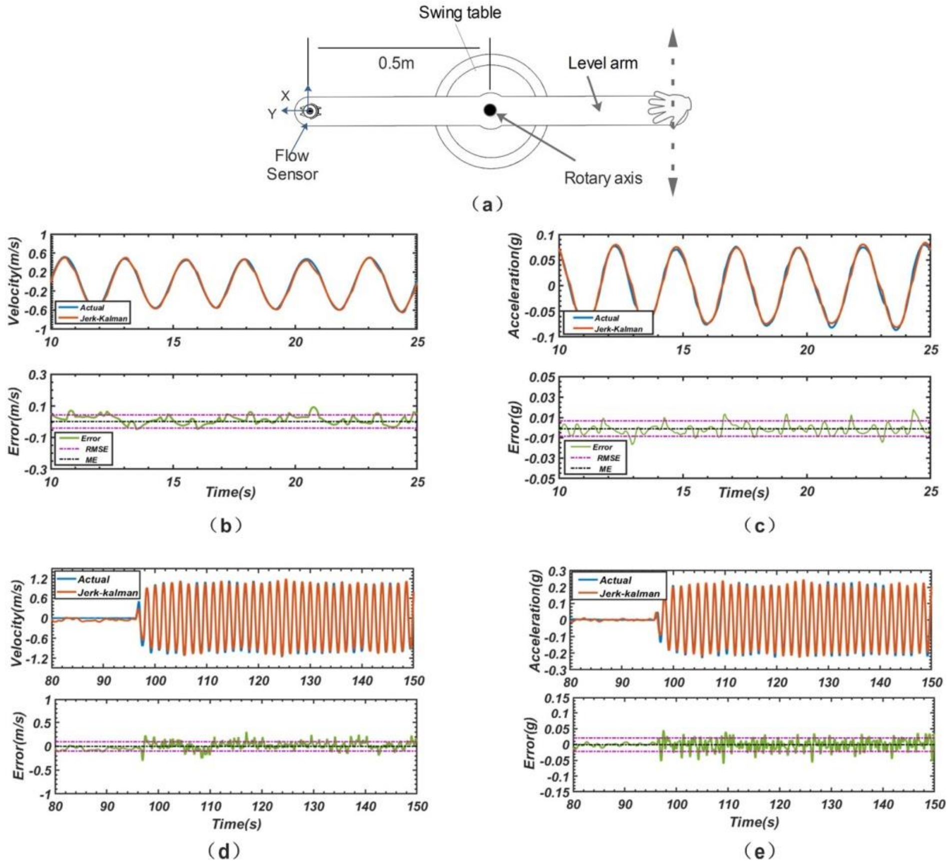

Figure. 5: Experimental set up and measurement results. (a)Experimental set up. (b)Estimated Velocity and Error. (c)Estimated Acceleration and Error. (d)Estimated Velocity and Errorin the condition of wind interference

Table. 2: Upper limb mass and centroid

Upper limb	*Mass (%)*	*Centroid (%)*
Upper arm	2.43	42.4
Forearm	1.25	36.6

Mass is the percentage of body weight. Centroid position starts from the adjacent joint.

Table. 3: Average kinetic power of upper limb

Swing frequency	*Upper limb*	*Average power (W/kg)*
0.9Hz	Upper arm	1.69
0.9Hz	Forearm	3.98
1.3Hz	Upper arm	4.67

1.3Hz	Forearm	15.14

A model-based data fusion approach, leveraging micro accelerometers and micro gyroscopes, was utilized to differentiate between the gravity vector and motion acceleration. This technique, as outlined in prior research [20], was employed to estimate motion acceleration for comparison purposes. However, directly measuring motion velocity using the IMU proved unfeasible. Instead, motion velocity was derived through integration of the motion acceleration, which was extracted using the Kalman filter model-based data fusion algorithm described earlier. The motion acceleration extracted contained inherent noises and errors, contributing to cumulative inaccuracies in the integral used for motion velocity estimation. Fig. 6(b) illustrates a comparison between estimated kinetic power, motion velocity, and acceleration of the forearm during swinging at a frequency of 0.9 Hz. Specifically, the X–Y results obtained from the IMU were juxtaposed with those detected using the flow sensor, considering arm swing as a quasi-2D motion.

Observations reveal that the inertial approach resulted in noticeable accumulated errors in both motion velocity and kinetic power determination. Conversely, the method relying on the flow sensor for forearm detection exhibited minimal accumulated errors during long-term monitoring, indicating robustness in dynamic motion measurement. Fig. 6(c) and (d) illustrate the estimated power, velocity, and acceleration of the upper arm, as detected by the flow sensor, across two swing cycles at frequencies of 0.9 Hz and 1.3 Hz, respectively. Correspondingly, Fig. 6(e) and (f) depict the corresponding results for the forearm, synchronized with the upper arm motion. Observations suggest that arm swinging at a higher frequency results in increased power generation, with the forearm exhibiting larger energetic expenditure compared to the upper arm during the swinging motion. Some researchers employ the average kinetic power as a metric to investigate the mechanics and energetics of human motion.

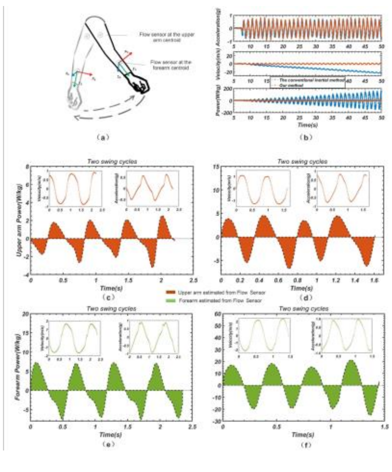

Figure. 6: Upper limb PAEE estimation

(a)Experimental setup. (b)The power, velocity, and acceleration estimation results by using the proposed method comparing with the conventional in ertial method. (c)Estimate the power, velocity, and acceleration of the upper arm from the flow sensor at a swing frequency of 0.9Hz... (f)Estimate the power, velocity, and acceleration of the forearm from the flow sensor at a swing frequency of 1.3Hz.

The average kinetic power can be used to estimate the Corresponding metabolic power for EE:

$$P_{met} = \frac{P}{n} \qquad (13)$$

Where P_{met} is the corresponding metabolic power. *η is* the efficiency of converting mechanical work into EE through muscle, and is generally about 0. It is provent ohavea value of 0.250.41 for lower limb joints in the scene of walking and running.[34]

Average kinetic power of the upper limbs was estimatedusing Eq. (12) and listed in Table. 3. It is seen that the average power of the forearm is about 23 times larger than the power of the upper arm. Experiment results validate the motion velocity and acceleration, and the EE of human limb can be estimated by using a flow sensor, which is useful for quantitative assessment of limb motion in clinical therapy and rehabilitation training of the patients with neurological conditions e.g. stroke, traumatic brain injury, and motor neurone diseases. Quantitativy Assessment of EE for human limbs providesaneffective way to help doctors a dnursesad Just treatment plans for patient sinatimely manner.

6. Conclusion:

We've engineered a wearable device based on a flow sensor to track human limb motion velocity, facilitating quantitative evaluation of energetic expenditure (EE) in post-stroke rehabilitation training. Our approach integrates a Jerk–Kalman algorithm for motion velocity and acceleration extraction, validated through experiments. Utilizing the obtained motion velocity and acceleration data, we conduct a quantitative assessment of EE by calculating average kinetic powers for both the upper arm and forearm. Experimental results confirm the effectiveness of our flow sensor-based method in estimating motion velocity and acceleration, enabling EE calculation for limb rehabilitation.

Our developed motion estimation device boasts robustness, user-friendliness, wear ability, and affordability, promising significant potential for precise assessment in personal rehabilitation treatments. In future endeavors, we aim to expand our experiments to include more subjects for statistical analyses in clinical applications. Additionally, we plan to explore a multi-sensor fusion approach, integrating the flow sensor with inertial sensors, to address motion and posture tracking challenges of human limbs. Comparative studies with devices like VICON will be undertaken to validate our approach further.

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