Original Research Article

A Study on the Relationship Between Respiratory Chest Expansion and Multi-Axis Body Motion Using a Wearable Belt Sensor

Yaoshan Jiang

Walnut High School, 400 N. Pierre Road, Walnut, CA 91789, United States

ABSTRACT

This study investigates the relationship between respiratory chest expansion and multi-axis body motion parameters measured using a wearable belt-like sensor equipped with an accelerometer and gyroscope. A chest-mounted elastic belt sensor simultaneously recorded three-axis linear acceleration, three-axis rotational velocity, and chest circumference displacement during a controlled breathing exercise performed by a single healthy participant in a seated posture (n = 1,282 observations). Pearson correlation analysis and multivariate linear regression were employed to quantify the associations among these seven variables. Results indicate that linear acceleration components, particularly along the vertical and lateral axes, exhibit moderate to strong correlations with chest expansion ($r = 0.429$ and $r = -0.422$ for the Y and Z axes, respectively, $p < 0.001$). Regression models for linear acceleration components demonstrated substantially higher explanatory power (R^2 up to 0.697) compared to rotational components ($R^2 < 0.06$), suggesting that translational body motion is more systematically coupled with respiratory chest expansion than rotational motion. These findings contribute to the growing field of wearable respiratory monitoring and demonstrate the feasibility of using low-cost inertial sensors to characterize breathing biomechanics.

Keywords: respiratory monitoring; wearable sensor; chest expansion; inertial measurement unit; accelerometer; correlation analysis; multivariate regression

INTRODUCTION

Respiratory monitoring is a fundamental aspect of physiological assessment, with applications spanning clinical diagnostics, rehabilitation, and wearable health technology. The mechanical act of breathing involves coordinated movement of the chest wall and abdominal compartment, driven primarily by the diaphragm, intercostal muscles, and abdominal muscles (1). These muscle groups produce measurable displacements of the thoracic and abdominal surfaces during each respiratory cycle, making external motion sensing a viable approach for non-invasive breath monitoring (2).

In recent years, advances in microelectromechanical systems (MEMS) have enabled the development of compact, low-cost inertial measurement units (IMUs) containing tri-axial accelerometers and gyroscopes that can be embedded in wearable devices such as chest straps and elastic belts (3). When mounted on the chest wall, these sensors capture both the gross translational accelerations and subtle rotational velocities produced by thoracic expansion and contraction during breathing (4). Simultaneously, stretch-sensitive elements integrated into elastic belts can measure changes in chest circumference, providing a direct proxy for

Corresponding author: Yaoshan Jiang, E-mail: carneyjiang888@gmail.com.

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respiratory volume changes (5).

Prior work has demonstrated that chest-worn accelerometers can reliably detect respiratory rate and even estimate tidal volume under controlled conditions (1). Studies comparing accelerometer and gyroscope performance for respiratory monitoring have found that accelerometer signals generally provide more accurate respiratory rate estimates than gyroscope signals, though both capture breathing-related chest wall movement (1). Furthermore, research using multiple IMU sensors placed at various thoracic and abdominal locations has shown that linear acceleration signals in particular exhibit strong associations with respiratory volumes measured by reference systems such as optoelectronic plethysmography (2).

Despite these advances, several gaps remain. Most existing studies focus on extracting a single respiratory parameter, typically respiratory rate, from inertial sensor data, and comparatively few have examined the full set of multi-axis acceleration and rotational signals simultaneously in relation to chest expansion. Additionally, studies employing multiple sensor modalities on a single wearable platform, combining both inertial sensing and stretch-based chest circumference measurement, remain limited (7). Understanding how the various axes of acceleration and rotation relate to one another and to chest expansion during breathing could inform the design of more accurate respiratory monitoring algorithms and provide insight into the biomechanics of chest wall motion.

The present study addresses these gaps by simultaneously recording tri-axial linear acceleration, tri-axial rotational velocity, and chest circumference displacement from a single wearable belt sensor during a controlled breathing exercise. Using Pearson correlation analysis and multivariate linear regression, this study aims to (1) characterize the pairwise relationships among all measured motion and expansion variables, (2) determine which motion components are most strongly associated with respiratory chest expansion, and (3) evaluate how well the measured variables collectively predict one another.

LITERATURE REVIEW

Wearable Sensors for Respiratory Monitoring

The use of wearable devices to monitor respiration has expanded rapidly in recent years. Chest belts employing various sensing modalities, including piezoresistive, piezoelectric, capacitive, and inductance-based elements, have been widely studied for their ability to detect respiratory patterns through chest and abdominal circumference changes (5, 9). These belt-based systems measure the expansion and contraction of the torso during breathing and can provide information about respiratory rate, relative breath amplitude, and breathing patterns (8). Dual-belt configurations, with one belt placed on the thorax and another on the abdomen, have been recommended for capturing both chest and diaphragmatic breathing contributions (5).

In parallel, IMU-based approaches have emerged as a complementary method for respiratory monitoring. By measuring the small inclination changes and accelerations of the chest wall surface during breathing, IMUs can extract respiratory signals without requiring direct strain measurement (3). Schiavoni *et al.* (3) demonstrated that a system of three IMU sensor units placed on the thorax, abdomen, and lower back could estimate breathing frequency with mean absolute errors below 2 breaths per minute when validated against optoelectronic plethysmography. Similarly, Erfianto *et al.* (4) proposed a cascade complementary filter method for fusing accelerometer and gyroscope data from an IMU mounted on the abdomen to extract stable respiratory signals.

Accelerometer and Gyroscope Signals in Chest Wall Motion

Accelerometers and gyroscopes capture fundamentally different aspects of chest wall motion. Accelerometers measure linear acceleration, which during quiet breathing reflects the gravitational component modulated by the changing orientation of the chest surface as it rises and falls (1). Gyroscopes measure angular velocity, capturing the rotational dynamics of the chest wall. Massaroni *et al.* (1) conducted a direct comparison of chest-worn accelerometer and gyroscope performance for respiratory rate monitoring and found that accelerometers consistently outperformed gyroscopes in estimation accuracy across seated, standing, and supine postures.

De la Fuente *et al.* (6) placed multiple accelerometers on the chest and abdominal wall and used principal component analysis and clustering algorithms to identify distinct regional movement patterns during tidal breathing. Their analysis revealed two primary clusters corresponding to a superior-costal pattern and an abdominal pattern, demonstrating that accelerometry can distinguish between regional contributions to breathing. Jafari Tadi *et al.* (10) further showed that seismocardiographic signals from a chest-mounted accelerometer contain a dominant low-frequency component corresponding to respiratory chest wall motion, which can be separated from higher-frequency cardiac vibrations through appropriate filtering.

Statistical Methods in Sensor-Based Respiratory Research

Correlation and regression analyses are standard tools for characterizing relationships among physiological sensor signals. The Pearson correlation coefficient is widely used to quantify the linear association between two continuous variables and is appropriate when both variables are approximately normally distributed and linearly related (11). In the context of respiratory sensor research, correlation analysis has been applied to validate accelerometer-derived respiratory signals against reference measurements from spirometry or respiratory belts (10).

Multivariate linear regression extends this framework by modeling how multiple predictor variables jointly influence a target variable, enabling researchers to assess the relative contribution of each predictor while controlling for the others (12). These methods have been applied in biomechanical studies to understand how different motion components relate to physiological outcomes. However, relatively few studies have applied multivariate regression to examine the full set of multi-axis inertial signals in relation to a direct measure of chest expansion, which motivates the analytical approach adopted in the present study.

METHODS AND MATERIALS

Experimental Setup and Data Collection

Data were collected from the author (male, age 16, height 175 cm, weight 56.7 kg, BMI 18.5), who served as both researcher and participant, during a controlled breathing exercise. The author was seated in an upright posture with feet flat on the floor and hands resting on the thighs. A wearable elastic belt sensor was strapped around the chest at the level of the lower ribs. The belt incorporated an inertial measurement unit (IMU) containing a tri-axial accelerometer and tri-axial gyroscope, as well as a stretch-sensitive element that measured changes in belt length corresponding to chest circumference displacement.

The sensor recorded seven variables simultaneously at a sampling rate of approximately 15 Hz. The recording session lasted approximately 85 seconds, yielding a total of n = 1,282 time-stamped observations after removal of incomplete records. The author breathed naturally at a comfortable pace throughout the recording period without external pacing or breathing cues.

Ethics and Consent

The experiment involved a non-invasive wearable belt sensor and posed minimal risk to the participant. As the author served as the sole participant and was under 18 years of age at the time of data collection, parental/guardian consent and author assent were obtained prior to the experiment. The procedure involved a non-invasive wearable belt sensor and posed minimal risk. No personally identifiable information beyond the authorship of this paper was recorded or included in the dataset.

Variable Definitions

The seven measured variables are defined as follows. *Acceleration X* represents vertical acceleration (m/s^2) along the cranial-caudal axis, where positive values indicate downward motion. *Acceleration Y* represents lateral acceleration (m/s^2) along the medial-lateral axis, capturing side-to-side movement. *Acceleration Z* represents anterior-posterior acceleration (m/s^2), reflecting forward and backward movement. *Rotational X* represents pitch rate (rad/s), the angular velocity around the sagittal plane. *Rotational Y* represents roll rate (rad/s), the angular velocity around the frontal plane. *Rotational Z* represents yaw rate (rad/s), the angular velocity around the transverse plane. *Length* represents chest circumference displacement (mm), measuring the linear expansion and contraction of the belt during breathing.

Sensor Calibration

The chest expansion sensor was calibrated using a linear regression of stretch sensor resistance against known length values. Seven calibration points spanning 10 to 70 mm yielded a strong linear relationship between resistance and length, with a slope of 4.986 Ω/mm and an intercept of approximately 32 Ω ($R^2 = 0.997$). The data acquisition firmware applied this slope as a divisor of 4.9 Ω/mm to convert measured resistance to Length values during recording. The additive intercept term from the calibration, together with the baseline resistance of the unstrained belt assembly, was not subtracted prior to data logging. Consequently, the reported Length values include a constant additive offset and do not correspond to absolute chest circumference. Because all subsequent analyses in this study depend on relative variation, this offset does not affect the reported statistical results: the standard deviation, range, Pearson correlation coefficients, and regression coefficients involving Length accurately reflect changes in chest expansion in millimeters.

Correlation Analysis

Correlation analysis was conducted to quantify the strength and direction of the linear relationship between each pair of measured variables. Pairwise relationships among all seven variables were evaluated using the Pearson correlation coefficient, which measures the degree of linear association between two continuous variables. The Pearson correlation coefficient is calculated as shown in [1].

$$r = \frac{\Sigma(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\Sigma(x_i - \bar{x})^2 \cdot \Sigma(y_i - \bar{y})^2}} \quad [1]$$

where x_i and y_i represent the observed values of the two variables, $\bar{x}$ and $\bar{y}$ are their sample means, and n is the total number of observations (11). The value of r ranges from −1 to +1, where positive values indicate a direct relationship and negative values indicate an inverse relationship. To evaluate statistical significance, a t-statistic was calculated as shown in [2].

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \quad [2]$$

This statistic follows a t-distribution with $n - 2 = 1{,}280$ degrees of freedom, permitting calculation of a p-value to test the null hypothesis that the true correlation is zero. A threshold of $p < 0.05$ was used to determine statistical significance. The assumptions of linearity, continuity, approximate normality, and independence of observations were assessed prior to analysis (11).

Multivariate Regression Analysis

To evaluate how multiple predictors jointly influence each outcome variable, multivariate linear regression models were constructed. Several regression families were developed, each containing multiple sub-models with different target variables. The target variables included the three acceleration components and the three rotational components. For each regression model, all remaining variables, including the chest circumference displacement (Length), were used as predictors. The general form of the multiple linear regression model is shown in [3].

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \varepsilon \quad [3]$$

where Y represents the target variable, $X_1, X_2, \ldots, X_k$ represent the predictor variables, β_0 is the intercept, β_1 through β_k are the regression coefficients, and ε is the random error term (12). Each coefficient represents the expected change in the target variable associated with a one-unit increase in the corresponding predictor while holding other predictors constant. Statistical significance of each predictor was assessed using a t-test as shown in [4].

$$t = \frac{\hat{\beta}_j}{\mathrm{SE}(\hat{\beta}_j)} \quad [4]$$

Model performance was evaluated using the coefficient of determination (R^2), adjusted R^2, mean absolute error (MAE), and root mean squared error (RMSE) (12). The assumptions of linearity, independence, normality of residuals, homoscedasticity, and absence of severe multicollinearity were considered in interpreting the results.

RESULTS

Descriptive Statistics

Table 1 summarizes the descriptive statistics for all measured variables across n = 1,282 observations. The mean Acceleration X value was 8.54 m/s^2 (SD = 0.13), Acceleration Y had a mean of 0.74 m/s^2 (SD = 0.16), and Acceleration Z had a mean of 4.33 m/s^2 (SD = 0.25). The rotational measurements exhibited means near zero with standard deviations ranging from 0.01 to 0.05 rad/s. The Length variable had a mean of 2815.23 mm (SD = 26.12). Linear acceleration variables showed greater magnitude and variability compared to rotational variables.

Table 1. *Descriptive statistics for all seven sensor variables recorded from a chest-mounted wearable belt during a seated breathing exercise (n = 1,282 observations). Acceleration variables are reported in m/s², rotational variables in rad/s, and chest circumference displacement (Length) in mm.*

Variable	Mean	Std. Dev.	Min	Max
Accel. X	8.54	0.13	8.15	10.11
Accel. Y	0.74	0.16	0.19	1.26
Accel. Z	4.33	0.25	2.34	4.92
Rot. X	−0.04	0.05	−0.23	0.14
Rot. Y	0.01	0.02	−0.29	0.12
Rot. Z	0.01	0.01	−0.06	0.06
Length	2815.23	26.12	2760.00	2877.00

Correlation Analysis

Figure 1 presents the pairwise correlation matrix for all measured variables. Among the acceleration variables, Acceleration X and Acceleration Y showed a moderate positive correlation ($r = 0.368$, $p < 0.001$). Acceleration X and Acceleration Z exhibited a strong negative correlation ($r = -0.785$, $p < 0.001$). Acceleration Y and Acceleration Z displayed a moderate negative relationship ($r = -0.506$, $p < 0.001$).

Regarding the chest expansion variable (Length), Acceleration Y showed the strongest positive association ($r = 0.429$, $p < 0.001$), followed by Acceleration X ($r = 0.252$, $p < 0.001$). Acceleration Z was moderately negatively correlated with Length ($r = -0.422$, $p < 0.001$). Rotational variables exhibited weaker relationships with Length, with correlation coefficients ranging from −0.074 to 0.113. Across all pairwise comparisons, linear acceleration variables showed stronger associations with Length than rotational variables.

Multivariate Regression Analysis: Paired Models

Table 2 presents the regression results for Models 1 through 3. In Model 1, Acceleration Z was a statistically significant negative predictor of Acceleration X ($\beta = -0.446$, $t = -40.407$, $p < 0.001$), and Length was also significant ($t = -4.557$, $p < 0.001$). In the Rotational X sub-model, Acceleration Y ($\beta = -0.035$, $p < 0.001$), Rotational Y ($\beta = 0.180$, $p < 0.001$), Rotational Z ($\beta = 0.687$, $p < 0.001$), and Length ($t = 4.762$, $p < 0.001$) were statistically significant predictors.

In Model 2, Acceleration Z was a significant negative predictor of Acceleration Y ($\beta = -0.275$, $p < 0.001$), and Length showed a positive association ($\beta = 0.002$, $t = 10.123$, $p < 0.001$). In Model 3, Acceleration X ($\beta = -1.259$, $p < 0.001$), Acceleration Y ($\beta = -0.287$, $p < 0.001$), and Length ($\beta = -0.002$, $t = -9.905$, $p < 0.001$) were statistically significant predictors of Acceleration Z. Across all six sub-models, the Length variable was a statistically significant predictor ($p < 0.05$).

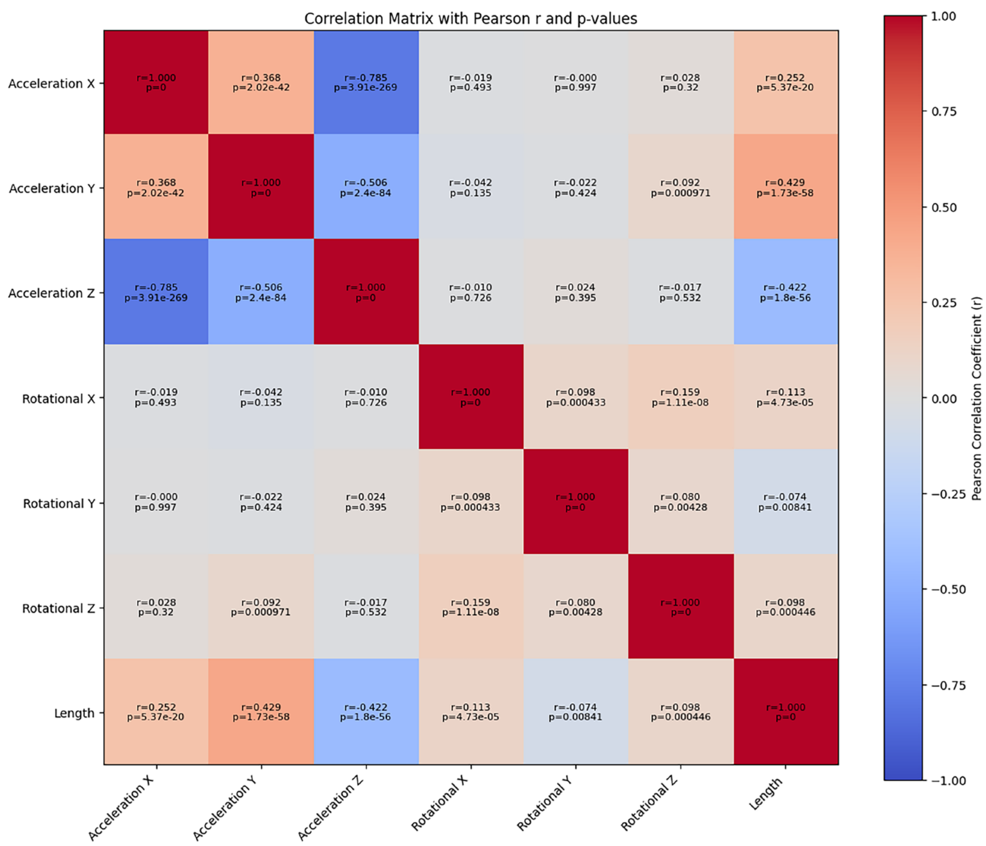

Figure 1. *Pairwise Pearson correlation matrix for all seven measured variables (n = 1,282). Values range from −1.0 (perfect negative linear association) to +1.0 (perfect positive linear association). Darker shading indicates stronger absolute correlation. Accel. = linear acceleration (m/s²); Rot. = angular velocity (rad/s); Length = chest circumference displacement (mm).*

Table 2. *Multivariate regression coefficients, t-values, and p-values for three paired models (n = 1,282). Each model uses one linear acceleration component and one rotational component as target variables, with all remaining variables as predictors. Coeff. = unstandardized regression coefficient; significant predictors (p < 0.05) are identified by p-values.*

Model	Target	Predictor	Coeff.	t-value	p-value	Model	Target	Predictor	Coeff.	t-value	p-value
1	Accel. X	const	11.769	39.337	<0.001	2	Rot. Y	const	0.210	1.595	0.111
	Accel. X	Accel. Y	−0.014	−0.838	0.402		Rot. Y	Accel. X	0.006	0.737	0.461
	Accel. X	Accel. Z	−0.446	−40.407	<0.001		Rot. Y	Accel. Y	0.002	0.424	0.672
	Accel. X	Rot. X	−0.067	−1.314	0.189		Rot. Y	Accel. Z	0.002	0.352	0.725
	Accel. X	Rot. Y	0.070	0.737	0.461		Rot. Y	Rot. X	0.053	3.503	<0.001
	Accel. X	Rot. Z	0.356	1.505	0.132		Rot. Y	Rot. Z	0.177	2.537	0.011
	Accel. X	Length	0.000	−4.557	<0.001		Rot. Y	Length	0.000	−3.053	0.002
	Rot. X	const	−0.549	−2.268	0.023	3	Accel. Z	const	19.884	39.820	<0.001
	Rot. X	Accel. X	−0.020	−1.314	0.189		Accel. Z	Accel. X	−1.259	−40.407	<0.001
	Rot. X	Accel. Y	−0.035	−3.772	<0.001		Accel. Z	Accel. Y	−0.287	−10.451	<0.001
	Rot. X	Accel. Z	−0.010	−1.103	0.270		Accel. Z	Rot. X	−0.095	−1.103	0.270
	Rot. X	Rot. Y	0.180	3.503	<0.001		Accel. Z	Rot. Y	0.056	0.352	0.725
	Rot. X	Rot. Z	0.687	5.388	<0.001		Accel. Z	Rot. Z	0.952	2.400	0.017
	Rot. X	Length	0.000	4.762	<0.001		Accel. Z	Length	−0.002	−9.905	<0.001
2	Accel. Y	const	−2.373	−3.252	0.001		Rot. Z	const	−0.135	−2.571	0.010
	Accel. Y	Accel. X	−0.039	−0.838	0.402		Rot. Z	Accel. X	0.005	1.505	0.132
	Accel. Y	Accel. Z	−0.275	−10.451	<0.001		Rot. Z	Accel. Y	0.006	3.112	0.002
	Accel. Y	Rot. X	−0.317	−3.772	<0.001		Rot. Z	Accel. Z	0.005	2.400	0.017
	Accel. Y	Rot. Y	0.066	0.424	0.672		Rot. Z	Rot. X	0.032	5.388	<0.001
	Accel. Y	Rot. Z	1.208	3.112	0.002		Rot. Z	Rot. Y	0.028	2.537	0.011
	Accel. Y	Length	0.002	10.123	<0.001		Rot. Z	Length	0.000	2.343	0.019

Model Performance Analysis

Table 3 summarizes the model performance metrics. The Acceleration Z model achieved the highest R^2 of 0.697, followed by the Acceleration X model (R^2 = 0.626) and the Acceleration Y model (R^2 = 0.324). The rotational models yielded lower R^2 values: Rotational X at 0.057, Rotational Z at 0.046, and Rotational Y at 0.023. Prediction errors for rotational variables were small in absolute terms (e.g., RMSE = 0.010 rad/s for Rotational Z), consistent with the limited magnitude and variability of rotational signals observed in the descriptive statistics.

DISCUSSION

The findings of this study reveal systematic relationships between respiratory chest expansion and multi-axis body motion parameters measured by a wearable belt sensor. The correlation analysis demonstrates that linear acceleration components, particularly Acceleration Y (lateral) and Acceleration Z (anterior-posterior), are moderately to strongly associated with chest circumference displacement, with correlation coefficients of 0.429 and −0.422, respectively. These associations are consistent with the biomechanical expectation that thoracic expansion during inhalation produces measurable displacements in multiple spatial directions (2). The negative correlation between Acceleration Z and Length may reflect the posterior displacement of the sensor as the chest expands anteriorly, while the positive correlation with Acceleration Y may result from lateral rib cage expansion during deep breaths.

The regression analyses further support the dynamic coupling between respiratory mechanics

Table 3. *Model performance metrics for all six regression sub-models (n = 1,282). R^2 = coefficient of determination (proportion of variance explained); Adj. R^2 = R^2 adjusted for number of predictors; MAE = mean absolute error; RMSE = root mean squared error. Units of MAE and RMSE correspond to the target variable (m/s² for acceleration, rad/s for rotation).*

Model	Target	R^2	Adj. R^2	MAE	RMSE
1	Accel. X	0.626	0.624	0.060	0.081
1	Rot. X	0.057	0.052	0.034	0.044
2	Accel. Y	0.324	0.321	0.105	0.134
2	Rot. Y	0.023	0.018	0.015	0.024
3	Accel. Z	0.697	0.696	0.103	0.136
3	Rot. Z	0.046	0.042	0.006	0.010

and body motion. The Length variable emerged as a statistically significant predictor in all six regression sub-models, regardless of the target variable or modeling configuration. This finding aligns with prior research demonstrating that chest wall movements during breathing are captured across multiple IMU axes (1, 3). The substantially higher explanatory power observed for linear acceleration models (R^2 up to 0.697) compared to rotational models ($R^2 < 0.06$) suggests that translational chest wall movements during breathing are more structured and predictable than rotational dynamics. This observation is consistent with the findings of Massaroni *et al*. (1), who reported that accelerometer signals generally provide more reliable respiratory information than gyroscope signals.

The strong interdependencies among the three acceleration axes, particularly the robust negative relationship between Acceleration X and Acceleration Z ($r = -0.785$), indicate that the chest wall moves in a coordinated multi-directional pattern during breathing rather than along a single axis. This finding is consistent with studies using optoelectronic plethysmography and multi-sensor IMU arrays that have documented complex three-dimensional chest wall kinematics during respiratory cycles (2, 6). The relatively weak associations between rotational components and the Length variable suggest that rotational dynamics during quiet breathing are subtler and potentially influenced by factors beyond respiratory motion, such as postural micro-adjustments or cardiac vibrations (10).

It is worth noting that the regression models explained substantially more variance in acceleration variables than in rotational variables, yet the absolute prediction errors for rotational components remained small. This indicates that while rotational signals are less systematically structured, they are also low in magnitude and variability, resulting in stable but uninformative regression models. Future studies may benefit from incorporating higher-order features or time-domain analyses to capture the dynamic patterns in rotational signals that linear regression models may miss.

Limitations

Several limitations of this study should be acknowledged. First, the dataset was collected from a single participant, which limits the generalizability of the findings to broader populations. Individual differences in body composition, chest wall compliance, breathing patterns, and posture could influence the observed relationships between motion variables and chest expansion. Second, data were collected only in a seated, upright posture during quiet breathing; the relationships reported here may not generalize to other postures (e.g., supine, standing) or breathing conditions (e.g., exercise, deep breathing, pathological breathing patterns) (1, 3).

Third, the respiratory expansion was measured using a single elastic belt sensor positioned at one level of the torso, which provides a simplified one-dimensional representation of chest wall motion. This approach does not capture the complex three-dimensional dynamics of thoracic and abdominal breathing, nor does it distinguish between rib cage and diaphragmatic contributions (5). More advanced systems such as optoelectronic plethysmography or multi-sensor arrays distributed across the chest and abdomen could provide greater spatial resolution (2).

Fourth, the statistical analyses employed (Pearson correlation and multivariate linear regression) assume linear relationships among variables. Respiratory biomechanics may involve non-linear coupling patterns that are not captured by these methods. Future work applying non-linear regression, time-series analysis, or machine learning approaches could reveal additional structure in the data.

CONCLUSION

This study investigated the relationships between respiratory chest expansion and multi-axis body motion using data from a wearable belt sensor equipped with an accelerometer, gyroscope, and stretch-sensitive element. The primary findings indicate that linear acceleration components are more strongly and consistently associated with chest circumference displacement than rotational components. Correlation analysis revealed moderate to strong associations between the lateral and anterior-posterior acceleration axes and chest expansion, while multivariate regression models demonstrated that chest expansion is a statistically significant predictor of motion across all spatial axes. The regression models for linear acceleration achieved R^2 values up to 0.697, whereas rotational models achieved R^2 values below 0.06.

These findings contribute to the understanding of how respiratory chest wall motion manifests in inertial sensor data and have practical implications for the design of wearable respiratory monitoring systems. By demonstrating that multi-axis acceleration signals contain meaningful respiratory information, this study supports the use of IMU-based approaches for non-invasive breathing assessment. As discussed in the Limitations section, the single-subject design and controlled conditions limit generalizability, and future research should incorporate larger and more diverse samples, multiple postures, and non-linear analytical methods to extend these findings.

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CONFLICT OF INTEREST

The author declares that there are no conflict of interests related to this work.

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