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CNN Based Sensory Seat-Belt Design for Posture Recognition and Heart Rate Monitoring

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Abstract—**Posture recognition and Heart-Rate measurement towards passenger safety without disturbing the vehicular ergonomics is much appreciated. In this work, we present a novel integrated system utilizing Velostat Pressure Sensitive Conductive (PSC) sensors and an accelerometer designed on a seat-belt. This system captures spatio-temporal data and employs a Convolutional Neural Network (CNN) model for the classification of five distinct sitting postures and non-wearing seat-belt detection. The accelerometer data is processed to estimate Heart-Rate using an algorithm, ensuring accurate and reliable measurements. The non-skin-contact accelerometer unit integrated to the seat-belt and recording heart-rate is preferred over other designs owing to the commuters convenience. The inclusion of a diverse subject pool to generate a comprehensive dataset, featuring an unoccupied seat state, ensures robust and realistic performance. The CNN model, interfaced with an edge computing system, with its ability to extract hidden features, achieved high accuracy in posture recognition. Additionally, the camera-less approach preserves user privacy, making it suitable for real-world applications. Our compact seat-belt incorporated sensory system represents a significant advancement in passenger monitoring technology, offering a practical and privacy-conscious solution for improving vehicle safety and ergonomics. The sensory dataset, along with design files, and source-codes are made freely available for further usage to designers and researchers community.**

Keywords*—*Seat-belt, Heart-Rate, Sitting Posture, Accelerometer, CNN, Velostat, Seismocardiography

I. INTRODUCTION

Passenger safety system is a crucial component in the vehicular system considering the urban population usage of hiring cab or taxi services is rising due to several reasons including limited or high parking fees, driving fatigue, unaffordability, and various other reasons [1]–[3]. The riders typically book the riding services through the installed app but the trust among the two parties including the driver and passenger remains unknown, although the ratings evaluated from the history of rides are known [4]. Besides these days, shared taxis where multiple co-passengers commute to nearby location is also popular, which additionally makes the passenger well-being throughout the journey very critical to the overall development of safe ecosystem. Additionally, the posture of the passenger throughout the journey offers valuable information which includes sudden movements due to any attack by the co-passenger or driver, and also incorrect posture for a long duration leading to prolonged effects causing musculoskeletal diseases such as lumbago, forward head posture syndrome, and cervical disk [5]–[8].

Earlier forms of tracking passenger movements including camera based surveillance [9], [10], thermal imaging [11]–[13], RADAR systems [14]–[16], LIDAR modules inside the vehicle [13], and IR camera's [17] are mentioned in the literature. Most of the solutions that are discussed in the literature assume the liability of extra footprint for tracking the passenger movements in the vehicle [18], [19]. In the past, in-seat passenger monitoring system using velostat [20] pressure sensors showed effective results [21]–[25]. Although effective for proof-of-concept level, embedding sensors on different variant of seats requires regulatory-body approval and all seat manufacturers may not agree holistically. Additionally, cushion based sensors has its own drawbacks in terms of additional footprint and availability of different materials which may lead to passengers discomfort.

Seat-belt is one of the regular component seen in most of the vehicles and in the recent past its commissioned for not only front seats but also for rear seats in a view to ensure safety across all passengers. The tight and sleak seat-belt offers enormous opportunity to track personalized as well as vehicular parameters while on the road. The authors have proposed one such prominent use-case by exploiting the fastened seat-belt equipped with additional sensors to provide posture information as well as approximate heart-rate. It also provides design-space to offer personalized health vitals on the move. Heart-Rate measurement is one of the unique health vital which is often reported for symptoms involving palpitations, dizziness, fainting, chest pain and shortness of breath. These symptoms while travelling is often ignored, leading to irrecoverable consequences. Typically the Heart-Rate readings are extracted from ECG signals or PPG signals which require the electrodes to be in contact with the skin. However, the same setup makes it inconvenient for the passenger while commuting. An accelerometer setup close to the chest was found reliable to estimate the Heart-Rate [26]. In the proposed work, the plan is to devise an accelerometer unit within the seat-belt, which is likely to offer similar trend of signal. The non-skin-contact accelerometer unit integrated to the seat-belt works in favor of the passenger's convenience while travelling. These vital information extracted from the sensory based seat-belt system aims to timely avert any emergency situation both on the physical and health front.

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[*] These authors contributed equally to this work.

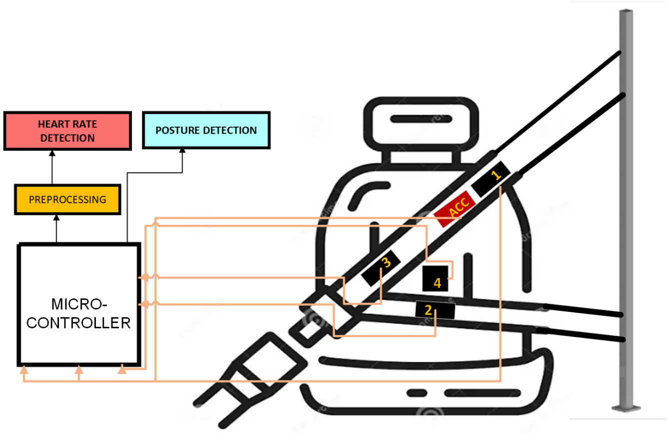
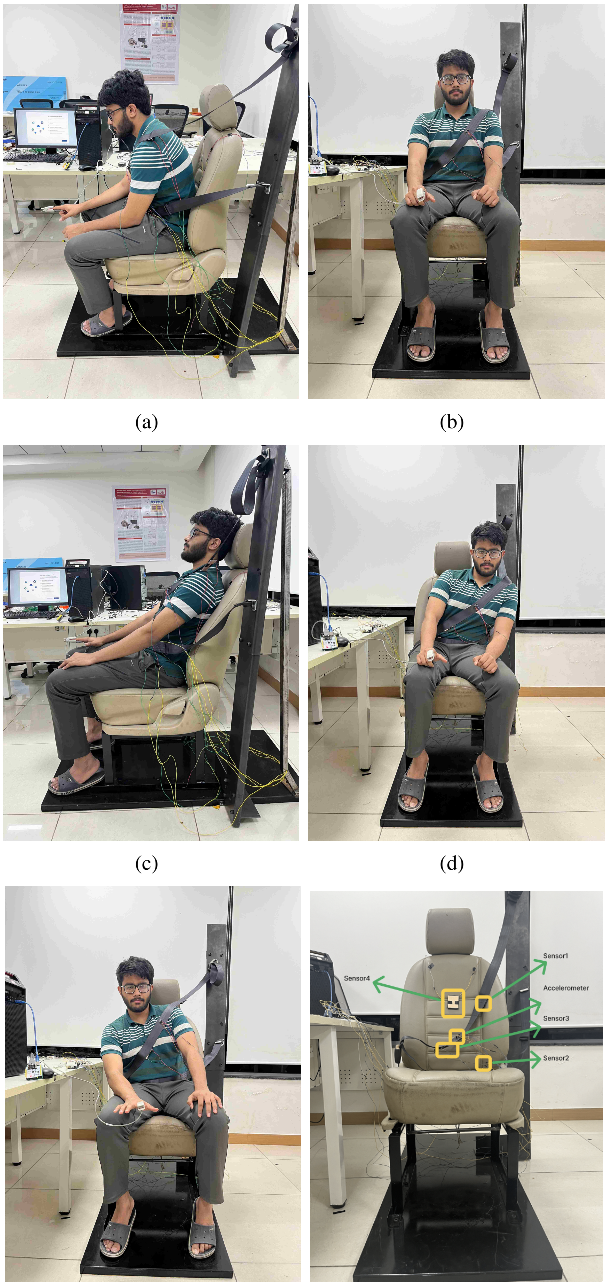


Fig. 1. Proposed Architecture of the system with the velostat sensors (#1, #2, #3, and #4), Accelerometer sensor (ACC), interfaced to the Micro-controller and further applied to the ML models.

II. PROPOSED DESIGN

A schematic illustrating the overall workflow involving Pressure Sensitive Conductive (PSC) Velostat (pressure) sensors, and tri-axial accelerometer interfaced with the microcontroller as data acquisition unit is shown in the Figure 1. Three sensors are strategically embedded in the seat-belt, two on the upper abdomen section and one on the lower abdomen section, supplemented by an additional sensor on the seat's backrest, totaling four optimally placed sensors. These sensors, configured as rectangular patches, ensure precise pressure detection. One additional velostat sensor (#4) is positioned on the back-rest of the seat to estimate the posture while the subject rests on the seat with a possibility of not contacting the seat-belt. An accelerometer is strategically positioned near the heart on the upper body section. The Figure also shows the pipeline of pressure sensors supplied to CNN model for detecting the posture of the seated individual, and processed accelerometer data fed to the other peak-detection unit for measuring the heart-rate of the individual in seat. The proposed system aims to categorize various sitting postures from the dynamically changing spatio-temporal features acquired from the sensory setup and detect heart-rate using Seismocardiography (SCG) signals which is a non-invasive method for measuring chest vibrations from cardiac activity to extract Heart-Rate [27]. A Convolution Neural Network (CNN) was applied to extract the hidden features and predict five specific sitting postures as shown in Figure 2. These five postures are defined as: i) *Posture-A*: 60° with the anteroposterior axis and 0°along the mediolateral axis as shown in Figure 2(a), ii) *Posture-B*: 90° with the anteroposterior axis and 0°along the mediolateral axis as shown in Figure 2(b), iii) *Posture-C*: 120° with the anteroposterior axis and 0°along the mediolateral axis as shown in Figure 2(c), iv) *Posture-D*: 90° with the anteroposterior axis and left of the mediolateral axis as shown in Figure 2(d), and *Posture-E*: 90° with the anteroposterior axis and right of the mediolateral axis as shown in Figure 2(e).



(a) (b)

(c) (d)

(e) (f)

Fig. 2. Snapshots showing 5 different sitting postures of a subject: (a) Posture-A, (b) Posture-B, (c) Posture-C, (d) Posture-D, and (e) Posture-E, and (f) An annotated snapshot illustrating the placement of three Velostat sensors and accelerometer on the seat-belt and one Velostat sensor on the back-rest seat, used for detecting sitting posture and heart rate.

A. Hardware Design

The hardware design of the proposed system involves a passenger seat setup mounted on an adjustable platform with a seat-belt attached to a stand, as illustrated in Figure 2 (f). The seat is mechanically adjustable, allowing forward and backward movement along a linear rail system, enabling angular adjustments of the backrest relative to desired angles to the sagittal axis. This ensures optimal ergonomic positioning for the subjects. The setup includes a buckle mechanism for the seat-belt, which is adjustable to accommodate diverse body types. The design incorporates four optimally placed Velostat PSC sensors and an ADXL345 Tri-axial accelerometer. The analog inputs from the Velostat sensors and the SDA and SCL pins of the tri-axial accelerometer are connected to the analog pins of the Arduino Uno micro-controller. Each PSC sensor module receives a 5V power supply from the Arduino and is connected to a 100 Ω current-limiting resistor, enabling the capture of time-varying voltages corresponding to the pressure exerted on each sensor module. This sensor array's temporal and spatial signals are crucial for identifying the passengers posture. The sensor readings, which ranges from 0 to 5 V, are digitized to a scale of 0-1023, using the integrated analog-to-digital converter (ADC) channels within the system. The accelerometer offers measurements along x, y, and z-axis and is processed to extract the heart rate measurement, by detecting variations due to the chest vibrations induced by cardiac activity. This setup facilitates Heart-Rate measurements by capturing the accelerometer's data on the chest's movements due to cardiac cycles. Signal from all four PSC sensors is collected at a sampling rate of 5 Hz and the accelerometer data is collected at a sampling rate of 50 Hz.

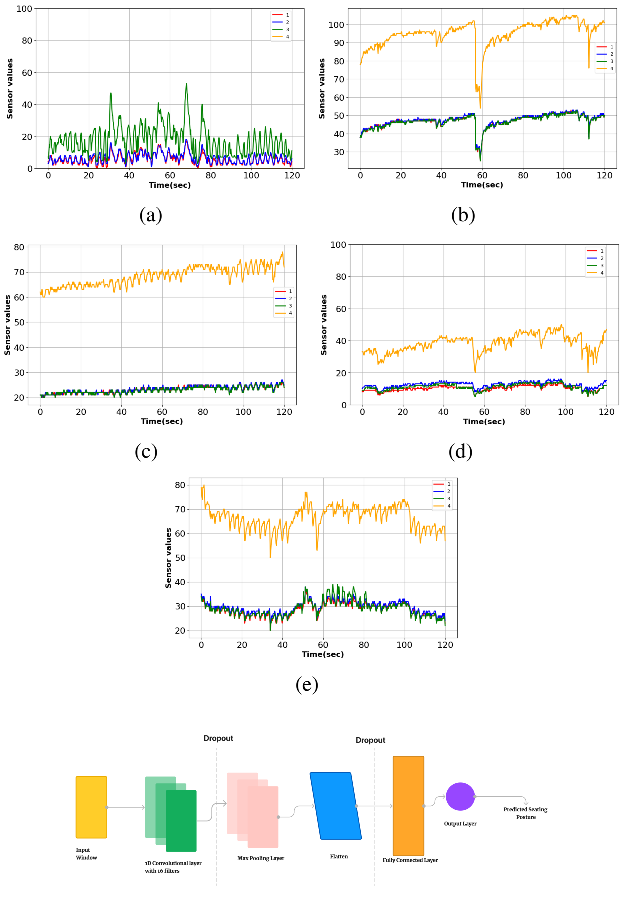
B. DataSet

The dataset construction involved 8 subjects of diverse body types, ensuring a comprehensive collection for robust analysis. Before initiating the experiment, the participants are provided with a short tutorial on the way to sit in different postures with the seatbelt. Additionally Ethical approval was taken from the Institute Review Board to carry out these experiments on the subjects. The data was collected in accordance with the Helsinki Declaration of 1975, as revised in 2000. Each subject assumed five distinct sitting postures for a duration of two minutes per posture enabling a thorough capture of dynamic changes in sitting postures. During data collection, a Tri-Axial accelerometer continuously recorded data. Mediapipe, a keypoint detection framework, was employed to capture ground-truth pose information, keyframes, and angles, facilitating precise labeling of the acquired signals representing distinct sitting poses. The dataset's versatility was further expanded by including a sixth state representing an unoccupied seat. This addition provided a unique dimension, enabling the analysis and differentiation of states when no individual was seated, thereby adding a layer of realism to the dataset. By incorporating the unoccupied state and recording accelerometer data, the designed system is capable of detected whether the seat-belt was applied by the seated individual. To ensure the accuracy of Heart-Rate data, a pulse-oximeter sensor was utilized to capture ground truth information. Both accelerometer data and the ground-truth data were collected simultaneously for each posture. This approach includes processing algorithms to extract heart-rate and using ground-truth data to measure deviations, ensuring the dataset accurately reflects various sitting variations.

III. EXPERIMENTAL RESULTS

A sample recording, depicting various sitting postures of a subject was obtained using four Velostat PSC sensors is illustrated in Figure 3(a-e). Sensors #1 to #4 depict the sensor readings mapped within 0 to 1023 range. The recorded voltage levels are plotted relative to the preceding sensor readings, presented in vertically stacked plots for clarity. The recorded data from these four sensors were used to train the CNN model, achieving an accuracy of 97.42%. The CNN model showcased superior performance over other trained models including SVM, KNN, XGBoost, and ANN as listed in the Table I. The architecture as shown in Figure 3 (f) commences with a one-dimensional (1D) convolutional layer featuring 16 filters and a kernel size of 3, employing ReLU activation function. This is followed by a max-pooling layer with a pool size of 2, which reduces dimensionality. Post flattening the pooled output, the model incorporates a fully connected (dense) layer with 128 units and a ReLU activation function, followed by a dropout layer with a dropout rate of 0.5 to prevent over-fitting. Finally, the output layer employs a soft-max activation function to facilitate multi-class detection. During training, the model utilizes categorical cross-entropy loss and the Adam optimizer. To assess its performance, the model is evaluated using a 60%:20%:20% split for training, validation, and testing respectively, ensuring that the test datasets are unseen during model training process. For Heart-Rate monitoring, the processing step involved filtering, normalization, and peak detection as suggested in [28]. The raw Z-axis acceleration data representing chest activity vector, undergoes rectification, followed by a Butterworth high pass filter of the fourth order with a cutoff frequency of 18 Hz to extract cardiac sounds. The first 100 samples of the filtered vector are discarded to eliminate distortion introduced by the filter, and the remaining samples are rectified. The processed signal is then normalized using the z-score method and rectified again. A threshold with 80% of the variance for the final signal energy, is computed. The extracted peaks from the signal corresponds to the closure of the aortic value, a cardiac event causing the maximal vibration of the chest. The Heart-Rate (HR) is computed as the mean of the time intervals between the detected peaks.

Figure 4 (a) illustrates the processed accelerometer data with the identified peaks. To validate the Heart-Rate measurements, ground truth data was collected using a pulse oximeter at different postures. The filtered accelerometer data was compared with the pulse-oximeter readings for all the volunteered subjects across all the postures to characterize average deviation of ± 8 bpm. These experimental results underscore the efficacy of the system in leveraging the robust CNN model for posture recognition and a meticulous signal-processing algorithm for Heart-Rate detection. The system's ability to achieve high accuracy in posture recognition and reliable Heart-Rate monitoring validates its potential for enhancing passenger overall safety including physical and health-wise, and yet maintain the ergonomics. The Heart-Rate measurement for unoccupied seat, and subject non-wearing the seat-belt was highly off showcasing an average of 11 bpm, and 39 bpm respectively, when compared to the subjects wearing the seat-belt in the range of 60 to 100 bpm. Figures 4 (b), and (c) shows Heart-Rate of the subject without wearing Seat-Belt, and with no-occupant in the seat respectively. The number of peaks extracted



(a) (b)

(c) (d)

(e)

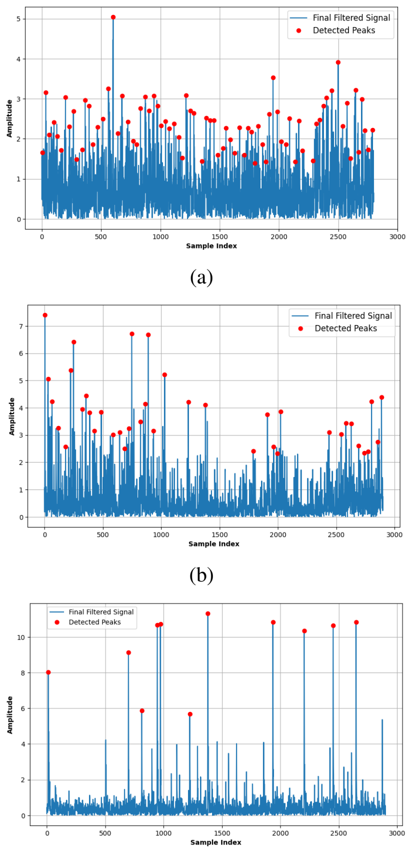
(f)

Fig. 3. Temporal data captured by four Velostat sensors (#1, #2, #3, and #4) for a subject across different postures: (a) Posture-A, (b) Posture-B, (c) Posture-C, (d) Posture-D, (e) Posture-E, and (f) Proposed CNN Architecture for posture recognition.

for both cases are low and the same is reflected in the average readings. Hence post Heart-Rate Estimation the non-usage of seat-belt and an unoccupied seat is clearly detected. Additionally, the temporal signal extracted from four sensors for unoccupied-seat state remains very low, and hence in the Posture recognition model it is easily distinguishable showcasing superior accuracy (97.42%) as stated before. The proposed ergonomically viable seat-belt system showcases a novel and appealing use-case for the vehicular system. Through the posture recognition model, continuous sudden change in the passenger sitting pose is reported as anomaly state which needs immediate attention. Similarly the Heart-Rate estimation offers insights of the passenger's health during the travel and immediate assistance could be further arranged if needed.

TABLE I. PERFORMANCE OF ML MODELS FOR POSTURE RECOGNITION AMONG 6 DIFFERENT STATES.

Models	Accuracy	Precision	Recall	F1 Score
SVM	84.07%	84.47	84.07	83.8
KNN	96.9%	96.83	96.96	96.95
XGBoost	97.19%	97.21	97.19	97.19
ANN	94.42%	94.9	94.42	94.28
CNN	**97.42%**	**97.41**	**97.42**	**97.41**



(a)

(b)

(c)

Fig. 4. Processed accelerometer data with the established Heart-Rate peaks for (a) subject occupying seat, by wearing seat-belt, (b) subject occupying seat but not wearing seat-belt, and (c) no-occupant.

IV. CONCLUSIONS

The proposed work offers a novel approach in monitoring passengers sitting posture and estimating Heart-Rate through an integrated system of Velostat PSC sensors and a Tri-axial accelerometer applied on the seat-belt. The proposed seat-belt integrated system with a 1-layer CNN model offers high accuracy of upto 97.42% for sitting posture recognition, besides estimating the heart-rate with an acceptable deviation of ±8 bpm over the ground truth results. The state of no-occupant and non-usage of seat-belt was also detected from Heart-Rate estimation and posture recognition model successfully. The camera-less seat-belt approach preserves user privacy, making it an ergonomically practical solution for real-world applications. The dataset along with source-code and design files are made freely available at [29] for easy adoption and further usage by the researchers and designers.

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