A Flexible Wearable Sensor with Machine Learning Augmentation for Physical Activity Monitoring

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***Abstract*—Recent advancements in flexible electronics have enabled new motion tracking and activity recognition approaches. The mechanical interactions of human or animal body vibrations and movements can be transformed to valuable data for their health monitoring. This paper presents a high-performance flexible sensor fabricated using inkjet-printing on a polyethylene terephthalate substrate with silver conductive ink for comprehensive activity monitoring. The sensor shows consistent response to various human activities including walking, running, clapping, writing, waving, and typing. Experimental results indicate reliable signal acquisition for physical activity monitoring. The sensor design offers practical advantages including low production cost, minimal power requirements, and straightforward integration into wearable systems. When combined with signal processing algorithms, the platform effectively classifies different activity patterns. The sensor offers several practical advantages — it is lightweight, low-cost, consumes minimal power, and supports easy integration into wearable devices. These characteristics make the sensor suitable for healthcare monitoring, sports analytics, rehabilitation tracking, and veterinary behavior studies where continuous motion capture is needed.**

***Index Terms*—Activity Monitoring, Capacitive Sensing, Flexible Sensor, Inkjet-Printing, Wearable Device.**

I. Introduction

Physical activity serves as a fundamental indicator of health, functionality, and behavioral patterns across diverse populations, including athletes, elderly individuals, and animals. Accurate monitoring of motion and posture can provide critical insights into performance optimization, early detection of musculoskeletal or neurological conditions, and overall well-being [1]–[3]. In elderly care, continuous activity monitoring facilitates the evaluation of mobility, identification of falls, and analysis of daily living patterns, thereby enabling independent aging and prompt clinical interventions [4], [5]. Similarly in veterinary applications, activity tracking aids behavioral analysis, welfare assessment, and early detection of diseases in both livestock and pets [6]–[8]. Detailed motion data can improve individualized feedback systems, maximize biomechanics, and help to minimize injuries in athletic training and rehabilitation [9], [10]. With the rising demand for reliable, real-time, and unobtrusive monitoring solutions, the advancement of sensing technologies that are both comfortable and adaptable to dynamic environments has become increasingly important.

Recent advancements in sensor technology have led to a new era of flexible sensors, redefining the collection, analysis, and application of physical data. These sensors, capable of withstanding bending, stretching, and twisting, offer mechanical adaptability that rigid sensors inherently lack [11], [12]. Their flexibility allows for effortless integration onto uneven and dynamic biological surfaces, such as human skin or animal limbs, garments, accessories, and soft structures, enabling continuous, unobtrusive monitoring without sacrificing user comfort, making them ideal for healthcare, animal monitoring, rehabilitation, and sports science [13]–[17].

Inkjet printing offers a scalable and cost-efficient approach to fabricating flexible sensors by precisely depositing conductive materials onto flexible substrates [18], [19]. This technique enables rapid prototyping and customization of sensor designs with minimal material waste [20]. Previous studies have demonstrated inkjet-printed piezoresistive and capacitive sensors for applications like gait analysis, gesture detection, and tactile monitoring [21]–[23]. Silver nanoparticle ink is widely used in inkjet printing due to their favorable electrical properties and mechanical flexibility. While inkjet-printed sensors may exhibit lower conductivity compared to conventionally fabricated counterparts these factors are often outweighed by the method's advantages in affordability, mechanical adaptability, and design flexibility. Ongoing improvements in ink formulations and printing resolution continue to address performance gaps, further reinforcing the promise of inkjet-printed sensors for reliable and practical use.

In this study, we present an unique pattern-based flexible capacitive sensor fabricated by printing silver conductive ink on a polyethylene terephthalate (PET) film using Voltera V-One printer. The schematic of the proposed sensor is illustrated in Fig. 1a. The sensors' capacity to detect various physical actions was evaluated, including walking, running, clapping, writing, waving, and typing. The demonstrated results highlight the sensor's capability to detect motion-related signals relevant to elderly care, athletic monitoring, and animal activity tracking and medical surveillance. With its light-weight, low-power, and low-cost profile, this sensor system presents a promising solution for smart wearable and embedded activity monitoring platforms.

The remainder of this paper is structured as follows: Section II outlines the sensor architecture, underlying

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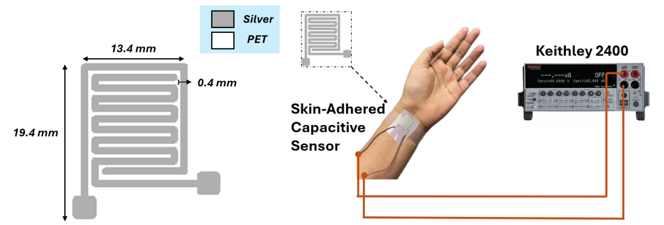


(a) (b)

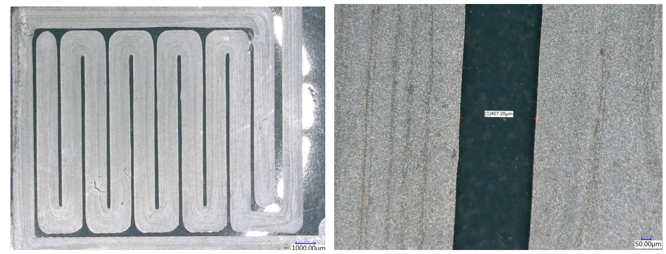
Fig. 1: (a) Schematic view of inkjet printed sensor, and (b) Activity sensing evaluation setup.

working principles, and the inkjet printing fabrication process. Section III introduces the data acquisition system and the experimental setup used to evaluate the sensor performance. Section IV analyzes the results obtained from monitoring various physical activities. Finally, the conclusion of this work is presented in Section V.

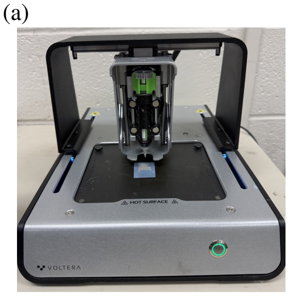
II. Device Formation and Modeling

Inkjet printing of electronics on flexible substrates has captured significant interest due to its flexibility, cost-effectiveness and improved efficiency. The wearable sensor pattern based on a comb-shaped electrode surrounded by a square ring electrode was developed using KiCad Software. The designed pattern was then converted to gerber file. A semitransparent PET film was used as the substrate with a thickness of 135 μm. Voltera V-One was utilized to print the generated gerber file onto the substrate with silver nanoparticle ink, as seen in Fig. 2c. At first a gerber file of the layout pattern was developed using KiCad Software. The layout was printed at room temperature using Voltera Conductor 3 ink which is a paste like silver nanoparticle ink. The trace width of the printed design is 0.5 mm. Subsequent to printing, the ink was cured by positioning the sensor on a hot plate at 70°C for ten minutes. The dimension of the printed sensor is displayed in Fig. 1a. The length and width of the whole device is 19.4 mm and 13.4 mm while the gap between the silver electrode patterns and their linewidth are 0.4 mm and 0.9 mm. Fig. 2a presents the top view of printed sensor through a digital microscope and Fig. 2b displays a closer view of the printed electrodes with silver nanoparticle ink.

The working principle of the inkjet-printed flexible sensor is based on capacitive effects induced by mechanical deformation. The printed device responds to vibration generated by different physical activities such as running, walking or waving. Slight stress or compression generated by physical activities results in the reconfiguration of the relative positions of silver nanoparticles within the printed lines. This leads to a variation in the capacitance of the structure. The outer rectangular electrode and the inner meander-shaped electrode are parallel to each other, and the current flow within the structure is defined by the following equation when a fixed bias voltage is applied.



(a) (b)



(c)

Fig. 2: (a) Top view of proposed sensor through digital microscope, (b) Closer View of silver nanoparticle ink based electrodes, and (c) Sensor fabrication using an inkjet-printer.

$$i = V \times \frac{dC}{dt} \tag{1}$$

The total capacitance C consists of a constant lateral capacitance C_l and a fringe capacitance C_f. The fringe-field capacitance C_f developed between the neighboring electrode fingers changes when vibration caused by physical movement alters the relative distance and overlap area. These fluctuations in capacitance vary the total impedance of the system resulting in change in current for a fixed bias voltage.

III. Data Acquisition and Experimental Methodology

The silver-based IJP sensor was tested for activity monitoring application. The sensor substrate was taped to skin on wrist with the silver lines on top and a high-precision source-meter, Keithley 2400, was used to monitor current variations of the printed sensor in response to different activities. The experimental setup is displayed in Fig. 1b. In our experiment, ten data collections were performed for 500 data points for each physical activity. Kickstart software interface was used to extract data from the source meter to excel. A voltage limit of 5 V was set up in the source meter to allow current flow through the prototype sensor, and the corresponding current profile was observed through the source meter. A student volunteer performed six different activities for the experiment- clapping, running, slow walking, typing, waving, and writing. As seen in Fig. 3, for different activities, the prototype sensor shows sensitivity as the current profile for each activity has visible difference when a fixed bias voltage is applied.

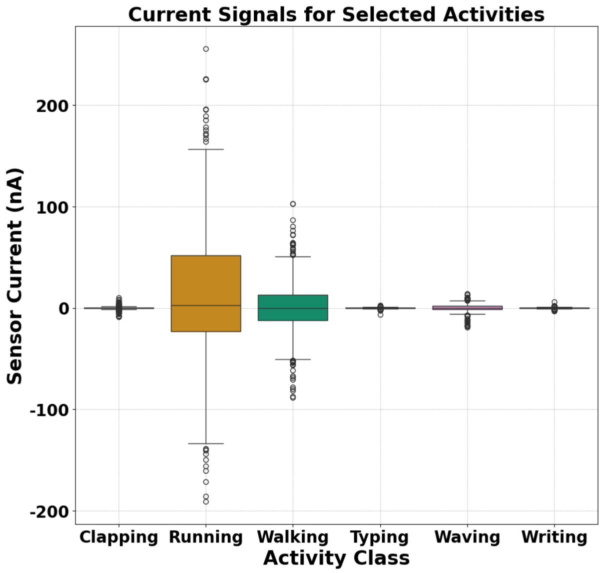


Fig. 3: Sensor's current response to different activities.

IV. Performance Evaluation

Time series data collected from different activities was used to train a machine learning model for activity classification. Due to the limited number of original samples (59), data augmentation techniques were employed to expand the dataset to 531 samples and reduce the risk of overfitting. The augmentation methods included jittering, scaling, wrapping, and window slicing [24]. The wrapping technique was applied in both the time and magnitude domains. In the jittering method, Gaussian noise was added to the time series signal with a mean of 0 and a standard deviation of 2×10^{-11}. For the wrapping and slicing methods, parameters were tuned to achieve the desired signal-to-noise ratio of 0.004. The resulting dataset was split into training and test sets using an 8:2 ratio with stratified sampling to maintain class distribution.

For classification, an Echo State Network (ESN) was selected due to its strong performance with time series data [25]–[27]. PyRCN library was used to design ESN in python interface [28]. Table I presents the hyperparameters used to configure the model. These hyperparameters were optimized using a three-stage grid search over spectral radius, alpha, input scaling, bias scaling, and leakage. K-fold cross-validation was applied with a value of $K = 20$ to ensure robust model evaluation.

To evaluate the performance of the ESN, precision, recall, and F1 score were used alongside accuracy. For accuracy assessment, both micro-average and weighted-average metrics were considered. Table II presents the classification report, and the confusion matrix is shown in Fig. 4. The model shows overall accuracy of 99%. According to Fig. 5, typing, writing, and clapping produced highly correlated time series signals, which leads to reduced classification performance for these activities. In contrast, due to their low correlation with other classes, running and walking were classified with the highest accuracy.

TABLE I: ESN Classifier Hyperparameters

Layer	Hyperparameter Settings
Input Layer	Bias scaling = 0.8333 Hidden layer size = 270 Activation function= ReLU Input scaling = 0.89
Reservoir	Hidden layer size = 270 Recurrent connectivity = 10 Leakage = 0.9 Activation function = ReLU Sparsity = 0.0370 Spectral radius = 10^{-5}
Output Layer	Alpha = 0.1 (Incremental Regression)

TABLE II: Classification Report of ESN Classifier

Class	Precision	Recall	F1-Score	Support
Clapping	1.00	0.99	0.99	72
Running	1.00	1.00	1.00	72
Walking	1.00	1.00	1.00	72
Typing	0.98	0.96	0.97	50
Waving	1.00	0.97	0.99	72
Writing	0.95	1.00	0.97	72
Accuracy			**0.99**	**410**
Macro avg	0.99	0.99	0.99	410
Weighted avg	0.99	0.99	0.99	410

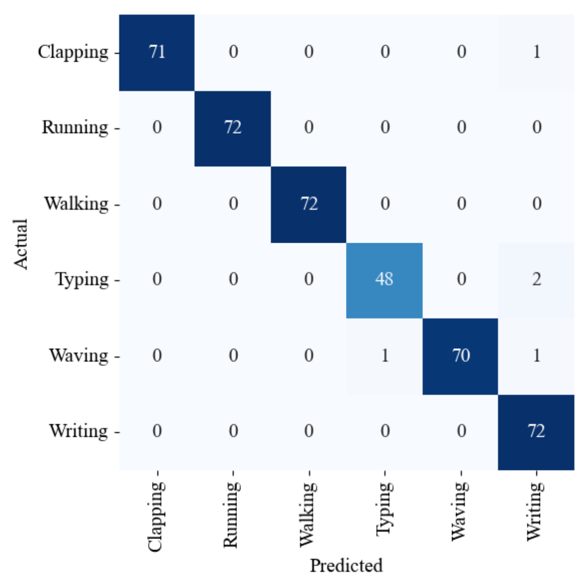


Fig. 4: Confusion matrix for ESN classifier.

V. Conclusion

In this work, an inkjet printed capacitive flexible sensor is presented as a wearable device for activity monitoring applications. Fabricated using an inkjet-printer with silver nanoparticle ink, this sensor offers a low-cost, light-weight, and practical solution for applications necessitating continuous tracking of physical activity. The sensor response to different physical activities was used to train an ESN network with an

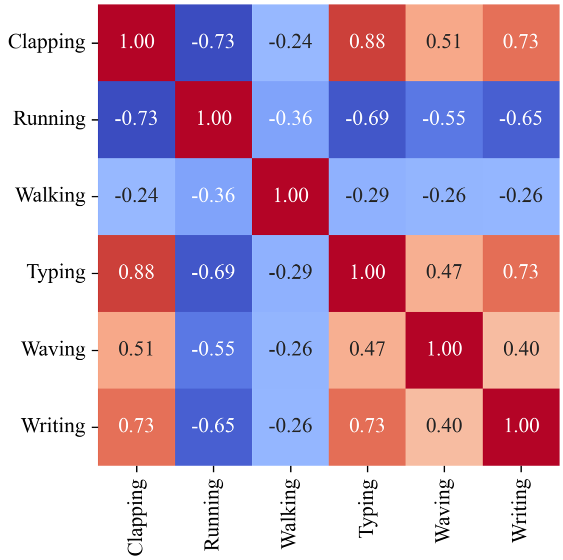


Fig. 5: Heat plot for the correlation matrix for different activities.

accuracy of 99%. As the need for continuous, comfortable, and accurate monitoring systems grows, the proposed flexible sensor shows promise serving across domains, from athletic optimization and elderly care to animal behavior analysis.

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