One Step Towards Secure Identification in Wireless Body Area Networks (WBANs): Intelligent Insole Sensor Systems

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***Abstract*—The ongoing development of the Sixth Generation (6G) wireless systems is opening up new fields of application and opportunities for integrating innovative near-body sensor technology and Body Area Networks (BANs). In light hereof, this work presents the design of an Insole Sensor System (ISS), particularly for identifying and authenticating individuals. An emphasis is thereby laid on the application of unique properties of flexible conductive materials and their seamless integration into future wireless networks. The system -consisting of a matrix of sensor connections- gathers data in real-time and captures individual print patterns, allowing for unique biometric factors. In terms of longevity and energy efficiency, the data is transmitted to a web application via a BLE, allowing integration into an overarching ecosystem of wearable technology and (Medical) Internet of Things ((M)IoT). Furthermore, the work addresses aspects and challenges of the ISS in terms of data protection, security and interoperability. By combining the ISS with machine learning (ML) methods, an accuracy of 95% is achieved, which is a significant improvement compared to standard sensor systems.**

***Index Terms*—Biometrics, CNN, Machine Learning, Deep Learning, Gait recognition**

I. Overview and Integrability

The ongoing research on 6G technology is said to revolutionize digital connectivity, emphasizing enhanced security measures, including robust authentication and identification. With its goal to amplify data transmission speeds, reduce latency, and increase device integration capacity, 6G aims to evolve beyond the current Internet of Things (IoT) paradigm to a health-centric (Medical) Internet of Things ((M)IoT) or a broader Internet of Everything (IoE). This intends to incorporate not just devices, but also the human body [1]. In this context, the topic of authentication, a vital component of information security, becomes crucial, especially concerning Body Area Networks (BANs). These networks include sensors and devices worn or implanted on the human body, necessitating reliable authentication methods for secure and private data communication [2].

The growing amount of interconnected devices underscores the importance of user-friendly, efficient biometric authentication systems. The proposed Insole Sensor System (ISS) addresses this need, using unique foot pressure patterns for user authentication [3]. When integrated within a BAN and subsequently within the larger 6G ecosystem, it enhances multi-factor authentication, thereby bolstering the security of the emerging (M)IoT and IoE paradigm [2]. Therefore, this work compares two developed Intelligent Insole Sensor Systems, emphasizing sensor design, material use, and the potential for multi-factor authentication system integration. Both sensor solutions are evaluated for identifying six individuals, demonstrating the accuracy of the insole system.

A. Background and Related Work

Gait recognition, a soft biometric, is a burgeoning field less prone to forgery due to its behavioral basis [3]. Its implementation varies but broadly falls into three categories: Machine Vision, Floor Sensory, and Wearable Sensory. Of these, wearable sensors offer unique benefits as they aren't locally bound and require active user participation, ensuring privacy [2]. These sensors, found in wearable devices like smartwatches and located on various body parts, can host a range of sensor types to extract diverse features [4][5].

A practical embodiment of wearable sensors is detailed by *Wang et al. (2019)*, who reported an 85 % recognition rate using an accelerometer, gyroscope, and magnetometer data classified by Support Vector Machine (SVM) [6]. *Marsico et al. (2019)* provides a comprehensive review of studies investigating wearable sensors, with a focus on those incorporated into mobile devices [7]. Despite technical challenges and variable performance, wearable sensors outdo floor sensory and machine vision approaches with their portability, continuous authentication, and their potential for health monitoring [8] [7].

For instance, *Zhang et al. (2022)* proposed textile-based sensing for prolonged gait analysis to aid lower-limb rehabilitation [9], while *Balakrishnan et al. (2022)* explored their potential for neurodegenerative disease assessment [10]. The smart insole presented in this work encapsulates these benefits, fusing healthcare and security aspects by enabling user authentication through a wearable insole.

B. Integration - Multi-Factor-Authentication System

The Insole Sensor System functions as a node within a Body Area Network (BAN), offering a distinct biometric signature via users' unique pressure patterns. This feature enhances authentication security and is highly resistant to forgery. Integrating this data with other biometric inputs from BAN wearables, such as heart rate or movement patterns, enables a comprehensive multi-factor authentication system [11]. The system's seamless integration with other sensors enhances security and data transmission efficiency within BANs [2]. Local data processing within the network reduces transmission needs, saving energy, while 6G technology ensures high-speed, real-time analysis [12].

Despite the advantages, challenges persist, notably in privacy and data security, necessitating strong encryption and secure communication protocols. Energy efficiency and standardized interoperability among devices are also crucial to address [13]. Overcoming these hurdles is essential for the Insole Sensor System's integration into BANs, which holds potential to advance biometric authentication and provide insights in healthcare and various other sectors [14]

II. Design and Implementation of the Insole-Sensor-System

The main goals in the development of the proposed ISS are to develop a system that combines a high rate of measurement intervals with a high resolution of pressure points, all encased in an easy-to-handle insole with no external wires.

A. Design goals of Insole Sensor System

a) **Minimally invasive:** Since the insole is supposed to measure gait data of the test person, it shouldn't change the natural gait of the person that is using it. In order to reach this a minimally invasive insole that's very thin and highly flexible has been devised.

b) **High-resolution sensor matrix:** A high resolution allows for a clearer image and therefore finer feature extraction. The high-resolution image can later on be down-scaled or sub sampled in order to find the minimum required resolution for accurate identification. Therefore a high-resolution sensor matrix is one of the design goals. A six-by-twelve matrix configuration would bring 72 sensor points and is the chosen configuration for this insole.

c) **High data aquisition rate of 50+ Hz:** The mean time a foot has contact with the ground in a normal step cycle is about 0.6-0.7 s [15]. Together with the goal data acquisition rate of 50+ Hz this would give us 30+ samples per step per foot. This requirement is equally argued as the high resolution of the sensor matrix in that a sub sampling is always possible. Furthermore, a higher resolution in the time domain allows for better feature extraction since the duration and change from one state in the step cycle to the next can be far better measured and used for analysis.

d) **Bluetooth Low Energy (BLE) connectivity:** BLE is to be used for transmitting the recorded data from the insole. BLE support is easy to find in Microcontroller Unit (MCU) and allows an easy and flexible way to connect to computers and mobile devices for recording and visualizing the incoming data from the insole in real time.

e) **Robust packaging:** The insole is working under extreme conditions in the shoe while recording the toe region of the shoe can bend up to 50°. Having a compliant sensor construction and all needed electronics and power supply inside the insole itself helps to keep the insole robust enough to survive the aggregation of data.

B. Basics of the sensor matrix

In the pursuit of developing a high-resolution sensor matrix, a variety of conductive materials have been explored to ascertain the most fitting and enduring solution to serve as a reliable base for the sensor. The fundamental design operates on a grid system. A pressure-sensitive foil is sandwiched between conductive traces arranged both horizontally and vertically. Each intersection point of the top and bottom traces serves as a measurement node, where the resistance of the foil can be quantified. The horizontally placed lines are put under voltage (feedlines), and the vertical ones are connected to analog inputs (senselines). The measured resistance of the foil provides a basis for deducing the pressure exerted at the specific location. This is due to the characteristic property of the pressure-sensitive foil that its conductivity increases proportionally with the rise in applied pressure. The pressure-sensitive foil utilized in this approach is *adafruits Velostat*. Velostat is readily available and demonstrates significant changes in its resistance based on pressure variations: it exhibits a resistance of approximately $5\,\mathrm{k}\Omega$ when no pressure is applied, which decreases to around $40\,\Omega$ under applied pressure. To avoid very small changes in resistance in the high-pressure area, multiple layers of the foil are used, until the 12 bit Analog Digital Converter (ADC) quantifies values in the middle of its measuring range, to produce usable data during test-walks.

C. Conductive flexible sensor design

Given the broad range of shoe sizes that the insole is designed to accommodate, employing a fixed-size conventional printed circuit board presents a challenge. Based on recent approaches of printing circuits and sensors onto flexible materials [16], conductive lines were printed with an inkjet printer onto a paper-like flexible substrate. To fabricate the flexible and thin insole pressure sensor, conductive inkjet printing was used [17]. The electrodes and conductive paths were printed with silver nanoparticle-based ink (Mitsubishi NBSIJ-MU01) on coated paper (Mitsubishi NB-RC-3GR120) using a commodity inkjet printer (EPSON WorkForce WF-2010W). Since this special conductive ink's physical resistance and electrical conductivity scale with its thickness, multiple layers are printed on top of each other. The durability and conductivity of the printed interface could be increased by printing the same pattern onto the substrate by 8 times. The fact that inkjet printers are not built to print multiple times on the same piece of paper with absolute accuracy, leads to some problems with crosstalk between different traces. Even with a distance of 0.8 mm - 1 mm between the traces, some short circuits have been observed, though all of them could easily be solved by carefully cutting the top layer of the flexible substrate.

The best-found solution to connect the inkjet printed circuit board with a classic fiberglass-based circuit board which houses the MCU and charge logic for the battery are enameled copper wires. Despite that the cable is very thin, it can still be soldered well. Direct soldering to the printed ink necessitates the use of a bismuth-based, very low-temperature solder (Sn42Bi57Ag1). This method is required to prevent damage to the ink and paper caused by high-temperature soldering. Upon successful implementation of the low-temperature soldering process, it was observed that using a certain amount of force on the wire results in the cured ink detaching from the substrate. To address this issue, copper tape (Adafruit 3483) was introduced as an intermediary layer between the wiring and the conductive ink. This modification effectively dispersed the applied forces over a broader area, ensuring the ink remained affixed to the paper substrate. Furthermore, the ensuing copper-to-copper connection between the tape and wire could easily be soldered using traditional soldering methods, enhancing the durability and resilience of the connections.

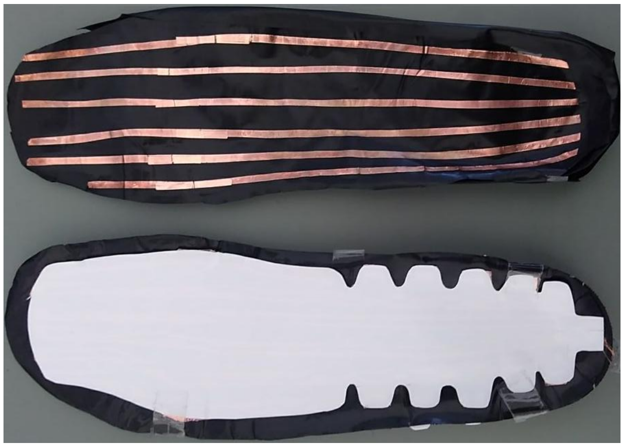

Fig. 1: Setup of Insole Sensor System - copper (top) and paperlike (bottom) substrate approaches.

The copper tape itself is attached to the conductive ink via a layer of conductive glue. Fig. 1 gives an insight into how both versions of the Sensor System are constructed.
The insole using copperlike imprinting forgoes the paper layers featuring the conductive ink and uses only the copper tape. The feedlines are glued to the TPU printed Insole and the senselines are attached to the *Velostat* foil. This variant reduces the number of moving layers from 3 (TPU insole - Paper - *Velostat* - Paper) to 1 (TPU insole - *Velostat*).

D. Comparison Paperlike Subtrate - Copperlike Imprinting

The paper-like substrate utilized in the sensor matrix presented certain pros and cons. On the plus side, the layers could shift during bending, creating a compliant sensor matrix, which lessened the strain on the ink, thus improving the insole's robustness. However, there were a few drawbacks. The ink used was vulnerable to bending and occasionally cracked, mandating reinforcement with copper tape in areas where bending occurs. Moreover, the shifting layers felt unstable to walk on and the paper-like substrate showed weakness against moisture.

Meanwhile, the copperlike imprinting technique had its own set of advantages and disadvantages. It offered the benefit of having only one moving layer, which simplified packaging and assembly. On the other hand, the tape, when glued, couldn't move with the bending insole, resulting in cracks over time. Additionally, the wires connecting the feedlines to the PCB became longer, and the exposed trace of the feedlines tended to oxidize after a few days, potentially skewing results.

III. Multi-Class Classification and Evaluation

To provide a proof-of-concept, different Machine Learning (ML) Algorithms to classify the data recorded from the insole are applied and compared. Each of them is designed to predict whether the input data belongs to a certain user. As already stored templates of all users are used for comparison, the approach corresponds to a multi-class classification and hence the results verify the applicability of the proposed insole as an authentication mechanism [7].

A. Machine Learning Classifiers

In this study, ML classifiers, specifically theRandom Forest Classifier (RFC) and K-Nearest Neighbour (KNN), are employed to analyze features for pattern recognition. The RFC uses multiple decision trees to boost accuracy, although it is prone to overfitting, particularly with large datasets. For the smaller dataset, RFC is optimized using Gini Gain to expedite training while maintaining precision, using an ensemble of 100 trees for robust analysis.

Conversely, KNN adopts a more straightforward approach, assigning data points to the most common class of their k nearest neighbors based on Euclidean distance, with k set to 5. This method is effective for small datasets but less so for larger ones due to increased performance and accuracy issues.

B. Convolutional Neural Network

To compare with the previously discussed classifiers, a Convolutional Neural Network (CNN) is deployed, distinguishing itself by negating the need for manual feature extraction. CNNs are selected for their prowess in handling data akin to images, making them ideal for interpreting pressure matrices [18]. A typical CNN structure includes convolutional, pooling, and fully connected layers, essential for this application's processing chain, beginning with a convolutional layer and ending with a fully connected one.

Edge information loss in convolutional layers is countered with padding, crucial for maintaining data integrity across the input matrix. To prevent the common issue of overfitting due to the high dimensionality inherent in image-like data, pooling layers are incorporated to simplify the feature landscape. Dropout layers further enforce model robustness by randomly disabling feature sets during training [18].

This specific CNN utilizes two convolutional layers integrated with Leaky ReLu activation to avoid the nullifying effects seen with standard ReLu in some CNN contexts. It concludes with two fully connected layers, where the final layer employs a softmax function to deliver normalized predictive outputs.

C. Preprocessing and feature extraction

The feature extraction process is critical for achieving reliable results and entails multiple preprocessing steps. Since data acquisition occurs during walking, it necessitates initial step separation. A Gaussian filter is then applied to each segmented step to eliminate noise and outliers, streamlining data for effective classifier performance. Distinct feature sets are derived for each step, segmented into eight phases based on gait analysis methodologies [8], optimizing the reflection of unique walking patterns.

The initial 60% of each step constitutes five phases, termed the 'standing phase,' while the final 40%, or phases 6 to 8, are defined as the 'swinging phase.' The feature for each phase is averaged from the corresponding pressure matrices, as illustrated in Figure 2, which depicts six frames of pressure data per step.

For the CNN, these eight feature matrices per step are sequenced in a time series, correlating with each step taken by an individual, summing up to 500 sequences for neural network

TABLE I: Comparison of accuracy of CNN, the Random Forest Classifier and the K-Nearest-Neighbour Classifier.

	CNN	RFC	KNN
Accuracy	93.2%	94.7%	94.4%

training. Post-convolution, phase duration data enhance the fully connected layer's inputs.

Conversely, traditional classifiers necessitate further feature distillation. The pressure data is divided into nine zones per matrix, focusing on areas like toes and heels to isolate significant traits. Each step's 72-point data is condensed into nine representative features, balancing detail richness against overfitting risks. To refine data quality, features from two random steps are averaged, and six-step features amalgamate into a singular matrix, enhancing robustness against anomalies.

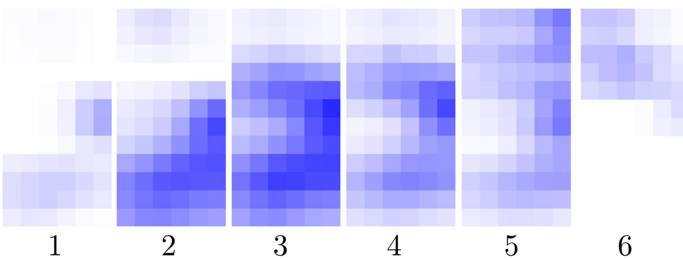

Fig. 2: Example of a step from left to right: Six frames, showing the aggregated pressure values and pressure pattern during the gait.

D. Results

Upon examining the dataset, the implemented algorithms yield diverse results for a dataset comprising 10 participants including 500 steps per person. Approximately 70 % are used for training, while the remaining 30 % are included in the test dataset. Table I provides an overview of achieved accuracies for both classification approaches.

IV. Conclusion and Outlook

This paper introduces an Insole Sensor System for biometric authentication, utilizing flexible conductive materials and designed for future wireless network integration. The system employs a sensor matrix to capture unique foot pressure patterns as biometric identifiers, showcasing a novel approach in the authentication field. Analysis reveals that using 72 features per dataset with Random Forest and K-Nearest Neighbor algorithms outperforms a Convolutional Neural Network, though CNN's performance could improve with further tuning. Despite potential privacy and security challenges, the Insole Sensor System offers promising prospects as a user-friendly and adaptable authentication solution, suggesting that future research should aim to resolve its existing limitations.

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