Self-Powered, Hybrid, Multifunctional Sensor for a Human Biomechanical Monitoring Device

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Abstract: For personal and daily activities, it is highly desirable to collect energy from multiple sources, not only for charging personal electronics but also for charging devices that may in the future sense and transmit information for healthcare and biomedical applications. In particular, hybridization of triboelectric and piezoelectric energy-harvesting generators with lightweight components and relatively simple structures have shown promise in self-powered sensors. Here, we present a self-powered multifunctional sensor (SPMS) based on hybridization with a novel design of a piezoelectrically curved spacer that functions concurrently with a zigzag shaped triboelectric harvester for a human biomechanical monitoring device. The optimized SPMS had an open-circuit voltage (VOC) of 103 V, short-circuit current (ISC) of 302 µA, load of 100 kΩ, and maximum average power output of 38 mW under the operational processes of compression/deformation/touch/release. To maximize the new sensor’s usage as a gait sensor that can detect and monitor human motion characteristics in rehabilitation circumstances, the deep learning long short-term memory (LSTM) model was developed with an accuracy of the personal sequence gait SPMS signal recognition of 81.8%.

Keywords: self-powered; hybrid multifunctional sensor; human biomechanical monitoring device; LSTM

1. Introduction

The rapid development of modern society and the increasingly accelerated pace of life can affect human health. Given the problem of an aging population, gait monitoring has attracted growing attention, particularly for health monitoring and initial diagnosis [1,2]. Researchers have also shown that the devices of gait monitoring can be employed in sports training to raise the performance of athletes [3,4], including in action-specific poses such as golfing [5]. To recover 3D human motion based on 2D data, the hybrid 2D–3D model correlation between 2D image data and 3D human body poses in real-life examples has been proposed [6]. More recently, self-powered hybrid nanogenerators for triggered biomechanical motions have been created [7,8].

Wearable, portable, and even implantable electronic systems may have a huge impact on health monitoring and interactive electronic devices for the well-being of humans [9,10]. In particular, unique and novel mechanisms of nanomaterials with nanostructure topologies have been developed, which represent a significant landmark in nanotechnology. Triboelectric nanogenerators (TENGs) have recently been developed and have unique advantages, namely, they have high output, are economical and light, and have a durable structure [11,12], which means they can harvest all kinds of extremely small quantities of mechanical energy (in the range of nW–mW). Triboelectric nanogenerators (TENGs) can be based on contact electrification via the conversion of mechanical energy into electrostatic induction output [13] and are a promising candidate for mechanical or multiple energy harvesting [14–19]. Adopting more general and practical methods to improve the energy...
conversion efficiency of TENGs has been actively encouraged. In terms of the actuation principle, recent research explored the potential harvesting of ineffective piezoelectric energy via two beams with a tapered cavity and asymmetry-augmented self-tuning of conjoined cantilevers for bandwidth enhancement [20,21]. Piezoelectric nanogenerators (PENG) can also provide higher conversion efficiency and more stable output power under weak and low-frequency mechanical stimuli compared with that of other types of nanogenerators (NGs) [22–24]. The hybridization of different types of NGs offers an effective method to increase the output power by collecting multiple energies simultaneously [25–27] and has the advantages of having high power density and being light-weight and stable.

In this paper, long short-term memory (LSTM) is utilized [28–31]. LSTM is an alternative artificial recurrent neural network (RNN) architecture for identifying sequential data, and it is used in the field of deep learning [32]. It has a feedback connection, unlike standard feedforward neural networks. It not only processes a single data point, but can also organize an entire data sequence (such as voice or video) [33]. It has a strong identification ability for data with time series. The signal sent by the self-powered multifunctional sensor (SPMS) device performs deep learning through LSTM and recognizes the relationship between different signals for actions to achieve the monitoring functions, such as stroke phase recognition [34], noise-robust automatic speech recognition (ASR) [35], and information retrieval [36].

2. Materials and Methods

Figure 1a shows a schematic diagram of the application with the entire self-powered multifunctional sensor (SPMS). Figure 1b illustrates the SPMS’ piezoelectric actuators and the zigzag structure of the triboelectric nanogenerator (TENG). The material used is an electrostatic generator composed of polytetrafluoroethylene (PTFE) and aluminum (Al). On top of the SPMS is a piezoelectric nanogenerator (PENG). The size of the SPMS is $5 \text{ cm} \times 4 \text{ cm} \times 1 \text{ cm}$. In addition, the size of the PTFE film is $4 \text{ cm} \times 4 \text{ cm} \times 0.3 \text{ mm}$ and the Al film is $4 \text{ cm} \times 4 \text{ cm} \times 0.16 \text{ mm}$. The zigzag-shaped electrostatic generator’s operation schematic diagram is presented in Supplementary Information Figure S1. Figure 1c illustrates a schematic diagram of the multilayered TENG with three basic contact-separation units in the amplified view. A 0.3 mm thick, 4 cm wide PTFE film and a 0.16 mm thick, 4 cm wide Al film are formed in a zigzag configuration and adhesively bonded with a copper tape electrode. Figure 1d is a schematic diagram of the structure inside the piezoelectric actuation of the PENG. The entire structure is beneath 304 stainless steel actuators, which also serve as the spacers in the SPMS for dynamic recovery. Lead zirconate titanate film (PZT) is the material of the piezoelectric layer in the middle of the structure with a thickness of 0.2 mm. In addition, the device uses a material called Thunder® (Face International Corporation, Norfolk, VA, USA), which consists of a layer of polyimide adhesive on the upper and lower parts with a thickness of 25.4 um. The outermost layer is coated with a layer of aluminum foil with a thickness of 25.4 um, which is formed when the composite laminate is heated under pressure to temperatures that allow the adhesive to bond and then cooled to room temperature [37].

In this study, the PTFE layer inside the TENG was ground to produce a microstructure on the surface to increase the contact area. Figure 1e is the scanning electron microscope (SEM) image of the surface microstructure of the PTFE after grinding with #1000 grit sandpaper. In addition, a layer of polyamide adhesive is on the upper PTFE surface, producing a microstructure on the surface. Many abrasive traces with widths of less than 20 um can be found on the PTFE surface. The method of grinding the PTFE surface is shown in Figure S2. Figure 1f shows the surface structure of #1000 grit sandpaper under SEM. In the following experiments, we showed that this microstructure can improve the overall performance of the TENG and increase the output. The external wire connects to the SPMS and oscilloscope to measure the output, then integrates the piezoelectric and electrostatic generators for a better output performance.
3. Results and Discussion

Figure 2a illustrates the working mechanism of the SPMS, showing the principle of electric moving action. When applying an external force, triboelectric positive and negative charges are induced in the Al and PTFE, respectively, after the contact. Almost simultaneously, a piezoelectric potential is generated owing to the deformation of the PENG. To balance the piezoelectric potential, the piezoelectric current flows along with the external load from the bottom to the top Al electrode. After removing the external force, the piezoelectric potential disappears due to the recovery of the PENG, which causes the piezoelectric current to flow reversely. Almost simultaneously, the triboelectric pairs of Al and PTFE separate from each other. To balance the triboelectric potential, the triboelectric current flows from the top to the bottom electrode. When an external force is applied again, the triboelectric current flows reversely. The SPMS is composed of piezoelectric structures and a warped and zigzag-structured triboelectric nanogenerator. The stainless
steel based PENG provides piezoelectricity. Furthermore, the TENG includes Al foil, PTFE tape, and copper tape electrodes that provide triboelectricity. The testing method was as follows: The total height of the device was fixed at 10 mm. The device was placed on the base and cyclical press/release operations were performed with a displacement of 7.5 mm to obtain an open-circuit voltage and short-circuit current. Both piezoelectric and triboelectric charge generation and electricity generation processes can be described by the compression/deformation/touch/release processes. When the piezoelectric stainless steel actuator begins to deform, the charge accumulation process in the opposite direction among the positive and negative charges can balance the induced dipole moment. Similarly, the mechanically actuated triboelectric signals can be generated from the SPMS while the three layers of PTFE films and the Al films as rubbing in the origami zigzag structure, generating triboelectric output. Physical contact between the PTFE and Al films can generate free electrons by injecting them into the Al film and produce triboelectric charges of opposite signs. When the piezoelectric actuators are forced to contact each other by the underlying electrostatic layers, the force is rebounded because of the natural spacer generated by the special polyimide actuator, and then it returns to the original position. The stability test of the SPMS is illustrated in Supplementary Information Figure S3, indicating the SPMS is highly robust and stable. The SPMS is capable of individually/simultaneously converting biomechanical energy to electricity. As compared with the TENG, the PENG has a much larger output voltage and current. As seen in Figure 2b, the piezoelectric voltage and current output were measured as ~84 V and ~293 µA, respectively. Figure 2c shows the triboelectric output. The average voltage and current output of the triboelectric were recorded as 22 V, 285 nA, respectively. Based on the measurement results of the piezoelectric output and the quantitative triboelectric output, it can be found that the voltage and current have a superimposed effect in Figure 2d. When both the PENG and the TENG are working simultaneously, the SPMS has a much better electrical performance than that of the individual energy harvesting units (PENG or TENG). The average voltage and current output were 103 V and 302 µA, respectively. To accurately analyze the superimposed output of the SPMS, the mechanical motion frequency was operating at 1 Hz. Superposition can be completed piezoelectrically and triboelectrically for the hybrid system as illustrated in Supplementary Information Figure S4 with the results of the open-circuit voltage (OCV) and short-circuit current (SCC) of the SPMS operating under various working frequencies from 0.5 to 2 Hz. Indistinct differences appeared in the results. Furthermore, Supplementary Information Figure S5 shows the validated piezoelectric tests of polarity for both forward and reverse connections.

Figure 3a presents #60 grit sandpaper, which was used to grind the PTFE surface as a triboelectric layer microstructure. The sandpaper had a coarse grit size with an average diameter of about 269 µm and the voltage output was about 3.9 V. The surface of the #120 grit sandpaper is shown in Figure 3b. The average diameter of the grit on the sandpaper surface was 115 µm. The data graph shows the voltage output was 3.8 V. As shown in Figure 3c, #600 grit sandpaper had an average grit diameter of 25.8 µm. The measurement chart shows the voltage output was approximately 4.5 V. Micromorphology of the #1000 grit sandpaper is presented in Figure 3d; it had a uniform surface with a grit diameter of 18.3 µm; it had the best voltage performance with a value of 6.6 V. The comparative test was set to measure the output of a single triboelectric layer. As shown in Figure 3e, the triboelectric output of the surface roughness test increased with smaller grit size. The reason is that the smaller the surface structure is, the larger is the total contact area compared to the surface with a larger-scale structure. The triboelectric layers’ contact area will make the triboelectric voltage output perform better.
Figure 2. (a) Working mechanism of the proposed SPMS whose piezoelectric and triboelectric charge generation and electricity generation processes can be described by the compression/deformation/touch/release processes. (b) The open-circuit voltage (OCV) and short-circuit current (SCC) of the triboelectric generators (TENG) with the PTFE film and Al film touch/release processes with an accumulated displacement ~0.35 mm were ~84 V and 300 µA, respectively. (c) The OCV and SCC of the piezoelectric device with an accumulated displacement ~5 mm was ~22 V and 285 nA, respectively. (d) The OCV and SCC of the superposition integrated SPMS were ~103 V and 302 µA, respectively.
Figure 3. (a) Scanning electron microscope (SEM) image of 60 grit sandpaper and the voltage output test in the TENG. (b) 120 grit sandpaper SEM image. (c) Micromorphology of 600 grit sandpaper with the voltage output test. (d) 1000 grit sandpaper SEM image and the voltage output test. (e) Particle size comparison of the voltage output with different microstructures and surface roughness.

The peak values of the voltage and current on different loads are displayed in Figure 4a, showing the trend of the signal when resistance increased. Figure 4b illustrates the instantaneous maximum power value. This discovery also indicated that if the load had a resistance of nearly 100 kΩ, the sensor ran most efficiently and the highest power output was about 38 mW. Figure 4c is the characterization of the sensor performance and the relationship between the applied force and electrical voltage, showing the promising potential of the self-powered pressure sensor. The human motion-induced testing mode was performed by pressing on top of the SPMS in a cyclic and reciprocating motion...
at the frequency of 1 Hz. From the above experimental results, it can be found that the sensitivity of the SPMS was practically linear. The experimental device of the sensitivity test is illustrated in Supplementary Information Figure S6. Figure 4d presents the results when using different thicknesses of PTFE as the friction layer of the TENG. From this chart, it can be seen that when 0.3 mm thick PTFE was used, a higher voltage output appeared at about 2 V. This test was the experimental result of friction using a single layer, smooth, flat PTFE and Al with the area of 2 cm × 2 cm. Figure 4e shows that the piezoelectric stainless steel sheet produced different voltage outputs when using different pressure methods. Figure 4e used the positive pressing method as shown in the SPMS structure diagram, while Figure 4f shows a graph of the opposite direction pressing method data. The tablet was pressed in turn, and it can be seen from the results that the positive pressing methods had a relatively high voltage output. When using the reverse pressing method, the reduction of deformation affected the piezoelectricity performance, thereby lessening the voltage output. The output energy produced per cycle was calculated by Equation (1).

\[
E_{\text{Out}} = \int I^2R \, dt
\]  

(1)

Figure 4. (a) Current and voltage output under different external load resistance. (b) Power output data. (c) The relationship between the applied force and the electrical voltage of the SPMS. (d) The voltage output comparison of the sensor by using different thicknesses of PTFE film. (e) Voltage output by pressing the front of the PENG, and (f) is the voltage output from pressing on the back.

As shown in Figure 5a–c, the testers are asked to put on a special leg-rehabilitation device when performing those actions (walk, run, jump, limp, hop); assistance was provided by the Landsseed International Hospital using AQUACAST 243. In this research, the tester made several sequential actions, namely, walking, running, jumping, limping, and hopping. Based on multiple consecutive tests, the tests show outstanding repeatability. The tested movements can cause the piezoelectric device to deform and cause a piezoelectric response. Features of different motions show their unique identity waveforms. While
wearing the rehabilitation device, the subject’s movement characteristics are affected by the rehabilitation device to generate different characteristic waveforms from the original walking mode. The action cycle diagram is shown in Supplementary Information Figure S7, showing the potential of in situ monitoring for rehabilitation. Figure 5d,e were generated when the rehabilitation device was used to perform the five actions: walking, running, jumping, limping, and hopping. With different voltage and current waveforms, it can be seen that the waveforms generated by the five actions are different from each other. Therefore, human biomechanical features can be identified through machine learning assisted by multiple training runs with stainless steel piezoelectric sensors such that useful waveforms are recorded from the SPMS and pattern recognition can be obtained.

Figure 5. Response to different types of action modes while wearing a leg-rehabilitation device. (a) Picture of rehabilitation device. (b) Picture of a test subject’s leg while wearing the rehabilitation device. (c) The relative position of the wearable rehabilitation device and the SPMS. (d) The data on the voltage output of five different action modes (walk, run, jump, limp, hop) while wearing a rehabilitation device. (e) The current measurement of five different action modes.
Figure 6a schematically shows a simplified LSTM memory block, comprising several multiplicative gates that control the activation and repeatedly connect hidden layers via the Softmax Regression neural network for data identification. To completely verify the capability of the SPMS, the number of actions was set to five samples. In this paper, the time-sequence hybrid signal provided by the SPMS was used as the signal for research and analysis, and the gait signals of three subjects provided biometrics as personal identification. Three testers were required to perform five different actions while wearing a rehabilitation device; the tester information is shown in Supplementary Information Table S1. The LSTM network was trained to identify the activities of the testers. The SPMS output sequence hybrid signal was the database for the personal gait judgment system with the LSTM model. In the training program, the hybrid signals involved stepping on the SPMS randomly to decompose into several sets; every training database had three seconds of action, and a training set contained at least one action cycle (press to release). The database for LSTM contained eight groups as the training set and two groups as the test set. In this paper, data received from the SPMS sensor was set on the leg-rehabilitation device given the time series data. These time-series data represent the SPMS readings with five different movement sequences of three characteristics and the same array length. The LSTM network architecture set the number of input features as 3 sequences and 200 hidden layers, outputs as the complete sequence, and the final standard of a completely connected layer of size 5 (five different actions: walk, run, jump, hop, and limp). Figure 6b displays the confusion matrix obtained from the test with the SPMS action identification results. The plurality of misclassification is the classification of limp and hop behaviors in the confusion matrix. The signals are partly similar in analysis processes. In contrast, the best motion classification results are run and hop, in which the predictive value of true positive was close to 99%. Experiments show that the real-time OCV/SCC signals of the five feature data set models can identify different actions, and the overall training accuracy rate was 81.8%. If the data (used to avoid bias) and the extraction of the time-frequency moment feature increases, which can overcome the inconstancy of training data and class disparity, the accuracy can be improved.
Figure 6. Classification of the SPMS motion identification by using machine learning via LSTM arithmetic. (a) The LSTM simplified architecture. (b) Confusion matrix for biomechanical motion-level classification corresponding to walking, running, jumping, hopping, and limping.

4. Conclusions

In conclusion, we developed a hybrid, curved spacer supported with a high-performance zigzag-shaped self-powered multifunctional sensor (SPMS) and data analytics for gait analysis. The piezoelectric actuators provided high and stable output performance with a natural curved spacer generated by the special polyimide actuator support of the SPMS’s active mechanism. Open circuit voltage reached 103 V and the short circuit current reached ~300 µA. The zigzag-shaped structure in the SPMS’s triboelectric nanogenerator provided a greater contact area to improve voltage and current output. The hybridization of the piezoelectric actuators and zigzag-shaped triboelectric nanogenerator provided a higher, stable power generation. As demonstrated, the zigzag-shaped self-powered multifunctional sensor was adopted as the sensor in a leg-rehabilitation device. To provide effective medical diagnosis and gait monitoring, a self-powered sensor in a leg-rehabilitation device was realized. In the developed automated system, the biomechanical force that was actuated was used to identify the individual movement characteristics of human individuals using the device. The recognition rate of the personal sequences of gaits from the SPMS signal was 81.8% when using the deep learning LSTM model. This research demonstrates the applications of the SPMS, showing the future potential and great opportunity in wearable, sensor-transmitter devices for healthcare and biomedical applications.

Supplementary Materials: The following are available online at https://www.mdpi.com/2076-3417/11/2/519/s1, Figure S1: The operation of the Zigzag shape electrostatic generator, the upper layer is a PTFE film containing microstructures, the lower layer is Al film. From left to right is the mode of action of TENG, Figure S2: The method of use sand papers to grind the surface of PTFE. Fix the PTFE and repeat the grinding action in parallel direction about 20 cycles, Figure S3: Long term Stability tested of PENG for three days. The output voltages of the PENG operating at 1 Hz for 10 min per day, Figure S4: Frequency test. The output of the NG with the increase in driving frequency, showing
its good stability, Figure S5: Validated tests of polarity. The peak voltage was obtained by (a) the forward connection and (b) reverse connection, Figure S6: Schematic diagram of the experimental method for the applied force-voltage output diagram, Figure S7: Isolated motion schematic image of five different action (walk, run, jump, limp, hop) in rehabilitation device application, Table S1: Tester Information.

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