Optimal Placement of Foot Pressure Sensors for Lower-Limb Exoskeletons Based on Multi-Objective Particle Swarm Optimization Algorithm

Ha-Yoon Song[1], Hyun-Joon Chung[1]*, Kwang-Woo Jeon[1], Tae-Hwan Kim[1], Junyoung Kim[1], Jin-Yeol Yoo[2], and Jae-Kwan Ryu[2]
[1] AI Robotics R&D Division, Korea Institute of Robotics & Technology Convergence, Seoul 06372, Republic of Korea
[2] Unmanned/Intelligent Robotic Systems R&D, LIG Nex1, Seongnam 13488, Republic of Korea
Email: {hayoon, hjchung, jeonkw, kthwan, junyoung.kim}@kiro.re.kr, {jinyeol.yoo, jaekwan.ryu}@lignex1.com

***Abstract*—This study proposes an optimization method for sensor placement in lower-limb exoskeleton robots, aiming to improve the accuracy of the Center of Pressure (CoP) estimation during various human activities. Utilizing the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm, the proposed method identifies an optimal sensor count, as the Root Mean Square Error (RMSE) decelerates when the sensor count exceeds 6. Application of this method resulted in a reduction of the Mean Absolute Error (MAE) to 4.13 mm and 8.92 mm on the mediolateral and anteroposterior axes respectively, a 22.8% improvement in CoP estimation accuracy compared to traditional anatomical methods. Further analysis revealed that weight parameters influence the CoP estimation accuracy, suggesting an enhancement in sensor placement efficiency through the adjustment of individual objectives' significance. The proposed sensor placement optimization method is expected to significantly enhance the performance of lower-limb exoskeleton robots and increase user satisfaction. Moreover, it could substantially contribute to the enhancement of human-computer interaction in robot control by providing a more accurate reflection of the user's intentions. These findings highlight the importance of continuing research in the field of lower-limb exoskeleton robots.**

Keywords—Lower-limb exoskeleton, sensor placement optimization, center of pressure, multi-objective particle swarm optimization

I. INTRODUCTION

Lower-limb exoskeleton robots are increasingly recognized as significant tools for physical rehabilitation and enhancement. They offer substantial benefits, especially to those who require physical strength augmentation, by contributing to the improvement of individual capabilities. However, the performance of these robots heavily relies on the accuracy of plantar pressure sensors, which provide crucial information for controlling the robot's movements and interactions with the user [1-3].

Despite the importance of these sensors, optimizing their quantity and placement presents a complex challenge. Increasing the number of sensors can enhance the robot's performance but also lead to increased costs, power consumption, and complexity in data processing [4, 5]. Accurate Center of Pressure (CoP) estimation with a limited number of sensors becomes a critical factor for the robot's stability and movement control.

To address this complexity, our study proposes the use of a multi-objective particle swarm optimization (MOPSO) algorithm. Inspired by the social behaviors of organisms such as birds or fish, the particle swarm optimization algorithm finds the optimal solution by mimicking a swarm of particles moving within a defined space [6]. The MOPSO algorithm is designed to achieve two goals simultaneously: maximizing the information content of the sensors and minimizing the CoP estimation error.

In this study, the MOPSO is applied to the sensor placement problem to optimize the sensor's position to estimate the CoP more accurately, which is closely related to the robot's performance. This approach ensures the effective use of lower-limb exoskeleton robots and presents new possibilities for future research on sensor placement optimization. The optimization method is intelligently designed, greatly enhancing human-computer interaction capabilities in robot control by using human activity-related data. It allows for a more accurate understanding and reflection of the user's intentions, improving the robot's movement control, and thus, increasing user convenience and satisfaction.

II. RELATED WORK

Several studies have demonstrated that the placement of sensors significantly influences the performance and efficiency of robots. Most of the previous research determines the locations of sensors based on anatomical points, indicating that a considerable number of individual insoles gather data on the count and positioning of sensors by anatomical principles and the characteristics of the static distribution. Claverie et al. [7] conducted experiments on the positioning of sensors in insoles in major foot areas, aiming to enhance the accuracy of plantar pressure analysis. Additionally, Ciniglio et al. [4] assessed a pressure insole embedded with plantar sensors, strategically positioned based on peak pressure locations across all trials.

However, these approaches encountered challenges in selecting sensor locations that can ensure the accuracy of CoP estimation. While they primarily considered key anatomical points, these methods did not factor in the accuracy of CoP estimation during sensor placement. As the resolution of plantar pressure measurement instruments improves, sensor placement needs to become more specific. Therefore, it's essential to design comprehensive guidelines for sensor placement, which leverages dynamic data for further optimization. This study aims to address these limitations and ensure accurate CoP (Center of Pressure) estimation by employing MOPSO (Multi-Objective Particle Swarm Optimization) to improve sensor placement in lower limb exoskeleton robots.

III. METHOD

In this section, we abstract the problem of optimal sensor placement and introduce a particle swarm optimization algorithm for optimizing data from a pressure measurement.

A. Objective Definition

In the context of a set of n potential sensor placement locations $S = \{s_1, s_2, \dots, s_n\}$, the task is to find an optimal subset $P = \{p_1, p_2, \dots, p_m\}$ such that $P \subset S$ and $m < n$. The objectives of this optimization process are twofold:

1) Maximize the unique information from each sensor.

2) Minimize the estimation error in the CoP.

The redundancy in sensor data can lead to overlapping information, thereby reducing the sensor network's efficiency. To quantify this redundancy, we calculate Pearson's correlation coefficient r_{ab} between placements a and b:

$$r_{ab} = \frac{\mathrm{cov}(\vec{S}_a, \vec{S}_b)}{\sigma(\vec{S}_a) \times \sigma(\vec{S}_b)} \tag{1}$$

where $\overrightarrow{S_a}$ and $\overrightarrow{S_b}$ represent the sensor data at placements a and b respectively.

Subsequently, we construct a correlation coefficient matrix *Rco(P)*, composed of correlations between all pairs of sensors within P. The 2-Norm $||Rco(P)||_2$ serves as an objective function *R(P),* signifying information yield:

$$R(P) = \| Rco(P) \|_2 \tag{2}$$

The error in CoP estimation is quantified by computing the Euclidean distance (ED) between estimated and actual CoP coordinates:

$$X_{esi} = \frac{\sum_{i=1}^{m} p_i x_i}{\sum_{i=1}^{m} p_i} \quad Y_{esi} = \frac{\sum_{i=1}^{m} p_i y_i}{\sum_{i=1}^{m} p_i} \tag{3}$$

where X_{esi} and Y_{esi} represent estimated CoP coordinates; p_i represents the pressure at the i-th location; x_i and y_i denote coordinates of the i-th location.

This error is further quantified using root mean square error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{T} \{(X_{esi} - X_{ref})^2 + (Y_{esi} - Y_{ref})^2\}}{T}} \tag{4}$$

where X_{ref} and Y_{ref} stand for reference CoP coordinates; T denotes total number of frames.

Taking into account these objectives for maximizing information yield R(P) while minimizing estimation error RMSE(P), we formulate our multi-objective optimization problem as follows:

$$\min f(P) = (\alpha RMSE(P), (1-\alpha) R(P))$$

$$\text{sub to } P = \{p_1, p_2, \dots, p_m\} \in S \tag{5}$$

$$0 < m < n$$

In this equation, α is a weight parameter controlling the balance between two objectives, and P represents a subset with m locations selected from the global set S with n locations.

B. Algorithm Selection

To address this problem, we employ a multi-objective particle swarm optimization (MOPSO) algorithm. This algorithm is designed to simultaneously optimize two objective functions minimizing CoP estimation error and maximizing information quantity. The balance between these objectives is maintained by adjusting a weight parameter that dictates the importance of each objective function in the optimization process. The MOPSO algorithm was chosen for its ability to find an optimal solution in a complex search space with multiple conflicting objectives, which makes it suitable for our sensor placement optimization problem.

Algorithm Multi-Objective Particle Swarm Optimization
Initialization:
Set the objective functions R(P) and RMSE(P),
the population size l, particle positions $\boldsymbol{X_i(0)}$ and $\boldsymbol{V_i(0)}$,
minimum and maximum position values $\boldsymbol{X_{min}}$, $\boldsymbol{X_{max}}$,
minimum and maximum velocity values $\boldsymbol{V_{min}}$, $\boldsymbol{V_{max}}$,
Maximum influence values $\boldsymbol{\Phi_1}$ and $\boldsymbol{\Phi_2}$
PSO parameters w, $\boldsymbol{c_1}$, $\boldsymbol{c_2}$, maximum iterations $\boldsymbol{T_{max}}$,
Particle's best positions $\boldsymbol{P_{best}}$ and global best position $\boldsymbol{G_{best}}$.
for $\boldsymbol{t \le T_{max}}$ **do**
for $\boldsymbol{i \le l}$ **do**
Generate a random vector $\boldsymbol{r_1 \sim U[0, \Phi_1]^d}$

Generate a random vector $\boldsymbol{r_2 \sim U[0, \Phi_2]^d}$
$\boldsymbol{V(t+1) \leftarrow w \cdot V_i(t) + c_1 \cdot r_1 \cdot \left(P_{best_i} - X_i(t)\right)}$
$\boldsymbol{+ c_2 \cdot r_2 \cdot \left(G_{best} - X_i(t)\right)}$.
$\boldsymbol{X_i(t+1) \leftarrow X_i(t) + V_i(t+1)}$.
if $\boldsymbol{f(X_i(t+1)) \le f(P_{best_i})}$ **then**
$\boldsymbol{P_{best_i} \leftarrow X_i(t+1)}$
if $\boldsymbol{f(P_{best_i}) < f(G_{best})}$ **then**
$\boldsymbol{G_{best} \leftarrow P_{best_i}}$
end for
end for
Output: The sensor placement corresponding to $\boldsymbol{G_{best}}$

C. Data Collection

In the data collection phase, we utilized a wearable insole equipped with 99 sensors spaced 25mm apart. The insole used was the Pedar-X sensor system. Participants were asked to wear this sensor-equipped insole and perform 12 different activities while their plantar pressure distribution data was recorded.

The tasks performed by participants included various movements and stances that are common in physical activities, such as standing with a ball, preparing to throw a ball, finding a ball, walking and throwing, walking under a load of 20 kg, standing throwing stance, standing throwing stance (with holding a ball), sitting throwing stance, sitting throwing stance (with holding a ball), normal walking at speeds of 4 kph and 6 kph, and rising from prone.

These diverse tasks were selected to represent different types of pressure distributions that can occur during real-world physical activities. This range of movements allowed us to test our optimization method under various conditions.

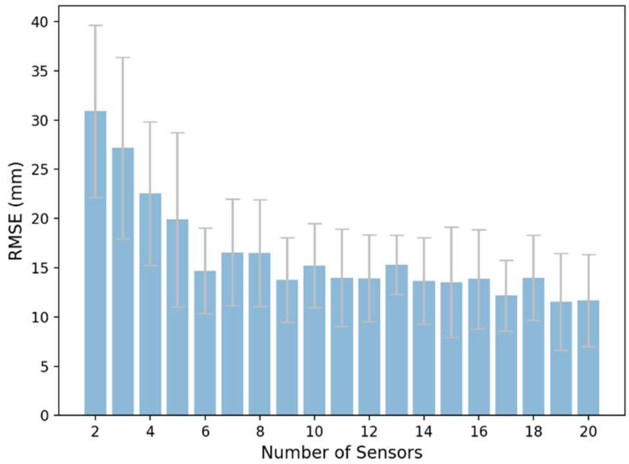

Fig. 1. RMSE of the estimation of CoP for all motion tasks based on the optimal placement with different numbers of sensors.

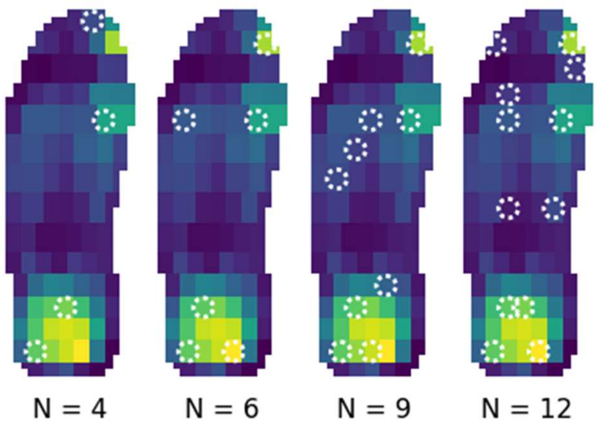

Fig. 2. The optimal placement with different numbers of sensors, when the number of sensors N is 4, 6, 9, 12.

IV. Results

In this study, we proposed a method for accurately estimating the CoP using MOPSO to optimize the plantar pressure sensor placement of lower-limb exoskeleton robots. As shown in Fig. 1, our experiments revealed a trend of decreasing Root Mean Square Error (RMSE) as the number of sensors increased. Interestingly, we observed a slowdown in the decrease of RMSE (N=6), which can be interpreted as a decrease in the amount of additional information that can be gained with an increased number of sensors.

According to Fig. 2, when the number of sensors was minimum (N=4), all pressure sensors were placed in anatomically important positions. However, as the number of sensors increased (N=9 and N=12), the sensors were placed too closely together or in areas with no pressure, leading to data redundancy or inefficient data arrangement. Consequently, based on our findings, we determined the optimal number of sensors to be 6.

Table I displays the Mean Absolute Error (MAE) for 12 different movements with 6 sensors, confirming the high accuracy of CoP estimation. This is evidenced by small errors of 4.13mm horizontally and 8.92mm vertically. These results provide strong proof that accurate sensor placement for CoP estimation is possible through the MOPSO algorithm.

TABLE I
MAE of CoP Estimation for 12 Activities Using 6 Sensors

Tasks	X_{CoP} (mm)		Y_{CoP} (mm)	
	MAE	***SD***	***MAE***	***SD***
Standing with a ball	2.72	1.28	9.15	1.15
Finding a ball	4.01	0.29	7.23	0.35
Rising from prone	5.34	2.52	11.62	2.97
Standing throwing stance	3.83	0.56	8.13	1.94
Standing throwing a ball	4.17	0.57	8.96	1.52
Sitting throwing stance	4.60	0.30	9.60	1.48
Sitting throwing a ball	4.77	0.66	10.48	2.18
Walking (4 kph)	3.89	0.34	8.03	1.72
Walking (6 kph)	3.42	0.34	6.14	0.45
Walking and throwing	5.60	0.57	10.28	2.30
Walking with a load of 20kg	4.55	0.38	8.81	0.77
Preparing to throw a ball	2.66	0.23	8.57	1.16
Mean (SD)	4.13 (0.67)		8.92 (1.49)	

TABLE II
COP Estimation Accuracy: Proposed vs. Anatomical Method

Method	**RMSE** (mm)
Ciniglio et al. [4]	18.41
Multi-objective PSO	**14.21**

TABLE III
Variability in CoP Estimation Accuracy according to Weight Parameter Values

	1.0	**0.8**	**0.5**	**0.2**
R(P)	2.89	2.99	2.87	2.62
RMSE (mm)	15.64	16.71	14.21	17.54

Our method, as detailed in Table II, improved the accuracy of CoP estimation by 22.8% compared to the traditional anatomical method. This significant improvement demonstrates that the method proposed in this study can contribute greatly to enhancing the performance of lower-limb exoskeleton robots. Furthermore, it substantiates the necessity of MOPSO over the traditional sensor placement method of an anatomical approach.

Finally, as presented in Table III, our analysis of the variability in the accuracy of CoP estimation according to weight parameter values confirmed that these values indeed influence the accuracy of CoP estimation.

V. Conclusion

In this study, we have focused on sensor placement optimization in the design of lower-limb exoskeleton robots, with a specific aim to improve the accuracy of Center of Pressure (CoP) estimation using a limited number of sensors. To achieve this goal, we have proposed a methodology based on the multi-objective particle swarm optimization algorithm.

This study proposes an intelligent methodology for optimal sensor placement in lower-limb exoskeleton robots, utilizing the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm. Traditional anatomical and geometrical approaches showed limitations in selecting sensor locations, and to address this, this study introduced the MOPSO algorithm. The results of this study demonstrate that it's possible to achieve sensor placement that improves the accuracy of CoP estimation and maximizes the information capacity of sensors.

Notably, it was found that RMSE slows down when the number of sensors exceeds six, leading to the determination of the optimal number of sensors. Moreover, the method proposed in this study improves the accuracy of CoP estimation by 22.8% compared to traditional anatomical methods. This proves the effectiveness of the MOPSO algorithm and indicates its potential contribution to improving the performance of lower-limb exoskeleton robots.

Lastly, through the analysis of changes in the accuracy of CoP estimation depending on the weight parameter, it was confirmed that the value of the weight parameter affects the accuracy of CoP estimation. It shows that more effective sensor placement can be derived by adjusting the importance of individual objectives. The sensor placement optimization method proposed in this study is expected to greatly contribute to the performance improvement of lower-limb exoskeleton robots, and through this, it is expected to enhance user convenience and satisfaction.

Furthermore, this method is expected to significantly contribute to improving human-computer interaction capabilities in robot control, thereby enabling robots to more accurately understand and reflect user intentions. These points signify that this study presents new possibilities for future research on sensor placement optimization. The results of this study present an important step in improving the performance of lower-limb exoskeleton robots through sensor placement optimization. This will make the use of robots more effective and provide significant benefits to people who need physical enhancement. These results emphasize the importance of lower-limb exoskeleton robots and underline the need to continue research in this field.

Acknowledgment

This research was supported by the Korea Research Institute for defense Technology planning and advancement (KRIT) funded by the Defense Acquisition Program Administration (DAPA) of the Korea government since 2021. (No. KRIT-CT-21- 039-00, Development of Techniques of Designing and Operating a Powered Full-Body Exoskeleton with Bulletproof Armor and Military Equipments (Contribution rate: 100%))

References

[1] T. Poliero et al., "Soft wearable device for lower limb assistance: assessment of an optimized energy efficient actuation prototype," in 2018 IEEE international conference on soft robotics (RoboSoft), 2018: IEEE, pp. 559-564.

[2] S. Net'uková et al., "Lower Limb Exoskeleton Sensors: State-of-the-Art," Sensors, vol. 22, p. 9091, 2022.

[3] H. Prasanth et al., "Wearable sensor-based real-time gait detection: A systematic review," Sensors, vol. 21, no. 8, p. 2727, 2021.

[4] A. Ciniglio, A. Guiotto, F. Spolaor, and Z. Sawacha, "The design and simulation of a 16-sensors plantar pressure insole layout for different applications: From sports to clinics, a pilot study," Sensors, vol. 21, no. 4, p. 1450, 2021.

[5] X. Xian, Z. Zhou, G. Huang, J. Nong, B. Liu, and L. Xie, "Optimal sensor placement for estimation of center of plantar pressure based on the improved genetic algorithms," IEEE Sensors Journal, vol. 21, no. 24, pp. 28077-28086, 2021.

[6] T. M. Shami, A. A. El-Saleh, M. Alswaitti, Q. Al-Tashi, M. A. Summakieh, and S. Mirjalili, "Particle swarm optimization: A comprehensive survey," IEEE Access, vol. 10, pp. 10031-10061, 2022.

[7] L. Claverie, A. Ille, and P. Moretto, "Discrete sensors distribution for accurate plantar pressure analyses," Medical engineering & physics, vol. 38, no. 12, pp. 1489-1494, 2016.