# Center of Pressure Estimation and Gait Pattern Recognition Using Shoes with Photo-reflective Sensors

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## ABSTRACT

Gait analysis is an important issue in various fields. In this paper, we developed a shoe-type device to measure the foot pressure when walking. Our device measures the deformation of the sole when pressure is applied and is detected by sensors embedded in the sole. As pressure is not applied directly onto the sensors, the system has better durability and a wider dynamic range. We then proposed a method to estimate the center of pressure (CoP), obtaining an average coefficient of determination of 0.69. Our device also identifies gait patterns by obtaining the discrimination rate of 9 types of walking methods, averaging to an accuracy of 88%.

## CCS CONCEPTS

• Human-centered computing → Interaction devices;

## KEYWORDS

Wearable sensor, Gait analysis, Shoe device

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## 1 INTRODUCTION

Walking is an important part of our daily life. Having a good walking posture will not only reduce the burdens on the knees and waist, but also enhance your appearance. In the medical and rehabilitation field, measuring and analyzing gait patterns between the impaired and healthy subjects are important issues as various diseases cause disturbance to one's gait. Islam and colleagues show that improvement in walking characteristics can be seen by measuring walking using wearable devices and intervention[6].


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**Figure 1: Shoe-type wearable device.**

In this paper, we aim to develop a wearable shoe-type pressure measuring device using photo-reflective sensors to estimate the CoP and recognize the gait state (Figure 1). We place sensors on the shoes' sole to measure the pressure applied to each part of the sole. As pressure is not applied directly onto the sensors, the system has better durability and a wider dynamic range.

## 2 RERATED WORK

### 2.1 Walking Measurement and Analysis

Walking can be expressed by parameters broken down into 2 properties; kinematics and kinetics.

Speed, step length and contact time are several examples of kinematic properties. Accelerometers or image analysis by cameras can obtain walking speed, sheets installed on the floor can record step length and Kinect can detect the changes in posture during exercise. Joint moment, ground reaction force (GRF) and physical strength are classified under kinetic properties. Force plates or insole-type pressure sensors can be used to measure the GRF and EMG can be used to measure the movement of the muscles when walking. Both kinematic and kinetic properties can be combined by integrating a force plate with a 3D motion analysis device. This method can measure the foot position and posture while acquiring the CoP and GRF. Reflective markers are placed onto the subject's body, which are photographed by several cameras to acquire the spatial coordinates in 3D. The force plate will give the CoP. By combining these values with inverse dynamics, the joint moment can be calculated. Lori et al. [7] used joint moment to measure the changes in gait pattern before and after a clubfoot leg surgery. The CoP can be used to measure and evaluate the trajectory of walking on a daily basis. The CoP for healthy people is said to pass through the outer side of the foot, escaping from around the thumb finger, similar to writing an arc from the heel. The CoP passes in a different way for flat feet and hemiplegic patients, making it possible to evaluate the trajectory. Halliday et al. [5] clarified that the trajectory of the CoP is peculiar for people with Parkinson's disease.

## 2.2 Analyzing the CoP

There are roughly 2 methods to measure gait pattern; using an environment-fixed sensor or a wearable sensor. Examples of environment-fixed type sensors are optical motion capture systems [9], systems using strain gauge as a GRF meter to measure the GRF and mat type systems to measure the sole pressure's distribution. These methods can obtain stable data and save the effort of attaching sensors to the body but the measurement are limited to the environment detectable by the sensors.

Wearable type device are directly attached to the subject's foot. Examples are Alvarez's accelerometer [2] to estimate step length and Watanabe et al's system [13] to recognize behavior and a wearable GRF measurement system with a small force meter attached to the shoes[11, 12]. Arami et al. [1] atacched a device with an infrared sensor to shoes and combined it with the IMU sensor. Since large-scale facilities are unnecessary, it encourages usage in daily scenarios. However, it is difficult to secure a wide area and device may affect the subject's gait. Another alternative is to embed small sensors in the insole to measure the sole pressure [8]. T Bamberg et al. utilized this method to measure pressure distribution [3]. This method reduces the sensor's influence on the gait, obtaining a more accurate data. However, durability may be an issue as forces are directly applied onto the sensor.

# 3 SYSTEM OVERVIEW

In this paper, we measure walking using a device with sensors embedded in the outsole instead of the insole to enhance its durability. To retrieve the pressure applied to the shoe in a non-pressed state, we place multiple sensors in the groove of the shoe sole. The sensors measure the deformation of each 16 cells in the shoe sole and the change is outputted as sensor value in each frame. A microcontroller attached to the shoe sends the values to the host PC where the program records the values on an average of 34.8fps and the timestamp of each data. After the measurement, data on the stance phase is extracted from the sensor data. We estimate the CoP position and identify the gait pattern by subjecting the stance data to machine learning.

Our system utilizes photo-reflective sensors, reflection type sensors that estimate the distance to an object by measuring the intensity of infrared light reflected from an object. Ogata et al. used these sensors to measure the skin deformation of the arm for gesture identification [10]. We placed the sensors in the sole, facing towards the ground, to measure the change in distance between the bottom of the cell and the sensors (Figure 2).

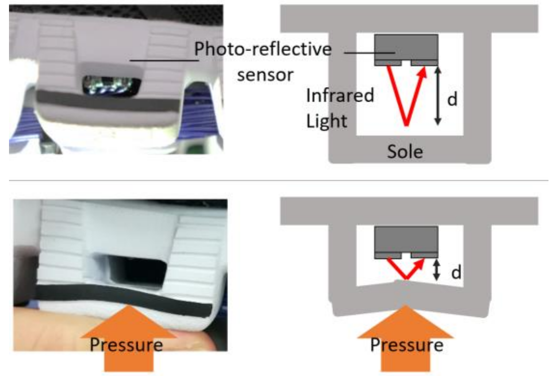


**Figure 2: Principle of estimating CoP by photo-reflective sensor in sole of shoes.**


**Figure 3: Overview of hardware.**

The sole deforms according to the amount of force applied, allowing the sensors to detect the magnitude of pressure applied. Figure 3 illustrates the appearance of the device consisting of Cloud shoes by On Inc., photo-reflective sensors (SG-105) and microcontroller (Arduino mini). In this example, we installed a sensor on each part of the sole, summing up to 16 sensors, all connected to the microcontroller.

# 4 ESTIMATION OF COP

We record the CoP, global coordinates of shoes and GRF of walks using a Vicon Nexus 2 and a force plate as data to be used for estimation. We attach 4 markers to 1 shoe for motion capturing purposes. We first transmit the sensor values acquired from the shoe devices to the PC, to be recorded as a time series data of walks. At the start of the measurement, we issue an analog signal from the program to synchronize the sensor value with the force plate and motion capture data. After the measurement, we extract data from the marker's position and the force plate's value when the shoe is in contact with the ground. Then, we calculate the CoP coordinate expressed in the shoe's local coordinate system using the extracted CoP and the shoes' 3D position in the global coordinate system acquired by motion capture. Here, the coordinate of the marker of the shoe's heel is taken as the local coordinates' origin. Then, we transform

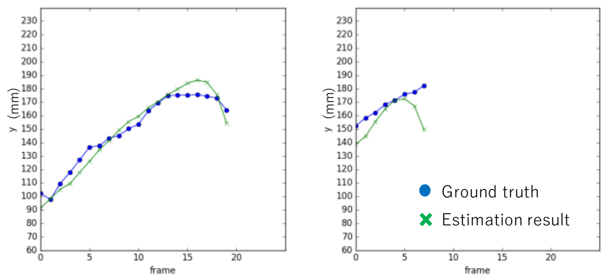


**Figure 4: Example of ground truth and estimation results of CoP when the decision coefficients is the highest(left) and lowest(right).**

the global coordinates to local coordinates by using a perpendicular line drawn from the heel marker's coordinates as the local coordinates' Y axis, with a straight line that connects the markers' coordinates attached to the left and right of the ankle. The following method generates a model to represent the relationship between the calculated CoP coordinates and the shoe's sensor value.

## 4.1 Learning of Regression Model

There are 2 models to convert sensor values to CoP coordinate; a dynamic model and a regression model. A dynamic model is a method to obtain the center of gravity by using the sensor's position and the pressure estimated from the sole's deformation. To obtain a detailed model, it is necessary to accurately measure the sensor's position in the shoe coordinate system and derive the relationship between the pressure and the deformation in each cell of the shoe.

Compared to a dynamic model that requires detailed sensor position and shoe deformation measurement, a regression model only requires sensor values, motion capture and force plate data. Therefore, we adopt the regression model which is more suitable for our system. From the characteristics of the photo-reflector, it is considered that the relationship between sensor value and shoe deformation becomes nonlinear. Therefore, we adopted the function of random forest regression contained in scikit-learn.

In this system, we first acquire sensor values, shoes' global coordinates and CoP using the optical motion capture system and the force plates as the learning phase and extract data when shoes is in contact with the ground. A regression analysis is performed on the sensor values and CoP at this time to generate a regression model. Thereafter, data are extracted in the same manner as at the time of estimation, and the sensor values at the time of contact are applied to the generated regression model, thereby estimating the CoP. Estimation can be made from the sensor value by referring to the learned regression model.

## 4.2 Experiment to Estimate the Accuracy of Evaluation of CoP

We conducted an experiment to estimate the accuracy of evaluation of CoP. We instructed participants to walk on the force plate at their usual speed while wearing the device. We utilized the CoP calculated by the force place and motion capture as true values. We conducted this study indoors with 2 male participants. We obtained data of each step that was extracted from the measured data set, totaling to 30 data detected by the marker. We divided the data into 5 pieces and utilized 4 pieces as the learning data for regression analysis and 1 piece as a test data for the regression model to calculate the coefficient of determination.

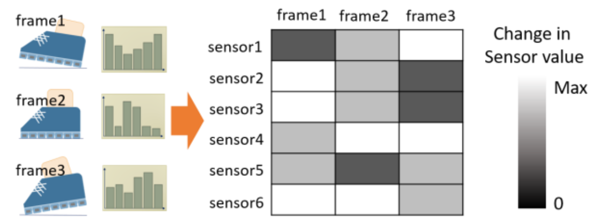


**Figure 5: Convert the change in sensor value to image.**

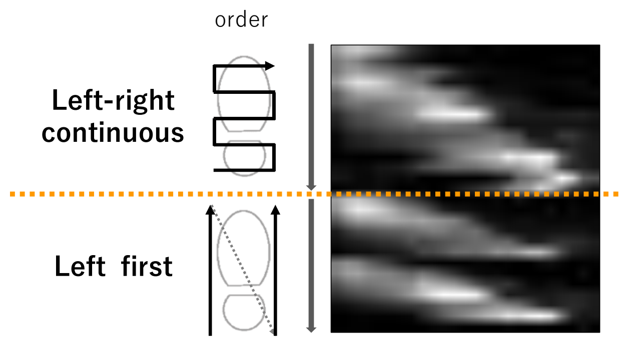


**Figure 6: Combine images made by 2 different orders.**

## 4.3 Experiment to Estimate the Accuracy

We conducted an experiment to estimate the accuracy of evaluating the walking speed with our shoe device. We found that the time taken for 1 step was 15.0 frame on average and the the coefficient of determination was 0.94 at maximum and 0.69 on average. We also observed that the root mean square was 11.35 mm, and the maximum deviation between the estimated value and the true value in all estimates was 32.7mm. Figure 4 shows the estimation results of the steps with the highest and lowest decision coefficients.

## 5 IDENTIFICATION OF GAIT PATTERN

A sensor value for 1 step is extracted from the walking data and is converted into image data. Feature qualities of this image data are then calculated to be used for machine learning, where we obtained the relationship between the deformation of cell of the device and gait pattern, and thus, identify the gait pattern.

## 5.1 Extraction of Data for One Step

We ask the users to walk in a specified gait pattern, and record the changes of sensor values to be used as learning data. We calculate the differences between the sensor values and non-pressure state values. The moment of contact is when the sum of differences of the sensors exceeds a fixed value and the moment of leaving is when the sum of the sensors falls below a threshold value after grounding.

## 5.2 Conversion of Sensor Values to Image Data

We process the acquired time series data to machine learning. Fukui et al. proposed a method of acquiring HOG feature quantities to be performed with machine learning with images using a wearable display [4]. By using the time series data as one image, they extracted features from the shade pattern of the image. We adopt a similar method in our system.

First, sensor data are arranged in 1 line in each frame. This is combined along the time axis to generate a matrix that stores the sensor data of 1 step. The amount changed in sensor value as compare to the non-pressure state is converted to 0~255 pixel values, to generate an image according to the value of the matrix. Figure 5 illustrates a generated grayscale image, where the row of the image represents time and the column represents value of one sensor. In the image, the white areas are where the pixel values are large due to the greater reaction of the sensor. By calculating the feature values of this image, we can obtain the difference for each gait pattern in the time series data and each pattern can be identified by machine learning.

For the movement of the part of the shoes which are under pressure, we utilize 2 types of arrangement of the sensor values of the image data when it is generated, to observe the difference in reaction of the sensor in the inside and outside of the shoe and the change in progress direction component.

Each figure shows 2 orders, one where the shoes are arranged from the heel to the toe in a left-right continuous state and another where the left row of the shoe is arranged first and the right row is arranged in the subsequent row. For the left-right consecutive order, the changes from the heel to the toe are largely reflected in the image. For the left and right arranged in order, the differences in the way of change between the inside and outside are largely reflected. The images were using these 2 different orders which are combined vertically in order for the same frames to be displayed on the same row. We created images of 9 types of gait patterns; normal, heel contact, toe contact, inner locus, outer locus, pigeon-toed, bowlegged, left turn and right turn.

We calculate HOG feature value of each images created from the time series data, and generate an identifier by using the gait pattern labeled with the acquired feature quantity as the learning data and Support Vector machine (SVM).

## 5.3 Experiment and result

To evaluate the gait patterns' identification accuracy, we obtain discrimination rates of 9 types of walking patterns. Below illustrates the environment of our experiment. Our study was conducted indoors with 5 male participants. We asked the participants to wear the shoe device and walked with specified conditions. We extracted data of 15 steps excluding the start and end of the walk that are expected to be different walking methods. These are classified into 9 types of identification; normal, heel contact, toe contact, inner locus, outer locus, pigeon-toed, bowlegged, left turn, right turn. We divided each obtained data into 5 pieces, and carried out a 5-fold cross validation with 4 pieces as the learning data and 1 piece as the test data. The recognition accuracy was 78% on average. The accuracy of pigeon-toed was 55% in the separated state, the lowest rate among all classes. The ratio of misidentifying pigeon-toed as bowlegged was 12%. This shows that it is still challenging to differentiate walking above the shoes.

# 6 DISCUSSION

In this research, the shoe sole's deformation is measured by utilizing photo-reflective sensors embedded in it, where only 1 sensor is arranged in the left and right of the x-axis direction. Since each sensor is about 1cm from the shoe's outer frame, it has difficulties to measure the deformation precisely. Therefore, it is challenging to estimate the X-axis direction of the CoP position estimation, as time changes are not taken into consideration.

The accuracy of the estimation increases when the center of gravity is within the sensor area. To increase the accuracy, we can either reduce the sensor's distance from the outer frame of the shoe or increase the number of sensors in the X direction. We may also improve the accuracy by comparing with the stationary standing position.

Since we are measuring the sole's deformation rather than the pressure asserted during a walk, a lag will always occur when the shoes deform from the movement of the CoP until the detection of the deformation. As we did not include this lag into the consideration, the accuracy of the estimation will decrease if the walking speed increases. This problem can be dealt with by including the measured time required for the deformation and time until the shoes return to their original state after deformation into the preprocessing of learning.

In this method, not only the position of the CoP but also the force applied to each can be calculated from the value of the sensor. By measuring the CoP and force fluctuation and analyzing the spectrum, it is possible to statistically obtain characteristics of each age. Spectral analysis makes it possible to detect diseases related to walking.

# 7 CONCLUSION

In this paper, we developed a wearable device that measures the sole's deformation using photo reflective sensors. We proposed a method to estimate the CoP from a walking shoe sole deformation to identify the gait pattern. Our experiments show that the coefficient of determination of estimation of CoP was 0.69 and the average accuracy of the identification of the gait pattern is about 78%.

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